

Survey of Hallucination in Natural Language Generation

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Natural Language Generation (NLG) has improved exponentially in recent years thanks to the development of sequence-to-sequence deep learning technologies such as Transformer-based language models. This advancement has led to more fluent and coherent NLG, leading to improved development in downstream tasks such as abstractive summarization, dialogue generation and data-to-text generation. However, it is also apparent that deep learning based generation is prone to hallucinate unintended text, which degrades the system performance and fails to meet user expectations in many real-world scenarios. To address this issue, many studies have been presented in measuring and mitigating hallucinated texts, but these have never been reviewed in a comprehensive manner before.

In this survey, we thus provide a broad overview of the research progress and challenges in the hallucination problem in NLG. The survey is organized into two parts: (1) a general overview of metrics, mitigation methods, and future directions; (2) an overview of task-specific research progress on hallucinations in the following downstream tasks, namely abstractive summarization, dialogue generation, generative question answering, data-to-text generation, machine translation, and visual-language generation; and (3) hallucinations in large language models (LLMs)¹. This survey serves to facilitate collaborative efforts among researchers in tackling the challenge of hallucinated texts in NLG.

CCS Concepts: • **Computing methodologies** → **Natural language generation; Neural networks.**

Additional Key Words and Phrases: Hallucination, Intrinsic Hallucination, Extrinsic Hallucination, Faithfulness in NLG, Factuality in NLG, Consistency in NLG

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¹This section was updated in Jan 2024.

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1 INTRODUCTION

Natural Language Generation (NLG) is one of the crucial yet challenging sub-fields of Natural Language Processing (NLP). NLG techniques are used in many downstream tasks such as summarization, dialogue generation, generative question answering (GQA), data-to-text generation, and machine translation. Recently, the rapid development of NLG has captured the imagination of many thanks to the advances in deep learning technologies, especially Transformer [262]-based models like BERT [43], BART [140], GPT-2 [209], and GPT-3 [19]. The conspicuous development of NLG tasks attracted the attention of many researchers, leading to an increased effort in the field.

Alongside the advancement of NLG models, attention towards their limitations and potential risks has also increased. Some early works [99, 277] focus on the potential pitfalls of utilizing the standard likelihood maximization objective in training and decoding of NLG models. They discovered that such likelihood maximization approaches could result in *degeneration*, which refers generated output that is bland, incoherent, or gets stuck in repetitive loops. Concurrently, it is discovered that NLG models often generate text that is nonsensical, or unfaithful to the provided source input [122, 215, 222, 263]. Researchers started referring to such undesirable generation as *hallucination* [177]².

Hallucination in NLG is concerning because it hinders performance and raises safety concerns for real-world applications. For instance, in medical applications, a hallucinatory summary generated from a patient information form could pose a risk to the patient. It may provoke a life-threatening incident for a patient if the instructions of a medicine generated by machine translation are hallucinatory. Hallucination can also lead to potential privacy violations. Carlini et al. [25] demonstrate that language models can be prompted to recover and generate sensitive personal information from the training corpus (e.g., email address, phone/fax number, and physical address). Such memorization and recovery of the training corpus is considered a form of hallucination because the model is generating text that is not “faithful” to the source input content (i.e., such private information does not exist in the source input).

Currently, there are many active efforts to address hallucination for various NLG tasks. Analyzing hallucinatory content in different NLG tasks and investigating their relationship would strengthen our understanding of this phenomenon and encourage the unification of efforts from different NLG fields. However, to date, little has been done to understand hallucinations from a broader perspective that encompasses all major NLG tasks. To the best of our knowledge, existing surveys have only focused specific tasks like abstractive summarization [104, 177] and translation [134]. Thus, in this paper, we present a survey of the research progress and challenges in the hallucination problem in NLG. And offer a comprehensive analysis of existing research on the phenomenon of hallucination in different NLG tasks, namely abstractive summarization, dialogue generation, generative question answering, data-to-text generation, and machine translation. We mainly discussed hallucination of the unimodal NLG tasks that have textual input sources upon which the generated text can be assessed. We also briefly summarize hallucinations in multi-modal settings such as visual-language tasks [3, 16]. This survey can provide researchers with a high-level insight derived from the similarities and differences of different approaches. Furthermore, given the various stages of development in studying hallucination from different tasks, the survey can assist researchers in drawing inspiration on concepts, metrics, and mitigation methods.

²The term “hallucination” first appeared in Computer Vision (CV) in Baker and Kanade [8] and carried more positive meanings, such as superresolution [8, 159], image inpainting [68], and image synthesizing [310]. Such hallucination is something we take advantage of rather than avoid in CV. Nevertheless, recent works have started to refer to a specific type of error as “hallucination” in image captioning [16, 222] and object detection [7, 120], which denotes non-existing objects detected or localized incorrectly at their expected position. The latter conception is similar to “hallucination” in NLG.

Organization of this Survey. The remainder of this survey is organized as follows. Section 2 ~ Section 6 provide an overview of the hallucination problem in NLG by discussing the definition and categorization, contributors, metrics, and mitigation methods of hallucinations, respectively. The second part of our survey discusses the hallucination problem associated with specific NLG tasks: abstractive summarization in Section 7, dialogue generation in Section 8, GQA in Section 9, data-to-text generation in Section 10, machine translation in Section 11, and VL generation in Section 12. The third part discusses this phenomenon in LLMs in Section 13. Finally, we conclude the whole survey in Section 14.

2 DEFINITIONS

In the general context outside of NLP, hallucination is a psychological term referring to a particular type of perception [72, 166]. Blom [17] define hallucination as **“a percept, experienced by a waking individual, in the absence of an appropriate stimulus from the extracorporeal world”**. Simply put, a hallucination is an unreal perception that feels real. The undesired phenomenon of **“NLG models generating unfaithful or nonsensical text”** shares similar characteristics with such psychological hallucinations – explaining the choice of terminology. Hallucinated text gives the impression of being fluent and natural despite being unfaithful and nonsensical. It appears to be grounded in the real context provided, although it is actually hard to specify or verify the existence of such contexts. Similar to psychological hallucination, which is hard to tell apart from other “real” perceptions, hallucinated text is also hard to capture at first glance.

Within the context of NLP, the above definition of hallucination, *the generated content that is nonsensical or unfaithful to the provided source content* [71, 177, 198, 326], is the most inclusive and standard. However, there do exist variations in definition across NLG tasks, which will be further described in the later task-specific sections.

2.1 Categorization

Following the categorization from previous works [59, 104, 177], there are two main types of hallucinations, namely intrinsic hallucination and extrinsic hallucination. To explain the definition and categorization more intuitively, we give examples of each category of hallucinations for each NLG downstream task in Table 1.

- (1) **Intrinsic Hallucinations:** The generated output that contradicts the source content. For instance, in the abstractive summarization task from Table 1, the generated summary *“The first Ebola vaccine was approved in 2021”* contradicts the source content *“The first vaccine for Ebola was approved by the FDA in 2019.”*
- (2) **Extrinsic Hallucinations:** The generated output that cannot be verified from the source content (i.e., output that can neither be supported nor contradicted by the source). For example, in the abstractive summarization task from Table 1, the information *“China has already started clinical trials of the COVID-19 vaccine.”* is not mentioned in source. We can neither find evidence for the generated output from the source nor assert that it is wrong. Notably, the extrinsic hallucination is not always erroneous because it could be from factually correct external information [177, 247]. Such factual hallucination can be helpful because it recalls additional background knowledge to improve the informativeness of the generated text. However, in most of the literature, extrinsic hallucination is still treated with caution because its unverifiable aspect of this additional information increases the risk from a factual safety perspective.

2.2 Task Comparison

The previous subsection is about the definition and categorization of hallucination commonly shared by many NLG tasks. Yet, there are some task-specific differences.

For the abstractive summarization, data-to-text, and dialogue tasks, the main difference is in what serves as the “source” and the level of tolerance towards hallucinations. The source in abstractive summarization is the input source text that is being summarized [228], while the source in data-to-text is non-linguistic data [80, 219], and the source(s) in the dialogue system is dialogue history and/or the external knowledge sentences. Tolerance towards hallucinations is very low in both the summarization [197] and data-to-text tasks [198, 269, 274] because it is essential to provide faithful generation. In contrast, the tolerance is relatively higher in dialogue systems because the desired characteristics are not only faithfulness but also user engagement, especially in open-domain dialogue systems [103, 109].

For the generative question answering (GQA) task, the exploration of hallucination is at its early stage, so there is no standard definition or categorization of hallucination yet. However, we can see that the GQA literature mainly focuses on “intrinsic hallucination” where the source is the world knowledge [142]. Lastly, unlike the aforementioned tasks, the categorizations of hallucinations in machine translation vary within the task. Most relevant literature agrees that translated text is considered a hallucination when the source text is completely disconnected from the translated target [134, 187, 215]. For further details, please refer to Section 11.

2.3 Terminology Clarification

Multiple terminologies are associated with the concept of hallucination. We provide clarification of the commonly used terminologies *hallucination*, *faithfulness*, and *factuality* to resolve any confusion. *Faithfulness* is defined as staying consistent and truthful to the provided source – an antonym to “hallucination.” Any work that tries to maximize faithfulness thus focuses on minimizing hallucination. For this reason, our survey includes all those works that address the faithfulness of machine-generated outputs. *Factuality* refers to the quality of being actual or based on fact. Depending on what serves as the “fact”, “factuality” and “faithfulness” may or may not be the same. Maynez et al. [177] differentiate “factuality” from “faithfulness” by defining the “fact” to be the world knowledge. In contrast, Dong et al. [50] use the source input as the “fact” to determine the factual correctness, making “factuality” indistinguishable from “faithfulness”. In this paper, we adopt the definition from Maynez et al. [177] because we believe having such a distinction between source knowledge and world knowledge provides a more clear understanding.

Note that the judging criteria for what is considered faithful or hallucinated (i.e., the definition of hallucination) can differ across tasks. For more details of these variation definitions, you can find in the later task-specific sections.

3 CONTRIBUTORS TO HALLUCINATION IN NLG

3.1 Hallucination from Data

The main cause of hallucination from data is source-reference divergence. This divergence happens 1) as an artifact of heuristic data collection or 2) due to the nature of some NLG tasks that inevitably contain such divergence. When a model is trained on data with source-reference(target) divergence, the model can be encouraged to generate text that is not necessarily grounded and not faithful to the provided source.

Heuristic data collection. When collecting large-scale datasets, some works heuristically select and pair real sentences or tables as the source and target [133, 283]. As a result, the target reference may contain information that cannot be supported by the source [198, 268]. For instance, when

| Task | Sub-Task | Type | Source | Output | | | | | | | | | | | | | | | | | | | | | |
|---------------------------------|---------------------|-----------|--|--|------|--------|------|-----|--------|-----|---------|---------|----|---|-----|----|---|---------|--------|----|----|----|----|---|--|
| Abstractive Summarization [197] | Task-oriented [153] | Intrinsic | The first vaccine for Ebola was approved by the FDA in 2019 in the US, five years after the initial outbreak in 2014. To produce the vaccine, scientists had to sequence the DNA of Ebola, then identify possible vaccines, and finally show successful clinical trials. Scientists say a vaccine for COVID-19 is unlikely to be ready this year, although clinical trials have already started. | The first Ebola vaccine was approved in 2021. | | | | | | | | | | | | | | | | | | | | | |
| | | Extrinsic | | China has already started clinical trials of the COVID-19 vaccine. | | | | | | | | | | | | | | | | | | | | | |
| Dialogue | Task-oriented [153] | Intrinsic | inform (NAME = pickwick hotel, PRICERANGE = moderate) | the hotel named pickwick hotel is in a high price range. | | | | | | | | | | | | | | | | | | | | | |
| | | Extrinsic | | the pickwick hotel in san diego is a moderate price range | | | | | | | | | | | | | | | | | | | | | |
| | Open-domain [226] | Intrinsic | Dialog History: Speaker 1: What do you think about Murray? Speaker 2: I think Murray is a great player he just needs to stay healthy in order to compete more. Who do you like best? | Speaker 1: I like Roger Nadal the most! | | | | | | | | | | | | | | | | | | | | | |
| | | Extrinsic | Knowledge: In tennis, the term Big Four refers to the quartet of men's singles players comprising Roger Federer, Rafael Nadal, Novak Djokovic, and Andy Murray. | Speaker 1: I like Djokovic. He has played in the top ten singles players of the world . | | | | | | | | | | | | | | | | | | | | | |
| Generative QA [191] | Task-oriented [153] | Intrinsic | Question: dow jones industrial average please? | Answer: The Dow Jones Industrial Average (DJIA) is an index of 30 major U.S. stock indexes . The DJIA was created in 1896 by Charles Dow, a statistician and editor of The Wall Street Journal. The index was first published in the mid-1880s, and was last updated on May 26, 1896 . | | | | | | | | | | | | | | | | | | | | | |
| | | Extrinsic | Question: definition of sadducee | Answer: Sadducees. noun. The definition of a sadducee is a person who acts in a deceitful or duplicitous manner. An example of a Sadducee is a politician who acts deceitfully in order to gain political power. 1 a member of a Jewish sect that was active during the Second Temple. | | | | | | | | | | | | | | | | | | | | | |
| Data2text [283] | Task-oriented [153] | Intrinsic | <table border="1"> <thead> <tr> <th>TEAM</th> <th>CITY</th> <th>WIN</th> <th>LOSS</th> <th>PTS</th> <th>FG_PCT</th> <th>BLK</th> </tr> </thead> <tbody> <tr> <td>Rockets</td> <td>Houston</td> <td>18</td> <td>5</td> <td>108</td> <td>44</td> <td>7</td> </tr> <tr> <td>Nuggets</td> <td>Denver</td> <td>10</td> <td>13</td> <td>96</td> <td>38</td> <td>7</td> </tr> </tbody> </table> | TEAM | CITY | WIN | LOSS | PTS | FG_PCT | BLK | Rockets | Houston | 18 | 5 | 108 | 44 | 7 | Nuggets | Denver | 10 | 13 | 96 | 38 | 7 | The Houston Rockets (18-4) defeated the Denver Nuggets (10-13) 108-96 on Saturday. |
| TEAM | | CITY | WIN | LOSS | PTS | FG_PCT | BLK | | | | | | | | | | | | | | | | | | |
| Rockets | Houston | 18 | 5 | 108 | 44 | 7 | | | | | | | | | | | | | | | | | | | |
| Nuggets | Denver | 10 | 13 | 96 | 38 | 7 | | | | | | | | | | | | | | | | | | | |
| Translation [326] | Task-oriented [153] | Intrinsic | 迈克尔去书店。(Michael went to the bookstore on Thursday.) | Jerry didn't go to the bookstore. | | | | | | | | | | | | | | | | | | | | | |
| | | Extrinsic | 迈克尔去书店。(Michael went to the bookstore on Thursday.) | Michael happily went to the bookstore with his friend . | | | | | | | | | | | | | | | | | | | | | |

Table 1. Examples of each category of hallucinations for each task. In the Data2Text task, H/A: home/away, MIN: minutes, PTS: points, REB: rebounds, AST: assists, BLK: blocks, FG_PCT: field goals percentage. The examples for VL tasks are shown in Figure 2 and Figure 3

| Category | Task | Works | |
|-------------------|---------------------------|--|--|
| Statistical | Dialogue | Shuster et al. [233] | |
| | Data2Text | Dhingra et al. [44], Wang et al. [274] | |
| | Translation | Martindale et al. [175] | |
| | Captioning | Rohrbach et al. [222] | |
| Automatic Metrics | Abstractive Summarization | Durmus et al. [53], Kryscinski et al. [127], Nan et al. [190], Wang et al. [264] Gabriel et al. [74], Goodrich et al. [86], Pagnoni et al. [197], Zhou et al. [326] Falke et al. [65], Laban et al. [132], Mishra et al. [185], Scialom et al. [227] | |
| | | Dialogue | Balakrishnan et al. [9], Honovich et al. [101], Li et al. [153] Dziri et al. [60], Gupta et al. [94], Santhanam et al. [226] |
| | Model-based | Generative QA | Sellam et al. [229]*, Zhang et al. [318]*, Durmus et al. [53]* Wang et al. [264]*, Su et al. [237] |
| | | Data2Text | Dušek and Kasner [56], Liu et al. [162], Wiseman et al. [283] Filippova [71], Rebuffel et al. [217], Tian et al. [251] |
| | Translation | Kong et al. [125], Lee et al. [134], Tu et al. [257] Feng et al. [70], Garg et al. [79], Zhou et al. [326] Parthasarathi et al. [199], Raunak et al. [215] | |
| | | Task-Agnostic | Goyal and Durrett [90], Liu et al. [160], Zhou et al. [326] |
| | Data-Related | Abstractive Summarization | Cao et al. [24], Nan et al. [190], Zhu et al. [329] Gunel et al. [92] |
| | | Dialogue | Honovich et al. [101], Shen et al. [230], Wu et al. [285] Santhanam et al. [226], Shuster et al. [233] |
| Generative QA | | Bi et al. [14], Fan et al. [66], Yin et al. [297] Liu et al. [162], Nie et al. [193], Parikh et al. [198], Wang [268] | |
| Data2Text | | Nie et al. [192], Rebuffel et al. [216] | |
| Translation | | Lee et al. [134], Raunak et al. [215] Briakou and Carpuat [18], Junczys-Dowmunt [112] | |
| | | Captioning | Biten et al. [16] |
| Mitigation Method | Abstractive Summarization | Huang et al. [102], Li et al. [143], Song et al. [235] Aralikatte et al. [6], Cao et al. [21], Cao and Wang [22] Albrecht and Hwa [4], Chen et al. [31], Zhao et al. [322] | |
| | | Dialogue | Balakrishnan et al. [9], Li et al. [153], Rashkin et al. [214] Dziri et al. [59] |
| | Modeling and Inference | Generative QA | Fan et al. [66], Krishna et al. [126], Li et al. [142] Nakano et al. [189], Su et al. [237] |
| | | Data2Text | Liu et al. [162], Tian et al. [251], Wang et al. [269, 274], Xu et al. [291] Filippova [71], Rebuffel et al. [216], Su et al. [239], Xiao and Wang [286] Puduppully and Lapata [208] |
| | Translation | Feng et al. [70], Lee et al. [134], Weng et al. [281] Li et al. [150], Raunak et al. [215], Wang and Sennrich [267] Bengio et al. [12], Zhou et al. [326] Goyal et al. [89], Xu et al. [290] | |
| | | Captioning | Dai et al. [41], Xiao and Wang [286] |

Table 2. Evaluation metrics and mitigation methods for each task. *The hallucination metrics are not specifically proposed for generative question answering (GQA), but they can be adapted for that task.

constructing WIKIBIO [133], a dataset for generating biographical notes based on the infoboxes of Wikipedia, the authors took the Wikipedia infobox as the source and the first sentence of the Wikipedia page as the target ground-truth reference. However, the first sentence of the Wikipedia article is not necessarily equivalent to the infobox in terms of the information they contain. Indeed, Dhingra et al. [44] points out that 62% of the first sentences in WIKIBIO have additional information not stated in the corresponding infobox. Such mismatch between source and target in datasets can lead to hallucination.

Another problematic scenario is when duplicates from the dataset are not properly filtered out. It is almost impossible to check hundreds of gigabytes of text corpora manually. Lee et al. [135] show that duplicated examples from the pretraining corpus bias the model to favor generating repeats of the memorized phrases from the duplicated examples.

Innate divergence. Some NLG tasks by nature do not always have factual knowledge alignment between the source input text and the target reference, especially those that value diversity in generated output. For instance, it is acceptable for open-domain dialogue systems to respond in chit-chat style, subjective style [214], or with a relevant fact that is not necessarily present in the user input, history or provided knowledge source – this improves the engagingness and diversity of the dialogue generation. However, researchers have discovered that such dataset characteristic leads to inevitable extrinsic hallucinations.

3.2 Hallucination from Training and Inference

As discussed in the previous subsection, source-reference divergence existing in dataset is one of the contributors of hallucination. However, Parikh et al. [198] show that hallucination problem still occurs even when there is very little divergence in dataset. This is because there is another contributor of hallucinations – training and modeling choices of neural models [122, 215, 222, 263].

Imperfect representation learning. The encoder has the role of comprehending and encoding input text into meaningful representations. An encoder with a defective comprehension ability could influence the degree of hallucination [198]. When encoders learn wrong correlations between different parts of the training data, it could result in erroneous generation that diverges from the input [6, 70, 143, 251].

Erroneous decoding. The decoder takes the encoded input from the encoder and generates the final target sequence. Two aspects of decoding contribute to hallucinations. First, decoders can attend to the wrong part of the encoded input source, leading to erroneous generation [251]. Such wrong association results in generation with facts mixed up between two similar entities [59, 233]. Second, the design of the decoding strategy itself can contribute to hallucinations. Dziri et al. [59] illustrate that a decoding strategy that improves the generation diversity, such as top-k sampling, is positively correlated with increased hallucination. We conjecture that deliberately added “randomness” by sampling from the top-k samples instead of choosing the most probable token increase the unexpected nature of the generation, leading to a higher chance of containing hallucinated content.

Exposure Bias. Regardless of decoding strategy choices, the exposure bias problem [12, 213], defined as the discrepancy in decoding between training and inference time, can be another contributor to hallucination. It is common practice to train the decoder with teacher-forced maximum likelihood estimation (MLE) training, where the decoder is encouraged to predict the next token conditioned on the ground-truth prefix sequences. However, during the inference generation, the model generates the next token conditioned on the historical sequences previously generated by itself [97]. Such a discrepancy can lead to increasingly erroneous generation, especially when the target sequence gets longer.

Parametric knowledge bias. Pre-training of models on a large corpus is known to result in the model memorizing knowledge in its parameters [169, 201, 221]. This so-called parametric knowledge helps improve the performance of downstream tasks but also serves as another contributor to hallucinatory generation. Large pre-trained models used for downstream NLG tasks are powerful in providing generalizability and coverage, but Longpre et al. [163] have discovered that such

models prioritize parametric knowledge over the provided input. In other words, models that favor generating output with their parametric knowledge instead of the information from the input source can result in the hallucination of excess information in the output. On the other hand, current research works [20, 114, 174, 212, 298] highlight a discrepancy between surface realization and inherent knowledge of the model in NLG tasks. Models can realize they are generating something hallucinated in some way.

4 METRICS MEASURING HALLUCINATION

Recently, various studies have illustrated that most conventional metrics used to measure the quality of writing are not adequate for quantifying the level of hallucination [218]. It has been shown that state-of-the-art abstractive summarization systems, evaluated with metrics such as ROUGE, BLEU, and METEOR, have hallucinated content in 25% of their generated summaries [65]. A similar phenomenon has been shown in other NLG tasks, where it has been discovered that traditional metrics have a poor correlation with human judgment in terms of the hallucination problem [44, 53, 101, 126]. Therefore, there are active research efforts to define effective metrics for quantifying hallucination. FRANK [197] surveys the faithfulness metrics for summarization and compares these metrics' correlations with human judgments. To assess the example-level accuracy of metrics in diverse tasks, TRUE [100] reports their Area Under the ROC Curve (ROC AUC) in regard to hallucinated example detection.

4.1 Statistical Metric

One of the simplest approaches is to leverage lexical features (n-grams) to calculate the information overlap and contradictions between the generated and the reference texts – the higher the mismatch counts, the lower the faithfulness and thus the higher the hallucination score.

Given that many traditional metrics leverage the target text as the ground-truth reference (e.g., ROUGE, BLEU, etc.), Dhingra et al. [44] build upon this idea and propose PARENT (Precision And Recall of Entailed n-grams from the Table)³, a metric which can also measure hallucinations using *both* the source and target text as references. Particularly, PARENT n-gram lexical entailment matches generated text with both the source table and target text. The F1-score that combines the precision and recall of the entailment reflects the accuracy in the table-to-text task. The source text is additionally used because it is not guaranteed that the output target text contains the complete set of information available in the input source text.

It is common for NLG tasks to have multiple plausible outputs from the same input, which is known as one-to-many mapping [91, 238]. In practice, however, covering all the possible outputs is too expensive and almost impossible. Thus, many works simplify the hallucination evaluation setup by relying on the source text as the sole reference. Their metrics just focus on the information referred by input sources to measure hallucinations, especially intrinsic hallucinations. For instance, Wang et al. [274] propose PARENT-T, which simplifies PARENT by only using table content as the reference. Similarly, Knowledge F1 [233] – a variant of unigram F1 – has been proposed for knowledge-grounded dialogue tasks to measure the overlap between the model's generation and the knowledge used to ground the dialogue during dataset collection.

Furthermore, Martindale et al. [175] proposed a bag-of-vectors sentence similarity (BVSS) metric for measuring sentence adequacy in machine translation, that only refers to the target text. This statistical metric helps to determine whether the MT output has a different amount of information than the translation reference.

³Note that PARENT is a general metric like ROUGE and BLEU, not only constrained to hallucination

Although simple and effective, one potential limitation of the lexical matching is that it can only handle the lexical information. Thus, it fails to deal with syntactic or semantic variations [229].

4.2 Model-based Metric

Model-based metrics leverage neural models to measure the hallucination degree in the generated text. They are proposed to handle more complex syntactic and even semantic variations. The model-based metrics comprehend the source and generated texts and detect the knowledge/content mismatches. However, the neural models can be subject to errors that can propagate and adversely affect the accurate quantification of hallucination.

4.2.1 Information Extraction (IE)-based. It is not always easy to determine which part of the generated text contains the knowledge that requires verification. IE-based metrics use IE models to represent the knowledge in a simpler relational tuple format (e.g., *subject, relation, object*), then verify against relation tuples extracted from the source/reference. Here, the IE model is identifying and extracting the “facts” that require verification. In this way, words containing no verifiable information (e.g., stopwords, conjunctions, etc) are not included in the verification step.

For example, ground-truth reference text “Brad Pitt was born in 1963” and generated text “Brad Pitt was born in 1961” will be mapped to the relation triples (Brad Pitt, born-in, 1963) and (Brad Pitt, born-in, 1961) respectively⁴. The mismatch between the dates (1963≠1961) indicates that there is hallucination. One limitation associated with this approach is the potential error propagation from the IE model.

4.2.2 QA-based. This approach implicitly measures the knowledge overlap or consistency between the generation and the source reference. This is based on the intuition that similar answers will be generated from a same question if the generation is factually consistent with the source reference. It is already put in use to evaluate hallucinations in many tasks, such as summarization [53, 227, 264], dialogue [101], and data2text generation [217].

QA-based metric that measures the faithfulness of the generated text is consisted of three parts: First, given a generated text, a question generation (QG) model generates a set of question-answer pairs. Second, a question answering (QA) model answers the generated questions given a ground-truth source text as the reference (containing knowledge). Lastly, the hallucination score is computed based on the similarity of the corresponding answers.

Similar to the IE-based metrics, the limitation of this approach is the potential error that might arise and propagated from either the QG model or the QA model.

4.2.3 Natural Language Inference (NLI) Metrics. There are not many labelled datasets for hallucination detection tasks, especially at the early stage when the hallucination problem starts to gain attention. As an alternative, many works leverage the NLI dataset to tackle hallucinations. Note that NLI is a task that determines whether a “hypothesis” is true (entailment), false (contradiction), or undetermined (neutral) given a “premise”. These metrics are based on the idea that only the source knowledge reference should entail the entirety of the information in faithful and hallucination-free generation [56, 60, 65, 101, 104, 127, 132, 185, 282]. More specifically, NLI-based metrics define the hallucination/faithfulness score to be the entailment probability between the source and its generated text, also known as the percentage of times generated text entails, neutral to, and contradicts the source.

According to Honovich et al. [101], NLI-based approaches are more robust to lexical variability than token matching approaches such as IE-based and QA-based metrics. Nevertheless, as illustrated by Falke et al. [65], off-the-shelf NLI models tend to transfer poorly to the abstractive summarization

⁴This is an example from [86]

task. Thus, there is a line of research in improving and extending the NLI paradigm specifically for hallucination evaluation purposes [60, 65]. Apart from generalizability, Goyal and Durrett [90] point out the potential limitation of using sentence-level entailment models, namely their incapability to pinpoint and locate which parts of the generation are erroneous. In response, the authors propose a new dependency-level entailment and attempt to identify factual inconsistencies in a more fine-grained manner.

4.2.4 Faithfulness Classification Metrics. To improve upon NLI-based metrics, task-specific datasets are constructed to improve from the NLI-based metrics. Liu et al. [160], Zhou et al. [326] constructed syntactic data by automatically inserting hallucinations into training instances. Santhanam et al. [226] and Honovich et al. [101] construct new corpora for faithfulness classification in dialogue responses. They manually annotate the Wizard-of-Wikipedia dataset [48], a knowledge grounded dialog dataset, by judging whether each response is hallucinated.

Faithfulness specific datasets can be better than NLI datasets because entailment or neutral labels of NLI datasets and faithfulness are not equivalent. For example, the hypothesis “Putin is U.S. president” can be considered to be either neutral to or entailed from the premise “Putin is president”. However, from the faithfulness perspective, the hypothesis contains unsupported information “U.S.”, which is deemed to be hallucination.

4.2.5 LM-based Metrics. These metrics leverage two language models (LMs) to determine if each token is supported or not: An unconditional LM is only trained on the targets (ground-truth references) in the dataset, while a conditional language model LM_x is trained on both source and target data. It is assumed that the next token is inconsistent with the input if unconditional LM gets a smaller loss than conditional LM_x during forced-path decoding [71, 251]. We classify the generated token as hallucinatory if the loss from LM is lower. The ratio of hallucinated tokens to the total number of target tokens $|y|$ can reflect the hallucination degree.

4.3 Human Evaluation

Due to the challenging and imperfect nature of the current automatic evaluation of hallucinations in NLG, human evaluation [226, 233] is still one of the most commonly used approaches. There are two main forms of human evaluation: (1) scoring, where human annotators rate the hallucination level in a range; and (2) comparing, where human annotators compare the output texts with baselines or ground-truth references [242].

Multiple terminologies, such as *faithfulness* [24, 31, 71, 177, 198, 214, 214, 239, 251, 286, 326], *factual consistency* [21, 22, 33, 226, 230, 285], *fidelity* [32], *factualness*⁵ [216], *factuality*⁴ [50], or on the other hand, *hallucination* [59, 102, 162, 226, 233], *fact contradicting* [192] are used in the human evaluation of hallucination to rate whether the generated text is in accord with the source input. Chen et al. [31], Nie et al. [193] use finer-grained metrics for *intrinsic hallucination* and *extrinsic hallucination* separately. Moreover, there are some broad metrics, such as *Correctness* [9, 14, 143, 269], *Accuracy* [142, 297], and *Informativeness* [153] considering both missing and additional contents (extrinsic hallucinations) compared to the input source.

5 HALLUCINATION MITIGATION METHODS

Common mitigation methods can be divided into two categories, in accordance with two main contributors of hallucinations: **Data-Related Methods**, and **Modeling and Inference Methods**.

⁵uses the source input as the “fact”.

5.1 Data-Related Methods

5.1.1 Building a Faithful Dataset. Considering that noisy data encourage hallucinations, constructing faithful datasets manually is an intuitive method, and there are various ways to build such datasets: One way is employing annotators to write clean and faithful targets from scratch given the source [78, 280], which may lack diversity [95, 198, 203]. Another way is employing annotators to rewrite real sentences on the web [198], or targets in the existing dataset [268]. Basically, the revision strategy consists of three stages: (1) phrase trimming: removing phrases unsupported by the source in the exemplar sentence; (2) decontextualization: resolving co-references and deleting phrases dependent on context; (3) syntax modification: making the purified sentences flow smoothly. Meanwhile, other works [74, 101] leverage the model to generate data and instruct annotators to label whether these outputs contain hallucinations or not. While this approach is typically used to build diagnostic evaluation datasets, it has the potential to build faithful datasets.

5.1.2 Cleaning Data Automatically. In order to alleviate semantic noise issues, another approach is to find information that is irrelevant or contradictory to the input from the existing parallel corpus and then filter or correct the data. This approach is suitable for the case where there is a low or moderate level of noise in the original data [71, 193].

Some works [162, 215, 230] have dealt with the hallucination issue at the instance level by using a score for each source-reference pair and filtering out hallucinated ones. This corpus filtering method consists of several steps: (1) measuring the quality of the training samples in terms of hallucination utilizing the metrics described above; (2) ranking these hallucination scores in descending order; (3) selecting and filtering out the untrustworthy samples at the bottom. Instance-level scores can lead to a signal loss because divergences occur at the word level; i.e., parts of the target sentence are loyal to the source input, while others diverge [216].

Considering this issue, other works [54, 193] correct paired training samples, specifically the input data, according to the references. This method is mainly applied in the data-to-text task because structured data are easier to correct than utterances. This method consists of two steps: (1) utilizing a model to parse the meaning representation (MR), such as attribute-value pairs, from original human textual references; (2) using the MR extracted from the reference to correct the input MR through slot matching. This method will enhance the semantic consistency between input and output without abandoning a part of the dataset.

5.1.3 Information Augmentation. It is intuitive that augmenting the inputs with external information will obtain a better representation of the source. Because the external knowledge, explicit alignment, extra training data, etc., can improve the correlation between the source and target and help the model learn better task-related features. Consequently, a better semantic understanding helps alleviate the divergence from the source issue. Examples of the augmented information include entity information [162], extracted relation triples from source document [24, 102] obtained by Fact Description Extraction, pre-executed operation results [192], synthetic data generated through replacement or perturbation [31, 134], retrieved external knowledge [14, 66, 92, 233, 329], and retrieved similar training samples [15].

These methods enforce a stronger alignment between inputs and outputs. However, they will bring challenges due to the gap between the original source and augmented information, such as the semantic gap between an ambiguous utterance and a distinct MR of structured data, and the format discrepancy between the structured knowledge graph and natural language.

5.2 Modeling and Inference Methods

5.2.1 Architecture.

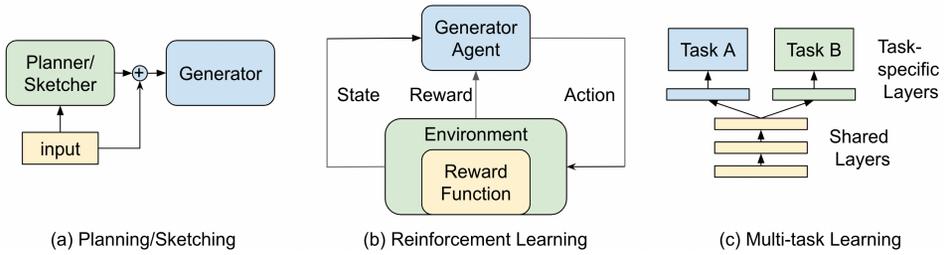


Fig. 1. The frameworks of training methods.

Encoder. The encoder learns to encode a variable-length sequence from input text into a fixed-length vector representation. As we mentioned above in Section 5.1.3, hallucination appears when the models lack semantic interpretation over the input. Some works have modified the encoder architecture in order to make it more compatible with input and learn a better representation. For example, Huang et al. [102] and Cao et al. [24] propose a dual encoder, consisting of a sequential document encoder and a structured graph encoder to deal with the additional knowledge.

Attention. The attention mechanism is an integral component in neural networks that selectively concentrates on some parts of sequences while ignoring others based on dependencies [262]. In order to encourage the generator to pay more attention to the source, Aralikkatte et al. [6] introduce a short circuit from the input document to the vocabulary distribution via source-conditioned bias. Krishna et al. [126] employ sparse attention to improve the model’s long-range dependencies in the hope of modeling more retrieved documents so as to mitigate the hallucination in the answer. Wu et al. [285] adopt inductive attention, which removes potentially uninformative attention links by injecting pre-established structural information to avoid hallucinations.

Decoder. The decoder is responsible for generating the final output in natural language given input representations [262]. Several work modified the decoder structures to mitigate hallucination, such as the multi-branch decoder [216], uncertainty-aware decoder [286], dual decoder, consisting of a sequential decoder and a tree-based decoder [235], and constrained decoder with lexical or structural limitations [9]. Based on the observation that the “randomness” from sampling-based decoding, especially near the end of sentences, can lead to hallucination, [137] propose to iteratively reduce the “randomness” through time. These decoders improve the possibility of faithful tokens while reducing the possibility of hallucinatory ones during inference by figuring out the implicit discrepancy and dependency between tokens or restricted by explicit constraints. Since such decoders may have more difficulty generating fluent or diverse text, there is a balance to be struck between them.

5.2.2 Training.

Planning/Sketching. Planning is a common method to control and restrict what the model generates by informing the content and its order [207]. Planning can be a separate step in a two-step generator [31, 162, 208, 239, 269], which is prone to progressive amplification of the hallucination problem. Or be injected into the end-to-end model during generation [291]. Sketching has a similar function to planning, and can also be adopted for handling hallucinations [269]. The difference is that the skeleton is treated as a part of the final generated text. While providing more controllability, such methods also need to strike a balance between faithfulness and diversity.

Reinforcement Learning (RL). As pointed out by Ranzato et al. [213], word-level maximum likelihood training leads to the problem of exposure bias. Some works [102, 125, 153, 181, 239] adopt RL to solve the hallucination problem, which utilizes different rewards to optimize the model. The

purpose of RL is for the agent to learn an optimal policy that maximizes the reward that accumulates from the environment [258]. The reward function is critical to RL and, if properly designed, it can provide training signals that help the model accomplish its goal of hallucination reduction. For example, Li et al. [153] propose a slot consistency reward which is the cardinality of the difference between generated template and the slot-value pairs extracted from input dialogue act. Improving the slot consistency can help reduce the hallucination phenomenon of missing or misplacing slot values in generated templates. Mesgar et al. [181] attain persona consistency sub-reward via an NLI model to reduce the hallucinations in personal facts. Huang et al. [102] use a combination of ROUGE and the multiple-choice cloze score as the reward function to improve the faithfulness of summarization outputs. The cloze score is similar to the QA-based metric, measuring how well a QA model can address the questions by reading the generated summary (as context), where the questions are automatically constructed from the reference summary. As the above examples show, some RL reward functions for mitigating hallucination are inspired by existing automatic evaluation metrics. Although RL is challenging to learn and converge due to the extremely large search space, this method has the potential to obtain the best policy for the task without an oracle.

Multi-task Learning. Multi-task learning is also utilized for handling hallucinations in different NLG tasks. In this training paradigm, a shared model is trained on multiple tasks simultaneously to learn the commonalities of the tasks. The hallucination problem may be derived from the reliance of the training process on a single dataset, leading to the fact that the model fails to learn the actual task features. By adding proper additional tasks along with the target task during training, the model can suffer less from the hallucination problem. For example, Weng et al. [281] and Garg et al. [79] incorporate a word alignment task into the translation model to improve the alignment accuracy between the input and output, and thus faithfulness. Li et al. [143] combine an entailment task with abstractive summarization to encourage models to generate summaries entailed by and faithful to the source. Li et al. [142] incorporate rationale extraction and the answer generation, which allows more confident and correct answers and reduces the hallucination problem. The Multi-task approach has several advantages, such as data efficiency improvement, overfitting reduction, and fast learning. It is crucial to choose which tasks should be learned jointly, and learning multiple tasks simultaneously presents new challenges of design and optimization [37].

Controllable Generation. Current works treat the hallucination level as a controllable attribute in order to remain the hallucination in outputs at a low level. Controllable generation techniques such as controlled re-sampling [214], control codes that can be provided manually [71, 214, 285], or predicted automatically [285] are leveraged to improve faithfulness. This method may require some annotated datasets for training. Considering that hallucination is not necessarily harmful and may bring some benefits, controllable methods can be further adapted to change the degree of hallucination to meet the demands of different real-world applications.

Other general training methods such as regularization [118, 134, 187] and loss reconstruction [150, 267, 274] have also been proposed to tackle the hallucination problem.

5.2.3 Post-Processing. Post-processing methods can correct hallucinations in the output, and this standalone task requires less training data. Especially for noisy datasets where a large proportion of the ground truth references suffer from hallucinations, modeling correction is a competitive choice to handle the hallucination problem [31]. Cao et al. [21], Chen et al. [31], Dong et al. [50], and Dziri et al. [59] follow a generate-then-refine strategy. While the post-processing correction step tends to result in ungrammatical texts, this method allows researchers to utilise SOTA models which perform best in respect of other attributes, such as fluency, and then correct the results specifically for faithfulness by using small amounts of automatically generated training data.

6 FUTURE DIRECTIONS

Many studies have been conducted to tackle the hallucination problem in NLG and its downstream tasks. As mentioned above, we have discussed common metrics and mitigation methods to advance research in these fields. From a broader perspective, we wish to point out open challenges and potential directions in regard to **metric** and **mitigation method**.

6.1 Future Directions in Metrics Design

Fine-grained Metrics. Most of the existing hallucination metrics measure intrinsic and extrinsic hallucinations together as a unified metric. However, it is common for a single generation to have both types and a number of hallucinatory sub-strings. Fine-grained metrics that can distinguish between the two types of hallucinations will provide richer insight to researchers.

In order to implement a fine-graded metric, the first step would be to identify the exact location of the hallucinatory sub-strings correctly. However, some metrics such as those that are QA-based cannot identify the individual hallucinatory sub-strings. Improvements in this aspect would help improve the quality and explainability of the metrics. The next step would be to categorize the detected hallucinatory sub-strings. The hallucinatory sub-string will be intrinsic if it is wrong or nonsensical, and extrinsic if it is non-existing in the source context. Future work that explores an automatic method of categorization would be beneficial.

Fact-Checking. The factual verification of extrinsic hallucinations requires fact-checking against world knowledge, which can be time consuming and laborious. Leveraging an automatic fact-checking system for extrinsic hallucination verification is, thus, other future work that requires attention. Fact-checking consists of the knowledge evidence selection and claim verification sub-tasks, and the following are the remaining challenges associated with each sub-task.

The main research problem associated with the evidence selection sub-task is how to retrieve evidence from the *world* knowledge. Most of the literature leverages Wikipedia as the knowledge source [136, 249, 300], which is only a small part of world knowledge. Other literature attempts to use the whole web as the knowledge source [64, 171]. However, this method leads to another research problem – “how to ensure the trustworthiness of the information we use from the web” [83]. Source-level methods that leverages the meta-information of the web source (e.g., web traffic, PageRank or URL structure) have been proposed to deal with this trustworthiness issue [10, 204, 205]. Addressing the aforementioned issues to allow evidence selection against world knowledge will be an important future research direction.

For the verification subtask, verification models perform relatively well if given correct evidence [138]. However, it has been shown that verification models are prone to adversarial attacks and are not robust to negation, numerical or comparative words [250]. Improving this weakness of verification models would also be crucial because the factuality of a sentence can easily be changed by small word changes (i.e., changes in negations, numbers, and entities).

Generalization. Although we can see that the source and output text of different tasks are in various forms, investigating their relationship and common ground and proposing general metrics to evaluate hallucinations are worth exploring. Task-agnostic metrics with cross-domain robustness could help the research community to build a unified benchmark. It is also important and meaningful to build open-source platforms to collaborate and standardize the evaluation metrics for NLG tasks.

Incorporation of Human Cognitive Perspective. A good automatic metric should correlate with human evaluation. Humans are sensitive to different types of information. For instance, proper nouns are usually more important than pronouns in the generated text. Mistakes concerning named entities are striking to human users, but automatic metrics treat them equally if not properly

designed. In order to address this issue, new metrics should be designed from the human cognitive perspective. The human ability to recognize salient information and filter the rest is evident in scenarios where the most important facts need to be determined and assessed. For instance, when signing an agreement, a prospective employee naturally skims the document to look at the entries with numbers first. In this way, humans classify what they believe is crucial.

Automatic check-worthy detection has the potential to be applied to improve the correlation with human judgement. Implementing the automatic human-like judgment mentioned above can further mitigate hallucination and improve NLG systems.

6.2 Future Directions in Mitigation Methods

General and robust data pre-processing approaches. Since the data format varies between downstream tasks, there is still a gap for data processing methods between tasks, and currently, no universal method is effective for all NLG tasks [141]. Data pre-processing might result in grammatical errors or semantic transformation between the original and processed data, which can negatively affect the performance of generation. Therefore, we believe that general and robust data pre-processing methods can help mitigate the hallucinations in NLG.

Hallucinations in numerals. Most existing mitigation methods do not focus on the hallucination of numerals. However, the correctness of numerals in generated text, such as date, quantities and scalars are important for readers [246, 316, 322]. For example, given the source document “*The optimal oxygen saturation (SpO_2) in adults with COVID-19 who are receiving supplemental oxygen is unknown. However, a target SpO_2 of 92% to 96% seems logical, considering that indirect evidence from patients without COVID-19 suggests that an SpO_2 of <92% or >96% may be harmful.*”⁶, the summary “*The target oxygen saturation range for patients with COVID-19 is 82–86%.*” includes wrong numbers, which could be fatal. Currently, some works [193, 246, 316] point out that using commonsense knowledge can help to gain better numeral representation. And Zhao et al. [322] alleviate numeral hallucinations by re-ranking candidate-generated summaries based on the verification score of quantity entities. Therefore, we believe that explicitly modeling numerals to mitigate hallucinations is a potential direction.

Extrinsic Hallucination Mitigation. Though many works on mitigating hallucinations have been published, most do not distinguish between intrinsic and extrinsic hallucination. Moreover, the main research focus has been on dealing with intrinsic hallucination, while extrinsic hallucination has been somewhat overlooked as it is more challenging to reduce [104]. Therefore, we believe it is worth exploring different mitigation methods for intrinsic and extrinsic hallucinations, and relevant methods in fact-checking can be potentially used for this purpose.

Hallucination in long text. Many tasks in NLG require the model to process long input texts, such as multi-document summarization and generative question answering. We think adopting existing approaches to a Longformer [11]-based model could help encode long inputs. Meanwhile, part of dialogue systems need to generate long output text, in which the latter part may contradict history generation. Therefore, reducing self-contradiction is also an important future direction.

Reasoning. Misunderstanding facts in the source context will lead to intrinsic hallucination and errors. To help models understand the facts correctly requires reasoning over the input table or text. Moreover, if the generated text can be reasoned backwards to the source, we can assume it is faithful. There are some reasoning works in the area of dialogue [38, 82, 272], but few in reducing hallucinations. Moreover, tasks with quantities, such as logical table-to-text generation, require

⁶<https://www.covid19treatmentguidelines.nih.gov/management/critical-care/oxygenation-and-ventilation/>

numerical reasoning. Therefore, adding reasoning ability to the hallucination mitigation methods is also an interesting future direction.

Controllability. Controllability means the ability of models to control the level of hallucination and strike a balance between faithfulness and diversity [59, 222]. As mentioned in Section 3, it is acceptable for chat models to generate a certain level of hallucinatory content as long as it is factual. Meanwhile, for the abstractive summarization task, there is no agreement in the research community about whether factual hallucinations are desirable or not [177]. Therefore, we believe controllability merits attention when exploring hallucination mitigation methods.

7 HALLUCINATION IN ABSTRACTIVE SUMMARIZATION

Abstractive summarization aims to extract essential information from source documents and to generate short, concise, and readable summaries [302]. Neural networks have achieved remarkable results on abstractive summarization. However, Maynez et al. [177] observe that neural abstractive summarization models are likely to generate hallucinatory content that is unfaithful to the source document. Falke et al. [65] analyze three recent abstractive summarization systems and show that 25% of the summaries generated from state-of-the-art models have hallucinated content. In addition, Zhou et al. [326] mention that even if a summary contains a large amount of hallucinatory content, it can achieve a high ROUGE [155] score. This has encouraged researchers to actively devise ways to improve the evaluation of abstractive summarization, especially from the hallucination perspective.

In this section, we review the current progress in automatic evaluation and the mitigation of hallucination, and list the remaining challenges for future work. In addition, it is worth mentioning that researchers have used various terms to describe the hallucination phenomenon, such as faithfulness, factual errors, and factual consistency, and we will use the original terms from their papers in the remainder of this section.

7.1 Hallucination Definition in Abstractive Summarization

The definition of hallucination in abstractive summarization follows that in Section 2. Specifically, we adopt the definition from [177]: given a document and its abstractive summary, a summary is hallucinated if it has any spans not supported by the input document. Once again, intrinsic hallucination refers to output content that contradicts the source, while extrinsic hallucination refers to output content that the source cannot verify. For instance, in Table 1, given the input article shown in the caption, an example of intrinsic hallucination is “*The Ebola vaccine was rejected by the FDA in 2019,*” because this statement contradicts the given content “*The first vaccine for Ebola was approved by the FDA in 2019 in the US*”. And an example of extrinsic hallucination is “*China has already started clinical trials of the COVID-19 vaccine,*” because this statement is not mentioned in the given content. We can neither find evidence of it from the input article nor assert that it is wrong.

Pagnoni et al. [197] define fine-grained types of factual errors in summaries. As mentioned in 2.3, since the “fact” here refers to source knowledge, “factual error” can be treated as hallucination, and we can adopt this classification as a sub-type of hallucination. They establish three categories as semantic frame error, discourse error, and content verifiability error.

7.2 Hallucination Metrics in Abstractive Summarization

Existing metrics for hallucination in abstractive summarization are mainly model-based. Following [104], we divide the hallucination metrics into two categories: (1) unsupervised metrics and (2) semi-supervised metrics. Note that existing hallucination metrics evaluate both intrinsic and

extrinsic hallucinations together in one metric because it is difficult to automatically distinguish between them.

7.2.1 Unsupervised Metrics. Given that hallucination is a newly emerging problem, there are only a few hallucination-related datasets. Therefore, researchers have proposed to adopt other datasets to build unsupervised hallucination metrics. There are three types of such unsupervised metrics: (1) information extraction (IE)-based metrics, (2) natural language inferencing (NLI)-based metrics, (3) question answering (QA)-based metrics.

IE-based Metrics. As mentioned in Section 4, IE-based metrics leverage IE models to extract knowledge as relation tuples (*subject, relation, object*) from both the generation and knowledge source to analyze the factual accuracy of the generation [86]. However, IE models are not 100% reliable yet (making errors in the identification of the relation tuples). Therefore, Nan et al. [190] propose an entity-based metric relying on the Named-Entity Recognition model, which is relatively more robust. Their metric builds on the assumption that there will be a different set of named entities in the gold and generated summary if there exists hallucination.

NLI-based Metrics. As mentioned in Section 4, the NLI-model (textual entailment model) can be utilized to measure hallucination based on the assumption that a faithful summary will be entailed by the gold source. However, Falke et al. [65] discover that models trained on NLI datasets can not transfer well to abstractive summarization tasks, degrading the reliability of NLI-based hallucination metrics. To improve NLI models for hallucination evaluation, they release collected annotations as additional test data. Other efforts have also been made to further improve NLI models. Mishra et al. [185] find that the low performance of NLI-based metrics is mainly caused by the length of the premises in NLI datasets being shorter than the source documents in abstractive summarization. Thus, the authors propose to convert multiple-choice reading comprehension datasets into long premise NLI datasets automatically. The results indicate that long-premise NLI datasets help the model achieve a higher performance than the original NLI datasets. In addition, Laban et al. [132] introduce a simple but efficient method called SUMMAC_{Conv} by applying NLI models to sentence units that are segmented from documents. The performance of their model is better than applying NLI models to the whole document.

QA-based Metrics. QA-based metrics measure the knowledge overlap or consistency between summaries and the source documents based on the intuition that QA models will achieve similar answers if the summaries are factually consistent with the source documents. QA-based metrics such as FEQA [53], QAGS [264], and QuestEval [227] follow three steps to obtain a final score: (1) a QG model generates questions from the summaries, (2) a QA model obtains answers from the source documents, and (3) calculate the score by comparing the set of answers from source documents and the set of answers from summaries. The results show that these reference-free metrics have substantially higher correlations with human judgments of faithfulness than the baseline metrics. Gabriel et al. [74] further analyze the FEQA and find that the effectiveness of QA-based metrics depends on the question. They also provide a meta-evaluation framework that includes QA metrics.

7.2.2 Semi-Supervised Metrics. Semi-supervised metrics are trained on the synthetic data generated from summarization datasets. Trained on these task-specific corpora, models can judge whether the generated summaries are hallucinatory. Kryscinski et al. [127] propose a weakly supervised model named FactCC for evaluating factual consistency. The model is trained jointly for three tasks: (1) checking whether the synthetic sentences remain factually consistent, (2) extracting supporting spans in the source documents, and (3) extracting inconsistent spans in the summaries, if any exist.

They transfer this model to check whether the summaries generated from summarization models are factually consistent. Results show that the performance of their FactCC model surpasses the classifiers trained on the MNLI or FEVER datasets. Zhou et al. [326] introduce a method to fine-tune a pre-trained language model on synthetic data with automatically inserted hallucinations in order to detect the hallucinatory content in summaries. The model can classify whether spans in the machine-generated summaries are faithful to the article. This method shows higher correlations with human factual consistency evaluation than the baselines.

7.3 Hallucination Mitigation in Abstractive Summarization

Recently, many approaches have been proposed to reduce the hallucination phenomenon in abstractive summarization.

7.3.1 Architecture Method. Seq-to-seq [244] models are widely used and achieve state-of-the-art performance in abstractive summarization. Researchers have made modifications to the architecture design of the seq-to-seq models to reduce hallucinated content in the summaries. We describe various efforts made to improve the encoder, decoder, or both the encoder and decoder of the seq-to-seq models.

Encoder. Zhu et al. [329] propose to use an explicit graph neural network (GNN) to encode the fact tuples extracted from source documents. In addition to an explicit graph encoder, Huang et al. [102] further design a multiple-choice cloze test reward to encourage the model to better understand entity interactions. Moreover, Gunel et al. [92] use external knowledge from Wikipedia to make knowledge embeddings, which the results show improve factual consistency.

Decoder. Song et al. [235] present the incorporation of a sequential decoder with a tree-based decoder to generate a summary sentence and its syntactic parse. This joint generation is performed improve faithfulness. Aralikkatte et al. [6] introduce the Focus Attention Mechanism, which encourages decoders to generate tokens similar or topical to the source documents. The results on the BBC extreme summarization task show that models augmented with the Focus Attention Mechanism generate more faithful summaries.

Encoder-decoder. Cao et al. [24] extract fact descriptions from the source text and apply a dual-attention seq-to-seq framework to force the summaries to be conditioned on both source documents and the extracted fact descriptions. Li et al. [143] propose an entailment-aware encoder and decoder with multi-task learning which incorporates the entailment knowledge into abstractive summarization models.

7.3.2 Training Method. Aside from architecture modification, some works improved the training approach to reduce hallucination. Cao and Wang [22] introduce a contrastive learning method to train summarization models. The positive training data are reference summaries, while the negative training data are automatically generated hallucinatory summaries, and the contrastive learning system is trained to distinguish between them. In the dialogue summarization field, Tang et al. [245] propose another contrastive fine-tuning strategy, named CONFIT, that can improve the factual consistency and overall quality of summaries.

7.3.3 Post-Processing Method. Some works carry out post-editing to reduce the hallucination of the model-generated summaries, which are viewed as draft summaries. Dong et al. [50] propose SpanFact, a pair of factual correction models that use knowledge learned from QA models to correct the spans in the generated summaries. Similar to SpanFact, Cao et al. [21] introduce a post-editing corrector module to identify and correct hallucinatory content in generated summaries. The corrector module is trained on synthetic data which are created by adding a series of heuristic

transformations to reference summaries. Zhao et al. [322] present HERMAN, a system that learns to recognize quantities (dates, amounts of money, etc.) in the generated summary and verify their factual consistency with the source text. According to the quantity hallucination score, the system chooses the most faithful summary where the source text supports its quantity terms from the candidate-generated summaries. Chen et al. [31] introduce a contrast candidate generation and selection system to do post-processing. The contrast candidate generation model replaces the named entities in the generated summaries with ones present in the source documents, and the contrast candidate selection model will select the best candidate as the final output summary.

7.4 Future Directions in Abstractive Summarization

Factual Hallucination Evaluation. Factual hallucinations contain information not found in source content, though it is factually correct. In the summarization task, this kind of hallucination could lead to better summaries. However, there is little work focused on evaluating factual hallucination explicitly. Fact-checking approaches could be potentially used in this regard.

Extrinsic Hallucination Mitigation. There has been little research on extrinsic hallucinations as it is more challenging to detect and mitigate content based on world knowledge. We believe it is worth exploring extrinsic hallucination in terms of evaluation metrics and mitigation methods.

Hallucination in Dialogue Summarization. In conversational data, the discourse relations between utterances and co-references between speakers are more complicated than from, say, news articles. For example, Zhong et al. [323] show that 74% of samples in the QMSum dataset consist of inconsistent facts. We believe exploring the hallucination issue in dialogue summarization is an important and special component of research into hallucination in abstractive summarization.

8 HALLUCINATION IN DIALOGUE GENERATION

Dialogue generation is an NLG task that automatically generates responses according to user utterances. The generated responses are required to be fluent, coherent, and consistent with the dialogue history. The dialogue generation task can be divided into two sub-tasks: (1) task-oriented dialogue generation; (2) open-domain dialogue generation. A task-oriented dialogue system aims to complete a certain task according to a user query in a specific domain, such as restaurant booking, hotel recommendation, and calendar checking. Meanwhile, an open-domain dialogue system aims to establish a multi-turn, long-term conversation with users while providing the users with an engaging experience.

8.1 Hallucination Definition in Dialogue Generation

The hallucination problem also exists in the dialogue generation task. It is important to note that a dialogue system is expected either to provide the user with the required information or to provide an engaging response without repeating utterances from the dialogue history. Thus, the tolerance for producing proper “hallucination” from the dialogue history is relatively higher.

The definition of hallucination in this task can be adopted from the general definition as follows: (1) **Intrinsic hallucination:** the generated response is contradictory to the dialogue history or the external knowledge sentences. In the examples of intrinsic hallucination shown in Table 1, we can verify that the output contradicts the inputs: In one example, the input is a “*moderate*” price range, but the model mistakenly generates a sentence with a “*high*” price range. In another case, the confusion of the names “*Roger Federer*” and “*Rafael Nadal*” causes the output generation of “*Roger Nadal*”. (2) **Extrinsic hallucination:** the generated response is hard to verify with the dialogue history or the external knowledge sentences. Responses with extrinsic hallucination are impossible to verify with the given inputs. “*Pickwick hotel*” might be “*in san diego*”, and Djokovic may have

been “*in the top ten singles players of the world*”. However, we do not have enough information to check the truth of these statements.

In the following sections, the hallucination problem in open-domain and task-oriented dialogue generation tasks will be separately discussed according to their natures.

8.2 Open-domain Dialogue Generation

While the term “hallucination” seems to have newly emerged in the NLP field, a related behavior, “inconsistency”, of neural models has been widely discussed. This behavior has been pointed out as a shortcoming of generation-based approaches for open-domain chatbots [103, 165, 223]. Two possible types of inconsistency occur in open-domain dialogue generation: (1) inconsistency among the system utterances, such as when the system contradicts its previous utterance; (2) inconsistency with an external source, such as factually incorrect utterances. Whereas the first type is described using the term “inconsistency” [149, 278, 309] or “incoherence” [13, 57], some have recently started to call the second type “hallucination” [183, 224]. Self-inconsistency can be considered as an intrinsic hallucination problem, while the external inconsistency involves both intrinsic and extrinsic hallucinations, depending on the reference source.

As mentioned earlier, a certain level of hallucination may be acceptable in open-domain chat-chat as long as it does not involve severe factual issues. Moreover, it is almost impossible to verify factual correctness since the system usually lacks a connection to external resources. With the introduction of knowledge-grounded dialogue tasks [48, 327], which provide an external reference, however, there has been more active discussion of hallucination in open-domain dialogue generation.

8.2.1 Self-Consistency. In end-to-end generative open-domain dialogue systems, the inconsistency among system utterances has been pointed out as the bottleneck to human-level performance [263]. We often observe an inconsistency in the answers to semantically similar yet not identical questions. For example, a system may answer the questions of “What is your name?” and “May I ask your name?” with different responses. Persona consistency has been the center of attention [145, 313] and it is one of the most obvious cases of self-contradiction regarding the character of the dialogue system. “Persona” is defined as the character that a dialogue system plays during a conversation, and can be composed of identity, language behavior, and an interaction style [145]. While some works have set their objective as teaching models to utilize speaker-level embeddings [145, 168], others condition generation with a set of descriptions about a persona, which we will discuss in detail in the next section.

8.2.2 External Consistency. Besides self-consistency, an open-domain dialogue system should also generate persona-consistent and informative responses corresponding so as to user utterances to further engage with the user during conversation. In this process, an external resource containing explicit persona information or world knowledge is introduced into the system to assist the model generation process.

The PersonaChat datasets [47, 313] have accelerated research into persona consistency [96, 129, 178, 284, 296, 307, 319]. In PersonaChat datasets, each conversation has persona descriptions such as “I like to ski” or “I am a high school teacher” attached. By conditioning the response generation on the persona description, a chat-chat model is expected to acquire an ability to generate a more persona-consistent response. Lately, the application of NLI methods [149, 234] or reinforcement learning frameworks [181] have been investigated. Although these methods conditioned on the PersonaChat datasets have been successful, further investigation of approaches that do not rely on a given set of persona descriptions is necessary because such descriptions are not always available, and covering every aspect of a persona with them is impossible.

In addition to PersonaChat-related research, the knowledge-grounded dialogue (KGD) task in the open-domain requires the model to generate informative responses with the help of an external knowledge graph (KG) or knowledge corpus [48, 327]. Hallucination in conversations, which is also considered as a factual consistency problem, has raised much research interest recently [59, 214, 226, 233]. Here, we continue to split the hallucination problem in the KGD task into intrinsic hallucination and extrinsic hallucination. Most of the KGD works tackle the hallucination problem when responses contain information that contradicts (intrinsic) or cannot be found in the provided knowledge input (extrinsic). Since world knowledge is enormous and ever-changing, the extrinsic hallucination may be factual but hard to verify. Dziri et al. [59] further adopt the same definition of hallucination as mentioned above to the knowledge graph-grounded dialogue task, where intrinsic hallucination indicates the case of misusing either the subject or object of the knowledge triple; and extrinsic hallucination indicates that there is no corresponding valid knowledge triple in the gold reference knowledge. Recently, there have been some attempts to generate informative responses without explicit knowledge inputs, but with the help of the implicit knowledge inside large pre-trained language models instead [292, 328] during the inference time. Under this setting, the study of extrinsic hallucination is of great value but still poorly investigated.

8.2.3 Hallucination Metrics. For generation-based dialogue systems, especially open-domain chatbots, the hallucination evaluation method remains an open problem [223]. As of now, there is no standard metric. Therefore, chatbots are usually evaluated by humans on factual consistency or factual correctness [226, 285]. We also introduce some automatic statistical and model-based metrics as a reference, which will be described in more detail below.

Variants of F1 Metrics. **Knowledge F1 (KF1)** measures the overlap between the generated responses and the gold knowledge sentences to which the human referred for conversation during dataset collection [233]. KF1 attempts to capture whether a model can generate knowledgeable responses by correctly utilizing the relevant knowledge. KF1 is only available for datasets with labeled ground-truth knowledge. Shuster et al. [233] further propose **Rare F1 (RF1)**, which only considers the infrequent words in the dataset when calculating F1 to avoid influence from the common uni-grams. The authors define an infrequent word as being in the lower half of the cumulative frequency distribution of the reference corpus.

Model-based Metric. Natural language has its natural on the flexibility of the surface forms with the same semantics, so overlap-based metrics cannot provide the comprehensive evaluation. Recently, several works have proposed evaluation metrics for measuring consistency, such as using natural language inference (NLI) [57, 278], training learnable evaluation metrics [309], or releasing an additional test set for coherence [13]. These methods are more flexible and supports the generated responses with different surface forms. For the KGD task, Dziri et al. [60] propose the BEGIN benchmark, which consists of samples taken from Dinan et al. [48] with additional human annotation and a new classification task extending the NLI paradigm. Honovich et al. [101] present a trainable metric for the KGD task, which also applies NLI. It is also noteworthy that Gupta et al. [94] propose datasets that can benefit fact-checking systems specialized for dialogue systems. The Conv-FEVER corpus [226] is a factual consistency detection dataset, which was created by adapting the Wizard-of-Wikipedia dataset [48]. It consists of both factually consistent and inconsistent responses and can be used to train a classifier to detect factually inconsistent responses with respect to the knowledge provided.

8.2.4 Mitigation Methods. The hallucination issue can be mitigated by data pre-processing, which includes introducing extra information into the data. Shen et al. [230] propose a measurement based on seven attributes of the dialogue quality, including self-consistency. Based on this measurement,

the untrustworthy samples which get lower scores are filtered out from the training set to improve the model performance in terms of self-consistency (i.e., intrinsic hallucination). Shuster et al. [233] conduct a comprehensive investigation on a retrieval-augmented KGD task where a retriever is introduced to the system for knowledge selection. The authors study several key problems, such as whether retrieval helps reduce hallucinations and how the generation should be augmented with the retrieved knowledge. The experimental results show that retrieval helps substantially in improving performance on KGD tasks and in reducing the hallucination in conversations without sacrificing conversational ability.

Rashkin et al. [214] introduce a set of control codes and concatenate them with dialogue inputs to reduce the hallucination by forcing the model to be more aware of how the response relies on the knowledge evidence in the response generation. Some researchers have also tried to reduce hallucinated responses during generation by improving dialogue modeling. Wu et al. [285] apply inductive attention into transformer-based dialogue models, and potentially uninformative attention links are removed with respect to a piece of pre-established structural information between the dialogue context and the provided knowledge. Instead of improving the dialogue response generation model itself, Dziri et al. [59] present a response refinement strategy with a token-level hallucination critic and entity-mention retriever, so that the original dialogue model is left without retraining. The former module is designed to label the hallucinated entity mentioned in the generated responses, while the retriever is trained to retrieve more faithful entities from the provided knowledge graph. RHO [?] is a framework that uses three mechanisms to tackle hallucinations, namely, local knowledge grounding, global knowledge grounding, and response re-ranking to tackle hallucinations in open-domain dialogues, and has been empirically shown to perform this.

8.3 Task-oriented Dialogue Generation

A task-oriented dialogue system is often composed of several modules: a natural language understanding (NLU) module, a dialogue manager (DM), and a natural language generation (NLG) module [76, 113]. Intrinsic hallucination can occur between the DM and NLG, where a dialogue act such as `recommend(NAME=peninsula hotel, AREA=tsim sha tsui)` is transformed into a natural language representation “the hotel named *peninsula hotel* is located in *tsim sha tsui* area.” [9, 153].

8.3.1 Hallucination Metrics. To evaluate hallucination, Li et al. [153] and Balakrishnan et al. [9] combine traditional metrics such as the BLEU score and human evaluation as well as hallucination-specific automatic metrics. Following previous works such as [55, 279], and [255], Li et al. [153] use the slot error rate, which is computed by $(p + q)/N$, where N represents the total number of slots extracted by another model in the dialogue act. Here, p stands for the missing slots in the generated template, and q is the number of redundant slots. On the other hand, Balakrishnan et al. [9] introduce a novel metric called the tree accuracy, which determines whether the prediction’s tree structure is identical to that of the input meaning representations.

8.3.2 Mitigation Methods. While Balakrishnan et al. [9] propose to adopt tree-structured semantic representations and add constraints on decoding, Li et al. [153] frame a reinforcement learning problem to which they apply a bootstrapping algorithm to sample training instances and then leverage a reward related to slot consistency. Recently, there has emerged another line of research in task-oriented dialogue, which is to build a single end-to-end system rather than connecting several modules (e.g., Eric and Manning [62], Madotto et al. [167, 170?]). As discussed in previous sections of this paper, there is potential for such end-to-end systems to produce extrinsic hallucinations, yet this remains less explored. For example, a model might generate a response with an entity that appears out of nowhere. In the example of hotel recommendation in Hong Kong given above, a

model could generate a response such as “the hotel named *raffles hotel* is located in *central area*,⁷” which cannot be verified from the knowledge base of the system.

8.4 Future Directions in Dialogue Generation

Self-Contradiction in Dialogue Systems. One of the possible reasons for self-contradiction is that current dialogue systems tend to have a short memory of dialogue history [223]. Firstly, common dialogue datasets provide several turns of conversation, yet these are not long enough to assess a model’s ability to deal with a long context. To overcome this, Xu et al. [287] introduce a new dataset that consists of, on average, over 40 utterances per episode. Secondly, we often truncate dialogue history into fewer turns to fit into models such as Transformer-based architectures, which makes it difficult for a model to memorize the past. In addition to the works on dialogue summarization, e.g., Gliwa et al. [84], it would be beneficial to apply other works which are aiming to grasp the longer context but do not focus on dialogue generation [11, 306, 320].

Fact-checking in dialogue systems. In addition to the factual consistency in responses from knowledge grounded dialogue systems, fact-checking is a future direction in dealing with the hallucination problem in dialogue systems [94]. Dialogue fact-checking involves verifiable claim detection, which is an important line in distinguishing hallucination-prone dialogue, and evidence retrieval from an external source. This fact-checking in the dialogue system could be utilized not only as an evaluation metric for facilitating factual consistency but also to model such a system.

9 HALLUCINATION IN GENERATIVE QUESTION ANSWERING

Generative question answering (GQA) aims to generate an abstractive answer rather than extract an answer to a given question from provided passages [67, 142]. It is an important task since many of the everyday questions that humans deal with and pose to search engines require in-depth explanations [121] (e.g., *why/how..?*), and the answers are normally long and cannot be directly extracted from existing phrase spans. A GQA system can be integrated with a search engine [182] to empower more intelligent search or combined with a virtual conversation agent to enhance user experience.

Normally, a GQA system involves searching an external knowledge source for information relevant to the question. Then it generates the answer based on the retrieved information [126]. In most cases, no single source (document) contains the answer, and multiple retrieved documents will be considered for answer generation. Those documents may contain redundant, complementary, or contradictory information. Thus, hallucination is common in the generated answers.

The hallucination problem is one of the most important challenges in GQA. Since an essential goal of a GQA system is to provide factually-correct answers given the question, hallucination in the answer will mislead the user and damage the system performance dramatically.

9.1 Hallucination Definition in GQA

As a challenging yet under-explored task, there is no standard definition of hallucination in GQA. However, almost all the works on GQA [67, 126, 189, 237] involve a human evaluation process, in which the *factual correctness* measuring the faithfulness of the generated answer can be seen as a measurement of the hallucination; i.e., the more faithful the answer is, the less hallucinated content it contains. The most recent such work [142] uses the term *semantic drift*, which indicates how the answer drifts away from a correct one during generation, and this can also be seen as a specific definition of hallucination in GQA.

⁷Raffles Hotel is a hotel located in Downtown Core, Singapore.

In line with the general categorization of hallucination in Section 2.1, we give two concrete hallucination examples in GQA in Table 1. The sources of both questions are Wikipedia web pages. For the first question, “*dow jones industrial average please?*”, the generated answer “*index of 30 major U.S. stock indexes*” conflicts with the statement “*of 30 prominent companies listed on stock exchanges in the United States*” from Wikipedia. So we categorize it as an intrinsic hallucination. For the second example, the sentences “*The definition of a Sadducee is a person who acts in a deceitful or duplicitous manner. An example of a Sadducee is a politician who acts deceitfully in order to gain political power*” in the generated answer can not be verified from the source documents; thus, we categorize it as an extrinsic hallucination.

9.2 Hallucination-related Metrics in GQA

Currently, there is no automatic metric to evaluate hallucination in GQA specifically. While most works on GQA use automatic evaluation metrics such as ROUGE score and F1 to measure the quality of the answer, these N-gram overlap-based metrics are not a meaningful way to evaluate hallucination due to their poor correlation with human judgments, as indicated by Krishna et al. [126]. On the other hand, almost all the GQA-related work involves a human evaluation process as a complement to the automatic evaluation. Normally, human annotators will be asked to assign a score indicating the faithfulness of the answer, which can also be viewed as a measurement of the answer hallucination. However, the metrics obtained via human evaluation come normally from a small sample of the data.

Metrics such as *semantic overlap* [229], a learned evaluation metric based on BERT that models human judgments, could be considered a better measurement of hallucination for GQA. Other metrics such as the *factual correctness* can also be considered as a way to measure hallucination in GQA. Zhang et al. [318] propose to explicitly measure the factual correctness of a generated text against the reference by first extracting facts via an information extraction (IE) module. Then they define and measure the factual accuracy score to be the ratio of facts in the generation text equal to the corresponding facts in the reference.

Factual consistency, which measures the faithfulness of the generated answer given its source documents, can be employed as another way to measure hallucination in GQA. Durmus et al. [53], Wang et al. [264] propose an automatic QA-based metric to measure faithfulness in summary, leveraging the recent advances in machine reading comprehension. They first use a question generation model to construct question-answer pairs from the summary, and then a QA model is applied to extract short answer spans from the given source document for the question. The extracted answers that do not match the provided answers indicate unfaithful information in the summary. While these metrics were first proposed in summarization works, they can be easily adopted in generative QA to measure hallucinations in the generated long-form answer.

The most recent work on GQA by Su et al. [237] proposed to estimate the faithfulness of the generated long-form answer via *zero-shot short answer recall* on extractive QA datasets. They first generate long-form answers for questions from two extractive QA datasets Natural Questions(NQ) [131] and HotpotQA [295], both of which contains large-scale question-answer pairs, then they measure the ratio of golden short answer span contained in the generated long answer as an estimation of faithfulness of the generated long-answer. While the idea is similar to the factual consistency metric in summarization work [53], and also matches with our intuition to some extent, its correlation with human evaluation on faithfulness has not been verified.

9.3 Hallucination Mitigation in GQA

Unlike conditional text generation tasks such as summarization, or data-to-text generation, in which the source documents are provided and normally related to the target generation, the hallucination

problem in GQA is more complicated. Generally speaking, it might come from two sources: 1) the incompetency of the retriever, which retrieves documents irrelevant to the answer, and 2) the *intrinsic* and *extrinsic* hallucination in the conditional generation model itself. Normally these two parts are interconnected and cause hallucinations in the answer.

Early works on GQA mostly tried to improve the faithfulness of the answer by investigating reliable external knowledge sources or incorporating multiple information sources. Yin et al. [297] propose Neural Generative Question Answering (GENQA), an end-to-end model that generates answers to simple factoid questions based on the knowledge base, while Bi et al. [14] propose the Knowledge-Enriched Answer Generator (KEAG) to generate a natural answer by integrating facts from four different information sources, namely, questions, passages, vocabulary, and knowledge. Nevertheless, these methods rely on the existence of high-quality, relevant resources which are not easily available.

Recent works focus more on the conditional generation model. Fan et al. [66] construct a local knowledge graph for each question to compress the information and reduce redundancy from the retrieved documents, which can be viewed as an early trial to mitigate hallucination. Li et al. [142] propose Rationale-Enriched Answer Generator (REAG), in which they add an extraction task to obtain the rationale for an answer at the encoding stage, and the decoder is expected to generate the answer based on both the extracted rationale and original input. The recent work [126] employs a Routing Transformer (RT), a sparse attention-based Transformer-based model that employs local attention and mini-batch k-means clustering for long-range dependence, as the answer generator in the hope of modeling more retrieved documents to mitigate the hallucination in the answer. Su et al. [237] propose a framework named RBG (**r**ead **b**efore **g**enerate), to jointly models answer generation with machine reading. They augment the generation model with fine-grained, answer-related salient information predicted by the MRC module, to enhance answer faithfulness. Such methods can exploit and utilize the information in the original input better, while they require the extra effort of building models to extract that information.

Most recently, Lin et al. [156] propose a benchmark, which comprises 817 questions that span 38 categories, to measure the truthfulness of a language model in the QA task. This work investigates the performances of GPT-3 [19], GPT-Neo/J [266], GPT-2 [209] and a T5-based model [210]. The results suggest that simply scaling up the model is less promising than fine-tuning it in terms of improving truthfulness since larger models are better at learning the training distribution from web data and thus tend to produce more imitative falsehoods. In another recent work, Nakano et al. [189] fine-tune GPT-3 to answer long-form questions with a web-browsing environment, which allows the model to navigate the web as well as use human feedback to optimize answer quality directly using imitation learning [107]. While this method seems promising, it also hinges on how that feedback is processed.

9.4 Future Directions in GQA

While GQA is challenging yet under-explored, many possible directions could be explored to improve the answer quality and mitigate hallucination. First, better automatic evaluation metrics are needed to measure hallucination. The previously mentioned metrics, such as the semantic overlap between the generated answer and the ground-truth answer, the faithfulness of the generated answer, and factual consistency between the answer and the source documents, only consider one aspect of hallucination. Metrics that can consider all the factors related to hallucination (such as semantic overlap, faithfulness, or factual consistency) could be designed. Second, datasets with hallucination annotations should be proposed since none of the current GQA datasets have that information. Another possible direction to mitigate hallucination in the answer is improving the performance of the models. We need better retrieval models that retrieve relevant information

according to queries and generation models that can synthesize more accurate answers from multi-source documents.

10 HALLUCINATION IN DATA-TO-TEXT GENERATION

Data-to-Text Generation is the task of generating natural language descriptions conditioned on structured data [128, 179], such as tables [198, 283], database records [35], and knowledge graphs [78]. Although this field has been recently boosted by neural text generation models, it is well known that these models are prone to hallucinations [283] because of the gap between structured data and text, which may cause semantic misunderstanding and erroneous correlation. Moreover, the tolerance of hallucination is very low when this task is applied to the real world, such as in the case of patient information table description [247], and analysis of experimental results tables in a scientific report. Recent years have seen a growth of interest in hallucinations in Data-to-Text Generation, and researchers have proposed works from the aspect of evaluation and mitigation.

10.1 Hallucination Definition in Data-to-Text Generation

The definition and categories of hallucination in Data-to-Text Generation follow the descriptions in Section 2. We follow the general hallucination definition in this task: (1) Intrinsic Hallucinations: the generated text contains information that is contradicted by the input data [193]. For example, in Table 1, “*The Houston Rockets (18-4)*” uses the information “[*TEAM: Rockets, CITY:Houston, WIN:18, LOSS: 5*]” in the source table. However, “(18-4)” is contradicted by “[*LOSS: 5*]” and it should be “(18-5)”. (2) Extrinsic Hallucinations: the generated text contains extra information irrelevant to the input [44, 193]. For example, in Table 1, “*Houston has won two straight games and six of their last seven.*” is not mentioned in the source table [268].

10.2 Hallucination Metrics in Data-to-Text Generation

Statistical. PARENT [44] measures the accuracy of table-to-text generation by aligning n-grams from the reference description R and generated texts G to the table T . And it is the average F-score by combining the entailment precision and recall. Wang et al. [274] modify PARENT and denote this table-focused version as PARENT-T. Different from PARENT, which evaluates i -th instance (T_i, R_i, G_i) , PARENT-T ignores the reference description R and evaluates each instance (T_i, G_i) .

IE-based. Liu et al. [162] estimate hallucination with two entity-centric metrics: table record coverage (the ratio of covered records in a table) and hallucinated ratio (the ratio of hallucinated entities in text). This metric firstly uses entity recognition to extract the entities of input and generated output, then aligns these entities by heuristic matching strategies, and finally calculates the ratios of faithful and hallucinated entities separately. Moreover, there are some general post-hoc IE-based metrics that could be applied to hallucination evaluation, such as Slot Error Rate (SER) [291], Content Selection (CS), Relation Generation (RG), and Content Ordering (CO) [268, 283].

QA-based. Data-QuestEval [217] adapt QuestEval [227] from summarization into data-to-text generation. First, a *textual QG model* is trained on a textual QA dataset. For each sample (structured data, textual descriptions), the *textual QG model* generates synthetic problems based on the descriptions. The structured data, textual descriptions (answers), and synthetic questions make up a synthetic QG/QA dataset to train *synthetic QA/QG models*. Then, the *synthetic QG model* generates questions based on the textual description to be evaluated. The *synthetic QA model* then generates answers based on a synthetic question and the structured input data. Finally, BERTScore [315] measures the similarity between the generated answer and description, indicating faithfulness.

NLI-based. Dušek and Kasner [56] recognize the textual entailment between the input data and the output text for both omissions and hallucinations with an NLI model. This work measures the

semantic accuracy in two directions: check omissions by inferring whether the input fact is entailed by the generated text and check hallucinations by inferring the generated text from the input.

LM-based. Filippova [71], Tian et al. [251] are based on the intuition that when an unconditional LM, only trained on the targets, gets a smaller loss than a conditional LM_x , trained on both sources and targets, the token is predicted unfaithfully. Thus, they calculate the ratio of hallucinated tokens to the total target length to measure the hallucination level.

10.3 Hallucination Mitigation in Data-to-Text Generation

Data-Related Methods. Several clean and faithful corpora are collected to tackle the challenges from data infidelity. TOTTO [198] is an open-domain faithful table-to-text dataset, where each sample includes a Wikipedia table with several highlighted cells and a description. To ensure that targets exclude hallucinations, the annotators revise existing Wikipedia candidate sentences and clear the parts unsupported by the table. Moreover, RotoWire-FG (Fact-Grounding) [268] is a purified and enlarged and enriched version of RotoWire [283] generating NBA game summaries from score tables. Annotators trim the hallucination part in target texts and extract the mapped table records as content plans to better align input tables and output summaries.

For data processing, OpAtt [192] designs a gating mechanism and a quantization module for the symbolic operation to augment the record table with pre-calculated results. Nie et al. [193] utilize a language understanding module to improve the equivalence between the input MR and the reference utterance in the dataset. They train an NLU model with an iterative relabeling procedure: First, they train the model on original data; parse the MR by model inference; train the model on new paired data with high confidence; and then repeat the above processes. Liu et al. [162] select training instances based on faithfulness ranking. Finer-grained than the above instance-level method, Rebuffel et al. [216] label tokens according to co-occurrence analysis and sentence structure through dependency parsing in the pre-processing step to explicate the correspondence between the input table and the text. Generally, the data-related methods are appropriate when the training dataset is noisy.

Modeling and Inference Methods. Planning and skeleton generation are common methods to improve the faithfulness to the input in data-to-text tasks. Liu et al. [162] propose a two-step generator with a separate text planner augmented by auxiliary entity information. The planner predicts the plausible content plan based on the input data. Then, given the above input data and the content plan, the sequence generator generates the text. Similarly, Plan-then-Generate [239] also consists of a content planner and a sequence generator. In addition, this work adopts a structure-aware RL training to generate output text following the generated content plan faithfully. Puduppully and Lapata [208] first induce a macro plan consisting of multiple sequences of entities and events from the input table and its corresponding multi-paragraph long document. The predicted macro plan then serves as the input to an encoder-decoder model for surface realization. SANA [269] is a skeleton-based two-stage model that includes skeleton generation to select key tokens from the source table and edit-based generation to produce texts via iterative insertion and deletion operations. In contrast to the above two-step model using planning or skeleton, AGGGEN [291] is an end-to-end model that jointly learns to plan and generate at the same time. This architecture with a Hidden Markov Model and Transformer encoder-decoder reintroduces explicit sentence planning stages into neural systems by aligning facts in the target text to input representations.

Other modeling methods have also been proposed to mitigate the hallucination problem. Conjecturing that hallucinations can be caused by inattention to the source, Tian et al. [251] propose a confidence score and a variational Bayes training framework to learn the score from data. Wang et al. [274] introduce a table-text optimal-transport matching loss and an embedding similarity loss

to encourage faithfulness. The hallucination degree can also be treated as a controllable factor in generating texts. In Filippova [71], the hallucination degree of each training sample is estimated and converted into a categorical value which is a part of the inputs as a controlled setting. This approach does not require the dismissal of any input or modification of the model structure.

To mitigate hallucinations at the inference step, Rebuffel et al. [216] propose a Multi-Branch Decoder that leverages word-level alignment labels between the input table and paired text to learn the relevant parts of the training instance. These word-level labels are gained through dependency parsing during the pre-processing step. The branches separately integrate three co-dependent control factors: content, hallucination, and fluency. Uncertainty-aware beam search (UABS) [286] is an extension to beam search to reduce hallucination. Considering that the hallucination probability is positively correlated with predictive uncertainty, this work adds a weighted penalty term in the beam search which is able to balance the predictive probability and uncertainty. This approach is task-agnostic and can also be applied to other tasks, such as image captioning.

These various types of methods do not necessarily conflict and can collaborate to solve the hallucination problem in data-to-text generation.

10.4 Future Directions in Data-to-Text Generation

Given the challenges brought by the discrepancy between structure data and natural text, and the low fault tolerance in the Data-to-Text Generation task, there are several potential directions worth exploring in terms of hallucination.

Firstly, numbers contain information about scales and are common and crucial in the Data-to-Text task [240, 316]. It is frequent to have errors in numbers, which results in hallucinations and infidelity. This is a serious problem for Data-to-Text generation, yet models rarely give special consideration to the numbers found in the table or text [246]. The current automatic metrics of hallucinations also do not specifically treat numbers. This indiscriminate treatment contradicts findings in cognitive neuroscience, where numbers are known to be represented differently from lexical words in a different part of the brain [85]. Thus, considering or highlighting numbers when mitigating and assessing hallucinations is worth exploring. This requires the generative model to learn a better numerical presentation and capture scales, which will reduce the hallucinations caused by the misunderstanding of numbers.

Moreover, for the logical data-to-text generation task, rather than surface-level generation, logical inference, calculation, and comparison are required, which is challenging and causes hallucinations more easily. Thus, reasoning (including numerical reasoning), which is usually combined with graph structures [33] is another direction to improve the accuracy of entity relationships and alleviate hallucinations.

11 HALLUCINATIONS IN NEURAL MACHINE TRANSLATION

Neural Machine Translation (NMT) is the task of generating translation of the source language into the target language via inference, given parallel data samples for training. Compared to statistical machine translation (SMT) the output of NMT is usually quite fluent and of human-level quality, which creates the danger of misinforming users when there are hallucinations [175].

11.1 Hallucinations Definition and Categories in NMT

The problem of hallucination was identified with the deployment of the first NMT models. Early work comparing SMT and NMT systems [123], without explicitly using the term “hallucination”, mentioned that NMT models tend to “sacrifice adequacy for the sake of fluency” especially when evaluated with out-of-domain test sets. Following further development of NMT, most of the relevant research papers agree that translated text is considered a hallucination when it is completely

| Category | Source | Correct Translation | Hallucinatory Translation |
|-------------|--|---|--|
| Intrinsic | 迈克周四去书店。 | Mike goes to the bookstore on Thursday. | Jerry doesn't go to the bookstore on Thursday. |
| Extrinsic | 迈克周四去书店。 | Mike goes to the bookstore on Thursday. | Mike happily goes to the bookstore on Thursday with his friend. |
| Detached | Das kann man nur feststellen, wenn die kontrollen mit einer großen intensität durchgeführt werden. | This can only be detected if controls undertaken are more rigorous. | Blood alone moves the wheel of history, i say to you and you will understand, it is a privilege to fight. |
| Oscillatory | 1995 das produktionsvolumen von 30 millionen pizzen wird erreicht. | 1995 the production reached 30 million pizzas. | The US, for example, has been in the past two decades, but has been in the same position as the US, and has been in the United States. |

Table 3. Categories and examples of hallucinations in MT by Zhou et al. [326] and Raunak et al. [215]

disconnected from the source [134, 187]. The categorization of hallucination in NMT is unlike that in any other NLG tasks, and uses various terms that are often overlapping. In order to maintain consistency with other NLG tasks, in this section we use the intrinsic and extrinsic hallucination categories applied to the NMT task by [326]. After a formal definition, we will describe other identified types of hallucinations and hallucination categories mentioned in the relevant literature.

Intrinsic and Extrinsic Hallucinations. Following the idea that hallucinations are outputs that are disconnected from the source, [326] suggest categorizing the hallucinatory content based on the way the output is disconnected:

- **Intrinsic Hallucination:** translations contain incorrect information compared to information present in the source. In Table 3, the example of such hallucination is “Jerry doesn’t go”, since the original name in the source is “Mike” and the verb “to go” is not negated.
- **Extrinsic Hallucination:** translations produce additional content without any regard to the source. In Table 3, “happily” and “with his friend” are the two examples of the hallucinatory content since they are added without any apparent connection to the input.

Other Categories and Types of Hallucinations. Raunak et al. [215] propose an alternative categorization of hallucinations. They divide hallucinations into hallucinations under perturbations and natural hallucinations. Hallucinations under perturbation are those that can be observed if a model tested on the perturbed and unperturbed test set returns drastically different content. Their work on hallucinations under perturbation strictly follows the algorithm proposed by Lee et al. [134]; see Section 11.2.2 on the entropy measure. The second category, natural hallucinations, are created with a connection to the noise in the dataset and can be further divided into detached and oscillatory, where detached hallucinations mean that a target translation is semantically disconnected from a source input, and oscillatory hallucinations mean those that are decoupled from the source by manifesting a repeating n-gram. Tu et al. [257] and Kong et al. [125] analyze this phenomenon under the name “over-translation”, that is, a repetitive appearance of words that were not in the source text. Conversely, under-translation is skipping the words that need to be translated [257]. Finally, abrupt jumps to the end of the sequence and outputs that remain mostly in the source language are also examples of hallucinatory content [134].

11.2 Hallucination Metrics in NMT

The definition of hallucinations in machine translation (MT) tends to be qualitative and subjective, and thus researchers often identify hallucinated content manually. Most detrimentally, the appearance of hallucinations is found not to affect the BLEU score of the translated text [251, 326]. There

are, nevertheless, several notable efforts to automatize and quantify the search for hallucinations using statistical methods.

11.2.1 Statistical Metrics. Martindale et al. [175] propose identifying sentence adequacy using the bag-of-vectors sentence similarity (BVSS) metric. This metric indicates that the information is lost because the reference contains more information than the MT output, or the MT output contains more information than the reference.

11.2.2 Model-Based Metrics.

Auxiliary Decoder. “Faithfulness” refers to the amount of source meaning that is faithfully expressed in the translation, and it is used interchangeably with the term “adequacy” [70, 256]. Feng et al. [70] propose adding another “evaluation decoder” apart from the standard translation decoder. In their work, faithfulness is based on word-by-word translation probabilities, and is calculated in the evaluation module along with translation fluency. The loss returned by the evaluation module helps to adjust the probability returned by the translation module.

Entropy Measure. In scenarios where the ground truth of a translation is not available, an entropy measure of the average attention distribution can be used to detect hallucinations. Tu et al. [257] and Garg et al. [79] show that hallucinations are visible in attention matrices. When the model outputs correct translation, the attention mechanism attends to the entire input sequence throughout decoding. However, it tends to concentrate on one point when the model outputs hallucinatory content. The entropy is calculated on the average attention weights when the model does or does not produce hallucinations during testing. For comparison, a clean test set is used along with the purposefully perturbed one, which is created to incite hallucinations (test sets featuring multiple repetitions). The mean entropy returned by hallucinatory models diverges from the mean of the models that do not produce hallucinations spontaneously [134].

Token Level Hallucination Detection. Zhou et al. [326] propose a method for detecting hallucinated tokens within a sentence, making the search more fine-grained. They use a synthetic dataset that is created by adding noise to the source data, more specifically it is generated by a language model with certain tokens of correct translations masked. Tokens in synthetic data are labeled as hallucinated (1) or not (0). Then the authors compute the hallucination prediction loss between binary labels and the tokens from the hallucinated sentence. This work further employs a word alignment-based method and overlap-based method as baselines for hallucination.

Similarity-based Methods. Zhou et al. [326] use an unsupervised model that extracts alignments from similarity matrices of word embeddings [225], and then predicts the target token as hallucinated if it is not aligned to the source. Parthasarathi et al. [199] propose calculating faithfulness by computing similarity scores between perturbed source sentence and target sentence after applying the same perturbation.

Overlap-based Methods. Zhou et al. [326] predict that the target token is hallucinated if it does not appear in the source. Since the target and source are two different languages, the authors use the density matching method for bilingual synonyms from Zhou et al. [325]. Kong et al. [125] suggest the Coverage Difference Ratio (CDR) as the metric to evaluate adequacy, which is especially successful in finding cases of under-translation. It is estimated by comparing source words covered by generated translation with human translations.

The overlap-based methods for detecting hallucinations are heuristics based on the assumption that all translated words should appear in the source. However, this is not always the case, e.g.,

when paraphrasing or using synonyms. Using word embeddings as similarity-based methods helps avoid such simplifications and allows more diverse, synonymous translations.

Approximate Natural Hallucination Detection. Raunak et al. [215] propose Approximate Natural Hallucination (ANH) detection based on the fact that hallucinations often occur as oscillations (repeating n-grams) and the lower unique bigram count indicates a higher appearance of oscillatory hallucinations. Furthermore, the ANH detection method searches for repeated targets in the translation output. Their method finds translation above a certain n-gram threshold and searches for repeated targets in the output translation, following the assumption that if hallucinations are often incited by aligning unique sources to the same target, then repeating targets will also appear during the inference [257].

11.3 Hallucination Mitigation Methods in NMT

Hallucinations in MT are hard to discover for a person who is not fluent in the target language, and thus they can lead to many possible errors, or even dangers. Out of all the natural language generation tasks, NMT engines such as Google in the English-speaking internet and Baidu in the Sinosphere are probably the most widely accessible to netizens. Consequently, there is a big interest in improving NMT's performance, also by mitigating hallucinations. This subsection compiles methods of mitigating hallucinations in NMT.

11.3.1 Data-Related. Data augmentation appears to be one of the most common methods for removing hallucination. Lee et al. [134] and Raunak et al. [215] suggest addition of perturbed sentences. Furthermore, perturbation, where the insertions of most common tokens are placed at the beginning of the sentence, seems to be the most successful in hallucination mitigation. A disadvantage of this method is the need to understand different types of hallucinations produced by the model in order to apply a correct augmentation method. Corpus filtering is a method of mitigating hallucinations caused by the noise in the dataset by removing the repetitive and mismatching source and target sequences [215]. Junczys-Dowmunt [112] implements a cross-entropy data filtering method for bilingual data, which uses cross-entropy scores calculated for noisy pairs according to two translation models trained on the clean data. The scores that suggest disagreement between sentence pairs from two models are subsequently penalized.

While [134, 215] and [112] define noise as mismatched source and target sentences, [18] analyzes the influence of fine-grained semantic divergences on NMT outputs. The authors consequently propose a mitigation method for fine-grained divergences based on semantic factors. The tags are applied to each source and target sentence to inform about the position of divergent tokens. Factorizing divergence not only helps to mitigate hallucinations, but improves the overall performance of the NMT. This shows that tagging small semantic divergences can provide useful information for the network during training.

11.3.2 Modeling and Inference. Overexposure bias is a common problem in NMT, amplified by the teacher-forcing technique used in sequence-to-sequence models. The models are trained on the ground truth, but during inference, they attend to the past predictions, which can be incorrect [125, 213]. To mitigate this problem, Wang and Sennrich [267] propose substituting MLE as a training objective with minimum risk training (MRT) [194]. Scheduled sampling is a classic method of mitigating overexposure bias first proposed by [12]. Based on that method, [89] create a differentiable approximation to greedy decoding that shows a good performance in the NMT task. [290] propose further improvement of the scheduled sampling algorithm for NMT by optimizing the probability of source and target word alignments. This improvement helps to address the issue flexibility in word order between a source and target language when performing scheduled sampling.

Zhou et al. [326] propose a method of improving self-training of NMT based on hallucination detection. They create hallucination labels (see Section 11.2.2), and then discard losses of tokens predicted as hallucinations, which is known as token loss truncation. This is similar to the method proposed by Kang and Hashimoto [117], the latter for full sentences in the summarization task. Furthermore, instead of adjusting losses, Zhou et al. [326] mask the hidden states of the discarded losses in the decoder in a procedure called decoder HS masking. Experimental results show both a translation quality improvement in terms of BLEU and also a large reduction in hallucination. The token loss truncation method shows good results in the low-resource languages scenario.

Another method to mitigate the impact of noisy datasets is tilted empirical risk minimization (TERM), a training objective proposed by Li et al. [150]. [134] mentions that techniques such as dropout, L2E regularization, and clipping tend to decrease the number of hallucinations. Lastly, several authors propose methods of improving phrase alignment that are helpful both in increasing translation accuracy and identifying content that did not appear in the source translation [79, 281, 311].

11.4 Future Directions in NMT

The future work on hallucinations in NMT is to define hallucinations in a quantifiable manner; i.e., to specify a cut-off value between translation error and hallucinated content using a particular metric. Martindale et al. [175] propose a threshold between fluency and adequacy which is the closest to this ideal. They, however, do not concentrate on hallucinated content as such, and thus fluent but inadequate sentences may not always indicate hallucinations but also other types of translation errors. Balakrishnan et al. [9] mention constrained decoding as a method to mitigate hallucinations in dialogue systems, but it could also be applied in NMT. [49, 98, 206, 236, 243, 289] and [288] use constrained decoding to incorporate specific terminology into MT, but the above methods can be repurposed to mitigate hallucinations.

Another direction for future work on hallucinations is improving existing methods of searching for hallucinatory content, such as the algorithms proposed by Feng et al. [70], Lee et al. [134] and Raunak et al. [215], that are computationally expensive [215] or require the creation of an additional perturbed test-set [134]. Similarly, for mitigation of lack of faithfulness and fluency, the method proposed by Feng et al. [70] requires the creation of a one-to-many architecture (one encoder and two decoders), which is also computationally expensive. Future directions would therefore include simplification of existing hallucination evaluation methods, applying them to different architectures like CNNs and transformers, and possibly conducting research on finding simpler hallucination search methods.

12 HALLUCINATION IN VISION-LANGUAGE GENERATION

With the vast advancement of the Transformer architecture [51, 262] in both CV and NLP, there is a trend to pre-train large-scale unified vision-language (VL) models [3, 40, 146, 270, 271, 275] to perform vision grounded text generation tasks, such as image captioning and visual question answering (VQA). Generally, there are two common schemas for vision-language pre-training: 1) pre-train from scratch with a massive amount of image-text pairs as well as optionally a large text-only corpus; or 2) initialize model parameters from a large pre-trained LM and then adapt it to the VL domain with adequate image-text pairs. Either way, the learned vision and language representations are aligned in the same multimodal space and the resulting model can be seen as a LM that understands visual information. Therefore, the hallucination problem is also observed in VL models due to similar reasons as found in NLG.

In the VL domain, the research on hallucination is still in its very early stage and how to measure and mitigate hallucination is an open question. In this section, we first review the hallucination in

image captioning as it is the only VL task that has corresponding previous research works. Then, we introduce hallucination phenomena found in other VL tasks. Finally, we discuss potential future research directions on this problem.

12.1 Object Hallucination in Image Captioning

Definition. Object hallucination is defined as models generating captions that contain non-existent or inaccurate objects from the input image. Following tasks in NLG, we also categorize object hallucination into intrinsic and extrinsic ones:



Intrinsic Object Hallucination

A chest of drawers with a mirror on top of it.

A chest of drawers and a football on top of it.

Extrinsic Object Hallucination

A chest of drawers and letters inside drawers.

A chest of drawers and a fan on the roof.

Fig. 2. Examples of intrinsic and extrinsic object hallucination in image captioning.

- **Intrinsic Object Hallucination:** captions contain incorrect or definitely non-existent objects given the input image. For example in Figure 2, there is no “*mirror*” or “*football*” on top of the chest in the given image.
- **Extrinsic Object Hallucination:** captions contain objects cannot be verified their existence from the input image. For example in Figure 2, we cannot verify whether there are “*letters*” in the drawer or a “*fan*” on the roof.

Metrics. To automatically measure object hallucination, Rohrbach et al. [222] propose the CHAIR (Caption Hallucination Assessment with Image Relevance) metric, which calculates what proportion of object words generated are actually in the image according to the ground truth captions. Specifically, there are two variants of it, which are CHAIR_i and CHAIR_s defined as follows,

$$\text{CHAIR}_i = \frac{\# \{\text{hallucinated objects}\}}{\# \{\text{all objects in ground truth}\}}, \text{CHAIR}_s = \frac{\# \{\text{hallucinated captions}\}}{\# \{\text{all captions}\}}.$$

CHAIR_i measures per-instance object hallucination, i.e. what fraction of object instances in each generated caption are hallucinated. CHAIR_s measures per-sentence object hallucination, i.e. what fraction of generated captions include at least one hallucinated object. For example, to calculate CHAIR scores for the MSCOCO dataset [158], Rohrbach et al. [222] apply the 80-object list used in the MSCOCO segmentation challenge Lu et al. [164] and find exact matches of object words or phrases in captions.

Mitigation. As a research problem that is in its early stage, there are currently a limited number of approaches proposed to mitigate object hallucination in image captioning. Biten et al. [16] hypothesize that the main cause of object hallucination is the systematic co-occurrence of particular object categories in input images. They propose three simple yet effective ways of data augmentation to make the co-occurrence statistics matrix more uniform to mitigate object hallucination. Results show that their introduced method can reduce object hallucination without changing model architectures. From another perspective, Xiao and Wang [286] propose an uncertainty-aware beam

search method for decoding and exhibit that reducing uncertainty can lead to less hallucination. Specifically, a weighted penalty term is added to the beam search objective to balance between log probability and predictive uncertainty of the selected word candidates. More recently, Dai et al. [41] analyze object hallucination in VL pre-training and propose a novel pre-training objective named object masked language modeling to alleviate this problem.

12.2 Hallucination in Other VL Tasks

In addition to image captioning, hallucination has also been observed in other VL tasks and raised as an open research question. For example, in open-ended visual question answering, Figure 3 (left and right) shows that the model could generate seem likely answers when we only see the text, however wrong when given the image. Moreover, Figure 3 (middle) indicates that hallucination can also be triggered by adversarially prompting an unanswerable question. The model will imagine an unsupported answer that commonly matches the given visual scene.



Question: What is on the phone screen? Answer: A text message from a friend.



Question: What can you see out the window? Answer: A parking lot.



*Question: Whom is the person texting? Answer: **The driver.***

Fig. 3. Examples of hallucination in visual question answering (taken from [3]). The bold text is the output generated by the model and the part before it is the input prompt.

12.3 Future Directions in VL

For future research on the hallucination problem in VL, we summarize three promising directions. Firstly, hallucination detection and mitigation in VL is still in the early stage. There is a lack of empirical and theoretical analyses in many tasks, such as visual storytelling, visual commonsense reasoning, video captioning, etc. Secondly, more effective evaluation metrics are needed. For example, although CHAIR can automatically evaluate the degree of object hallucination in image captioning, it requires a pre-defined list of object categories, which does not generalize well. Furthermore, currently there is no automatic metric for the hallucination types discussed in Section 12.2. Therefore, we cannot perform quantitative evaluations for them. Thirdly, we believe how to perform controlled generation [41, 216] with visual grounding is a promising direction to mitigate hallucination in VL.

13 HALLUCINATION IN LARGE LANGUAGE MODELS

Scaling up model and data size for language models has shown great empirical success. The resulting Large Language Models (LLMs) not only have achieved significant performance improvements upon previous PLMs across a diverse array of NLP tasks, but have also demonstrated many emerging abilities and strong steerability after instruction tuning and Reinforcement Learning from Human

Feedback (RLHF) [276, 321]. However, they still exhibit the hallucination problem. Even worse, since LLMs generate highly fluent and convincing responses, their hallucinations become more difficult to identify, and more likely to have harmful consequences. The launch of ChatGPT as an LLM with a conversational user interface led to the popularity of LLMs and their wide range of real-world applications. The research on the identification and mitigation of hallucination in LLMs has intensified. LLMs are usually open-ended general-purpose systems, which differ much from task-specific models, and their architectural designs, data coverage, training methodologies, and model behaviors are also different from PLMs mentioned in previous sections. Therefore, in the following sections, we specifically discuss the hallucination problem in LLMs, by covering more recent works, introducing novel strategies for measuring and mitigating hallucination, as well as listing unsolved questions and future directions.⁸

13.1 Hallucination Definition in LLMs

In the realm of LLMs, hallucination takes on a broader definition, reflecting the vastness of their training data, the breadth of their knowledge base, and their multitasking capability. Hallucination in LLMs not only signifies deviations from the source input but also extends to deviations from world knowledge. In this context, the “fact” discussed in Section 2.3 includes both the input source and the world knowledge. The hallucination degree reflects and encapsulates the model’s capacity to accurately and faithfully comprehend and represent the world. This includes a grasp of factual information, an understanding of linguistic subtleties, and an ability to navigate the intricate labyrinth of human knowledge and experience. Therefore, LLM hallucination is more oriented toward the extrinsic type involving unfaithful or nonsensical facts. Researchers explore the model’s ability to maintain the integrity of its parameterized knowledge, contextual understanding, recall relevant knowledge, and reasoning abilities [111]. This definition of hallucination in LLMs underscores the challenges and opportunities in developing these models. It highlights the need for robust mechanisms to prevent hallucination, to ensure the accuracy and reliability of the models, and to harness their potential in a responsible and beneficial manner.

13.2 Hallucination Metrics for LLMs

Hallucination metrics for LLMs are designed to either measure the level of hallucination in LLM-generated content, or quantify the hallucination risk of individual LLMs. Most of the related work focuses on measuring extrinsic hallucinations in the open domain. Depending on whether a metric requires golden references to identify hallucinations, we divide existing hallucination metrics for LLMs into reference-dependent and reference-free ones. In reference-dependent metrics, generations of LLM are analyzed based on references sourced from verified knowledge bases such as Wikipedia, news articles, books, and knowledge graphs. For reference-free metrics, hallucinations are identified by token probability-based uncertainty measures or self-consistency checks.

13.2.1 Reference-dependent Metrics. Reference-dependent metrics are often formatted as “hallucination benchmarks” that measure the hallucination level not risks of different LLMs. Most benchmarks utilize multiple choice QA or fill-in-the-blank QA to assess model hallucination, while some efforts further consider the ratio of partially incorrect answers [241] or instances where the model admits that it cannot answer [157]. Some benchmarks adopt the open domain and open-ended QA setting, where exact-match-based evaluations generally fail to recognize semantically equivalent answers [115]. Free-form responses from LLMs can be analyzed based on atomized decomposition

⁸This section was updated in Jan 2024.

(FactualityPrompt [137] and FActScore [184]), LLM-based evaluation (self-judgment [220] or GPT-4-based judgment [2]), or by measuring the discrepancy of the vanilla response and the response giving the knowledge for reference [106, 202, 301].

Human-annotated Hallucination Benchmarks. Collecting human-verified QA samples to test the factual knowledge of LLMs is the most straightforward method. Since the training corpora of LLMs are extremely large, high frequency count knowledge and basic commonsense can be easily memorized. As a result, examining low frequency, long-tailed knowledge becomes a primary focus of these hallucination benchmarks. Testing samples for long-tail knowledge can be selected based on frequency of appearance (e.g., in pretraining corpora [116] or Wikitext [52]), popularity measurements based on website traffic data (e.g., PopQA [173], Head-to-Tail [241]), recency (RealTimeQA [119]), or from specific domains (e.g., ExpertQA [172] and Med-HALT [259]). In addition to long-tail knowledge, another way to build challenging benchmarks is to gather questions that are more likely to lead to hallucinations – a methodology similar to adversarial prompting [130, 330] and red teaming [75]. The most representative example is TruthfulQA [157], a benchmark containing challenging questions that some humans would answer falsely due to false beliefs or misconceptions (e.g., question “*If it’s cold outside, what does that tell us about global warming?*” leads to GPT-3 answers “*It tells us that global warming is a hoax*”). Similarly, the DecodingTrust [265] evaluated the trustworthiness of GPT models in terms of adversarial robustness, OOD knowledge, vulnerability of jail-breaking, misleading instructions, etc. Known-Unknown [5] and SeflAware [299] evaluated LLMs’ awareness of uncertainty for question without definitive answer (e.g., “*If the Universe started at the Big Bang, what existed before then?*”)

Automated Hallucination Benchmarking. Manual question collection and answer annotation are labor intensive, hard to scale, and hard to adapt to new domains. To address this issue, annotation-free benchmarking methods have been proposed, which can be further divided into 1) automated benchmark generation and 2) automated evidence retrieval. For the first type of methods [29, 186], factual but unstructured corpora (for example, Wikipedia and reliable news articles) are transformed into a unified QA format based on information extraction and answer candidate generation. The second type of methods automatically retrieves evidence related to LLM generations from the Internet, similar to automated fact checking [93, 248]. They typically adopt a chained pipeline, where search queries are first generated (by an LLM) based on the content that needs to be verified, and then a model determines whether it contains hallucinations according to the retrieved evidence [77]). This pipeline can be further enhanced by upgrading the verification model from an NLI model [77] to prompted/fine-tuned LLMs (as in AttributionScore [305] and [260]), or by adding additional steps to the pipeline, such as tool interaction (as in FactTool [34] and CRITIC [87]), claim decomposition (Self-Checker [148]), additional second stage fine-grained retrieval and claim-focused summarization (as in [28]), or chain-of-verification [45].

13.2.2 Reference-free Metrics. Reference-free metrics aim to assess the hallucination risk of LLMs without relying on external references or ground truth. Although not as reliable as reference-based ones, these metrics are particularly useful when golden references are unavailable, expensive to obtain, or when hallucination identification needs to be performed in real time. Reference-free metrics generally fall into two categories: uncertainty-based and consistency-based hallucination detection. Uncertainty-based methods rely on the token probabilities assigned by the LLM during generation, whereas consistency-based methods evaluate the coherence of multiple completions generated by the LLM. There are also some benchmarks to measure the effectiveness of these reference-free hallucination metrics, which are also termed “hallucination detection benchmarks”,

such as HaluEval [144] and HaDes [161]. These benchmarks serve as meta-metrics of hallucination metrics, offering valuable resources for developing more effective methods to identify hallucinations.

Uncertainty-based Hallucination Detection. This type of method assumes that LLMs assign high probabilities to tokens that they are confident of, and low probabilities to uncertain tokens, which usually contain hallucinated information. It has a close relationship with classical uncertainty estimation methods [1, 180], since the generation of each token can be viewed as a vocabulary size classification problem. The difference here is that autoregressive text generation of LLM is a chained classification process, therefore individual token (subword) probabilities need to be aggregated so that they can reflect word-/sentence-/passage-level uncertainty. Such aggregation can be done by average-/max-/min-pooling on token probabilities, calculating the normalized product of the token probabilities, or calculating the maximum/averaged entropy [105, 174, 261?]. These methods can be further extended by adding prompts like “Generate factually consistent summary for the following text: <source-text> <generated-text>” [73] for fine-grained control (factuality evaluation on summarization), or “<question> <generated-answer> The answer is true.” [?] for self-evaluation of QA samples.

Consistency-based Hallucination Detection. is the more reliable and common approach. In practical applications, many LLMs only offer an API while internal logits remain inaccessible (*i.e.*, the “black-box setting”), thus making uncertainty-based methods inapplicable. Efforts have been made to create surrogate approximations of token probability. Specifically, LLMs first generate multiple completions with stochastic sampling given a fixed context, and then the consistency of these completions is used to reflect the uncertainty. Consistency can be measured by the BLUE-based variation ratio [105], BERTScore [174, 211], n-gram approximation [174], NER-based overlap ratio [211], NLI model [61, 211], or LLM-based judgment [188].

13.3 Hallucination Mitigation in LLMs

13.3.1 Data-Related Methods.

Data for Pretraining. Recent studies [324] showed that the knowledge within LLMs is almost entirely acquired during pretraining. Accordingly, a strong emphasis should be placed on ensuring the quality of the pretraining data. This can be performed through the collection of pretraining data from credible sources [253] and the minimization of defective and noisy data such as those that are unreliable or unverifiable [317]. A representative example of such data-driven methods can be found in the development of Llama-2 [254], where the most factual sources within the pretraining data were up-sampled in order to reduce hallucinations. Similarly, Falcon LLM [200] also demonstrated that their data refinement methods including rigorously filtering and deduplicating can significantly boost LLM performance. Due to the extensive pretraining datasets, some approaches have been developed to overcome the impracticalities that arise from manually selecting them. For instance, for the pretraining of GPT-3 [19], a classifier-based automatic filtering method was applied to remove low-quality documents. However, as pretraining data is being continuously scaled up, it is becoming increasingly costly for the research community to even access the entire pretraining dataset. As an alternative, small LLMs like phi-1.5 [151], which are trained on strictly controlled “textbooks-style” small-scale corpus, provide a valuable opportunity for doing rigorous ablations to investigate the relationship between pretraining data and model hallucination.

Data for Instruction-tuning. During the fine-tuning stage, data refinement can also be used to dampen hallucinations. As the size of fine-tuning data is significantly smaller, manual approaches can also be practically used [317]. For example, the authors of LIMA collected a diverse dataset of 1,000 carefully curated prompts and responses which are aligned with each other [324]. Conversely,

Chen et al. [30] point out that widely used fine-tuning datasets e.g. Alpaca's 52k data contain low-quality instances with incorrect or irrelevant responses which are detrimental to fine-tuning, used an automated approach leveraging strong LLMs to identify and discard such low-quality data. Alongside, the authors of InstructMining [23], proposed linear rules for selecting high-quality instruction fine-tuning data and avoided the need for human or machine annotations.

Data for Reward Model Training. Training reliable reward models such that desirable and undesirable outputs are distinguished is an effective method in mitigating hallucination. These models can subsequently be incorporated into reinforcement learning pipelines. Since the effectiveness of the system is constrained by the performance of the reward model itself, emphasis has been placed on determining the most effective training methods [154]. Thus, OpenAI released a dataset, namely, PRM800K, which resulted in a SOTA reward model [154]. In the development of GPT-4 [195], two different approaches were implemented. Firstly, in tackling open-domain hallucinations, OpenAI collected real-world ChatGPT data that were flagged as non-factual by users and used it together with additional labelled comparison data to train their reward models. Secondly, for closed-domain hallucinations, OpenAI utilised GPT-4 itself to generate and subsequently utilise synthetic data for reward model training.

Information Augmentation. Hallucinations can be mitigated via the use of external knowledge, or tools. Retrieval Augmented Generation (RAG) is a framework that utilizes data to improve the quality of LLM performances through grounding the model with an external knowledge base [176, 314] which is a popular method used to mitigate hallucination [63]. However, although being a common approach, Zhang et al. [314] argue that despite improving end-task performance, RAG does not consistently mitigate the issue of hallucinations due to misalignment between user questions and stored knowledge. The LLM may, as a result, draw invalid correlations or utilize biased model knowledge to override retrieved knowledge and subsequently hallucinate. To enhance this alignment, automatic question refinement such as MixAlign [314] achieves this question-knowledge alignment through the use of a language model. Furthermore, it can also achieve further enhancement, if necessary, through human user clarifications. More specifically, the framework employs the LLM to map the conditions and constraints of the user question to corresponding ones in the knowledge base and in cases where this mapping process yields uncertainties or the evidence remains elusive, MixAlign generates a question seeking further clarification from the user. This approach has been shown to not only decrease model hallucinations but also improve the quality of generated responses.

Examples of leveraging external knowledge for answer refinement REFEED [304]. REFEED is an approach that first generates initial outputs, uses a retrieval model to acquire information from large document collections, and lastly refines the initial output by incorporating this retrieved information, and LLM-Augmenter, which is a plug-and-play method that uses automatic feedback. CRITIC [88] is an example of a framework that uses external tools such as search engines and code interpreters to verify the initial output and successively amend it based on the critiques of the verification.

13.3.2 Modelling and Inference Methods.

Reinforcement Learning with Human Feedback and Safety Fine-Tuning. Reinforcement learning with human feedback (RLHF) and safety fine-tuning are one of the most dominant methods utilized to mitigate hallucination. One notable example is the resultant model of GPT-3 having undergone fine-tuning and further fine tuning using supervised learning and RLHF respectively, coined as InstructGPT, which roughly halved the hallucination rate from 41% to 21% in closed domain tasks such as summarization and closed domain QA [196]. In another well-known study, the authors

of Llama-2-Chat [254] observed a compelling finding, which is that after various RLHF iterations, despite the rise in temperature of the LLM, for prompts based on factual information, the model learns to consistently provide the same factual response whilst retaining its capability in generating diversity when fed creativity-based prompts. Furthermore, the authors utilize RLHF with the aim to improve the helpfulness (defined as how well the LLM responses fulfill users' requests and provide requested information) and safety of the LLM [254], which can decrease hallucination. Moreover, supervised safety fine-tuning was also carried out to improve model safety. It should be noted that the criterion for safety in this study not only involves whether harmful responses were produced, but also unhelpful ones [254]. As part of RLHF, the reward models were initialized from pretrained chat model checkpoints to ensure that both the chat model and reward model benefit from knowledge acquired from pretraining thereby avoiding an information mismatch which could give rise to hallucinations [254].

Decoding Methods. The modular architecture of LLMs can also be leveraged to combat hallucination. For example, researchers from MIT and Microsoft propose an approach, namely, Decoding by Contrasting Layers (DoLa), which emphasises knowledge from higher layers of an LLM whilst downplaying lower or intermediate layer knowledge [36]. Since factual knowledge is progressively injected by higher layers, the probability of the correct next word increases further up the architecture. Therefore, by exploiting the modularity of knowledge encoding in LLMs, the authors propose to amplify factual knowledge of LLMs via obtaining the probability of the next word from the difference between logits produced by a higher and lower layer. By making this contrast, the prominence of the correct next word's probability is increased. Results from the study demonstrate that DoLa consistently improves truthfulness which consequently reduces hallucination.

Similarly, Context-Aware Decoding (CAD) [231], also exploits logits and uses a contrastive approach to mitigate hallucination. However, instead of contrasting between layers, CAD amplifies the difference between the output probabilities when a model is used with context and without. This approach effectively suppresses prior knowledge when contextual information is provided.

Model Editing. Subtracting the parameters of a "negative expert" fine-tuned on negative samples from a pre-trained LLM can also serve to reduce hallucination [39]. However, given that some parameters are more responsible than others in causing hallucination, Daheim et al. [39] proposed an improved method coined as Elastic Weight Removal (EWR), which uses an approximation of the Fisher Information matrix, to weigh their individual performance, and computes a vector of differences between pre-trained and hallucination (anti-)expert models (trained with synthetic data) based on the weighting. Similarly, parameter interpolations with an abstractiveness expert model were also performed to prevent an increase in extractives, which is a potential side-effect of discouraging hallucinations. This steers the model towards being able to re-phrase ground-truth knowledge and drawing new valid conclusions rather than directly copying sections from documents with a limited understanding of their meaning.

Based on the notion that models "know" more than they "say", the researchers at Harvard [147] studied the difference between generation accuracy determined by a model's output and the probe accuracy (i.e. sentence classification using a model's intermediate activations as input to a classifier). The difference observed was 40%, which shows a major gap between the information present at intermediate layers and the output. Thus, to narrow this gap, the authors propose Inference-Time intervention, a computationally inexpensive and data-efficient technique that requires only a few hundred samples. The approach involves first using supervised learning to identify attention heads with high linear probing accuracy for truthfulness, in other words, identifying latent vectors related to factual outputs using supervised learning. And secondly, during LLM inference, shift model activations along these truth-correlated directions. The same

intervention is repeated autoregressively until the entire answer is generated. ITI was shown to improve truthfulness from 32.5% to 65.1% on Alpaca, an instruction fine-tuned Llama, which suggests the effectiveness of this approach in mitigating hallucinations.

Chain-of-Thought and Variants. Chain-of-Thought can be leveraged to reduce hallucinations. For example, simply adding the prompt, “Let’s think step by step”, encourages LLMs to reason prior to arriving to an answer, which improves model performance [124]. This is further evidenced in a related study where error rates were significantly reduced through using the same prompting strategy [312].

At inference, reasoning-based methods such as Chain-of-Verification (COVE) [46] and Chain of Natural Language Inference (CoNLI) [139] have been developed to reduce hallucination. The COVE method consists of four steps where an LLM first drafts an initial response, plans verification questions to fact check this, answers the questions independently to ensure the answers are not biased by other responses, and finally generates its final verified response. The framework, CoNLI, involves three steps, that is, to firstly select sentences (considered in this case as a set of hypotheses), secondly detect hallucinations with sentence and entity level detectors through prompting the LLM to solve a sequence of inference problems, and lastly to use a mitigation agent which uses detection reasonings as mitigation instructions to produce a refined response.

Self-reflection and self-collaboration is another approach that can be used to combat hallucination [111, 232, 273]. Ji et al. [111] is an iterative feedback loop process that involves generating relevant background knowledge for a given question followed by a factuality evaluation. When discrepancies are detected, the model is made to self-correct, which leverages its inherent capacity to reflect and thereby refine the knowledge. This iteration is continued until a satisfactory level of factuality is attained. Furthermore, during the answering stage, a similar generation-score-refine strategy is used along with an entailment evaluation to determine whether the answer properly addresses the question. If the answer fails to do so, the process returns back to the initial stage and repeats the cycle. This dynamic interaction between the system and its knowledge enhances the model to provide accurate, reliable, as well as factually grounded responses. A Solo Performance Prompting (SPP) [273] is proposed in light of LLMs’ tendency to struggle with tasks that require intensive domain knowledge and complex reasoning. Through prompting the LLM to engage in multi-turn self-collaboration with multiple personas, SPP transforms a sole LLM into an intelligent agent that works with multiple minds such that their individual strengths and knowledge are combined in order to boost overall problem-solving and performance in such tasks.

Ensemble. Ensembling multiple models to mitigate hallucination is another way. The “Society of Minds” approach can be used as an alternative to methods that are data-driven, modeling-driven, or at inference. One example of such [?], where multiple LLMs individually produce a response and then jointly debate each other on the responses and reasoning, such that a single common answer is reached, has been demonstrated to improve the factuality of generated content and reduce hallucination. This multi-agent interaction more specifically involves multiple instances of an LLM to first generate individual candidate answers to a given query. Subsequently, each individual model instance reads and critiques the responses of all other models and uses this content to refine its own answer; a step which is reiterated several times. This entire process steers the models towards constructing answers that are consistent with their own internal criticism and also sensible provided the response from other agents.

Post-processing. PURR (Petite Unsupervised Research and Revision) [26], requires LLMs to introduce corruptions/noises into data and subsequently fine-tune an editor to denoise these corruptions.

Specifically, PURR, a fusion-in-decoder T5 model, is trained to denoise corruptions when simultaneously given relevant evidence. Given an ungrounded output generated by LLMs, PURR generates questions to search for relevant evidence, which is subsequently used to produce an edit for the output.

13.4 Future Directions of Hallucination Mitigation in LLMs

13.4.1 Hallucination in Large Multimodal Models. Large multimodal models (LMMs) such as GPT-4V can generate rich and detailed response for visual inputs, and therefore being inherently riskier compared to previous VLMs for single-sentence captioning and short-answer VQA. Furthermore, images convey different levels of information encompassing object existence, attributes (color, shape, etc), spatial relationships, and sometimes high-level emotional responses they elicit (peaceful, beautiful, etc.), which makes mitigating hallucination in LMM even more challenging. The exploration of this area is still in its early stage, with a primary focus on object existence hallucination [152]. However, it is imperative for LMMs to analyze images well beyond that surface level, otherwise the use of LMM would be redundant and a simple object detector would suffice. The most crucial factor in this problem is the availability and quality of data and supervision. Language-supervised representations (e.g., CLIP) have demonstrated inherent shortcomings in recognizing certain types of visual patterns, such as object orientation, quantity, and viewpoint [252]. Even with perfect representation, imperfect vision-language alignment can result in a significant gap between the visual recognition abilities of the LMM and its visual backbone [308]. The cost of annotation during the mitigation of multimodal hallucination should also be considered. While there are works on the visual extension of faithfulness-oriented RLHF [303], these essentially involve labeling more data, which is expensive and difficult to scale. The versatility of the visual domains also makes it challenging to guarantee robustness and generalization. Large-scale self-supervision may be the path forward, as supervised learning has proven to be insufficient for both the CV and NLP in the past decade.

13.4.2 Hallucination in Long-tail and Low-resource Domains. Hallucinations in LLMs in long-tail and low-resource domains still remains a significant challenge. This has become a new research focus – for example, many recent hallucination benchmarks are proposed to measure LLM hallucination in various long-tail and low-resource domains (see Section 13.2.1). However, our scope should not be confined to only narrow professional areas (e.g., medical, legal, finance), but should also consider broader scenarios which are also long-tailed and low-resource. For example, hallucination in low-resource languages is a less explored area, as hallucination mitigation methods applied to rich-resource languages do not necessarily generalize to low-resource ones. Similarly, the temporal axis also impacts the frequency of world knowledge appearance, where more recent data could also be considered as long-tailed and low-resource. Furthermore, beyond textual data, multi-modal scenarios are inherently low-resource for text-only pretrained LLMs. In light of the above, instead of developing domain-specific methods for hallucination mitigation, we need to design unified framework and generalizable strategies for addressing hallucination in various imbalanced scenarios.

13.4.3 Estimating the Knowledge Boundary and Expressing the Uncertainty. Despite the vast size and continuous scaling of pretraining datasets for LLMs, it is impossible for them to encompass all the world’s knowledge. Consequently, teaching models to express their inability to answer specific questions and honestly admit “I don’t know” is crucial, and it requires LLMs to accurately model their knowledge boundaries. Notably, this task lies in a different dimension from other objectives that we expect LLMs to achieve (e.g., improving QA task accuracy) since it is not explicitly included in the pretraining corpora, making it more challenging. Furthermore, the diverse sources and

complex distributions of LLM pretraining data, along with varying training corpora for different LLMs, exacerbate the difficulty of this task. Related research is still in its early stages, with existing methods including calibration-based uncertainty estimation [114] and posterior approaches based on QA testing results [294], but none of them can satisfactorily solve this issue. For instances near the knowledge boundary, the situation is no longer a binary opposition between knowing and not knowing. In these cases, accurately expressing the model’s uncertainty level with fine granularity becomes a critical research question that warrants further exploration.

13.4.4 Minimizing the Alignment Tax During Hallucination Mitigation. Several studies have confirmed that the performance of ChatGPT and GPT-4 degrades over time due to continuous safety fine-tuning. This phenomenon is a typical example of an alignment tax. Similarly, when addressing hallucination problems in low-resource languages, the rate of hallucination in the original languages may increase. In the process of enhancing the faithfulness of LLMs’ multi-modal perception through visual instruction tuning on VQA datasets, the “politeness” of LLM responses may decrease due to the overly succinct nature of VQA answer annotations [27]. Furthermore, the alignment tax problem is not confined to fine-tuning-based methods but also extends to prompting-based methods such as Retrieval-Augmented Generation (RAG). These methods may also compromise the quality of responses when the quality of retrieved evidence is sub-optimal. In light of these findings, it is clear that we must explore strategies to minimize the cost during hallucination mitigation and prevent LLMs from becoming overly conservative, losing their creativity, or suffering from catastrophic forgetting in task performance.

13.4.5 Understanding Hallucination in LLMs. Although the research community has put extensive efforts to develop empirical methods for measuring and mitigating hallucinations, our understanding of LLM hallucination still remains limited. The absence of reliable theoretical frameworks and rigorous mathematical formulations hinders our ability to answer fundamental questions and make further advancements. For instance, how does hallucination correlate with model and data size (e.g., scaling laws)? What is the relationship between hallucination and auto-regressive generation? Does SFT and RLHF employ different mechanism to mitigate hallucinations? What is the lower-bound of hallucination across different tasks and domains? These questions are also intrinsically linked to a broader question – although now there are a lot of effort on empirically investigating what LLM can and cannot do from different dimensions, we still don’t understand why and how it works. There has been some attempts from various perspectives, such as knowledge encoding [81], compression [42], model selection [293], compositionality [58], computational perspective [69], but we are still a long way from truly understanding the mechanism behind various LLM behaviours.

14 CONCLUSION

In this survey, we provide the first comprehensive overview of the hallucination problem in NLG, summarizing existing evaluation metrics, mitigation methods, and the remaining challenges for future research. Hallucination is an artifact of neural-based NLG and is of concern because they appear fluent and can therefore be misleading to users. In some scenarios and tasks, hallucination can cause harm. We survey various contributors to hallucination, ranging from noisy data, erroneous parametric knowledge, incorrect attention mechanism, inappropriate training strategy, to inference exposure bias, etc. We show that there are two categories of hallucinations, namely intrinsic hallucination and extrinsic hallucination, and they need to be treated differently with diverse mitigation strategies. Hallucination is relatively easy to detect in abstractive summarization and in NMT against the evidence in the source. For dialogue systems, it is important to balance diversity vs consistency in dialogue responses. Hallucination in GQA and VL tasks is detrimental to the

performance, but research on mitigation methods is still very preliminary in these areas. For data-to-text generation, hallucination arises from the discrepancy between the input and output format. Most methods to mitigate hallucinations in NMT either aim to reduce dataset noise or alleviate exposure bias. In the VL domain, models also generate unfaithful output given the visual scene, and recent works have mainly focused on the object hallucination problem. There remain many challenges ahead in identifying and mitigating hallucinations in NLG, and we hope research in this area can benefit from this survey.

REFERENCES

- [1] Moloud Abdar, Farhad Pourpanah, Sadiq Hussain, Dana Rezazadegan, Li Liu, Mohammad Ghavamzadeh, Paul W. Fieguth, Xiaochun Cao, Abbas Khosravi, U. Rajendra Acharya, Vladimir Makarenkov, and Saeid Nahavandi. 2020. A Review of Uncertainty Quantification in Deep Learning: Techniques, Applications and Challenges. *CoRR* abs/2011.06225 (2020). arXiv:2011.06225 <https://arxiv.org/abs/2011.06225>
- [2] Vaibhav Adlakha, Parishad BehnamGhader, Xing Han Lu, Nicholas Meade, and Siva Reddy. 2023. Evaluating Correctness and Faithfulness of Instruction-Following Models for Question Answering. *CoRR* abs/2307.16877 (2023). <https://doi.org/10.48550/arXiv.2307.16877> arXiv:2307.16877
- [3] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katie Millican, Malcolm Reynolds, Roman Ring, Eliza Rutherford, Serkan Cabi, Tengda Han, Zhitao Gong, Sina Samangooei, Marianne Monteiro, Jacob Menick, Sebastian Borgeaud, Andy Brock, Aida Nematzadeh, Sahand Sharifzadeh, Mikolaj Binkowski, Ricardo Barreira, Oriol Vinyals, Andrew Zisserman, and Karen Simonyan. 2022. Flamingo: a Visual Language Model for Few-Shot Learning. *ArXiv* abs/2204.14198 (2022).
- [4] Joshua Albrecht and Rebecca Hwa. 2007. A Re-examination of Machine Learning Approaches for Sentence-Level MT Evaluation. In *Proceedings of the 45th Annual Meeting of the Association of Computational Linguistics*. Association for Computational Linguistics, Prague, Czech Republic, 880–887. <https://aclanthology.org/P07-1111>
- [5] Alfonso Amayuelas, Liangming Pan, Wenhui Chen, and William Yang Wang. 2023. Knowledge of Knowledge: Exploring Known-Unknowns Uncertainty with Large Language Models. *CoRR* abs/2305.13712 (2023). <https://doi.org/10.48550/arXiv.2305.13712> arXiv:2305.13712
- [6] Rahul Aralikkatte, Shashi Narayan, Joshua Maynez, Sascha Rothe, and Ryan McDonald. 2021. Focus Attention: Promoting Faithfulness and Diversity in Summarization. *ACL* (2021).
- [7] Xiang Bai, Xinggang Wang, Longin Jan Latecki, Wenyu Liu, and Zhuowen Tu. 2009. Active Skeleton for Non-rigid Object Detection. In *2009 IEEE 12th International Conference on Computer Vision*. 575–582. <https://doi.org/10.1109/ICCV.2009.5459188>
- [8] S. Baker and T. Kanade. 2000. Hallucinating Faces. In *Proceedings Fourth IEEE International Conference on Automatic Face and Gesture Recognition (Cat. No. PR00580)*. 83–88. <https://doi.org/10.1109/AFGR.2000.840616>
- [9] Anusha Balakrishnan, Jinfeng Rao, Kartikeya Upasani, Michael White, and Rajen Subba. 2019. Constrained Decoding for Neural NLG from Compositional Representations in Task-Oriented Dialogue. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Florence, Italy, 831–844. <https://doi.org/10.18653/v1/P19-1080>
- [10] Ramy Baly, Georgi Karadzhov, Dimitar Alexandrov, James Glass, and Preslav Nakov. 2018. Predicting Factuality of Reporting and Bias of News Media Sources. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. 3528–3539.
- [11] Iz Beltagy, Matthew E. Peters, and Arman Cohan. 2020. Longformer: The Long-Document Transformer. *arXiv:2004.05150* (2020).
- [12] Samy Bengio, Oriol Vinyals, Navdeep Jaitly, and Noam Shazeer. 2015. Scheduled Sampling for Sequence Prediction with Recurrent Neural Networks. *Advances in neural information processing systems* 28 (2015).
- [13] Anne Beyer, Sharid Loáiciga, and David Schlangen. 2021. Is Incoherence Surprising? Targeted Evaluation of Coherence Prediction from Language Models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Association for Computational Linguistics, Online, 4164–4173. <https://doi.org/10.18653/v1/2021.naacl-main.328>
- [14] Bin Bi, Chen Wu, Ming Yan, Wei Wang, Jiangnan Xia, and Chenliang Li. 2019. Incorporating External Knowledge into Machine Reading for Generative Question Answering. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. 2521–2530.
- [15] Andrzej Białecki, Robert Muir, Grant Ingersoll, and Lucid Imagination. 2012. Apache lucene 4. In *SIGIR 2012 workshop on open source information retrieval*. 17.

- [16] Ali Furkan Biten, Lluís Gómez, and Dimosthenis Karatzas. 2022. Let There Be a Clock on the Beach: Reducing Object Hallucination in Image Captioning. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*. 1381–1390.
- [17] Jan Dirk Blom. [n. d.]. *A Dictionary of Hallucinations*. Springer.
- [18] Eleftheria Briakou and Marine Carpuat. 2021. Beyond Noise: Mitigating the Impact of Fine-grained Semantic Divergences on Neural Machine Translation. *CoRR* abs/2105.15087 (2021). arXiv:2105.15087 <https://arxiv.org/abs/2105.15087>
- [19] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. In *Advances in Neural Information Processing Systems*, H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin (Eds.), Vol. 33. Curran Associates, Inc., 1877–1901. <https://proceedings.neurips.cc/paper/2020/file/1457c0d6bfc4967418bfb8ac142f64a-Paper.pdf>
- [20] Collin Burns, Haotian Ye, Dan Klein, and Jacob Steinhardt. 2022. Discovering Latent Knowledge in Language Models Without Supervision. In *The Eleventh International Conference on Learning Representations*.
- [21] Meng Cao, Yue Dong, Jiapeng Wu, and Jackie Chi Kit Cheung. 2020. Factual Error Correction for Abstractive Summarization Models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 6251–6258.
- [22] Shuyang Cao and Lu Wang. 2021. CLIFF: Contrastive Learning for Improving Faithfulness and Factuality in Abstractive Summarization. *EMNLP* (2021).
- [23] Yihan Cao, Yanbin Kang, Chi Wang, and Lichao Sun. 2023. INSTRUCTION MINING: WHEN DATA MINING MEETS LARGE LANGUAGE MODEL FINETUNING. *arXiv preprint arXiv:2307.06290* (2023).
- [24] Ziqiang Cao, Furu Wei, Wenjie Li, and Sujian Li. 2018. Faithful to the Original: Fact Aware Neural Abstractive Summarization. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 32.
- [25] Nicholas Carlini, Florian Tramèr, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom B Brown, Dawn Song, Úlfar Erlingsson, et al. 2020. Extracting Training Data from Large Language Models. (2020).
- [26] Anthony Chen, Panupong Pasupat, Sameer Singh, Hongrae Lee, and Kelvin Guu. 2023. PURR: Efficiently Editing Language Model Hallucinations by Denoising Language Model Corruptions. *arXiv preprint arXiv:2305.14908* (2023).
- [27] Delong Chen, Jianfeng Liu, Wenliang Dai, and Baoyuan Wang. 2023. Visual Instruction Tuning with Polite Flamingo. *CoRR* abs/2307.01003 (2023). <https://doi.org/10.48550/ARXIV.2307.01003> arXiv:2307.01003
- [28] Jifan Chen, Grace Kim, Aniruddh Sriram, Greg Durrett, and Eunsol Choi. 2023. Complex Claim Verification with Evidence Retrieved in the Wild. *CoRR* abs/2305.11859 (2023). <https://doi.org/10.48550/arXiv.2305.11859> arXiv:2305.11859
- [29] Jiawei Chen, Hongyu Lin, Xianpei Han, and Le Sun. 2023. Benchmarking Large Language Models in Retrieval-Augmented Generation. *CoRR* abs/2309.01431 (2023). <https://doi.org/10.48550/arXiv.2309.01431> arXiv:2309.01431
- [30] Lichang Chen, Shiyang Li, Jun Yan, Hai Wang, Kalpa Gunaratna, Vikas Yadav, Zheng Tang, Vijay Srinivasan, Tianyi Zhou, Heng Huang, and Hongxia Jin. 2023. AlpaGasus: Training A Better Alpaca with Fewer Data. *arXiv preprint arXiv:2307.08701* (7 2023). <http://arxiv.org/abs/2307.08701>
- [31] Sihao Chen, Fan Zhang, Kazuo Sone, and Dan Roth. 2021. Improving Faithfulness in Abstractive Summarization with Contrast Candidate Generation and Selection. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 5935–5941.
- [32] Wenqing Chen, Jidong Tian, Yitian Li, Hao He, and Yaohui Jin. 2021. De-Confounded Variational Encoder-Decoder for Logical Table-to-Text Generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 5532–5542.
- [33] Zhiyu Chen, Wenhu Chen, Hanwen Zha, Xiyu Zhou, Yunkai Zhang, Sairam Sundaresan, and William Yang Wang. 2020. Logic2Text: High-Fidelity Natural Language Generation from Logical Forms. In *EMNLP (Findings)*.
- [34] I-Chun Chern, Steffi Chern, Shiqi Chen, Weizhe Yuan, Kehua Feng, Chunting Zhou, Junxian He, Graham Neubig, and Pengfei Liu. 2023. FacTool: Factuality Detection in Generative AI - A Tool Augmented Framework for Multi-Task and Multi-Domain Scenarios. *CoRR* abs/2307.13528 (2023). <https://doi.org/10.48550/arXiv.2307.13528> arXiv:2307.13528
- [35] Andrew Chisholm, Will Radford, and Ben Hachey. 2017. Learning to generate one-sentence biographies from Wikidata. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*. 633–642.
- [36] Yung-Sung Chuang, Yujia Xie, Hongyin Luo, Yoon Kim, James Glass, and Pengcheng He. 2023. DOLA: DECODING BY CONTRASTING LAYERS IMPROVES FACTUALITY IN LARGE LANGUAGE MODELS. *arXiv preprint arXiv:2309.03883* (2023).

- [37] Michael Crawshaw. 2020. Multi-Task Learning with Deep Neural Networks: A Survey. *arXiv preprint arXiv:2009.09796* (2020).
- [38] Leyang Cui, Yu Wu, Shujie Liu, Yue Zhang, and Ming Zhou. 2020. MuTual: A Dataset for Multi-Turn Dialogue Reasoning. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 1406–1416.
- [39] Nico Daheim, Nouha Dziri, Mrinmaya Sachan, Iryna Gurevych, and Edoardo M Ponti. 2023. Elastic Weight Removal for Faithful and Abstractive Dialogue Generation. *arXiv preprint arXiv:2303.17574* (2023).
- [40] Wenliang Dai, Lu Hou, Lifeng Shang, Xin Jiang, Qun Liu, and Pascale Fung. 2022. Enabling Multimodal Generation on CLIP via Vision-Language Knowledge Distillation. In *Findings of the Association for Computational Linguistics: ACL 2022*. Association for Computational Linguistics, Dublin, Ireland, 2383–2395. <https://doi.org/10.18653/v1/2022.findings-acl.187>
- [41] Wenliang Dai, Zihan Liu, Ziwei Ji, Dan Su, and Pascale Fung. 2022. Plausible May Not Be Faithful: Probing Object Hallucination in Vision-Language Pre-training. *ArXiv abs/2210.07688* (2022).
- [42] Grégoire Delétang, Anian Ruoss, Paul-Ambroise Duquenne, Elliot Catt, Tim Genewein, Christopher Mattern, Jordi Grau-Moya, Li Kevin Wenliang, Matthew Aitchison, Laurent Orseau, Marcus Hutter, and Joel Veness. 2023. Language Modeling Is Compression. *CoRR abs/2309.10668* (2023). <https://doi.org/10.48550/ARXIV.2309.10668> arXiv:2309.10668
- [43] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. Association for Computational Linguistics, Minneapolis, Minnesota, 4171–4186. <https://doi.org/10.18653/v1/N19-1423>
- [44] Bhuwan Dhingra, Manaal Faruqui, Ankur Parikh, Ming-Wei Chang, Dipanjan Das, and William Cohen. 2019. Handling Divergent Reference Texts when Evaluating Table-to-Text Generation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. 4884–4895.
- [45] Shehzaad Dhuliawala, Mojtaba Komeili, Jing Xu, Roberta Raileanu, Xian Li, Asli Celikyilmaz, and Jason Weston. 2023. Chain-of-Verification Reduces Hallucination in Large Language Models. *arXiv preprint arXiv:2309.11495* (2023).
- [46] Shehzaad Dhuliawala, Mojtaba Komeili, Jing Xu, Roberta Raileanu, Xian Li, Asli Celikyilmaz, and Jason Weston. 2023. CHAIN-OF-VERIFICATION REDUCES HALLUCINATION IN LARGE LANGUAGE MODELS. *arXiv preprint arXiv:2309.11495* (2023).
- [47] Emily Dinan, Varvara Logacheva, Valentin Malykh, Alexander Miller, Kurt Shuster, Jack Urbanek, Douwe Kiela, Arthur Szlam, Iulian Serban, Ryan Lowe, et al. 2020. The Second Conversational Intelligence Challenge (ConvAI2). In *The NeurIPS’18 Competition*. Springer, 187–208.
- [48] Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. 2019. Wizard of Wikipedia: Knowledge-Powered Conversational agents. *ICLR* (2019).
- [49] Georgiana Dinu, Prashant Mathur, Marcello Federico, and Yaser Al-Onaizan. 2019. Training Neural Machine Translation To Apply Terminology Constraints. *ACL 2019 - 57th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference* (6 2019), 3063–3068. <https://doi.org/10.18653/v1/p19-1294>
- [50] Yue Dong, Shuohang Wang, Zhe Gan, Yu Cheng, Jackie Chi Kit Cheung, and Jingjing Liu. 2020. Multi-Fact Correction in Abstractive Text Summarization. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 9320–9331.
- [51] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. 2021. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. In *9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021*. OpenReview.net. <https://openreview.net/forum?id=YicbFdNTTy>
- [52] Li Du, Yequan Wang, Xingrun Xing, Yiqun Ya, Xiang Li, Xin Jiang, and Xuezhi Fang. 2023. Quantifying and Attributing the Hallucination of Large Language Models via Association Analysis. *CoRR abs/2309.05217* (2023). <https://doi.org/10.48550/arXiv.2309.05217> arXiv:2309.05217
- [53] Esin Durmus, He He, and Mona Diab. 2020. FEQA: A Question Answering Evaluation Framework for Faithfulness Assessment in Abstractive Summarization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 5055–5070.
- [54] Ondřej Dušek, David M Howcroft, and Verena Rieser. 2019. Semantic Noise Matters for Neural Natural Language Generation. In *Proceedings of the 12th International Conference on Natural Language Generation*. 421–426.
- [55] Ondřej Dušek and Filip Jurčiček. 2016. Sequence-to-Sequence Generation for Spoken Dialogue via Deep Syntax Trees and Strings. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*. Association for Computational Linguistics, Berlin, Germany, 45–51. <https://doi.org/10.18653/v1/P16-2008>
- [56] Ondřej Dušek and Zdeněk Kasner. 2020. Evaluating Semantic Accuracy of Data-to-Text Generation with Natural Language Inference. In *Proceedings of the 13th International Conference on Natural Language Generation*. Association for Computational Linguistics, Dublin, Ireland, 131–137. <https://aclanthology.org/2020.inlg-1.19>

- [57] Nouha Dziri, Ehsan Kamaloo, Kory Mathewson, and Osmar Zaiane. 2019. Evaluating Coherence in Dialogue Systems using Entailment. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. Association for Computational Linguistics, Minneapolis, Minnesota, 3806–3812. <https://doi.org/10.18653/v1/N19-1381>
- [58] Nouha Dziri, Ximing Lu, Melanie Sclar, Xiang Lorraine Li, Liwei Jiang, Bill Yuchen Lin, Peter West, Chandra Bhagavatula, Ronan Le Bras, Jena D. Hwang, Soumya Sanyal, Sean Welleck, Xiang Ren, Allyson Ettinger, Zaïd Harchaoui, and Yejin Choi. 2023. Faith and Fate: Limits of Transformers on Compositionality. *CoRR abs/2305.18654* (2023). <https://doi.org/10.48550/ARXIV.2305.18654> arXiv:2305.18654
- [59] Nouha Dziri, Andrea Madotto, Osmar Zaiane, and Avishek Joey Bose. 2021. Neural Path Hunter: Reducing Hallucination in Dialogue Systems via Path Grounding. *EMNLP* (2021).
- [60] Nouha Dziri, Hannah Rashkin, Tal Linzen, and David Reitter. 2021. Evaluating Groundedness in Dialogue Systems: The BEGIN Benchmark. *Findings of ACL* (2021).
- [61] Mohamed Elaraby, Mengyin Lu, Jacob Dunn, Xueying Zhang, Yu Wang, and Shizhu Liu. 2023. Halo: Estimation and Reduction of Hallucinations in Open-Source Weak Large Language Models. *CoRR abs/2308.11764* (2023). <https://doi.org/10.48550/arXiv.2308.11764> arXiv:2308.11764
- [62] Mihail Eric and Christopher Manning. 2017. A Copy-Augmented Sequence-to-Sequence Architecture Gives Good Performance on Task-Oriented Dialogue. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*. Association for Computational Linguistics, Valencia, Spain, 468–473. <https://aclanthology.org/E17-2075>
- [63] Shahul Es, Jithin James, Luis Espinosa-Anke, and Steven Schockaert. 2023. RAGAS: Automated Evaluation of Retrieval Augmented Generation. *arXiv preprint arXiv:2309.15217* (9 2023). <http://arxiv.org/abs/2309.15217>
- [64] Oren Etzioni, Michele Banko, Stephen Soderland, and Daniel S. Weld. 2008. Open Information Extraction from the Web. *Commun. ACM* 51, 12 (Dec. 2008), 68–74. <https://doi.org/10.1145/1409360.1409378>
- [65] Tobias Falke, Leonardo FR Ribeiro, Prasetya Ajie Utama, Ido Dagan, and Iryna Gurevych. 2019. Ranking Generated Summaries by Correctness: An Interesting but Challenging Application for Natural Language Inference. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. 2214–2220.
- [66] Angela Fan, Claire Gardent, Chloé Braud, and Antoine Bordes. 2019. Using Local Knowledge Graph Construction to Scale Seq2Seq Models to Multi-Document Inputs. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. 4186–4196.
- [67] Angela Fan, Yacine Jernite, Ethan Perez, David Grangier, Jason Weston, and Michael Auli. 2019. ELI5: Long Form Question Answering. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. 3558–3567.
- [68] Alhussein Fawzi, Horst Samulowitz, Deepak Turaga, and Pascal Frossard. 2016. Image Inpainting through Neural Networks Hallucinations. In *2016 IEEE 12th Image, Video, and Multidimensional Signal Processing Workshop (IVMSP)*. Ieee, 1–5.
- [69] Guhao Feng, Bohang Zhang, Yuntian Gu, Haotian Ye, Di He, and Liwei Wang. 2023. Towards Revealing the Mystery behind Chain of Thought: a Theoretical Perspective. *CoRR abs/2305.15408* (2023). <https://doi.org/10.48550/ARXIV.2305.15408> arXiv:2305.15408
- [70] Yang Feng, Wanying Xie, Shuhao Gu, Chenze Shao, Wen Zhang, Zhengxin Yang, and Dong Yu. 2020. Modeling Fluency and Faithfulness for Diverse Neural Machine Translation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 34. 59–66.
- [71] Katja Filippova. 2020. Controlled Hallucinations: Learning to Generate Faithfully from Noisy Data. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings*. 864–870.
- [72] William Fish et al. 2009. *Perception, hallucination, and illusion*. OUP USA.
- [73] Jinlan Fu, See-Kiong Ng, Zhengbao Jiang, and Pengfei Liu. 2023. GPTScore: Evaluate as You Desire. *CoRR abs/2302.04166* (2023). <https://doi.org/10.48550/arXiv.2302.04166> arXiv:2302.04166
- [74] Saadia Gabriel, Asli Celikyilmaz, Rahul Jha, Yejin Choi, and Jianfeng Gao. 2021. GO FIGURE: A Meta Evaluation of Factuality in Summarization. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*. Association for Computational Linguistics, Online, 478–487. <https://doi.org/10.18653/v1/2021.findings-acl.42>
- [75] Deep Ganguli, Liane Lovitt, Jackson Kernion, Amanda Askell, Yuntao Bai, Saurav Kadavath, Ben Mann, Ethan Perez, Nicholas Schiefer, Kamal Noudou, Andy Jones, Sam Bowman, Anna Chen, Tom Conerly, Nova DasSarma, Dawn Drain, Nelson Elhage, Sheer El Showk, Stanislaw Fort, Zac Hatfield-Dodds, Tom Henighan, Danny Hernandez, Tristan Hume, Josh Jacobson, Scott Johnston, Shauna Kravec, Catherine Olsson, Sam Ringer, Eli Tran-Johnson, Dario Amodei, Tom Brown, Nicholas Joseph, Sam McCandlish, Chris Olah, Jared Kaplan, and Jack Clark. 2022. Red Teaming Language Models to Reduce Harms: Methods, Scaling Behaviors, and Lessons Learned. *CoRR abs/2209.07858* (2022). <https://doi.org/10.48550/arXiv.2209.07858> arXiv:2209.07858

- [76] Jianfeng Gao, Michel Galley, and Lihong Li. 2018. Neural Approaches to Conversational AI. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics: Tutorial Abstracts*. Association for Computational Linguistics, Melbourne, Australia, 2–7. <https://doi.org/10.18653/v1/P18-5002>
- [77] Luyu Gao, Zhuyun Dai, Panupong Pasupat, Anthony Chen, Arun Tejasvi Chaganty, Yicheng Fan, Vincent Y. Zhao, Ni Lao, Hongrae Lee, Da-Cheng Juan, and Kelvin Guu. 2023. RARR: Researching and Revising What Language Models Say, Using Language Models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023*, Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (Eds.). Association for Computational Linguistics, 16477–16508. <https://doi.org/10.18653/v1/2023.acl-long.910>
- [78] Claire Gardent, Anastasia Shimorina, Shashi Narayan, and Laura Perez-Beltrachini. 2017. Creating Training Corpora for NLG Micro-Planning. In *55th annual meeting of the Association for Computational Linguistics (ACL)*.
- [79] Sarthak Garg, Stephan Peitz, Udhayakumar Nallasamy, and Matthias Paulik. 2019. Jointly Learning to Align and Translate with Transformer Models. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. 4453–4462.
- [80] Albert Gatt and Emiel Krahmer. 2018. Survey of the State of the Art in Natural Language Generation: Core tasks, applications and evaluation. *Journal of Artificial Intelligence Research* 61 (2018), 65–170.
- [81] Mor Geva, Roi Schuster, Jonathan Berant, and Omer Levy. 2021. Transformer Feed-Forward Layers Are Key-Value Memories. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021*, Marie-Francine Moens, Xuanjing Huang, Lucia Specia, and Scott Wen-tau Yih (Eds.). Association for Computational Linguistics, 5484–5495. <https://doi.org/10.18653/V1/2021.EMNLP-MAIN.446>
- [82] Deepanway Ghosal, Pengfei Hong, Siqi Shen, Navonil Majumder, Rada Mihalcea, and Soujanya Poria. 2021. CIDER: Commonsense Inference for Dialogue Explanation and Reasoning. *ACL (2021)*.
- [83] Alexandru L Ginsca, Adrian Popescu, and Mihai Lupu. 2015. Credibility in Information Retrieval. *Foundations and Trends in Information Retrieval* 9, 5 (2015), 355–475.
- [84] Bogdan Gliwa, Iwona Mochol, Maciej Biesek, and Aleksander Wawer. 2019. SAMSum Corpus: A Human-annotated Dialogue Dataset for Abstractive Summarization. In *Proceedings of the 2nd Workshop on New Frontiers in Summarization*. Association for Computational Linguistics, Hong Kong, China, 70–79. <https://doi.org/10.18653/v1/D19-5409>
- [85] Silke M Göbel and Matthew FS Rushworth. 2004. Cognitive Neuroscience: Acting on Numbers. *Current Biology* 14, 13 (2004), R517–R519.
- [86] Ben Goodrich, Vinay Rao, Peter J Liu, and Mohammad Saleh. 2019. Assessing the Factual Accuracy of Generated Text. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 166–175.
- [87] Zhibin Gou, Zhihong Shao, Yeyun Gong, Yelong Shen, Yujiu Yang, Nan Duan, and Weizhu Chen. 2023. CRITIC: Large Language Models Can Self-Correct with Tool-Interactive Critiquing. *CoRR* abs/2305.11738 (2023). <https://doi.org/10.48550/arXiv.2305.11738> arXiv:2305.11738
- [88] Zhibin Gou, Zhihong Shao, Yeyun Gong, Yelong Shen, Yujiu Yang, Nan Duan, and Weizhu Chen. 2023. CRITIC: LARGE LANGUAGE MODELS CAN SELF-CORRECT WITH TOOL-INTERACTIVE CRITIQUING. *arXiv preprint arXiv:2305.11738* (2023).
- [89] Kartik Goyal, Chris Dyer, and Taylor Berg-Kirkpatrick. 2017. Differentiable Scheduled Sampling for Credit Assignment. *ACL 2017 - 55th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference (Long Papers) 2* (4 2017), 366–371. <https://doi.org/10.18653/v1/P17-2058>
- [90] Tanya Goyal and Greg Durrett. 2020. Evaluating Factuality in Generation with Dependency-level Entailment. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings*. 3592–3603.
- [91] Jian Guan and Minlie Huang. 2020. UNION: An Unreferenced Metric for Evaluating Open-ended Story Generation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 9157–9166.
- [92] Beliz Gunel, Chenguang Zhu, Michael Zeng, and Xuedong Huang. 2019. Mind the facts: Knowledge-Boosted Coherent Abstractive Text Summarization. *NeurIPS, Knowledge Representation & Reasoning Meets Machine Learning (KR2ML workshop)* (2019).
- [93] Zhijiang Guo, Michael Sejr Schlichtkrull, and Andreas Vlachos. 2022. A Survey on Automated Fact-Checking. *Trans. Assoc. Comput. Linguistics* 10 (2022), 178–206. https://doi.org/10.1162/tacl_a_00454
- [94] Prakhar Gupta, Chien-Sheng Wu, Wenhao Liu, and Caiming Xiong. 2021. DialFact: A Benchmark for Fact-Checking in Dialogue. *arXiv preprint arXiv:2110.08222* (2021).
- [95] Suchin Gururangan, Swabha Swayamdipta, Omer Levy, Roy Schwartz, Samuel Bowman, and Noah A Smith. 2018. Annotation Artifacts in Natural Language Inference Data. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*. 107–112.
- [96] Braden Hancock, Antoine Bordes, Pierre-Emmanuel Mazare, and Jason Weston. 2019. Learning from Dialogue after Deployment: Feed Yourself, Chatbot!. In *Proceedings of the 57th Annual Meeting of the Association for Computational*

- Linguistics*. Association for Computational Linguistics, Florence, Italy, 3667–3684. <https://doi.org/10.18653/v1/P19-1358>
- [97] Tianxing He, Jingzhao Zhang, Zhiming Zhou, and James Glass. 2021. Exposure Bias versus Self-Recovery: Are Distortions Really Incremental for Autoregressive Text Generation?. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 5087–5102.
- [98] Chris Hokamp and Qun Liu. 2017. Lexically Constrained Decoding for Sequence Generation Using Grid Beam Search. *ACL 2017 - 55th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference (Long Papers)* 1 (4 2017), 1535–1546. <https://doi.org/10.18653/v1/P17-1141>
- [99] Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2019. The Curious Case of Neural Text Degeneration. In *International Conference on Learning Representations*.
- [100] Or Honovich, Roei Aharoni, Jonathan Herzig, Hagai Taitelbaum, Doron Kukliansy, Vered Cohen, Thomas Scialom, Idan Szpektor, Avinatan Hassidim, and Yossi Matias. 2022. TRUE: Re-evaluating Factual Consistency Evaluation. In *Proceedings of the Second DialDoc Workshop on Document-grounded Dialogue and Conversational Question Answering*. 161–175.
- [101] Or Honovich, Leshem Choshen, Roei Aharoni, Ella Neeman, Idan Szpektor, and Omri Abend. 2021. Q²: Evaluating Factual Consistency in Knowledge-Grounded Dialogues via Question Generation and Question Answering. *EMNLP* (2021).
- [102] Luyang Huang, Lingfei Wu, and Lu Wang. 2020. Knowledge Graph-Augmented Abstractive Summarization with Semantic-Driven Cloze Reward. *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics* (2020).
- [103] Minlie Huang, Xiaoyan Zhu, and Jianfeng Gao. 2020. Challenges in Building Intelligent Open-domain Dialog Systems. *ACM Transactions on Information Systems (TOIS)* 38, 3 (2020), 1–32.
- [104] Yichong Huang, Xiachong Feng, Xiaocheng Feng, and Bing Qin. 2021. The Factual Inconsistency Problem in Abstractive Text Summarization: A Survey. *arXiv preprint arXiv:2104.14839* (2021).
- [105] Yuheng Huang, Jiayang Song, Zhijie Wang, Huaming Chen, and Lei Ma. 2023. Look Before You Leap: An Exploratory Study of Uncertainty Measurement for Large Language Models. *CoRR* abs/2307.10236 (2023). <https://doi.org/10.48550/arXiv.2307.10236> arXiv:2307.10236
- [106] Siqing Huo, Negar Arabzadeh, and Charles L. A. Clarke. 2023. Retrieving Supporting Evidence for LLMs Generated Answers. *CoRR* abs/2306.13781 (2023). <https://doi.org/10.48550/arXiv.2306.13781> arXiv:2306.13781
- [107] Ahmed Hussein, Mohamed Medhat Gaber, Eyad Elyan, and Chrisina Jayne. 2017. Imitation Learning: A Survey of Learning Methods. *ACM Comput. Surv.* 50, 2, Article 21 (apr 2017), 35 pages. <https://doi.org/10.1145/3054912>
- [108] Ziwei Ji, Zihan Liu, Nayeon Lee, Tiezheng Yu, Bryan Wilie, Min Zeng, and Pascale Fung. 2023. RHO: Reducing Hallucination in Open-domain Dialogues with Knowledge Grounding. *arXiv preprint arXiv:2212.01588* (10 2023).
- [109] Ziwei Ji, Yan Xu, I-Tsun Cheng, Samuel Cahyawijaya, Rita Frieske, Etsuko Ishii, Min Zeng, Andrea Madotto, and Pascale Fung. 2022. VScript: Controllable Script Generation with Visual Presentation. arXiv:2203.00314
- [110] Ziwei Ji, Tiezheng Yu, Yan Xu, Nayeon Lee, Etsuko Ishii, and Pascale Fung. 2023. Towards Mitigating Hallucination in Large Language Models via Self-Reflection. *arXiv preprint arXiv:2310.06271* (5 2023). <https://arxiv.org/pdf/2310.06271.pdf>
- [111] Ziwei Ji, Tiezheng Yu, Yan Xu, Nayeon Lee, Etsuko Ishii, and Pascale Fung. 2023. Towards Mitigating Hallucination in Large Language Models via Self-Reflection. *EMNLP Findings* (2023).
- [112] Marcin Junczys-Dowmunt. 2018. Dual Conditional Cross-Entropy Filtering of Noisy Parallel Corpora. In *Proceedings of the Third Conference on Machine Translation: Shared Task Papers*. Association for Computational Linguistics, Belgium, Brussels, 888–895. <https://doi.org/10.18653/v1/W18-6478>
- [113] Daniel Jurafsky and James H. Marin. 2019. *Speech and Language Processing*. Draft of October 16th, 2019, Website: <https://web.stanford.edu/~jurafsky/slp3/26.pdf>, Chapter 26.
- [114] Saurav Kadavath, Tom Conerly, Amanda Askell, Tom Henighan, Dawn Drain, Ethan Perez, Nicholas Schiefer, Zac Hatfield-Dodds, Nova DasSarma, Eli Tran-Johnson, et al. 2022. Language models (mostly) know what they know. *arXiv preprint arXiv:2207.05221* (2022).
- [115] Ehsan Kamaloo, Nouha Dziri, Charles L. A. Clarke, and Davood Rafiei. 2023. Evaluating Open-Domain Question Answering in the Era of Large Language Models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023*, Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (Eds.). Association for Computational Linguistics, 5591–5606. <https://doi.org/10.18653/v1/2023.acl-long.307>
- [116] Nikhil Kandpal, Haikang Deng, Adam Roberts, Eric Wallace, and Colin Raffel. 2023. Large Language Models Struggle to Learn Long-Tail Knowledge. In *International Conference on Machine Learning, ICML 2023, 23-29 July 2023, Honolulu, Hawaii, USA (Proceedings of Machine Learning Research, Vol. 202)*, Andreas Krause, Emma Brunskill, Kyunghyun Cho, Barbara Engelhardt, Sivan Sabato, and Jonathan Scarlett (Eds.). PMLR, 15696–15707. <https://doi.org/10.26434/chemrxiv-2023-15696>

- //proceedings.mlr.press/v202/kandpal23a.html
- [117] Daniel Kang and Tatsunori Hashimoto. 2020. Improved Natural Language Generation via Loss Truncation. (4 2020), 718–731. <https://arxiv.org/abs/2004.14589v2>
- [118] Daniel Kang and Tatsunori B Hashimoto. 2020. Improved Natural Language Generation via Loss Truncation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 718–731.
- [119] Jungo Kasai, Keisuke Sakaguchi, Yoichi Takahashi, Ronan Le Bras, Akari Asai, Xinyan Yu, Dragomir R. Radev, Noah A. Smith, Yejin Choi, and Kentaro Inui. 2022. RealTime QA: What’s the Answer Right Now? *CoRR* abs/2207.13332 (2022). <https://doi.org/10.48550/arXiv.2207.13332> arXiv:2207.13332
- [120] Osman Semih Kayhan, Bart Vredebregt, and Jan C van Gemert. 2021. Hallucination In Object Detection—A Study In Visual Part VERIFICATION. In *2021 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2234–2238.
- [121] Daniel Khashabi, Amos Ng, Tushar Khot, Ashish Sabharwal, Hannaneh Hajishirzi, and Chris Callison-Burch. 2021. GooAQ: Open Question Answering with Diverse Answer Types. In *Findings of the Association for Computational Linguistics: EMNLP 2021*. Association for Computational Linguistics, Punta Cana, Dominican Republic, 421–433. <https://doi.org/10.18653/v1/2021.findings-emnlp.38>
- [122] Philipp Koehn and Rebecca Knowles. 2017. Six Challenges for Neural Machine Translation. In *First Workshop on Neural Machine Translation*. Association for Computational Linguistics, 28–39.
- [123] Philipp Koehn and Rebecca Knowles. 2017. Six Challenges for Neural Machine Translation. (2017), 28–39. <http://www.statmt.org/wmt17/>
- [124] Takeshi Kojima, Shixiang Shane Gu, Machel Reid Google Research, Yutaka Matsuo, and Yusuke Iwasawa. 2023. Large Language Models are Zero-Shot Reasoners. URL <https://arxiv.org/abs/2205.11916> (2023).
- [125] Xiang Kong, Zhaopeng Tu, Shuming Shi, Eduard Hovy, and Tong Zhang. 2019. Neural Machine Translation with Adequacy-Oriented Learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 6618–6625.
- [126] Kalpesh Krishna, Aurko Roy, and Mohit Iyyer. 2021. Hurdles to Progress in Long-form Question Answering. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 4940–4957.
- [127] Wojciech Kryscinski, Bryan McCann, Caiming Xiong, and Richard Socher. 2020. Evaluating the Factual Consistency of Abstractive Text Summarization. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 9332–9346.
- [128] Karen Kukich. 1983. Design of a Knowledge-based Report Generator. In *21st Annual Meeting of the Association for Computational Linguistics*. 145–150.
- [129] Ilia Kulikov, Alexander H. Miller, Kyunghyun Cho, and Jason Weston. 2019. Importance of Search and Evaluation Strategies in Neural Dialogue Modeling. In *Proceedings of the 12th International Conference on Natural Language Generation, INLG 2019, Tokyo, Japan, October 29 - November 1, 2019*, Kees van Deemter, Chenghua Lin, and Hiroya Takamura (Eds.). Association for Computational Linguistics, 76–87. <https://doi.org/10.18653/v1/W19-8609>
- [130] Aounon Kumar, Chirag Agarwal, Suraj Srinivas, Soheil Feizi, and Hima Lakkaraju. 2023. Certifying LLM Safety against Adversarial Prompting. *CoRR* abs/2309.02705 (2023). <https://doi.org/10.48550/arXiv.2309.02705> arXiv:2309.02705
- [131] Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. 2019. Natural Questions: A Benchmark for Question Answering Research. *Transactions of the Association for Computational Linguistics* 7 (2019), 452–466.
- [132] Philippe Laban, Tobias Schnabel, Paul N Bennett, and Marti A Hearst. 2022. SummaC: Re-Visiting NLI-based Models for Inconsistency Detection in Summarization. *Transactions of the Association for Computational Linguistics* 10 (2022), 163–177.
- [133] Rémi Lebret, David Grangier, and Michael Auli. 2016. Neural Text Generation from Structured Data with Application to the Biography Domain. *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (2016)*.
- [134] Katherine Lee, Orhan Firat, Ashish Agarwal, Clara Fannjiang, and David Sussillo. 2019. Hallucinations in Neural Machine Translation. *ICLR* (2019).
- [135] Katherine Lee, Daphne Ippolito, Andrew Nystrom, Chiyuan Zhang, Douglas Eck, Chris Callison-Burch, and Nicholas Carlini. 2021. Deduplicating Training Data Makes Language Models Better. *arXiv preprint arXiv:2107.06499* (2021).
- [136] Nayeon Lee, Belinda Z Li, Sinong Wang, Wen-Tau Yih, Hao Ma, and Madian Khabsa. 2020. Language Models as Fact Checkers? *ACL 2020* (2020), 36.
- [137] Nayeon Lee, Wei Ping, Peng Xu, Mostofa Patwary, Mohammad Shoeybi, and Bryan Catanzaro. 2022. Factuality Enhanced Language Models for Open-Ended Text Generation. *arXiv preprint arXiv:2206.04624* (2022).
- [138] Nayeon Lee, Chien-Sheng Wu, and Pascale Fung. [n. d.]. Improving Large-Scale Fact-Checking using Decomposable Attention Models and Lexical Tagging. ([n. d.]).
- [139] Deren Lei, Yaxi Li, Mengya Hu, Mingyu Wang, Vincent Yun, Emily Ching, and Eslam Kamal. 2023. Chain of Natural Language Inference for Reducing Large Language Model Ungrounded Hallucinations. *arXiv preprint arXiv:2310.03951*

- (2023). <https://arxiv.org/pdf/2310.03951.pdf>
- [140] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 7871–7880.
- [141] Bohan Li, Yutai Hou, and Wanxiang Che. 2021. Data Augmentation Approaches in Natural Language Processing: A Survey. *arXiv preprint arXiv:2110.01852* (2021).
- [142] Chenliang Li, Bin Bi, Ming Yan, Wei Wang, and Songfang Huang. 2021. Addressing Semantic Drift in Generative Question Answering with Auxiliary Extraction. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*. 942–947.
- [143] Haoran Li, Junnan Zhu, Jiajun Zhang, and Chengqing Zong. 2018. Ensure the Correctness of the Summary: Incorporate Entailment Knowledge into Abstractive Sentence Summarization. In *Proceedings of the 27th International Conference on Computational Linguistics*. Association for Computational Linguistics, Santa Fe, New Mexico, USA, 1430–1441. <https://aclanthology.org/C18-1121>
- [144] Junyi Li, Xiaoxue Cheng, Wayne Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. 2023. HaluEval: A Large-Scale Hallucination Evaluation Benchmark for Large Language Models. *CoRR* abs/2305.11747 (2023). <https://doi.org/10.48550/arXiv.2305.11747> arXiv:2305.11747
- [145] Jiwei Li, Michel Galley, Chris Brockett, Georgios Spithourakis, Jianfeng Gao, and Bill Dolan. 2016. A Persona-Based Neural Conversation Model. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Berlin, Germany, 994–1003. <https://doi.org/10.18653/v1/P16-1094>
- [146] Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. 2022. BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation. In *ICML*.
- [147] Kenneth Li, Oam Patel, Fernanda Viégas, Hanspeter Pfister, and Martin Wattenberg. 2023. Inference-Time Intervention: Eliciting Truthful Answers from a Language Model. *arXiv preprint arXiv:2306.03341* (2023).
- [148] Miaoran Li, Baolin Peng, and Zhu Zhang. 2023. Self-Checker: Plug-and-Play Modules for Fact-Checking with Large Language Models. *CoRR* abs/2305.14623 (2023). <https://doi.org/10.48550/arXiv.2305.14623> arXiv:2305.14623
- [149] Margaret Li, Stephen Roller, Ilya Kulikov, Sean Welleck, Y-Lan Boureau, Kyunghyun Cho, and Jason Weston. 2020. Don't Say That! Making Inconsistent Dialogue Unlikely with Unlikelihood Training. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Online, 4715–4728. <https://doi.org/10.18653/v1/2020.acl-main.428>
- [150] Tian Li, Ahmad Beirami, Maziar Sanjabi, and Virginia Smith. 2020. Tilted Empirical Risk Minimization. In *International Conference on Learning Representations*.
- [151] Yuanzhi Li, Sébastien Bubeck, Ronen Eldan, Allie Del Giorno, Suriya Gunasekar, and Yin Tat Lee. 2023. Textbooks Are All You Need II: phi-1.5 technical report. <https://arxiv.org/pdf/2309.05463.pdf>
- [152] Yifan Li, Yifan Du, Kun Zhou, Jinpeng Wang, Wayne Xin Zhao, and Ji-Rong Wen. 2023. Evaluating Object Hallucination in Large Vision-Language Models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023*, Houda Bouamor, Juan Pino, and Kalika Bali (Eds.). Association for Computational Linguistics, 292–305. <https://aclanthology.org/2023.emnlp-main.20>
- [153] Yangming Li, Kaisheng Yao, Libo Qin, Wanxiang Che, Xiaolong Li, and Ting Liu. 2020. Slot-consistent NLG for Task-oriented Dialogue Systems with Iterative Rectification Network. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Online, 97–106. <https://doi.org/10.18653/v1/2020.acl-main.10>
- [154] Hunter Lightman, Vineet Kosaraju, Yura Burda, Harri Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. 2023. Let's Verify Step by Step. *arXiv preprint arXiv:2305.20050* (5 2023). <http://arxiv.org/abs/2305.20050>
- [155] Chin-Yew Lin. 2004. Rouge: A Package for Automatic Evaluation of Summaries. In *Text summarization branches out*. 74–81.
- [156] Stephanie Lin, Jacob Hilton, and Owain Evans. 2021. TruthfulQA: Measuring How Models Mimic Human Falsehoods. *arXiv preprint arXiv:2109.07958* (2021).
- [157] Stephanie Lin, Jacob Hilton, and Owain Evans. 2022. TruthfulQA: Measuring How Models Mimic Human Falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (Eds.). Association for Computational Linguistics, 3214–3252. <https://doi.org/10.18653/v1/2022.acl-long.229>
- [158] Tsung-Yi Lin, Michael Maire, Serge J. Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. 2014. Microsoft COCO: Common Objects in Context. *ArXiv* abs/1405.0312 (2014).

- [159] Ce Liu, Heung-Yeung Shum, and William T Freeman. 2007. Face Hallucination: Theory and Practice. *International Journal of Computer Vision* 75, 1 (2007), 115–134.
- [160] Tianyu Liu, Yizhe Zhang, Chris Brockett, Yi Mao, Zhifang Sui, Weizhu Chen, and Bill Dolan. 2021. A Token-level Reference-free Hallucination Detection Benchmark for Free-form Text Generation. *arXiv preprint arXiv:2104.08704* (2021).
- [161] Tianyu Liu, Yizhe Zhang, Chris Brockett, Yi Mao, Zhifang Sui, Weizhu Chen, and Bill Dolan. 2022. A Token-level Reference-free Hallucination Detection Benchmark for Free-form Text Generation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (Eds.). Association for Computational Linguistics, 6723–6737. <https://doi.org/10.18653/v1/2022.acl-long.464>
- [162] Tianyu Liu, Xin Zheng, Baobao Chang, and Zhifang Sui. 2021. Towards Faithfulness in Open Domain Table-to-text Generation from an Entity-centric View. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35. 13415–13423.
- [163] Shayne Longpre, Kartik Perisetla, Anthony Chen, Nikhil Ramesh, Chris DuBois, and Sameer Singh. 2021. Entity-Based Knowledge Conflicts in Question Answering. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 7052–7063.
- [164] Jiasen Lu, Jianwei Yang, Dhruv Batra, and Devi Parikh. 2018. Neural Baby Talk. In *CVPR*.
- [165] Yukun Ma, Khanh Linh Nguyen, Frank Z Xing, and Erik Cambria. 2020. A Survey on Empathetic Dialogue Systems. *Information Fusion* 64 (2020), 50–70.
- [166] Fiona Macpherson and Dimitris Platchias. 2013. *Hallucination: Philosophy and psychology*. MIT Press.
- [167] Andrea Madotto, Samuel Cahyawijaya, Genta Indra Winata, Yan Xu, Zihan Liu, Zhaoyang Lin, and Pascale Fung. 2020. Learning Knowledge Bases with Parameters for Task-Oriented Dialogue Systems. In *Findings of the Association for Computational Linguistics: EMNLP 2020*. Association for Computational Linguistics, Online, 2372–2394. <https://doi.org/10.18653/v1/2020.findings-emnlp.215>
- [168] Andrea Madotto, Zhaoyang Lin, Chien-Sheng Wu, and Pascale Fung. 2019. Personalizing dialogue agents via meta-learning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. 5454–5459.
- [169] Andrea Madotto, Zihan Liu, Zhaoyang Lin, and Pascale Fung. 2020. Language Models as Few-Shot Learner for Task-Oriented Dialogue Systems. *arXiv:2008.06239 [cs.CL]*
- [170] Andrea Madotto, Chien-Sheng Wu, and Pascale Fung. 2018. Mem2Seq: Effectively Incorporating Knowledge Bases into End-to-End Task-Oriented Dialog Systems. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Melbourne, Australia, 1468–1478. <https://doi.org/10.18653/v1/P18-1136>
- [171] Amr Magdy and Nayer Wanas. 2010. Web-based Statistical Fact Checking of Textual Documents. In *Proceedings of the 2nd international workshop on Search and mining user-generated contents*. 103–110.
- [172] Chaitanya Malaviya, Subin Lee, Sihao Chen, Elizabeth Sieber, Mark Yatskar, and Dan Roth. 2023. ExpertQA: Expert-Curated Questions and Attributed Answers. *CoRR abs/2309.07852* (2023). <https://doi.org/10.48550/arXiv.2309.07852> *arXiv:2309.07852*
- [173] Alex Mallen, Akari Asai, Victor Zhong, Rajarshi Das, Daniel Khashabi, and Hannaneh Hajishirzi. 2023. When Not to Trust Language Models: Investigating Effectiveness of Parametric and Non-Parametric Memories. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2023, Toronto, Canada, July 9-14, 2023*, Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (Eds.). Association for Computational Linguistics, 9802–9822. <https://doi.org/10.18653/v1/2023.acl-long.546>
- [174] Potsawee Manakul, Adian Liusie, and Mark J. F. Gales. 2023. SelfCheckGPT: Zero-Resource Black-Box Hallucination Detection for Generative Large Language Models. *CoRR abs/2303.08896* (2023). <https://doi.org/10.48550/arXiv.2303.08896> *arXiv:2303.08896*
- [175] Marianna J. Martindale, Marine Carpuat, Kevin Duh, and Paul McNamee. 2019. Identifying Fluently Inadequate Output in Neural and Statistical Machine Translation. In *MTSummit*.
- [176] Kim Martineau. 2023. *What is retrieval-augmented generation?* <https://research.ibm.com/blog/retrieval-augmented-generation-RAG>
- [177] Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. On Faithfulness and Factuality in Abstractive Summarization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 1906–1919.
- [178] Pierre-Emmanuel Mazaré, Samuel Humeau, Martin Raison, and Antoine Bordes. 2018. Training Millions of Personalized Dialogue Agents. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Brussels, Belgium, 2775–2779. <https://doi.org/10.18653/v1/D18-1298>
- [179] Kathleen McKeown. 1992. *Text Generation*. Cambridge University Press.

- [180] José Mena, Oriol Pujol, and Jordi Vitrià. 2022. A Survey on Uncertainty Estimation in Deep Learning Classification Systems from a Bayesian Perspective. *ACM Comput. Surv.* 54, 9 (2022), 193:1–193:35. <https://doi.org/10.1145/3477140>
- [181] Mohsen Mesgar, Edwin Simpson, and Iryna Gurevych. 2021. Improving Factual Consistency Between a Response and Persona Facts. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. Association for Computational Linguistics, Online, 549–562. <https://doi.org/10.18653/v1/2021.eacl-main.44>
- [182] Donald Metzler, Yi Tay, Dara Bahri, and Marc Najork. 2021. Rethinking Search: Making Experts out of Dilettantes. *arXiv preprint arXiv:2105.02274* (2021).
- [183] Sabrina J Mielke, Arthur Szlam, Y-Lan Boureau, and Emily Dinan. 2020. Linguistic calibration through metacognition: aligning dialogue agent responses with expected correctness. *arXiv preprint arXiv:2012.14983* (2020).
- [184] Sewon Min, Kalpesh Krishna, Xinxin Lyu, Mike Lewis, Wen-tau Yih, Pang Wei Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2023. FActScore: Fine-grained Atomic Evaluation of Factual Precision in Long Form Text Generation. *CoRR abs/2305.14251* (2023). <https://doi.org/10.48550/arXiv.2305.14251> arXiv:2305.14251
- [185] Anshuman Mishra, Dhruv Patel, Aparna Vijayakumar, Xiang Lorraine Li, Pavan Kapanipathi, and Kartik Talamadupula. 2021. Looking Beyond Sentence-Level Natural Language Inference for Question Answering and Text Summarization. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 1322–1336.
- [186] Dor Muhlgay, Ori Ram, Inbal Magar, Yoav Levine, Nir Ratner, Yonatan Belinkov, Omri Abend, Kevin Leyton-Brown, Amnon Shashua, and Yoav Shoham. 2023. Generating Benchmarks for Factuality Evaluation of Language Models. *CoRR abs/2307.06908* (2023). <https://doi.org/10.48550/arXiv.2307.06908> arXiv:2307.06908
- [187] Mathias Müller, Annette Rios, and Rico Sennrich. 2020. Domain Robustness in Neural Machine Translation. In *14th Conference of the Association for Machine Translation in the Americas*. Association for Machine Translation in the Americas, AMTA, 151–164.
- [188] Niels Mündler, Jingxuan He, Slobodan Jenko, and Martin T. Vechev. 2023. Self-contradictory Hallucinations of Large Language Models: Evaluation, Detection and Mitigation. *CoRR abs/2305.15852* (2023). <https://doi.org/10.48550/arXiv.2305.15852> arXiv:2305.15852
- [189] Reiichiro Nakano, Jacob Hilton, Suchir Balaji, Jeff Wu, Long Ouyang, Christina Kim, Christopher Hesse, Shantanu Jain, Vineet Kosaraju, William Saunders, et al. 2021. WebGPT: Browser-assisted question-answering with human feedback. *arXiv preprint arXiv:2112.09332* (2021).
- [190] Feng Nan, Ramesh Nallapati, Zhiguo Wang, Cicero dos Santos, Henghui Zhu, Dejiao Zhang, Kathleen McKeown, and Bing Xiang. 2021. Entity-level Factual Consistency of Abstractive Text Summarization. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2727–2733.
- [191] Tri Nguyen, Mir Rosenberg, Xia Song, Jianfeng Gao, Saurabh Tiwary, Rangan Majumder, and Li Deng. 2016. MS MARCO: A human generated machine reading comprehension dataset. In *CoCo@NIPS*.
- [192] Feng Nie, Jinpeng Wang, Jin-Ge Yao, Rong Pan, and Chin-Yew Lin. 2018. Operation-guided Neural Networks for High Fidelity Data-To-Text Generation. In *EMNLP*.
- [193] Feng Nie, Jin-Ge Yao, Jinpeng Wang, Rong Pan, and Chin-Yew Lin. 2019. A Simple Recipe towards Reducing Hallucination in Neural Surface Realisation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Florence, Italy, 2673–2679. <https://doi.org/10.18653/v1/P19-1256>
- [194] Franz Josef Och. 2003. Minimum Error Rate Training in Statistical Machine Translation. In *Proceedings of the 41st annual meeting of the Association for Computational Linguistics*. 160–167.
- [195] OpenAI. 2023. GPT-4 Technical Report. *arXiv preprint arXiv:2303.08774* (3 2023). <http://arxiv.org/abs/2303.08774>
- [196] Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang Sandhini Agarwal Katarina Slama Alex Ray John Schulman Jacob Hilton Fraser Kelton Luke Miller Maddie Simens Amanda Askell, Peter Welinder Paul Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems* 35 (2022), 27730–27744.
- [197] Artidoro Pagnoni, Vidhisha Balachandran, and Yulia Tsvetkov. 2021. Understanding Factuality in Abstractive Summarization with FRANK: A Benchmark for Factuality Metrics. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 4812–4829.
- [198] Ankur Parikh, Xuezhi Wang, Sebastian Gehrmann, Manaal Faruqi, Bhuvan Dhingra, Diyi Yang, and Dipanjan Das. 2020. ToTTo: A Controlled Table-To-Text Generation Dataset. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 1173–1186.
- [199] Prasanna Parthasarathi, Koustuv Sinha, Joelle Pineau, and Adina Williams. 2021. Sometimes We Want Ungrammatical Translations. In *Findings of the Association for Computational Linguistics: EMNLP 2021*. Association for Computational Linguistics, Punta Cana, Dominican Republic, 3205–3227. <https://doi.org/10.18653/v1/2021.findings-emnlp.275>

- [200] Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Alessandro Cappelli, Hamza Alobeidli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Launay. 2023. The RefinedWeb Dataset for Falcon LLM: Outperforming Curated Corpora with Web Data, and Web Data Only The Falcon LLM team The RefinedWeb dataset for Falcon LLM. *arXiv preprint arXiv:2306.01116* (2023). <https://arxiv.org/pdf/2306.01116.pdf>
- [201] Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhtin, Yuxiang Wu, and Alexander Miller. 2019. Language Models as Knowledge Bases?. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. Association for Computational Linguistics, Hong Kong, China, 2463–2473. <https://doi.org/10.18653/v1/D19-1250>
- [202] Pouya Pezeshkpour. 2023. Measuring and Modifying Factual Knowledge in Large Language Models. *CoRR abs/2306.06264* (2023). <https://doi.org/10.48550/arXiv.2306.06264> arXiv:2306.06264
- [203] Adam Poliak, Jason Naradowsky, Aparajita Haldar, Rachel Rudinger, and Benjamin Van Durme. 2018. Hypothesis Only Baselines in Natural Language Inference. In *Proceedings of the Seventh Joint Conference on Lexical and Computational Semantics*. 180–191.
- [204] Kashyap Papat, Subhabrata Mukherjee, Jannik Strötgen, and Gerhard Weikum. 2016. Credibility Assessment of Textual Claims on the Web. In *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management*. 2173–2178.
- [205] Kashyap Papat, Subhabrata Mukherjee, Andrew Yates, and Gerhard Weikum. 2018. DeClarE: Debunking Fake News and False Claims using Evidence-Aware Deep Learning. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Brussels, Belgium, 22–32. <https://doi.org/10.18653/v1/D18-1003>
- [206] Matt Post and David Vilar. 2018. Fast Lexically Constrained Decoding with Dynamic Beam Allocation for Neural Machine Translation. *NAACL HLT 2018 - 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference 1* (4 2018), 1314–1324. <https://doi.org/10.18653/v1/n18-1119>
- [207] Ratish Puduppully, Li Dong, and Mirella Lapata. 2019. Data-to-text generation with content selection and planning. In *Proceedings of the AAAI conference on artificial intelligence*.
- [208] Ratish Puduppully and Mirella Lapata. 2021. Data-to-text generation with macro planning. *Transactions of the Association for Computational Linguistics* (2021).
- [209] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language Models are Unsupervised Multitask Learners. *OpenAI Blog* 1, 8 (2019), 9.
- [210] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. *Journal of Machine Learning Research* 21, 140 (2020), 1–67. <http://jmlr.org/papers/v21/20-074.html>
- [211] Harsh Raj, Domenic Rosati, and Subhabrata Majumdar. 2022. Measuring Reliability of Large Language Models through Semantic Consistency. *CoRR abs/2211.05853* (2022). <https://doi.org/10.48550/arXiv.2211.05853> arXiv:2211.05853
- [212] Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. Know What You Don’t Know: Unanswerable Questions for SQuAD. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*. Association for Computational Linguistics.
- [213] Marc’Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. 2016. Sequence Level Training with Recurrent Neural Networks. *ICLR* (2016).
- [214] Hannah Rashkin, David Reitter, Gaurav Singh Tomar, and Dipanjan Das. 2021. Increasing Faithfulness in Knowledge-Grounded Dialogue with Controllable Features. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. Association for Computational Linguistics, Online, 704–718. <https://doi.org/10.18653/v1/2021.acl-long.58>
- [215] Vikas Raunak, Arul Menezes, and Marcin Junczys-Dowmunt. 2021. The Curious Case of Hallucinations in Neural Machine Translation. (4 2021), 1172–1183. <https://arxiv.org/abs/2104.06683v1>
- [216] Clément Rebuffel, Marco Roberti, Laure Soulier, Geoffrey Scuttheeten, Rossella Cancelliere, and Patrick Gallinari. 2022. Controlling hallucinations at word level in data-to-text generation. *Data Mining and Knowledge Discovery* 36, 1 (2022), 318–354.
- [217] Clément Rebuffel, Thomas Scialom, Laure Soulier, Benjamin Piwowarski, Sylvain Lamprier, Jacopo Staiano, Geoffrey Scuttheeten, and Patrick Gallinari. 2021. Data-QuestEval: A Reference-less Metric for Data-to-Text Semantic Evaluation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*.
- [218] Ehud Reiter. 2018. A Structured Review of the Validity of BLEU. *Computational Linguistics* 44, 3 (Sept. 2018), 393–401. https://doi.org/10.1162/coli_a_00322
- [219] Ehud Reiter and Robert Dale. 1997. Building Applied Natural Language Generation Systems. *Natural Language Engineering* 3, 1 (1997), 57–87.

- [220] Ruiyang Ren, Yuhao Wang, Yingqi Qu, Wayne Xin Zhao, Jing Liu, Hao Tian, Hua Wu, Ji-Rong Wen, and Haifeng Wang. 2023. Investigating the Factual Knowledge Boundary of Large Language Models with Retrieval Augmentation. *CoRR* abs/2307.11019 (2023). <https://doi.org/10.48550/arXiv.2307.11019> arXiv:2307.11019
- [221] Adam Roberts, Colin Raffel, and Noam Shazeer. 2020. How Much Knowledge Can You Pack Into the Parameters of a Language Model?. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Association for Computational Linguistics, Online, 5418–5426. <https://doi.org/10.18653/v1/2020.emnlp-main.437>
- [222] Anna Rohrbach, Lisa Anne Hendricks, Kaylee Burns, Trevor Darrell, and Kate Saenko. 2018. Object Hallucination in Image Captioning. In *EMNLP*.
- [223] Stephen Roller, Y-Lan Boureau, Jason Weston, Antoine Bordes, Emily Dinan, Angela Fan, David Gunning, Da Ju, Margaret Li, Spencer Poff, et al. 2020. Open-Domain Conversational Agents: Current Progress, Open Problems, and Future Directions. *arXiv preprint arXiv:2006.12442* (2020).
- [224] Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Eric Michael Smith, Y-Lan Boureau, et al. 2021. Recipes for Building an Open-Domain Chatbot. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 300–325.
- [225] Masoud Jalili Sabet, Philipp Duffer, François Yvon, and Hinrich Schütze. 2020. SimAlign: High Quality Word Alignments Without Parallel Training Data Using Static and Contextualized Embeddings. In *Findings of the Association for Computational Linguistics: EMNLP 2020*. 1627–1643.
- [226] Sashank Santhanam, Behnam Hedayatnia, Spandana Gella, Aishwarya Padmakumar, Seokhwan Kim, Yang Liu, and Dilek Hakkani-Tur. 2021. Rome was built in 1776: A Case Study on Factual Correctness in Knowledge-Grounded Response Generation. *arXiv preprint arXiv:2110.05456* (2021).
- [227] Thomas Scialom, Paul-Alexis Dray, Patrick Gallinari, Sylvain Lamprier, Benjamin Piwowarski, Jacopo Staiano, and Alex Wang. 2021. Questeval: Summarization asks for fact-based evaluation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*.
- [228] Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get To The Point: Summarization with Pointer-Generator Networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Vancouver, Canada, 1073–1083. <https://doi.org/10.18653/v1/P17-1099>
- [229] Thibault Sellam, Dipanjan Das, and Ankur Parikh. 2020. BLEURT: Learning Robust Metrics for Text Generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 7881–7892.
- [230] Lei Shen, Haolan Zhan, Xin Shen, Hongshen Chen, Xiaofang Zhao, and Xiaodan Zhu. 2021. Identifying Untrustworthy Samples: Data Filtering for Open-domain Dialogues with Bayesian Optimization. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*. 1598–1608.
- [231] Weijia Shi, Xiao Chuang Han, Mike Lewis, Yulia Tsvetkov, Luke Zettlemoyer, and Scott Yih. 2023. Trusting Your Evidence: Hallucinate Less with Context-aware Decoding. *arXiv preprint arXiv:2305.14739* (2023).
- [232] Noah Shinn, Beck Labash, and Ashwin Gopinath. 2023. Reflexion: an autonomous agent with dynamic memory and self-reflection. *arXiv preprint arXiv:2303.11366* (2023).
- [233] Kurt Shuster, Spencer Poff, Moya Chen, Douwe Kiela, and Jason Weston. 2021. Retrieval Augmentation Reduces Hallucination in Conversation. *EMNLP* (2021).
- [234] Haoyu Song, Wei-Nan Zhang, Jingwen Hu, and Ting Liu. 2020. Generating Persona Consistent Dialogues by Exploiting Natural Language Inference. *Proceedings of the AAAI Conference on Artificial Intelligence* 34, 05 (Apr. 2020), 8878–8885. <https://doi.org/10.1609/aaai.v34i05.6417>
- [235] Kaiqiang Song, Logan Lebanoff, Qipeng Guo, Xipeng Qiu, Xiangyang Xue, Chen Li, Dong Yu, and Fei Liu. 2020. Joint Parsing and Generation for Abstractive Summarization. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 34. 8894–8901.
- [236] Kai Song, Yue Zhang, Heng Yu, Weihua Luo, Kun Wang, and Min Zhang. 2019. Code-Switching for Enhancing NMT with Pre-Specified Translation. *NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference 1* (4 2019), 449–459. <https://arxiv.org/abs/1904.09107v4>
- [237] Dan Su, Xiaoguang Li, Jindi Zhang, Lifeng Shang, Xin Jiang, Qun Liu, and Pascale Fung. 2022. Read before Generate! Faithful Long Form Question Answering with Machine Reading. arXiv:2203.00343 [cs.CL]
- [238] Hui Su, Xiaoyu Shen, Sanqiang Zhao, Zhou Xiao, Pengwei Hu, Cheng Niu, and Jie Zhou. 2020. Diversifying Dialogue Generation with Non-Conversational Text. In *58th Annual Meeting of the Association for Computational Linguistics*. ACL, 7087–7097.
- [239] Yixuan Su, David Vandyke, Sihui Wang, Yimai Fang, and Nigel Collier. 2021. Plan-then-Generate: Controlled Data-to-Text Generation via Planning. *Findings of EMNLP* (2021).
- [240] Lya Hulliyatus Suadaa, Hidetaka Kamigaito, Kotaro Funakoshi, Manabu Okumura, and Hiroya Takamura. 2021. Towards Table-to-text Generation with Numerical Reasoning. In *Proceedings of the 59th Annual Meeting of the*

- Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 1451–1465.
- [241] Kai Sun, Yifan Ethan Xu, Hanwen Zha, Yue Liu, and Xin Luna Dong. 2023. Head-to-Tail: How Knowledgeable are Large Language Models (LLM)? A.K.A. Will LLMs Replace Knowledge Graphs? *CoRR abs/2308.10168* (2023). <https://doi.org/10.48550/arXiv.2308.10168> arXiv:2308.10168
- [242] Yanli Sun. 2010. Mining the Correlation between Human and Automatic Evaluation at Sentence Level. In *LREC*.
- [243] Raymond Hendy Susanto, Shamil Chollampatt, and Liling Tan. 2020. Lexically Constrained Neural Machine Translation with Levenshtein Transformer. (7 2020), 3536–3543. <https://doi.org/10.18653/V1/2020.ACL-MAIN.325>
- [244] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to sequence learning with neural networks. *Advances in neural information processing systems* 27 (2014).
- [245] Xiangru Tang, Arjun Nair, Borui Wang, Bingyao Wang, Jai Desai, Aaron Wade, Haoran Li, Asli Celikyilmaz, Yashar Mehdad, and Dragomir Radev. 2021. CONFIT: Toward Faithful Dialogue Summarization with Linguistically-Informed Contrastive Fine-tuning. *arXiv preprint arXiv:2112.08713* (2021).
- [246] Avijit Thawani, Jay Pujara, Filip Ilievski, and Pedro Szekely. 2021. Representing Numbers in NLP: a Survey and a Vision. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 644–656.
- [247] Craig Thomson and Ehud Reiter. 2020. A Gold Standard Methodology for Evaluating Accuracy in Data-To-Text Systems. In *Proceedings of the 13th International Conference on Natural Language Generation*. 158–168.
- [248] James Thorne and Andreas Vlachos. 2018. Automated Fact Checking: Task Formulations, Methods and Future Directions. In *Proceedings of the 27th International Conference on Computational Linguistics, COLING 2018, Santa Fe, New Mexico, USA, August 20-26, 2018*, Emily M. Bender, Leon Derczynski, and Pierre Isabelle (Eds.). Association for Computational Linguistics, 3346–3359. <https://aclanthology.org/C18-1283/>
- [249] James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2018. FEVER: a Large-scale Dataset for Fact Extraction and VERification. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*. Association for Computational Linguistics, New Orleans, Louisiana, 809–819. <https://doi.org/10.18653/v1/N18-1074>
- [250] James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. 2019. Evaluating adversarial attacks against multiple fact verification systems. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. Association for Computational Linguistics, 2944–2953. <https://doi.org/10.18653/v1/D19-1292>
- [251] Ran Tian, Shashi Narayan, Thibault Sellam, and Ankur P. Parikh. 2020. Sticking to the Facts: Confident Decoding for Faithful Data-to-Text Generation. *arXiv:1910.08684* [cs.CL]
- [252] Shengbang Tong, Zhuang Liu, Yuexiang Zhai, Yi Ma, Yann LeCun, and Saining Xie. 2024. Eyes Wide Shut? Exploring the Visual Shortcomings of Multimodal LLMs. *arXiv preprint arXiv:2401.06209* (2024).
- [253] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. 2023. LLaMA: Open and Efficient Foundation Language Models. *arXiv preprint arXiv:2302.13971* (2023). <https://arxiv.org/pdf/2302.13971.pdf>
- [254] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shrutu Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open Foundation and Fine-Tuned Chat Models. *arXiv preprint arXiv:2307.09288* (7 2023). <http://arxiv.org/abs/2307.09288>
- [255] Van-Khanh Tran and Le-Minh Nguyen. 2017. Natural Language Generation for Spoken Dialogue System using RNN Encoder-Decoder Networks. In *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017)*. Association for Computational Linguistics, Vancouver, Canada, 442–451. <https://doi.org/10.18653/v1/K17-1044>
- [256] Zhaopeng Tu, Yang Liu, Lifeng Shang, Xiaohua Liu, and Hang Li. 2017. Neural Machine Translation with Reconstruction. In *Thirty-First AAAI Conference on Artificial Intelligence*.
- [257] Zhaopeng Tu, Zhengdong Lu, Yang Liu, Xiaohua Liu, and Hang Li. 2016. Modeling Coverage for Neural Machine Translation. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 76–85.

- [258] Victor Uc-Cetina, Nicolas Navarro-Guerrero, Anabel Martin-Gonzalez, Cornelius Weber, and Stefan Wermter. 2021. Survey on reinforcement learning for language processing. *arXiv preprint arXiv:2104.05565* (2021).
- [259] Logesh Kumar Umapathi, Ankit Pal, and Malaikannan Sankarasubbu. 2023. Med-HALT: Medical Domain Hallucination Test for Large Language Models. *CoRR abs/2307.15343* (2023). <https://doi.org/10.48550/arXiv.2307.15343> arXiv:2307.15343
- [260] Neeraj Varshney, Wenlin Yao, Hongming Zhang, Jianshu Chen, and Dong Yu. 2023. A Stitch in Time Saves Nine: Detecting and Mitigating Hallucinations of LLMs by Validating Low-Confidence Generation. *CoRR abs/2307.03987* (2023). <https://doi.org/10.48550/arXiv.2307.03987> arXiv:2307.03987
- [261] Neeraj Varshney, Wenlin Yao, Hongming Zhang, Jianshu Chen, and Dong Yu. 2023. A Stitch in Time Saves Nine: Detecting and Mitigating Hallucinations of LLMs by Validating Low-Confidence Generation. *CoRR abs/2307.03987* (2023). <https://doi.org/10.48550/arXiv.2307.03987>
- [262] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In *Advances in Neural Information Processing Systems*, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (Eds.), Vol. 30. 5998–6008. <https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf>
- [263] Oriol Vinyals and Quoc Le. 2015. A Neural Conversational Model. *ICML Deep Learning Workshop* (2015).
- [264] Alex Wang, Kyunghyun Cho, and Mike Lewis. 2020. Asking and Answering Questions to Evaluate the Factual Consistency of Summaries. *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics* (2020).
- [265] Boxin Wang, Weixin Chen, Hengzhi Pei, Chulin Xie, Mintong Kang, Chenhui Zhang, Chejian Xu, Zidi Xiong, Ritik Dutta, Rylan Schaeffer, Sang T. Truong, Simran Arora, Mantas Mazeika, Dan Hendrycks, Zinan Lin, Yu Cheng, Sanmi Koyejo, Dawn Song, and Bo Li. 2023. DecodingTrust: A Comprehensive Assessment of Trustworthiness in GPT Models. *CoRR abs/2306.11698* (2023). <https://doi.org/10.48550/arXiv.2306.11698> arXiv:2306.11698
- [266] Ben Wang and Aran Komatsuzaki. 2021. GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model. <https://github.com/kingoflolz/mesh-transformer-jax>.
- [267] Chaojun Wang and Rico Sennrich. 2020. On Exposure Bias, Hallucination and Domain Shift in Neural Machine Translation. In *2020 Annual Conference of the Association for Computational Linguistics*. Association for Computational Linguistics (ACL), 3544–3552.
- [268] Hongmin Wang. 2019. Revisiting Challenges in Data-to-Text Generation with Fact Grounding. In *Proceedings of the 12th International Conference on Natural Language Generation*. 311–322.
- [269] Peng Wang, Junyang Lin, An Yang, Chang Zhou, Yichang Zhang, Jingren Zhou, and Hongxia Yang. 2021. Sketch and Refine: Towards Faithful and Informative Table-to-Text Generation. *ACL* (2021).
- [270] Peng Wang, An Yang, Rui Men, Junyang Lin, Shuai Bai, Zhikang Li, Jianxin Ma, Chang Zhou, Jingren Zhou, and Hongxia Yang. 2022. OFA: Unifying Architectures, Tasks, and Modalities Through a Simple Sequence-to-Sequence Learning Framework. *CoRR abs/2202.03052* (2022).
- [271] Wenhui Wang, Hangbo Bao, Li Dong, Johan Bjorck, Zhiliang Peng, Qiang Liu, Kriti Aggarwal, Owais Mohammed, Saksham Singhal, Subhojit Som, and Furu Wei. 2022. Image as a Foreign Language: BEiT Pretraining for All Vision and Vision-Language Tasks. *ArXiv abs/2208.10442* (2022).
- [272] Xu Wang, Hainan Zhang, Shuai Zhao, Yanyan Zou, Hongshen Chen, Zhuoye Ding, Bo Cheng, and Yanyan Lan. 2021. FCM: A Fine-grained Comparison Model for Multi-turn Dialogue Reasoning. *EMNLP Findings* (2021).
- [273] Zhenhailong Wang, Shaoguang Mao, Wenshan Wu, Tao Ge, Furu Wei, and Heng Ji. 2023. Unleashing Cognitive Synergy in Large Language Models: A Task-Solving Agent through Multi-Persona Self-Collaboration. *arXiv preprint arXiv:2307.05300* (7 2023). <http://arxiv.org/abs/2307.05300>
- [274] Zhenyi Wang, Xiaoyang Wang, Bang An, Dong Yu, and Changyou Chen. 2020. Towards Faithful Neural Table-to-Text Generation with Content-Matching Constraints. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 1072–1086.
- [275] Zirui Wang, Jiahui Yu, Adams Wei Yu, Zihang Dai, Yulia Tsvetkov, and Yuan Cao. 2022. SimVLM: Simple Visual Language Model Pretraining with Weak Supervision. *ArXiv abs/2108.10904* (2022).
- [276] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. 2022. Emergent abilities of large language models. *arXiv preprint arXiv:2206.07682* (2022).
- [277] Sean Welleck, Ilya Kulikov, Stephen Roller, Emily Dinan, Kyunghyun Cho, and Jason Weston. 2019. Neural Text Generation With Unlikelihood Training. In *International Conference on Learning Representations*.
- [278] Sean Welleck, Jason Weston, Arthur Szlam, and Kyunghyun Cho. 2019. Dialogue Natural Language Inference. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Florence, Italy, 3731–3741. <https://doi.org/10.18653/v1/P19-1363>

- [279] Tsung-Hsien Wen, Milica Gašić, Dongho Kim, Nikola Mrkšić, Pei-Hao Su, David Vandyke, and Steve Young. 2015. Stochastic Language Generation in Dialogue using Recurrent Neural Networks with Convolutional Sentence Reranking. In *Proceedings of the 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue*. Association for Computational Linguistics, Prague, Czech Republic, 275–284. <https://doi.org/10.18653/v1/W15-4639>
- [280] Tsung-Hsien Wen, Milica Gasic, Nikola Mrksic, Pei-hao Su, David Vandyke, and Steve J Young. 2015. Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems. In *EMNLP*.
- [281] Rongxiang Weng, Heng Yu, Xiangpeng Wei, and Weihua Luo. 2020. Towards Enhancing Faithfulness for Neural Machine Translation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 2675–2684.
- [282] Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*. Association for Computational Linguistics, New Orleans, Louisiana, 1112–1122. <https://doi.org/10.18653/v1/N18-1101>
- [283] Sam Wiseman, Stuart Shieber, and Alexander Rush. 2017. Challenges in Data-to-Document Generation. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, Copenhagen, Denmark, 2253–2263. <https://doi.org/10.18653/v1/D17-1239>
- [284] Thomas Wolf, Victor Sanh, Julien Chaumond, and Clement Delangue. 2019. TransferTransfo: A Transfer Learning Approach for Neural Network Based Conversational Agents. *CoRR* abs/1901.08149 (2019). arXiv:1901.08149 <http://arxiv.org/abs/1901.08149>
- [285] Zeqiu Wu, Michel Galley, Chris Brockett, Yizhe Zhang, Xiang Gao, Chris Quirk, Rik Koncel-Kedziorski, Jianfeng Gao, Hannaneh Hajishirzi, Mari Ostendorf, et al. 2021. A Controllable Model of Grounded Response Generation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35. 14085–14093.
- [286] Yijun Xiao and William Yang Wang. 2021. On Hallucination and Predictive Uncertainty in Conditional Language Generation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*. 2734–2744.
- [287] Jing Xu, Arthur D. Szlam, and Jason Weston. 2021. Beyond Goldfish Memory: Long-Term Open-Domain Conversation. *ArXiv* abs/2107.07567 (2021).
- [288] Weijia Xu and Marine Carpuat. 2020. EDITOR: an Edit-Based Transformer with Repositioning for Neural Machine Translation with Soft Lexical Constraints. *Transactions of the Association for Computational Linguistics* 9 (11 2020), 311–328. https://doi.org/10.1162/tacl_a_00368d3/2021.
- [289] Weijia Xu and Marine Carpuat. 2021. Rule-based Morphological Inflection Improves Neural Terminology Translation. (9 2021), 5902–5914. <https://doi.org/10.18653/v1/2021.emnlp-main.477>
- [290] Weijia Xu, Xing Niu, and Marine Carpuat. 2019. Differentiable Sampling with Flexible Reference Word Order for Neural Machine Translation. *NAACL HLT 2019 - 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies - Proceedings of the Conference 1* (4 2019), 2047–2053. <https://doi.org/10.18653/v1/n19-1207>
- [291] Xinnuo Xu, Ondřej Dušek, Verena Rieser, and Ioannis Konstas. 2021. AGGGEN: Ordering and Aggregating while Generating. *roceedings of the 59th Annual Meeting of the Association for Computational Linguistics (ACL2021)* (2021).
- [292] Yan Xu, Etsuko Ishii, Samuel Cahyawijaya, Zihan Liu, Genta Indra Winata, Andrea Madotto, Dan Su, and Pascale Fung. 2021. Retrieval-Free Knowledge-Grounded Dialogue Response Generation with Adapters. *arXiv preprint arXiv:2105.06232* (2021).
- [293] Steve Yadlowsky, Lyric Doshi, and Nilesh Tripuraneni. 2023. Pretraining Data Mixtures Enable Narrow Model Selection Capabilities in Transformer Models. *CoRR* abs/2311.00871 (2023). <https://doi.org/10.48550/ARXIV.2311.00871> arXiv:2311.00871
- [294] Yuqing Yang, Ethan Chern, Xipeng Qiu, Graham Neubig, and Pengfei Liu. 2023. Alignment for Honesty. <https://api.semanticscholar.org/CorpusID:266174420>
- [295] Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D Manning. 2018. HotpotQA: A Dataset for Diverse, Explainable Multi-hop Question Answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. 2369–2380.
- [296] Semih Yavuz, Abhinav Rastogi, Guan-Lin Chao, and Dilek Hakkani-Tur. 2019. DEEPCOPY: Grounded Response Generation with Hierarchical Pointer Networks. In *Proceedings of SIGdial*.
- [297] Jun Yin, Xin Jiang, Zhengdong Lu, Lifeng Shang, Hang Li, and Xiaoming Li. 2016. Neural generative question answering. In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence*. 2972–2978.
- [298] Zhangyue Yin, Qiushi Sun, Qipeng Guo, Jiawen Wu, Xipeng Qiu, and Xuanjing Huang. 2023. Do Large Language Models Know What They Don't Know?. In *Findings of the Association for Computational Linguistics: ACL 2023*. Association for Computational Linguistics, Toronto, Canada, 8653–8665. <https://doi.org/10.18653/v1/2023.findings-acl.551>

- [299] Zhangyue Yin, Qiushi Sun, Qipeng Guo, Jiawen Wu, Xipeng Qiu, and Xuanjing Huang. 2023. Do Large Language Models Know What They Don't Know?. In *Findings of the Association for Computational Linguistics: ACL 2023, Toronto, Canada, July 9-14, 2023*, Anna Rogers, Jordan L. Boyd-Graber, and Naoaki Okazaki (Eds.). Association for Computational Linguistics, 8653–8665. <https://doi.org/10.18653/v1/2023.findings-acl.551>
- [300] Takuma Yoneda, Jeff Mitchell, Johannes Welbl, Pontus Stenetorp, and Sebastian Riedel. 2018. UCL Machine Reading Group: Four Factor Framework For Fact Finding (HexaF). In *Proceedings of the First Workshop on Fact Extraction and VERification (FEVER)*, Association for Computational Linguistics, Brussels, Belgium, 97–102. <https://doi.org/10.18653/v1/W18-5515>
- [301] Jifan Yu, Xiaozhi Wang, Shangqing Tu, Shulin Cao, Daniel Zhang-li, Xin Lv, Hao Peng, Zijun Yao, Xiaohan Zhang, Hanming Li, Chunyang Li, Zheyuan Zhang, Yushi Bai, Yantao Liu, Amy Xin, Nianyi Lin, Kaifeng Yun, Linlu Gong, Jianhui Chen, Zhili Wu, Yunjia Qi, Weikai Li, Yong Guan, Kaisheng Zeng, Ji Qi, Hailong Jin, Jinxin Liu, Yu Gu, Yuan Yao, Ning Ding, Lei Hou, Zhiyuan Liu, Bin Xu, Jie Tang, and Juanzi Li. 2023. KoLA: Carefully Benchmarking World Knowledge of Large Language Models. *CoRR abs/2306.09296* (2023). <https://doi.org/10.48550/arXiv.2306.09296>
- [302] Tiezhen Yu, Zihan Liu, and Pascale Fung. 2021. AdaptSum: Towards Low-Resource Domain Adaptation for Abstractive Summarization. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 5892–5904.
- [303] Tianyu Yu, Yuan Yao, Haoye Zhang, Taiwen He, Yifeng Han, Ganqu Cui, Jinyi Hu, Zhiyuan Liu, Hai-Tao Zheng, Maosong Sun, and Tat-Seng Chua. 2023. RLHF-V: Towards Trustworthy MLLMs via Behavior Alignment from Fine-grained Correctional Human Feedback. *CoRR abs/2312.00849* (2023). <https://doi.org/10.48550/ARXIV.2312.00849>
- [304] Wenhao Yu, Zhihan Zhang, Zhenwen Liang, Meng Jiang, and Ashish Sabharwal. 2023. Improving Language Models via Plug-and-Play Retrieval Feedback. *arXiv preprint arXiv:2305.14002* (2023).
- [305] Xiang Yue, Boshi Wang, Kai Zhang, Ziru Chen, Yu Su, and Huan Sun. 2023. Automatic Evaluation of Attribution by Large Language Models. *CoRR abs/2305.06311* (2023). <https://doi.org/10.48550/arXiv.2305.06311>
- [306] Manzil Zaheer, Guru Guruganesh, Kumar Avinava Dubey, Joshua Ainslie, Chris Alberti, Santiago Ontanon, Philip Pham, Anirudh Ravula, Qifan Wang, Li Yang, and Amr Ahmed. 2020. Big Bird: Transformers for Longer Sequences. In *Advances in Neural Information Processing Systems*, H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin (Eds.), Vol. 33. Curran Associates, Inc., 17283–17297. <https://proceedings.neurips.cc/paper/2020/file/c8512d142a2d849725f31a9a7a361ab9-Paper.pdf>
- [307] Yury Zemlyanskiy and Fei Sha. 2018. Aiming to Know You Better Perhaps Makes Me a More Engaging Dialogue Partner. In *Proceedings of the 22nd Conference on Computational Natural Language Learning*. Association for Computational Linguistics, Brussels, Belgium, 551–561. <https://doi.org/10.18653/v1/K18-1053>
- [308] Yuexiang Zhai, Shengbang Tong, Xiao Li, Mu Cai, Qing Qu, Yong Jae Lee, and Yi Ma. 2023. Investigating the catastrophic forgetting in multimodal large language models. *arXiv preprint arXiv:2309.10313* (2023).
- [309] Chen Zhang, Grandee Lee, Luis Fernando D'Haro, and Haizhou Li. 2021. D-score: Holistic dialogue evaluation without reference. *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 29 (2021), 2502–2516.
- [310] Hongguang Zhang, Jing Zhang, and Piotr Koniusz. 2019. Few-Shot Learning via Saliency-Guided Hallucination of Samples. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019*. Computer Vision Foundation / IEEE, 2770–2779. <https://doi.org/10.1109/CVPR.2019.00288>
- [311] Jiacheng Zhang, Huanbo Luan, Maosong Sun, Feifei Zhai, Jingfang Xu, and Yang Liu. 2021. Neural Machine Translation with Explicit Phrase Alignment. *IEEE/ACM Transactions on Audio, Speech, and Language Processing* 29 (2021), 1001–1010.
- [312] Muru Zhang, Ofir Press, William Merrill, Alisa Liu, and Noah A. Smith. 2023. How Language Model Hallucinations Can Snowball. *arXiv preprint arXiv:2305.13534* (5 2023). <http://arxiv.org/abs/2305.13534>
- [313] Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. 2018. Personalizing Dialogue Agents: I have a dog, do you have pets too?. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2204–2213.
- [314] Shuo Zhang, Liangming Pan, Junzhou Zhao, and William Yang Wang. 2023. Mitigating Language Model Hallucination with Interactive Question-Knowledge Alignment. *arXiv preprint arXiv:2305.13669* (5 2023). <http://arxiv.org/abs/2305.13669>
- [315] Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q Weinberger, and Yoav Artzi. 2019. BERTScore: Evaluating Text Generation with BERT. In *International Conference on Learning Representations*.
- [316] Xikun Zhang, Deepak Ramachandran, Ian Tenney, Yanai Elazar, and Dan Roth. 2020. Do Language Embeddings capture Scales?. In *Proceedings of the Third BlackboxNLP Workshop on Analyzing and Interpreting Neural Networks for NLP*. 292–299.

- [317] Yue Zhang, Yafu Li, Leyang Cui, Deng Cai, Lemao Liu, Tingchen Fu, Xinting Huang, Enbo Zhao, Yu Zhang, Yulong Chen, Longyue Wang, Anh Tuan Luu, Wei Bi, Freda Shi, and Shuming Shi. 2023. Siren’s Song in the AI Ocean: A Survey on Hallucination in Large Language Models. *arXiv preprint arXiv:2309.01219* (9 2023). <http://arxiv.org/abs/2309.01219>
- [318] Yuhao Zhang, Derek Merck, Emily Tsai, Christopher D Manning, and Curtis Langlotz. 2020. Optimizing the Factual Correctness of a Summary: A Study of Summarizing Radiology Reports. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 5108–5120.
- [319] Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2020. DIALOGPT : Large-Scale Generative Pre-training for Conversational Response Generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*. Association for Computational Linguistics, Online, 270–278. <https://doi.org/10.18653/v1/2020.acl-demos.30>
- [320] Jing Zhao, Junwei Bao, Yifan Wang, Yongwei Zhou, Youzheng Wu, Xiaodong He, and Bowen Zhou. 2021. RoR: Read-over-Read for Long Document Machine Reading Comprehension. In *Findings of the Association for Computational Linguistics: EMNLP 2021*. Association for Computational Linguistics, Punta Cana, Dominican Republic, 1862–1872. <https://aclanthology.org/2021.findings-emnlp.160>
- [321] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. 2023. A survey of large language models. *arXiv preprint arXiv:2303.18223* (2023).
- [322] Zheng Zhao, Shay B. Cohen, and Bonnie Webber. 2020. Reducing Quantity Hallucinations in Abstractive Summarization. In *Findings of the Association for Computational Linguistics: EMNLP 2020*. Association for Computational Linguistics, Online, 2237–2249. <https://doi.org/10.18653/v1/2020.findings-emnlp.203>
- [323] Ming Zhong, Da Yin, Tao Yu, Ahmad Zaidi, Mutethia Mutuma, Rahul Jha, Ahmed Hassan, Asli Celikyilmaz, Yang Liu, Xipeng Qiu, et al. 2021. QMSum: A New Benchmark for Query-based Multi-domain Meeting Summarization. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 5905–5921.
- [324] Chunting Zhou, Pengfei Liu, Puxin Xu, Srinu Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, Susan Zhang, Gargi Ghosh, Mike Lewis, Luke Zettlemoyer, and Omer Levy. 2023. LIMA: Less Is More for Alignment. *arXiv preprint arXiv:2305.11206* (2023). <https://arxiv.org/pdf/2305.11206.pdf>
- [325] Chunting Zhou, Xuezhe Ma, Di Wang, and Graham Neubig. 2019. Density Matching for Bilingual Word Embedding. In *NAACL*.
- [326] Chunting Zhou, Graham Neubig, Jiatao Gu, Mona Diab, Francisco Guzmán, Luke Zettlemoyer, and Marjan Ghazvininejad. 2021. Detecting Hallucinated Content in Conditional Neural Sequence Generation. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*. 1393–1404.
- [327] Kangyan Zhou, Shrimai Prabhumoye, and Alan W Black. 2018. A Dataset for Document Grounded Conversations. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. 708–713.
- [328] Pei Zhou, Karthik Gopalakrishnan, Behnam Hedayatnia, Seokhwan Kim, Jay Pujara, Xiang Ren, Yang Liu, and Dilek Hakkani-Tur. 2021. Think Before You Speak: Using Self-talk to Generate Implicit Commonsense Knowledge for Response Generation. *arXiv preprint arXiv:2110.08501* (2021).
- [329] Chenguang Zhu, William Hinthorn, Ruo Chen Xu, Qingkai Zeng, Michael Zeng, Xuedong Huang, and Meng Jiang. 2021. Enhancing Factual Consistency of Abstractive Summarization. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 718–733.
- [330] Kaijie Zhu, Jindong Wang, Jiaheng Zhou, Zichen Wang, Hao Chen, Yidong Wang, Linyi Yang, Wei Ye, Neil Zhenqiang Gong, Yue Zhang, et al. 2023. PromptBench: Towards Evaluating the Robustness of Large Language Models on Adversarial Prompts. *arXiv preprint arXiv:2306.04528* (2023).