Rethinking Label Smoothing on Multi-hop Question Answering

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Abstract

Multi-Hop Question Answering (MHQA) is a significant area in question answering, requiring multiple reasoning components, including document retrieval, supporting sentence prediction, and answer span extraction. In this work, we analyze the primary factors limiting the performance of multi-hop reasoning and introduce label smoothing into the MHQA task. This is aimed at enhancing the generalization capabilities of MHQA systems and mitigating overfitting of answer spans and reasoning paths in training set. We propose a novel label smoothing technique, F1 Smoothing, which incorporates uncertainty into the learning process and is specifically tailored for Machine Reading Comprehension (MRC) tasks. Inspired by the principles of curriculum learning, we introduce the Linear Decay Label Smoothing Algorithm (LDLA), which progressively reduces uncertainty throughout the training process. Experiment on the HotpotQA dataset demonstrates the effectiveness of our methods in enhancing performance and generalizability in multi-hop reasoning, achieving new state-of-the-art results on the leaderboard.

1 Introduction

Multi-Hop Question Answering (MHQA) is a rapidly evolving research area within question answering that involves answering complex questions by gathering information from multiple sources (Asai et al., 2020; Chen et al., 2021). This requires a model capable of performing several reasoning steps and handling diverse information sources (Mavi et al., 2022). In recent years, MHQA has attracted significant interest from researchers due to its potential for addressing real-world problems. The mainstream approach to MHQA typically incorporates several components, including a document retriever, a supporting sentence selector, and a reading comprehension module (Tu et al., 2020; Li et al., 2022). These components collaborate to accurately retrieve and integrate relevant information from multiple sources, ultimately providing a precise answer to the given question (Feldman and El-Yaniv, 2019).

MHQA models have shown remarkable capabilities in multi-hop reasoning. However, they still struggle with answer span errors and multi-hop reasoning errors. A recent study by S2G (Wu et al., 2021) reveals that the primary error source is answer span errors, constituting 74.55%, followed by multi-hop reasoning errors. We identify that answer span errors arise from differences in the annotation of answer spans between the training and validation sets. As depicted in Figure 1, the training set answer includes the quantifier "times", which is notably missing in the validation set. We observe that such discrepancies in answer spans are prevalent across both the training and validation sets. This demands that models possess a robust ability to generalize answer spans, thereby preventing overfitting to a specific answer span distribution present in the training set.

Furthermore, we discover the existence of unannotated yet feasible multi-hop reasoning paths within the training set. As depicted in Figure 2, a non-gold document "Tysons, Virginia" contains essential information to deduce the answer "Fairfax County", but is marked as irrelevant. During training, this forces the model to ignore such reasoning paths and solely rely on the annotated ones. This potentially

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Training Set:

Gold Doc1: Love or Leave

"Love or Leave" was the Lithuanian entry in the Eurovision Song Contest 2007, performed in English by 4FUN.

Gold Doc2: Lithuania in the Eurovision Song Contest

Lithuania has participated in the Eurovision Song Contest (known in Lithuania as "Eurovizija") 18 times since its debut in 1994, where Ovidijus Vyšniauskas finished last, receiving nul points.

Question: How many times does the song writer of "Love or Leave" have participated in the Eurovision Song Contest?

Answer: 18 times

Validation Set:

Gold Doc1: Binocular (horse)

"Love or Leave" was the Lithuanian entry in the Eurovision Song Contest 2007, performed in English by 4FUN.

Gold Doc2: Tony McCoy

Based in Ireland and the UK, McCoy rode a record 4,358 winners, and was Champion Jockey a record 20 consecutive times, every year he was a professional.

Question: The primary jockey of Binocular was Champion Jockey how many consecutive times?

Answer: 20

Figure 1: Different Answer Span.

Non-Gold Doc: Tysons, Virginia

- Tysons, or formerly "Tysons Corner" is a census-designated place (CDP) and unincorporated community ...
- (2) Located in Northern Virginia between the community of McLean and the town of Vienna along the Capital Beltway (I-495), ...
- (3)Tysons is home to two super-regional shopping malls—Tysons Corner Center and Tysons Galleria—and the corporate headquarters of numerous companies such as Intelsat, Gannett, Hilton Worldwide, Freddie Mac, Capital One and Booz Allen Hamilton.
- (4) Tysons is Fairfax County's central business district and a regional commercial center.

Gold Doc1: Tysons Galleria

(1) Tysons Galleria is a three-level super-regional mall owned by General Growth Properties located at 2001 International Drive, McLean, Virginia, in Tysons Corner.

Gold Doc2: McLean, Virginia

(1) McLean () is a census-designated place (CDP) in Fairfax County in Northern Virginia.

Question: Tysons Galleria is located in what county?

Answer: Fairfax County

Evidence Sentences: ["McLean, Virginia", 0], ["Tysons Galleria",0]

Figure 2: Multiple Feasible Reasoning Paths.

Figure 3: Causes of errors in answer span and multi-hop reasoning in the HotpotQA dataset (Yang et al., 2018). In Figure 1, the answer from the training set contains a quantifier, while the answer from the validation set does not. In Figure 2, the correct answer can be inferred using a non-gold document without requiring information from gold document.

leads models to overfit specific multi-hop reasoning patterns labeled in the training set, consequently impairing their generalization capabilities on test sets. Hence, these observations naturally lead us to the research question we explore in this paper: *How can we prevent MHQA models from overfitting answer spans and reasoning paths in the training set?*

Label smoothing has proven to be a highly effective technique for mitigating overfitting (Müller et al., 2019; Lukasik et al., 2020a; Xu et al., 2020), and it has been extensively employed across a diverse range of machine learning researches (Szegedy et al., 2016; Yuan et al., 2020; Li et al., 2020). In this study, we pioneer the application of label smoothing to multi-hop reasoning tasks, aiming to reduce overfitting of answer spans and reasoning paths. Our proposed MHQA model, termed \mathbf{R}^3 , integrates three key components: Retrieval, Refinement, and Reading Comprehension.

Inspired by the F1 score, a widely used metric for evaluating Machine Reading Comprehension (MRC) task performance, we develop F1 Smoothing, a novel technique that calculates the importance of each token within the smooth distribution. Moreover, we incorporate curriculum learning (Bengio et al., 2009) and devise the Linear Decay Label Smoothing Algorithm (LDLA), which gradually reduces the smoothing weight, allowing the model to focus on more challenging samples during training. Experimental results on the HotpotQA dataset (Yang et al., 2018) demonstrate that incorporating F1 smoothing and LDLA into the ${\bf R}^3$ model significantly enhances performance in document retrieval, supporting sentence prediction, and answer span extraction, achieving new state-of-the-art results among all published works. Our main contributions are as follows:

- To our best knowledge, we are the first to adapt label smoothing for multi-hop reasoning tasks, encapsulated within our innovative \mathbf{R}^3 framework, featuring retrieval, refinement, and reading comprehension modules.
- We propose F1 smoothing, a pioneering label smoothing method tailored for MRC tasks, which alleviates errors caused by answer span discrepancies.
- We present the Linear Decay Label Smoothing Algorithm (LDLA), an innovative approach that combines the principles of curriculum learning for progressive training.
- Experiment on the HotpotQA dataset demonstrates that label smoothing effectively enhances the MHQA model's performance, achieving new state-of-the-art performance on the leaderborad.

2 Related Work

Label Smoothing. Label smoothing is a regularization technique first introduced in computer vision to improve classification accuracy on ImageNet (Szegedy et al., 2016). The basic idea of label smoothing is to soften the distribution of true labels by replacing their one-hot encoding with a smoother distribution. This approach encourages the model to be less confident in its predictions and consider a broader range of possibilities, reducing overfitting and enhancing generalization (Pereyra et al., 2017; Müller et al., 2019; Lukasik et al., 2020a). Label smoothing has been widely adopted across various natural language processing tasks, including speech recognition (Chorowski and Jaitly, 2017), document retrieval (Penha and Hauff, 2021), dialogue generation (Saha et al., 2021), and neural machine translation (Gao et al., 2020; Lukasik et al., 2020b; Graça et al., 2019).

Recent studies are increasingly concentrating on enhancing and refining the conventional methods of label smoothing. For example, Xu et al. (2020) suggest the Two-Stage LAbel (TSLA) smoothing algorithm, which employs a smoothing distribution in the first stage and the original distribution in the second stage. Experimental results demonstrate that TSLA effectively promotes training convergence and enhances performance. Penha and Hauff (2021) introduce label smoothing for retrieval tasks and propose using BM25 to compute the label smoothing distribution, which outperforms the uniform distribution. Zhao et al. (2020) propose Word Overlapping, which uses maximum likelihood estimation (Su et al., 2020) to optimize the target distribution during training.

Multi-hop Question Answering. Multi-hop reading comprehension (MHRC) is a challenging task in the field of machine reading comprehension (MRC) that closely resembles the human reasoning process in real-world scenarios. Consequently, it has gained significant attention in the field of natural language understanding in recent years. Several datasets have been developed to foster research in this area, including HotpotQA (Yang et al., 2018), WikiHop (Welbl et al., 2018), and NarrativeQA (Kočiský et al., 2018). Among these, HotpotQA (Yang et al., 2018) is particularly representative and challenging, as it requires the model to not only extract the correct answer span from the context but also identify a series of supporting sentences as evidence for MHRC.

Recent advances in MHRC have led to the development of several graph-free models, such as QUARK (Groeneveld et al., 2020), C2FReader (Shao et al., 2020), and S2G (Wu et al., 2021), which have challenged the dominance of previous graph-based approaches like DFGN (Qiu et al., 2019), SAE (Tu et al., 2020), and HGN (Fang et al., 2020). C2FReader (Shao et al., 2020) suggests that the performance difference between graph attention and self-attention is minimal, while S2G's (Wu et al., 2021) strong performance demonstrates the potential of graph-free modeling in MHRC. FE2H (Li et al., 2022), which uses a two-stage selector and a multi-task reader, significantly enhances the performance on HotpotQA, indicating that pre-trained language models are sufficient for modeling multi-hop reasoning. However, these approaches still suffer from answer spanning errors and multi-hop reasoning errors, primarily attributable to their restricted generalization abilities in multi-hop reasoning.

3 Framework

Figure 4 depicts the overall architecture of \mathbb{R}^3 . The retrieval module sift through and exclude irrelevant documents, effectively selecting those that are pertinent to the question for utilization in the subsequent modules. In this example, Document 1, 3, and 4 are selected due to their higher relevance scores, while the other documents are filtered out. Subsequently, the refinement module further selects documents based on their combined relevance. In this case, Document 1 and 4 are chosen. Following this, the question and Document 1 and 4 are concatenated and used as input for the reading comprehension module. Within the reading comprehension module, we employ a multi-task approach to simultaneously train for supporting sentence prediction, answer span extraction, and answer type selection.

3.1 Retrieval Module

In the retrieval module, each question Q is typically accompanied by a set of M documents D_1, D_2, \ldots, D_M , but only C, |C| << M (two in HotpotQA) are labeled as relevant to the question Q.

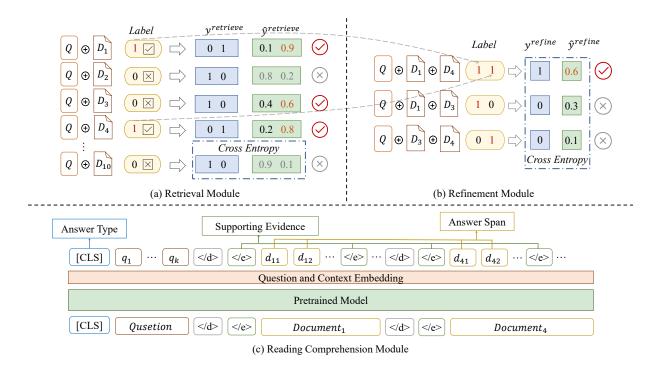


Figure 4: Overview of our \mathbb{R}^3 model, which consists of three main modules: **R**etrieval, **R**efinement, and **R**eading Comprehension. \mathbb{R}^3 sequentially executes each module to arrive at the final answer.

We model the retrieval process as a binary classification task. Specifically, for each question-document pair, we generate an input by concatenating "[CLS], question, [SEP], document, [SEP]" in sequence. We then feed the [CLS] token output from the model into a linear classifier. $\mathcal{L}_{retrieve}$ represents the crossentropy between the predicted probability and the gold label. In contrast to S2G (Wu et al., 2021), which employs a complex pairwise learning-to-rank loss, we opt for a simple binary cross-entropy loss, as it maintains high performance while being significantly more efficient.

$$\mathcal{L}_{\text{retrieve}} = \mathbb{E}\left[-\frac{1}{M} \sum_{i=1}^{M} (y_i^{\text{retrieve}} \cdot log(\hat{y}_i^{\text{retrieve}}) + (1 - y_i^{\text{retrieve}}) \cdot log(1 - \hat{y}_i^{\text{retrieve}}))\right], \tag{1}$$

where $\hat{y}_i^{\text{retrieve}}$ is the probability predicted by the model and y_i^{retrieve} is the ground-truth label. M is the number of provided documents. \mathbb{E} means the expectation of all samples.

$$y_i^{\text{retrieve}} = \begin{cases} 1 & D_i \text{ is a gold document.} \\ 0 & D_i \text{ is a non-gold document.} \end{cases}$$
 (2)

3.2 Refinement Module

The refinement module is designed to identify document combinations that are capable of supporting the entire multi-hop reasoning processes. We combine the K documents obtained from the retrieval module to form C_K^2 document pairs. These are concatenated into the following sequence: "[CLS], question, [SEP], document1, [SEP], document2, [SEP]". Similar to the retrieval module, we extract the [CLS] token output from the model and pass it through a classifier. Document pairs containing two gold documents are labeled as 1, while others are labeled as 0. We model multi-hop reasoning as a selection task, focusing on choosing document combinations that effectively convey complete multi-hop reasoning information to the subsequent modules.

$$\mathcal{L}_{\text{refine}} = \mathbb{E}\left[-\sum_{i=1}^{C_K^2} y_i^{\text{refine}} log(\hat{y}_i^{\text{refine}})\right],\tag{3}$$

where $\hat{y}_i^{\text{refine}}$ is predicted document pair probability and y_i^{refine} is the ground-truth label, C_K^2 is number of all combination.

$$y_i^{\text{refine}} = \begin{cases} 1 & C_i \text{ consists of two gold documents.} \\ 0 & \text{otherwise.} \end{cases}$$
 (4)

We use a single pretrained language model as the encoder for both the retrieval and refinement module, and the final loss is a weighted sum of $\mathcal{L}_{\text{retrieve}}$ and $\mathcal{L}_{\text{refine}}$. λ_1 and λ_2 are accordingly coefficients of $\mathcal{L}_{\text{retrieve}}$ and $\mathcal{L}_{\text{refine}}$.

$$\mathcal{L}_{\text{total}} = \lambda_1 \mathcal{L}_{\text{retrieve}} + \lambda_2 \mathcal{L}_{\text{refine}}.$$
 (5)

3.3 Reading Comprehension Module

In the reading comprehension module, we use multi-task learning to simultaneously predict supporting sentences and extract answer span. HotpotQA (Yang et al., 2018) contains samples labeled as "yes" or "no". The practice of splicing "yes" or "no" tokens at the beginning of the sequence (Li et al., 2022) could corrupt the original text's semantic information. To avoid the impact of irrelevant information, we introduce an answer type selection header trained with a cross-entropy loss function.

$$\mathcal{L}_{\text{type}} = \mathbb{E}\left[-\sum_{i=1}^{3} y_i^{\text{type}} log(\hat{y}_i^{\text{type}})\right],\tag{6}$$

where \hat{y}_i^{type} represents the predicted probability of answer type generated by our model, and y_i^{type} denotes the ground-truth label. Answer type includes "yes", "no" and "span".

$$y_i^{\text{type}} = \begin{cases} 0 & \text{Answer is no.} \\ 1 & \text{Answer is yes.} \\ 2 & \text{Answer is a span.} \end{cases}$$
 (7)

To extract the span of answers, we use a linear layer on the contextual representation to identify the start and end positions of answers, and adopts cross-entropy as the loss function. The corresponding loss terms are denoted as $\mathcal{L}_{\text{start}}$ and \mathcal{L}_{end} respectively. Similar to previous work S2G (Wu et al., 2021) and FE2H (Li et al., 2022), we also inject a special placeholder token $</e> and use a linear binary classifier on the output of <math></e> to determine whether a sentence is a supporting fact. The classification loss of the supporting facts is denoted as <math>\mathcal{L}_{\text{sup}}$, and we jointly optimize all of these objectives in our model.

$$\mathcal{L}_{\text{reading}} = \lambda_3 \mathcal{L}_{\text{type}} + \lambda_4 (\mathcal{L}_{\text{start}} + \mathcal{L}_{\text{end}}) + \lambda_5 \mathcal{L}_{\text{sup}}. \tag{8}$$

4 Label Smoothing

Label smoothing is a regularization technique that aims to improve generalization in a classifier by modifying the ground truth labels of the training data. In the one-hot setting, the probability of the correct category q(y|x) for a training sample (x,y) is typically defined as 1, while the probabilities of all other categories $q(\neg y|x)$ are defined as 0. The cross-entropy loss function used in this setting is typically defined as follows:

$$\mathcal{L} = -\sum_{k=1}^{K} q(k|x) \log(p(k|x)), \tag{9}$$

where p(k|x) is the probability of the model's prediction for the k-th class. Specifically, label smoothing mixes q(k|x) with a uniform distribution u(k), independent of the training samples, to produce a new distribution q'(k|x).

$$q'(k|x) = (1 - \epsilon)q(k|x) + \epsilon u(k), \tag{10}$$

where ϵ is the weight controls the importance of q(k|x) and u(k) in the resulting distribution. u(k) is construed as $\frac{1}{K}$ of the uniform distribution, where K is the total number of categories. Next, we introduce two novel label smoothing methods.

Algorithm 1 Linear Decay Label Smoothing.

```
Require: Training epochs n > 0; Smoothing weight \epsilon \in [0, 1]; Decay rate \tau \in [0, 1]; Uniform distribu-
  1: Initialize: Model parameter w_0 \in \mathcal{W};
  2: Input: Optimization algorithm A
  3: for i = 0, 1, ..., n do
          \epsilon_i \leftarrow \epsilon - i\tau
  4:
  5:
         if \epsilon_i < 0 then
             \epsilon_i \leftarrow 0
  6:
          end if
  7:
          sample(x_t, y_t)
  8:
         y_t^{LS} \leftarrow (1 - \epsilon_i)y_i + \epsilon u \\ w_{i+1} \leftarrow \mathcal{A} - step(w_i; x_i, y_i^{LS})
  9:
10:
11: end for
```

4.1 Linear Decay Label Smoothing

Our proposed Linear Decay Label Smoothing Algorithm (LDLA) addresses the abrupt changes in training distribution caused by the two-stage approach of TSLA, which can negatively impact the training process. Compared to TSLA, LDLA progressively decays the smoothing weight at a constant rate per epoch, which facilitates a more gradual learning process.

Given a total of n epochs in the training process and a decay size of τ , the smoothing weight ϵ for the i-th epoch can be calculated as follows:

$$\epsilon_i = \begin{cases} \epsilon - i\tau & \epsilon - i\tau \ge 0\\ 0 & \epsilon - i\tau < 0 \end{cases}$$
 (11)

Algorithm 1 provides a detailed overview of the LDLA algorithm. LDLA employs the concept of curriculum learning by gradually transitioning the model's learning target from a smoothed distribution to the original distribution throughout the training process. This approach methodically reduces uncertainty during training, enabling the model to progressively concentrate on more challenging samples. The gradual shift from learning under conditions of uncertainty to a state of certainty ensures the stability of the learning process. As a result, the LDLA algorithm facilitates a learning process that is more stable and efficient.

4.2 F1 Smoothing

Unlike traditional classification tasks, MRC requires identifying both the start and end positions of a span. To address the specific nature of this task, a specialized smoothing method is required to prevent overfitting the specific answer span distribution in the training set. In this section, we introduce F1 Smoothing, a technique that calculates the significance of answer span based on its F1 score.

Consider a sample x that contains a context S and an answer a_{gold} . The total length of the context is denoted by L. We use $q_s(t|x)$ to denote the F1 score between a span of arbitrary length starting at position t in S and the ground truth answer a_{gold} . Similarly, $q_e(t|x)$ denotes the F1 score between a_{gold} and a span of arbitrary length ending at position t in S.

$$q_s(t|x) = \sum_{\xi=t}^{L-1} F1\left((t,\xi), a_{\text{gold}}\right). \tag{12}$$

$$q_e(t|x) = \sum_{\xi=0}^{t} F1((\xi, t), a_{\text{gold}}).$$
 (13)

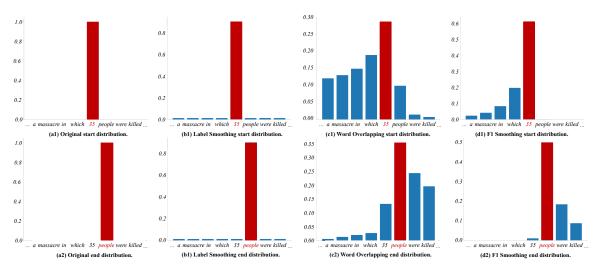


Figure 5: Visualization of original distribution and different label smoothing distributions, including Label Smoothing, Word Overlapping, and F1 Smoothing. The first row shows the distribution of the start token, and the second row shows the distribution of the end token. The gold start and end tokens are highlighted in red.

The normalized distributions are noted as $q_s^{'}(t|x)$ and $q_e^{'}(t|x)$, respectively.

$$q_s'(t|x) = \frac{exp(q_s(t|x))}{\sum_{i=0}^{L-1} exp(q_s(i|x))}.$$
(14)

$$q'_{e}(t|x) = \frac{exp(q_{e}(t|x))}{\sum_{i=0}^{L-1} exp(q_{e}(i|x))}.$$
(15)

To decrease the computational complexity of F1 Smoothing, we present a computationally efficient version in Appendix 7.2. Previous research (Zhao et al., 2020) has investigated various label smoothing methods for MRC, encompassing traditional label smoothing and word overlap smoothing. As illustrated in Figure 5, F1 Smoothing offers a more accurate distribution of token importance in comparison to Word Overlap method. This method reduces the probability of irrelevant tokens and prevents the model from being misled during training.

5 Experiment

5.1 Dataset

We evaluate our approach on the distractor setting of HotpotQA (Yang et al., 2018), a multi-hop question-answer dataset with 90k training samples, 7.4k validation samples, and 7.4k test samples. Each question in this dataset is provided with several candidate documents, two of which are labeled as gold. In addition, HotpotQA also provides supporting sentences for each question, encouraging the model to explain the reasoning path of the multi-hop question answering. We use the Exact Match (EM) and F1 score (F1) to evaluate the performance of our approach in terms of document retrieval, supporting sentence prediction, and answer extraction.

5.2 Implementation Details

Our model is built using the Pre-trained Language Models (PLMs) provided by HuggingFace's Transformers library (Wolf et al., 2020).

Retrieval and Refinement Module. We use RoBERTa-large (Liu et al., 2019) and ELECTRA-large (Clark et al., 2020) as our PLMs and conduct an analysis on RoBERTa-large (Liu et al., 2019) in Section 5.4. Training on a single RTX3090 GPU, we set the number of epochs to 8 and the batch size to 16. We employ the AdamW (Loshchilov and Hutter, 2017) optimizer with a learning rate of 5e-6 and a weight decay of 1e-2.

Model	Answer		Supporting	
Wiodei	EM	F1	EM	F1
Baseline Model (Yang et al., 2018)	45.60	59.02	20.32	64.49
QFE (Nishida et al., 2019)	53.86	68.06	57.75	84.49
DFGN (Qiu et al., 2019)	56.31	69.69	51.50	81.62
SAE-large (Tu et al., 2020)	66.92	79.62	61.53	86.86
C2F Reader (Shao et al., 2020)	67.98	81.24	60.81	87.63
HGN-large (Fang et al., 2020)	69.22	82.19	62.76	88.47
FE2H on ELECTRA (Li et al., 2022)	69.54	82.69	64.78	88.71
AMGN+ (Li et al., 2021)	70.53	83.37	63.57	88.83
S2G+EGA (Wu et al., 2021)	70.92	83.44	63.86	88.68
FE2H on ALBERT (Li et al., 2022)	71.89	84.44	64.98	89.14
\mathbf{R}^3 (ours)	71.27	83.57	65.25	88.98
Smoothing \mathbb{R}^3 (ours)	72.07	84.34	65.44	89.55

Table 1: In the distractor setting of the HotpotQA test set, our proposed F1 Smoothing and LDLA has led to significant improvements in the performance of the Smoothing \mathbf{R}^3 model compared to the \mathbf{R}^3 model. Furthermore, the Smoothing \mathbf{R}^3 model has outperformed a series of strong baselines and achieved remarkable state-of-the-art performance.

Model	EM	F1
SAE _{large} (Tu et al., 2020)	91.98	95.76
S2G _{large} (Wu et al., 2021)	95.77	97.82
$FE2H_{large}$ (Li et al., 2022)	96.32	98.02
\mathbf{R}^3 (ours)	96.50	98.10
Smoothing ${f R}^3$	96.85	98.32

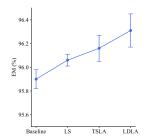
Table 2: Comparison of our \mathbb{R}^3 and Smoothing \mathbb{R}^3 model with several strong baselines in document retrieval task on HotpotQA validation set. Smoothing \mathbb{R}^3 model demonstrates further performance enhancement compared to \mathbb{R}^3 .

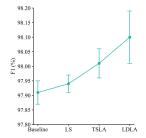
Reading Comprehension Module. We employ RoBERTa-large (Liu et al., 2019) and DeBERTa-v2-xxlarge (He et al., 2021) as our Pre-trained Language Models (PLMs), with our analyses primarily conducted using RoBERTa-large (Liu et al., 2019). To train RoBERTa-large, we use an RTX3090 GPU, setting the number of epochs to 16 and the batch size to 16. For the larger DeBERTa-v2-xxlarge model, we employ an A100 GPU, setting the number of epochs to 8 and the batch size to 16. We use the AdamW optimizer (Loshchilov and Hutter, 2017) with a learning rate of 4e-6 for RoBERTa-large and 2e-6 for DeBERTa-v2-xxlarge, along with a weight decay of 1e-2 for optimization.

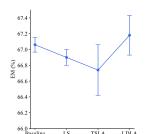
5.3 Experimental Results

We utilize ELECTRA-large (Clark et al., 2020) as the PLM for the retrieval and refinement modules, and DeBERTa-v2-xxlarge for the reading comprehension module. The ${\bf R}^3$ model incorporating F1 Smoothing and LDLA methods is referred to as Smoothing ${\bf R}^3$. LDLA is employed for document retrieval and supporting sentence prediction, while F1 Smoothing is applied for answer span extraction. As shown in Table 1, compared to a series of previous strong baselines, Smoothing ${\bf R}^3$ has achieved the best performance on the stringent Exact Match (EM) metric. Additionally, compared to ${\bf R}^3$, Smoothing ${\bf R}^3$ shows an improvement of 0.8% and 0.77% in EM and F1 scores for the answer extraction task. For the supporting sentence prediction task, there is an increase of 0.19% and 0.57% in EM and F1 scores. These results indicate that label smoothing effectively enhances the model's performance across various metrics.

Document Retrieval. We compare the performance of our retrieval and refinement module, using ELECTRA-large as a backbone, to three advanced methods: SAE (Tu et al., 2020), S2G (Wu et al., 2021), and FE2H (Li et al., 2022). These methods employ sophisticated selectors for retrieving relevant







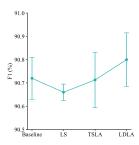


Figure 6: Performance comparison of a series of smoothing methods in document retrieval task.

Figure 7: Comparison of various smoothing methods in supporting sentence prediction task.

Model	Answer		Supporting	
Model	EM	F1	EM	F1
SAE	67.70	80.75	63.30	87.38
S2G	70.80	-	65.70	-
\mathbf{R}^3	71.39	83.84	66.32	89.54
Smoothing \mathbf{R}^3	71.89	84.65	66.75	90.08

Table 3: Comparison of cascade results between our method and several previous methods on the validation set of HotpotQA.

documents. We evaluate the performance of document retrieval using the EM and F1 metrics. Table 2 demonstrates that our \mathbb{R}^3 method outperforms these three strong baselines, with Smoothing \mathbb{R}^3 further enhancing performance.

Supporting Sentence Prediction and Answer Span Extraction. In Table 3, we evaluate the performance of the reading comprehension module, which employs DeBERTa-v2-xxlarge (He et al., 2021) as the backbone, on documents retrieved by the retrieval and refinement module. Our ${\bf R}^3$ model outperforms strong baselines SAE and S2G, and further improvements are achieved by incorporating F1 Smoothing and LDLA. These results emphasize the potential for enhancing performance through the application of label smoothing techniques.

5.4 Label Smoothing Analysis

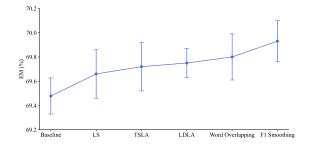
In our analysis of label smoothing, we use RoBERTa-large (Liu et al., 2019) as the backbone. To ensure the reliability of our experimental results, we conduct multiple runs with different random number seeds (41, 42, 43, and 44).

In our experiments, we compare three label smoothing methods: Label Smoothing (LS), Two-Stage Label smoothing (TSLA), and Linear Decay Label smoothing (LDLA). The initial value of ϵ in our experiments was 0.1, and in the first stage of TSLA, the number of epochs was set to 4. For each epoch in LDLA, ϵ was decreased by 0.01.

Document Retrieval. As shown in Figure 6, label smoothing effectively enhances the generalization performance of the retrieval module. LDLA label smoothing approach has more effectively enhanced the model's performance in document retrieval tasks compared to other label smoothing methods.

Supporting Sentence Prediction. We assess the impact of label smoothing on the supporting sentence prediction task. As illustrated in Figure 7, we observe that label smoothing and the TSLA method do not exhibit significant advantages over the baseline and even lead to decreased performance. In contrast, our proposed LDLA method effectively improves the model's performance in the sentence prediction task. This demonstrates the broader task applicability and effectiveness of the LDLA method.

Answer Span Extraction. The impact of label smoothing methods on answer span extraction in the reading comprehension module is depicted in Figure 8. Compared to the baseline, methods such as label smoothing, TSLA, and LDLA can mitigate the performance decline caused by overfitting, thereby



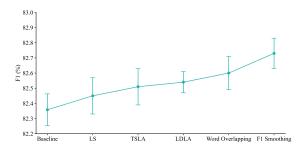


Figure 8: Analysis of different label smoothing methods in answer span extraction task.

Model	Answer Span Errors	Multi-Hop Reasoning Errors
S2G	1612	550
${f R}^3$	1556	562
Smoothing ${f R}^3$	1536 (\ 1.3\%)	545(\psi 3.0%)

Table 4: Error analysis on Answer Span Errors and Multi-hop Reasoning Errors.

enhancing the model's performance. F1 Smoothing shows a significant improvement over label smoothing, TSLA, and LDLA, and also has a notable advantage over the Word Overlapping method. This indicates that F1 Smoothing, by assigning appropriate weights to different tokens in a sentence, more effectively and precisely calculates the suitable target distribution, thereby significantly improving the model's performance in answer span extraction tasks.

5.5 Error Analysis

To more comprehensively understand the role of label smoothing in enhancing model performance, our analysis delves into the model's outputs on the validation set, with a particular emphasis on answer span and multi-hop reasoning errors. These errors are defined as follows:

- Answer Span Errors: Occur when the model's predicted answer and the ground truth answer share some overlap (after excluding stop words) but are not entirely the same.
- Multi-hop Reasoning Errors: Arise when the model's reasoning process leads to a predicted answer that is entirely different from the ground truth answer.

The implementation of label smoothing has led to notable improvements, as detailed in Table 4. Specifically, Smoothing ${\bf R}^3$ achieved a 1.3% reduction in answer span errors, decreasing from 1556 to 1536 instances, and a 3.0% decrease in multi-hop reasoning errors, reducing the count from 562 to 545. These reductions in both error types are significant when compared to the performance of the S2G model. This evidence strongly suggests that label smoothing, when integrated during training, can prevent the model from excessively fitting to specific answer spans and reasoning pathways found in the training set. Consequently, this leads to enhanced generalization capabilities and improved overall performance of the model.

6 Conclusion

In this study, we first identify the primary challenges hindering the performance of MHQA systems and propose using label smoothing to mitigate overfitting issues during MHQA training. We introduce F1 smoothing, a novel smoothing method inspired by the widely-used F1 score in MRC tasks. Additionally, we present LDLA, a progressive label smoothing algorithm that incorporates the concept of curriculum learning. Comprehensive experiments on the HotpotQA dataset demonstrate that our proposed model, Smoothing ${\bf R}^3$, achieves significant performance improvement when using F1 smoothing and LDLA. Further analysis indicates that label smoothing is a valuable technique for MHQA, effectively improving the model's generalization while minimizing overfitting to particular patterns in the training set.

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References

- Akari Asai, Kazuma Hashimoto, Hannaneh Hajishirzi, Richard Socher, and Caiming Xiong. 2020. Learning to retrieve reasoning paths over wikipedia graph for question answering. In *International Conference on Learning Representations*.
- Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. 2009. Curriculum learning. In Andrea Pohoreckyj Danyluk, Léon Bottou, and Michael L. Littman, editors, *Proceedings of the 26th Annual International Conference on Machine Learning, ICML 2009, Montreal, Quebec, Canada, June 14-18, 2009*, volume 382 of *ACM International Conference Proceeding Series*, pages 41–48. ACM.
- Jifan Chen, Shih ting Lin, and Greg Durrett. 2021. Multi-hop question answering via reasoning chains.
- Jan Chorowski and Navdeep Jaitly. 2017. Towards better decoding and language model integration in sequence to sequence models. In *INTERSPEECH*.
- Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. 2020. ELECTRA: pre-training text encoders as discriminators rather than generators. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net.
- Yuwei Fang, Siqi Sun, Zhe Gan, Rohit Pillai, Shuohang Wang, and Jingjing Liu. 2020. Hierarchical graph network for multi-hop question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8823–8838, Online. Association for Computational Linguistics.
- Yair Feldman and Ran El-Yaniv. 2019. Multi-hop paragraph retrieval for open-domain question answering. In Anna Korhonen, David Traum, and Lluís Màrquez, editors, *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2296–2309, Florence, Italy, July. Association for Computational Linguistics.
- Yingbo Gao, Weiyue Wang, Christian Herold, Zijian Yang, and Hermann Ney. 2020. Towards a better understanding of label smoothing in neural machine translation. In *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing*, pages 212–223, Suzhou, China. Association for Computational Linguistics.
- Miguel Graça, Yunsu Kim, Julian Schamper, Shahram Khadivi, and Hermann Ney. 2019. Generalizing backtranslation in neural machine translation. In *Proceedings of the Fourth Conference on Machine Translation (Volume 1: Research Papers)*, pages 45–52, Florence, Italy. Association for Computational Linguistics.
- Dirk Groeneveld, Tushar Khot, Mausam, and Ashish Sabharwal. 2020. A simple yet strong pipeline for HotpotQA. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 8839–8845, Online. Association for Computational Linguistics.
- Pengcheng He, Jianfeng Gao, and Weizhu Chen. 2021. Debertav3: Improving deberta using electra-style pretraining with gradient-disentangled embedding sharing. *ArXiv preprint*, abs/2111.09543.
- Tomáš Kočiský, Jonathan Schwarz, Phil Blunsom, Chris Dyer, Karl Moritz Hermann, Gábor Melis, and Edward Grefenstette. 2018. The NarrativeQA reading comprehension challenge. *Transactions of the Association for Computational Linguistics*, 6:317–328.
- Weizhi Li, Gautam Dasarathy, and Visar Berisha. 2020. Regularization via structural label smoothing. In *International Conference on Artificial Intelligence and Statistics*, pages 1453–1463. PMLR.
- Ronghan Li, Lifang Wang, Shengli Wang, and Zejun Jiang. 2021. Asynchronous multi-grained graph network for interpretable multi-hop reading comprehension. In *IJCAI*, pages 3857–3863.

- Xin-Yi Li, Wei-Jun Lei, and Yu-Bin Yang. 2022. From easy to hard: Two-stage selector and reader for multi-hop question answering. *ArXiv preprint*, abs/2205.11729.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *ArXiv* preprint, abs/1907.11692.
- Ilya Loshchilov and Frank Hutter. 2017. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101.
- Michal Lukasik, Srinadh Bhojanapalli, Aditya Krishna Menon, and Sanjiv Kumar. 2020a. Does label smoothing mitigate label noise? In *Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event*, volume 119 of *Proceedings of Machine Learning Research*, pages 6448–6458. PMLR.
- Michal Lukasik, Himanshu Jain, Aditya Menon, Seungyeon Kim, Srinadh Bhojanapalli, Felix Yu, and Sanjiv Kumar. 2020b. Semantic label smoothing for sequence to sequence problems. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4992–4998, Online. Association for Computational Linguistics.
- Vaibhav Mavi, Anubhav Jangra, and Adam Jatowt. 2022. A survey on multi-hop question answering and generation.
- Rafael Müller, Simon Kornblith, and Geoffrey E. Hinton. 2019. When does label smoothing help? In Hanna M. Wallach, Hugo Larochelle, Alina Beygelzimer, Florence d'Alché-Buc, Emily B. Fox, and Roman Garnett, editors, Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada, pages 4696–4705.
- Kosuke Nishida, Kyosuke Nishida, Masaaki Nagata, Atsushi Otsuka, Itsumi Saito, Hisako Asano, and Junji Tomita. 2019. Answering while summarizing: Multi-task learning for multi-hop QA with evidence extraction. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 2335–2345, Florence, Italy. Association for Computational Linguistics.
- Gustavo Penha and Claudia Hauff. 2021. Weakly supervised label smoothing. In *European Conference on Information Retrieval*, pages 334–341. Springer.
- Gabriel Pereyra, George Tucker, Jan Chorowski, Łukasz Kaiser, and Geoffrey Hinton. 2017. Regularizing neural networks by penalizing confident output distributions. *arXiv* preprint arXiv:1701.06548.
- Lin Qiu, Yunxuan Xiao, Yanru Qu, Hao Zhou, Lei Li, Weinan Zhang, and Yong Yu. 2019. Dynamically fused graph network for multi-hop reasoning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 6140–6150, Florence, Italy. Association for Computational Linguistics.
- Sougata Saha, Souvik Das, and Rohini Srihari. 2021. Similarity based label smoothing for dialogue generation. *ArXiv preprint*, abs/2107.11481.
- Nan Shao, Yiming Cui, Ting Liu, Shijin Wang, and Guoping Hu. 2020. Is Graph Structure Necessary for Multi-hop Question Answering? In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7187–7192, Online. Association for Computational Linguistics.
- Lixin Su, Jiafeng Guo, Yixing Fan, Yanyan Lan, and Xueqi Cheng. 2020. Label distribution augmented maximum likelihood estimation for reading comprehension. In James Caverlee, Xia (Ben) Hu, Mounia Lalmas, and Wei Wang, editors, WSDM '20: The Thirteenth ACM International Conference on Web Search and Data Mining, Houston, TX, USA, February 3-7, 2020, pages 564–572. ACM.
- Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, and Zbigniew Wojna. 2016. Rethinking the inception architecture for computer vision. In 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pages 2818–2826. IEEE Computer Society.
- Ming Tu, Kevin Huang, Guangtao Wang, Jing Huang, Xiaodong He, and Bowen Zhou. 2020. Select, answer and explain: Interpretable multi-hop reading comprehension over multiple documents.
- Johannes Welbl, Pontus Stenetorp, and Sebastian Riedel. 2018. Constructing datasets for multi-hop reading comprehension across documents. *Transactions of the Association for Computational Linguistics*, 6:287–302.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Bohong Wu, Zhuosheng Zhang, and Hai Zhao. 2021. Graph-free multi-hop reading comprehension: A select-to-guide strategy. *ArXiv preprint*, abs/2107.11823.

Yi Xu, Yuanhong Xu, Qi Qian, Hao Li, and Rong Jin. 2020. Towards understanding label smoothing. *ArXiv* preprint, abs/2006.11653.

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*, pages 2369–2380, Brussels, Belgium. Association for Computational Linguistics.

Li Yuan, Francis EH Tay, Guilin Li, Tao Wang, and Jiashi Feng. 2020. Revisiting knowledge distillation via label smoothing regularization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3903–3911.

Zhenyu Zhao, Shuangzhi Wu, Muyun Yang, Kehai Chen, and Tiejun Zhao. 2020. Robust machine reading comprehension by learning soft labels. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 2754–2759, Barcelona, Spain (Online). International Committee on Computational Linguistics

7 Appendix A

7.1 Implementation Details

Our Github repository showcases more details and specific implementations.

7.2 Efficient F1 Smoothing

In order to alleviate the complexity introduced by multiple for loops in the F1 Smoothing method, we have optimized Eq. (12) and Eq. (13). We use $L_a = e^* - s^* + 1$ and $L_p = e - s + 1$ to denote respectively the length of gold answer and predicted answer.

$$q_s(t|x) = \sum_{\xi=t}^{L-1} \text{F1}\left((t,\xi), a_{\text{gold}}\right). \tag{16}$$

If $t < s^*$, the distribution is

$$q_s(t|x) = \sum_{\xi=s^*}^{e^*} \frac{2(\xi - s^* + 1)}{L_p + L_a} + \sum_{\xi=e^* + 1}^{L-1} \frac{2L_a}{L_p + L_a},$$
(17)

else if $s^* \leq t \leq e^*$, we have the following distribution

$$q_s(t|x) = \sum_{\xi=s}^{e^*} \frac{2L_p}{L_p + L_a} + \sum_{\xi=e^*+1}^{L-1} \frac{2(e^* - s + 1)}{L_p + L_a}.$$
 (18)

In equation 17 and 18, $L_p = e - i + 1$.

We can get $q_e(t|x)$ similarly. If $t > e^*$,

$$q_e(t|x) = \sum_{\xi=s^*}^{e^*} \frac{2(e^* - \xi + 1)}{L_p + L_a} + \sum_{\xi=0}^{s^* - 1} \frac{2L_a}{L_p + L_a},\tag{19}$$

else if $s^* \le t \le e^*$,

$$q_e(t|x) = \sum_{\xi=s^*}^{e} \frac{2L_p}{L_p + L_a} + \sum_{\xi=0}^{s^*-1} \frac{2(e-s^*+1)}{L_p + L_a}.$$
 (20)

In equation 19 and 20, $L_p = i - s + 1$.