CREDENCE: Counterfactual Explanations for Document Ranking

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Abstract—Towards better explainability in the field of information retrieval, we present CREDENCE, an interactive tool capable of generating counterfactual explanations for document rankers. Embracing the unique properties of the ranking problem, we present counterfactual explanations in terms of document perturbations, query perturbations, and even other documents. Additionally, users may build and test their own perturbations, and extract insights about their query, documents, and ranker.

I. INTRODUCTION

With the rise of deep learning (DL), significant advances have been made by the data science community, though often at the cost of increased model complexity. For many modern DL models, the underlying decision-making process is nearly unintelligible for data scientists and users [1]. With the growing adoption of data science in critical domains, such as medicine and law, *explainability* has become a priority in many deployment scenarios. In critical applications, explanations build trust between models and their users, and enable auditing that works to ensure regulation adherence, mitigation of bias, and sufficient justification.

In recent years, researchers have developed a variety of solutions that support *explainable artificial intelligence (XAI)*, which combat the increasing complexity that renders DL models uninterpretable. Among different types of *local* explanations, which aim to rationalize individual predictions (decisions), *counterfactual* explanations [2] [3] have emerged as a popular and pragmatic explanation format to impart behavioral insight. Generally, counterfactual explanation methods identify sets of minimal changes to the features of an input, such that a change is observed in a model's prediction.

In the field of information retrieval (IR), complex DL models have been employed for a variety of tasks, most notably for document ranking. Naturally, the decision-making and ranking logic behind document ranking models (rankers) is often unclear to their users [4]. Explainability for document rankers has been limited to derivatives of *saliency* explanations [5] [6] [7] [8], which attempt to approximate the relative importance of model features (e.g., query or document terms). To the best of our knowledge, counterfactual explanations have not yet been adapted for document rankers. To fill this

gap, we demonstrate CREDENCE, the first tool for *CREating DocumEnt raNking explanations CountErfactually*.¹

Our interactive tool produces several types of counterfactual explanations, which collectively expose the decision-making logic behind a ranking model:

- 1) **Counterfactual Documents.** Explore minimal perturbations to a given document that lower its rank (towards the bottom of the ranking) beyond some threshold.
- Counterfactual Queries. Explore minimal perturbations to a search query that raise the rank of a given document (towards the top of the ranking).
- Instance-Based Counterfactual Documents. For a given relevant document, discover similar documents that were deemed non-relevant.
- Build-Your-Own Counterfactual Documents. Interactively edit a given ranked document, then compare the resulting ranking against the original.

II. SYSTEM DESCRIPTION

A. Preliminaries

In the document ranking problem, a user poses a search query q to a ranking model M. Given a set of indexed documents D (i.e., the corpus), the ranking model M is tasked with producing a ranking (i.e., an ordered list of documents) D^M such that, when treated like a set, $D^M \subseteq D$. Naturally, q, D, and M jointly contextualize the definition of D^M . In practice, it is often the case that $|D^M| \ll |D|$, since many rankers need only to identify and rank the top-k relevant documents (i.e., $|D^M| = k$ for some parameter k).

Let R(q, d, D, M) denote the ranking function representing a ranking model M. R returns the rank $r \in [1, |D|]$ assigned by M, corresponding to the predicted relevance of a document $d \in D$ to a search query q. R and M are defined generally, such that the ranker (e.g., a machine learning model) is considered a *black box*. However, we assume that R assesses rank using only the body of each document. In future work, we plan to explain ranking models that support richer sets of features (e.g., user preferences).

¹A video is available at https://vimeo.com/762787210.

The tool is available at http://lg-research-1.uwaterloo.ca:8091/credence.

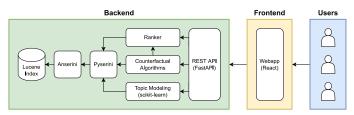


Fig. 1. The architecture behind the CREDENCE system.

B. System Architecture

CREDENCE is an interactive web application built with the React framework, along with other JavaScript libraries, such as Material UI to render user interface components. The backend is implemented in Python 3.9.14, and ultimately runs as an ASGI web server (via Uvicorn). Our server takes the form of a REST API, built using the FastAPI framework, which exposes endpoints to retrieve all data displayed in the web application. Both applications are hosted on a server running Ubuntu 22.04, with an AMD Opteron 6348 Processor, 128 GB of DDR3 RAM, and GeForce RTX 2080 Ti GPU.

The architecture of CREDENCE is illustrated in Figure 1. To facilitate all retrieval functionality, we create a Lucene index using the Pyserini library [9], which is a Python interface for the Anserini retrieval toolkit [10]. Although any compatible ranker could be used to rank documents in our index, we utilize the monoT5 neural ranker from the PyGaggle library.² We implement several counterfactual algorithms, each repeatedly querying the ranker and index to develop understanding of the relationships between documents, search queries, and their rankings. Also, we offer a topic modeling module, allowing users to browse clusters of terms found in selected documents, for the purpose of discovering important terms that may influence relevance. Topic modeling capabilities are enabled through the scikit-learn implementation of the Latent Dirichlet Allocation (LDA) model [11]. Using the FastAPI framework, we expose REST endpoints to perform ranking, generate counterfactual explanations, and discover topics.

C. Counterfactual Document Explanations

To generate counterfactual explanations in terms of a selected *document* without corrupting its grammar, we consider removing *sentences*. An explanation identifies a minimal subset of sentences in a given instance document whose removal lowers the rank of the document beyond k.

Intuitively, in any query-based retrieval setting, the removal of search query terms from a document is likely to lower document rank, at least more than non-query terms. Building on this intuition, we propose an algorithm that calculates an importance score for each sentence in the instance document d, equal to the number of sentence terms that appear in the search query q. The algorithm then iterates through explanations in sorted order. Candidate documents are first sorted by perturbation size (i.e., number of removed sentences) in increasing order, then by their importance score (i.e., the sum

²http://pygaggle.ai.

of importance scores across removed sentences) in decreasing order. In each iteration, the perturbed document is reranked, then added to a final explanation set P if deemed nonrelevant. This process continues until |P| = n, where n is a maximum number of desired explanations. This method guarantees explanation *minimality*, as all perturbations with j removals must be evaluated before those with j + 1.

D. Counterfactual Query Explanations

To generate counterfactual explanations in terms of a *search query*, we append terms from the instance document to the query, which intuitively increases the document's relevance with every addition. Although other terms and other types of perturbation could be used, they are likely to identify relevance-raising search query perturbations at a much slower pace. In our specific formulation, a valid explanation identifies a minimal set of terms that, when appended to the query, raises the rank of a selected document beyond some threshold.

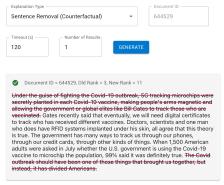
Once more, we propose an iterative algorithm to identify n valid explanations quickly. Our algorithm builds a set of candidate terms from the instance document, excluding terms that do not already appear in the search query, and aims to evaluate terms in order of their importance to the document. Although other importance measures could be used, we choose to score each candidate term using TF-IDF, which scores terms based on their frequency in, and exclusivity to, the instance document d (among the set of ranked documents D^M). All combinations of candidate terms are then iterated, first in increasing order of perturbation size (i.e., the number of appended terms), then in decreasing order of their TF-IDF scores (summed over constituent terms). As with our algorithm for counterfactual document explanations, iterating first by perturbation size guarantees explanation minimality.

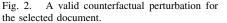
E. Instance-Based Counterfactual Explanations

To enable users to prioritize the *plausibility* of their counterfactual explanations, we implement two instance-based (document) counterfactual algorithms, which output actual documents from the corpus rather than arbitrary perturbations. In our formulation, a valid explanation for a relevant document identifies a non-relevant document with a high degree of similarity. Here, *relevance* is dictated by k.

The instance-based algorithm is a specialization of our regular document counterfactual algorithm. To find a non-relevant document d' that is similar to the instance document d, we implement two variations of the same counterfactual algorithm, each employing different notions of similarity and different document sampling techniques. In the first method, we train a Doc2Vec embedding model [12]. In the second method, we build numeric vector representations of each corpus document using their BM25 scores, though any similar collection statistic (e.g., TF-IDF scores) would suffice. In either case, with numeric document vectors in hand, we calculate similarity using a cosine similarity formula. In the first method, we simply return the n most similar documents. However, in the second method, we sample s non-relevant

2. Generate Explanation





documents (ranked k + 1 and below), ideally where $n \ll s$, then return the *n* documents with the highest similarity.

III. DEMONSTRATION PLAN

In this demonstration, conference participants will generate minimal counterfactual document and search query explanations, instance-based document explanations, and build their own document explanations. Together, these components enable diverse explainability for individual ranking predictions.

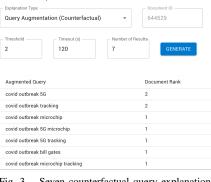
A. Counterfactual Document and Query Explanations

On the *Explanations* page, the user is prompted to select a supported corpus, type an arbitrary query, and select a value of k. Once the Rank button has been clicked, a ranking of the top-k documents appears beneath in a table. By clicking individual documents in the table, the user spawns a new *Generate Explanation* pane to the right, from which four types of counterfactual explanation may be generated. In the following example, we demonstrate and explain the motivation behind the generation of these explanations.

Consider a scenario where a user is investigating a fake news (misleading information) article that has ranked 3/10 in their search for "covid outbreak", while exploring the COVID-19 Articles corpus. Seeking document counterfactual explanations, the user selects the Sentence Removal type, requests one explanation, then clicks GENERATE. As illustrated in Figure 2, the resulting explanation renders the original body of the document, crossing out sentences that the counterfactual perturbation has removed. In this case, removing both sentences mentioning *covid* and *outbreak* lowers the document rank sufficiently to render it non-relevant (i.e., its rank of 11 surpasses k = 10). Our algorithm, which scores sentences by the number of query terms present, assigns both the first and last sentence a score of two. Thus, they are heavily prioritized while exploring perturbations, until their combination (score of four) is discovered to be a valid counterfactual. Using this explanation, the user has quickly learned why this fake news article has ranked among the top-k.

Seeking to discover terms that distinguish it from others, the user now wonders which search queries would raise the rank of this fake news article even higher. With this motivation, the user selects the *Query Augmentation* explanation type, which

2. Generate Explanation



 Explanation Type
 Document ID

 DocZVec Nearest (Instance-Based Counterf._ •
 644529

 Number of Results
 644529

 1
 CENERATE

 ©
 Document ID = 310782, Similarity = 0.75

 Attention loyal followers. 5G tracking microchips are being secretly planted in all second dose waccines, allowing the government to rglobal elites like Bill Gates to track these who are vaccinated. Doctors, scientists and my next door neighbor (who has an RFID system implanted under his skin) all agree that this theory is true. The government hare ways to track us through our phones, through our credit cards, through other kinds of things. When 1,500 American adults were asked in July whether the U.S. government is using this vaccine to spread the news.

Fig. 4. A valid counterfactual document instance.

generates a search-query counterfactual explanation. Without changing their query, the user selects this new explanation type, and requests seven explanations with a threshold of two. A table of queries appears, seen in Figure 3. In this case, the user learns that the ranker would bestow the fake news article a rank of 2/10 for the augmented query "covid outbreak 5G", and 1/10 for "covid outbreak 5G microchip". In our algorithm, these distinguishing terms (e.g., 5G and microchip) are assigned high (TF-IDF) scores, since they do not appear in the other nine relevant documents, and therefore increase the priority of query augmentations that contain them. By highlighting these terms, these explanations yield insight into the relevance of the document within the corpus. Moreover, the user may continue reformulating their own search query, perhaps using these insights to discover other fake news articles.

2. Generate Explanation

B. Instance-Based Counterfactual Explanations

On the *Explanations* page, two instance-based counterfactual methods are available in the *Explanation Type* dropdown: *Cosine Sampled* and *Doc2Vec Nearest*. The cosine sampled explanation requires a number of samples, which controls the number of documents for which the cosine similarity is calculated. In either case, each resulting explanation is a single document, whose body is rendered beneath the prompt.

By evaluating the similarities and differences between a selected document and counterfactual instance, a user may gain insight into the behavior of a ranker. Continuing our example for the query "covid outbreak", the user selects *Doc2Vec Nearest* type from the dropdown. Upon clicking GENERATE, a valid counterfactual document instance is rendered beneath the prompt, stating its numeric similarity to the document being explained. The document presented in the user's output (Figure 4) is 75% similar to the fake news article being explained, despite not being ranked among the original top-10.

The inconsistency between a document and its counterfactual instance inherently delineates a decision boundary respected by the ranker. Upon closer inspection of Figure 4, the user will notice that the instance document is a near copy of the original fake news article, but likely ranked lower due to absence of the terms *covid* and *outbreak*. By exploring these instance-based explanations, the user may discover other

Fig. 3. Seven counterfactual query explanations augmenting the original query "covid outbreak".

1. Generate a Ranking

COVID-19	Articles	covid outbreak			
Select	a Document	3. Edit Document BROWSE TOPICS EDIT DOCUMENT RE-RANK 4. N	lew Ra	anking	
Rank	Document ID	Valid Counterfactual	nange	Rank	Document ID
1	521330	Under the guise of fighting the Covid 19 outbreakflu , 5G tracking microchips		1	521330
2	273576	were secretly planted in each Govid 19fu vaccine, making people's arms magnetic and allowing the government or global elites like Bill Gates to track those who are vaccinated. Gates recently said that eventually, we will need digital certificates to track who has received different vaccines. Doctors, scientists and one man who does have RFID systems implanted under his skin, all agree that this theory is true. The government has many ways to track us through our phones, through our credit cards, through other kinds of things. When 1,500 American adults were asked in July whether the U.S. government is using the Govid 19flu vaccine to microchip the population, 99% said it was definitely true. The Govidflu outbreak should have been one of those things that brought us together, but instead, it has divided Americans.	-	2	273576
3	644529			3	130868
4	130868			4	365576
5	365576			5	308087
6	308087		•	6	100916
7	100916			7	718832
8	718832			8	524510
9	524510		•	9	901333
10	901333	+	-	10	997611
				11	644529

Fig. 5. The counterfactual builder page. By replacing all occurrences of 'covid-19' with 'flu', and removing occurrences of 'outbreak', the document no longer ranks among the top-10. The green check mark verifies this fact, denoting the perturbation as a valid counterfactual.

fake news articles that were absent from the original ranking, while deriving insights about the relevance of the original fake news article. Moreover, presenting actual instances bypasses the issues of finding perturbations that maintain grammar or meaning. In the next subsection, we present one further alternative to this perturbation issue: allow the user to build perturbations interactively.

C. Build-Your-Own Counterfactual Documents

On the Builder page, users may build their own counterfactual document perturbation, then test its counterfactual validity against the other ranked documents. The user is prompted to select a supported corpus, type an arbitrary search query, and select a value of k. Upon clicking the RANK button, a ranking of the top-k documents is obtained from the ranking model, and displayed inside a table. Upon clicking a document in the table, the document body is loaded into an interactive text field, allowing the user to compose arbitrary edits. The BROWSE TOPICS button can be clicked to spawn a modal, allowing the user to generate and explore topics found across all k documents. After finalizing document edits, clicking the RE-RANK button obtains a new ranking from the ranking model. Behind the scenes, the edited document is substituted for the original, then re-ranked alongside the other top k+1documents. The new ranking of k+1 documents is displayed in another table, with coloured arrows to indicate whether the rank of each document has been raised, lowered, or left unchanged. The originally hidden document with rank k+1is given an orange *plus* icon to distinguish itself.

In our running example, the user poses the usual "covid outbreak" query for k = 10, then receives a familiar ranking of top-10 documents. Clicking the fake news article at rank 3, they create several counterfactual perturbations of their own. As illustrated in Figure 5, the user chooses to replace *covid* and *covid-19* occurrences with an alternative term *flu*, and refactor

the term *outbreak* in favour of *the flu*. After re-ranking, the green check mark confirms the counterfactual validity of the perturbation, since its rank has been lowered from 3 to 11 (i.e., k+1). Using this interactive explanation format, the user tested their own plausible perturbations, receiving valuable relevance insights that transcend simple lexical manipulations. In this example, the user quickly learned how to edit this fake news document, so as to ensure it is not deemed relevant to their query.

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