One word at a time: adversarial attacks on retrieval models

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ABSTRACT
Adversarial examples, generated by applying small perturbations to input features, are widely used to fool classifiers and measure their robustness to noisy inputs. However, little work has been done to evaluate the robustness of ranking models through adversarial examples. In this work, we present a systematic approach of leveraging adversarial examples to measure the robustness of popular ranking models. We explore a simple method to generate adversarial examples that forces a ranker to incorrectly rank the documents. Using this approach, we analyze the robustness of various ranking models and the quality of perturbations generated by the adversarial attacker across two datasets. Our findings suggest that with very few token changes (1-3), the attacker can yield semantically similar perturbed documents that can fool different rankers into changing a document’s score, lowering its rank by several positions.

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1 INTRODUCTION
Deep learning ranking models increasingly represent the state-of-the-art in ranking documents with respect to a user query. Different neural architectures [3, 6, 13] are used to model interaction between query and document text to compute relevance. These models rely heavily on the tokens and their embeddings for non-linear transformations for similarity computation. Thus, they capture semantic similarity between query and document tokens circumventing the exact-match limitation of previous models such as BM25 [9].

The complexity of deep learning models arises from their high dimensional decision boundaries. The hyperplanes are known to be very sensitive to changes in feature values. In computer vision literature [15] and text based classification tasks [8, 12], researchers have shown that deep learning models can change their predictions with slight variations in inputs. There is a large body of work that investigates adversarial attacks [12] on deep networks to quantify their robustness against noise. There is, however, lack of such experiments and evaluation in information retrieval literature. Mitra et al. [7] demonstrated how word replacement in documents can lead to difference in word representations which leaves room for more investigation of the robustness of deep ranking models to adversarial attacks.

Usually, adversarial attackers perturb images to reverse a model’s decision. Noise addition to images is performed at pixel level such that a human eye cannot distinguish true image from noisy image. In text classification tasks, characters or words [5, 8] are modified to change the classifier output. The objective of the adversary is to reverse model’s decision with minimum amount of noise injection. In information retrieval, however, it remains an open problem as to how does one design an adversary for a ranking model. We posit that the objective of an adversary in information retrieval would be to change the position of a document with respect to the query. We follow a similar approach used in text classification tasks [5, 8] and perturb tokens in documents, replacing them with semantically similar tokens such that the rank of the document changes.

In this work, we demonstrate by means of false negative adversarial attacks that three state-of-the-art retrieval models can change a document’s position with slight changes in its text. We evaluate the robustness of these ranking models on publicly available datasets by injecting varied length of noisy text in documents. We propose a black-box adversarial attack model that takes a query, document pair as input and generates a noisy document such that its pushed lower in the ranked list. Our system does not need access to the ranker’s internal architecture, only its output given the (query, document) tuple as input.

Our findings suggest that ranking models can be sensitive to even single token perturbations. Table 1 shows some examples generated by our model of one word perturbations along with changes in document position when ranked by DRMM.

| Query | Relevant Document | Replaced by | Rank |
|-------|-------------------|-------------|------|
| what can be powered by wind | Wind power is the conversion of wind energy into a usable form of energy, such as using wind turbines to make electrical power, windmills for mechanical power, wind pumps for water pumping or drainage, or sails to propel ships. | wind | 1 |
| what causes heart disease | The causes of cardiovascular disease are diverse but hypertension and hyperlipidemia are the most common | disorder | 1 |
| how many books are included in the protestant bible? | The Protestant canon consists of the thirty-nine books of the Old Testament and the thirty-nine books of the New Testament. | christian | 5 |
| how many numbers on a credit card | An ISO/IEC 7812 card number is typically 16 digits in length, and consists of | identification | 4 |
| what is the monarch in a monarchy | A monarchy is a form of government in which sovereignty is actually or nominally embodied in a single individual (the monarch). | throne | 4 |

Table 1: Examples of our one word adversarial perturbation and change in document position when ranked by DRMM.

2 RELATED WORK
Adversarial attack on deep neural networks has been extensively explored in vision [11] and text classification [8, 12]. Existing work...
has proposed adversarial attacks with either white-box or black-box access to the model. In this work, our focus is on black-box attacks since access to ranking models is not always available. Existing work is also limited in that the focus is on changing classifier decisions and not document positions in ranked list with respect to a query. In this work we explore utility of (query,doc) pair in adversarial attacks on ranking models.

3 OUR APPROACH

Our goal is to minimally perturb a document such that the rank of the document changes. In particular, we target top-ranked documents and attempt to lower their rank through noise injection. Assuming relevant documents are ranked higher, the objective is to lower the position of a document with minimal change in its text.

3.1 Problem Statement

Let \( q, d \) and \( F \) represent a query, a document and a ranking model, respectively. Given a query-document pair \((q, d)\), the ranker outputs a score \( s = F(q, d) \) indicating the relevance of the document \( d \) to the query \( q \), where higher score means higher relevance. Given a query and a list of documents, the ranker computes scores for every document w.r.t. the given query and rank documents based on a descending order of the scores. Given \( q \) and \( d \), our goal is to find a perturbed document \( d' \) such that \( F(q, d') << F(q, d) \) so that it ranks lower than its original rank. At the same time we want to minimize the perturbation in the document.

We assume that both query and document are represented as vectors which could be either sequence of terms or other suitable representations such as word embedding. Let \( q = (q_1, q_2, ..., q_p) \) be a \( p \)-dimensional query vector and \( d = (d_1, d_2, ..., d_q) \) be a \( q \)-dimensional document vector. We construct a perturbed document \( d' = (d + n) \) by adding a \( q \)-dimensional noise vector \( n = (n_1, n_2, ..., n_q) \). Our goal is to find a noise vector that reduces a document’s score without changing many terms in the document. We formulate this problem as an optimization problem as follows:

\[
\begin{align*}
\text{minimize} & \quad F(q, d + n) \\
\text{subject to} & \quad ||n||_0 \leq c
\end{align*}
\]

(1)

Here, \( c \) is a sparsity parameter that controls the number of perturbed terms. Although, the above formulation provides a sparse solution, we do not have any control over the magnitude of the noise vector. In other words, even though we change only few terms in a document we may end up changing them significantly. To address this problem, we modify the objective function as follows:

\[
\begin{align*}
\text{minimize} & \quad F(q, d + n) + \sum_{i=1}^{q} D(d_i, (d_i + n_i)) \\
\text{subject to} & \quad ||n||_0 \leq c
\end{align*}
\]

(2)

Here, \( D \) can be any suitable distance function (e.g., cosine distance) that computes distance between two terms. It ensures that the modified terms are close to the original terms. We found this formulation too strict. In particular, it penalizes perturbations of query terms as well non-query terms in a document. Hence, we modify the objective function to penalize only query terms since we want to ensure that the perturbed document stays relevant to the query.

The modified objective function is as follows:

\[
\begin{align*}
\text{minimize} & \quad F(q, d + n) + \sum_{i=1}^{q} \mathbb{1}_{d_i \in q} [D(d_i, (d_i + n_i))] \\
\text{subject to} & \quad ||n||_0 \leq c
\end{align*}
\]

(3)

Here, \( \mathbb{1}_{x} \) is an indicator function with \( x = 1 \) when \( x \) is true and \( 0 \) otherwise. The first term in the objective function ensures that the ranker gives low score to the perturbed document while the second term incurs penalty of changing query terms in the document. The constrains limits the number of changed terms in a document to \( c \).

3.2 Method

A popular approach to solve the above problem relies on computing gradient of the model’s output (score) with respect to the input and use this gradient to find a noise vector that reduces model’s score on noisy input [2]. Such gradient based methods do not work well with textual data due to non-differentiable components such as an embedding layer. A common workaround is to find perturbation in the embedding space and project the perturbation vector in the input space through techniques like nearest neighbour search. In general, gradient based methods are limited in that the focus is on changing classifier decisions and not document positions in ranked list with respect to a query. In this work we explore utility of (query,doc) pair in adversarial attacks on ranking models.

A stochastic evolutionary algorithm. It can be applied to a variety of optimization problems including non-differentiable and multimodal objective functions. DE is a population-based optimization method which works as follows: Let’s say we want to optimize over \( l \) parameters. Given the population size \( m \), it randomly initializes \( m \) candidate solutions \( X_i = (x_{i1}, x_{i2}, ..., x_{il}) \), each of length \( l \). From these parent solutions it generates candidate child solutions using the following mutation criteria:

\[
x_{a,t+1} = x_{b,t} + F(x_{c,t} - x_{d,t})
\]

(4)

Here, \( a, b, c, d \) are randomly chosen distinct indices in the population, and \( F \) is a mutation factor in \([0, 2]\). Next, these children are compared against their parents using a fitness function and \( m \) candidates are selected that have the highest fitness (i.e., minimizes the fitness function). This process is repeated until either it converges or reaches the maximum number of iterations.

We use DE to find a perturbation vector \( n \) that changes the document’s rank without significantly modifying it. In particular, we need to find what terms to perturb in the document and the magnitude of each perturbation. Hence, we represent the solution (perturbation vector) as a sequence of tuples \((i, v)\) where \( i \in [0, |d|] \) represents an index of the term to perturb and \( v \) represents the perturbation value. The length of the solution vector is set to \( c \) (the sparsity parameter). We use the objective function proposed earlier as a fitness function for DE and run the algorithm for a fixed number of iterations. Based on the choice of the fitness function, we propose three variants of the attack, \( A1 \) (Equation 1), \( A2 \) (Equation 2) and \( A3 \) (Equation 3). The final solution vector is used to construct the perturbed document \( d' \). A similar approach has been used to perturb images in order to fool a classifier [11].
We compare the performance of the proposed attacks against a random baseline $A0$ where the adversary perturbs a word at random from the text and replaces it with the most similar word (minimum cosine distance in the embedding space) from the corpus.

\[ S@k = \frac{\sum_{d_i d_j > 0} \mathbb{I} (R(d) - R(d')) = k}{\sum_{d_i d_j > 0} \mathbb{I}} \]

Here, $d'$ is a perturbation of $d$ generated by the attacker. We also measure the number of non-relevant documents crossed (NRC) by perturbing $d$ to $d'$ as defined below:

\[ \text{NRC} = \sum_{d_i d_j = 0} \mathbb{I} (R(d) < R(d') < R(d')) \]

We found that non-relevant documents can be perturbed easily by adding noisy text.

\[ \text{Model} \quad \text{Atk} \quad \text{1 token} \quad \text{3 tokens} \quad \text{5 tokens} \]

| Dataset | Model | $A0$ | $A1$ | $A2$ | $A3$ |
|---------|-------|------|------|------|------|
| WikiQA  | DRMM  | 1.09 | 1.09 | 1.11 | 1.11 |
|         | Duet  | 1.11 | 1.11 | 1.11 | 1.11 |
|         | KNRM  | 1.13 | 1.13 | 1.13 | 1.13 |
| MSMarco | DRMM  | 1.13 | 1.13 | 1.13 | 1.13 |
|         | Duet  | 1.15 | 1.15 | 1.15 | 1.15 |
|         | KNRM  | 1.17 | 1.17 | 1.17 | 1.17 |

Table 2: Attackers’ success on changing document’s position.

4 EXPERIMENTAL SETUP

In this section, we provide details about the datasets, model training, perturbation and evaluation metrics.

Data: We use WikiQA [14] and MSMarco passage ranking dataset [1] for training ranking models and evaluating attacks on three ranking models. For WikiQA, we use 2k queries for training and 240 queries for evaluation. For MSMarco, we use 20K randomly sampled queries for training and 220 queries for evaluation. For each test query, we randomly sample 5 positive documents and 45 negative documents for evaluation.

Model training: We use the following ranking models: DRMM [3], DUET [6] and KNRM [13]. We use 300 dimensional Glove embeddings [4] to represent each token.

Perturbation: In our experiments, we perturb only relevant documents in top 5 results for each query in the test set. We perturb documents using all three attackers ($A1$, $A2$, and $A3$) and evaluate ranker performance on the perturbed documents. The number of iterations and population size are fixed to 100 and 500 respectively.

Evaluation: We explore several metrics for understanding the effectiveness of perturbations and their impact on ranker performance. The goal of an attacker is to fool the ranker into lowering the position of the document in the list. The success of the attacker is measured as the percentage of relevant documents whose position changed by $k$ when perturbed by the attacker. Let $R(d)$ denote the rank of a document $d$ and $l_d$ denote its relevance. Then, the attacker’s success at $k$ ($S@k$) is defined as follows:

\[ S@k = \frac{\sum_{d_i d_j > 0} \mathbb{I} (R(d) - R(d')) = k}{\sum_{d_i d_j > 0} \mathbb{I}} \]

We compare the performance of the proposed attacks against a random baseline $A0$ where the adversary perturbs a word at random from the text and replaces it with the most similar word (minimum cosine distance in the embedding space) from the corpus.

5 RESULTS AND DISCUSSION

We focus on three research questions to investigate the impact of adversarial attacks on ranking models.

RQ1: What is the attacker’s success in changing a document’s position without significantly changing the document? To answer this question, we measure an attacker’s success ($S@k$) when we restrict the number of perturbed words to one in each document. The results for $k = 1$ and $k = 5$ are given in Table 2. Notice that $A0$ can change the rank of almost half of the relevant documents but not beyond five positions. Both $A1$ and $A3$ can change the rank of all the relevant documents by just changing one term in the document. In case of MSMarco, they can lower the rank of more than 80% relevant documents by more than four positions except for DRMM ranker. Overall, we found that $A1$ has the highest success rate among all the attackers as it has greater flexibility to change the terms.

We report mean and variance of NRC on the test sets in Table 3 and 4 for MSMarco and WikiQA datasets respectively. Increasing the number of perturbed words increases NRC across all the attackers. On MSMarco dataset, KNRM is the most vulnerable ranker across all the attackers. On average $A1$ can push a relevant document beyond 11 non-relevant documents by changing only one token when evaluated against KNRM ranker. On the other hand, the performance of attackers across all the models is similar on the WikiQA dataset. Overall, all the attackers perform better on MSMarco dataset compared to WikiQA. We argue that the larger dataset has more flexibility to change the terms.

RQ2: What is the similarity between perturbed and original text when we restrict the number of perturbed words to $p_1 = \{1, 3, 5\}$ in each document? Adversarial perturbations may cause the meaning of document text to change. Thus, it is important to control this
It is interesting to note that all attackers are able to reduce DRMM P@5 by single token perturbations by highest margin. However, in MS-Marco, DRMM P@5 is the highest amongst all other models, thus hardest to fool by all attackers. We observe very little drop in precision for A2 attacker across models in both datasets which indicates that very strict attackers may not be able to find suitable candidates to perturb documents. One interesting finding was that in some cases the attacker replaced document text with query tokens to lower document score as shown in Table 1.

6 CONCLUSION

Adversarial attacks on classification models both in text and vision have helped reduce the generalization error of such models. However, there is limited literature on adversarial attacks on information retrieval models. In this work, we explored effectiveness and quality of three simple methods of attacking black box deep learning models. The attackers were designed to change document text such that an information retrieval model is fooled into lowering the document position. We found that perturbed text generated by these attackers by changing few tokens is semantically similar to original text and can fool the ranker to push a relevant document below ~2-3 non-relevant documents. Our findings can be further used to train rankers with adversarial examples to reduce their generalization error.

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Table 5: % drop in P@5 due to perturbed text change such that perturbed words are semantically similar to original text. We measure the semantic similarity between embeddings of original text and perturbed text using cosine distance as done in previous work [12]. Figure 1 shows similarity b/w perturbed and original text when 1, 3 or 5 tokens are changed in MS-Marco passage text for three different models. We only focus on similarity for A1 and A3 attackers due to space limitations.

Overall, the cosine similarity between perturbed and original text across attackers is relatively high (~0.97), even though the document may be pushed below ~20 non-relevant documents with only single token perturbations. As expected, perturbing more tokens leads to lower similarity. Cosine similarity drops to ~0.90 across models for 5 word perturbations. Both A1 and A3 attackers can push documents to relatively lower positions with 1-3 token perturbations, however, we found that A1 tends to perturb query tokens in passages to change ranker output. We found that A1 changed query tokens in 65% (DRMM), 11% (Duet) and 2% (KNRM) documents in MS-Marco and 50%, 17% and 3% documents in WikiQA respectively. However, A3 achieves similar performance in terms of similarity and rank change without changing any query tokens.

RQ3: What is the ranker performance after adversarial attacks? We evaluate model robustness against an adversarial attacker with P@5. We compute perturbed P@5 by replacing the original document’s (d_i) ranker score s_i with the new score s_i’ given by the ranker on the perturbed input d_i’. 2 So, for every document the attacker perturbs, its new score replaces the old ranker score and P@5 is recomputed. We report the % drop in P@5 for both datasets in Table 5. We find that A1 and A3 attackers are able to reduce P@5 significantly, in some cases as much as ~20% in WikiQA and ~50% in MS-Marco by changing one token in the text. Although, A3’s drop in P@5 is lower than that of A1’s across all datasets since it is penalized for changing query terms.

We also found % drop in P@5 to be a function of ranker performance. Models with higher precision were harder to beat by the attacker, i.e., were more robust to token changes in document text. For example, in WikiQA original P@5 (mean,std) for DRMM, Duet and KNRM was 0.204±0.17, 0.207±0.18 and 0.22±0.20 respectively.

We measure the semantic similarity between embeddings of original text and perturbed text using cosine distance as done in previous work: BM25 and beyond [9].

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