Toward the Understanding of Deep Text Matching Models for Information Retrieval

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ABSTRACT
Semantic text matching is a critical problem in information retrieval. Recently, deep learning techniques have been widely used in this area and obtained significant performance improvements. However, most models are black boxes and it is hard to understand what happened in the matching process, due to the poor interpretability of deep learning. This paper aims at tackling this problem. The key idea is to test whether existing deep text matching methods satisfy some fundamental heuristics in information retrieval. Specifically, four heuristics are used in our study, i.e., term frequency constraint, term discrimination constraint, length normalization constraints, and TF-length constraint. Since deep matching models usually contain many parameters, it is difficult to conduct a theoretical study for these complicated functions. In this paper, We propose an empirical testing method. Specifically, We first construct some queries and documents to make them satisfy the assumption in a constraint, and then test to which extent a deep text matching model trained on the original dataset satisfy the corresponding constraint. Besides, a famous attribution based interpretation method, namely integrated gradient, is adopted to conduct detailed analysis and guide for feasible improvement. Experimental results on LETOR 4.0 and MS Marco show that all the investigated deep text matching methods, both representation and interaction based methods, satisfy the above constraints with high probabilities in statistics. We further extend these constraints to the semantic settings, which are shown to be better satisfied for all the deep text matching models. These empirical findings give clear understandings on why deep text matching models usually perform well in information retrieval. We believe the proposed evaluation methodology will be useful for testing future deep text matching models.

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1 INTRODUCTION
Matching two sentences is a core problem in many information retrieval (IR) applications, such as web search [19], question answering [4] and paraphrasing identification[10]. Take web search as an example, given a query and a document, the matching score is usually used to determine the relevance between them.

Recently, deep neural networks have been widely applied in this area and achieved great progresses. These deep text matching models are usually divided into two categories, i.e., representation and interaction based methods. The representation based methods use deep neural network to obtain the representations of each object, then conduct the interaction information to output a matching score. Representative models includes DSSM [17], CDSSM [34] and ARC-I [16], etc. While the interaction based methods directly apply deep neural networks on the interaction matrix of the two objects to output the matching score. DRMM [15], MatchPyramid [28], KNRM[44], DeepMatch[32] and ARC-II[16] have been recognized as some typical models of this kind. More recently, the popular pre-training technique, e.g. BERT [9] has also been applied to deep text matching models and gain increasing attention.

Though deep text matching models have shown good performance in information retrieval, it is unclear what happened in the matching process. Features are not explicit any more in these deep text matching models, as compared with the traditional learning-to-rank methods. Deep learning models are black boxes themselves. Therefore, it is very hard to understand why deep text matching models perform well, and what kind of knowledge/principles do they learn or capture in the matching process. This is exactly the motivation of this paper. We should note that this problem is very challenging. Firstly, interpretation itself is a difficult problem for in the field of deep learning, though the direction has obtained significant attentions and several different interpretation methods have been proposed, such as feature visualizations [26], attribution methods [1], and sample importance methods [21]. Secondly, the formal definition of interpretability is not clear, and may differ for various applications.

Looking back at IR heuristic, some IR heuristics, i.e., several basic desirable constraints, have been proposed in [12, 13]. The performance of a retrieval formula is tightly related to how well it satisfies these constraints. Inspired by this finding, we propose to conduct the understanding of existing deep text matching methods from the perspective of IR heuristics, including term frequency constraints
(TFCs) [33], term discrimination constraint (TDC), length normalization constraints (LNCs) [45], and TF-length constraint (TF-LNC). We noticed that [31] has conducted a similar empirical study. However, they focus on diagnosing the deep model whether they can be improved by adding some data which satisfy the assumption of the constraints. Therefore, there are two problems in this approach: 1) it fails to detect whether these constraints are truly satisfied by a deep text matching model; 2) comparisons between different deep learning models are not allowed.

To address these limitations, this paper focuses on studying whether these deep text matching models satisfy the existing IR constraint. Since the deep text matching models are usually very complicated and contain many parameters, it is not feasible any more to directly conduct mathematical derivations to achieve the conclusion. So we propose to test the trained models on constructed test data. Firstly, we train a deep text matching model on training data. Then we construct queries and documents which satisfy the assumption of a constraint to form a test data. Finally, the trained model is applied on test data, and the proportion of data that satisfy the constraint can be obtained. This value reflects to what extent the deep text matching model satisfies this constraint. Furthermore, the interpretation method Integrated Gradient (IG) [39], which has been proven to be stable and reliable in many different applications, is used in our experiments to conduct detailed analysis and improvements.

We experiment on two widely used datasets in IR, i.e., LETOR 4.0 and MS Marco. Three kinds of deep text matching models are tested, including representation based methods such as ARC-I, interaction based methods such as MatchPyramid, KNRM and BERT, and the hybrid models such as RI-Match and DUET. The results show that these deep text matching models satisfy the four concerned constraints with high probabilities in statistics, which explain why deep text matching models usually perform well on many IR tasks. Furthermore, we extend the above constraints to the semantic versions, by incorporating the word embeddings into the definitions. Experiments show that the deep text matching models satisfy semantic constraints with higher probabilities, which explains the mechanism of how these models capture the semantic matching relations between queries and documents in the scenario of IR.

Our main contributions include: 1) the proposal of a method to test whether a deep text matching model satisfies the existing IR heuristics, which can be used for existing and future deep learning models; 2) the extensive empirical studies on LETOR 4.0 and MS Marco, including both representation and interaction based models; 3) the extension of existing IR constraints to the semantic versions, which provide some foundations for potential investigations of modern deep learning based retrieval models.

## 2 Backgrounds

In this section, we introduce backgrounds that include existing deep matching models for IR, and the interpretation method used in this paper, i.e., integrated gradient (IG).

### 2.1 Deep Text Matching Models

Recently, deep text matching technique has been widely applied in IR, and existing models can be mainly divided into two categories, i.e., representation based methods and interaction based methods.

Representation based methods focus on representing query and document to two vectors by using different deep neural networks, such as CNNs [8, 18] and RNNs [22, 40]. Then matching score is computed by similarity function or multiple layer perceptron (MLP).

Typical representation based models include DSSM, CDSSM, ARC-I, LST-M-RNN[27]. DSSM adopts a feed forward neural network with letter trigram representation as the input. CDSSM and ARC-I both represent the input by CNN. For CDSSM, the input format is letter trigram representation, while ARC-I is a CNN with word embeddings as the input. LSTM-RNN utilize RNN embeds document into a semantic vector. In general, this approach is straightforward and capture the high level semantic meanings of each sentence.

Though representation based models are easy to understand and implement, they usually lose rich detailed interaction features. Interaction based models have been proposed to overcome shortcomings. Therefore, a matching matrix is firstly used to capture the word level query-document interaction features. Then different deep neural networks are utilized to further capture the high level matching features. At last, similar to representation based models, the matching score is produced by a simple similarity function or a MLP. Typical interaction based text matching models include ARC-II [16], MatchPyramid[28], Match-SRNN[42], KNRM[44] and BiMPM[43]. In ARC-II and MatchPyramid, interaction information is calculated by a mapping function to map query/document to a sequence of word representations, then ARC-II adopts 1-D CNN structure to scan each patch of words from query and document, while MatchPyramid adopts CNN to obtain it. Match-SRNN utilizes tensor operation to incorporate high dimensional word level interactions, then 2D-GRU structure used to process the information. In KNRM, the translation layer calculates the word-word similarities to form the translation matrix, the kernel pooling process above matrix. BiMPM utilizes multi-perspective matching operation including the attentive matching to capture the interaction information. BERT obtain the interaction information by the Transformer structure.

Both interaction information and text representations are needed to determine the matching score. To further improve performance of deep text matching models, DUET[24] and RI-Match [7] are proposed to combine the merits of both deep matching approaches to improve the performance of text matching.

Although the existing deep text matching models have achieved great success in many IR tasks, models are still black boxes for us. The understandings of these models are critical because they can not only help explain how these model work, but also give some insights on how to design better models. However, rare studies have been conducted in this area. The only work on this topic is [31], which is very similar to us because they also conduct an empirical study for deep text matching models on IR heuristics. However, it should be noted that our approach are quite different from them. They mainly diagnose a deep model by adding data satisfying the constraint. If a model achieves performance improvements on added data, it is recognized as a good model. However, this approach cannot truly determine whether a model satisfy the IR constraints. Furthermore, using the performance improvement for a single model on different data fail to achieve an comparison between different models. Our work addresses these two limitations. In addition, we adopt an interpretation algorithm to conduct a detailed data analysis on important words to demonstrate some potential improvements. We
also extend these existing constraints to the semantic versions to better fit the deep learning scenario.

2.2 Interpretation Methods

Recently, interpretable machine learning has attracted increasing attention, and many interpretation methods have been proposed, including feature visualization [26], attribution methods[1, 2, 5, 33, 38] and sample importance methods[21]. Among these methods, attribution methods is the most popular approach. It adopts the attribution concept to understand the input output behaviour of a deep neural network. Formally, we have a deep network $F$ with the input $x = [x_1, ..., x_m]$ and output $y = [y_1, ..., y_n]$, where $m$ and $n$ separately stands for the dimensions of $x$ and $y$. The goal of attribution methods is to calculate the attrition $A_i = [a_1, ..., a_n]$ for each feature of the input $x$ for the corresponding output value $y_i$.

Saliency[37] is the first attribution method, it uses gradients to generate the saliency maps. For a given image and the corresponding class saliency map, it first computes the object segmentation using the GraphCut[6] colour segmentation, then calculates the absolute value of $\frac{\partial F(x)}{\partial x_i}$ as the attrition value. Intuitively, this value indicates those input features that can be perturbed the least in order for the target output to change the most. In order to addresses the limitation of gradient-based approaches because the difference from the reference may be non-zero even when the gradient is zero, GradInput [36] has been proposed. Since GradInput scores are computed using a backpropagation like algorithm, they can be obtained efficiently in a single backward pass after a prediction has been made.

Integrated Gradient calculates the average value of gradients at all points which along a straight line path from the baseline $x'$ to input $x$. For image networks, the baseline is the black image [3]. For text models, the baseline $x'$ is set to be zero vector. For the input $x$ and baseline $x'$ can be defined as follows which along the $i^{th}$ dimension. Here, $\frac{\partial F(x)}{\partial x_i}$ is the gradient of $F(x)$ along $i^{th}$ dimension.

$$\text{IntegratedGrads}(x; F)_i = (x_i - x'_i) \times \int_{a=0}^1 \frac{\partial F(x'_i + a \times (x - x'_i))}{\partial x_i} \, da$$

The above formula is the ideal state, but it is hard to calculate. So Integratd Gradient usually adopts the summation operation to approximate the integral operation. To calculate the integral of integrated gradients, we simply summarize the gradients at points along the path from baseline $x'$ to input $x$ with the small intervals.

$$\text{IntegratedGrads}^{approx}(x; F)_i = \frac{x_i - x'_i}{m} \times \sum_{k=1}^{m} \frac{\partial F(x'_i + \frac{k}{m} \times (x - x'_i))}{\partial x_i},$$

where $m$ is the number of steps from baseline $x'$ to input $x$. In theory, the smaller the $m$ is, the closer the two formulas are to each other. We set $m$ to 50 in following experiments. There are also many other paths that monotonically interpolate between baseline $x'$ and input $x$. Integrated Gradient has been widely used in interpreting different machine learning methods in text or image applications.

Considering the advantage of Integrated Gradient, we use it as our interpretation method to facilitate our study.

3 EXPERIMENTS ON INTEGRATED GRADIENT

In this section, we study interpretation of deep text matching models on IR heuristics. First, we introduce empirical settings, including the details of two datasets and the investigated deep text matching models. Then we will describe our interpretation results of these models by using integrated gradient algorithm on four IR heuristics.

3.1 Empirical Settings

3.1.1 Datasets. To facilitate our empirical study, We experiment on two datasets, i.e LETOR4.0 [LT] and MS Marco[MS]. They are both web search ranking dataset that includes queries and documents. Text matching models can be used to achieve the document ranking list for a specific query. We experiment on both datasets to compare the ranking performances of different models.

LETOR4.0 [30] is a benchmark data for evaluating learning to rank methods. This dataset sampled from the GOV2 corpus using the TREC 2007 and TREC 2008 to generate two separate subsets, i.e. MQ2007 and MQ2008. MQ2007 is a bit larger, which contains 1692 queries and 65,323 documents. While MQ2008 only contains 784 queries and 14,384 documents. The query number in MQ2008 is too mall that may cause the serious insufficient training problem, we merge them into one dataset, denoted as LETOR4.0. In total, LETOR4.0 contains 69,623 and 84,834 query-document pairs. The ground-truth labels are collected by human annotators using 3-level graded labeling strategy, i.e. 0, 1, and 2 stands for irrelevant, relevant, and most relevant, respectively.

MS MARCO[25] is a large scale dataset focused on machine reading comprehension, question answering, and passage ranking. The data are collected from real search engine. All 13000 queries are sampled from real anonymous user queries. The 204638 context passages are extracted from real Web documents. We experiment on the data for passage ranking task. For this task, given a query $q$ and the 1000 candidate passages $P = p_1, p_2, p_3, ..., p_{1000}$, it is expected that the most relevant passages be ranked as high as possible. Since there are only one document labeled as relevant, the positive and negative data are extremely imbalanced, i.e., 1000. So we randomly sampled 20 passages from the irrelevant passages to construct our negative samples for each query. In total, 10000, 3000 and 3000 queries are randomly selected to construct the training, validation, and test data, respectively.

3.1.2 Deep Text Matching Models. We study both representation and interaction based deep text matching models, and also the hybrid ones. Specifically, ARC-I is chosen as the representative of the representation based models, MatchPyramid, BERT and KNRM are chosen as the representative of the interaction based models. DUET and RI-Match are the hybrid models used in our experiments.

ARC-I utilizes CNN to obtain representations of the input query and document. Then two vectors are concatenated to one vector, and a multi-layer perceptron (MLP) [23] is used to output the matching
score. It concatenates two vectors into one vector. The model is an end-to-end neural network structure [14].

**MatchPyramid** [MP] constructs a word level interaction matrix, with each element stands for the similarity of two corresponding words in the query and document. Then interaction matrix is fed as a image to a two dimensional CNN to extract high level matching patterns. Finally, a MLP is used to obtain matching degree.

**KNRM** uses matching matrix as used in MatchPyramid to obtain the word level matching signals. The difference lies in the second step, where KNRM uses a new kernel-pooling technique, instead of CNN to extract high level matching patterns. The advantage of using the kernel-pooling technique is that they can help to extract multi-level soft match features. At last, a learning-to-rank layer is utilized to combine these features to obtain the final ranking score.

**DUET** is composed of two separate deep neural networks. One matches the query and the document using a local representation. Another one matches the query and the document using learned distributed representations. The two networks are jointly trained as part of a single neural network.

**RI-Match** combines the benefits of representation and interaction based models. Firstly, the word level and sentence level matching matrices are created by using various matching functions. Then these matrices are fed into a spatial recurrent neural network [42] to generate high level matching patterns. After a k-max pooling [41], the vector is fed into a MLP to output the final ranking score.

**BERT** is a language representation model which stands for Bidirectional Encoder Representations from Transformers. It pre-trains deep bidirectional representation from huge unlabeled text to obtain contextual word representations. The pre-trained BERT model can be further fine-tuned with additional output layer for a specific task. For text matching task, we output the matching degree of two texts as a classification task.

3.1.3 **Parameter Setting.** For all deep models, we trained them by using their implementations in MatchZoo[11]. All the hyperparameters were tuned using the same experimental setup as described in the respective papers. For the input word embeddings, we initialize the embedding layer with the 300-dimensional GloVe[29] word vectors pre-trained in the 840B Common Crawl corpus[3]. For the out-of-vocabulary (OOV) words, we initialize the word vectors to zero. We leverage Adam[20] as our optimizer to update the parameters of models, and minimize the categorical cross entropy on the training set until the model converges.

3.1.4 **Ranking Performance.** To conduct the interpretation analysis, we need to guarantee that the models have been trained sufficiently. So we first give the ranking performance of the deep text matching on both datasets, as shown in Table 1 and Table 2. From the table, we can see that most deep text matching models have been trained to achieve the SOTA results, except for BERT on LETOR dataset. It is mainly because the dataset size is relatively too small for the huge BERT model and may cause overfitting. Therefore, it is reasonable to conduct further interpretation analysis based on these models.

### Table 1: Performance on LETOR4.0 datasets.

| Model   | MAP(%) | NDCG@3(%) | NDCG@5(%) |
|---------|--------|-----------|-----------|
| ARC-I   | 42.69  | 33.22     | 35.28     |
| Duet    | 43.27  | 35.47     | 36.98     |
| RI-Match| 44.54  | 36.49     | 37.54     |
| MatchPyramid | 44.37 | 36.29     | 37.51     |
| KNRM    | 44.06  | 36.73     | 37.50     |
| BERT    | 41.42  | 32.42     | 34.46     |

### Table 2: Performance on MS Marco datasets.

| Model   | MRR(%) | NDCG@3(%) | NDCG@5(%) |
|---------|--------|-----------|-----------|
| ARC-I   | 50.06  | 49.99     | 54.13     |
| Duet    | 50.70  | 50.15     | 54.10     |
| RI-Match| 52.21  | 51.86     | 55.77     |
| MatchPyramid | 52.57 | 51.94     | 55.49     |
| KNRM    | 52.35  | 50.77     | 55.79     |
| BERT    | 55.62  | 54.38     | 55.16     |

3.2 **Interpretation Analysis.** In this paper, we use Integrated Gradient as the interpretation method to analyze the deep text matching models. As we introduced in Section 2.2, it computes the integral of integrated gradients to show the importance of each input attribution for the output. Applying IG to our analysis, we can view each trained deep text matching model as the function $F$ in the computation of IG, and output the integral of integrated gradients. For visualization, we use the brightness of different colors to show the value of these gradients. Therefore, we can obtain the significance of each word both in query and document, to show their contributions to the matching score. Figure 1 shows an example of such analysis. From this example, we can see that the word “spokane” is the most attributed term to the matching score of the example query and document, which is accordant with human’s understanding. In the following experiments, we will continue to use this analysis technique to facilitate our study.

Before we begin our analysis on IR intrinsics, we first introduce some notations. Formally, we use $q = (q_1, \ldots, q_m)$ to denote a query, $d$ or $d_i$ to denote a document, $\omega$ or $\omega_i$ to denote a query term, and $\omega$ to denote a non-query term. The length of document $d$ is expressed as $|d|$, $c(\omega, d)$ stands for the count of word $\omega$ in document $d$. $f$ stands for a matching function, and $f(d, q)$ calculates the matching score of document $d$ with respect to query $q$. $idf(\omega)$ stands for

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1. https://github.com/NTMC-Community/MatchZoo/tree/1.0
2. http://index.commoncrawl.org/
the IDF discrimination value of a query term \( \omega \). While \( df(\omega) \) and \( tf(\omega) \) denote the term frequency of term \( \omega \) in the datasets and the document, respectively.

Now we formally study whether the above learned deep text matching models satisfy the four IR intrinsic constraints, i.e., term frequency constraint (TFCs), term discrimination constraint (TDC), length normalization constraint (LNCs), and TF-length constraint (TF-LNC). We first introduce the detailed definition of each constraint, and then demonstrate how we construct data to test whether the trained deep text matching models satisfy the constraints. We also show some further investigations on the reason of the results.

### 3.3 Term Frequency Constraint

There are two term frequency constraint, denoted as TFC1 and TFC2. Both constraints are to capture the desired contribution of the TF of a term to scoring. The first constraint captures the basic TF heuristic, which gives a higher score to a document with more occurrences of a query term when the only difference between two documents is the occurrences of the query term. While the second constraint ensures that the increase in the score due to an increase in TF is smaller for larger TFs (i.e., the second partial derivative w.r.t. the TF variable should be negative). The formal definitions are shown as follows.

**TFC1**: Let \( q = \{ \omega \} \) which has only one term \( \omega \). Assume \( |d_1| = |d_2| \), if \( c(\omega, d_1) > c(\omega, d_2) \), then \( f(d_1, q) > f(d_2, q) \).

**TFC2**: Let \( q = \{ \omega \} \) which has only one term \( \omega \). Assume \( |d_1| = |d_2| = |d_3| \), \( c(\omega, d_1) > 0 \), if \( c(\omega, d_2) - c(\omega, d_1) = 1 \) and \( c(\omega, d_1) - c(\omega, d_2) = 1 \), then \( f(d_2, q) - f(d_1, q) > f(d_3, q) - f(d_2, q) \).

To evaluate how much the learned matching function satisfies the desired TFC constraints, we need to construct data which satisfy the above conditions. For TFC1, we can see that the condition is mainly on the query and document length, so we can construct data as follows. Suppose the query \( q \) contains \( m \) query terms \( \{ q_1, \ldots, q_m \} \). For each two associated documents \( d_1 \) and \( d_2 \), we can truncate them to be with length \( \min(|d_1|, |d_2|) \), still denoted as \( d_1 \) and \( d_2 \). Then each \( q_i, d_1 \) and \( q_i, d_2 \) becomes a pair satisfying the condition of TFC1, we can test whether the learned function output an accordant score w.r.t. the occurrence of the query term in each document.

The data construction for TFC2 is a little bit more complicated. For query term \( \omega \), we first select three documents that contains \( \omega \). Then we select three documents according to the occurrence of \( \omega \) in the documents. The document with least \( \omega \) is denoted as \( d_1 \). For \( d_2 \), we delete extra \( \omega \) to make \( c(\omega, d_2) - c(\omega, d_1) = 1 \). If \( c(\omega, d_2) = c(\omega, d_1) \), we add one \( \omega \) to the \( d_2 \) randomly. Then we need to make \( |d_1| = |d_2| \). If \( |d_1| < |d_2| \), we delete other words in \( d_2 \) except for \( \omega \) until \( |d_1| = |d_2| \). If \( |d_1| > |d_2| \), we add other words to \( d_2 \) except for \( \omega \) until \( |d_1| = |d_2| \). For \( d_3 \), we do similar constructions to make \( |d_2| = |d_3| \) and \( c(\omega, d_2) - c(\omega, d_1) = 1 \).

To evaluate the degree to which the deep text matching models satisfy the TFC constraints, we calculate the proportion of data where the constraints are satisfied. Please note that the data construction could be conducted on both training and test data for LETOR4.0 and Ms MARCO, so we give the experimental results on those four data, denoted as LT-Train, LT-Test, MS-Train, and MS-Test, respectively, as shown in Table 3 and Table 5.

### 3.4 Term Discrimination Constraint

Term Discrimination Constraint captures the interaction between TF and IDF, and emphasizes the effect of using IDF in the scoring of text matching, denoted as TDC. Specifically, given a fixed times of occurrences of query terms, a document should obtain higher matching score if it has more discriminative terms, measured by IDF. The formal definition is shown as follows. **TDC**: Let \( q \) be a query and has two query terms, then \( q = \{ \omega_1, \omega_2 \} \). Assume \( |d_1| = |d_2| \), \( c(\omega_1, d_1) + c(\omega_2, d_1) = c(\omega_1, d_2) + c(\omega_2, d_2) \). If \( idf(\omega_1) \geq idf(\omega_2) \) and \( c(\omega_1, d_1) > c(\omega_1, d_2) \), then \( f(d_1, q) > f(d_2, q) \).

To evaluate how much the learned matching function satisfies the desired TDC constraints, we need to construct data which satisfy the above conditions. Suppose the query \( q \) contains several words

| Models  | LT-Train(%) | LT-Test(%) | MS-Train(%) | MS-Test(%) |
|---------|-------------|------------|-------------|------------|
| ARC-I   | 79.96       | 74.54      | 87.17       | 84.89      |
| DUET    | 80.36       | 75.37      | 88.27       | 85.97      |
| RI-Match| 81.61       | 76.98      | 90.82       | 87.53      |
| MP      | 93.95       | 81.61      | 95.66       | 91.54      |
| KNRM    | 95.68       | 89.23      | 94.84       | 90.37      |
| BERT    | 77.36       | 75.28      | 96.57       | 92.46      |

| Models  | LT-Train(%) | LT-Test(%) | MS-Train(%) | MS-Test(%) |
|---------|-------------|------------|-------------|------------|
| ARC-I   | 81.47       | 77.23      | 88.87       | 82.82      |
| DUET    | 82.63       | 78.46      | 89.92       | 82.66      |
| RI-Match| 83.56       | 78.64      | 92.62       | 86.89      |
| MP      | 95.06       | 87.01      | 95.99       | 88.33      |
| KNRM    | 96.20       | 88.52      | 95.23       | 87.71      |
| BERT    | 79.54       | 77.12      | 97.47       | 90.45      |

| Models  | LT-Train(%) | LT-Test(%) | MS-Train(%) | MS-Test(%) |
|---------|-------------|------------|-------------|------------|
| ARC-I   | 83.44       | 77.35      | 82.83       | 78.64      |
| DUET    | 84.84       | 78.29      | 82.20       | 79.74      |
| RI-Match| 85.62       | 78.40      | 84.43       | 79.28      |
| MP      | 87.27       | 79.46      | 86.26       | 82.68      |
| KNRM    | 86.92       | 78.82      | 87.23       | 84.67      |
| BERT    | 81.11       | 79.27      | 90.89       | 88.56      |

From Table 4, we can see that all deep text matching models satisfy the TFC constraints with a high probability. TFC2 result is not as good as TFC1 result. That is mainly because a lot of matching degree attributes to some more frequent words, such as ‘in’ and ‘for’, shown as in Fig. 1. As stated in [12, 13], words with large DF usually play a negative correlation role in the matching process, so we limit the df of all words to eliminate the influence of these words. Table 4 show the performance of different deep text matching models in terms of TFC1 under the condition \( df(\omega) < 5000 \) in the training data, where consistency is significantly improved.
Table 7: Results of deep text matching models on TDC with \( c(\omega_1, d_2) \leq c(\omega_2, d_1) \).

| Models | LT-Train(%) | LT-Test(%) | MS-Train(%) | MS-Test(%) |
|--------|-------------|-------------|-------------|-------------|
| ARC-I  | 87.48       | 79.49       | 87.83       | 83.00       |
| DUET   | 87.13       | 82.23       | 86.49       | 82.56       |
| RI-Match | 88.58   | 83.56       | 87.76       | 84.85       |
| MP     | 89.34       | 83.65       | 88.73       | 84.23       |
| KNRM   | 88.75       | 84.68       | 90.45       | 84.80       |
| BERT   | 83.45       | 80.45       | 91.54       | 86.27       |

Table 8: Results of deep text matching models on LNC1.

| Models | LT-Train(%) | LT-Test(%) | MS-Train(%) | MS-Test(%) |
|--------|-------------|-------------|-------------|-------------|
| ARC-I  | 70.36       | 67.23       | 70.21       | 66.67       |
| DUET   | 71.55       | 67.94       | 72.63       | 68.89       |
| RI-Match | 72.56   | 68.34       | 71.35       | 68.12       |
| MP     | 74.28       | 69.45       | 72.66       | 67.28       |
| KNRM   | 74.18       | 69.26       | 71.38       | 68.31       |
| BERT   | 69.24       | 66.26       | 73.57       | 69.23       |

Table 9: Results of deep text matching models on LNC2.

| Models | LT-Train(%) | LT-Test(%) | MS-Train(%) | MS-Test(%) |
|--------|-------------|-------------|-------------|-------------|
| ARC-I  | 96.7        | 88.12       | 87.23       | 83.59       |
| DUET   | 96.23       | 87.93       | 88.25       | 84.38       |
| RI-Match | 96.56   | 87.85       | 89.35       | 84.67       |
| MP     | 100.00      | 89.87       | 96.07       | 90.28       |
| KNRM   | 99.01       | 87.28       | 93.79       | 89.06       |
| BERT   | 94.34       | 986.23      | 100.00      | 93.26       |

3.5 Length Normalization Constraint

There are two length normalization constraints, denoted as LNC1 and LNC2. Both constraints capture contribution of the length of document in the scoring process. LNC1 says that if we add one extra non-relevant word to form a new document, then the matching degree of the new document with respect to the query will decrease. While LNC2 says that if we duplicate a document \( k \) times to form a new document, the new document will obtain higher matching score than the original document. The formal definitions are shown as follows.

**LNC1**: Let \( q \) be a query and \( d_1, d_2 \) be two documents. If for some word \( \omega' \not\in q, c(\omega', d_2) = c(\omega', d_1) + 1 \), but for any query term \( \omega, c(\omega, d_2) = c(\omega, d_1) \), we have \( f(d_1, q) > f(d_2, q) \).

**LNC2**: Let \( q \) be a query. \( \forall k > 1, d_1 \) and \( d_2 \) are two documents with \( |d_1| = k \cdot |d_2| \). If for any query term \( \omega, c(\omega, d_1) = k \cdot c(\omega, d_2) \), we have \( f(d_1, q) > f(d_2, q) \).

To evaluate how much the learned matching function satisfies the desired LNC constraints, we need to construct data which satisfy the constraints. For LNC1, suppose that the query \( q \) contains several terms \( \{q_1, ..., q_m\} \) and the document is \( d_1 \). We first find a word in the document does not exist in the query \( q \). Appending this word to the end of the document \( d_1 \) to form a new document \( d_2 \), then \((q, d_1)\) and \((q, d_2)\) form a data pair that satisfies the LNC1 constraint.

The data construction for LNC2 is a little bit more easy. Suppose that the query is \( q \) and the document is \( d_1 \) with length \( |d_1| \). Here, we set \( k = 2 \) as an example. We first duplicate document \( d_1 \) to form the new document \( d_2 \) with length \( 2|d_1| \), then \((q, d_1)\) and \((q, d_2)\) forms a data pair that satisfies the constraints.

After that, we calculate the proportion of data that satisfy the constraints. The results on LT-Train, LT-Test, MS-Train, and MS-Test are shown in Table 8 and Table 9. From the results, we can see that LNC1 constraint is not so well satisfied for deep text matching models as LNC2. So we utilize the IG algorithm to conduct the attribution analysis.

We found that one key difference between LNC1 and LNC2 is that, the influence of duplicated words are different. We show two examples in Figure 2 and 3. We can see that the word "map" has the positive attribution value in the original document. When it is added to form a new document, it still has a positive attribution value and will improve the matching degree of the documents. That is contradiction with the LNC1 constraint. While for LNC2, though most duplicated word still attribute with the same sign, some key words like "primary" change their attribution sign from positive to negative. So we conclude that the attribution sign plays an important role in LNC1, and we need to take this factor into account. Specifically, when we construct the data for LNC1, the
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Figure 2: An example for LNC1.

Table 10: Results of deep text matching models on LNC1 with $IG_{value}(\omega') < 0$.

| Models     | LT-Train(%) | LT-Test(%) | MS-Train(%) | MS-Test(%) |
|------------|-------------|------------|-------------|------------|
| ARC-I      | 83.57       | 80.37      | 85.99       | 82.09      |
| DUET       | 84.62       | 81.88      | 86.46       | 82.72      |
| RI-Match   | 86.35       | 82.55      | 87.86       | 83.86      |
| MP         | 87.29       | 83.54      | 87.12       | 84.21      |
| KNRM       | 86.48       | 82.70      | 88.08       | 84.92      |
| BERT       | 81.37       | 80.03      | 90.32       | 87.53      |

Figure 3: An example for LNC2.

Table 11: Results of deep text matching models on LNC1 with $IG_{value}(\omega') > 0$.

| Models     | LT-Train(%) | LT-Test(%) | MS-Train(%) | MS-Test(%) |
|------------|-------------|------------|-------------|------------|
| ARC-I      | 62.37       | 55.32      | 61.41       | 58.54      |
| DUET       | 63.56       | 58.35      | 62.23       | 59.47      |
| RI-Match   | 66.45       | 63.26      | 62.46       | 60.48      |
| MP         | 67.57       | 64.30      | 64.24       | 62.67      |
| KNRM       | 66.25       | 60.37      | 64.28       | 62.25      |
| BERT       | 60.23       | 51.46      | 59.28       | 57.28      |

Table 12: The ratio of duplicated words with consistency attributions on LNC2.

| DataSet  | ARC-I | DUET | RI-Match | MP | KNRM | BERT |
|----------|-------|------|----------|----|------|------|
| Letor 4.0| 0.707 | 0.728| 0.739    | 0.758| 0.742| 0.693|
| MS Marco | 0.692 | 0.712| 0.724    | 0.735| 0.726| 0.758|

3.6 TF-Length Constraint

TF-Length constraint captures the interaction between TF and document length, denoted as TF-LNC. It says that if $d_1$ is constructed by adding more query term to $d_2$, the matching score of $d_1$ will be higher than $d_2$. The formal definition is shown as follows.

TF-LNC: Let $q = \{\omega\}$ be the query which has only one term $\omega$. Assume $c(\omega, d_1) > c(\omega, d_2)$ and $|d_1| = |d_2| + c(\omega, d_1) - c(\omega, d_2)$, we have $f(d_1, q) > f(d_2, q)$. To evaluate how much the learned matching function satisfy the desired TF-LNC constraint, we need to construct data which satisfy the above condition in the definition. We first add $c(\omega, d_1) - c(\omega, d_2)$ words (not $\omega$) to document $d_2$. Then we calculate the proportion of data where the constraint is satisfied, and the results are shown in Table 13. From the table, we can see that most of deep text matching models well satisfy the TF-LNC. We further apply the IG algorithm to analyse the attribution of each word, and an example is shown in Figure 4. In the example, the query contains only one query term "muscle", and $c(q, d_1) > c(q, d_2)$. Although the document length of $d_1$ is larger, most of the "muscle" appearing in the document attribute positively to the matching score. That explains why $d_1$ is more relevant than $d_2$ with respect to the query. We further make a statistics on the proportion of part, the consistency ratio of these words is helpful to enhance the matching degree between query and document globally.

Figure 4: An example for TF-LNC.
we train deep text matching model on original training data, and words in \(d_1\) with greater attribution value than \(d_2\) in the dataset, as shown in Table 14. We can see that most words remain their attribution signs in the duplication process.

4 EXTENSION TO SEMANTIC IR HEURISTICS

From the above studies, we can conclude that the existing deep text matching models well satisfy the four IR heuristics. However, all the IR heuristics only consider the exact matching, which may be limited in the semantic scenario that deep learning models are good at. So we propose to extend the previous IR heuristics to incorporate the semantic meanings, namely semantic IR heuristics including TFC1-E, TDC-E, and TF-LNC-E. The precise definitions are described as follows.

TFC1-E: Let \(q = \{\omega\}\) which has only one term \(\omega\). Assume \(|d_1| = |d_2|, \theta \in [0, 1]\) is the threshold of the cosine similarity, \(y_i\) stands for the \(i\)-th word in document \(d\). We define the semantic count \([Sc]\) of \(\omega\) for \(d\) in the Equation 1. Assume \(Sc(\omega, d_1) \geq Sc(\omega, d_2)\), where \(f\) denotes the cosine similarity function, we have \(f(d_1, q) > f(d_2, q)\).

\[
\text{SemanticCount}(\omega, d) = \sum_{i=1}^{d} [f(\omega, y_i)](f(\omega, y_i) \geq \theta) \tag{1}
\]

TDC-E: Let \(q = \{\omega_1, \omega_2\}\) which has two query terms \(q = \{\omega_1, \omega_2\}\). Assume \(|d_1| = |d_2|, Sc(\omega_1, d_1) + Sc(\omega_2, d_2) - [Sc(\omega_1, d_2) + Sc(\omega_2, d_2)] < \epsilon\), here we set \(\epsilon = 0.1\). If \(idf(\omega_1) \geq idf(\omega_2)\) and \(Sc(\omega_1, d_1) > Sc(\omega_2, d_2)\), we have \(f(d_1, q) > f(d_2, q)\).

TF-LNC-E: Let \(q = \{\omega\}\) which has only one term \(\omega\). Assume \(|d_1| = |d_2|, [Sc(\omega, d_1) - Sc(\omega, d_2)]\) and \(Sc(\omega, d_1) > Sc(\omega, d_2)\), where the \([\ ]\) denotes the floor function, we have \(f(d_1, q) > f(d_2, q)\).

We compare the previous IR heuristics and our proposed extension versions by comparing the satisfied data proportion, shown in Table 15, 16, 17, and 18. The experimental results show that existing deep text matching models better satisfy our proposed extension versions than the previous IR heuristics, which better explain the existing deep text matching models than traditional ones.

5 CONCLUSION

In this paper, we propose to understand deep text matching model from the perspective of how much do they satisfy the IR heuristics. We propose an empirical method to facilitate our study. First, we train deep text matching model on original training data, and then apply it to some constructed data satisfying the assumption of a constraint. As a result, the proportion of data satisfying the constraint can be used as our required qualitative measure. In our experiments, we test six representative deep text matching models (ARC-I, MatchPyramid, KNRM, RI-Match, BERT and DUET), in terms of four IR heuristics (TFCs, TDC, LNCs, and TF-LNC). Experimental results show that all six models satisfy heuristics with high probabilities in statistics. Moreover, we extend the existing IR heuristics to the semantic version, and experimental results show that these semantic constraints can be better satisfied by these models.
deep text matching models. So the semantic IR heuristics can better explain the success of deep text matching models, as compared with traditional ones. Except for these revealed understandings, we believe the proposed evaluation methodology will be useful for testing existing and future deep text matching models.

In future, we plan to extend our study to other deep text matching models and IR heuristics, to complete a more thorough investigation. Furthermore, we are interested in how to design more suitable IR heuristics for deep learning, and how to use the proposed semantic heuristics to help us design better deep text matching models.

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