Simple Attention-Based Representation Learning for Ranking Short Social Media Posts

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Abstract

This paper explores the problem of ranking short social media posts with respect to user queries using neural networks. Instead of starting with a complex architecture, we proceed from the bottom up and examine the effectiveness of a simple, word-level Siamese architecture augmented with attention-based mechanisms for capturing semantic “soft” matches between query and post terms. Extensive experiments on datasets from the TREC Microblog Tracks show that our simple models not only demonstrate better effectiveness than existing approaches that are far more complex or exploit a more diverse set of relevance signals, but also achieve 4× speedup in model training and inference.

1 Introduction

Despite a large body of work on neural ranking models for “traditional” ad hoc retrieval over web pages and newswire documents (Huang et al., 2013; Shen et al., 2014; Guo et al., 2016; Pang et al., 2016; Xiong et al., 2017; Mitra et al., 2017; Pang et al., 2017; Dai et al., 2018; McDonald et al., 2018), there has been surprisingly little work on applying neural networks to searching short social media posts such as tweets on Twitter. Rao et al. (2018) identified short document length, informality of language, and heterogeneous relevance signals as main challenges in relevance modeling, and proposed a model specifically designed to handle these characteristics. Evaluation on a number of datasets from the TREC Microblog Tracks demonstrates state-of-the-art effectiveness as well as the necessity of different model components to capture a multitude of relevance signals.

In this paper, we also examine the problem of modeling relevance for ranking short social media posts, but from a complementary perspective. As Weissenborn et al. (2017) argues, most systems are built in a top-down process: authors proposing a complex architecture and validating design decisions with ablation experiments. However, such experiments often lack comparisons to strong baselines, which raises the question as to whether model complexity is empirically justified. As an alternative, they advocate a bottom-up approach where architectural complexity is gradually increased. We adopt exactly such an approach, focused exclusively on word-level modeling. As shown in Figure 1, we examine variants of a simple, generic architecture that has emerged as “best practice” of the NLP community for tackling modeling problems on two input sequences: a Siamese CNN architecture for learning representations over both inputs (a query and a social media post in our case), followed by fully-connected layers that produces a final relevance prediction (Severyn and Moschitti, 2015; He et al., 2015; Rao et al., 2016), which we refer to as a General Sentence Encoder in Section 2.1. Further adopting best practices, we incorporate query-aware convolutions with an aggregation layer in the representation learning process.

Figure 1: Our model architecture: a general sentence encoder is applied on query and post embeddings to generate \( g_q \) and \( g_p \); an attention encoder is applied on post embeddings to generate variable-length query-aware features \( h_i \). These features are further aggregated to yield \( v \), which feeds into the final prediction.
Recently, a number of researchers (Petrochuk and Zettlemoyer, 2018; Conneau et al., 2017) have started to reexamine simple baselines and found them to be highly competitive with the state of the art, especially with proper tuning. For example, the InferSent approach (Conneau et al., 2017) uses a simple BiLSTM with max pooling that achieves quite impressive accuracy on several classification benchmarks. Our contribution is exactly along this line by exploring simple yet strong baselines for ranking social media posts, to gain more insights into query–post matching using standard neural architectures. Experiments with data from the TREC Microblog Tracks show that our simple models not only demonstrate better effectiveness than existing approaches that are far more complex or exploit a more diverse set of relevance signals, but also achieve 4× speedup in model training and inference.

2 Model

Our model comprises a representation learning layer with convolutional encoders (Section 2.1) and another simple aggregation layer (Section 2.2).

2.1 Representation Learning Layer

General Sentence Encoder: The general sentence encoder uses a standard convolutional layer with randomly initialized kernels to learn semantic representations for text. More formally, given query $q$ and post $p$ as sentence inputs, we first convert them to embedding matrixes $Q$ and $P$ through an embedding lookup layer, where $Q \in \mathbb{R}^{n \times d}$ and $P \in \mathbb{R}^{m \times d}$, $d$ is the dimension of embeddings, and $n$ and $m$ are the number of tokens in $q$ and $p$, respectively. Then we apply a standard convolution operation with kernel window size $k$ over the embedding matrix $Q$ and $P$. The convolution operation is parameterized by a weight term $W \in \mathbb{R}^{F \times k \times d}$ and a bias term $b_w \in \mathbb{R}^{F}$, where $F$ is the number of convolutional kernels. This generates semantic representation $O_q \in \mathbb{R}^{n \times F}$ and $O_p \in \mathbb{R}^{m \times F}$, on which max pooling and an MLP are applied to obtain query representation $g_q \in \mathbb{R}^d$ and post representation $g_p \in \mathbb{R}^d$.

The weakness of the kernels in the general sentence encoder is that they do not have a priori knowledge from the query when they capture feature patterns from the post. Inspired by the attention mechanism (Bahdanau et al., 2014), we propose two novel approaches to incorporate query information when encoding the post representation, which we introduce below.

Query-aware Attention Encoder (QAtt): In QAtt, for each query token, we construct a token-specific convolutional kernel to inject the query information. Unlike methods that apply attention mechanisms after the sentence representations are generated (Bahdanau et al., 2014; Seo et al., 2016), our approach aims to model the representation learning process jointly with attention mechanism. Formally, for each query token $t_q$, the QAtt kernel $W_{QAtt}^{t_q}$ is composed as follows:

$$W_{QAtt}^{t_q} = U \otimes Q_{t_q}$$ (1)

where $U \in \mathbb{R}^{F \times k \times d}$ is trainable parameter, $Q_{t_q}$ is the embedding of token $t_q$ with size $\mathbb{R}^d$. The element-wise product $\otimes$ is applied between the token embedding $Q_{t_q}$ and the last dimension of kernel weight $U$. Intuitively, when the QAtt tokenspecific kernel is applied, it moves through the post embeddings $P$ as a sliding window and automatically learns soft-matchings to each query token to generate query-aware post representations. On the top of the QAtt kernel, we apply max-pooling and an MLP to produce a set of post representations $\{h_i\}$, with each $h_i$ standing for the representation learned from query token $t_q$.

Position-aware Attention Encoder (PAtt): In the QAtt encoder, the token-specific kernel learns soft-matchings to the query. However, it still ignores position information when encoding the post semantics, which has been shown to be effective on sequence modeling (Gehring et al., 2017). Therefore, we propose an alternative attention encoder that captures the positional information through interactions between query embeddings and post embeddings. Given a query token $t_q$ and
the \( j \)-th position in post \( p \), we compute the interaction scores by taking the cosine similarity between the word embeddings of token \( t_j \) and post tokens \( t_{p:j+k-1} \) from position \( j \) to \( j + k - 1 \):

\[
S_j = [\cos(t_q, t_{p}); \ldots; \cos(t_q, t_{p:j+k-1})]
\]  

(2)

where \( S_j \in \mathbb{R}^{k \times 1} \). Then we populate the similarity vector \( S_j \) to a matrix form as below:

\[
\hat{S}_j = S_j \cdot \mathbb{1}, \hat{S}_j \in \mathbb{R}^{k \times d}
\]  

(3)

where \( \mathbb{1} \in \mathbb{R}^{1 \times d} \) with each element set to 1. Finally, the PAtt convolution kernel for query token \( t_q \) at \( j \)-th position is constructed as below:

\[
W_{\text{PA}t}^{f_{q,j}} = V \otimes \hat{S}_j
\]  

(4)

where \( V \in \mathbb{R}^{F \times k \times d} \) is system trainable parameter. The element-wise product \( \otimes \) is applied between the attention weights \( S_j \) and the last two dimensions of kernel weight \( V \) (see Figure 2). This operation can be thought as adding a soft attention term (with value range in \([-1, 1]\)) to regularize the learning of \( F \) convolutional filters. Same as QAtt, the PAtt encoder with max-pooling and an MLP generates a set of post representations \( \{h_i\} \), with each \( h_i \) standing for the representation learned from query token \( t_q \).

It's worth noting that both the QAtt and PAtt encoder have no extra parameters over a general sentence encoder. However, incorporating the query-aware and position-aware information enables more effective representation learning, as our experiments show later. The QAtt and PAtt encoder can also be used as plug-in modules in standard convolutional architectures to enhance the sequence learning ability.

### 2.2 Aggregation Layer

After the representation layer, a set of vectors \( \{g_q, g_p, \{h_i\}\} \) is obtained. Because our model yields different number of \( h_i \) regarding queries of different lengths, a further aggregation step is needed to output a global feature \( v \). For simplicity, we directly average all vectors \( v = \frac{1}{N_q} \sum h_i \) as the aggregated feature, where \( N_q \) is the length of the query.

### 2.3 Training

To obtain the final score, the feature vectors \( g_q, g_p \) and \( v \) are concatenated and fed into an MLP with ReLU activate function for dimension reduction and obtain \( o \), followed by batch normalization and fully-connected layer and softmax to output the final prediction. The model is trained end-to-end with Stochastic Gradient Decent optimizer, and negative log-likelihood loss function is used.

### 3 Experiment

#### Experimental Setup

Our models are evaluated on four tweets test collections from the TREC 2011–2014 Microblog (MB) Tracks (Ounis et al., 2011; Soboroff et al., 2012; Lin and Efron, 2013; Lin et al., 2014). Each dataset contains around 50 queries and the more detailed statistics are shown in Table 1. Following Rao et al. (2018), we evaluate our models in a reranking task, where the inputs are up to the top 1000 tweets retrieved from the classical query likelihood (QL) language model (Ponte and Croft, 1998). We run four-fold cross-validation test split by year (i.e., train on three year’s data, test on one year’s data), and we randomly sample 10 queries from each year in the training sets (in total 30 queries) as our validation set. The mean average precision (MAP) and precision at top 30 (P30) are adopted as our evaluation metrics. We also conducted Fisher’s two-sided, paired randomization test (Smucker et al., 2007) to test for statistical significance at \( p < 0.05 \). We randomly tried ten different seeds with the same hyperparameters and obtain an average score over each query-post pair for final ranking, to eliminate the effects of random parameter initialization (Crane, 2018). Our code is released for further reproduction. The best model hyper-parameters are shown in Table 4 in Appendix section.

#### Baselines

QL is a competitive language modeling baseline. RM3 (Lavrenko and Croft, 2001) is an interpolation model combining the QL score with a relevance model using pseudo-relevance feedback. MP-HCNN (Rao et al., 2018) is the first neural model that captures the characteristics of social media domain. Their method improves current neural IR methods, e.g., K-NRM (Xiong et al., 2017), DUET (Mitra et al., 2017), by a signifi-

| Year | 2011 | 2012 | 2013 | 2014 |
|------|------|------|------|------|
| # queries | 49 | 60 | 60 | 55 |
| # tweets | 39,780 | 49,879 | 46,192 | 41,579 |
| # relevant | 1,940 | 4,298 | 3,405 | 6,812 |
| % relevant | 4.87 | 8.62 | 7.37 | 16.38 |

Table 1: Statistics of TREC MB 2011–2014 datasets.
Table 2: Results of non-neural and neural models on the TREC Microblog Tracks datasets. Results from 5 - 8 are adopted from Rao et al. (2018). Models denoted with (+URL) represents utilizing the URL information. Models denoted with +QL are interpolated with QL baseline. Bi-CNN denotes general sentence encoder architecture. Both superscripts and subscripts indicate the row indexes for which a metric difference is statistically significant at $p < 0.05$.

![Image](https://via.placeholder.com/150)

Figure 3: t-NSE visualization on query id 158 with the hidden states from BiCNN, QAtt and PAtt respectively. Grey dot means irrelevant posts and red dot means relevant posts.

In the view of representation learning, PAtt model produces better hidden states in most of the case compared with QAtt and BiCNN model. We project the hidden states $o$ into low-dimension vector with t-SNE (Laurens van der and Geoffrey, 2008) for visualization. Figure 3 is an example of query id 158 hush puppies meal. We can observe that with BiCNN model, the relevant posts are scattered. With QAtt, the relevant posts group closer, though they are still mixed with irrelevant posts. Under PAtt setting, most of the relevant posts are concentrated and separate from most of the irrelevant posts.

Another interesting question is that, when does neural model fail, compared against QL baseline. Figure 4 shows the per-query MAP differences between PAtt model and QL baseline on TREC 2013. For query id 125 Oscars snub Affleck, PAtt model loses 0.50 in MAP and 0.11 in P30. We sample top 30 posts ranked by PAtt model for case study. There are 18 irrelevant posts in top 30. From Table 3 we can observe that the neural models indeed capture the match patterns mostly on Oscars and Affleck (18 exact match on Oscars and 13 exact match on Oscars, Affleck). However this
Table 3: Match patterns for query Oscars snub Affleck

| Match                     | Count |
|---------------------------|-------|
| Oscars                    | 18    |
| snub                      | 5     |
| Affleck                   | 13    |
| Oscars, snub              | 5     |
| snub, Affleck             | 2     |
| Oscars, Affleck           | 13    |
| Oscars, snub, Affleck     | 2     |
| **Total irrelevant posts**| **18**|

query semantically emphasizes the snub. Furthermore, after observing relevant posts, Oscars information is often expressed implicitly. For example argo wins retributions for the snub of ben affleck. However, QL baseline can give more weights on snub because of the inverse-document-frequency feature.

In terms of training and inference speed, under the same setting, we measure the average training time and inference time per query-post pair with GPU setting. Our PAtt-ave model only has 2–4 times on training and inference time, which is about \( \frac{1}{4} \) compared to MP-HCNN.

5 Conclusion

In this work, we propose two novel attention-based convolutional encoders to incorporate query-aware and position-aware information in learning document representations, without introducing any new parameter over a standard convolutional operation. The approaches are kept simple but demonstrate competitive effectiveness and 4× speedup in model training and inference against state-of-the-art models.

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A Supplemental Material

| Param        | Value | Param             | Value |
|--------------|-------|-------------------|-------|
| Embedding size | 300   | $k$               | 0.05  |
| Hidden size  | 200   | Final hidden size | 100   |
| Kernel number| 250   | Dropout ratio     | 0.5   |
| kernel size  | 2     | learning rate     | 0.03  |

Table 4: Hyper-Parameters for our models. GloVe (Pennington et al., 2014) Embedding is used and fine-tuned during training. Unknown word is initialized from uniform distribution $[-k, k]$. 