Co-PACRR:
A Context-Aware Neural IR Model for Ad-hoc Retrieval

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1 INTRODUCTION
State-of-the-art neural models for ad-hoc information retrieval aim to model the interactions between a query and a document to produce a relevance score, which are analogous to traditional interaction signals such as BM25 scores. Guo et al. [7] pointed out that a neural IR model should capture query-document interactions in terms of relevance matching signals rather than capturing semantic matching signals as commonly used in natural language processing (NLP). Relevance matching focuses on the pertinence of local parts of the document with respect to the query (e.g., via n-gram matches), whereas semantic matching captures the overall semantic similarity between the query and the entire document. Accordingly, relevance matching over unigrams has been successfully modeled using histograms in the DRMM model [7], using a convolutional layer in DUET’s local model [15], and using a pool of kernels in the more recent K-NRM model [23]. In addition, position-aware relevance matching signals are further captured in PACRR [10] with the goal of encoding matching signals beyond unigrams, such as n-gram matches and “soft” n-gram matches, in which the order of some terms is modified.

Existing models have achieved strong results by focusing on modeling relevance matching signals. However, we argue that the context of such signals are also important but has yet to be fully accounted for in these models. Intuitively, a matching signal contributes to the final relevance score within the context of its local text window and the context of all matching signals from the whole document. Given a matching signal, a text window that embeds the signal is referred to as its local context, whereas all matching signals from the same document are referred to as the signal’s global context. Inspired by past research within the IR community, we first highlight three particular shortcomings that can be addressed by incorporating context. Thereafter, we introduce novel neural components to address the shortcomings within PACRR [10], a state-of-the-art neural IR model. This ultimately leads to Co-PACRR (context-aware PACRR), a novel model as summarized in Figure 1.

To start with, when disregarding the local context, the matching signals extracted between terms from a query and a document may suffer from ambiguity. For example, in the query “Jaguar SUV price,” the term “Jaguar” refers to a car brand, but “Jaguar” also happens to be the name of a species of animal. Such ambiguity can mislead a model to extract false positive matching signals. In the above example, an occurrence of the term “Jaguar” referring to the animal should not contribute much to the document’s relevance score.

Beyond this, accounting for the global document context may be important as well. Some such signals are desirable, while others need to be disregarded. In particular, we conjecture that the location of the matches is important to better account for the level of reading effort needed to reach the relevant information. For example, consider two pseudo-documents that are both concatenations...
of one relevant and one non-relevant document, but in a different order. Although the same relevant information is present, extra effort is required when reading the pseudo-document where the non-relevant document appears first.

Not all aspects of the document context, however, are beneficial. In particular, we argue that the order in which the document matches different query terms may vary, as there can be many elds including DRMM, K-NRM, the local model in DUET, MatchPyramid, and it is also unnecessary because positional information is already accounted for in an earlier layer.

To close these gaps, we introduce neural components to cater to both the local and the global context. Intuitively, to avoid extracting false positive matching signals due to ambiguity, matching signals are double-checked based on their local context and penalized if there is a mismatch between the senses of words between the document and the query. To consider the global context of matching signals, the signals’ strengths at different document positions are considered. To disregard the absolute positions of terms in the query, the sequential dependency over query terms is decoupled before the aggregating combination layer. While these ideas apply more generally, we incorporate them into the PACRR architecture to develop specific neural components, which leads to the Co-PACRR model that contains the following new components:

- A disambiguation building block to address the challenge of ambiguity by co-considering salient matching signals together with the local text window in which they occurred.
- A cascade k-max pooling approach in place of regular k-max pooling layers, enabling the model to benefit from information about the location of matches. These locations are jointly modeled together with the matching signals. This is inspired by the cascade model [4], which is based on the idea that relevance gains are inluenced by the amount of relevant information that has already been observed.
- A shu ing combination layer to regularize the model so as to disregard the absolute positions of terms within the query. Removing query-dependent context before combination improves the generalization ability of the model.

Contributions. We incorporate the aforementioned building blocks into the established PACRR model, leading to the novel Co-PACRR model, jointly modeling matching signals with their local and global context. Through a comparison with multiple state-of-the-art models including DRMM, K-NRM, the local model in DUET, MatchPyramid, and the PACRR model on six years of Trec Web Track benchmarks, we demonstrate the superior performance of Co-PACRR. Remarkably, when re-ranking the search results from a naive initial ranker, namely a query-likelihood ranking model, the re-ranked runs are ranked within the top-3 on at least five years based on
ERR@20. In addition, we also investigate the individual and joint effects of the proposed components to better understand the proposed model in an ablation analysis.

Organization. The rest of this paper unfolds as follows. We discuss related work in Section 2 and put our work in context. Section 3 recaps the basic neural-IR model PACRR, and thereafter Section 4 describes the proposed building components in detail. The setup, results, and analyses of our extensive experimental evaluation can be found in Section 5 and Section 6, before concluding in Section 7.

2 RELATED WORK

In ad-hoc retrieval, a system aims at creating a ranking of documents according to their relevance relative to a given query. The recent promises of deep learning methods as potential drivers for further advances in retrieval quality have attracted significant attention. Unlike learning-to-rank methods, where models are learned on top of a list of handcrafted features [13], a neural IR model aims at modeling the interactions between a query and a document directly based on their free text. Actually, the interactions being learned in a neural IR model correspond to one of the feature groups employed in learning-to-rank methods. They involve both a query and a document, as do BM25 scores. The proposed Co-PACRR belongs to this class of neural IR models and is hence compared with other neural IR models in Section 5.

As described in Section 1, neural IR approaches can be categorized as semantic matching and relevance matching models. The former follows the embedding approach adopted in many natural language processing tasks, aiming at computing the meaning of two pieces of text by mapping both into a low-dimensional representation space. Therefore, models developed for natural language processing tasks can also be used as retrieval models by assigning a similarity score to individual query-document pairs. For example, ARC-I and ARC-II [19] are two such models developed for the tasks of sentence completion, identifying the response to a microblog post, and performing paraphrase detection. In addition, Huang et al. [9] proposed Deep Structured Semantic Models (DSSM), which learn low-dimensional representations of a query and a document in a semantic space before evaluating the document according to its cosine similarity relative to the query. Similar approaches such as C-DSSM [20] further employed alternative means to learn dense representations of the documents.

In comparison, Guo et al. [7] argued that the matching required in information retrieval is different from the matching used in NLP tasks, and that relevance matching is better suited for retrieval tasks. Relevance matching compares two text sequences jointly, namely, a document and a query, by directly modeling their interactions. In relevance matching, local signals such as unigram matches are important. Meanwhile, semantic matching seeks to model the semantic meaning of the two text sequences independently, and the matching is considered in a semantic space. Accordingly, the Deep Relevance Matching Model (DRMM) [7] was proposed to model unigram relevance matching by encoding a query-document pair in terms of a histogram of similarities between terms from the query and the document. More recently, K-NRM [23] relied on a pool of kernels in place of the histogram, capturing the unigram relevance matching in a more smooth manner, addressing the issues of bin boundaries in generating histograms. In addition to the unigram signals, position-aware neural IR models have been proposed, such as MatchPyramid [8, 18], which is motivated by works from computer vision [21], and PACRR [10], which follows the ideas of term dependency [12, 14] and query term proximity [22] modeling from ad-hoc retrieval. Both encode matching signals beyond a single term with convolutional neural networks (CNNs). Beyond that, Mitra et al. [15] proposed DUT, a hybrid deep ranking model combining both kinds of matching, with two independent building blocks, namely, a local model for relevance matching and a distributed model for semantic matching. The proposed Co-PACRR model belongs to the class of relevance matching models, and attempts to further incorporate the context of matching signals.

3 BACKGROUND

In this section, we summarize the PACRR model [10], which we build upon by proposing novel components. When describing PACRR, we follow the notation from [10]. In general, PACRR takes a similarity matrix between a query and a document as input, and the output of the model is a scalar, namely, rel(d, q), indicating the relevance of document d to query q. PACRR attempts to model query-document interactions based on these similarity matrices. At training time, the relevance scores for one relevant and one non-relevant document, denoted as d+ and d-, respectively, are fed into a max-margin loss as in Eq. 1.

$$\mathcal{L}(q, d^+, d^-; \Theta) = \max(0, 1 - \text{rel}(q, d^+) + \text{rel}(q, d^-))$$  \hspace{1cm} (1)

In the following, PACRR is introduced component-by-component.

1. **Input:** the similarity matrix $\text{sim}_{q \times d}$, where both $l_q$ and $l_d$ are hyper-parameters defining the dimensions of the input similarity matrices. $l_q$ is set to the longest query length, and $l_d$ is tuned on the validation dataset. Given the settings for both $l_q$ and $l_d$, a similarity matrix between a query and a document is truncated or zero-padded accordingly;

2. **CNN kernels and max-pooling layers:** multiple CNN kernels with $l_f$ filters capture the query-document interactions, like n-gram matching, corresponding to different text window lengths, namely 2, 3, …, $l_q$. The hyper-parameters $l_q$ and $l_f$ govern the longest text window under consideration and the number of filters, respectively. These CNN kernels are followed by a max-pooling layer on the filter dimension to retain the strongest matching signal for each kernel, leading to $l_f$ matrices, denoted as $C_{l_q \times l_f \times 1}$,

3. **k-max pooling:** subsequently, the matching signals in $C_{1}, \cdots, C_{l_f}$ from these kernels are further pooled with k-max pooling layers, keeping the top-$n_f$ strongest signals for each query term and CNN kernel pair, leading to $P_{l_q \times n_f}$,

which are further concatenated for individual query terms, resulting in a matrix $P_{l_q \times (l_f \cdot n_f)}$;
(4) combination of the signals from different query terms: the signals in $P_{q} \times (x_{\text{i}}, n_{s})$, together with the inverse document frequency for individual query terms, are fed into an LSTM layer to generate the ultimate relevance score $\text{rel}(d, q)$.

**Tweaks.** Before moving on, we make two changes in order to ease the development of the proposed model. For simplicity, this revised model is denoted as PACRR in the following sections. First, according to our pilot experiments, the performance of the model does not change when replacing the LSTM layer with a stack of dense layers, which have been demonstrated to be able to simulate an arbitrary function [6]. Such dense layers can easily be trained in parallel, leading to faster training [6], whereas back-propagation through an LSTM layer is much more expensive due to its sequential nature. From Section 5, it can be seen that efficiency is important for this study due to the number of model variants to be trained and the limited availability of hardware at our disposal. Finally, another tweak is to switch the max-margin loss to a cross-entropy loss as in Eq. 2, following [5], where it has been demonstrated that another tweak is to switch the max-margin loss to a cross-entropy loss for this study due to the number of model variants to be trained.

**5 EVALUATION**

In this section, we empirically compare the proposed Co-PACRR with multiple state-of-the-art neural IR models using manual relevance judgments from six years of the Trec Web Track. Following [10], the comparison is based on three benchmarks, namely, re-ranking search results from a simple initial ranker, denoted as RERANKSIMPLE, re-ranking all runs from the Trec Web Track, denoted as RERANKALL, and further examining the classification accuracy in determining the order of document pairs, denoted as making the matrices $P_{q} \times (x_{\text{i}}, n_{s})$ become $P_{q} \times (2l_{d}, n_{s})$. This enables the aggregating layers, namely, a feed-forward network, to take any ambiguity into account when determining the ultimate score. For example, in the “jaguar” example from Section 1, if the context of “jaguar” consists of terms like “big cat” and “habitat”, the context will have a low similarity with a query context containing terms such as “SUV” and “price”, informing the model that such occurrences of “jaguar” actually refer to a different concept than the one in the query.

Cascade k-max pooling: encode the location of the relevance information. As discussed in Section 1, to put individual relevance signals into the context of the whole document, both the strength and the positions of match signals matter. We propose to encode such global context by conducting k-max pooling at multiple positions in a document, instead of pooling only on the entire document. For example, one could conduct multiple k-max pooling operations at 25%, 50%, 75%, and 100% of a document, ending up with $P_{q} \times (4l_{d}, n_{s})$. This corresponds to when a user sifts through a document and evaluates the gained useful information after reading the first, second, third, and fourth quarters of the document. The list of offsets at which cascade k-max pooling is conducted is governed by an array $c_{pos}$, e.g., $c_{pos} = [25\%, 50\%, 75\%, 100\%]$ in the above example. We set the length of this array using a hyper-parameter $n_{c}$ and perform pooling at equal intervals. For example, $n_{c} = 4$ in the previous example, and $n_{c} = 2$ results in $c_{pos} = [50\%, 100\%]$.

Shuffling combination: regularizing the query-dependent information. As mentioned in Section 1, the combination of relevance signals among different query terms is supposed to be query-independent to avoid learning a dependency on query term positions. In light of this, we propose to randomly shuffle rows in $P_{q} \times (l_{d}, n_{s})$ before aggregating them. Note that each row contains signals for multiple n-gram lengths; shuffling the rows does not prevent the model from recognizing n-grams. We argue that, taking advantage of this independence, the shuffling regularizes the query-dependent information and effectively improves the generalization ability of the model by making the computation of the relevance scores depend solely on the importance of a query term ($idf$) and the relevance signals aggregated on it. This should be particularly helpful when training on short queries ($(|q| < l_{q})$, where padded zeros are normally in the tail of $sim_{q \times l_{d}}$ [11]. Without shuffling, a model might remember that the relevance signals at the tail of a query (i.e., the several final rows in $sim_{q \times l_{d}}$) contribute very little and are mostly zero, leading to it mistakenly degrade the contribution from terms at tail positions when inferring relevance scores for longer queries.

We employ pre-trained word2vec embeddings due to their widespread availability. In the future, one may desire to replace this with specialized embeddings such as dual embeddings [16] or relevance-based embeddings [24].

Intuitively, to address the challenge of false positive matches stemming from ambiguity, the extracted matching signals on position $i$ are adjusted in the model according to the corresponding similarity between its context and the query. In particular, when combining the top-$n_{s}$ signals from individual query terms, the corresponding similarities for these top-$n_{s}$ signals are also concatenated,
We rely on the 2009–2014 Trec Web Track when enough relevant documents have been observed earlier \cite{2}. Training. Models are trained and tested in a round-robin manner, Track \cite{3}, which is computed with the script from \texttt{qrels}. Six years (2009–14) of query-likelihood baselines (\texttt{QL}) provided by the Lemur project’s online Indri services\footnote{\url{http://boston.lti.cs.cmu.edu/Services/clueweb09_batch/}}\footnote{\url{http://trec.nist.gov/data/web/12/gdeval.pl}}\footnote{\url{http://boston.lti.cs.cmu.edu/Services/clueweb12_batch/}}\footnote{\url{http://trec.nist.gov/tracks.html}} are employed to indicate the significant difference between the two vectors with five scores for individual years of the Web Track, with 50 queries per year. Practically, the available judgments are considered in accordance with the individual years as training, validation, and test data. Specifically, the available judgments are considered in accordance with the individual years of the Web Track, with 50 queries per year. Proceeding in a round-robin manner, we report test results on one year by using combinations of every four years and the two remaining years for training and validation. Model parameters and the number of training iterations are chosen by maximizing the ERR@20 on the validation set for each training/validation combination separately. Thereafter, the selected model is used to make predictions on the test data. Hence, for each test year, there are five different predictions each from a training and validation combination. Akin to the procedure in cross-validation, we report the average of these five test results as the ultimate results for individual test years, and conduct a Student’s t-test over them to determine whether there is a statistically significant difference between different methods. For example, a significant difference between two evaluated methods on a particular test year is claimed if there exists a significant difference between the two vectors with five scores for individual methods. This was motivated by an observation that the closeness of the subsets for training and for validation can adversely influence the model selection. We argue that this approach minimizes the effects of the choice of training and validation data. Upper/lower-case characters are employed to indicate the significant difference under two-tailed Student’s t-tests at 95\% or 90\% confidence levels relative to the corresponding approach, denoted as P/p for PACRR, M/m for MatchPyramid, D/d for DRMM, L/l for DUETL and K/k for K-NRM.

\textbf{Variants of Co-PACRR.} With the proposed components, namely, the cascade k-max pooling (C), the disambiguation component (D), and the shuffling combination (S), there are seven model variants in total by including or excluding one of the three building blocks. They are denoted as X(XX)-PACRR, where the X represents the building blocks that are turned on. For example, with cascade k-max pooling and shuffling combination turned on, the model is denoted as CS-PACRR. Meanwhile, with all three components, namely CDS-PACRR, the model is simply referred to as Co-PACRR. In evaluations based on the \texttt{RerankSimple} and \texttt{RerankALL} benchmarks, only the results for Co-PACRR are reported. Meanwhile, the results for the other six variants are reported in Section 6.1 on the \texttt{PairAccuracy} benchmark for an ablation test.

\textbf{Choice of hyper-parameters.} In this work, we focus on evaluating the effects of the proposed building blocks and their interactions, without exhaustively fine-tuning hyper-parameters due to limited computing resources. For the disambiguation building block, we fix the size of the context window as \( w_c = 4 \) on both sides, leading to a context vector computed over 9 terms, namely, 4+4+1. For the cascade component, we conduct k-max pooling with \( \epsilon = [25\%, 50\%, 75\%, 100\%] \), namely, \( n_c = 4 \). For the combination phase, we use two fully connected layers of size 16. Apart from the two modifications mentioned in Section 3, we further fix the model choices for PACRR following the original configurations \cite{10}. In particular, the PACRR-firstk variant is employed, fixing the unified similarity matrix dimensions \( l_d = 800 \) and \( l_q = 16 \), the k-max pooling size \( n_s = 3 \), the maximum n-gram size \( l_y = 3 \), and the number of filters used in convolutional layers is \( n_f = 32 \). Beyond that, we fix the batch size to 16 and we train individual models to at most 150 iterations. Note that most of the aforementioned hyper-parameters can be tuned given sufficient time and hardware, and the chosen parameters follow those in Hui et al. \cite{10} or are based on preliminary experiments for a better focus on the proposed models. In Section 6.2 we consider the impact of the disambiguation parameter \( w_c \) and the cascade parameter \( n_c \).

Due to the availability of training data, K-NRM is trained with a frozen word embedding layer, and with an extra fully connected middle layer including 30 neurons to partially compensate for lost strength due to the frozen word embeddings. This is slightly different from the model architecture described in Xiong et al. \cite{23}. This setting also serves for the purpose of allowing fair model comparisons, given that all the compared models could be co-trained with the word embeddings, resulting in a better model capacity at the costs of prolonged training times and a need for much more training data \cite{10}. Note that with the frozen embedding layer, the evaluation can focus on the model strength that comes from different model architectures, demonstrating the capacity of relatively small models in performing ad-hoc retrieval. All the models are trained with a cross-entropy loss as summarized in Eq. 2, given that different loss functions can also influence the results.

\begin{eqnarray*}
\end{eqnarray*}

\begin{eqnarray*}
\end{eqnarray*}
Table 1: ERR@20 on Trec Web Track 2009–14 when re-ranking search results from QL. The relative improvements (%) relative to QL and ranks among all runs within the respective years according to ERR@20 are also reported.

<table>
<thead>
<tr>
<th>Year</th>
<th>Co-PACRR</th>
<th>PACRR</th>
<th>MatchPyramid</th>
<th>DRMM</th>
<th>DUETL</th>
<th>K-NRM</th>
</tr>
</thead>
<tbody>
<tr>
<td>wt09</td>
<td>0.096 (D)</td>
<td>0.102 (D)</td>
<td>0.103</td>
<td>0.103</td>
<td>0.106 (P)</td>
<td>-9%</td>
</tr>
<tr>
<td>wt10</td>
<td>0.169 (P</td>
<td>D</td>
<td>D</td>
<td>L</td>
<td>T</td>
<td>L</td>
</tr>
<tr>
<td>wt11</td>
<td>0.161 (P</td>
<td>D</td>
<td>D</td>
<td>L</td>
<td>T</td>
<td>L</td>
</tr>
<tr>
<td>wt12</td>
<td>0.183 (P</td>
<td>D</td>
<td>D</td>
<td>L</td>
<td>T</td>
<td>L</td>
</tr>
<tr>
<td>wt13</td>
<td>0.232 (P</td>
<td>D</td>
<td>D</td>
<td>L</td>
<td>T</td>
<td>L</td>
</tr>
</tbody>
</table>

5.2 Results for Co-PACRR

**RerankSimple.** We first examine how well the proposed model performs when re-ranking search results from a simple initial ranker, namely, the query-likelihood (QL) model, to put our results in context as in Guo et al. [7]. The ultimate quality of the re-ranked search results depends on both the strength of the initial ranker and the quality of the re-ranker. The query-likelihood model, as one of the most widely used retrieval models, is used due to its efficiency and practical availability, given that it is included in most retrieval toolkits like Terrier [17]. The results are summarized in Table 1. The ERR@20 of the re-ranked runs is reported, together with the improvements relative to the original QL. The ranks of the re-ranked runs are also reported when sorting the re-ranked search results together with other competing runs from the same year according to ERR@20.

It can be seen that, by simply re-ranking the search results from the query-likelihood method, Co-PACRR can already achieve the top-3 best results in 2010–14. Whereas for 2009, very limited improvements are observed. Combined with Table 3, though variants of Co-PACRR can improve different runs in Trec around 90%, the relative improvements w.r.t. QL are less than 10%, which is worse than the improvements from PACRR and MatchPyramid on 2009. This illustrates that the re-ranking model cannot work independently, as its performance highly depends on the initial ranker. Actually, in Table 1 all compared models experience difficulties in improving QL on 2009, where DRMM even receives a worse performance than the improvements from PACRR and MatchPyramid on 2009. Relative improvements w.r.t. QL are less than 10%, which is worse than assigning a degree of relevance as Rel and HRel, which makes it difficult to compare navigational documents with other kinds of documents.

**PairAccuracy.** Ideally, a re-ranking model should make correct decisions when ranking all kinds of documents. Therefore, we further rely on a pairwise ranking task to compare different models in this regard. Compared with the other two benchmarks, we argue that PairAccuracy can lead to more comprehensive and more robust comparisons, as a result of its inclusion of all the labeled ground-truth data and its removal of the effects of initial rankers.

In particular, given a query and a set of documents, different models assign a score to each document according to their inferred relevance relative to the given query. Thereafter, all pairs of documents are examined and the pairs that are ranked in concordance with the ground-truth judgments from Trec are deemed correct, based on which an aggregated accuracy is reported on all such document pairs in different years. For example, given query q and two documents \( d_1 \) and \( d_2 \), along with their ground-truth judgments \( \text{label}(d_1) \) and \( \text{label}(d_2) \), a re-ranking model provides their relevance scores as \( \text{rel}(q, d_1) \) and \( \text{rel}(q, d_2) \). The re-ranking model is correct when it predicts these two documents to be ranked in the same order as in the ranking from the ground-truth label, e.g., \( \text{rel}(q, d_1) > \text{rel}(q, d_2) \) and \( \text{label}(d_1) > \text{label}(d_2) \). The relevance judgments in the Trec Web Track include up to six relevance levels: junk pages (Junk), non-relevant (NRel), relevant (Rel), highly relevant (HRel), key pages (Key), and navigational pages (Nav). Note that the label Nav actually indicates that a document can satisfy a navigational intent rather than assigning a degree of relevance as Rel and HRel, which makes it difficult to compare navigational documents with other kinds of
Table 2: The percentage of runs that show improvements in terms of ERR@20 when re-ranking all runs from the Trec Web Track 2009–14.

<table>
<thead>
<tr>
<th>Year</th>
<th>Co-PACRR</th>
<th>PACRR</th>
<th>MatchPyramid</th>
<th>DRMM</th>
<th>DUETL</th>
<th>K-NRM</th>
</tr>
</thead>
<tbody>
<tr>
<td>wt09</td>
<td>98% (D[D][L])</td>
<td>93% (D[D][L])</td>
<td>88% (D[D][L])</td>
<td>70% (P[K][M][L])</td>
<td>74% (P[K][M][L])</td>
<td>89% (D[D][L])</td>
</tr>
<tr>
<td>wt10</td>
<td>98% (P[K],D[L][M])</td>
<td>96% (D[L][M])</td>
<td>89% (P[K],L)</td>
<td>91% (P[K],L)</td>
<td>74% (P[K],D[M])</td>
<td>95% (D[L][M])</td>
</tr>
<tr>
<td>wt11</td>
<td>98% (P[K],D[L][M])</td>
<td>95% (K[L][M])</td>
<td>73% (P[K],L)</td>
<td>94% (K[L][M])</td>
<td>72% (P[K],L)</td>
<td>83% (P[L][M])</td>
</tr>
<tr>
<td>wt12</td>
<td>93% (P[K],D[L][M])</td>
<td>86% (K[L][M])</td>
<td>56% (P[K],L)</td>
<td>87% (K[L][M])</td>
<td>43% (P[K],L)</td>
<td>63% (P[D][L])</td>
</tr>
<tr>
<td>wt13</td>
<td>96% (K[L][M])</td>
<td>84% (K[L][M])</td>
<td>61% (P[K],L)</td>
<td>69% (K[L][M])</td>
<td>39% (P[D][M])</td>
<td>43% (P[D][M])</td>
</tr>
<tr>
<td>wt14</td>
<td>96% (K[L][M])</td>
<td>84% (K[L][M])</td>
<td>61% (P[K],L)</td>
<td>69% (K[L][M])</td>
<td>39% (P[D][M])</td>
<td>43% (P[D][M])</td>
</tr>
</tbody>
</table>

Table 3: The average differences of the measure score for individual runs when re-ranking all runs from the Trec Web Track 2009–14 based on ERR@20.

<table>
<thead>
<tr>
<th>Year</th>
<th>Co-PACRR</th>
<th>PACRR</th>
<th>MatchPyramid</th>
<th>DRMM</th>
<th>DUETL</th>
<th>K-NRM</th>
</tr>
</thead>
<tbody>
<tr>
<td>wt09</td>
<td>47% (P[K],D[L][M])</td>
<td>42% (K[D][L][M])</td>
<td>29% (P[D][L])</td>
<td>17% (P[K],M)</td>
<td>16% (P[K],M)</td>
<td>35% (P[D][L])</td>
</tr>
<tr>
<td>wt10</td>
<td>93% (P[K],D[L][M])</td>
<td>76% (D[L][M])</td>
<td>55% (P[K],L)</td>
<td>48% (P[K],L)</td>
<td>27% (P[K],D[M])</td>
<td>38% (P[D][M])</td>
</tr>
<tr>
<td>wt11</td>
<td>39% (P[K],D[L][M])</td>
<td>16% (D[L][M])</td>
<td>22% (P[K],L)</td>
<td>-3% (P[K],L)</td>
<td>-17% (P[K],D[M])</td>
<td>8% (P[D][M])</td>
</tr>
<tr>
<td>wt12</td>
<td>84% (K[L][M])</td>
<td>74% (K[L][M])</td>
<td>28% (P[D],L)</td>
<td>69% (K[L][M])</td>
<td>29% (P[D],L)</td>
<td>44% (P[D],L)</td>
</tr>
<tr>
<td>wt13</td>
<td>38% (P[K],D[L][M])</td>
<td>30% (K[L][M])</td>
<td>4% (P[D],L)</td>
<td>22% (K[L][M])</td>
<td>-4% (P[K],D[L])</td>
<td>11% (P[D],L)</td>
</tr>
<tr>
<td>wt14</td>
<td>34% (P[K],D[L][M])</td>
<td>20% (K[L][M])</td>
<td>6% (P[K],L)</td>
<td>10% (P[K],L)</td>
<td>-4% (P[D],M)</td>
<td>-4% (P[D],M)</td>
</tr>
</tbody>
</table>

relevant documents, e.g., a navigational document versus a document labeled as HRel. Thus, documents labeled with Nav are not considered in this task. Moreover, documents labeled as Junk and NRel, and documents labeled as HRel and Key are merged into HRel and HRel, respectively, due to their limited number. After aggregating the labels as described, all pairs of documents with different labels are generated as test pairs. From the “volume” and “# queries” columns in Table 4, we can see that different label pairs actually account for quite different volumes in the ground truth, making their respective degrees of influence different. On the other hand, different label pairs actually also represent different difficulties in making a correct prediction, as the closeness of two documents in terms of their relevance determines the difficulty of the predictions. Intuitively, it is easier to distinguish between HRel and NRel documents than to compare a HRel document with a Rel document. Actually, human assessors tend to also disagree more when dealing with document pairs that are very close with each other in terms of their relevance [1]. It can also be seen that these three label pairs being considered account for 95% of all document pairs from Table 4.

From the upper part of Table 4, for the label pair HRel-NRel, Co-PACRR achieves the highest accuracy in terms of the absolute number, and significantly outperforms all baselines on three years. We have similar observations for Rel-NRel, where, however, Co-PACRR performs worse than PACRR in 2013. As for the label pair HRel-Rel, however, Co-PACRR performs very close to the other models, and on 2011, it performs worse than DUETL. Therefore, we can conclude that Co-PACRR outperforms the other baseline results when comparing documents that are far away in terms of relevance, while performing similarly in dealing with harder pairs. In terms of the absolute accuracy, on average, Co-PACRR yields correct predictions on 78.7%, 73.6%, and 58.7% of document pairs for the label pairs HRel–NRel, Rel–NRel, and HRel–Rel, respectively, where the decreasing accuracy confirms the different difficulties in making predictions for different kinds of pairs.

Figure 2: The accuracy on document pairs when using different number of cascade positions \( n_c \) for the cascade \( k \)-max pooling layer.

Figure 3: The accuracy on document pairs when varying the size of the context window \( w_c \) for the disambiguation component.
Table 4: Comparisons among tested methods in terms of accuracy in ranking document pairs with different label pairs. The columns “volume” and "# queries" record the occurrences of each label combination out of the total pairs, and the number of queries that include a particular label combination among all six years, respectively.

<table>
<thead>
<tr>
<th>Label Pair</th>
<th>volume (%)</th>
<th># queries</th>
<th>Year</th>
<th>Co-PACRR</th>
<th>PACRR</th>
<th>MatchPyramid</th>
<th>DRMM</th>
<th>DUETL</th>
<th>K-NRM</th>
</tr>
</thead>
<tbody>
<tr>
<td>HRel-NRel 23.1%</td>
<td>262</td>
<td></td>
<td></td>
<td>0.720 (P)</td>
<td>0.695 (D)</td>
<td>0.654 (P)</td>
<td>0.597 (P)</td>
<td>0.594 (P)</td>
<td>0.689 (D)</td>
</tr>
<tr>
<td>HRel-Rd 8.4%</td>
<td>257</td>
<td></td>
<td></td>
<td>0.811 (K)</td>
<td>0.791 (K)</td>
<td>0.708 (P)</td>
<td>0.710 (P)</td>
<td>0.693 (P)</td>
<td>0.751 (K)</td>
</tr>
<tr>
<td>Rel-NRel 65.5%</td>
<td>290</td>
<td></td>
<td></td>
<td>0.787 (K)</td>
<td>0.770 (K)</td>
<td>0.616 (P)</td>
<td>0.607 (P)</td>
<td>0.621 (P)</td>
<td>0.711 (P)</td>
</tr>
</tbody>
</table>

6 DISCUSSION

6.1 Ablation Analysis

In this section, we attempt to gain further insights about the usefulness of the proposed model components, namely, the cascade k-max pooling (C), the disambiguation (D) and the shuffling combination (S) layer, by drawing comparisons among different model variants. As mentioned, the PairAccuracy benchmark is the most comprehensive due to its inclusion of all document pairs and its removal of the effects of an initial ranker; making the analysis based solely on the proposed neural models. Therefore, our analysis in this section mainly considers PairAccuracy.

**Effects of the individual building blocks.** We first incorporate the proposed components into PACRR one at a time, leading to the C-PACRR, D-PACRR, and S-PACRR model variants, which we use to examine the effects of these building blocks separately. Table 4 demonstrates that the shuffling combination (S-PACRR) alone can boost the performance on three different label pairs, significantly outperforming PACRR on two to three years out of six years for all three label combinations, and performing at least as well as PACRR on the remaining years. As mentioned in Section 1, the shuffling combination performs regularization by preventing the model from learning query-dependent patterns. On the other hand, adding the C-PACRR or D-PACRR component to PACRR actually hurts the performance on 2014 over the Rel-NRel label pair, and only occasionally improves PACRR on other years. Intuitively, both building blocks introduce extra weights into PACRR, increasing the number of nodes for combination by adding the context vectors or by using multiple pooling layers, making the model more prone to overfitting. Such changes might be an issue when only limited training data is available.

**Joint effects of different components.** To resolve the extra complexity introduced by the cascade pooling layers and the disambiguation building blocks, we further combine these two with the shuffling component, leading to CS-PACRR and DS-PACRR. Meanwhile, we also investigate the joint effects between them by examining CD-PACRR. From Table 4, compared with the PACRR model, both CS-PACRR and DS-PACRR achieve better results not only relative to C-PACRR and D-PACRR, but also to S-PACRR. This is especially true for CS-PACRR, which significantly outperforms
PACRR on all years for HRel-NRel pairs, and on five years for Rel-NRel pairs. This demonstrates that both the cascade pooling and the disambiguation components can help only after introducing extra regularization to offset the extra complexity being introduced. As for CD-PACRR, not surprisingly, it performs on a par with C-PACRR and D-PACRR, and worse than the CS-PACRR and DS-PACRR. Finally, we put all components together and end up with the Co-PACRR model discussed in Section 5, which performs better than C-PACRR and D-PACRR, and similar to S-PACRR, but occasionally worse than CS-PACRR on 2012–14. We argue that this is due to the joint usage of the cascade k-max pooling and the disambiguation, making the model much more complex and thereby expensive to train like CD-PACRR, therefore requiring more training data to work well. We note that DS-PACRR performs better than the S-PACRR variant, supporting our argument that the full model’s decreased performance is caused by the added complexity, and not by adding the disambiguation component itself, and this also applies to the cascade k-max pooling layer. In short, we conclude that all three components can lead to improved results. Moreover, we suggest that, when limited training data is available, either CS-PACRR or DS-PACRR could be employed in place of Co-PACRR, since they are less data-hungry compared with Co-PACRR.

6.2 Tuning of Hyper-parameters

Finally, we further investigate the effects of the two hyper-parameters introduced by our proposed components, namely, the number of cascade positions \(n_c\) and the size of the context window \(w_c\), which govern the cascade k-max pooling component and the disambiguation component, respectively. Figures 2 and 3 show the effects of applying different \(n_c\) and \(w_c\) on 2010, where the x-axis represents the configurations of the hyper-parameter, and the y-axis represents the corresponding accuracy on document pairs. In the case of cascade k-max pooling, we uniformly divide [0%, 100%] into \(n_c\) parts, e.g., with \(n_c = 5\) we have \(cpos = [20\%, 40\%, 60\%, 80\%, and 100\%]\). Owing to space constraints, we omit the plots for other years. From Figures 2 and 3, we observe that the model is robust against different choices of \(n_c\) and \(w_c\) within the investigated ranges, and the trend of the accuracy relative to different choices of hyper-parameters is consistent among the three kinds of label pairs. Furthermore, increasing the number of cascade positions slightly increases the accuracy, whereas increasing the context window size past \(w_c = 4\) reduces the accuracy.

7 CONCLUSION

In this work we proposed the novel Co-PACRR neural IR model that incorporates the local and global context of matching signals into the PACRR model through the use of a disambiguation building block, a cascade k-max pooling layer, and a shuffling combination layer. Extensive experiments on TREC Web Track data demonstrated the superior performance of the proposed Co-PACRR model. Notably, the model is trained using TREC data consisting of about 100k training instances, illustrating that models performing ad-hoc retrieval can greatly benefit from architectural improvements as well as an increase in training data. As for future work, one potential direction is the combination of handcrafted learning-to-rank features with the interactions learned by Co-PACRR, where an effective way to learn such features (e.g., PageRank scores) inside the neural model appears non-trivial.

REFERENCES