Multi-Cast Attention Networks

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ABSTRACT

Attention is typically used to select informative sub-phrases that are used for prediction. This paper investigates the novel use of attention as a form of feature augmentation, i.e, *casted attention*. We propose Multi-Cast Attention Networks (MCAN), a new attention mechanism and general model architecture for a potpourri of ranking tasks in the conversational modeling and question answering domains. Our approach performs a series of soft attention operations, each time casting a scalar feature upon the inner word embeddings. The key idea is to provide a real-valued hint (feature) to a subsequent encoder layer and is targeted at improving the representation learning process. There are several advantages to this design, e.g., it allows an arbitrary number of attention mechanisms to be casted, allowing for multiple attention types (e.g., co-attention, intra-attention) and attention variants (e.g., alignment-pooling, max-pooling, mean-pooling) to be executed simultaneously. This not only eliminates the costly need to tune the nature of the co-attention layer, but also provides greater extents of explainability to practitioners. Via extensive experiments on four well-known benchmark datasets, we show that MCAN achieves state-of-the-art performance. On the Ubuntu Dialogue Corpus, MCAN outperforms existing state-of-the-art models by 9%. MCAN also achieves the best performing score to date on the well-studied TrecQA dataset.

KEYWORDS

Deep Learning; Information Retrieval; Question Answering; Conversation Modeling

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1 INTRODUCTION

Modeling textual relevance between document query pairs lives at the heart of information retrieval (IR) research. Intuitively, this enables a wide assortment of real life applications, ranging from standard web search to automated chatbots. The key idea is that these systems learn a scoring function between document-query pairs, providing a ranked list of candidates as an output. A considerable fraction of such IR systems are focused on short textual documents, e.g., answering facts based questions or selecting the best response in the context of a chat-based system. The application of retrieval-based response and question answering (QA) systems is overall versatile, potentially serving as a powerful standalone domain-specific system or a crucial component in larger, general purpose chat systems such as Alexa. This paper presents a universal neural ranking model for such tasks.

Neural networks (or deep learning) have garnered considerable attention for retrieval-based systems [8, 27, 29, 39, 52]. Notably, the dominant state-of-the-art systems for many benchmarks are now neural models, almost completely dispensing with traditional feature engineering techniques altogether. In these systems, convolutional or recurrent networks are empowered with recent techniques such as neural attention [1, 25, 39], achieving very competitive results on standard benchmarks. The key idea of attention is to extract only the most relevant information that is useful for prediction. In the context of textual data, attention learns to weight words and sub-phrases within documents based on how important they are. In the same vein, co-attention mechanisms [5, 28, 50, 54] are a form of attention mechanisms that learn joint pairwise attentions, with respect to both document and query.

Attention is traditionally used and commonly imagined as a feature extractor. It's behavior can be thought of as a dynamic form of pooling as it learns to select and compose different words to form the final document representation. This paper re-imagines attention as a form of feature augmentation method. Attention is casted with the purpose of not compositional learning or pooling but to provide hints for subsequent layers. To the best of our knowledge, this is a new way to exploit attention in neural ranking models. We begin by describing not only its advantages but also how it handles the weaknesses of existing models designed today.

Typically, attention is applied once to a sentence [25, 39]. A final representation is learned, and then passed to prediction layers. In the context of handling sequence pairs, co-attention is applied and a final representation for each sentence is learned [5, 28, 54]. An obvious drawback which applies to many existing models is that they are generally restricted to one attention variant. In the case where one or more attention calls are used (e.g., co-attention and intra-attention, etc.), concatenation is generally used to fuse representations [20, 28]. Unfortunately, this incurs cost in subsequent layers by doubling the representation size per call.

The rationale for desiring more than one attention call is intuitive. In [20, 28], Co-Attention and Intra-Attention are both used because each provides a different view of the document pair, learning high quality representations that could be used for prediction. Hence, this can significantly improve performance. Moreover, Co-Attention also comes in different flavors and can either be used with extractive

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max-mean pooling [5, 54] or alignment-based pooling [3, 20, 28]. Each co-attention type produces different document representations. In max-pooling, signals are extracted based on a word's *largest* contribution to the other text sequence. Mean-pooling calculates its contribution to the overall sentence. Alignment-pooling is another flavor of co-attention, which aligns semantically similar sub-phrases together. As such, different pooling operators provide a different view of sentence pairs. This is often tuned as a hyperparameter, i.e., performing architectural engineering to find the best variation that works best on each problem domain and dataset.

Our approach is targeted at serving two important purposes - (1) It removes the need for architectural engineering of this component by enabling attention to be called for an arbitrary k times with hardly any consequence and (2) concurrently it improves performance by modeling multiple views via multiple attention calls. As such, our method is in similar spirit to multi-headed attention, albeit efficient. To this end, we introduce *Multi-Cast Attention Networks* (MCAN), a new deep learning architecture for a potpourri of tasks in the question answering and conversation modeling domains. In our approach, attention is **casted**, in contrast to the most other works that use it as a pooling operation. We cast co-attention multiple times, each time returning a compressed **scalar** feature that is re-attached to the original word representations. The key intuition is that compression enables scalable casting of multiple attention calls, aiming to provide subsequent layers with a *hint* of not only global knowledge but also cross sentence knowledge. Intuitively, when passing these enhanced embeddings into a compositional encoder (such as a long short-term memory encoder), the LSTM can then benefit from this hint and alter its representation learning process accordingly.

1.1 Our Contributions

In summary, the prime contributions of this work are:

- For the first time, we propose a new paradigm of utilizing attentions not as a pooling operator but as a form of feature augmentation. We propose an overall architecture, Multi-Cast Attention Networks (MCAN) for generic sequence pair modeling.
- We evaluate our proposed model on four benchmark tasks, i.e., Dialogue Reply Prediction (Ubuntu dialogue corpus), Factoid Question Answering (TrecQA), Community Question Answering (QatarLiving forums from SemEval 2016) and Tweet Reply Prediction (Customer support). On Ubuntu dialogue corpus, MCAN outperforms the existing state-of-the-art models by 9%. MCAN also achieves the best performing score of 0.838 MAP and 0.904 MRR on the well-studied TrecQA dataset.
- We provide a comprehensive and in-depth analysis of the inner workings of our proposed MCAN model. We show that the casted attention features are interpretable and are capable of learning (1) a neural adaptation of word overlap and (2) a differentiation of evidence and anti-evidence words/patterns.

2 MULTI-CAST ATTENTION NETWORKS

In this section, we describe our proposed MCAN model. The inputs to our model are two text sequences which we denote as query q and document d. In our problem, query-document can be generalizable to different problem domains such as question-answering or message-response prediction. Figure 1 illustrates the overall model architecture for question-answer retrieval.

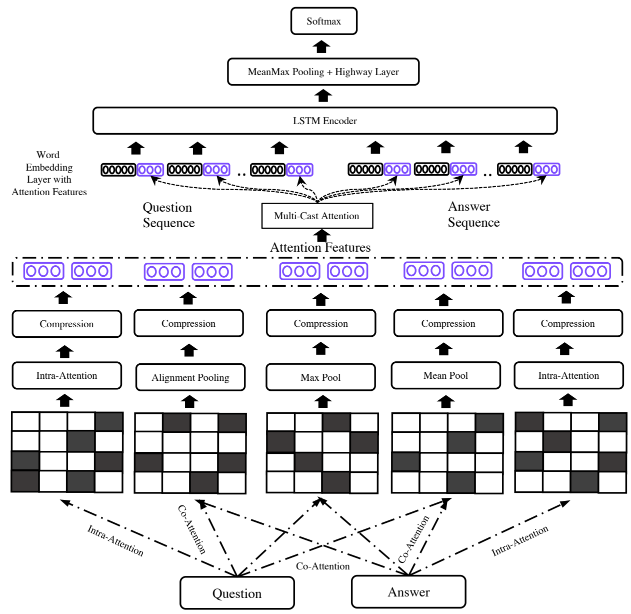


Figure 1: Illustration of our proposed Multi-Cast Attention Networks (*Best viewed in color*). MCAN is a wide multi-headed attention architecture that utilizes compression functions and attention as features. Example is given for question-answer retrieval. Input Encoding layer is ommitted for clarity.

2.1 Input Encoder

The document and query inputs are passed in as one-hot encoded vectors. A word embedding layer parameterized by $W_e \in \mathbb{R}^{d \times |V|}$ converts each word to a dense word representation $w \in \mathbb{R}^d$. V is the set of all words in the vocabulary.

2.1.1 Highway Encoder. Each word embedding is passed through a highway encoder layer. Highway networks [31] are gated nonlinear transform layers which control information flow to subsequent layers. Many works adopt a projection layer that is trained in place of the raw word embeddings. Not only does this save computation cost but also reduces the number of trainable parameters. Our work extends this projection layer to use a highway encoder. The intuition for doing so is simple, i.e., highway encoders can be interpreted as data-driven word filters. As such, we can imagine them to parametrically learn which words have an inclination to be important and not important to the task at hand. For example, filtering stop words and words that usually do not contribute much to the prediction. Similar to recurrent models that are gated in nature, this highway encoder layer controls how much information (of each word) is flowed to the subsequent layers.

Let $H(.)$ and $T(.)$ be single layered affine transforms with ReLU and sigmoid activation functions respectively. A single highway network layer is defined as:

$$y = H(x, W_H) \cdot T(x, W_T) + (1 - T(x, W_T)) \cdot x \tag{1}$$

where $W_H, W_T \in \mathbb{R}^{r \times d}$. Notably, the dimensions of the affine transform might be different from the size of the input vector. In this case, an additional nonlinear transform is used to project x to the same dimensionality.

2.2 Co-Attention

Co-Attention [50] is a pairwise attention mechanism that enables attending to text sequence pairs jointly. In this section, we introduce four variants of attention, i.e., (1) max-pooling, (2) mean-pooling, (3) alignment-pooling, and finally (4) intra-attention (or self attention). The first step in co-attention is to learn an affinity (or similarity) matrix between each word across both sequences. Following Parikh et al. [20], we adopt the following formulation for learning the affinity matrix.

$$s_{ij} = F(q_i)^T F(d_j) \tag{2}$$

where $F(.)$ is a function such as a multi-layered perceptron (MLP). Alternate forms of co-attention are also possible such as $s_{ij} = q_i^\top M d_j$ and $s_{ij} = F([q_i; d_j])$.

2.2.1 Extractive Pooling. The most common variant of extractive co-attention is the *max-pooling* co-attention, which attends to each word based on its maximum influence it has on the other text sequence.

$$q' = Soft(\max_{col}(s))^\top q \quad \text{and} \quad d' = Soft(\max_{row}(s))^\top d \tag{3}$$

where q', d' are the co-attentive representations of q and d respectively. Soft(.) is the Softmax operator. Alternatively, the mean row and column-wise pooling of matrix s can be also used:

$$q' = Soft(\underset{col}{mean}(s))^\top q \quad \text{and} \quad d' = Soft(\underset{row}{mean}(s))^\top d \tag{4}$$

However, each pooling operator has different impacts and can be intuitively understood as follows: max-pooling selects each word based on its maximum importance of all words in the other text. Mean-pooling is a more *wholesome* comparison, paying attention to a word based on its overall influence on the other text. This is usually dataset-dependent, regarded as a hyperparameter and is tuned to see which performs best on the held out set.

2.2.2 Alignment-Pooling. Soft alignment-based pooling has also been utilized for learning co-attentive representations [20]. However, the key difference with soft alignment is that it *realigns* sequence pairs while standard co-attention simply learns to weight and score important words. The co-attentive representations are then learned as follows:

$$d_i' := \sum_{j=1}^{\ell_q} \frac{exp(s_{ij})}{\sum_{k=1}^{\ell_q} exp(s_{ik})} q_j \quad \text{and} \quad q_j' := \sum_{i=1}^{\ell_d} \frac{exp(s_{ij})}{\sum_{k=1}^{\ell_d} exp(s_{kj})} d_i \tag{5}$$

where d_i' is the sub-phrase in q that is softly aligned to d_i. Intuitively, d_i' is a weighted sum across $\{q_j\}_{j=1}^{\ell_q}$, selecting the most relevant parts of q to represent d_i.

2.2.3 Intra-Attention. Intra-Attention, or Self-Attention was recently proposed to learn representations that are aware of long-term dependencies. This is often formulated as an co-attention (or alignment) operation with respect to itself. In this case, we apply intra-attention to both document and query independently. For notational simplicity, we refer to them as x instead of q or d here. The Intra-Attention function is defined as:

$$x_i' := \sum_{j=1}^{\ell} \frac{exp(s_{ij})}{\sum_{k=1}^{\ell} exp(s_{ik})} x_j \tag{6}$$

where x_i' is the intra-attentional representation of x_j.

2.3 Multi-Cast Attention

At this point, it is easy to make several observations. Firstly, each attention mechanism provides a different flavor to the model. Secondly, attention is used to alter the original representation either by re-weighting or realigning. As such, most neural architectures only make use of one type of co-attention or alignment function [5, 20]. However, this requires the right model architecture to be tuned and potentially missing out from the benefits brought by using multiple variations of co-attention mechanism. As such, our work casts each attention operation as a **word-level** feature.

2.3.1 Casted Attention. Let x be either q or d and $\bar{x}$ is the representation[1] of x after applying co-attention or soft attention alignment. The attention features for the co-attention operators are:

$$f_c = F_c([\bar{x}; x]) \tag{7}$$

$$f_m = F_c(\bar{x} \odot x) \tag{8}$$

$$f_s = F_c(\bar{x} - x) \tag{9}$$

where $\odot$ is the Hadamard product and $[.; .]$ is the concatenation operator. $F_c(.)$ is a compression function used to reduce features to a scalar. Intuitively, what is achieved here is that we are modeling the influence of co-attention by comparing representations before and after co-attention. For soft-attention alignment, a critical note here is that x and $\bar{x}$ (though of equal lengths) have *'exchanged'* semantics. In other words, in the case of q, $\bar{q}$ actually contains the aligned representation of d. Finally, the usage of multiple comparison operators (subtractive, concatenation and multiplicative operators) is to capture multiple perspectives and is inspired by the ESIM model [3].

2.3.2 Compression Function. This section defines $F_c(.)$ the compression function used. The rationale for compression is simple and intuitive - we do not want to *bloat* subsequent layers with a high dimensional vector which consequently incurs parameter costs in subsequent layers. We investigate the usage of three compression functions, which are capable of reducing a n dimensional vector to a scalar.

- **Sum** (SM) Function is a non-parameterized function that sums the entire vector, returning a scalar as an output.

$$F(x) = \sum_{i}^{n} x_i \ , \ \forall x_i \in x \tag{10}$$

[1] We omit subscripts for clarity.

- **Neural Network** (NN) is a fully-connected layer that converts each n dimensional feature vector as follows:
$$F(x) = ReLU(W_c(x) + b_c). \tag{11}$$
where $W_c \times \mathbb{R}^{n \times 1}$ and $b_c \in \mathbb{R}$ are the parameters of the FC layer.
- **Factorization Machines** (FM) are general purpose machine learning techniques that accept a real-valued feature vector $x \in \mathbb{R}^n$ and return a scalar output.
$$F(x) = w_0 + \sum_{i=1}^{n} w_i \, x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \langle v_i, v_j \rangle \, x_i \, x_j \tag{12}$$
where $w_0 \in \mathbb{R}$, $w_i \in \mathbb{R}^n$ and $\{v_1, \cdots v_n\} \in \mathbb{R}^{n \times k}$ are the parameters of the FM model. FMs are expressive models that capture pairwise interactions between features using factorized parameters. k is the number of factors of the FM model. For more details, we refer interested readers to [24].

Note that we do not share parameters across multiple attention casts because each attention cast is aimed at modeling a different view. Our experiments report the above mentioned variants under the model name MCAN (SM), MCAN (NN) and MCAN (FM) respectively.

2.3.3 Multi-Cast. The key idea behind our architecture is the facilitation of k attention calls (or casts), with each cast augmenting raw word embeddings with a real-valued attentional hint. We formally describe the Multi-cast Attention mechanism. For each query-document pair, we apply (1) Co-Attention with mean-pooling (2) Co-Attention with max-Pooling and (3) Co-Attention with alignment-pooling. Additionally, we apply Intra-Attention to both query and document individually. Each attention cast produces three scalars (per word) which are concatenated with the word embedding. The final casted feature vector is $z \in \mathbb{R}^{12}$. As such, for each word w_i, the new word representation becomes $\bar{w}_i = [w_i; z_i]$.

2.4 Long Short-Term Memory Encoder

Next, the word representations with casted attention $\bar{w}_1, \bar{w}_2, \dots \bar{w}_\ell$ are then passed into a sequential encoder layer. We adopt a standard vanilla long short-term memory (LSTM) encoder:
$$h_i = LSTM(u, i), \forall i \in [1, \dots \ell] \tag{13}$$
where ℓ represents the maximum length of the sequence. Notably, the parameters of the LSTM are *'siamese'* in nature, sharing weights between document and query. The key idea is that the LSTM encoder learns representations that are aware of sequential dependencies by the usage of nonlinear transformations as gating functions. Since LSTMs are standard neural building blocks, we omit technical details in favor of brevity. As such, the key idea behind casting attention as features right before this layer is that it provides the LSTM encoder with hints that provide information such as (1) long-term and global sentence knowledge and (2) knowledge between sentence pairs (document and query).

2.4.1 Pooling Operation. Finally, a pooling function is applied across the hidden states $\{h_1 \dots h_\ell\}$ of each sentence, converting the sequence into a fixed dimensional representation.
$$h = MeanMax[h_1 \dots h_\ell] \tag{14}$$
We adopt the *MeanMax* pooling operator, which concatenates the result of the mean pooling and max pooling together. We found this to consistently perform better than using *max* or *mean* pooling in isolation.

2.5 Prediction Layer and Optimization

Finally, given a fixed dimensional representation of the document-query pair, we pass their concatenation into a two-layer h-dimensional highway network. The final prediction layer of our model is computed as follows:
$$y_{out} = H_2(H_1([x_q; x_d; x_q \odot x_d; x_q - x_d])) \tag{15}$$
where $H_1(.), H_2(.)$ are highway network layers with ReLU activation. The output is then passed into a final linear softmax layer.
$$y_{pred} = softmax(W_F \cdot y_{out} + b_F) \tag{16}$$
where $W_F \in \mathbb{R}^{h \times 2}$ and $b_F \in \mathbb{R}^2$. The network is then trained using standard multi-class cross entropy loss with L2 regularization.
$$J(\theta) = -\sum_{i=1}^{N} [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)] + \lambda ||\theta||_{L2} \tag{17}$$
where θ are the parameters of the network. $\hat{y}$ is the output of the network. $||\theta||_{L2}$ is the L2 regularization and λ is the weight of the regularizer.

3 EMPIRICAL EVALUATION

In our experiments, we aim to answer the following research questions (**RQs**):

1. **RQ1** - Does our proposed approach achieve state-of-the-art performance on question answering and conversation modeling tasks? What is the relative improvement over well-established baselines?
2. **RQ2** - What are the impacts of architectural design on performance? Is the LSTM encoder necessary to make use of the casted features? Does all the variations of co-attention contribute to the overall model performance?
3. **RQ3** - Can we explain the inner workings of our proposed model? Can we interpret the casted attention features?

3.1 Experiment 1 - Dialogue Prediction

In this first task, we evaluate our model on its ability to successfully predict the next reply in conversations.

3.1.1 Dataset and Evaluation Metric. For this experiment, we utilize the large and well-known large-scale Ubuntu Dialogue Corpus (UDC) [15]. We use the same testing splits provided by Xu et al. [51]. In this task, the goal is to match a sentence with its reply. Following [46], the task mainly utilizes the last two utterances in each conversation, predicting if the latter follows the former. The training set consists of **one million** message-response pairs with a 1 : 1 positive-negative ratio. The development and testing sets have a 9 : 1 ratio. Following [46, 51], we use the evaluation metrics of recall@k ($R_n@K$) which indicates whether the ground truth exists in the top k results from n candidates. The four evaluation metrics used are $R_2@1$, $R_{10}@1$, $R_{10}@2$ and $R_{10}@5$.

3.1.2 Competitive Baselines and Implementation Details. We compare against a large number of competitive baselines, e.g., MLP, DeepMatch [16], ARC-I / ARC-II [9], CNTN [21], MatchPyramid [19], vanilla LSTM, Attentive Pooling LSTM [5], MV-LSTM [37] and finally the state-of-the-art Knowledge Enhanced Hybrid Neural Network (KEHNN) [46]. A detailed description of baselines can be found at [46]. Since testing splits are the same, we report the results directly from [46]. For fair comparison, we set the LSTM encoder size in MCAN to $d = 100$ which makes it equal to the models in [46]. We optimize MCAN with Adam optimizer [13] with an initial learning rate of 3×10^{-4}. A dropout rate of 0.2 is applied to all layers except the word embedding layer. The sequences are dynamically truncated or padded to their batch-wise maximums (with a hard limit of 50 tokens). We initialize the word embedding layer with pretrained GloVe embeddings.

3.1.3 Experimental Results. Table 1 reports the results of our experiments. Clearly, we observe that all MCAN models achieve a huge performance gain over existing state-of-the-art models. More specifically, the improvement across all metrics are $\approx 5\% - 9\%$ better than KEHNN. The performance improvement over strong baselines such as AP-LSTM and MV-LSTM are even greater, hitting an improvement of 15% in terms of $R_{10}@1$. This ascertains the effectiveness of the MCAN model. Overall, MCAN (FM) and MCAN (NN) are comparable in terms of performance. MCAN (SM) is marginally lower than both MCAN (FM) and MCAN (NN). However, its performance is still considerably higher than the existing state-of-the-art models.

	$R_2@1$	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$
MLP	0.651	0.256	0.380	0.703
DeepMatch	0.593	0.345	0.376	0.693
ARC-I	0.665	0.221	0.360	0.684
ARC-II	0.736	0.380	0.534	0.777
CNTN	0.743	0.349	0.512	0.797
MatchPyramid	0.743	0.420	0.554	0.786
LSTM	0.725	0.361	0.494	0.801
AP-LSTM	0.758	0.381	0.545	0.801
MV-LSTM	0.767	0.410	0.565	0.800
KEHNN	0.786	0.460	0.591	0.819
MCAN (SM)	0.831	0.548	0.682	0.873
MCAN (NN)	<u>0.833</u>	<u>0.549</u>	**0.686**	**0.875**
MCAN (FM)	**0.834**	**0.551**	<u>0.684</u>	**0.875**

Table 1: Performance Comparison on Ubuntu Dialogue Corpus. Best result is in boldface and second best is underlined.

3.2 Experiment 2 - Factoid Question Answering

Factoid question answering is the task of answering factual based questions. In this task, the goal is to provide a ranked list of answers to a given question.

3.2.1 Dataset and Evaluation Metric. We utilize the QA dataset from TREC (Text Retrieval Conference). TrecQA is one of the most widely evaluated dataset, competitive and long standing benchmark for QA. This dataset was prepared by Wang et al. [41] and contains $53K$ QA pairs for training and 1100/1500 pairs for development and testing respectively. Following the recent works, we evaluate on the clean setting as noted by [22]. The evaluation metrics for this task are the MAP (mean average precision) and MRR (mean reciprocal rank) scores which are well-known IR metrics.

3.2.2 Competitive Baselines and Implementation Details. We compare against all previously published works on this dataset. The competitive baselines for this task are QA-LSTM / AP-CNN [5], LDC model [45], MPCNN [7], MPCNN+NCE [22], HyperQA [35], BiMPM [44] and IWAN [28]. For our model, the size of the LSTM used is 300. The dimensions of the highway prediction layer is 200. We use the Adam optimizer with a 3×10^{-4} learning rate. The L2 regularization is set to 10^{-6}. A dropout rate of 0.2 is applied to all layers except the embedding layer. We use pretrained $300d$ GloVe embeddings and fix the embeddings during training. For MCAN (FM), we use a FM model with 10 factors. We pad all sequences to the maximum sequence length and truncate them to the batch-wise maximums.

3.2.3 Experimental Results. Table 2 reports our results on TrecQA. All MCAN variations outperform all existing state-of-the-art models. Notably, MCAN (FM) is currently the best performing model on this extensively studied dataset. MCAN (NN) comes in second which marginally outperforms the highly competitive and recent IWAN model. Finally, MCAN (SM) remains competitive to IWAN, despite naively summing over casted attention features.

Model	MAP	MRR
QA-LSTM (dos Santos et al.)	0.728	0.832
AP-CNN (dos Santos et al.)	0.753	0.851
LDC Model (Wang et al.)	0.771	0.845
MPCNN (He et al.)	0.777	0.836
HyperQA (Tay et al.)	0.784	0.865
MPCNN + NCE (Rao et al.)	0.801	0.877
BiMPM (Wang et al.)	0.802	0.899
IWAN (Shen et al.)	0.822	0.889
MCAN (SM)	0.827	0.880
MCAN (NN)	<u>0.827</u>	<u>0.890</u>
MCAN (FM)	**0.838**	**0.904**

Table 2: Performance Comparison on TrecQA (*clean*) dataset. Best result is in boldface and second best is underlined.

3.3 Experiment 3 - Community Question Answering (cQA)

This task is concerned with ranking answers in community forums. Different from factoid QA, answers are generally subjective instead of factual. Moreover, answer lengths are also much longer.

3.3.1 Dataset and Evaluation. We use the QatarLiving dataset, a well-studied benchmark dataset from SemEval-2016 Task 3 Subtask A (cQA) and have been used extensively as a benchmark for recent state-of-the-art neural network models for cQA [34, 54]. This is a real world dataset obtained from Qatar Living Forums and comprises $36K$ training pairs, $2.4K$ development pairs and $3.6K$ testing pairs. In this dataset, there are ten answers in each question 'thread' which are marked as 'Good', 'Potentially Useful' or ''Bad'.

Following [54], 'Good' is regarded as positive and anything else is regarded as negative labels. We evaluate on two metrics, namely the Precision@1 (P@1) and Mean Average Precision (MAP) metric.

3.3.2 Competitive Baselines and Implementation Details. The key competitors of this dataset are the CNN-based ARC-I/II architecture by Hu et al. [9], the Attentive Pooling CNN [5], Kelp [6] a feature engineering based SVM method, ConvKN [2] a combination of convolutional tree kernels with CNN and finally AI-CNN (Attentive Interactive CNN) [54], a tensor-based attentive pooling neural model. We also compare with the *Cross Temporal Recurrent Networks* (CTRN) [34], a recently proposed model for ranking QA pairs which have achieved very competitive performance on this dataset. Following [34], we initialize MCAN with domain-specific 200 dimensional word embeddings using the unannotated QatarLiving corpus. Word embeddings are not updated during training. The size of the highway projection layer, LSTM encoder and highway prediction layer are all set to 200. The model is optimized with Adam optimizer with learning rate of 3×10^{-4}.

Model	P@1	MAP
ARC-I (Hu et al.)	0.741	0.771
ARC-II (Hu et al.)	0.753	0.780
AP-CNN (dos Santos et al.)	0.755	0.771
Kelp (Filice et al.)	0.751	0.792
ConvKN (Barron Cedeno et al.)	0.755	0.777
AI-CNN (Zhang et al.)	0.763	0.792
CTRN (Tay et al.)	0.788	<u>0.794</u>
MCAN (SM)	<u>0.803</u>	0.787
MCAN (NN)	0.802	0.784
MCAN (FM)	**0.804**	**0.803**

Table 3: Performance comparison on QatarLiving dataset for community question answering. Best result is in boldface and second best is underlined.

3.3.3 Experimental Results. Table 3 reports the performance comparison on the QatarLiving dataset. Our best performing MCAN model achieves state-of-the-art performance on this dataset. Performance improvement over recent, competitive neural network baselines is significant. Notably, the improvement of MCAN (FM) over AI-CNN on the $P@1$ metric is 4.1% and 1.1% in terms of MAP. MCAN (FM) also achieves competitive results relative to the CTRN model. The performance of MCAN (NN) and MCAN (SM) is lower than MCAN (FM) but still remains competitive on this benchmark.

3.4 Experiment 4 - Tweet Reply Prediction

This experiment is concerned with predicting an appropriate reply given a tweet.

3.4.1 Dataset and Evaluation Metrics. We utilize a customer support dataset obtained from Kaggle[2]. This dataset contains tweet-response pairs of tweets to famous brands and their replies. For each Tweet-Reply pair, we randomly selected *four* tweets as negative samples that originate from the same brand. The dataset is split into 8 : 1 : 1 train-dev-test split. The evaluation metrics for this task are MRR (Mean reciprocal rank) and Precision@1 (accuracy). Unlike previous datasets, there are no published works on this dataset. As such, we implement the baselines ourselves. We implement standard baselines such as (1) CBOW (sum embeddings) passed into a 2 layer MLP with ReLU activations, (2) standard vanilla LSTM and CNN models and (3) BiLSTM and CNN with standard Co-Attention (AP-BiLSTM, AP-CNN) following [5]. All models minimize the binary cross entropy loss (pointwise) since we found performance to be much better than using ranking loss. We also include the recent AI-CNN (Attentive Interactive CNN) which uses multi-dimensional co-attention. We set all LSTM dimensions to $d = 100$ and the number of CNN filters is 100. The CNN filter width is set to 3. We train all models with Adam optimizer with 3×10^{-4} learning rate. Word embeddings are initialized with GloVe and fixed during training. A dropout of 0.2 is applied to all layers except the word embedding layer.

3.4.2 Experimental Results. Table 4 reports our results on the Tweets dataset. MCAN (FM) achieves the top performance by a significant margin. The performance of MCAN (NN) falls short of MCAN (FM), but is still highly competitive. Our best MCAN model outperforms AP-BiLSTM by 3.4% in terms of MRR and 5.3% in terms of P@1. The performance improvement of AI-CNN is even greater, i.e., 8.4% in terms of MRR and 12.5% in terms of P@1. The strongest baseline is AP-BiLSTM which significantly outperforms AI-CNN and AP-CNN.

Model	MRR	P@1
CBOW + MLP	0.658	0.442
LSTM	0.652	0.431
CNN	0.657	0.441
AP-CNN (dos Santos et al.)	0.643	0.426
AI-CNN (Zhang et al.)	0.675	0.465
AP-BiLSTM (dos Santos et al.)	0.725	0.540
MCAN (SM)	0.722	0.548
MCAN (NN)	<u>0.747</u>	<u>0.585</u>
MCAN (FM)	**0.759**	**0.593**

Table 4: Performance comparison on Reply Prediction on Tweets dataset. Best performance is in boldface and second best is underlined.

3.5 Ablation Analysis

This section aims to demonstrate the relative effectiveness of different components of our proposed MCAN model. Table 5 reports the results on the validation set of the TrecQA dataset. We report the scores of seven different configurations. In (1), we replace all highway layers with regular feed-forward neural networks. In (2), we remove the LSTM encoder before the prediction layer. In (3), we remove the entire multi-cast attention mechanism. This is equivalent to removing the twelve attention features. In (4-7), we remove different attention casts, aiming to showcase that removing either one results in some performance drop.

From our ablation analysis, we can easily observe the crucial components to our model. Firstly, we observe that removing MCA

[2]https://www.kaggle.com/soaxelbrooke/customer-support-on-twitter

entirely significantly decreases the performance (ablation 3). In this case, validation MAP drops from 0.866 to 0.670. As such, our casted attention features contribute a lot to the performance of the model. Secondly, we also observe that the LSTM encoder is necessary. This is intuitive because the goal of MCAN is to provide features as hints for a compositional encoder. As such, removing the LSTM encoder allows our attention hints to go unused. While the upper prediction might still manage to learn from these features, it is still sub-optimal compared to using a LSTM encoder. Thirdly, we observed that removing Max or Mean Co-Attention decreases performance marginally. However, removing the Alignment Co-Attention decreases the performance significantly. As such, it is clear that the alignment-based attention is most important for our model. However, Max, Mean and Intra attention all contribute to the performance of MCAN. Hence, using multiple attention casts can improve performance. Finally, we also note that the highway layers also contribute slightly to performance.

Setting	MAP	MRR
Original	**0.866**	**0.922**
(1) Remove Highway	0.825	0.863
(2) Remove LSTM	0.765	0.809
(3) Remove MCA	0.670	0.749
(4) Remove Intra	0.834	0.910
(5) Remove Align	0.682	0.726
(6) Remove Mean	0.858	0.906
(7) Remove Max	0.862	0.915

Table 5: Ablation analysis (validation set) on TrecQA dataset.

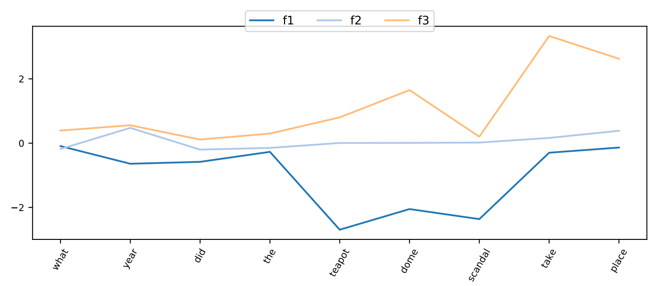
3.6 In-depth Model Analysis

In this section, we aim to provide insights pertaining to the inner workings of our model. More specifically, we list several observations by visual inspection of the casted attention features. We trained a MCAN model with FM compression and extracted the word-level casted attention features. The features are referred to as f_i where $i \in [1, 12]$. f_1, f_2, f_3 are generated from alignment-pooling. f_4, f_5, f_6 and f_7, f_8, f_9 are generated from max and mean pooled co-attention respectively. f_{10}, f_{11}, f_{12} are generated from intra-attention.

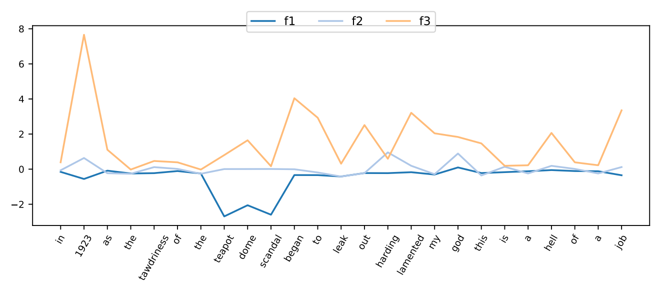
3.6.1 Observation 1: Features learn a Neural Adaptation of Word Overlap. Figure 2 and Figure 3 show a positive and negative QA pair from the TrecQA test set. Firstly, we analyze[3] the first three features f_1, f_2 and f_3. These features correspond to the alignment attention and multiply, subtract and concat composition respectively. From the figures, we observe that f_1 spikes (in the negative direction) when there is a word overlap across sentences, e.g., '*teapot*' in Figure 3 and *'teapot dome scandal'* in Figure 2. Hence, f_1 (dark blue line) behaves as a neural adaptation of the conventional overlap feature. Moreover, in contrary to traditional binary overlap features, we also notice that the value of the neural word overlap feature is dependent on the word itself, i.e., '*teapot*' and '*dome*' have different values. As such, it encodes more information over the traditional binary feature.

[3]This is done primarily for clear visualisation, lest the diagram becomes too cluttered.

3.6.2 Observation 2: Features React to Evidence and Anti-Evidence. While f_1 is primarily aimed at modeling overlap, we observe that f_3 tries to gather supporting evidence for the given QA pair. In Figure 2, the words *'year'* and *'1923'* have spiked. It also tries to extract key verbs such as *''take place'* (question) and *'began'* (answer) which are related verbs generally used to describe events. Finally, we observe that f_2 (subtractive composition) seems to be searching for anti-evidence, i.e., a contradictory or irrelevant information. However, this appears to be more subtle as compared to f_1 and f_3. In Figure 3, we note that the words *'died' and 'attack'* (answer) have spiked. We find this example particularly interesting because the correct answer '*1923*' is in fact found in the answer. However, the pair is **wrong** because the text sample refers to the '*death of Harding*' and does not answer the question correctly. In the negative answer, we found that the word *'died'* has the highest f_2 value. As such, we believe that f_2 is actively finding anti-evidence to why this QA pair should be negative. Additionally, irrelevant words such as *'attack*' and *'god'* experience nudges by f_2. Finally, it is good to note that MCAN classifies these two samples correctly while a standard Bidirectional LSTM does not.



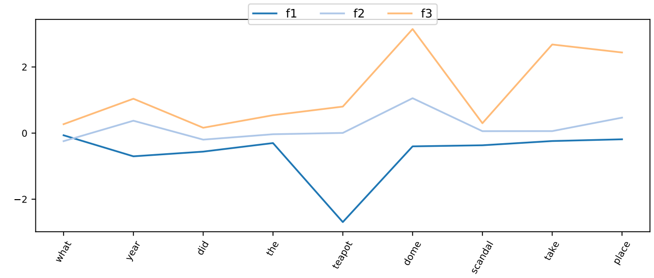
(a) Features f_1, f_2, f_3 for question.



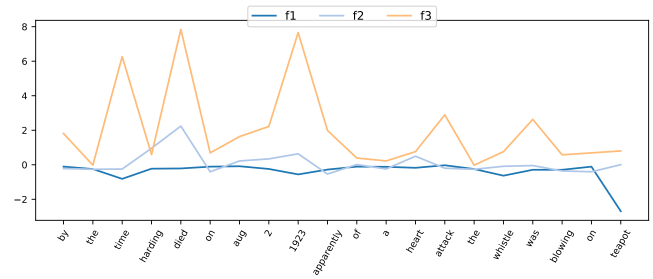
(b) Features f_1, f_2, f_3 for answer.

Figure 2: Visualization of Casted Attention Features (f_1, f_2, f_3) on a *positive* test sample from TrecQA.

3.6.3 Observation 3: Diversity of Multiple Casts. One of the key motivators for a multi-casted attention is that each attention cast produces features from different views of the sentence pair. While

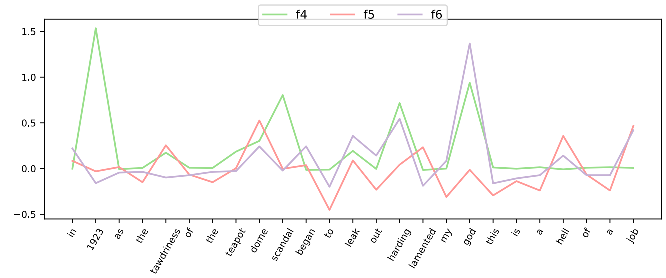


(a) Features f_1, f_2, f_3 for question.

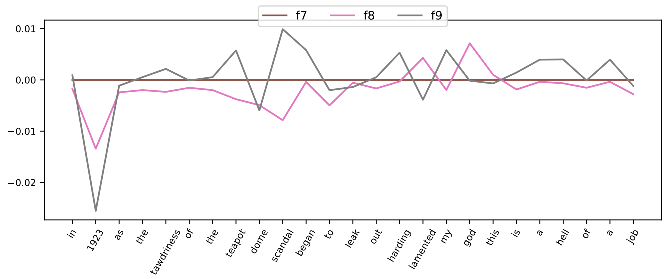


(b) Features f_1, f_2, f_3 for answer.

Figure 3: Visualization of Casted Attention Features (f_1, f_2, f_3) on a *negative* test sample from TrecQA.



(a) Features generated from *max*-pool Co-Attention.



(b) Features generated from *mean*-pool Co-Attention.

Figure 4: Differences between Max and Mean-pooled Casted Attention Features on answer text from TrecQA dataset. Diverse features are learned by different attention casts.

we have shown in our ablation study that all attention casts contributed to the overall performance, this section qualitatively analyzes the output features. Figure 4 shows the casted attention features (answer text) for max-pooled attention (f_4, f_5, f_6) and mean-pooled[4] attention (f_7, f_8, f_9). Note that the corresponding question is the same as Figure 2 and Figure 3 which allows a direct comparison with the alignment-based attention. We observe that both attention casts produce extremely diverse features. More specifically, not only the spikes are all at different words but the overall sequential pattern is very different. We also note that the feature patterns differ a lot from alignment-based attention (Figure 2). While we were aiming to capture more diverse patterns, we also acknowledge that these features are much less interpretable than f_1, f_2 and f_3. Even so, some patterns can still be interpreted, e.g., the value of f_5 is high for important words and low (negative) whenever the words are generic and unimportant such as *'to', 'the', 'a'*. Nevertheless, the main objective here is to ensure that these features are not learning identical patterns.

4 RELATED WORK

Learning to rank short document pairs is a long standing problem in IR research. The dominant state-of-the-art models for learning-to-rank today are mostly neural network based models. Neural network models, such as convolutional neural networks (CNN) [9, 29, 32, 40], recurrent neural networks (RNN) [18, 28, 46] or recursive neural networks [38] are used for learning document representations. A parameterized fuction such as multi-layered perceptrons [27], tensor layers [21] or holographic layers [32] then learns a similarity score between document pairs.

Recent advances in neural ranking models go beyond independent representation learning. There are several main architectural paradigms that invoke interactions between document pairs which intuitively improve performance due to matching at a deeper and finer granularity. The first can be thought of as extracting features from a constructed word-by-word similarity matrix [19, 37]. The second invokes matching across multiple views and perspectives [7, 23, 44]. The third method involves learning pairwise attention weights (i.e., co-attention). In these models, the similarity matrix is used to learn attention weights, learning to attend to each document based on its partner. Attentive Pooling Networks [5] and Attentive Interactive Networks [54] are models that are grounded in this paradigm, utilizing *extractive max-pooling* to learn the relative importance of a word based on its maximum importance to all words in the other document. The Compare-Aggregate model [42] used a co-attention model for matching and then a convolutional feature extractor for aggregating features. Notably, other related problem domains such as machine comprehension [26, 43, 50] and review-based recommendation [36] also extensively make use of co-attention mechanisms.

[4]The values on f_7 are not constant. They appear to be since the max-min range is much smaller than f_8 and f_9.

Learning sequence alignments via attention have been also popularized by models in related problem domains such as natural language inference [3, 20, 33]. Notably, MCAN can be viewed as an extension of the CAFE model proposed in [33] for natural language inference. However, the key differences of this work is that (1) the propagated features in MCAN are *multi-casted* (e.g., multiple co-attention variants are used consecutively) and (2) MCAN is extensively evaluated on a different and diverse set of problem domains and tasks.

There are several other notable and novel classes of model architectures which have been proposed for learning to rank. Examples include knowledge-enhanced models [46, 48], lexical decomposition [45], fused temporal gates [34] and coupled LSTMs [14]. Novel metric learning techniques such as hyperbolic spaces have also been proposed [35]. [53] proposed a quantum-like model for matching QA pairs.

Our work is also closely related to the problem domain of ranking for web search, in which a myriad of neural ranking models were also proposed [4, 10–12, 17, 29, 30, 49]. Ranking models for multi-turn response selection on Ubuntu corpus was also proposed in [47].

5 CONCLUSION

We proposed a new state-of-the-art neural model for a myriad of retrieval and matching tasks in the domain of question answering and conversation modeling. Our proposed model is based on a re-imagination of the standard and widely applied neural attention. For the first time, we utilize attention not as a pooling operator but as a form of feature augmentation. We propose three methods to compress attentional matrices into scalar features. Via visualisation and qualitative analysis, we show that these casted features can be interpreted and understood. Our proposed model achieves highly competitive results on four benchmark tasks and datasets. The achievements of our proposed model are as follows: (1) our model obtains the highest performing result on the well-studied TrecQA dataset, (2) our model achieves 9% improvement on Ubuntu dialogue corpus relative to the best exisiting model, and (3) our model achieves strong results on Community Question Answering and Tweet Reply Prediction.

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