Abstract Text-based Question Answering (QA) is a challenging task which aims at finding short concrete answers for users' questions. This line of research has been widely studied with information retrieval techniques and has received increasing attention in the recent years by considering deep neural network approaches. Deep learning approaches, which is the main focus of this paper, provide a powerful technique to learn multiple layers of representations and interaction between questions and texts. In this paper, we provide a comprehensive overview of different models proposed for the QA task, including both traditional information retrieval perspective, and more recent deep neural network perspective. We also introduce well-known datasets for the task and present available results from the literature to have a comparison between different techniques.

Keywords Text-based Question Answering · Deep Learning · Information Retrieval

1 Introduction

Question Answering (QA) is a fast-growing research problem in computer science which aims to find short concrete answers. There are two major approaches for QA systems: text-based QA, and knowledge-based QA. Knowledge-based QAs rely on knowledge bases (KB) for finding the answer of the user’s
question. Freebase is one of the most popular KBs (Bollacker et al., 2008) which has been widely used as a benchmark in many recent works on knowledge-based QA. KBs include entities, relations, and facts. Facts in knowledge base are stored in (subject, predicate, object) format where the subject and the object are entities and the predicate is a relation, indicating the relation between the object and the subject. For example, answer of the question ‘Which forest is Fires Creek in?’ could be stored in a fact like (fires creek, containedby, nan-tahala national forest) (Bordes et al., 2015). In this task there are two types of questions: single-relation and multi-relation questions. A simple question is answered by one fact in KB, while the answer of a multi-relation question is found by reasoning over more than one fact in the KB (Yu et al., 2017). SimpleQuestions and WebQSP are the major datasets of the single-relation and multi-relation questions, respectively.

In text-based QA, answer of a candidate question is obtained by finding the most similar answer text between candidate answer texts. Consider the question Q and set of answers \( \{A_1, A_2, \ldots, A_n\} \), the goal of this system is finding the best answer among these answers. Recent works have proposed different deep neural models in text-based QA which compares two segments of texts and produces a similarity score. In this paper, we focus on this type of QA and review the available methods on text-based QA.

This paper organizes as follows: In section 2, we review the most popular QA datasets. In section 3, we introduce evaluation metrics used in QA. In section 4, we present the architecture of QA systems. We discuss about information retrieval-based models used for question answer similarity in section 5 and deep learning models in section 6, respectively. In section 7 we report and compare results of reviewed models. We conclude this paper in section 8.

2 Datasets for QA

In this section, we describe five datasets which have been widely used for evaluating the QA tasks.

1. WikiQA is an open domain QA dataset (Yang et al., 2015). This dataset is collected from Bing query logs. Question-like queries which are issued by at least 5 different users and have clicks to Wikipedia pages are selected as questions in this dataset and the sentences of the summary section of the corresponding Wikipedia page are considered as candidate answers to the related question. The candidate answers are labeled as correct or incorrect with crowdsourcing and then the correct answer is selected. This dataset consists 3047 questions and 1473 answers, more statistics about this dataset is presented in Table 1. A noted feature of WikiQA is that not all the questions in this dataset have the correct answer which makes it possible to use this dataset in answer triggering component. Answer triggering component’s task is finding whether the question has answer or not.
2. TREC-QA is collected from Text REtrieval Conference (TREC) 8-13 QA dataset (Wang et al., 2007). Questions of TREC 8-12 are used as training dataset and questions of TREC 13 are used as development and test dataset. Statistics of TREC-QA dataset is presented in Table 2. TREC-QA contains two training datasets, TRAIN and TRAIN-ALL. TRAIN dataset includes first 94 questions of TREC 8-12 and its candidate answers are judged manually, while in TRAIN-ALL dataset, correct answers are recognized by matching the answers with predefined patterns of the answer regular expression.

3. MovieQA is gathered from diverse data sources (Tapaswi et al., 2016) which is a unique feature of this dataset. It contains 14944 questions where each question is associated with five answers, including one correct answer and four deceiving answers. Statistics of this dataset is shown in Table 3.

4. InsuranceQA is a close domain dataset for QA in insurance domain (Feng et al., 2015). Question/answer pairs of this dataset are collected from internet. This dataset includes Train, Development, Test1, and Test2 parts. More detailed statistics about InsuranceQA is presented in Table 4.
Table 4 Statistics of the InsuranceQA Dataset

|          | Train | Dev | Test1 | Test2 |
|----------|-------|-----|-------|-------|
| Questions| 12887 | 1000| 1800  | 1800  |
| Answers  | 18540 | 1454| 2616  | 2593  |
| Word Count| 92095 | 7158| 12893 | 12905 |

5. Yahoo! Dataset is collected from Yahoo! Answers QA system. Yahoo! includes 142,627 question/answer pairs. But in the literature [Wan et al., 2016b,a] a subset of this dataset is selected as positive pair and for each question in this subset, four other negative pairs are constructed. The (question, answer) pairs which the question and its answer length is between 5 to 50 words are selected as positive pairs (including 60564 pairs). Four negative answers for each question are selected by querying the whole answers set by the correct answer and selecting the four answers randomly among 1000 top retrieved answers.

3 Evaluation

For evaluation of QA, three metrics are used: Mean Reciprocal Rank (MRR), Mean Average Precision (MAP), and accuracy. MRR indicates the ability of the system to answer a question. Reciprocal Rank (RR) for one question is inverse of the rank of the first correct answer, if there exist any correct answer, or zero if there exist no correct answer. RR of each question is computed and then the average of RRs is considered as MRR.

\[
MRR = \frac{1}{|Q|} \sum_{i=1}^{|Q|} \frac{1}{\text{rank}_i}
\]  

\[
\text{rank}_i = \begin{cases} 
1 & \text{the rank of the first correct answer} \\
0 & \text{if no correct answer} 
\end{cases} 
\]

Second metric is MAP. MAP is mean of the average of the precisions at each rank, when a correct answer is detected [Diefenbach et al., 2018]. Precision@k is the number of correct answers among first k retrieved answers divided by k. Precision indicates how many of the answers are correct and is calculated as follows:

\[
MAP = \frac{1}{Q} \sum_{q=1}^{Q} AP(q)
\]

\[
AP(q) = \frac{1}{K} \sum_{k=1}^{K} p@k
\]
Precision@k = \frac{\text{number of correct answers among first } k \text{ results}}{k}

where \( k \) is the rank of correctly retrieved answers.

Accuracy is used for evaluating datasets whose questions have just one correct answer or one label. Accuracy indicates how many of the questions are answered correctly.

Accuracy = \frac{\text{number of correct answered questions}}{\text{number of questions}} \quad (3)

4 Architecture of Question Answering

Architecture of QA, as illustrated in Figure 1, includes three major phases: question processing, document and passage retrieval, and answer extraction. Each of these phases are described below (Jurafsky and Martin, 2009).

1. Question processing: This phase includes two major steps, namely query formulation and answer type detection. In query formulation step, a query for given question is generated for retrieving relevant documents by employing an Information Retrieval (IR) engine. The query, which is generated by query reformulation rules, looks like a subset of intended answer. In the answer type detection step, a classifier is used for classifying questions based on the type of expected answer. Different neural-based or feature-based classifiers can be used in this step.

2. Document and passage retrieval: Generated query in the query formulation step, is passed through an IR engine and top \( n \) retrieved documents are returned. As answer extraction models mostly work on short segments of documents, a passage retrieval model is applied on retrieved documents to receive short segments of text. This is the core component of QA that can find similar passages/sentence to the input question.

3. Answer extraction: In the final phase of QA, the most relevant answer is retrieved from given passage. In this step, we need to measure similarity of the input question and the extracted answer.

As mentioned, estimating similarity of question and answer sentences is the main important part of text-based QA systems. Since the retrieved sentences are short enough to satisfy users, the output of this step can also be represented to users without any further answer extraction. Similarity of question and answer sentences can be measured by information retrieval or deep learning approaches. In Sections 5 and 6, we review related works from the information retrieval perspective and the deep learning approaches, respectively.

5 Question Answer Similarity from Information Retrieval Perspective

Although lexical-based information retrieval models have been widely used in ad-hoc retrieval, they have less applied to QA tasks because the length of
answer sentences is shorter than normal web documents and the vocabulary gap between question and answer sentence in QA is more pronoun than ad-hoc retrieval. It motivated researches to use advanced information retrieval approaches in QA. Some of these approaches are described in this section.

Yang et al. (2015) presented the WikiQA dataset for open domain QA. They have evaluated WikiQA and QASent datasets with information retrieval-based models like Word Count (Word Cnt), Weighted Word Count (Wgt Word Cnt), Learning Constrained Latent Representation (LCLR) (Yih et al., 2013), and Paragraph Vector (PV) (Le and Mikolov, 2014). Word Cnt model works by counting the non-stop words in question which also have occurred in the answer sentence. Wgt Word Cnt is the same as Word Cnt, but it also reweights the counts by Inverse document Frequency (IDF) weight of the question words. The Idea behind the model proposed by Yih et al. (2013) is adopting a probabilistic classifier for predicting whether a pair of question and answer are related or not, using semantic model of the question and answer. They used synonym/antonym, hyponym/hypernym and semantic word similarity of each pair of words from question and answer sentences for creating the semantic model. They adopted Learning Constrained Latent Representation (LCLR) (Chang et al., 2010) for classifying pairs of question and answer. Details of this classifier is shown in the following equations.

\[
\min_{\theta} \frac{1}{2} ||\theta||^2 + C \sum_i \xi_i^2 \\
\text{s.t. } \xi_i \geq 1 - y_i \max_h \theta^T \phi(x, h) \\
\arg \max_h \theta^T \phi(x, h)
\]

Murdock and Croft (2004) suggested a translation model for QA. In their model, probability of the question (Q) given the answer (A), denoted as \(P(Q|A)\), is computed by the following equations:

\[
p(Q|A) = \prod_{i=1}^{m} \left[ \beta \left( \lambda \sum_{j=1}^{n} p(q_i|a_j) p(a_j|A) + (1-\lambda)p(q_i|C) \right) + (1-\beta) \left( \lambda p(q_i|D_A) + (1-\lambda)p(q_i|C) \right) \right]
\]
\[
p(q_i|a_j) p(a_j|A) = t_i p(q_i|A) + (1 - t_i) \sum_{1 \leq j \leq n, a_j \neq q_i} p(q_i|a_j) p(a_j|A) \tag{6}
\]

where \(\lambda\) is the smoothing parameter, \(D_A\) is the document containing answer \(A\), and \(C\) is the collection. The idea is based on the model proposed by Berger and Lafferty (1999) while different similarity model is used for calculating \(P(q_i|a_j)\).

Momtazi and Klakow (2009) proposed class-based language models for sentence retrieval in QA. Their class-based language model aims to mitigate the word mismatch problem by finding the relation between words. The Brown word clustering algorithm is adopted for clustering the words in this model and the probability of generating question \(Q\), having the answer sentence \(S\) is calculated by the following equations:

\[
P_{\text{class}}(Q|S) = \prod_{i=1}^{M} P(q_i|C_{q_i}, S) P(C_{q_i}|S) \tag{7}
\]

\[
P_{\text{class}}(C_{q_i}|S) = \frac{f_S(C_{q_i})}{\sum_w f_S(w)}
\]

where \(P(q_i|C_{q_i}, S)\) is the probability of term \(q_i\) having its cluster \((C_{q_i})\) and answer sentence model \((S)\), \(P(C_{q_i}|S)\) is the probability of cluster \(C_{q_i}\) given the sentence model \(S\), \(f_S(C_{q_i})\) is the number of occurrences of all the words in the cluster of term \(q_i\) in sentence \(S\), and \(w\) represents the vocabulary words.

Momtazi and Klakow (2011, 2015) proposed a trained trigger language model. In their model, the word mismatch problem is mitigated by using the contextual information between words. The idea behind this model is to find the pair of trigger and target words, whereas appearance of a target word in answer sentence and trigger word in question sentence means as a relation between the related words. They have trained a model for extracting these trigger-target pairs from a corpus, and this model is used for calculating the probability of question word \(q_i\), having the answer \(S\), denoted as \(P(q_i|S)\), as follows:

\[
P_{\text{trigger}}(q_i|S) = \frac{1}{N} \sum_{j=1}^{N} P_{\text{trigger}}(q_i|s_j) \tag{8}
\]

\[
P_{\text{trigger}}(q_i|s_j) = \frac{f_C(q_i, s_j)}{\sum_{q_i, s_j} f_C(q_i, s_j)}
\]

where \(s_j\) and \(q_i\) denote the \(j^{th}\) term in answer sentence, and \(i^{th}\) term in the question sentence, respectively. \(f_C(q_i, s_j)\) is the number of times term \(q_i\) triggers term \(s_j\) in the model created upon corpus \(C\). \(P(q_i|S)\) is the probability of \(q_i\) having the sentence \(S\), and \(N\) is sentence length.

Having the above probabilities, the probability of question \((Q)\), having the answer \((S)\), is calculated as follows:
\[ P_{\text{trigger}}(Q|S) = \left( \frac{1}{N} \right)^M \prod_{i=1}^{M} \sum_{j=1}^{N} f_C(q_i, s_j) \left( \sum_{q} f_C(q_i, s_j) \right) \]  \hspace{1cm} (9)

where \( M \) is question length.

Yadav et al. (2018) proposed a model which for each question-answer pair calculates a matching score in three steps. In the first step, IDF weight of each word is calculated by the following equation:

\[ \text{idf} (q_i) = \log \frac{N - \text{docfreq}(q_i) + 0.5}{\text{docfreq}(q_i) + 0.5} \]  \hspace{1cm} (10)

where \( N \) is the count of questions, and \( \text{docfreq}(q_i) \) is the number of questions which word \( q_i \) has occurred in. In the second step, one-to-many alignments are performed between terms in question and answer. Cosine similarity between Glove word embedding (Pennington et al., 2014) of each question word \( q_i \) and each answer word \( a_i \) is considered as their similarity. Then the top \( K^+ \) most similar words \( \{a_{q_i,1}^+, a_{q_i,2}^+, a_{q_i,3}^+, \ldots, a_{q_i,K^+}^+\} \) and \( K^- \) least similar words \( \{a_{q_i,1}^-, a_{q_i,2}^-, a_{q_i,3}^-, \ldots, a_{q_i,K^-}^-\} \) of answer are found. Finally in the third step the similarity score \( S(Q,A) \) between each question and answer sentence is calculated by the following equations:

\[ s(Q,A) = \sum_{i=1}^{N} \text{idf} (q_i) \cdot \text{align} (q_i, A) \]  \hspace{1cm} (11)

\[ \text{align} (q_i, A) = \text{pos} (q_i, A) + \lambda \cdot \text{neg} (q_i, A) \]

\[ \text{pos} (q_i, A) = \sum_{k=1}^{K^+} \frac{1}{K} \cdot a_{q_i,k}^+ \]

\[ \text{neg} (q_i, A) = \sum_{k=1}^{K^-} \frac{1}{K} \cdot a_{q_i,k}^- \]

where \( \text{align}(q_i, A) \) is the alignment score between \( q_i \) and answer \( A \), \( \lambda \) is the negative information’s weight, \( \text{pos}(q_i, A) \) and \( \text{neg}(q_i, A) \) represent the one-to-many alignment score for the \( K^+ \) most and \( K^- \) least similar words. They have also proposed two other baselines single-alignment (one-to-one), and one-to-all. In one-to-one approach, just the single alignment score \( \text{align}(q_i, A) \) changes the \( \text{align}(q_i, A) \) to the following equation:

\[ \text{align} (q_i, A) = \sum_{k=1}^{m} \frac{1}{K} \cdot \text{cosSim} \left( q_i, a_{q_i,k}^+ \right) \]  \hspace{1cm} (12)

where \( M \) is the count of the words in the answer sentence.
6 Question Answer Similarity from Deep Learning Perspective

Deep learning models can be divided into three major categories: representation-based, interaction-based, and hybrid (Guo et al., 2016). Representation-based models construct a fixed-dimensional vector representation for both the question and the candidate answer separately and then perform matching within the latent space. Interaction-based models compute the interaction between each individual term of question and candidate answer sentences where an interaction can be identity or syntactic/semantic similarity. Hybrid models combine both interaction and representation models. They consist of a representation component that combines a sequence of words into a fixed-dimensional representation and an interaction component. These components could occur in parallel or serial. In this section we will review the structure of the proposed deep neural models and specify the type of model according to the mentioned categories.

6.1 Representation-based Models

Yu et al. (2014) proposed a generative neural network-based model for binary classification of each question/answer pair as related or not. This model captures the semantic features of question and answer sentences. Each sample is represented with a triple \((q_i, a_{ij}, y_{ij})\) where \(q_i \in Q\) is question, \(a_{ij}\) is a candidate answer for question \(q_i\), and label \(y_{ij}\) shows whether \(a_{ij}\) is a correct answer for \(q_i\) or not. For each answer, a related question is generated and then the semantic similarity of generated question and the given question is captured by using dot product. This similarity is used for predicting whether the candidate answer is a correct answer for given question or not. The probability of the answer being correct is formulated as:

\[
P(y = 1|q, a) = \sigma(q'^{T} Ma + b)
\]

where \(q' = Ma\) is the generated question. The model is trained by minimizing the cross entropy of all labelled data QA pairs as:

\[
L = -\log \prod_n p(y_n|q_n, a_n) + \frac{\lambda}{2} \|\theta\|^2_F
\]

\[
= -\sum_n y_n \log \sigma(q_n^{T} f Ma_n + b) + (1 - y_n) \log (1 - \sigma(q_n^{T} M a_n + b)) + \frac{\lambda}{2} \|\theta\|^2_F
\]

where \(\|\theta\|^2_F\) is the Frobenius norm of \(\theta\).

Each sentence is modeled by bag of word and bigram approaches. In bag of words model, a sentence is represented by averaging embeddings of all the words (except stop words) within it. The bigram model has the ability to capture features of bigrams independent of their positions in the sentence. As architecture of bigram model is shown in Figure 2, one convolutional layer and
one pooling layer is used for modeling the sentence in bigram model. Every bigram is projected into a feature value $c_i$, which is computed as:

$$c_i = \tanh (T \cdot s_{i:i+1} + b)$$  \hspace{1cm} (15)

where $s$ is the vector representation of the sentence. All bigram features are combined in average pooling layer and finally a full-sentence representation with the same dimensionality as the initial word embeddings is produced by the following equation:

$$s = \sum_{i=1}^{|s|} \tanh (T_Ls_i + T_Rs_{i+1} + b)$$  \hspace{1cm} (16)

Severyn and Moschitti (2015) proposed a framework for answer sentence selection. They divided their task into two main subtasks: (1) mapping the original space of words to a feature space encoding, and (2) learning a similarity function between pairs of objects. They used a Convolutional Neural Network (CNN) architecture for learning to map input text, either query or document, to a vector space model. For the second part, they used the idea of noisy channel approach to find a transformation of document to be as close as possible to the query: $\text{Sim}(x_q, x_d) = x_q^T M x_d$. To this end, they used a neural network architecture to train the similarity matrix $M$. According to Figure 3, the vector representation of query and document that are derived from the first CNN model are jointly fed to the second CNN to train and build the similarity matrix.

Wang and Nyberg (2015) used a multilayer stacked Bidirectional Long Short-term Memory (BiLSTM) for answer sentence selection task. As represented in Figure 4, a sequence of word2vec representation of question and answer sentence terms are fed to this model. Symbol, $< S >$, is placed between question $q$ and answer $a$ for distinguishing the question and answer. Among different Recurrent Neural Network (RNN) architectures, stacked BiLSTM is chosen as first bidirectional RNN extracts the contextual information of question and answer pair from both directions in other words it uses the future
information, second stacked BiLSTM provides better results due to its ability in extracting higher levels of abstraction, and third LSTM is a more complicated RNN block which mitigates the gradient vanishing problem of standard RNNs. The final output of each time step indicates whether the given answer is a correct answer for the question or not.

In this model the stacked BiLSTM relevance model is combined by Gradient Boosted Regression Tree (GBDT) method for exact matching the proper nouns and cardinal numbers in question and answer sentences. 

Tay et al. (2017) proposed Holographic-dual LSTM (HD-LSTM), a binary classifier model for QA task. As is shown in Figure 5, HD-LSTM consists four major parts. In representation layer, two multi-layered LSTMs denoted as Q-LSTM and A-LSTM are used for learning the representations of the question and answer. A holographic composition is used for measuring the similarity of the outputs of Q-LSTM and A-LSTM. Finally, a fully connected hidden
layer is used for performing the binary classification of QA pair as correct or incorrect. Each part of HD-LSTM is described in the following:

1. Learning QA Representations: Instead of learning word embeddings, pre-trained weights of SkipGram embeddings [Mikolov et al., 2013] denoted as $W$ are used in this layer. Embeddings of both the question and the answer sequences are fed into Q-LSTM and A-LSTM. Representation of question and answer are generated in the last hidden output of Q-LSTM and A-LSTM.

2. Holographic Matching of QA pairs: Embeddings of the question and answer which learned in previous layer are passed into the holographic layer and circular correlation of vectors is used for modeling the similarity of them. Similarity of question and answer is modeled by the following equation:

$$[qa]_k = \sum_{i=0}^{d-1} qa(k+i) \mod d$$

$qa = F^{-1}(F(q) \odot F(a))$

where $F$ is Fast Fourier transform, $q$ is question, $a$ is answer, and $d$ is dimension of embeddings. In the above equation, question and answer embeddings must have the same dimension.

3. Holographic Hidden Layer: This is a fully connected dense layer. Input and output of this layer are $[qa, Sim(q,a), X_{feat}]$ and $h_{out}$, respectively. $(X_{feat})$ is word overlap feature, and $Sim(q,a)$ is bilinear similarity function between $q$ and $a$ which is defined as:

$$Sim(q,a) = q^T M a$$

where $M \in R^{n \times n}$ is a similarity matrix between $q \in R^n$ and $a \in R^n$. Concatenation of $Sim(q,a)$ with $[qa]$ makes the model perform worse. So, in order to mitigate this weakness $(X_{feat})$ is concatenated to make model work better.
Tan et al. (2016) proposed a basic model called QA-LSTM, shown in Figure 6 for sentence matching. According to this figure, in the basic model, word embeddings of question and answer sentences are fed into a BiLSTM network. A fixed size representation is obtained for each sentence in three different ways: (1) concatenating the last output of both directions, (2) average pooling and max pooling over all the outputs of the BiLSTM, and finally, (3) using the cosine similarity, semantic matching between question and answer sentences is scored. LSTM is a powerful architecture in capturing long range dependencies, but it suffers from not paying attention to local n-grams. Although convolutional structures pay more attention to local n-grams, they do not consider long range dependencies. Therefore each of the CNN and RNN blocks has their own pros and cons. Three different variants of the basic QA-LSTM are proposed in this work which one of them belongs to the hybrid models and is described in section 6.3. In the following, two other variants of QA-LSTM, belonging to the representation-based models, are described.

1. Convolutional pooling LSTM: As is shown in Figure 7, pooling layer is replaced with a convolutional layer for capturing richer local information and on top of this layer an output layer is placed for generating representation of the input sentence. Representation of the input sentence is generated by the following equations:

   \[
   C = \tanh(W_{cp}Z), \quad [O_j] = \max_{1 \leq i \leq L}[C_{j,i}]
   \]

   where \( Z \in R^{k|h} \times L \) and \( m \)-th column is generated by concatenation of the \( k \) hidden vectors of BiLSTM centralized in the \( m \)-th token of the sequence, \( L \) is length of the sequence, and \( W_{cp} \) is the network parameter.
2. Convolutional-based LSTM: Architecture of this model is shown in Figure 8. In this model, word embeddings are first fed to a CNN for retrieving the local $n$-gram interactions at the lower level. Output of the convolution is then fed into the BiLSTM network for capturing long-range dependencies. Max pooling is used over the output of the BiLSTM for producing the sentence representation. Output of the convolution layer, named $X$, is obtained by the following equation:

$$X = \tanh(W_{cb}D)$$

(21)

where $D \in \mathbb{R}^{kE \times L}$ is input of this model and column $l$ of $D$ is concatenation of $k$ word vectors of size $E$ centered at the $l$-th word.
6.2 Interaction-based Models

*Yin et al.* (2016) proposed a Basic CNN (BCNN) model and three Attention-based CNN (ABCNN) models for text matching. ABCNN models belong to the hybrid category and are described in section 6.3. In the following, architecture of BCNN is described.

**Basic CNN (BCNN):** Architecture of this model is shown in Figure 9. This model is based on the Siamese architecture (Bromley et al., 1993). The model provides representation of each sentence using convolutional, \( w - ap \) pooling and \( all - ap \) pooling layers, and then compares these two representations with logistic regression. Different layers in BCNN are as follows:

1. **Input layer:** Each sentence is passed to the model with a \( d_0 \times s \) matrix, where \( d_0 \) is the dimension of word2vec (Mikolov et al., 2013) embedding.
of each word and \(s\) is maximum length of the two sentences (the shorter sentence is padded to the larger sentence length).

2. Convolution layer: Embedding of words within a sentence with window size of \(w\) are concatenated and represented as \(c_i \in \mathbb{R}^{w \times d_0}\) where \(0 < i < s + w\) (\(s\) is length of the sentence). Then each \(c_i\) is converted to \(p_i\) by the following equation:

\[
P_i = tanh(Wc_i + b)
\]

let \(W \in \mathbb{R}^{d_1 \times w \times d_0}\) be the convolution weights, and \(b \in \mathbb{R}^{d_1}\) be the bias.

3. Average pooling layer: This model utilizes two types of average pooling, namely \(\text{all} - \text{ap}\) and \(\text{w} - \text{ap}\), for extracting the robust features from convolution. \(\text{All} - \text{ap}\) pooling is used in the last convolution layer and calculates average of each column. \(\text{W} - \text{ap}\) pooling is used in the middle convolution layers and calculates average of each \(w\) consecutive columns.

4. Output layer: In the output layer logistic regression is applied to final representations in order to classify the question and answer sentences as related or not.

He and Lin (2016) proposed a model for QA task which consists of four major components. Architecture of the model is shown in Figure 10. Different components of this model are described below:

1. Context modeling: This is the first component and uses a BiLSTM for modeling context of each word.

2. Pairwise word interaction modeling: This component compares two hidden states of BiLSTM with Cosine, L2 Euclidean, and dot product distance measures:

\[
\text{CoU}(h_1, h_2) = \{\text{Cos}(h_1, h_2), \text{L2Euclid}(h_1, h_2), \text{DotProduct}(h_1, h_2)\}
\]

Output of this component is a cube with size \(\mathbb{R}^{13 \times |\text{sent}_1| \times |\text{sent}_2|}\), where \(|\text{sent}_1|\) and \(|\text{sent}_2|\) are the size of the first and the second sentences, respectively. For each pair of words 12 different similarity distances and one extra padding are considered.

3. Similarity focus: In this layer word interactions are assigned weights by maximizing the weight of the important word interactions. Output of this component is a cube named FocusCube and words identified as important have more weight in this cube.

4. Similarity classification: In this layer a CNN is used for finding the patterns of strong pairwise word interactions. Question and answer sentences in FocusCube are fed to this layer and a similarity score is computed.

Yang et al. (2016) proposed aNMM-1 and aNMM-2 neural matching models. ANMM-1 works in three major steps as follows:

1. Building QA matching matrix: Each cell in this matrix represents the similarity of corresponding question and answer words. Similarity is calculated by dot product of the normalized word embeddings.
2. Learning semantic matching: Various length of answer sentences results in variable size for QA matrix. To fix this problem, value shared weights method is used. In value shared weights method, each node is weighted based on its value where value of a node represents the similarity between two words. Input to the hidden layer for each question term is defined as follows:

\[ h_j = \delta \left( \sum_{k=0}^{K} w_k \cdot x_{jk} \right) \]  

(24)

where \( j \) is the index of the question term, \( w_k \) is the model parameter, and \( x_{jk} \) is the sum of all matching signals within the range \( k \) (the range of possible matching signals is divided to \( k \) equal bins, and each matching score is assigned to one bin).

3. Question attention network: An attention layer with question word embedding weights is applied to hidden states \( h_j \). Finally match score is computed by the following equation:
\[ y = \sum_{j=1}^{M} g_j \cdot h_j = \sum_{j=1}^{M} \frac{\exp(v \cdot q_j)}{\sum_{l=1}^{L} \exp(v \cdot q_l)} \cdot \delta \left( \sum_{k=0}^{K} w_k \cdot x_{jk} \right) \quad (25) \]

where \( v \) is model parameter and dot product of the question word embedding and \( v \) are fed to the softMax function.

In aNNM-2, more than one value-shared weights are used for each question answer matching vector then in the first hidden layer there are multiple intermediate nodes. As architecture of aNNM-2 is shown in the Figure 11, final output of the model \( y \) is defined as:

\[ y = \sum_{j=1}^{M} \tau(v \cdot q_j) \cdot \delta \left( \sum_{t=0}^{T} r_t \cdot \delta \left( \sum_{k=0}^{K} w_k t x_{jk} \right) \right) \quad (26) \]

where \( T \) is the number of nodes in hidden layer 1, \( r_t \) is the model parameter from hidden layer 1 to hidden layer 2, and \( \tau(v, q_j) \) is calculated as follows:

\[ \frac{\exp(v \cdot q_j)}{\sum_{l=1}^{L} \exp(v \cdot q_l)} \quad (27) \]

**Wan et al. (2016b)** proposed a recursive semantic matching model called Match-SRNN. According to Figure 12 which shows the architecture of Match-SRNN, Match-SRNN works in three major steps: In the first step word-level interactions are modeled. In the second step a special case of interaction between two prefixes of two different sentences (\( S_1[1:i] \) and \( S_2[1:j] \) ) is modeled as a function of the interaction between \( S_1[1:i-1] \) and \( S_2[1:j] \), \( S_1[1:i] \) and \( S_2[1:j-1] \), \( S_1[1:i-1] \) and \( S_2[1:j-1] \), and interaction between words \( w_i \) and \( v_j \). Then the equation for this special interaction is:

\[ h_{ij} = f(h_{i-1,j}, h_{i,j-1}, h_{i-1,j-1}, s(w_i, v_j)) \quad (28) \]
where $h_{ij}$ is the interaction between $S1[1:i]$ and $S2[1:j]$. This recursive way of modeling the interaction helps to capture the long-term dependencies between two sentences. In the third step a linear function is used for measuring the matching score of two given sentences. More details about these steps are below.

1. Neural tensor network: The interaction between two words $w_i$ and $v_j$ is captured by a neural tensor network according to the following equation:

$$s_{ij} = F\left(u_i^T T_{i,j} u_j + W \frac{u_i}{u_j} + b\right)$$

(29)

where $s_{ij}$ is a vector representation of the similarity between $w_i$ and $v_j$ words, $T_i$ is one slice of the tensor parameters, $W$ and $b$ are parameters and $F(Z) = \text{max}(0, Z)$.

2. Spatial RNN: In this layer, GRU is used as an RNN because of its easy implementation for implementing a Spatial-GRU which models the $h_{ij}$. Figure 13 shows architecture of the 1D-GRU and Spatial-GRU which is used in this work.

According to the right part in Figure 13 Spatial-GRU has four updating gates, and three reset gates. Function $f$ in the Spatial-GRU is computed as follow:

$$q^T = [h_{i-1,j}^T, h_{i,j-1}^T, h_{i-1,j-1}^T, s_{ij}^T]^T$$

(30)
\[ r_t = \sigma \left(W^{(r_t)}q + b^{(r_t)}\right), \quad r_d = \sigma \left(W^{(r_d)}q + b^{(r_d)}\right) \]

\[ \mathbf{r}^T = \left[r_T^T, r_t^T, r_d^T\right]^T \]

\[ z_i' = W^{(z_i)}q + b^{(z_i)}, \quad z_l' = W^{(z_l)}q + b^{(z_l)} \]
\[ z_t' = W^{(z_t)}q + b^{(z_t)}, \quad z_d' = W^{(z_d)}q + b^{(z_d)} \]

\[ [z_i, z_l, z_t, z_d] = \text{SoftmaxByRow} \left([z_i', z_l', z_t', z_d']\right) \]

\[ h_{ij}' = \phi \left(Ws_{ij} + U \left(r \odot [h_{i,j-1}^T, h_{i-1,j}^T, h_{i-1,j-1}^T]\right) + b\right) \]

\[ h_{ij} = z_t \odot h_{i,j-1} + z_l \odot h_{i-1,j} + z_d \odot h_{i-1,j-1} + z_i \odot h_{ij}' \]

3. Linear Scoring Function: Final matching score of two given sentences is computed by the equation: 
\[ M(S_1, S_2) = W^{(s)}h_{mn} + b^{(s)} \]
where \( h_{mn} \) is the global interaction between two sentences, and \( W^{(s)} \) and \( b^{(s)} \) are network parameters.

Devlin et al. (2019) proposed Bidirectional Encoder Representations from Transformers (BERT) model which is a language modeling neural network. BERT has a multi-layered bidirectional architecture, in which each layer is a transformer encoder. Transformer was proposed by Vaswani et al. (2017) and has an encoder-decoder architecture. The same decoder segment of transformer model is used in BERT. BERT is used in a wide range of NLP tasks, including QA, natural language inference, and text classification. BERT is pre-trained on large corpora by two different approaches, namely masked language model and next sentence prediction, and then fine-tuned on each specific task based on the application. Architecture of BERT including both pre-training and fine-tuning steps is shown in Figure 14. Input of BERT is a sequence of input representation of words. Input representation of each word is built by summing its token embeddings, segment embeddings, and position embeddings as shown in Figure 15. In the QA domain, a (CLS) token is used in the first position of the sequence, then the question and the candidate answer followed by a (SEP) token are placed in the sequence, respectively. Output of BERT is encoded representation for each token.

Li et al. (2019) proposed BERTSel which fine-tunes BERT model for answer selection task as is shown in Figure 16. Each question \((q)\) with a correct answer \((p)\) and a wrong answer \((n)\) are fed to this model \((q, p, n)\). In the fine-tuning step, the question once with the correct answer \((q, p)\) and once with the wrong answer \((q, n)\) is passed to BERT. In this model, encoded representation of [CLS] token is passed to a fully-connected layer followed by a sigmoid function for predicting the matching score of given question and answer pair.
6.3 Hybrid Models

Wan et al. (2016a) proposed MV-LSTM for matching two sentences using representation of different positions of sentences. As shown in Figure 14, representation of different positions in each sentence is created and multiple tensors are created by calculating the interaction between different positions.
of these two sentences with different similarity metrics. Then a $k$-max pooling layer and a multi-layered LSTM are used for modeling the matching score of two given sentences. Architecture of MV-LSTM is explained in more details in following three steps:

1. Positional Sentence Representation: Positional sentence representation or representation of sentence at one position is obtained by BiLSTM. BiLSTM is used for capturing the long and short-term dependencies in one sentence. An LSTM layer similar to the implementation used in (Graves et al., 2013) is used here. Given a sentence $S = (x_0, x_1, ..., x_T)$, LSTM represents position $t$ of the sentence $h_t$ as follows:

   \[
   i_t = \sigma (W_{xi}x_t + W_{hi}h_{t-1} + b_i) \\
   f_t = \sigma (W_{xf}x_t + W_{hf}h_{t-1} + b_f) \\
   c_t = f_t c_{t-1} + i_t \tanh (W_{xc}x_t + W_{hc}h_{t-1} + b_c) \\
   o_t = \sigma (W_{xo}x_t + W_{ho}h_{t-1} + b_o) \\
   h_t = o_t \tanh (c_t)
   \]

   Utilizing the BiLSTM layer, two different representations $\hat{h}_t$ and $\tilde{h}_t$ are generated for each position and final representation of each position is considered as the concatenation of these two representations $[\hat{h}_t, \tilde{h}_t]$.

2. Interactions between two sentences: Cosine, bilinear, and tensor similarity functions are used in this step for modeling the interaction between two positions. Bilinear function which captures more complicated interactions compared to cosine is as follows:

   \[
   S(u, v) = u^T M v + b
   \]
where $b$ is bias and $M$ is a matrix for reweighting $u$ and $v$ in different dimensions. Tensor function models the interaction between two vectors more powerfully. It uses the following equation for modeling the interaction:

$$s(u, v) = f \left( u^T M^{[1:c]} v + W_{uv} \begin{bmatrix} u \\ v \end{bmatrix} + b \right)$$  \hspace{1cm} (33)

where $W_{uv}$ and $b$ are parameters, $M_i$ is one slice of the tensor parameter, and $f$ is rectifier function. Output of the cosine and bilinear similarities are interaction matrices while the output of tensor layer is an interaction tensor.

3. Interaction aggregation: Third step uses the interaction between different positional sentence representations in order to measure the matching score of two given sentences. $K$-max pooling is applied to extract a vector $q$ which includes the top $k$ values of matrix, or the top $k$ values of each slice of the tensor. A new representation $r$ is obtained by feeding the output of $k$-max pooling into a fully connected hidden layer. And finally, the matching score $s$ is obtained by the following function:

$$r = f(W_r q + b_r), s = W_s r + b_s$$  \hspace{1cm} (34)

where $W_r$ and $W_s$ are model parameters and $b_r$ and $b_s$ are biases.

Tan et al. (2016) proposed attentive LSTM, a variant of QA-LSTM model, for mitigating some problems of two other variants of QA-LSTM: convolutional-based LSTM and convolutional pooling LSTM. These two previous models, which are described in section 6.1, suffer from a common issue that happens when the answer is very long and contains a lot of not related words to the question sentence. Attention mechanism by considering the question in constructing the answer sentence’s representation can solve this issue. In this model attention mechanism works by learning weights for hidden vectors of BiLSTM. As shown in Figure 18 output of the BiLSTM is multiplied by a softMax weight, which is obtained from the question representation. Model gives more weight to each word of the answer, based on the information from question representation. Finally representation of answer sentence is obtained by the following equations:

$$m_{a,q}(t) = W_{am} h_a(t) + W_{qm} o_q$$  \hspace{1cm} (35)

$$s_{a,q}(t) \propto \exp \left( w_{ms}^T \tanh (m_{a,q}(t)) \right)$$

$$\tilde{h}_a(t) = h_a(t) s_{a,q}(t)$$

where $h_a(t)$ is the output vector of answer BiLSTM at time step $t$, $o_q$ is question representation, $W_{am}$, $W_{qm}$, and $W_{ms}$ are attention parameters, and $\tilde{h}_a(t)$ indicates the attention-based representation of $h_a(t)$.

Wang et al. (2016a) proposed four inner attention-based RNN models. These models try to mitigate the attention bias problem which traditional attention-based RNN models suffer from. In the following, first a traditional
attention-based RNN model and then four variants of inner attention-based RNN (IARNN) models are described.

1. Traditional attention based RNN models (OARNN): In OARNN first of all an RNN block is used for encoding sentences, and then attention weights from question embedding are used in generating answer sentence’s representation. This type of attention mechanism, which is done after learning embeddings, biases toward the later hidden states, because they contain more information than the nearer ones about the sentence. Architecture of OARNN is shown in Figure 19. This model is named OARNN (stands for outer attention-based RNN) as it adds the attention layer after RNN block. Last hidden layer or average of all hidden states are considered as representation of the question sentence, where the representation of answer is obtained by using attention weights from question representation.

2. Inner attention-based RNNs (IARNN): IARNN models are proposed to mitigate the bias problems of OARNN in generating representation of answer sentence. In these models, the attention weights are added before that RNN blocks generate hidden layers. Architecture of four different IARNN models are described in the following.
2.1. IARNN-WORD: Architecture of this model is shown in Figure 20. Representation of each word is generated using the question attention weights, then the whole sentence’s representation is obtained by using the RNN model. GRU is chosen among RNN blocks because it has less parameters and trains fast. Representation of the sentence is generated by weighted average of the hidden states $h_t$.

2.2. IARNN-Context: Due to the inability of IARNN-WORD model in capturing the multiple related words, in IARNN-Context, contextual information of answer sentence is fed into the attention weights. Architecture of this model is shown in the Figure 21.

2.3. IARNN-GATE: As GRU gates control the flow of the information in hidden stages, attention information is fed to these gates. Architecture of this model is shown in the Figure 22.

2.4. IARNN-OCCAM: This model is named after the Occam’s Razor which says: "Between the whole words set, fewest number of words which can represent the sentence must be chosen". Based on the type of the
question, different number of relevant words to the question are required for answering the question. For example "what" and "where" questions need smaller number of relevant words than "why" and "how" questions in answer sentence. This issue is handled in IARNN-OCCAM by using a regulation value. Therefore more sparsity should be imposed on the summation of the attention in "what" and "where" questions and a smaller number should be assigned to the regulation value in "why" and "how" questions. This regulation model just could be used in IARNN-context and IARNN-word models.

Yin et al. (2016) proposed four different attention-based variants of BCNN (ABCNN) for text-matching task. In the following, architecture of these ABCNN models are described.

– Attention-based CNN (ABCNN): Three different attention-based models are proposed in this work. In ABCNN-1, which is shown in the Figure 23, an attention matrix $A$ is generated by comparing each unit of two feature maps. Let $S_1$ and $S_0$ be feature maps representing a sentence. Each row in the matrix $A$ shows the attention distribution of corresponding unit in $S_0$ respect to $S_1$, and each column of $A$ represents the attention distribution of corresponding unit in $S_1$ respect to $S_0$. Then matrix $A$ is transformed to two attention feature map matrices with the same dimension of representation feature map. According to Figure 23 representation feature map and attention feature map are fed to the convolution layer as order-3 tensors. Given representation of two feature maps of sentences $i = 0, 1$ ($F_{i,r} \in \mathbb{R}^{d \times s}$), each cell in attention matrix ($A \in \mathbb{R}^{s \times s}$) is computed as follows:
A_{i,j} = \text{match-score}\left(F_{0,r}[; i], F_{1,r}[; j]\right) \quad (36)

where \( \frac{1}{(1+|x-y|)} \) is match-score function for inputs \( x \) and \( y \). Attention matrix \( A \) is converted to two given feature maps \( F_{0,a} \) and \( F_{1,a} \) by the following equations where \( W_0, W_1 \in \mathbb{R}^{d \times s} \) are model parameters to be learned.

\[
F_{0,a} = W_0 \cdot A^\top, \quad F_{1,a} = W_1 \cdot A \quad (37)
\]

A higher-level representation for the corresponding sentence is generated by passing these matrices to the convolution layer.

- **ABCNN-2**: In this architecture (shown in Figure 24) attention mechanism is applied to output of convolutional layers. Each cell in attention matrix \( A \) is calculated by comparing corresponding units from convolution outputs. Each row in convolution output matrix represents one unit of the given sentence. Attention weight of each unit is computed by summing all attention values of that unit. Attention weight of unit \( j \) in sentence \( i \) is shown with \( a_{i,j} \) and computed by:

\[
a_{0,j} = \sum A[j,:], \quad a_{1,j} = \sum A[; j] \quad (38)
\]

then the new feature map \( F_{i,r}' \in \mathbb{R}^{d \times s_i} \) is calculated with \( w - ap \) pooling as follows:

\[
F_{i,r}'[; j] = \sum_{k=j:w} a_{i,k} F_{i,r}[; k], \quad j = 1 \ldots s_i \quad (39)
\]

- **ABCNN-3**: As it is shown in Figure 25, ABCNN-3 combines two previous models by employing the attention mechanism before and after the convolution layer. Output of convolution layer has larger granularity than its input. That means if the input of the convolution layer has a word-level granularity, then its output has phrase-level granularity. Therefore in the ABCNN-1 model, attention mechanism is employed on smaller level of granularity than the ABCNN-2 model, and in the ABCNN-3, it is employed on two different levels of granularity.
Bian et al. (2017) proposed a model which estimates the relevance score $P(y|Q,A)$ between question ($Q$) and answer ($A$). As we see in Figure 26, this model consists of four major layers. First, word representation of each sentence is passed to an attention layer and then output of attention layer is compared by sentence representation. Output of comparison layers are passed to a CNN layer for aggregating and then matching score of two given sentences is obtained in this layer. These layers are described below.

1. **Word representation layer:** Word representations of question $q = (q_1, ..., q_l_q)$ and answer $a = (a_1, ..., a_l_a)$ are fed to the attention layer.
2. **Attention layer:** The aim of applying attention layer is finding the relevance between local text substructure of question and answer pairs. $h^a_q$ and $h^q_i$ are obtained in this layer by the following equations:

\[
 w^a_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{l_a} \exp(e_{ik})}, \quad w^q_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{l_q} \exp(e_{ik})}
\]  

(40)
where $e_{ij} = q_i . a_j$ and $w$ indicate attention weight. This attention model has two problems: First, only a small number of interactions between two sentences are related and the semantic relation is being ambiguous by considering irrelevant interactions. It is proper to consider just relevant interactions. Second, if one token from answer sentence doesn’t have any semantic matching with all the words from question sentence, it is better to omit that token. For tackling the mentioned problems, two filtering approaches, which are called $k$-max attention and $k$-threshold attention, are proposed. Implementation of these two filtering models in computing $h_{ja}$ is described below.

- $K$-max attention: This filtering model helps to discard irrelevant fragments, by sorting $w$ in decreasing order and preserving the top $k$ weights and setting other weights to zero.
- $K$- threshold attention: This filtering just preserves attention weights which are larger than $K$. This filtering works by omitting the units with no semantic matching in another sentence.

3. Comparison: Each sentence and weighted version of the other sentence which is obtained in attention layer are compared in this layer. For example $a_j$ is compared with $h_{ja}$ by using comparison function $f$ as follows:
where \( t_{ja} \) represents the comparison result.

4. Aggregation: Comparison vectors of the previous layer for each sentence are aggregated using a one-layer CNN, and finally, the relevance score between question and answer sentences is computed by the following equation:

\[
\begin{align*}
    r_a &= \text{CNN} \left( \left[ t_{a1}^a, \ldots, t_{aL_a}^a \right] \right), \\
    r_q &= \text{CNN} \left( \left[ t_{q1}^q, \ldots, t_{qL_q}^q \right] \right) \\
    \text{Score} &= [r_a, r_q]^T W
\end{align*}
\]

[1] Wang et al. (2017) proposed Bilateral Multi-Perspective Matching Model (BiMPM), a paraphrase-based method for the QA task. In BiMPM, each sample is represented with \((P, Q, y)\), where \(P = (p_1, p_2, \ldots, p_M)\) is answer sentence with length \(M\), \(Q = (q_1, q_2, \ldots, q_N)\) is question sentence with length \(N\), and \(y = 0, 1\) is a label indicating whether the answer is related to the question or not. \(y = 1\) means \(P\) is a relevant answer for question \(Q\) and \(y = 0\) means \(P\) is not a relevant answer for question \(Q\). Figure 27 shows the architecture of BiMPM. BiMPM consists of five major layers which are described in the following.

1. Word representation layer: Each word is represented with a \(d\)-dimensional vector constructed by a word embedding and a character-composed embedding. Word embeddings are obtained from pre-trained GloVe [Pennington]
et al., 2014) or word2vec (Mikolov et al., 2013) embeddings. Character-composed embeddings are generated by feeding characters of words into an LSTM (Hochreiter and Schmidhuber, 1997).

2. Context representation layer: A BiLSTM is used in order to combine contextual information of a sentence with its representation.

3. Matching layer: In this layer, each contextual embedding of one sentence is compared with all the contextual representations of the other sentence using a multi-perspective matching operation. Also question and answer sentences are matched in two directions. Multi-perspective cosine matching function is defined as:

\[ M = f_m(v_1, v_2; W) \]  

where \( v_1 \) and \( v_2 \) are \( d \)-dimensional vectors, \( W \in \mathbb{R}^{l \times d} \) is trainable parameter and each perspective is controlled by one row of \( W \), and \( M \) is a \( l \)-dimensional vector. Each \( M_k \) is calculated as follows:

\[ M_k = \text{cosine}(w_k \circ v_1, w_k \circ v_2) \]

let \( w_k \) be \( k \)-th row of \( W \) and \( \circ \) be element-wise multiplication.

Four different matching strategies are proposed based on different \( f_m \) functions. These matching strategies are shown in Figure 28 and described just for one direction in the following.

- Full-Matching: Each forward time step representation of the answer sentence \( \overrightarrow{h}_p^i \) is compared with every forward time step representations of the question sentence \( \overrightarrow{h}_q^j \). This strategy is shown in Figure 28 (a).
- Maxpooling-Matching: Maximum similarity for each forward time step representation of the answer sentence with all the time steps of the forward representation of the question sentence is returned. This strategy is shown in Figure 28 (b).
- Attentive-Matching: Cosine similarity between each forward time step representation of the answer sentence \( \overrightarrow{h}_p^i \) and each forward time step representation of the question sentence \( \overrightarrow{h}_q^j \) is considered as attention weight. This strategy is shown in Figure 28 (c). Then the new representation of the question sentence \( Q \) called \( h_{i^{\text{mean}}} \) is generated by calculating the weighted average of its forward time steps representations by using attention weights. And finally, the matching vector for each time step representation of answer sentence is calculated with its corresponding attentive vector \( h_{i^{\text{mean}}} \).
- Max-Attentive-Matching: This strategy is different from attentive-matching strategy just in generating attentive vector \( h_{i^{\text{mean}}} \). Attentive vector here is the contextual embedding with the highest similarity. This strategy is shown in Figure 28 (d). Finally for each direction all of these strategies are applied for each time-step and eight generated vectors are concatenated and considered as the matching in that direction.
4. Aggregation layer: Two sequences of matching vectors of both sentences, obtained from matching layer, are fed into a BiLSTM. Then a fixed-length matching vector is obtained by concatenating the last four output vectors of two BiLSTMs.

5. Prediction layer: In this layer, \( P(y|P,Q) \) is predicted using a two layer feed-forward neural network followed by a softMax layer. The fixed length matching-vector is fed to this layer.

\[ \text{Wang and Jiang (2017)} \] proposed a compare-aggregate model for matching two sentences. This model for each pair of \( Q \) and \( A \) predicts a label \( y \) which shows whether the candidate answer \( A \) is a correct answer for question \( Q \) or not. According to the architecture of this model, which is shown in the Figure 29 this model consists four following major layer:

1. Preprocessing layer: This layer constructs an embedding for each word which represents the word and its contextual information. \( Q \) and \( A \) are inputs of this layer. A version of LSTM/GRU, which uses only the input gates, is applied for generating \( \overline{Q} \in \mathbb{R}^{l \times Q} \) and \( \overline{A} \in \mathbb{R}^{l \times A} \) matrices.

\[
\begin{align*}
\overline{Q} &= \sigma (W^iQ + b^i \odot e_Q) \odot \tanh (W^uQ + b^u \odot e_Q) \\
\overline{A} &= \sigma (W^iA + b^i \odot e_A) \odot \tanh (W^uA + b^u \odot e_A)
\end{align*}
\] (45)
where $W^a, W^u \in \mathbb{R}^{l \times d}$ and $b^i, b^u \in \mathbb{R}^d$ are parameters, and $(. \otimes e_X)$ generates a matrix by repeating the vector on the left for $X$ times.

2. Attention layer: This layer is applied on output of the previous layer. Attention-weighted vector $H \in \mathbb{R}^{l \times A}$ is obtained by the following equations. The $j^{th}$ column of $H$ indicates the part of $Q$ that best matches the $j^{th}$ word in $A$.

$$G = \text{softmax} \left( \left( W^g Q + b^g \otimes e_Q \right)^T A \right)$$

$$H = QG$$

where $W^g \in \mathbb{R}^{l \times l}$ and $b^g \in \mathbb{R}$ are parameters, and $G \in \mathbb{R}^{Q \times A}$ is the attention weight matrix.

3. Comparison layer: Embedding of each word $a_j$ in answer is matched with the corresponding attention weight $h_j$ and the comparison result is indicated with vector $t_j$. In this work, six different comparison functions are introduced.

- Neural Net (NN):
  $$t_j = f (\overline{a}_j, h_j) = \text{ReLU} \left( W \left[ \begin{array}{c} a_j \\ h_j \end{array} \right] + b \right)$$

- Neural Tensor Net (NTN):
  $$t_j = f (\overline{a}_j, h_j) = \text{ReLU} \left( a_j^T T^{(1:1)} h_j + b \right)$$

- Euclidean distance or cosine similarity (EucCos):
  $$t_j = f (\overline{a}_j, h_j) = \left[ \frac{\|a_j - h_j\|_2}{\cos (\overline{a}_j, h_j)} \right]$$
- Subtraction (Sub):

\[ t_j = f (\overline{a}_j, h_j) = (\overline{a}_j - h_j) \odot (\overline{a}_j - h_j) \] (50)

- Multiplication (Mult):

\[ t_j = f (\overline{a}_j, h_j) = \overline{a}_j \odot h_j \] (51)

- Submult + NN:

\[ t_j = f (\overline{a}_j, h_j) = \text{ReLU} \left( W \left[ \frac{(\overline{a}_j - h_j) \odot (\overline{a}_j - h_j)}{\overline{a}_j \odot h_j} \right] + b \right) \] (52)

Among these comparison functions NN and NTN do not capture the similarity well. EucCos may ignore some important information. Sub and Mult are similar to the Euclidean distance and Cosine similarity, and the last model is the combination of the Sub, Mult, and NN.

4. Aggregation: A one-layer CNN is used for combining \( t_j \) vectors. Output of the aggregation is \( r \in \mathbb{R}^{nl} \) which is used in the final classifier.

\[ r = \text{CNN} ([t_1, \ldots, t_A]) \] (53)

[Tay et al. (2018)] proposed Multi-Cast Attention Network (MCAN) for retrieval-based QA. Inputs of MCAN are two sentences: question \( q \) and document \( d \) sentences. As is shown in Figure 30, MCAN has five major layers. These layers are described in the following.

1. Input Encoder: Input sentences are fed to this network as one-hot encoded vectors and word embeddings are generated by passing through an embedding layer. Highway encoder like RNNs by using gating mechanism controls the flow of the information. A highway encoder layer is used for detecting important and not important words in given sentence. A single highway network is formulated as:

\[ y = H(x, W_H) \cdot T(x, W_T) + (1 - T(x, W_T)) \cdot x \] (54)

where \( H(\cdot) \) and \( T(\cdot) \) are one-layer affine transforms with ReLU and sigmoid activation functions, and \( W_H, W_T \in \mathbb{R}^{r \times d} \).

2. Co-Attention: In this layer a similarity matrix which denotes the similarity between each pair of words across both sentences is learned by the following formulations:

\[ s_{ij} = F(q_i)^T F(d_j) \] (55)
\[ s_{ij} = q_i^T M d_j \]
\[ s_{ij} = F[q_i; d_j] \]

where \( F \) could be a multi-layered perceptron.
2.1. Extractive Pooling: Max-pooling and mean-pooling are two variants of this type. Formulation of these two poolings are as below:

\[ q' = \text{Soft} \left( \max_{\text{col}}(s) \right)^\top q \quad \text{and} \quad d' = \text{Soft} \left( \max_{\text{row}}(s) \right)^\top d \]

\[ q' = \text{Soft} \left( \text{mean}(s) \right)^\top q \quad \text{and} \quad d' = \text{Soft} \left( \text{mean}_{\text{row}}(s) \right)^\top d \]

where Soft is softmax function, and \( d' \) and \( q' \) are co-attentive representations of the document and question. Performance of these poolings varies on different datasets, but in general max-pooling pays attention to words based on their maximum influence and mean-pooling pays attention to words based on their total influence on the words of the other sentence.

2.2. Alignment Pooling: Word pairs from two sentences are realigned in this pooling strategy. Co-attentive representations are learned as below:

\[ d'_i := \frac{\sum_{j=1}^{L_q} \exp(s_{ij})}{\sum_{k=1}^{L_d} \exp(s_{ik})} q_j \quad \text{and} \quad q'_j := \frac{\sum_{i=1}^{L_d} \exp(s_{ij})}{\sum_{k=1}^{L_d} \exp(s_{ik})} d_i \]

let \( d'_i \) be the sub-phrase of \( q \) which is aligned to \( d_i \).
2.3. Intra-attention: Intra-attention attempts to represent long-term dependencies in one sentence. Representation of each sentence is learned regardless of the other sentence. So, it is applied on both the document and the question separately. Co-attentive representations are learned as below:

\[ x'_i := \frac{\sum_{j=1}^{\ell} \exp(s_{ij}) x_j}{\sum_{k=1}^{\ell} \exp(s_{ik})} \]

where \( x'_i \) is Intra-attention representation of \( x_i \).

3. Multi-Cast Attention: This model utilizes all of the mentioned pooling functions. Following values are calculated for output of each co-attention function.

\[ f_c = F_c([\tau; x]), f_m = F_c(\tau \odot x), f_s = F_c(\tau - x) \]

where \( \tau \) denotes the co-attention representation of \( x \), and \( F_C \) is a compression function. In the above formulations \( \tau \) and \( x \) are compared by three different operators for modeling the difference between \( \tau \) and \( x \) from different perspectives. Difference between \( \tau \) and \( x \) is an \( n \)-dimensional vector which is compressed by a compression function to a scalar. Three different compression functions: sum, fully-connected layer, and Factorization Machines (FM) are used. As is shown in Figure 30 given a document question pair, co-attention with three different poolings (1) mean-pooling, (2) Max-pooling, (3) alignment-pooling are applied on pair of question and document and (4) Intra-attention is applied on document and question separately. 12 scalars are generated for each word and concatenated with word embedding. Then each word \( w_i \) is represented as \( w_i = [w_i; z_i] \) where \( z \in \mathbb{R}^{12} \) is output of multi-cast layer.

4. LSTM encoder: Casted representation of words of a sentence which are generated by multi-cast attention are fed to an LSTM encoder, and a meanMax pooling is applied on hidden states of the LSTM. Casted representations of words helps the LSTM network with its knowledge about each sentence and between question and document, in extracting long-term dependencies.

\[ H_i = \text{LSTM}(u, i), \forall i \in [1, 2, \ldots, 1] \]

\[ H = \text{MeanMax} [h_1 \ldots h_l] \]

5. Prediction layer and optimization: Given representation of the document and the question, prediction is computed by using two-layer highway network and a softMax layer as follows:

\[ y_{out} = H_2 (H_1 ([x_q; x_d; x_q \odot x_d; x_q - x_d])) \]

\[ y_{pred} = \text{softmax} (W_F \cdot y_{out} + b_F) \]

where \( H_1 \), and \( H_2 \) are highway network layers with ReLU activation and \( W_F \in \mathbb{R}^{h \times 2}, b_F \in \mathbb{R}^2 \).
Yoon et al. (2019) proposed CompClip for predicting matching score \( (y) \) of given pair of question \( (Q = q_1, ..., q_n) \) and answer \( (A = a_1, ..., a_n) \). For improving the performance of CompClip, they have applied transfer learning technique by training it on question-answering NLI (QNLI) corpus (Wang et al., 2018). They have also used pointwise learning to rank approach for training this model. The most prominent feature of their work is using ELMo language model for achieving more meaningful contextual information of question and answer sentences. Architecture of CompClip consists of six layers, as is illustrated in Figure 31. These layers are described below:

1. Language model: Instead of using a word embedding layer, ELMo language model (Peters et al., 2018) is used for extracting contextual information of given sentence in a more efficient way. After applying ELMo language model, new representation of question and answer are denoted as \( L_Q \) and \( L_A \), respectively.

2. Context representation: This part of model learns the weight \( W \) for extracting contextual information of given sentence and generating its contextual representation by following equations:

\[
\begin{align*}
\bar{Q} &= \sigma (W^Q \bar{Q}) \odot \tanh (W^w \bar{Q}) \\
\bar{A} &= \sigma (W^A \bar{A}) \odot \tanh (W^w \bar{A})
\end{align*}
\]  

(61)

after applying Elmo language model, \( Q \) and \( A \) are replaced by \( L_Q \) and \( L_A \), respectively.

3. Attention: Attentional representation of question \( H^Q \) and answer \( H^A \) sentences are generated utilizing dynamic-clip attention (Bian et al., 2017) as follows:
4. Comparison: Each term form question and answer sentences are compared by element-wise multiplication of question and answer representations with \( H^Q \) and \( H^A \), respectively.

\[
C^Q = \mathbf{X} \odot H^Q, (C^Q \in \mathbb{R}^{L \times A})
\]

\[
C^A = \mathbf{Q} \odot H^A, (C^A \in \mathbb{R}^{L \times Q})
\]

5. Aggregation layer: For aggregating outputs of comparison layer, a CNN with \( n \)-types of filters is employed. Aim of this layer is computing the matching score (score) between question and answer as follows:

\[
R^Q = \text{CNN}(C^Q), R^A = \text{CNN}(C^A)
\]

\[
\text{score} = \sigma \left( [R^Q; R^A]^\top W \right)
\]

6. Latent clustering: In order to improve performance of model, latent clustering information of corpus is used for obtaining cluster information of question and answer sentences. Latent clustering information of sentences is generated using the following equations:

\[
p_{1:n} = \mathbf{s}^\top \mathbf{W} \mathbf{M}_{1:n}
\]

\[
\overline{p}_{1:k} = k - \text{max-pool}(p_{1:n})
\]

\[
\alpha_{1:k} = \text{softmax}(\overline{p}_{1:k})
\]

\[
M_{LC} = \sum_k \alpha_k \mathbf{M}_k
\]

where \( \mathbf{M}_{1:n} \in \mathbb{R}^{d \times n} \) is latent memory and \( W \in \mathbb{R}^{d \times d'} \) is parameter of the model. Latent clustering function \( f \) is applied on context representation of question and answer sentences and cluster information of question and answer, \( M^Q_{LC} \) and \( M^A_{LC} \), vectors, are generated, respectively. \( M^Q_{LC} \) and \( M^A_{LC} \) are concatenated with \( C^Q \) and \( C^A \) which results in generating \( C^Q_{\text{new}} \) and \( C^A_{\text{new}} \) representations, respectively. \( C^Q_{\text{new}} \) and \( C^A_{\text{new}} \) could be considered as input of aggregation layer.

\[
C^Q_{\text{new}} = [C^Q; M^Q_{LC}], C^A_{\text{new}} = [C^A; M^A_{LC}]
\]
7 Available Results from the Literature

As mentioned in Section 2, WikiQA (Yang et al., 2015), TREC-QA (Wang et al., 2007), MovieQA (Tapaswi et al., 2016), InsuranceQA (Feng et al., 2015), and Yahoo! (Wan et al., 2016b,a) are the main datasets that have been used.

Table 5 Results of Different Models on WikiQA Dataset

| Model                   | Setting          | MAP   | MRR   |
|-------------------------|------------------|-------|-------|
| Yih et al. (2013)       | LCLR             | 0.5993| 0.6986|
| Le and Mikolov (2014)   | PV               | 0.5110| 0.5160|
| Yu et al. (2014)        | CNN              | 0.6190| 0.6281|
| Yang et al. (2015)      | Word Count       | 0.5707| 0.6266|
|                         | Wgt Word Count   | 0.5961| 0.6515|
|                         | PV-Cnt           | 0.5976| 0.6058|
|                         | CNN-Cnt          | 0.6520| 0.6652|
| He and Golub (2016)     |                 | 0.6391| 0.7060|
| dos Santos et al. (2016)|                 | 0.689 | 0.696 |
| Miao et al. (2016)      |                 | 0.689 | 0.707 |
| Wang et al. (2016b)     |                 | 0.706 | 0.723 |
| Hao et al. (2016)       |                 | 0.701 | 0.718 |
| R: Yin et al. (2016)    | BCNN, one-conv   | 0.6629| 0.6813|
|                         | BCNN, two-conv   | 0.6593| 0.6793|
| I: He and Lin (2016)    |                 | 0.7090| 0.7254|
| I: Li et al. (2019)     | BERTSel (base)   | 0.770 | 0.753 |
|                         | BERTSel (large)  | 0.875 | 0.860 |
| H: Wang et al. (2016a)  | IARNN-word       | 0.7098| 0.7234|
|                         | IARNN-Occam(word) | 0.7121| 0.7318|
|                         | IARNN-context    | 0.7182| 0.7339|
|                         | IARNN-Occam(context) | 0.7341| 0.7418|
|                         | IARNN-Gate       | 0.7258| 0.7394|
|                         | GRU              | 0.6581| 0.6691|
|                         | OARNN            | 0.6881| 0.7013|
| H: Yin et al. (2016)    | ABCNN-1, one-conv | 0.6810| 0.6979|
|                         | ABCNN-1, two-conv| 0.6855| 0.7025|
|                         | ABCNN-2, one-conv| 0.6885| 0.7054|
|                         | ABCNN-2, two-conv| 0.6879| 0.7068|
|                         | ABCNN-3, one-conv| 0.6914| 0.7127|
|                         | ABCNN-3, two-conv| 0.6921| 0.7108|
| H: Bian et al. (2017)   | listwise         | 0.746 | 0.759 |
|                         | with k-max       | 0.754 | 0.764 |
|                         | with k-threshold | 0.753 | 0.764 |
| H: Wang et al. (2017)   | BiMPPM           | 0.718 | 0.731 |
| H: Wang and Jiang (2017)| NN               | 0.7102| 0.7224|
|                         | NTN              | 0.7349| 0.7456|
|                         | EucCos           | 0.6740| 0.6882|
|                         | Sub              | 0.7019| 0.7151|
|                         | Mult             | 0.7433| 0.7545|
|                         | SUBMULT+NN       | 0.7332| 0.7477|
| H: Yoon et al. (2019)   | Comp-Clip        | 0.714 | 0.732 |
|                         | Comp-Clip + LM   | 0.746 | 0.762 |
|                         | Comp-Clip + LM + LC | 0.764 | 0.784 |
|                         | Comp-Clip + LM + LC + TL | 0.834 | 0.848 |
for evaluating text-based QA systems. In this section, we report the results of different models on the mentioned datasets to have a comparison on the quality of the state-of-the-art models. It has to be mentioned that considering a large number of models reviewed in this paper, it is not possible to reimplement all of them to have a comprehensive comparison and we only report the results based upon their availability.

Table 5 reports the results of different representation-based (R), interaction-based (I), and hybrid (H) methods on the WikiQA dataset and compares it with other baseline models.

As can be seen BERTSel (Li et al., 2019) achieved the best results over all methods on the WikiQA dataset in MRR and MAP metrics. Although this interaction-based technique is the best state-of-the-art model in the field, comparing the rest of models, we can see that the general performance of hybrid models are better than interaction-based models and the next best results are all from the hybrid models.

Table 6 reports the results of different models which are described in Section 6 as well as their baseline methods on TREC-QA dataset. According to this table, the proposed model by Yoon et al. (2019) which uses ELMo language model, latent clustering, as well as transfer learning achieved best results over all models on the TREC-QA dataset in MRR. The BERTSel (Li et al., 2019) model achieved the best result in MAP.

Table 6: Results of Different Models on TREC-QA Dataset.

| Model | Setting | MAP  | MRR  |
|-------|---------|------|------|
| Cui et al. (2005) | | 0.4271 | 0.5259 |
| Wang et al. (2007) | | 0.6029 | 0.6852 |
| Heilman and Smith (2010) | | 0.6091 | 0.6917 |
| Wang and Manning (2010) | | 0.5951 | 0.6951 |
| Yao et al. (2013) | | 0.6307 | 0.7477 |
| Feng et al. (2015) | Architecture-II | 0.711 | 0.800 |
| Wang and Ittycheriah (2015) | | 0.746 | 0.820 |
| dos Santos et al. (2016) | | 0.7530 | 0.8511 |
| Meng and Li (2016) | | 0.779 | 0.848 |
| Rao et al. (2016) | | 0.801 | 0.877 |
| R: Yih et al. (2013) | LR | 0.6818 | 0.7616 |
| | BDT | 0.6940 | 0.7894 |
| | LCLR | 0.7092 | 0.7700 |
| R: Yu et al. (2014) | TRAIN bigram + count | 0.7058 | 0.7800 |
| | TRAIN-ALL bigram + count | 0.7113 | 0.7846 |
| | TRAIN unigram + count | 0.6889 | 0.7727 |
| | TRAIN-ALL unigram + count | 0.6934 | 0.7677 |
| | TRAIN unigram | 0.5387 | 0.6284 |
| | TRAIN-ALL unigram | 0.5470 | 0.6329 |
| | TRAIN bigram | 0.5476 | 0.5476 |
| | TRAIN-ALL bigram | 0.5693 | 0.6613 |
| R: Yang et al. (2015) | Word Count | 0.5707 | 0.6266 |
| | Wgt Word Count | 0.5961 | 0.6515 |
| R: Severyn and Moschitti (2015) | TRAIN | 0.7329 | 0.7962 |
| | TRAIN-ALL | 0.7459 | 0.8078 |
Performance of different models from Section 6 and their baselines on Yahoo! dataset is reported in Table 7. One representation-based model [Tay et al., 2017], two interaction-based models [Wan et al., 2016b; Li et al., 2019], and one hybrid model [Wan et al., 2016a] are evaluated on the Yahoo! dataset. As can be seen, Bi-Match-SRNN, proposed by Wan et al. (2016b) and BERTSel, proposed by Li et al. (2019), outperforms other models in P@1 and MRR metrics, respectively. Except BERTSel, which has superior performance on all datasets, this is the only dataset in which an interaction-based model, namely Bi-Match-SRNN, performs better than hybrid model.

Table 8 reports the results of different models on Insurance-QA dataset. Among three categories of deep models (representation-based, interaction-based, and hybrid models) hybrid models achieve the best accuracy on Insurance-QA dataset too. Proposed model by Wang and Jiang (2017) with SUBMULT+NN
Table 7 Results of Different Models on Yahoo! Dataset

| Model                     | Setting         | P@1  | MRR  |
|---------------------------|-----------------|------|------|
| Random Guess              |                 | 0.2  | 0.4570 |
| Okapi BM-25               |                 | 0.2250 | 0.4927 |
| CNN                       |                 | 0.4725 | 0.6323 |
| CNTN                      |                 | 0.4654 | 0.6687 |
| LSTM                      |                 | 0.4875 | 0.6829 |
| NTN-LSTM                  |                 | 0.5448 | 0.7369 |
| and Walker et al. (1995)  | BM25            | 0.579 | 0.726 |
| Socher et al. (2011)      | RAE             | 0.398 | 0.652 |
| Hu et al. (2014)          | ARC-1           | 0.581 | 0.756 |
|                            | ARC-2           | 0.766 | 0.869 |
|                            | Deep Match      | 0.452 | 0.679 |
| Qu and Huang (2015)       | CNTN            | 0.626 | 0.781 |
| Yin and Schütze (2019)    | MultiGranCNN    | 0.725 | 0.840 |
| Palangi et al. (2016)     | LSTM-RNN        | 0.690 | 0.822 |
| Wan et al. (2016a)        | MV-LSTM         | 0.591 | 0.765 |
| Pang et al. (2016)        | MatchPyramid-Tensor | 0.764 | 0.867 |
| R: Tay et al. (2017)      | HD-LSTM         | 0.5969 | 0.7347 |
| Wan et al. (2016b)        | Match-SRNN      | 0.785 | 0.879 |
|                            | Bi-Match-SRNN   | 0.790 | 0.882 |
| L: Li et al. (2019)       | BERTSel (base)  | -    | 0.942 |
|                            | BERTSel (large0)| -    | 0.938 |
| H: Wan et al. (2016a)     | MV-LSTM-Cosine  | 0.739 | 0.852 |
|                            | MV-LSTM-Bilinear| 0.751 | 0.860 |
|                            | MV-LSTM-Tensor  | 0.766 | 0.869 |

comparison function on TEST1, and with Mult comparison function on TEST2 achieves the best accuracy.

8 Conclusion

In this paper, we provided a comprehensive review of the state-of-the-art methods on text-based QA systems. We first introduced the general architecture of QA systems, and then proposed a categorization for existing publications in the field. In the first step, publications are divided to two classes: information retrieval-based techniques, and deep learning-based techniques. We reviewed the main methods from both categories and highlighted deep learning-based approaches in more detail by following the well-know categorization for neural text matching, namely representation-based, interaction-based, and hybrid models. The existing publications with the deep learning perspective are categorized in these classes. We also reviewed available datasets that are widely used for training, validating and testing text-based QA methods. The available results from different techniques on these datasets are presented in the paper to have a naive comparison on the techniques.
# Table 8 Results of Different Models on Insurance-QA Dataset

| Model | Setting | TEST1 | TEST2 |
|-------|---------|-------|-------|
| Bag-of-word | | 0.321 | 0.322 |
| Metzler-Bendersky IR model | | 0.351 | 0.368 |
| Feng et al. (2015) | CNN | 0.628 | 0.692 |
| Feng et al. (2015) | CNN with GESD | 0.653 | 0.610 |
| dos Santos et al. (2016) | | 0.678 | 0.603 |
| R: Tan et al. (2016) | QA-LSTM (head/tail) | 0.536 | 0.510 |
| R: Tan et al. (2016) | QA-LSTM (avg pooling, k=50) | 0.557 | 0.524 |
| R: Tan et al. (2016) | QA-LSTM (max pooling, k=1) | 0.631 | 0.580 |
| R: Tan et al. (2016) | QA-LSTM (max pooling, k=50) | 0.666 | 0.637 |
| R: Tan et al. (2016) | Conv-pooling LSTM (c=4000, k=1) | 0.646 | 0.622 |
| R: Tan et al. (2016) | Conv-pooling LSTM (c=200, k=1) | 0.674 | 0.635 |
| R: Tan et al. (2016) | Conv-pooling LSTM (c=400, k=50) | 0.675 | 0.644 |
| R: Tan et al. (2016) | Conv-based LSTM (|h|=200, k=50) | 0.661 | 0.630 |
| R: Tan et al. (2016) | Conv-based LSTM (|h|=400, k=50) | 0.676 | 0.644 |
| R: Tan et al. (2016) | QA-CNN (max-pooling, k = 3) | 0.622 | 0.579 |
| H: Tan et al. (2016) | Attentive CNN (max-pooling, k = 3) | 0.633 | 0.602 |
| H: Tan et al. (2016) | Attentive LSTM (avg-pooling k=1) | 0.681 | 0.622 |
| H: Tan et al. (2016) | Attentive LSTM (avg-pooling k=50) | 0.678 | 0.632 |
| H: Tan et al. (2016) | Attentive LSTM (max-pooling k=50) | 0.690 | 0.648 |
| H: Wang et al. (2016a) | IARNN-word | 0.671 | 0.616 |
| H: Wang et al. (2016a) | IARNN-Occam (word) | 0.696 | 0.637 |
| H: Wang et al. (2016a) | IARNN-context | 0.667 | 0.631 |
| H: Wang et al. (2016a) | IARNN-Occam (context) | 0.689 | 0.651 |
| H: Wang et al. (2016a) | IARNN-Gate | 0.701 | 0.628 |
| H: Wang et al. (2016a) | GRU | 0.532 | 0.581 |
| H: Wang et al. (2016a) | OARNN | 0.661 | 0.602 |
| H: Wang and Jiang (2017) | NN | 0.749 | 0.724 |
| H: Wang and Jiang (2017) | NTN | 0.750 | 0.725 |
| H: Wang and Jiang (2017) | EucCos | 0.702 | 0.679 |
| H: Wang and Jiang (2017) | Sub | 0.713 | 0.682 |
| H: Wang and Jiang (2017) | Mult | 0.752 | 0.734 |
| H: Wang and Jiang (2017) | SUBMULT+NN | **0.756** | 0.723 |

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