Tracing Origins: Coref-aware Machine Reading Comprehension

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Abstract

Machine reading comprehension is a heavily-studied research and test field for evaluating new pre-trained models and fine-tuning strategies, and recent studies have enriched the pre-trained models with syntactic, semantic and other linguistic information to improve the performance of the model. In this paper, we imitated the human’s reading process in connecting the anaphoric expressions and explicitly leverage the coreference information to enhance the word embeddings from the pre-trained model, in order to highlight the coreference mentions that must be identified for coreference-intensive question answering in QUOREF, a relatively new dataset that is specifically designed to evaluate the coreference-related performance of a model.

We used an additional BERT layer to focus on the coreference mentions, and a Relational Graph Convolutional Network to model the coreference relations. We demonstrated that the explicit incorporation of the coreference information in fine-tuning stage performed better than the incorporation of the coreference information in training a pre-trained language models.

1 Introduction

Machine reading comprehension (MRC), a task that automatically identifies the candidate answering from some context for the given questions, is widely used in information retrieving, search engines, etc. Several datasets on MRC that limited the answer to one single word or phrase are compiled, including TREC (Voorhees and Harman, 2003), SQuAD (Rajpurkar et al., 2018), NewsQA (Trischler et al., 2017), SearchQA (Dunn et al., 2017), and QuAC (Choi et al., 2018), and intensive efforts were made to surpass the human performance on these datasets, including the pre-trained models (Devlin et al., 2019; Liu et al., 2019; Yang et al., 2019) or the ensemble fined models outperforming the human, in particular SQuAD (Lan et al., 2020; Yamada et al., 2020; Zhang et al., 2020b).

Human texts, especially long texts, are abound in deictic and anaphoric expressions that refer to the entities in the same text. These deictic and anaphoric expressions, in particular, constrains the generalization of the models trained without explicit awareness of the coreference. QUOREF dataset (Dasigi et al., 2019) is specifically designed to validate the performance of the models in coreferential reasoning, in that “78% of the manually analyzed questions cannot be answered without coreference” (Dasigi et al., 2019). The example in Table 1 shows that the answers to the two questions cannot be directly retrieved from the sentences due to the anaphoric pronoun he that refers to the antecedent Frankie. This coreference resolution is required to achieve the task in machine reading com-
prehension in the SQuAD-style QUOREF dataset.

Pre-trained models, including BERT QA, RoBERTa QA and XLNet QA, that were pre-trained through self-supervised language modeling objectives like masked language modeling, perform rather poorly in the QUOREF dataset. We argue that the pre-trained models did learn the background knowledge for coreference resolution but didn’t learn adequately the coreference information required for the coreference-intensive reading comprehension tasks because in the human reading process, “anaphoric resolution requires a reader to perform a text-connecting task across textual units by successfully linking an appropriate antecedent (among several prior antecedents) with a specific anaphoric referent (Pretorius, 2005)” and the direct instruction on anaphoric resolution elevated the readers’ comprehension of the text (Bau mann, 1986), and the pre-trained language models only captured the semantic representations of the words and sentences, and didn’t explicitly perform such text-connecting in the specific coreference-intensive reading comprehension task, thus they didn’t learn enough knowledge to solve the problems based on the simple self-supervised language modeling tasks during pre-training.

Explicitly injecting external knowledge such as linguistics and knowledge graph entities, has been shown effective to broaden the scope of the pre-trained models’ capacity, which are often known as X-aware pre-trained models (Zhang et al., 2020a; Liu et al., 2020; Kumar et al., 2021). It is plausible that we may imitate the anaphoric resolution process in human’s anaphoric resolution and explicitly made the text-connecting task in our fine-tuning stage.

As an important medium to reflect the relationship between words or phrases, coreference resolution that clusters the mentions of the same entity within a given text is an active field in NLP (Kirstain et al., 2021; Joshi et al., 2020), with neural networks taking the lead in the coreference resolution challenges. The incorporation of the coreference resolution results in the pre-training to obtain the coref-informed pre-trained models, such as CorefBERT and CorefRoBERTa (Ye et al., 2020), had shown positive improvements on the QUOREF dataset, a dataset that is specially designed for measuring the models’ coreference capability, but were still considerably below the human performance.

In this paper, we made a different attempt to solve the coreference resolution to complete the anaphoric resolution process in the reading comprehension. We proposed a fine-tuned coref-aware that directly instructed the model to learn the coreference information by connecting the anaphoric expression clusters. Our model can be roughly divided into four major components: 1) pre-trained model component. We used the contextualized representations from the pre-trained models as the token embeddings for the downstream reading comprehension tasks. 2) coreference resolution component. NeuralCoref, an extension to the Spacy, was applied here to extract the mention cluster from the passage. 3) relation-enhanced graph-attention network. We used a graph neural network to obtain the graph representation of the context that enhanced the relations among the coreference clusters. 4) fusing layers. We applied three methods in incorporating the coreference knowledge: additive attention (Britz et al., 2017), dot product attention and GNN (Graph Neural Network)+auto-regressive layer.

In this paper, we demonstrated that by simulating the human behavior in explicitly connecting the anaphoric expressions to the antecedent entities and fusing the coreference knowledge into the model, our performance surpassed that of the pre-trained coref-models on the QUOREF dataset.

2 Background and related work

Recent studies on machine reading comprehension mainly relies on the neural network approaches. Before the prevalence of the pre-trained models, the main focus was to guide and fuse the attentions between questions and paragraphs in their own models, in order to gain better global and attended representation (Huang et al., 2018; Hu et al., 2018; Wang et al., 2018).

After the advent of the BERT (Devlin et al., 2019), there were two trends in solving the machine reading comprehension. The first trend was to develop better pre-trained models that captured the representation of contexts and questions (Liu et al., 2019; Yang et al., 2019; Lewis et al., 2020), and more datasets on question answering were compiled, including NewsQA (Trischler et al., 2017), SearchQA (Dunn et al., 2017), and QuAC (Choi et al., 2018) to increase the difficulty in this task. Efforts had also been made on enriching the pre-trained models with specific syntactic/semantic information (Ye et al., 2020; Zhang et al., 2020b). Another trend was to fine-tune the pre-trained model
and added additional layers to incorporate task-specific information to gain better representation, in particular the coreference information (Ouyang et al., 2021; Liu et al., 2021).

3 Coref-aware Machine Reading Comprehension

Our model consists of four parts, namely, pre-trained models, coreference resolution, graph encoder and fusing layer, as shown in Figure 1. Context in the machine reading comprehension task is first processed by coreference resolution model to explicitly identify the underlying coreference clusters. Then the clusters are processed into a coreference matrix that labels the individual cluster. Meanwhile, the context are tokenized by the tokenizer defined in the pre-trained model to retrieve the embeddings for each token. Our model used the coreference matrix to construct a graph neural network with the edges corresponding to the coreference relations. The graph representation in the graph neural network then concatenated with the embeddings of the context, and finally fed into the classifier to calculate the start/end span of the question.

3.1 Coreference Resolution

Coreference resolution is the process that identifies the expressions that refers to the same entity, clusters them together as coreference clusters, and locates their start positions. For example, after coreference resolution for the text "Losing his nerve, Frankie calls up his employers to tell them he wants to quit the job," we obtained two mention clusters [Frankie: [his, Frankie, his, he], his employers: [his employers, them]], as shown in Figure 2.

As pre-trained models use subwords in their tokenization, for the input sequence \(X = \{x_1,...,x_m\}\) of length \(n\), the words \(W = \{w_1,...,w_n\}\) obtained from the coreference tokenization are mapped to the corresponding subwords (tokens) \(T = \{t_1,...,t_k\}\) from the tokenizer in the pre-trained models, with one word contains one or more than one subwords. Then we constructed a coreference array with the following rule:

\[
\text{coref}(i) = \begin{cases} 
0 & \text{if tokens}[i] \in S_m, \\
n & \text{if tokens}[i] \notin S_m,
\end{cases}
\]

where \(i\) is the position of the token, \(S_m\) is a set of all tokens in the coreference mentions, \(n\) is the order number of the mention cluster and \(n \geq 1\). Tokens in the same mention cluster have the same order number \(n\) in the coreference array.

3.2 Graph Neural Network

We used the standard relational graph convolutional network (RGCN) (Sejr Schlichtkrull et al., 2018) to obtain the graph representation of the context enriched with coreference information. We used the coreference matrix and the word
embeddings to construct a directed and labeled graph \( G = (V, E, R) \), with nodes (word) \( v_i \in V \), edges (relations) \( (v_i, r, v_j) \in E \), where \( r \in R \) is one of the two relation types (1 indicates coreference relation; 2 indicates global relation), as shown in Figure 3.

The constructed graph is then fed into the RGCN, with the differentiable message passing and the basis decomposition to reduce model parameter size and prevent overfitting:

\[
    h_i^{l+1} = \sigma \left( W_0 h_i^l + \sum_{r \in R} \sum_{j \in N_i^r} \frac{1}{c_{i,r}} W_r^{(l)} h_j^{(l)} \right),
\]

\[
    W_r^{(l)} = \sum_{b=1}^B a_{rb}^{(l)} V_b^{(l)},
\]

where \( N_i^r \) denotes the set of neighbor indices of node \( i \) under the relation \( r \in R \), \( c_{i,r} \) is the normalization constant, and \( W_r^{(l)} \) is a linear combination of basis transformation \( V_b^{(l)} \) with coefficient \( a_{rb}^{(l)} \).

### 3.3 Coreference-enhanced Attention

In addition to the Graph Neural Network (GNN) method, we also explored the possibility of using the self-attention mechanism (Vaswani et al., 2017) to explicitly add a BERT layer, incorporate the coreference information into the attention heads and guide the model to identify the mentions in the cluster as the same entity.

We used two methods to fuse the coreference information and the original embeddings from the pre-trained model: additive attention fusing and dot product attention fusing (multiplication). Given the coreference array \( A = \{m_1, 0, m_1, 0, m_2, 0, m_3, 0, m_3, m_1\ldots\} \), where \( m_n \) denotes the nth mention cluster, and 0 denotes no mentions, the enriched attention for additive attention fusing is formulated as:

\[
    Attention(Q, K, V) = \text{Softmax} \left( \frac{QK^T}{\sqrt{d_k}} \| A \right) V,
\]

\[
    head_i = Attention(QW_i^Q, KW_i^K, VW_i^V),
\]

where \( Q, K, V \) are the query, key and value respectively, \( d_k \) is the dimension of the keys, and \( W_i \) is trainable parameter. For dot product (multiplication) fusing, it is formulated as:

\[
    Attention(Q, K, V) = \text{Softmax} \left( \frac{QK^T}{\sqrt{d_k}} \odot A \right) V,
\]

\[
    head_i = Attention(QW_i^Q, KW_i^K, VW_i^V),
\]

where we calculate the dot product of \( \frac{QK^T}{\sqrt{d_k}} \) and the coreference array \( A \).

### 3.4 Integration

A machine reading comprehension task expects the model to output the start and end positions of the answer. We fuse the hidden state of nodes \( v_i \) in the last layer of RCGN and the embeddings from the pre-trained models and calculate the start/end positions of the answer.

\[
    E = FC(E_{prLM} || E_{gnn}),
\]

\[
    P_s = \arg \max (\text{softmax}(W_s S)),
\]

where \( E_{prLM} \) denotes the embeddings from the pre-trained language model, \( E_{gnn} \) denotes the embeddings from the graph encoder, \( P_s \) denotes the predicted start positions, \( W_s \) denotes the weight matrix and \( S \) denotes the text feature. Following the practice of Ye et al. (2020) in handling multiple answers for the same question, we use the cross
entropy to calculate the losses for each answer if the question has multiple answers:

\[ L_n = FC(E_{prLM}, n), \]
\[ L_s = \sum_n H(p_s^i, q_s^i), \]
\[ L_e = \sum_n H(p_e^i, q_e^i), \]
\[ L_{\text{total}} = \text{avg}(L_s + L_e + H(L_n, n)), \]

where \( n \) denotes the answer count, \( L_n \) denotes the loss in predicting the answer count, \( L_s \) denotes the total loss of start positions, \( L_e \) denotes the total loss of end positions and \( L_{\text{total}} \) denotes the combined total loss.

### 4 Experiments

#### 4.1 Model Settings

We developed three models based on the sequence-to-sequence Transformer architecture. The pre-trained RoBERTa-large was used as the base model and then we used the following three methods to fine-tuned it: 1) Coref-GNN: feeding the coreference information into a GNN and then fuse the representations; 2) Coref-ConcatAtt: concatenate the coreference information with the self-attention; 3) Coref-MultiAtt: calculate the dot product of the coreference information with the self-attention. We used the results for CorefRoBERTa (Ye et al., 2020) as our base lines.

#### 4.2 Setup

Our coreference resolution was implemented in Spacy (Honnibal and Montani, 2017) and NeuralCoref. NeuralCoref is an extension for Spacy that is trained on the OntoNotes coreference resolution dataset, which identifies the coreference clusters in the text as mentions, and locates their start positions.

The neural network implementation was implemented in PyTorch (Paszke et al., 2019) and Hugging Face Transformers (Wolf et al., 2020). We used the embeddings of the pre-trained language models, with the relational graph convolutional network implemented in Deep Graph Library (DGL) (Wang et al., 2020). We used Adam (Kingma and Ba, 2015) as our optimizer, and the learning-rate was \( \{1e-5, 2e-5, 3e-5\} \). We trained each model for \{4, 6\} epochs and selected the best checkpoints on the development dataset with Exact match and F1 scores. All experiments were run on two TITAN RTX GPU, each with 24GB memory.

#### 4.3 Tasks and Datasets

Our evaluation was performed on the QUOREF dataset (Dasigi et al., 2019). The dataset contains a train set with 3,771 paragraphs and 19,399 questions, and a validation set with 454 paragraphs and 2,418 questions. The test set is not publicly available for evaluation.

#### 4.4 Results

We quantitatively evaluated the three methods and reported the standard metrics: exact match score (EM) and word-level F1-score (F1) (Rajpurkar et al., 2016).

As shown in Table 2, compared with the base model CorefRoBERTa, the performance of our models improved significantly. In particular, CorefMultiAtt performed best with 5.12%, 4.38% improvements in Exact Match and F1 score respectively. CorefGNN and CorefConcatAtt also showed consistent improvements.

### 5 Analysis

#### 5.1 Ablation Study

As shown in Table 2, compared with RoBERTaLARGE, our methods added only a component that explicitly incorporated the coreference information, and the three methods we used all exhibited considerable improvements over the base lines. Compared with RoBERTaLARGE, CorefConcatAtt and the CorefMultiAtt added a BERT layer, which added over 12M parameters.
Ross is the child of Trish and Heroin Bob... he also begrudgingly goes on a road trip to a punk rock concert with his only friend, Crash, as well as Crash’s friend Penny.

Ross is the child of Trish and Heroin Bob... Ross also begrudgingly goes on a road trip to a punk rock concert with Ross only friend, Crash, as well as Crash’s friend Penny.

What is the name of the friend of Heroin Bob’s son?

Penny

Crash

Crash

After the song was completed, they wanted to play it to Rihanna, but Blanco was skeptical about the reaction towards the song because of its slow sound. After StarGate played it to her, they called Blanco from London and told him that she liked the song: ‘Rihanna’s flippin’ out.

After the song was completed, the keyboards wanted to play the song to Rihanna, but Benny Blanco was skeptical about the reaction towards the song because of the song slow sound. After StarGate played it to Rihanna, the keyboards called Benny Blanco from London and told Benny Blanco that Rihanna liked the song: ‘Rihanna’s flippin’ out.

Who liked a song?

Blanco

Rihanna

Rihanna

For the CorefGNN method, we added one hidden layer in GNN and two linear layers to convert the feature dimensions, with around 68.7K params in total. Our predictions are that intuitively with more focuses on the coreference clues, the models performs better on the task that requires intensive coreference resolution, as we had explicitly increased the attention weights to connect the words in the same coreference mention clusters. However, the overall performance of the models is also limited by the performance of the coreference component we use.

5.2 Case studies

To understand the model’s performance beyond the automated metrics, we analyse our predicted answers qualitatively. Table 3 compares the representative answers predicted by our models and RoBERTa. These examples demonstrate that, enhancing with the coreference information by connecting the anaphoric expression with its antecedents, such as the connection from his to Ross in the first example and the connection from she to Rihanna in the second example, our model accurately predicts the entity name among several names in the context, which the RoBERTa model fails to uncover.
5.3 Error analysis

To understand why the model fails to predict the correct answer, we analyse several error cases. Table 4 shows two types of errors. The first one is caused because the coreference resolution model fails to connect its with the antecedents, despite that the second Gilman is correctly connected to Rockwell "Rocky" Gilman and resolved accordingly. The second one is more complicated, which shows that our models fails to perform relatively long-chained reasoning. To correctly answer the second question, it requires that the model should understand the fact that Mathew Knowles is the father of Beyoncé and Beyoncé’s last name is the same as her father’s.

6 Conclusion

In this paper, we presented intuitive methods to solve conference-intensive machine reading comprehension tasks by following the reading process of human that connects anaphoric expressions with explicit instructions. We demonstrated that our fine-tuned methods were superior to the pre-trained models that incorporated the coreference information in the pre-trained stage. As the fine-tuned methods relied on the coreference resolution supplied by other scholars, their performance was also constrained by the coreference resolution models. In addition, we introduced the GNN-based coreference graph that demonstrated promising comparable performance with other two methods, which could be enriched with more edge types to imitate the human reasoning in the future.

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