Adaptive Active Learning for Coreference Resolution

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Abstract

Training coreference resolution models require comprehensively labeled data. A model trained on one dataset may not successfully transfer to new domains. This paper investigates an approach to active learning for coreference resolution that feeds discrete annotations to an incremental clustering model. The recent developments in incremental coreference resolution allow for a novel approach to active learning in this setting. Through this new framework, we analyze important factors in data acquisition, like sources of model uncertainty and balancing reading and labeling costs. We explore different settings through simulated labeling with gold data. By lowering the data barrier for coreference, coreference resolvers can rapidly adapt to a series of previously unconsidered domains.

1 Introduction

Linguistic expressions are coreferent if they refer to the same entity. The task of clustering coreferent mentions is known as coreference resolution. Through identifying coreferent expressions in the text, the model can learn the relationship between entities. Recently, neural models achieve state-of-the-art results in coreference resolution (Lee et al., 2017; Joshi et al., 2020; Wu et al., 2020). These models are usually trained and evaluated on OntoNotes 5.0 (Pradhan et al., 2013). While new resolvers have improved results on OntoNotes, they may not immediately generalize to other datasets. Across domains, there are differences in content, writing style, and annotation guidelines (Figure 1). On new datasets, the model needs to be trained on copious amount of labeled in-domain data (Poot and van Cranenburgh, 2020; Bamman et al., 2020).

Despite expensive annotation costs, adapting coreference resolvers is still an important problem. Mention clustering has numerous applications, such as uncovering information about proteins in biomedicine (Kim et al., 2012) and distinguishing entities in legal documents (Gupta et al., 2018). If a coreference resolver could quickly adapt to a new domain, this would benefit urgent scenarios like clinical trials and court cases.

To reduce annotation time and cost, active learning finds the most relevant examples to label (Settles, 2009). Zhao and Ng (2014) apply active learning to domain adaptation in coreference resolution. However, their approach relies on heavy feature engineering to project instances from different domains into the same space. Moreover, like prior work (Gasperin, 2009; Miller et al., 2012), their strategy involves pairwise annotations. The issue with pairwise annotations is that labeling each pair of spans in the document is expensive and infeasible. Li et al. (2020) overcome this issue through discrete annotations. Instead of providing feedback on whether two spans are coreferent, the annotator directly labels the antecedent of a span. While discretizing annotations decreases labeling costs, their approach relies on optimizing pairwise links. They require repeated conversions between discrete annotations and pairwise links, which causes inefficiency and may introduce inaccurate links.

Beyond incompatibility between model input and user annotation, there are other inherent problems in active learning for coreference resolution. For simpler tasks like classification, active learning typically targets the examples with highest predic-

Figure 1: The span “his work” is not annotated in OntoNotes because singletons are not labeled. In QB-Coref, this span is important for coreference resolution because trivia questions often discuss literary works.
tive uncertainty (Lewis and Gale, 1994). If the model is uncertain about its prediction, then more information should be queried about that example. For coreference resolution, the source of uncertainty is less obvious. Ambiguity could stem from either mention detection, mention clustering, or a combination of both. Another overlooked issue is the cost associated with reading documents. While labeling spans from the same document minimizes reading time, labeling spans from multiple documents may relieve model uncertainty.

Our paper advances prior work in active learning for coreference resolution. We focus on domain adaptation by transferring a model finetuned on OntoNotes to different datasets. With this framework, we make the following contributions:

1. We apply discrete annotations (Li et al., 2020) to a memory-efficient incremental clustering model (Xia et al., 2020) so that the model optimizes on mention clusters, rather than pairwise links. (Section 3.1).
2. Prior work only focus on uncertainty in mention linking. We analyze different sources of uncertainty in the coreference resolver to improve active learning (Section 3.2).
3. We investigate the trade-off between labeling and reading costs. While Miller et al. (2012) has compared sampling spans to sampling documents, our study offers more insight toward sampling trade-offs to adapt models for new domains (Section 3.3).

Our contributions enable rapid data creation for transferring coreference resolution models to a variety of domains distinct from existing resources.

2 End-to-end Coreference Resolution

This section explains background information for understanding our work in active learning. Recent neural models show impressive automation in coreference resolution (Lee et al., 2017). A widely-used model is c2f-coref (Lee et al., 2018). The model’s task is to assign an antecedent \( y \) to mention span \( x \). The set \( \mathcal{Y} \) of possible antecedent spans consists of dummy antecedent \( \epsilon \) and all spans preceding \( x \). If span \( x \) has no antecedent, then \( x \) is assigned to the dummy antecedent \( \epsilon \). Given entity mention \( x \), the model learns a distribution over its candidate antecedents in \( \mathcal{Y} \):

\[
P(Y = y) = \frac{\exp \{ s(x, y) \}}{\sum_{y' \in \mathcal{Y}} \exp \{ s(x, y') \}},
\]

The scores \( s(x, y) \) are computed by the model’s pairwise scorer (Appendix A.1).

The training data only provides gold coreference clusters, so the best antecedent of each span is a latent variable. Suppose that a document \( d = (x_i)_{i=1}^n \) is a sequence of \( n \) spans. Let \( \text{GOLD}(x_i) \) be the set of spans in gold cluster of \( x_i \). If \( x_i \) has no annotated gold cluster, then \( \text{GOLD}(x_i) = \{ \epsilon \} \). During training, the c2f-coref model first ranks spans based on unary mention scores \( s_m \). To reduce computation, the top \( \Theta(n) \) spans are pruned. Given document \( d \) with annotated gold clusters, the model optimizes the marginal log-likelihood of possibly correct antecedents implied by the span’s gold cluster.

\[
f_{\text{PAIR}}(d) = \log \prod_{i=1}^n \sum_{\hat{y} \in \mathcal{Y}(x_i) \setminus \text{GOLD}(x_i)} P(\hat{y}),
\]

where \( \mathcal{Y}(x_i) \) are the possible antecedents of \( x_i \). Li et al. (2020) conduct active learning by applying discrete annotations to the c2f-coref model. In section 3.1, we show how the c2f-coref model is incompatible with discrete annotations. We instead feed discrete annotations to an incremental variant of the c2f-coref model.

2.1 Incremental Clustering

We introduce the incremental clustering model (Xia et al., 2020), which will be useful for active learning in later sections. The original motivation for incremental clustering is to reduce memory usage. While the c2f-coref model requires up to \( \Theta(n^2) \) memory, incremental clustering only needs \( \Theta(1) \) space. For incremental clustering, we want to assign mention span \( x \) to an entity cluster \( c \) from the set of observed clusters \( C \).

\[
P(C = c) = \frac{\exp \{ s(x, c) \}}{\sum_{c' \in C} \exp \{ s(x, c') \}},
\]

Instead of scoring antecedents against spans with the pairwise scorer, the model scores clusters against spans. As the algorithm processes spans in the document, each span is either placed in a cluster from \( C \) or added to a new cluster (Appendix A.1). If gold clusters are provided for training, then let \( y_i^* \) be the most recent antecedent of \( x_i \) in \( \text{GOLD}(x_i) \).

\[
y_i^* = \arg\max_{x_j \in \mathcal{Y}(x_i) \setminus \text{GOLD}(x_i)} j.
\]
The model optimizes the marginal log-likelihood of the most recent antecedent’s cluster,

\[ f_{\text{CLUSTER}}(d) = \log \prod_{i=1}^{n} P(c_{y^*_i}), \]

where \( c_{y^*_i} \) is the cluster assigned to \( y^*_i \) by the model.

Xia et al. (2020) reuse weights of the pairwise scorer, mention scorer, and encoder from Joshi et al. (2020) to initialize the incremental algorithm. Through these modifications, memory usage is greatly reduced and average \( F_1 \) remains relatively the same. The reduction in memory complements active learning’s goal for minimizing resources during model development. More importantly, the model optimizes for span-cluster likelihood, rather than span-span likelihood, which naturally lends itself to discrete annotations (Section 3.1).

2.2 Datasets

The OntoNotes 5.0 dataset is most commonly used for training and evaluating coreference resolvers (Pradhan et al., 2013). The dataset contains text from sources like news articles, talk shows, and telephone conversations. Only non-singleton mentions are annotated. Recent work have publicly released models that are already fine-tuned on OntoNotes (Joshi et al., 2020; Xia et al., 2020; Wu et al., 2020). With ubiquitous access to these models, it is more realistic to adapt them rather than train a coreference resolver from scratch. Now, the goal is to transfer the model fine-tuned on OntoNotes to other domains. In this paper, we use active learning to adapt to PreCo and QBCoref.

PreCo The PreCo dataset is a large corpus of grade-school reading comprehension texts (Chen et al., 2018). Unlike OntoNotes, PreCo has annotated singleton mentions and there are fewer named entities. There are 37K training, 500 validation, and 500 test documents. Due to enormous size of training set, Chen et al. (2018) only analyze subsets of 2.5K documents. In our paper, we also reduce the training set to a random subset of 2.5K documents for faster active learning simulation.

QBCoref The QBCoref dataset contains trivia questions from quiz bowl tournaments (Guha et al., 2015). Quiz bowl questions are densely packed with entities from a variety of topics. Like PreCo, singleton mentions are annotated. Unlike other datasets, coreference resolution is difficult because of the idiosyncratic syntax. Examples include pronouns before first mention of named entities and ambiguous references like “this polity”. These long, complicated structures are unnatural for question answering but serve as challenging examples for coreference resolution. There are 240 training, 80 validation, and 80 test documents.

3 Adaptive Active Learning

While neural models have shown state-of-the-art results on OntoNotes, similar success may not be immediately achieved on other datasets because of shifts in domain or annotation standards (Poot and van Cranenburgh, 2020). Moreover, retraining a model from scratch for new domains is challenging if in-domain data is scarce. This makes coreference resolution infeasible for real-time applications in time-pressing situations. To avoid the nontrivial costs of labeling data, we can use active learning to find examples that most confuse the model.

In this section, we explore active learning for coreference resolution with simulated labeling from gold data. For our setting, the standard active learning cycle would proceed with the following steps. First, we begin with a source model that has all layers already fine-tuned on OntoNotes (Joshi et al., 2020; Xia et al., 2020; Wu et al., 2020). With ubiquitous access to these models, it is more realistic to adapt them rather than train a coreference resolver from scratch. Now, the goal is to transfer the model fine-tuned on OntoNotes to other domains. In this paper, we use active learning to adapt to PreCo and QBCoref.

3.1 Discrete Annotations

Prior active learning strategies sample pairs of spans and retrieve pairwise annotation (Miller et al., 2012; Sachan et al., 2015). However, annotating each pair of spans in a document is impractical. Instead of asking the annotator whether a pair of spans is coreferent, we could ask the annotator for the antecedent of a given span. By converting annotations from pairwise to discrete, the number of required annotations is significantly reduced.

Li et al. (2020) apply discrete annotations to the original c2f-coref model. An issue with their approach is that the c2f-coref model is incompat-
ible with discrete annotations. The model optimizes over likelihood between span and possible antecedents (Equation 2), but discrete annotations assign a single antecedent $y$ to span $x$. Their solution is to repeatedly update transitivity links: if span $x_i$ is an antecedent of span $x_j$ and span $x_j$ is an antecedent of span $x_k$, then span $x_i$ is an antecedent of span $x_k$. These updates slow down active learning and can easily introduce false links. If human annotators accidentally label the wrong antecedent for a span, this mistake will propagate throughout the entire document.

To bypass the transitivity link updates, we propose a novel solution by applying discrete annotations to the incremental variant of the c2f-coref model (Section 2.1). The incremental clustering model optimizes over the likelihood of a span belonging to a cluster (Equation 5). To train the algorithm, it only needs the most recent antecedent of the span, rather than all possibly correct spans. We do not need to keep track of the transitivity links. Thus, incremental clustering naturally lends itself to active learning with discrete annotations.

While Li et al. (2020) ask for the first mention, we ask for the most recent one to adapt to the training objective of incremental clustering. Furthermore, this keeps annotation more local, which would be beneficial on long documents. We then use incremental clustering to optimize over the batch of discrete annotations.

### 3.2 Uncertainty Sampling

A well-known active learning strategy is uncertainty sampling. A common measure of uncertainty is the entropy of the distribution in model’s predictions (Lewis and Gale, 1994). By labeling the examples with highest predictive entropy, we can reduce uncertainty in model’s prediction and improve overall accuracy. For text classification, finding uncertainty is straightforward. For coreference resolution, uncertainty could appear in multiple places, like mention detection or mention clustering. Lu and Ng (2020) observe that better mention detection leads to improved coreference resolvers. Thus, we should explore active learning based on different types of uncertainty.

To discuss various sources of uncertainty, we first formalize mention detection and clustering. Given span $x$, assume that $X$ is the random variable associated with whether $x$ is an entity mention. The variable $X$ can either signify that span $x$ is an entity mention (1), or not an entity mention (0). In Section 2, we assume that the cluster distribution $P(C)$ does not depend on $X$. This is because the coreference resolvers are usually trained on OntoNotes where no singleton mentions are annotated. So, $P(C) = P(C | X)$. For other datasets, singleton mentions are annotated (Section 2.2). In this paper, we analyze the following uncertainty sampling strategies:

- **ment-ent** Sample $k$ spans with highest mention detection entropy,
  \[
  H_{MENT}(x) = H(X) = -\sum_{i=0}^{1} P(X = i) \log P(X = i),
  \]
  where $X$ is the random variable associated with whether span $x$ is an entity mention. The probability $P(X)$ is computed from normalized mention scores $s_m$ (Equation 11). This strategy will sample spans that are not usually entities. If an annotator can clarify whether certain spans are entity mentions, the mention detector can learn to distinguish entities.

- **clust-ent** Sample $k$ spans with highest mention clustering entropy,
  \[
  H_{CLUST}(x) = H(C \mid X = 1) = -\sum_{c \in C} P(C = c \mid X = 1) \log P(C = c \mid X = 1).
  \]
  Like in OntoNotes, we assume that all spans are entity mentions for this strategy. The probability likelihood $P(C \mid X = 1)$ are computed from incremental clustering algorithm (Equation 3). Prior work focus on this type of entropy (Li et al., 2020). This strategy solely focuses on the scores from the clustering distribution without addressing scores from the detector.

- **cond-ent** Sample $k$ spans with highest conditional entropy,
  \[
  H_{COND}(x) = H(C \mid X) = \sum_{i=0}^{1} P(X = i) H(C \mid X = i) = P(X = 1) H(C \mid X = 1) = P(X = 1) H_{CLUST}(x).
  \]
We reach the last equation because there is no uncertainty in clustering \(x\) if \(x\) is not an entity mention. So, \(H(C \mid X = 0) = 0\). For conditional entropy, we are taking uncertainty of mention detection into account. This strategy is likely to sample spans like pronouns, which are obviously entity mentions yet difficult to cluster.

### Joint-ent
Sample \(k\) spans with highest joint entropy,

\[
H_{\text{JOINT}}(x) = H(X, C) = H(X) + H(C \mid X) = H_{\text{MENT}}(x) + H_{\text{COND}}(x).
\]

For joint entropy, we look at ambiguity in both detection and linking. We may sample spans that are difficult to detect as entity mentions and challenging to cluster. This sampling strategy most closely aligns to the uncertainty of the training objective.

### 3.3 Trade-off between Reading and Labeling

For coreference resolution, the annotator must read the document context to label the antecedent of a mention span. Thus, it would be inefficient for the user to annotate spans from different documents. However, restricting span sampling to the same document may cause redundant labeling. Prior work neglects the cost of reading documents. While Miller et al. (2012) compare sampling spans against sampling documents, their experiments simulate annotation with synthetic labels.

To understand the trade-off between reading and labeling, we explore different configurations with the number of annotated spans, \(k\), and the maximum number of documents being read, \(m\). Given source model \(h_0\) already fine-tuned on OntoNotes, we want to adapt \(h_0\) to a target domain through active learning. The steps of active learning for coreference resolution (Algorithm 1) are:

**Scoring** To sample \(k\) spans from the unlabeled data \(\mathcal{U}\) of the target domain, we first score spans based on a labeling criteria. Assume that we have a active learning strategy \(S\) that scores each span based on an acquisition model (Lowell et al., 2019). In our paper, the acquisition model is the model fine-tuned from the last cycle \(h_{t-1}\). The acquisition score quantifies the need for span’s label given active learning strategy and acquisition model.

**Reading** Typically, active learning would sample \(k\) spans with the highest acquisition score. Since we consider the number of read documents \(m\) as a parameter, we add this constraint to the ranking. The selected spans cannot belong to more than \(m\) different documents. To enforce this constraint, we find the documents of the \(m\) spans with highest acquisition score and only sample spans from those documents. Thus, the \(k\) sampled spans will only belong to at most \(m\) documents.

Our approach is similar to Miller et al. (2012) where they sample spans based on highest uncertainty and continue sampling from the same document until uncertainty is below a threshold. Then, they sample the most uncertain span from a different document. We modify their method because the uncertainty threshold is not feasible for domain adaptation as it varies for different datasets and models. So, we instead use the number of read documents to control document switching. Realistically, this parameter will be fixed after knowing the number of documents that can be read by the annotator during a labeling session.

**Labeling** After sampling \(k\) spans belonging to at most \(m\) documents, an oracle (e.g. human annotator or gold data) labels the antecedents with discrete annotations (Section 3.1).

**Fine-tuning** We combine the data labeled from the current cycle and all past cycles. Then, we fine-tune the source model \(h_0\) on the labeled data. Prior work show that fine-tuning the source model from scratch avoids warmstarting problems (Ash and Adams, 2019).

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**Algorithm 1 Active Learning for Coreference**

**Require:** Source model \(h_0\), Unlabeled data \(\mathcal{U}\), Active learning strategy \(S\), No. of cycles \(T\), No. of labeled spans \(k\), Max. no. of read docs \(m\)

1: Labeled data \(\mathcal{L} = \{\}\)
2: for cycles \(t = 1, \ldots, T\) do
3: \(a_x \leftarrow \text{Score span } x \in \mathcal{U} \text{ by } S(h_{t-1}, x)\)
4: \(Q \leftarrow \text{Sort (desc.) } x \in \mathcal{U} \text{ by scores } a_x\)
5: \(Q_m \leftarrow \text{Top-}m\text{ spans in } Q\)
6: \(D \leftarrow \{d_x \mid x \in Q_m\} \text{ where } d_x \text{ is doc of } x\)
7: \(\tilde{Q} \leftarrow \text{Filter } Q \text{ s.t. spans belong to } d \in D\)
8: \(Q_k \leftarrow \text{Top-}k\text{ spans in } \tilde{Q}\)
9: \(L_k \leftarrow \text{Label antecedents for } \tilde{Q}_k\)
10: \(\mathcal{L} \leftarrow \mathcal{L} \cup L_k\)
11: \(h_t \leftarrow \text{Fine-tune } h_0 \text{ on } \mathcal{L}\)

return \(h_T\)
Figure 2: Comparing active learning strategies across reading/labeling configurations. Each column varies in \(m\), the maximum number of read documents per cycle. Each row varies in \(k\), the number of annotated spans per cycle. For QBCoref, the number of read documents is fixed to five. For all experiments, the total number of spans sampled is 300 spans. The dashed line indicates the test accuracy from fine-tuning on full training dataset. Mention entropy outperforms other methods, but there are some cases where other strategies show greater gains in average F\(_1\).

4 Annotation Simulation

We simulate active learning with gold data for PreCo and QBCoref (Section 2.2). For each simulation, we repeat five runs with different random seed initializations. Our source model is the incremental clustering variant of c2f-coref. The model’s encoder is SpanBERT-large-cased. The SpanBERT encoder embeds pre-trained information about spans and span boundaries. We use the public, best checkpoint of the model already fine-tuned on OntoNotes (Xia et al., 2020). For model fine-tuning, we optimize with fixed parameter configuration (Appendix A.2). For model evaluation, we primarily look at average F\(_1\) score of MUC (Vilain et al., 1995), B\(^3\) (Bagga and Baldwin, 1998), and CEAF\(_{\phi}\) (Luo, 2005).

For PreCo, we run extensive experiments that trade-off the number of read documents \(m\) with the number of annotated spans \(k\) (Figure 2a). We vary \(m\) between one document, five documents, and an unconstrained number of documents. The unconstrained setting assumes that annotators can...
read unlimited documents. We vary $k$ between ten, twenty, and fifty spans. The total number of spans sampled is fixed to 300 spans. In most settings, mention entropy shows higher $F_1$. Interestingly, random sampling has advantage over mention entropy when the number of documents is unconstrained. While conditional and joint entropy are intuitive strategies, we observe significant drops in $F_1$ as more spans are sampled. Possibly, the coreference resolver only fine-tunes on entity mentions, so it will try to cluster all spans in the text. However, arbitrary spans are not entity mentions, and should not be clustered. By sampling by mention entropy, we improve the model’s mention detection, which is important for resolving coreference.

For QBCoref, we fix $m$ to five documents and vary $k$ between ten, fifty, and a hundred spans (Figure 2b). The total number of spans is set to 300 spans. We observe less fluctuation between the sampling strategies, but uncertainty sampling outperforms random sampling. When sampling ten spans per cycle, mention entropy has consistent higher average $F_1$. When sampling fifty or a hundred spans per cycle, other entropy sampling strategies perform better. The reason why conditional and joint entropy show higher $F_1$ on QBCoref could be because of the unique syntax of quiz bowl questions (Section 2.2). Also, when more spans are sampled, conditional and joint entropy select non-entities as well. This helps bypass the diversity problems that we observe with PreCo.

Recent work in neural active learning use pairwise penalty matrix to compare strategies (Ash et al., 2020). The matrix show results of two-sided $t$-tests over all pairwise comparisons (Figure 3). Given a specified dataset, $m$, $k$, and a cycle number, we look at the $F_1$ scores of each active learning strategy. We run a two-sided $t$ test between strategy $i$ and strategy $j$. If strategy $i$ outperforms strategy $j$ with statistical significance, we add 1 to the $(i, j)$ entry in the penalty matrix. Then, the entries penalty matrix are normalized. The last row shows columnwise averages. Mention entropy sampling shows lowest penalty among all results.

From these results, we conclude that mention entropy is better than random sampling. For some domains, sampling by joint or conditional entropy can further improve average $F_1$. Future work will focus on deciding the appropriate sampling strategy for a given domain and annotation setup.

5 Related Work

Gasperin (2009) present the first work on active learning for coreference resolution. However, the authors present negative results for probabilistic, pairwise classifiers: active learning is not more effective than random sampling. Miller et al. (2012) explore different settings for labeling. First, they sample the most uncertain pairs of spans across the entire corpus and retrieve labels for sampled pairs. Then, they sample the most uncertain documents and retrieve all coreference annotations for those documents. While the first approach outperforms random sampling, it is unrealistic because the annotator needs to read a different document to label a pair. Unfortunately, the second approach does not demonstrate the same gains.

The negative results from early work motivate further improvements in active learning for coreference resolution. Zhao and Ng (2014) emphasize active learning for domain adaptation of coreference resolution. They introduce the setting of training the coreference model on a source domain and then use active learning to quickly adapt it to target domains. Sachan et al. (2015) treat pairwise annotations as constraints in the optimization function. Finally, Li et al. (2020) make more improvements upon past work. They propose discrete annotations and mention clustering so that uncertainty of a span is computed over mention clusters, rather than antecedents. Moreover, they are the first to deploy active learning on neural, end-to-end coreference resolution models.

6 Conclusion

The issue of current coreference resolvers is the dependency on large, labeled data. We employ active learning to acquire data for existing models. Specifically, we transfer a model fine-tuned on OntoNotes, the “de facto” dataset for this task, over to different domains. For feasible active learning, we develop a new framework that uses discrete annotations and an incremental clustering model. With this framework, we address important issues in active learning for coreference resolution, like sources of uncertainty and reading costs. For future work, we look forward to experiments with real humans in the loop. Through user experiments, we hope to calibrate our metrics that account for the relative cost of reading an initial context, against providing incremental annotations on that same context.
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A Appendix

A.1 Neural Coreference Resolution

Pairwise scoring In the c2f-coref model, a pairwise scorer computes $s(x, y)$ to learn antecedent distribution $P(Y)$ (Equation 1). The model’s pairwise scorer judges whether span $x$ and span $y$ are coreferent based on their antecedent score $s_a$ and individual mention scores $s_m$.

$$s(x, y) = \begin{cases} 0 & y = \epsilon, \\ s_m(x) + s_m(y) + s_a(x, y) & y \neq \epsilon \end{cases}$$  \hspace{1cm} (10)

Suppose $g_x$ and $g_y$ are the span representations of $x$ and $y$, respectively. Mention scores and antecedent scores are then computed with feedforward networks $FFNN_m$ and $FFNN_e$.

$$s_m(x) = FFNN_m(g_x)$$  \hspace{1cm} (11)

$$s_c(x, y) = FFNN_e(g_x, g_y, \phi(x, y)).$$  \hspace{1cm} (12)

Lee et al. (2018) provide more details about the pairwise scorer and span pruning.

Incremental clustering To learn the distribution over clusters (Equation 3), the algorithm first creates a cluster representation $g_c$ that is an aggregate of span representations over spans that currently exist in the cluster (Equation 13). With cluster and span representations, individual spans and entity clusters are mapped into a shared space. Thus, we can compute $s(x, c)$ using the same pairwise scorer as before (Equation 10).

Suppose that $c^* = \arg \max_{c \in \mathcal{C}} s(x, c)$. Now, the algorithm makes one of two decisions:

1. If $s(x, c^*) > 0$, then $x$ is assigned to $c^*$ and update $g_{c^*}$ such that

$$g_{c^*} = s_e(c^*, x)g_{c^*} + (1 - s_e(c^*, x))g_x, \hspace{1cm} (13)$$

where $s_e$ is a learned weight.

2. If $s(x, c^*) \leq 0$, then a new entity cluster $c_x = \{x\}$ is added to $\mathcal{C}$.

The algorithm repeats these steps for each span $x_i$ in document $d$.

A.2 Fine-tuning Parameters

For model fine-tuning, we train for a maximum of fifty epochs and implement early stopping with a patience of ten epochs. We set top span pruning to 0.4, dropout to 0.4, gradient clipping to 10.0, and learning rate to 1e-4 for Adam optimizer. The hyperparameter configuration is based on results from Xia et al. (2020).