Adapting Coreference Resolution Models through Active Learning

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Coreference Resolution (CR)

The task of discovering spans of text that refer to the same entity

Source (Finance)

Traders said municipals were underpinned by influences, including the climb in Treasury issue prices. Also, municipal bonds lured buying because the stock market remains wobbly, traders contended. Mainly though, it was a favorable outlook for yesterday's new supply that propped up municipals , some traders said. Among the new issues was Massachusetts's $230 million of general obligation bonds . The bonds were won by a Goldman Sachs & Co. group with a true interest cost of 7.17%.

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Neural, end-to-end models (Lee et al., 2018; Joshi et al., 2020) are SOTA for OntoNotes 5.0

Problem: Adapting CR Models

Models trained on OntoNotes may not immediately generalize to new domains

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Target (Science)

A molecule is a group of atoms held together by chemical bonds . Imagine you and your friends standing in a circle holding hands. Each person stands for one atom, your hands represent **the bonds** , and the entire circle represents a molecule.

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Impedes immediate application for scenarios like distinguishing entities in scientific articles

Problem: Adapting CR Models

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- (Xia and Van Durme, 2021) show the benefits of *continued training* where a model trained on OntoNotes is further trained on the target dataset
- However, they assume labeled data already exist in the target domain
- How can we adapt CR models without requiring large amounts of newly annotated data?

Method: Active Learning

Find particular spans of text for users to label

Target (Science)

(1)

A molecule is a group of atoms held together by chemical bonds . Imagine you and your friends standing in a circle holding hands. Each person stands for one atom, your hands represent the bonds , and the entire circle represents a molecule.

Active query: the bonds *Answer:* chemical bonds

Queries: your the bonds a molecule

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(2)

Dr. Raizman thinks the animals help decrease patients' stress by increasing the release of oxytocin, which is the hormone that bonds mothers to babies. Studies have shown patients who spend time with dogs have higher levels of dopamine.

Active query: bonds *Answer:* query is not entity

Queries: oxytocin bonds patients dogs

Method: Active Learning

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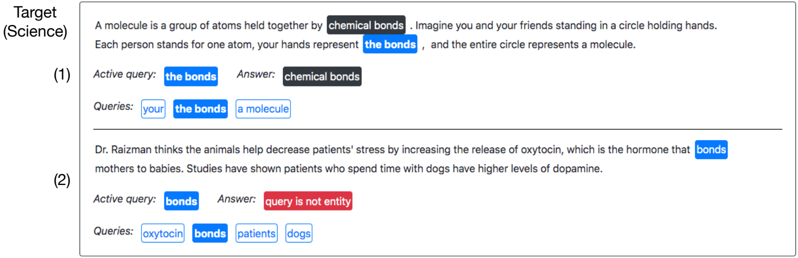

The goal is to adapt the model to the target domain by continue training it on these newly labeled spans

Method: Active Learning

We explore active learning for adapting CR models by:

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1. Sampling spans according to different sources of model uncertainty
2. Understanding the trade-off between reading and labeling costs

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- Maximum entropy sampling (Lewis and Gale, 1994) chooses data with highest predictive entropy
- For CR, these strategies are not as straightforward because the model has different scores for mention detection and clustering

Decomposing Decisions in CR

1. **Mention detection:**
   - Given a span of text x, let X be the random variable encoding whether x is an entity mention (1) or not (0)
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2. **Mention clustering:**
   - Given span x, let C be the random variable associated with the entity cluster of x
   - For spans that are likely entity mentions, the CR model determines $P(C=c \mid X=1)$ for each observed entity cluster c

Maximum Entropy Sampling for CR

ment-ent: Mention detection entropy

$$\mathrm{H}_{\mathrm{MENT}}(x) = \mathrm{H}(X) \tag{1}$$

$$= -\sum_{i=0}^{1} P(X=i)\log P(X=i).$$

Samples spans that challenge mention detection (e.g. class-ambiguous words like “park”).

Maximum Entropy Sampling for CR

clust-ent: Mention clustering entropy

$$\begin{aligned}\mathrm{H}_{\mathrm{CLUST}}(x) &= \mathrm{H}(C \mid X = 1) \\ &= -\sum_{c \in \mathcal{C}} P(C = c \mid X = 1) \log \\ &\quad P(C = c \mid X = 1).\end{aligned} \tag{2}$$

Entropy computation does not explicitly address uncertainty in mention detection.

Maximum Entropy Sampling for CR

cond-ent: Conditional entropy

$$
\begin{aligned}
\mathrm{H}_{\mathrm{COND}}(x) &= \mathrm{H}(C \mid X) \\
&= \sum_{i=0}^{1} P(X=i)\mathrm{H}(C \mid X=i) \\
&= P(X=1)\mathrm{H}(C \mid X=1) \\
&= P(X=1)\mathrm{H}_{\mathrm{CLUST}}(x).
\end{aligned} \tag{3}
$$

Samples words like pronouns because they are obviously entity mentions but difficult to cluster.

Maximum Entropy Sampling for CR

joint-ent: Joint entropy

$$\begin{aligned} \mathrm{H}_{\mathrm{JOINT}}(x) &= \mathrm{H}(X, C) = \mathrm{H}(X) + \mathrm{H}(C \mid X) \\ &= \mathrm{H}_{\mathrm{MENT}}(x) + \mathrm{H}_{\mathrm{COND}}(x). \end{aligned} \tag{4}$$

Samples spans that are difficult to detect as entity mentions *and* too confusing to cluster.

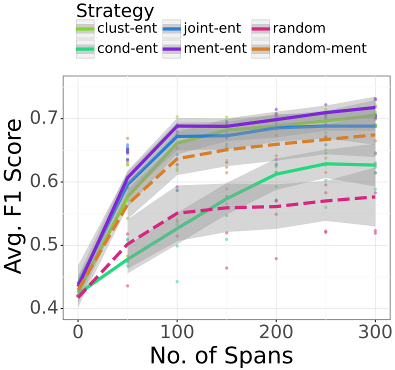
Experiments: Baselines

1. **random:** Sample from all spans in the document
2. **random-ment:** Like other uncertainty strategies, sample only from the pool of spans that are likely entity mentions

Experiments: Datasets

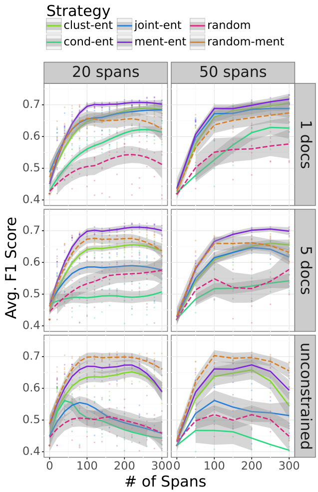
1. **OntoNotes 5.0 (source):** Most common dataset for training and evaluating CR that contains news articles and telephone conversations (Pradhan et al., 2013). Only non-singletons are annotated.
2. **PreCo (target):** Large corpus of grade-school reading comprehension texts with annotated singletons (Chen et al., 2018).

Evaluating Active Learning



- Test Avg. F1 on PreCo of models trained with each strategy
- Each cycle simulates fifty spans from one document being labeled
- **Ment-ent**, **clust-ent**, and **joint-ent** are effective while **random** performs worst

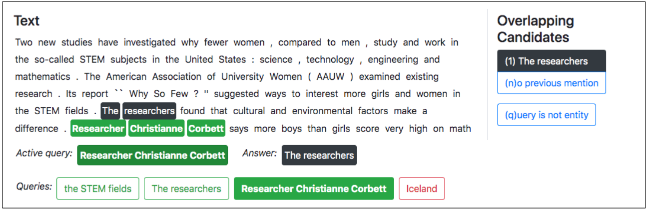
Reading and Labeling Trade-off



- Test Avg F1 on PreCo of models trained with each strategy
- Each column varies in max. number of docs. read per cycle
- Each row varies in number of labeled spans per cycle
- For unconstrained reading, model training is unstable

Reading and Labeling for Humans

Three users label spans sampled from PreCo



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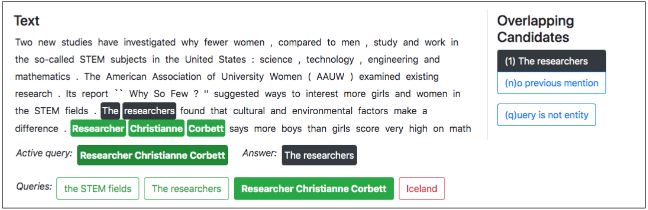
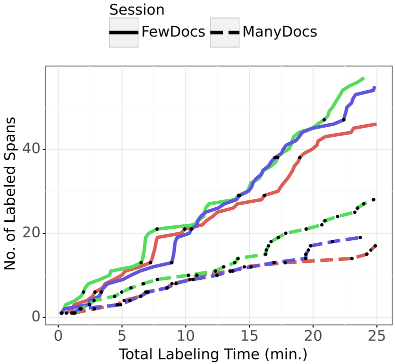


Users complete two twenty-five minute sessions:

1. **FewDocs:** Read fewer docs. and label multiple spans per doc.
2. **ManyDocs:** Read more docs. and label one span per doc.

Reading and Labeling for Humans



- Each color indicates one of three users and the linetype designates the session
- Black dots mark the first span labeled in a different document
- Users label at least twice as many spans during **FewDocs** than they do for **ManyDocs**

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3. Surprisingly, sampling by mention detection entropy is more useful for domains like PreCo

Summary

1. To reduce annotation for transferring coreference resolution models, we use active learning to choose text spans for users to label
2. We explore various aspects of active learning for coreference resolution, like sources of model uncertainty and the trade-off between reading and labeling
3. Surprisingly, sampling by mention detection entropy is more useful for domains like PreCo
4. In both simulations and the user study, there are more benefits from sampling spans from the same document rather than different contexts

Thanks

Any Questions?

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Slides customized from UFGTeX

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