Adapting Coreference Resolution Models through Active Learning

ACL 2022

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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%.

Cluster: { municipals , municipal bonds , municipals , general obligation bonds , The bonds }

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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

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- The goal is to adapt the model to the target domain by continue training it on spans labeled from active learning

What should we label?

A fantastic experience, very informative, very time consuming but enjoyable. So much information to take in about Guinness that you would've never known. For example, the brewery hired the statistician Willam Gosset in 1899. The "student" was known for developing the Student's t-test, a well-known method in statistical inference.

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Uncertainty in mention detection

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Uncertainty in mention clustering

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Uncertainty in mention clustering conditioned on mention detection

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Uncertainty in both mention detection and mention clustering

Experiments: Strategies

1. **ment-ent:** Mention detection entropy
2. **clust-ent:** Mention clustering entropy
3. **cond-ent:** Conditional entropy
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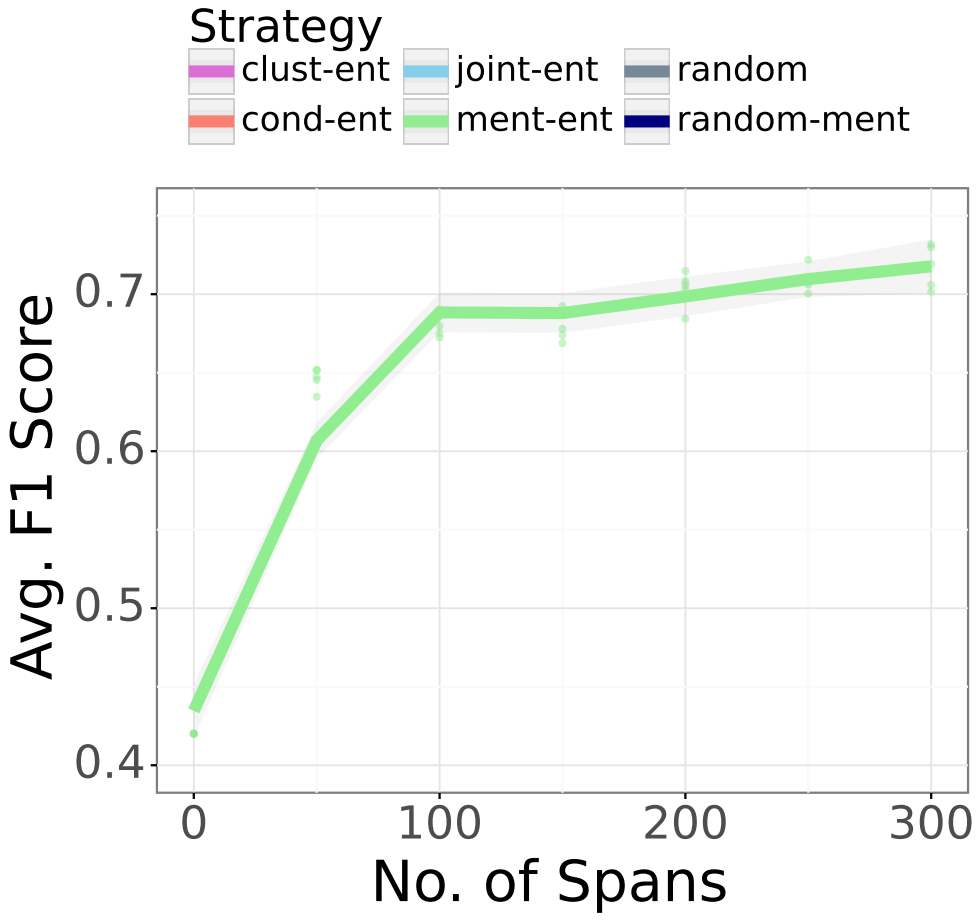
5. **random:** Randomly sample from all spans in the document
6. **random-ment:** Randomly sample only from the pool of spans that are likely entity mentions

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).

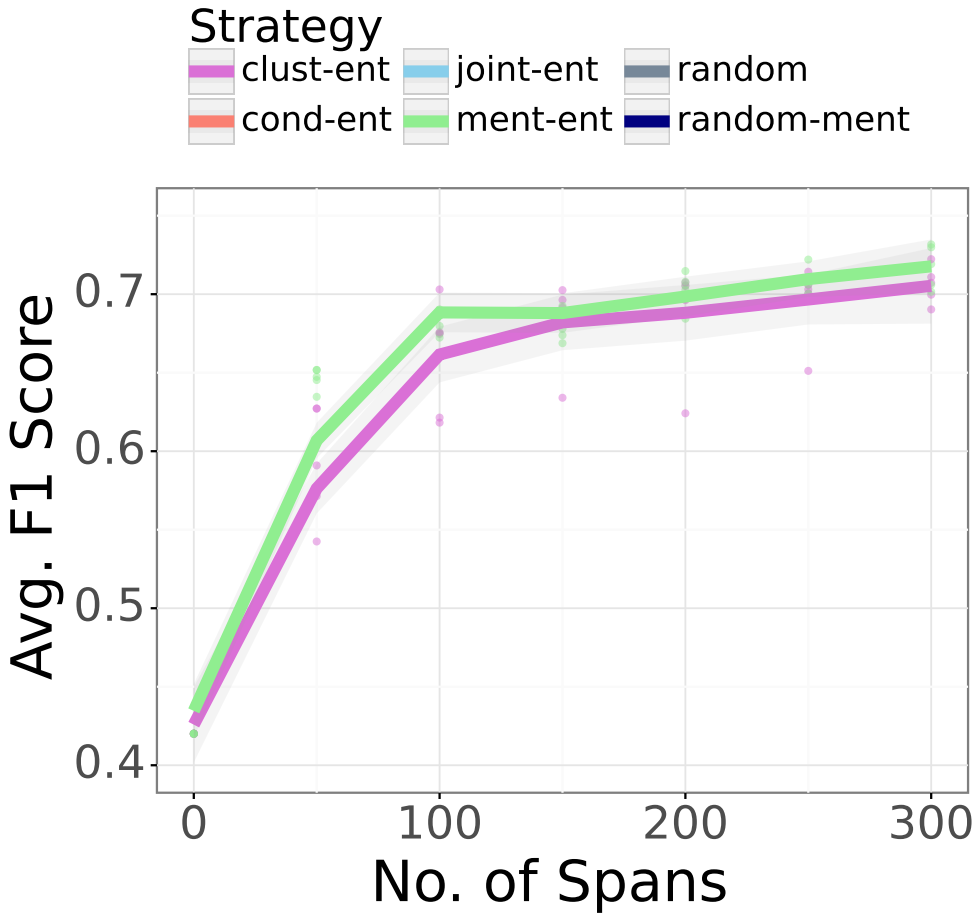
Comparing Strategies



Mention Detection Entropy

- Test Avg. F1 on PreCo
- For each cycle, we simulate labeling fifty spans from one document

Comparing Strategies



Mention Clustering Entropy

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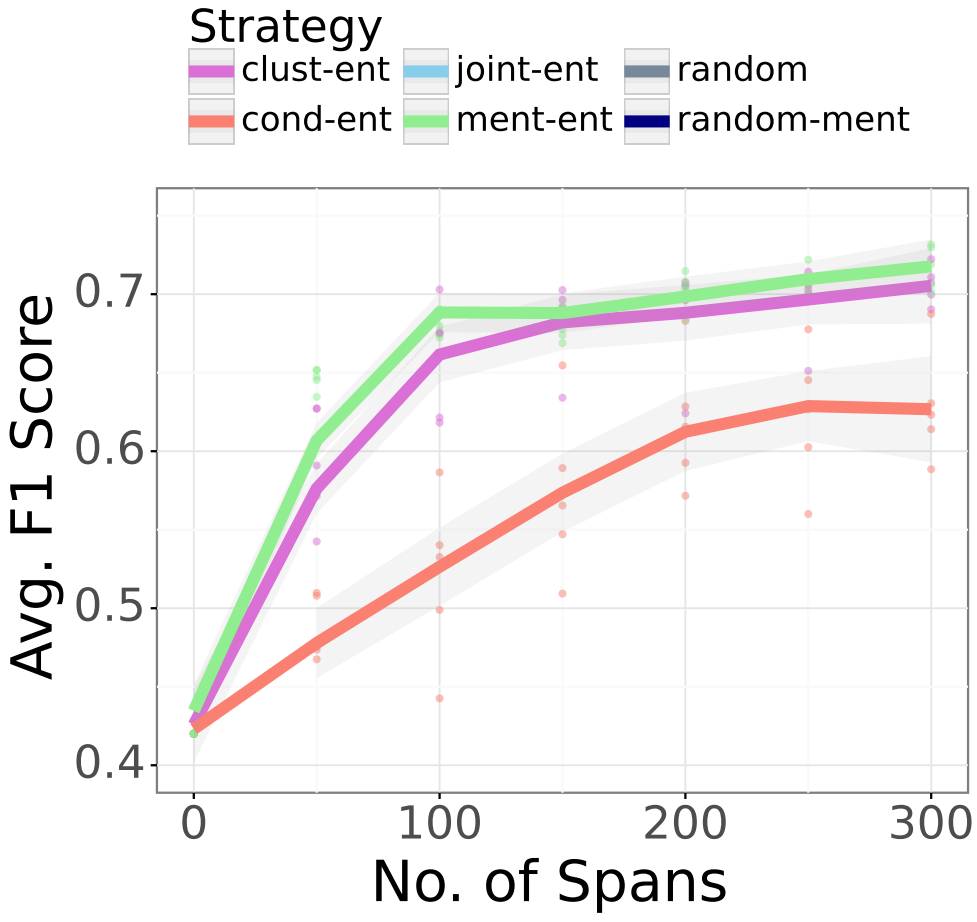

Conditional Entropy

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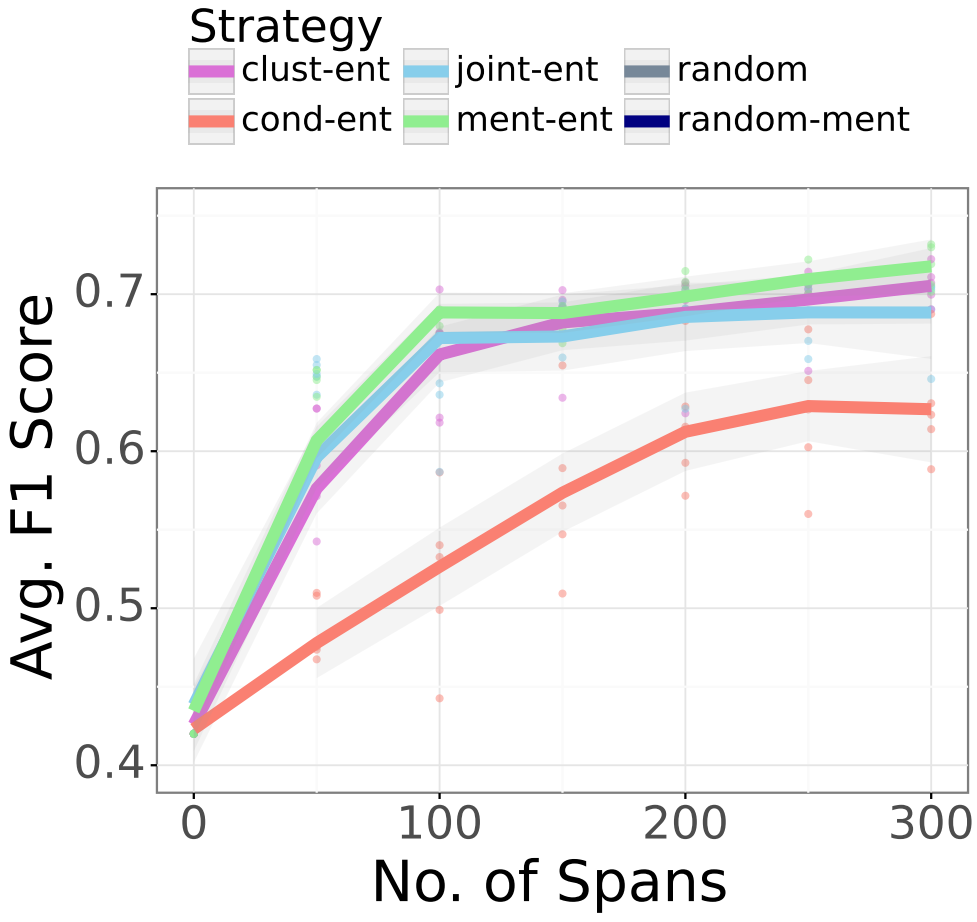

Joint Entropy

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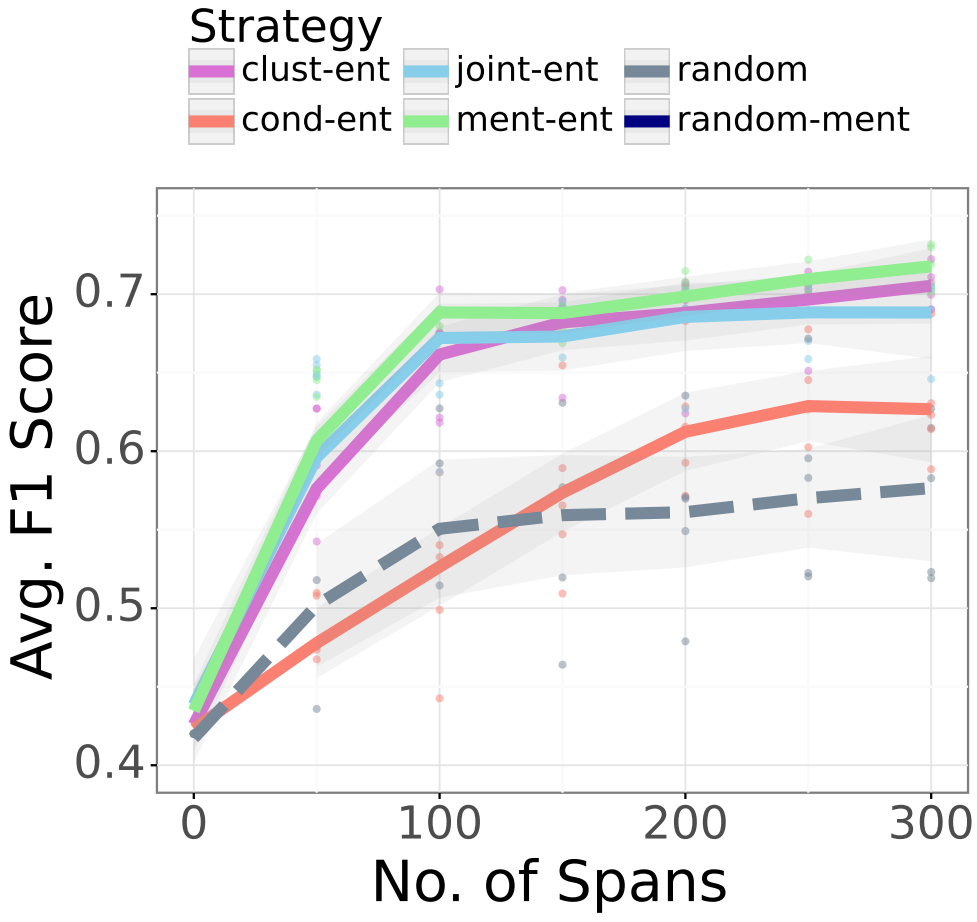

Random

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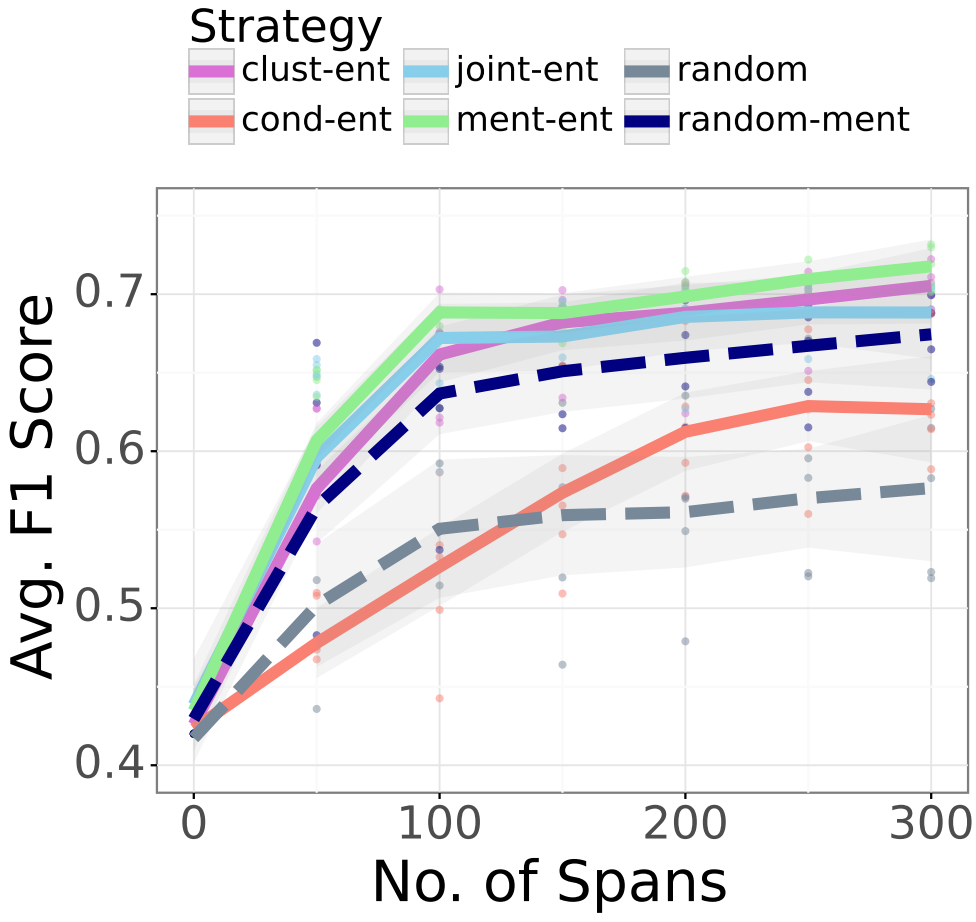

Random Entity Mentions

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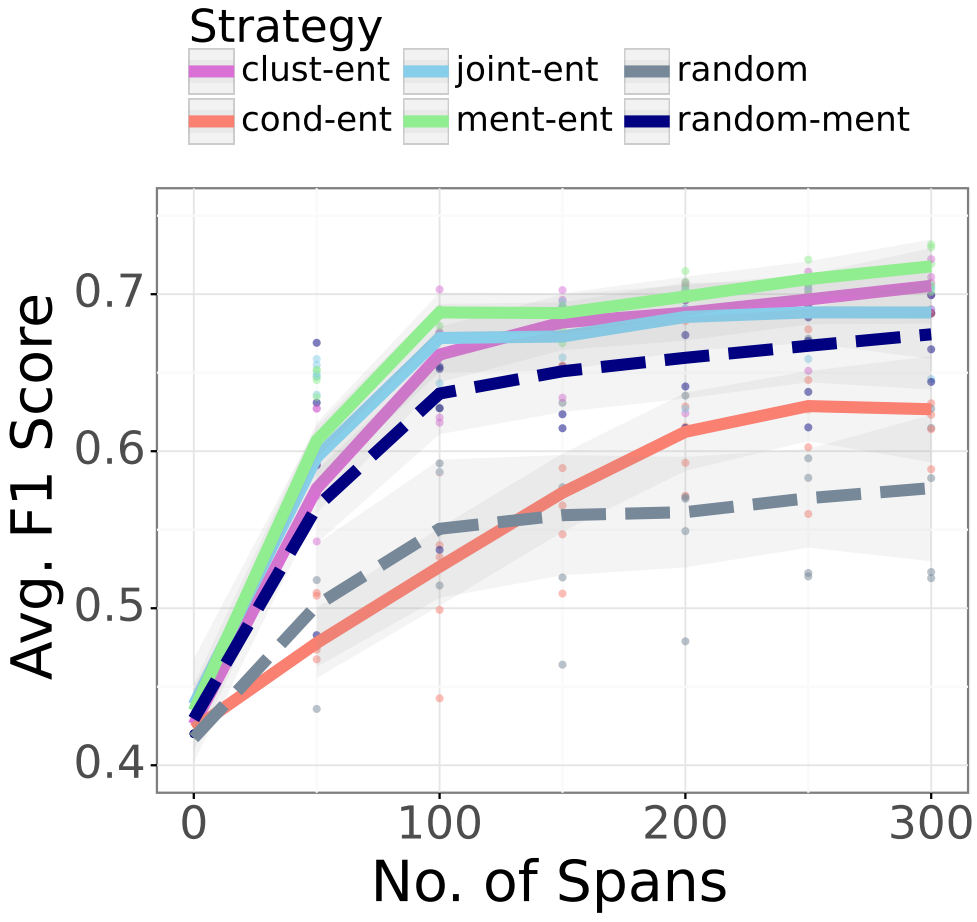
Comparing Strategies



- Test Avg. F1 on PreCo
- For each cycle, we simulate labeling fifty spans from one document
- **Ment-ent**, **clust-ent**, and **joint-ent** are effective while **random** performs worst

Should we label spans within or across documents?

A fantastic experience, very informative, very time consuming but enjoyable. So much information to take in about Guinness that you would've never known. For example, the brewery hired the statistician Willam Gosset in 1899. The "student" was known for developing the Student's t-test, a well-known method in statistical inference.

Ha'penny Bridge might look like it's just another bridge. But if you read about the history, you will know how significant this bridge is. Apparently half a penny was the toll that had to be paid from 1816 until the year 1919 in order to cross the Liffey Bridge.

Lovely park. Easy to get to on public transport. I recommend getting the bikes for hire when you get there, it made getting around really easy and you can cut across the fields to go and see the deer more easily!

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Across

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- Test Avg. F1 on PreCo of each strategy
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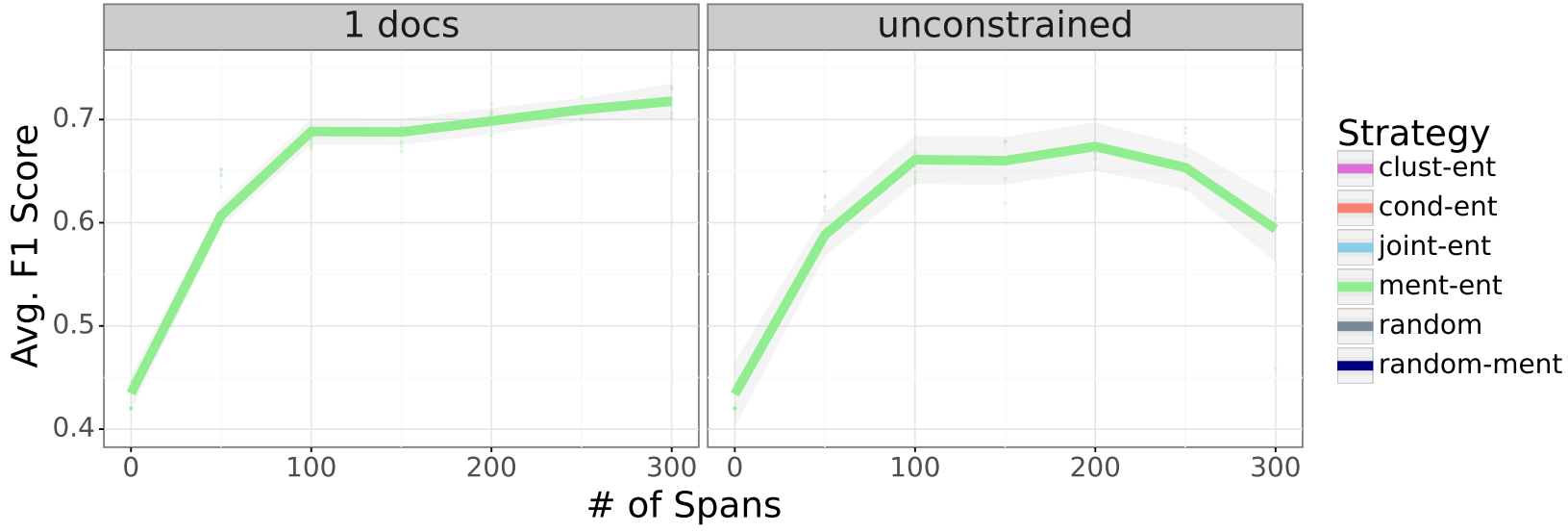

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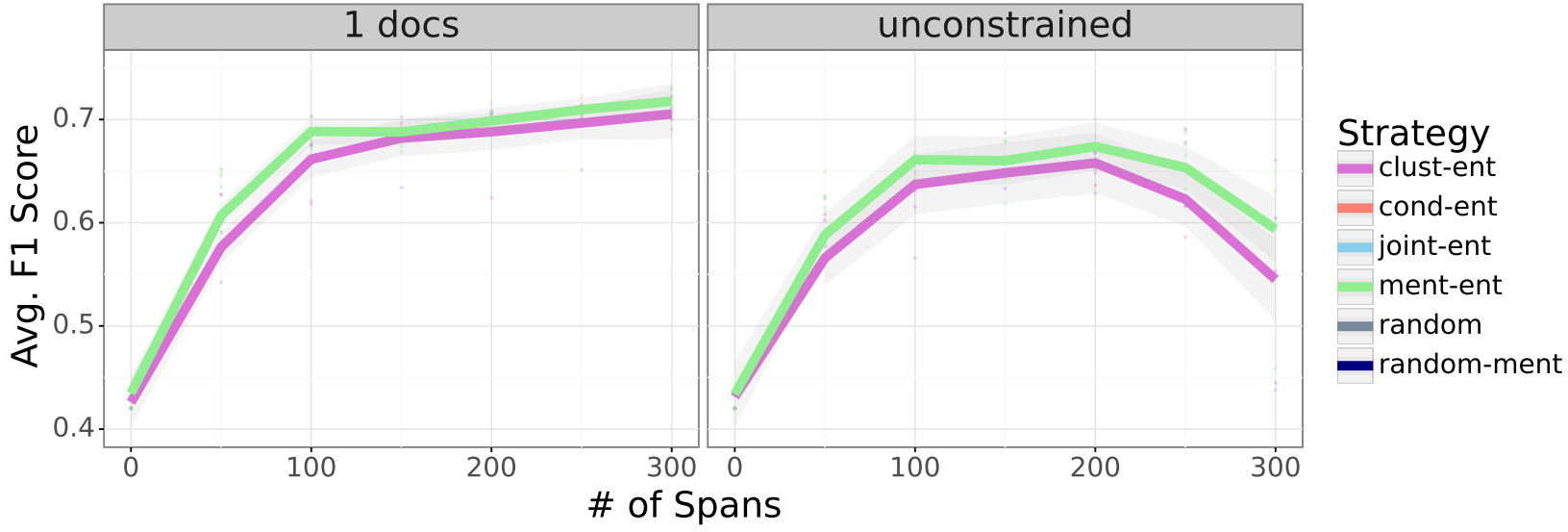

Mention Clustering Entropy

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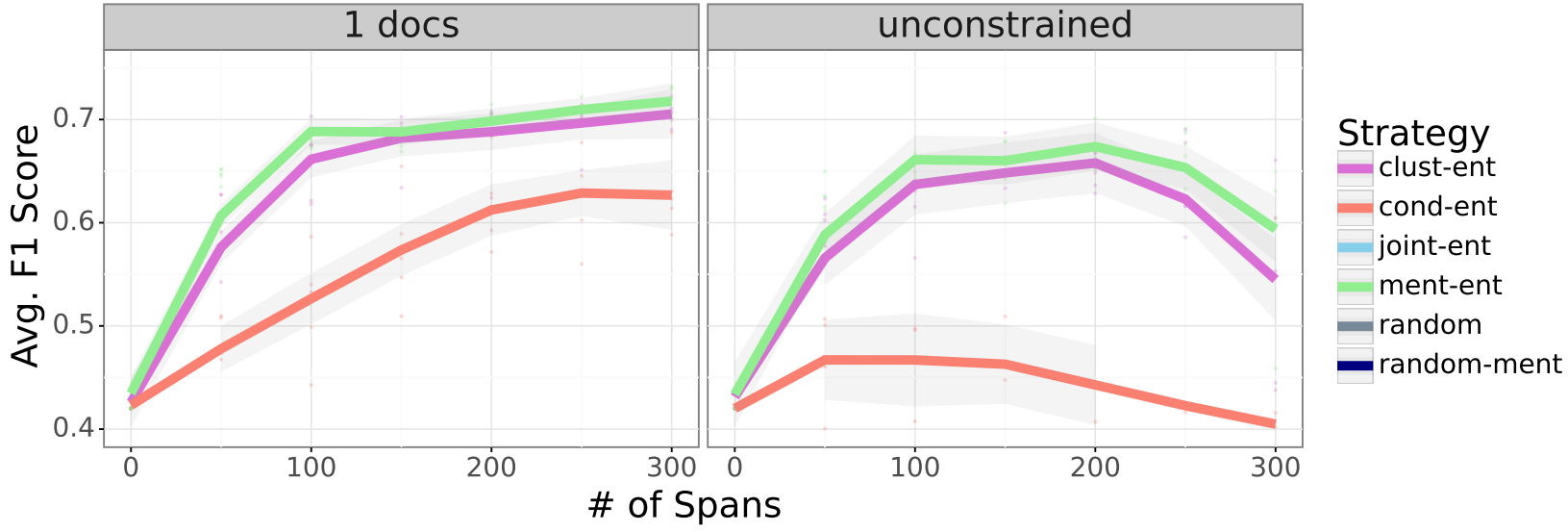

Conditional Entropy

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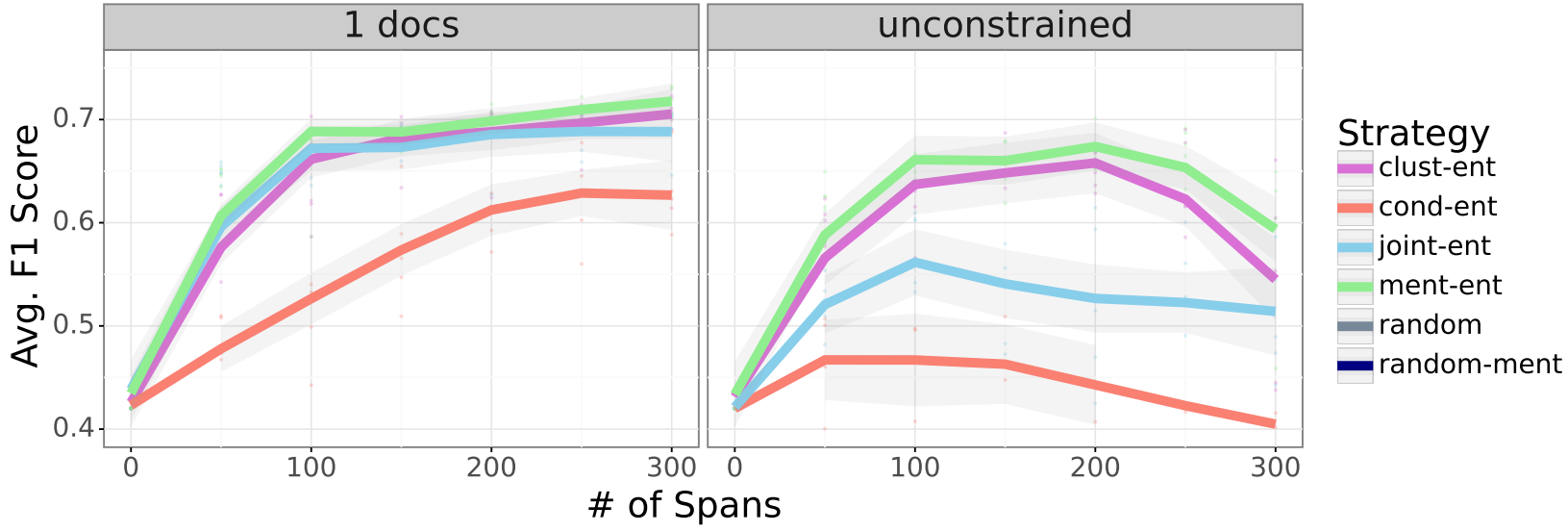

Joint Entropy

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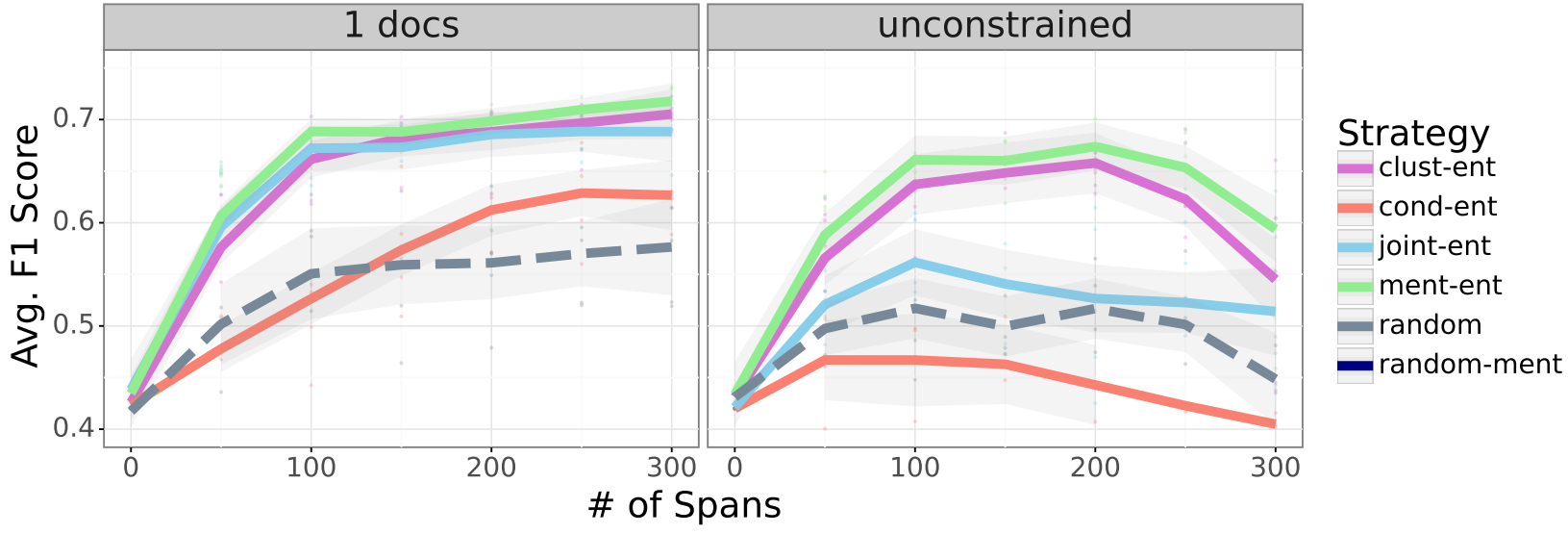

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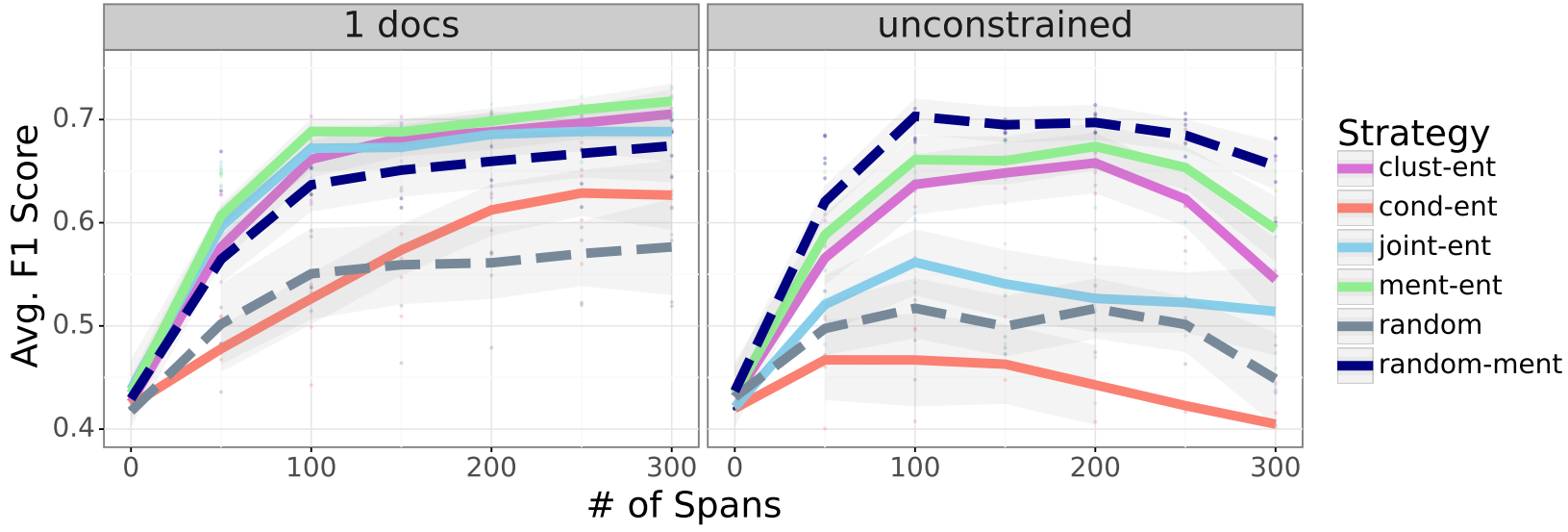

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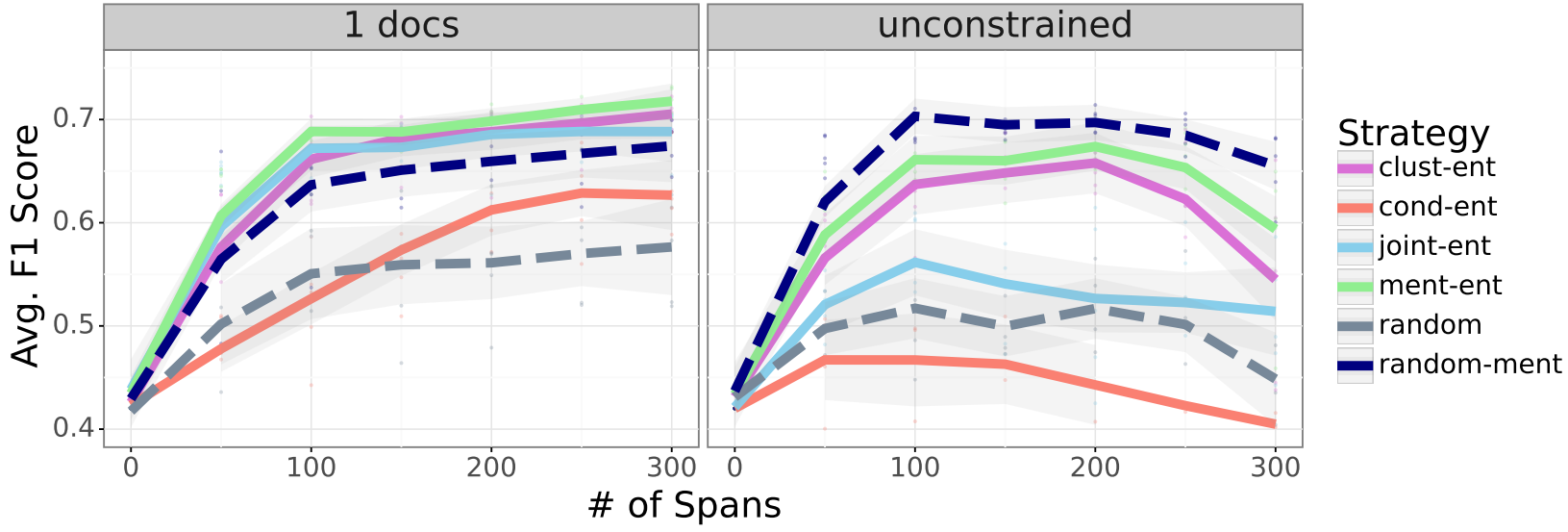
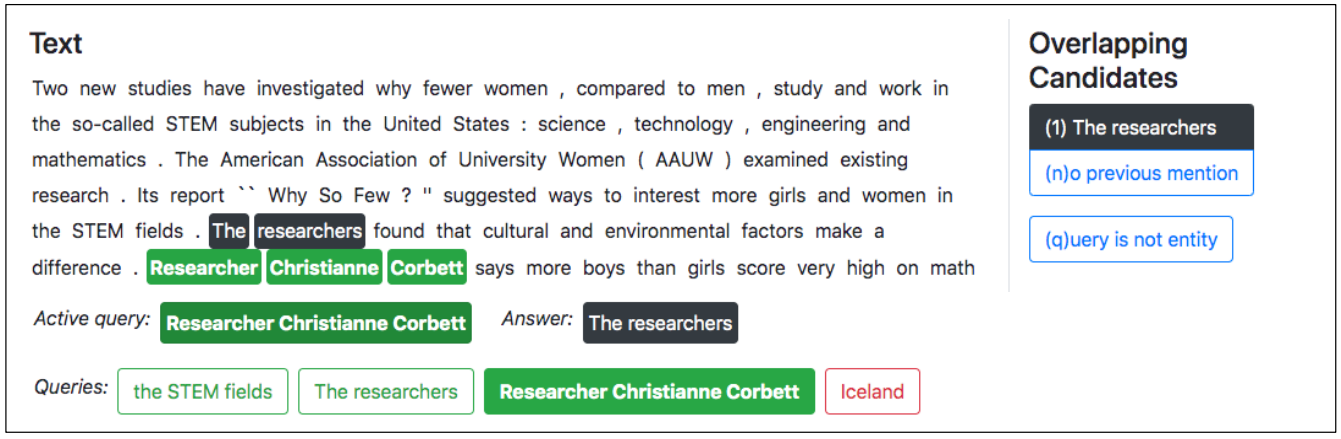


Model training is unstable with unconstrained sampling

Reading and Labeling for Humans

Three users label spans sampled from PreCo



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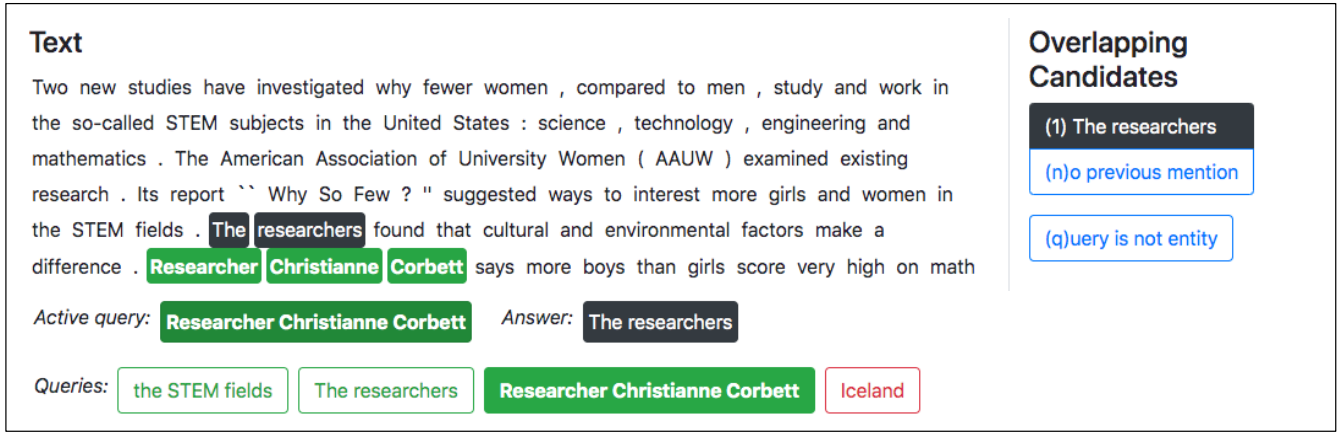
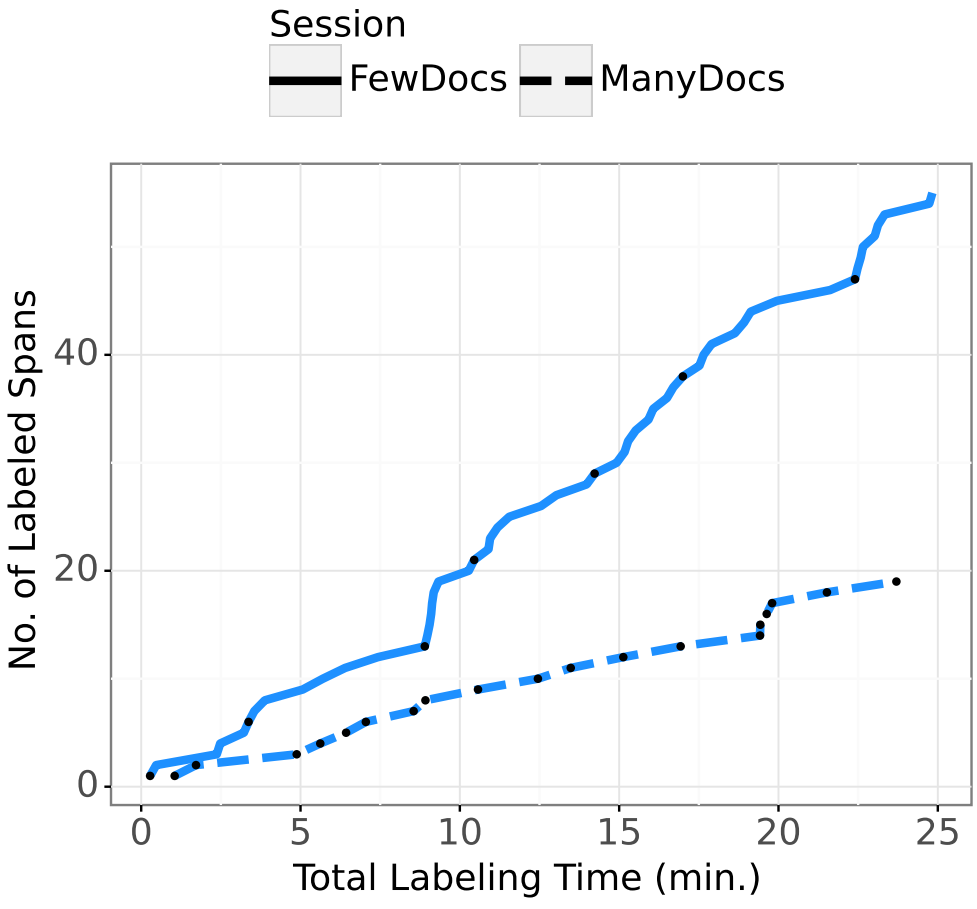


Users complete two twenty-five minute sessions:

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

Labeling Throughput At Least Doubles in FewDocs



- Each color indicates one of three users and the linetype designates the session
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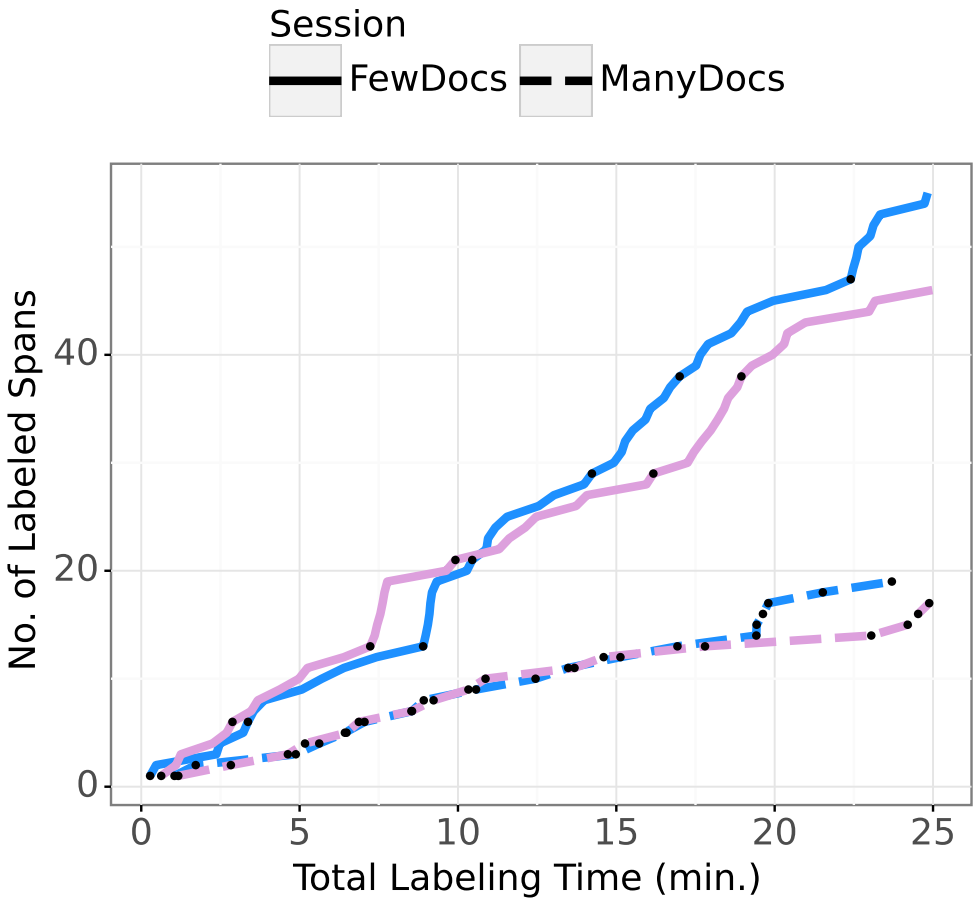

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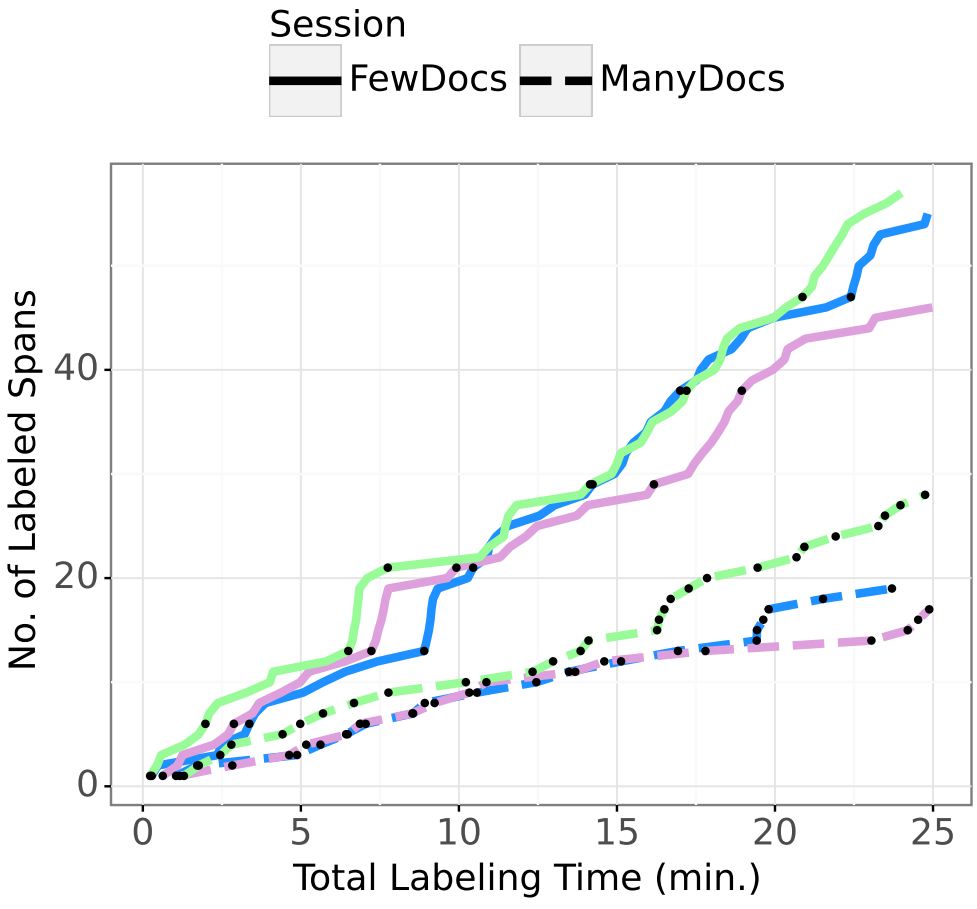

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Thanks

Any Questions?

myuan@cs.umd.edu

DEPARTMENT OF
COMPUTER SCIENCE

Slides customized from UFGTeX

References I

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