# Incremental Neural Coreference Resolution in Constant Memory

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## Outline

- 1. Background and Motivation
- 2. Algorithm and Model
- 3. Experiments and Results

## Background

## • Span Detection → Mention Pair Scoring (Lee et al., 2017)



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## Extensions

- Higher-order resolution: re-score against cluster average (Lee et al., 2018)
- ELMo/BERT/SpanBERT: Fine-tune pretrained encoders (Joshi et al., 2019)
- "Machine reading comprehension" scorer (Wu et al., 2020)

## Motivation

- For long documents (roughly >3000 tokens), GPUs run out of memory
  - The encoder is not always the bottleneck
- Some documents (books) exceed 100K tokens



Memory Profile for a long document with model by Joshi et al., 2019

## Some solutions...

- Some fixes:
  - Sparse Transformer
  - Sequential pairwise scoring
- ... but they do not resolve:
  - Span ranking is linear in document size
  - All spans are needed in decoding
  - Even sparse Transformers need Ω(document size)

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## Approach

- Limited-memory incremental algorithm for coreference resolution (Webster and Curran, 2014)
  - Similar to shift-reduce algorithms
- Neural components + **explicit** entity representations



#### Document



## Algorithm 1 FindClusters(Document)





### Document <mark>Christmas</mark> won't "It's so oe Christmas dreadful to without any be poor!" presents," sighed Meg, grumbled <mark>Jo</mark>, looking lying on <mark>the rug</mark>. down at her old dress.



#### Document Christmas won't "It's so <mark>be Christmas</mark> dreadful to without any be poor!" presents," sighed Meg, grumbled <mark>Jo</mark>, looking lying on <mark>the rug</mark>. down at her old dress.

## Algorithm 1 FindClusters(Document)





## Algorithm 1 FindClusters(Document)









## Algorithm 1 FindClusters(Document)

![](_page_16_Figure_0.jpeg)

![](_page_16_Figure_1.jpeg)

{Christmas, Christmas}, {any presents}

#### Document

![](_page_17_Picture_3.jpeg)

### Algorithm 1 FindClusters(Document)

{Christmas, Christmas}, {any presents}

#### Document

![](_page_18_Picture_3.jpeg)

{Christmas, Christmas}, {any presents}, {Jo}

#### Document

![](_page_19_Picture_3.jpeg)

### Algorithm 1 FindClusters(Document)

{Christmas, Christmas}, {any presents}, {Jo}

#### Document

![](_page_20_Picture_3.jpeg)

{Christmas, Christmas},
{any presents},
{Jo},
{the rug}

#### Document

![](_page_21_Picture_3.jpeg)

### Algorithm 1 FindClusters(Document)

{Christmas, Christmas},
{any presents},
{Jo},
{the rug}

#### Document

![](_page_22_Picture_3.jpeg)

## Algorithm 1 FindClusters(Document)

{Christmas, Christmas}, {<del>any presents},</del> {Jo}, {<del>the rug}</del>

#### Document

![](_page_23_Picture_3.jpeg)

## Algorithm 1 FindClusters(Document)

![](_page_24_Figure_1.jpeg)

#### Document

![](_page_24_Picture_3.jpeg)

## Algorithm 1 FindClusters(Document)

## Implementation

- Encoder: SpanBERT
- **Spans**: top-*k* spans based on learned scorer
- **PairScore**: FFNN(m, e)
- Update: learned average of spans
- Evict: all old entities

## Algorithm 1 FindClusters(Document)

```
Create an empty Entity List, E
for segment \in Document do
    M \leftarrow \text{SPANS(segment)}
    for m \in M do
        scores \leftarrow PAIRSCORE(m, E)
        top\_score \leftarrow \max(scores)
        top_e \leftarrow \operatorname{argmax}(scores)
        if top\_score > 0 then
            UPDATE(top\_e, m)
        else
            ADD_NEW_ENTITY(E, m)
    EVICT(E)
return E
```

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## Experiments

- OntoNotes 5.0 (English)
- Evaluated with average F1 (MUC, B<sup>3</sup>, and CEAF $_{\varphi 4}$ )
- Goal: compare performance between incremental algorithm vs. fulldocument model

## Results

- 79.6 F1 → 79.4 F1
  - Virtually no loss in performance
- Constant space implementation at inference (2GB) and training (<10GB)</li>
- Our algorithm has O(1) space complexity
  - A fixed-sized set of entities kept across time

![](_page_28_Figure_6.jpeg)

## Entity Analysis

 Coreference is well-suited for (online) clustering: coreferent mentions are close in embedding space

![](_page_29_Figure_2.jpeg)

## Conclusions

- Constant memory algorithm + model for coreference resolution
- Can be applied to future SOTA models
- Detailed analysis of document and segment lengths in paper!
- Thanks!

Code and models at github.com/pitrack/incremental-coref