End-to-end Neural Coreference Resolution

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Introduction

Coreference Resolution

The task of finding all expressions that refer to the same entity in a text.

“I voted for Nader because he was most aligned with my values,” she said.
First end-to-end coreference resolution model
• Significantly outperforms all previous work
• Without using a syntactic parser or hand-engineered mention detector
• Instead, used a novel attention mechanism for head words and span-ranking model for mention detection
Model: End to End

• Input: Word embedding along with metadata such as speaker and genre information.

• Two steps model:
  • First step computes mention score and encodes span embedding
  • Second step computes the final coreference score by summing antecedent scores from pairs of span representations and the mentions score for each span

• Output:
  • Assign to each span i an antecedent $y_i$. 
Model: Step one
Step one: Span Embeddings
Head-finding Attention

For each span $i$, for each word $t$:

$$\alpha_t = \mathbf{w}_\alpha \cdot \text{FFNN}_\alpha(\mathbf{x}_t^*)$$

$$a_{i,t} = \frac{\exp(\alpha_t)}{\sum_{k=\text{START}(i)}^{\text{END}(i)} \exp(\alpha_k)}$$

$$\hat{\mathbf{x}}_i = \sum_{t=\text{START}(i)}^{\text{END}(i)} a_{i,t} \cdot \mathbf{x}_t$$
Span Representation

\[ g_i = [x_{\text{START}}^*(i), x_{\text{END}}^*(i), \hat{x}_i, \phi(i)] \]

\( \phi(i) \) just encodes the size of span i.
Pruning

Time complexity: complete model requires $O(T^4)$ in the document length $T$.

Aggressive Pruning:

- only consider spans with up to $L$ words
- only keep up to $\lambda T$ spans with the highest mention scores
- only consider up to $K$ antecedents for each.
Mention Score and Antecedent score

Unary mention scores and pairwise antecedent scores

\[ s_m(i) = w_m \cdot \text{FFNN}_m(g_i) \]
\[ s_a(i, j) = w_a \cdot \text{FFNN}_a([g_i, g_j, g_i \circ g_j, \phi(i, j)]) \]
Model: Step two

Softmax ($P(y_i \mid D)$)

$\text{s}(\text{the company, } \epsilon) = 0$

Coreference score ($s$)

$\text{s}(\text{the company, General Electric})$

$\text{s}(\text{the company, the Postal Service})$

Antecedent score ($s_a$)

Mention score ($s_m$)

Span representation ($g$)

General Electric  the Postal Service  the company
Learning:

Conditional probability distribution

\[
P(y_1, \ldots, y_N \mid D) = \prod_{i=1}^{N} P(y_i \mid D) = \prod_{i=1}^{N} \frac{\exp(s(i, y_i))}{\sum_{y' \in y(i)} \exp(s(i, y'))}
\]

\[
s(i, j) = \begin{cases} 
0 & j = \epsilon \\
 s_m(i) + s_m(j) + s_a(i, j) & j \neq \epsilon
\end{cases}
\]
Learning: Optimization

Marginal log-likelihood of all correct antecedents implied by the gold clustering:

$$\log \prod_{i=1}^{N} \sum_{\hat{y} \in \mathcal{Y}(i) \cap \text{GOLD}(i)} P(\hat{y})$$
Experiment

• **Dataset:** English coreference resolution data from the CoNLL-2012 shared task

• **Word representations:** 300-dimensional GloVe embeddings and 50-dimensional embeddings from Turian

• **Feature encoding:**
  • encode speaker information as a binary feature
  • the distance feature are binned into the following buckets [1, 2, 3, 4, 5-7, 8-15, 16-31, 32-63, 64+]
<table>
<thead>
<tr>
<th>Model</th>
<th>MUC Prec.</th>
<th>MUC Rec.</th>
<th>MUC F1</th>
<th>B³ Prec.</th>
<th>B³ Rec.</th>
<th>B³ F1</th>
<th>CEAF$_{\phi_4}$ Prec.</th>
<th>CEAF$_{\phi_4}$ Rec.</th>
<th>CEAF$_{\phi_4}$ F1</th>
<th>Avg. F1</th>
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<td>81.2</td>
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<td>60.2</td>
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<td>75.8</td>
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<td>Clark and Manning (2016a)</td>
<td>79.2</td>
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<td>74.6</td>
<td>69.9</td>
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<td>55.5</td>
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<td>69.3</td>
<td>74.2</td>
<td>71.0</td>
<td>56.5</td>
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Ablations

How the ablation of different parts of this model will affect the performance?

<table>
<thead>
<tr>
<th></th>
<th>Avg. F1</th>
<th>Δ</th>
</tr>
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<tbody>
<tr>
<td>Our model (ensemble)</td>
<td>69.0</td>
<td>+1.3</td>
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<tr>
<td>Our model (single)</td>
<td>67.7</td>
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<tr>
<td>– distance and width features</td>
<td>63.9</td>
<td>-3.8</td>
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<tr>
<td>– GloVe embeddings</td>
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<td>-2.4</td>
</tr>
<tr>
<td>– speaker and genre metadata</td>
<td>66.3</td>
<td>-1.4</td>
</tr>
<tr>
<td>– head-finding attention</td>
<td>66.4</td>
<td>-1.3</td>
</tr>
<tr>
<td>– character CNN</td>
<td>66.8</td>
<td>-0.9</td>
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<tr>
<td>– Turian embeddings</td>
<td>66.9</td>
<td>-0.8</td>
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<td>Our model (joint mention scoring)</td>
<td>67.7</td>
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<tr>
<td>w/ rule-based mentions</td>
<td>66.7</td>
<td>-1.0</td>
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<tr>
<td>w/ oracle mentions</td>
<td>85.2</td>
<td>+17.5</td>
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</tbody>
</table>
Span Pruning Strategies
Strength and Weakness

Strength

• Novel head-finding attention mechanism detects relatively long and complex noun phrases
• Word embeddings to capture similarity between words

Weakness

• Prone to predicting false positive links when the model conflates paraphrasing with relatedness or similarity
• Does not incorporate world knowledge
Strength and Weakness: Example

(Prince Charles and his new wife Camilla) have jumped across the pond and are touring the United States making their first stop today in New York. It’s Charles’ first opportunity to showcase his new 4 wife, but few Americans seem to care. Here’s Jeanie Mowth. What a difference two decades make. (Charles and Diana) visited a JC Penney’s on the prince’s last official US tour. Twenty years later here’s the prince with his new wife.
Summary

• New model: State-of-the-art coreference resolution model
• New mechanism: A novel head-finding attention mechanism
• New insight: Proves that syntactic parser or hand-engineered mention detector isn’t necessary