Natural Language Processing with Deep Learning
CS224N/Ling284

Christopher Manning

Lecture 17: Coreference Resolution

Announcements

- Week 9: We’re heading into end-of-quarter crunch time
  - Do all take care of yourselves!!! And get some sleep!
- Final project milestones: Thank you! Lots of interesting stuff!
  - We’ll get them back to you this week!
- Good luck with your final projects!
  - Do keep working on your final projects!
  - Do talk to your mentor(s) and/or other course staff for help!
  - The finish line is in sight!
  - See you at the poster session!!! Mon, Mar 20, 5–9pm, Tressider

Lecture Plan:

Lecture 17: Coreference Resolution

1. What is Coreference Resolution? (10 mins)
2. Applications of coreference resolution (5 mins)
3. Mention Detection (5 mins)
4. Some Linguistics: Types of Reference (5 mins)

Three Kinds of Coreference Resolution Models

5. Rule-based (Hobbs Algorithm) (10 mins)
6. Mention-pair and mention-ranking models (15 mins)
7. Current state-of-the-art neural coreference systems (10 mins)
8. Evaluation and current results (10 mins)

1. What is Coreference Resolution?

- Identify all **mentions** that refer to the same entity in the word

A couple of years later, Vanaja met Akhila at the local park. Akhila's son Prajwal was just two months younger than her son Akash, and they went to the same school. For the pre-school play, Prajwal was chosen for the lead role of the naughty child Lord Krishna. Akash was to be a tree. She resigned herself to make Akash the best tree that anybody had ever seen. She bought him a brown T-shirt and brown trousers to represent the tree trunk. Then she made a large cardboard cutout of a tree's foliage, with a circular opening in the middle for Akash's face. She attached red balls to it to represent fruits. It truly was the nicest tree.

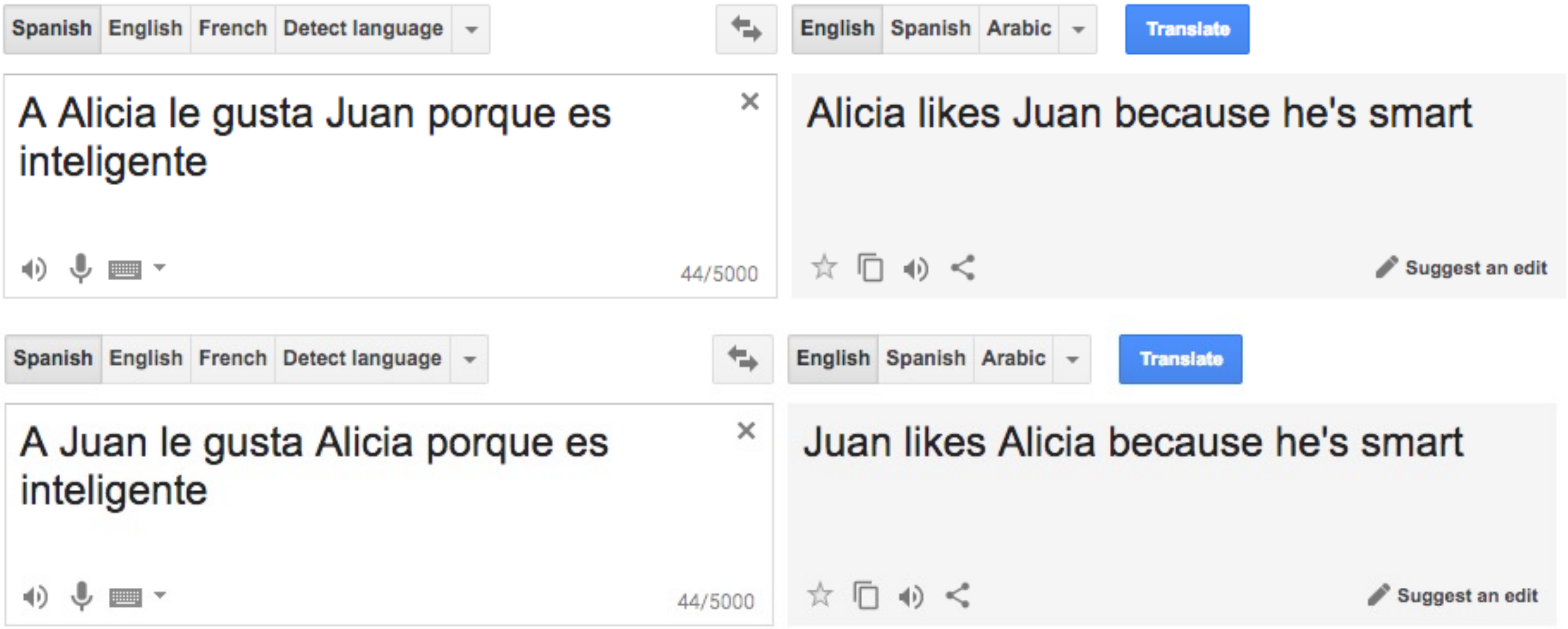
From The Star by Shruthi Rao, with some shortening.

Applications

- Full text understanding
  - information extraction, question answering, summarization, …
  - “He was born in 1961”   (Who?)

Applications

- Full text understanding
- Machine translation
  - languages have different features for gender, number, dropped pronouns, etc.



Applications

- Full text understanding
- Machine translation
- Dialogue Systems

  "Book tickets to see James Bond"

  "Spectre is playing near you at 2:00 and 3:00 today. How many tickets would you like?"

  "Two tickets for the showing at three"

Coreference Resolution in Two Steps

1. Detect the mentions (easy)

   "[I] voted for [Nader] because [he] was most aligned with [[my] values]," [she] said

   - mentions can be nested!

2. Cluster the mentions (hard)

   "[I] voted for [Nader] because [he] was most aligned with [[my] values]," [she] said

3. Mention Detection

- Mention: A span of text referring to some entity

- Three kinds of mentions:

1. Pronouns
   - I, your, it, she, him, etc.

2. Named entities
   - People, places, etc.: Paris, Joe Biden, Nike

3. Noun phrases
   - “a dog,” “the big fluffy cat stuck in the tree”

Mention Detection

- Mention: A span of text referring to some entity
- For detection: traditionally, use a pipeline of other NLP systems

1. Pronouns
   - Use a part-of-speech tagger (assigns noun, verb, auxiliary, etc. to words)
2. Named entities
   - Use a Named Entity Recognition system
3. Noun phrases
   - Use a parser (easiest: a constituency parser for noun phrases!)

Mention Detection: Not Quite So Simple

- Marking all pronouns, named entities, and NPs as mentions over-generates mentions
- Are these mentions?
  - It is sunny
  - The best donut in the world
  - 100 miles

How to deal with these bad mentions?

- Could train a classifier to filter out spurious mentions

- Much more common: keep all mentions as “candidate mentions”
  - After your coreference system is done running discard all singleton mentions (i.e., ones that have not been marked as coreference with anything else)
    - But you might well want to know about referential singletons!

Avoiding a traditional pipeline system

- We could instead train a classifier specifically for mention detection instead of using a POS tagger, NER system, and parser.
  - Or we can not even try to do mention detection explicitly:
- We can build a model that begins with all spans and jointly does mention-detection and coreference resolution end-to-end in one model
  - Will cover later in this lecture!

4. On to Coreference! First, some linguistics

- **Coreference** is when two mentions refer to the same entity in the world
  - *Barack Obama traveled to … Obama ...*

- A different-but-related linguistic concept is **anaphora:** when a term (anaphor) refers to another term (antecedent)
  - the interpretation of the anaphor is in some way determined by the interpretation of the antecedent
  - *Barack Obama said he would sign the bill.*
    antecedent anaphor

Anaphora vs. Coreference

Coreference with named entities

text — Barack Obama — Obama

world

Anaphora

text — Barack Obama — he

world

Not all anaphoric relations are coreferential

- Not all noun phrases have reference

- *Every dancer* twisted *her knee*.
- *No dancer* twisted *her knee.*

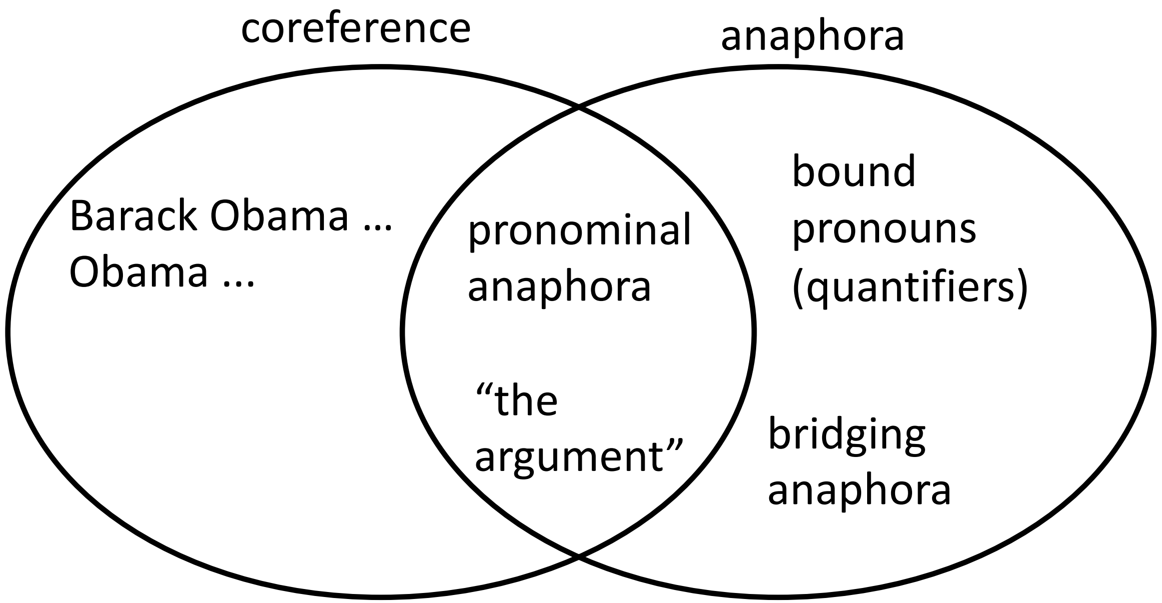
- There are three NPs in each of these sentences; because the first one is non-referential (or a group), the other two aren't either.

Anaphora vs. Coreference

- Not all anaphoric relations are coreferential

We went to see a concert last night. The tickets were really expensive.

- This is referred to as bridging anaphora.



Anaphora vs. Cataphora

- Usually, the antecedent comes before the anaphor (e.g., a pronoun), but not always

Cataphora

“From the corner of the divan of Persian saddle-bags on which he was lying, smoking, as was his custom, innumerable cigarettes, Lord Henry Wotton could just catch the gleam of the honey-sweet and honey-coloured blossoms of a laburnum…”

(Oscar Wilde – The Picture of Dorian Gray)

Taking stock …

- It's often said that language is interpreted "in context"
- We've seen some examples, like word-sense disambiguation:
  - I took money out of the bank vs. The boat disembarked from the bank
- Coreference is another key example of this:
  - Obama was the president of the U.S. from 2008 to 2016. He was born in Hawaii.
- As we progress through an article, or dialogue, or webpage, we build up a (potentially very complex) **discourse model**, and we interpret new sentences/utterances with respect to our **world model** and our discourse model of what's come before.
- Coreference and anaphora are all we see in this class of whole-discourse meaning
  - But it's a big part of human language understanding!
    - There's more in CS224U next quarter!

Three Coreference Models

- Rule-based (pronominal anaphora resolution)
- Mention Pair/Mention Ranking
- End-to-end neural coreference

5. Traditional pronominal anaphora resolution: Hobbs' naive algorithm

1. Begin at the NP immediately dominating the pronoun
2. Go up tree to first NP or S. Call this X, and the path p.
3. Traverse all branches below X to the left of p, left-to-right, breadth-first. Propose as antecedent any NP that has a NP or S between it and X
4. If X is the highest S in the sentence, traverse the parse trees of the previous sentences in the order of recency. Traverse each tree left-to-right, breadth first. When an NP is encountered, propose as antecedent. If X not the highest node, go to step 5.

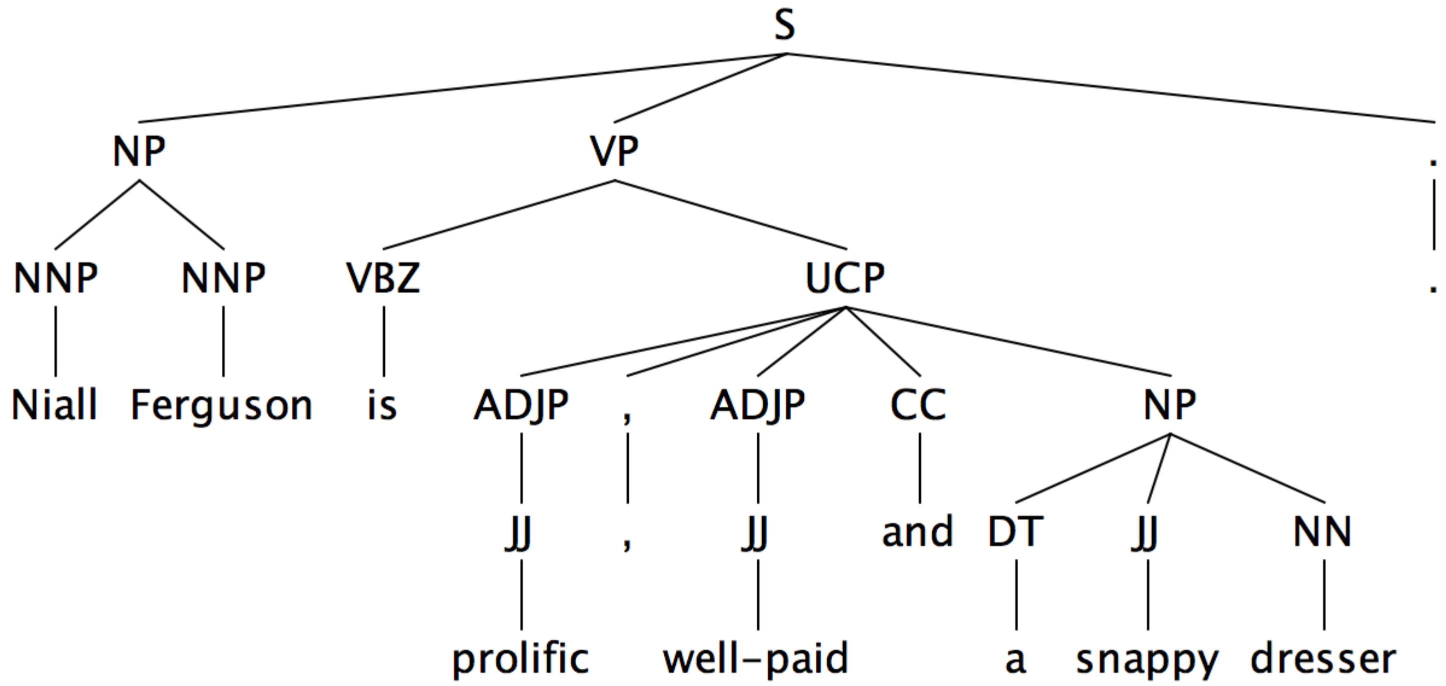
Hobbs' naive algorithm (1976)

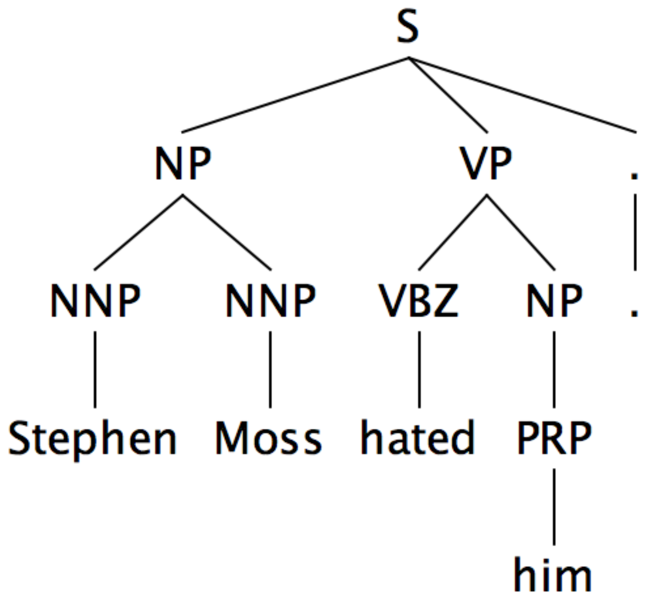
5. From node X, go up the tree to the first NP or S. Call it X, and the path p.
6. If X is an NP and the path p to X came from a non-head phrase of X (a specifier or adjunct, such as a possessive, PP, apposition, or relative clause), propose X as antecedent

   (The original said "did not pass through the N' that X immediately dominates", but the Penn Treebank grammar lacks N' nodes....)
7. Traverse all branches below X to the left of the path, in a left-to-right, breadth first manner. Propose any NP encountered as the antecedent
8. If X is an S node, traverse all branches of X to the right of the path but do not go below any NP or S encountered. Propose any NP as the antecedent.
9. Go to step 4

Until deep learning still often used as a feature in ML systems!

Hobbs Algorithm Example





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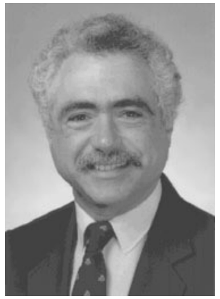
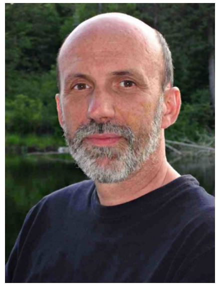
Knowledge-based Pronominal Coreference

- She poured water from the pitcher into the cup until it was full.
- She poured water from the pitcher into the cup until it was empty.



- The city council refused the women a permit because they feared violence.
- The city council refused the women a permit because they advocated violence.
  - Winograd (1972)



- These are called **Winograd Schema**
  - Proposed as an alternative to the Turing test
    - See: Hector J. Levesque "On our best behaviour" IJCAI 2013 http://www.cs.toronto.edu/~hector/Papers/ijcai-13-paper.pdf
    - http://commonsensereasoning.org/winograd.html
  - If you've fully solved coreference, arguably you've solved AI !!!

Hobbs' algorithm: commentary

"… the naïve approach is quite good. Computationally speaking, it will be a long time before a semantically based algorithm is sophisticated enough to perform as well, and these results set a very high standard for any other approach to aim for.

"Yet there is every reason to pursue a semantically based approach. The naïve algorithm does not work. Any one can think of examples where it fails. In these cases, it not only fails; it gives no indication that it has failed and offers no help in finding the real antecedent."

— Hobbs (1978), *Lingua*, p. 345

6. Coreference Models: Mention Pair

*“**I** voted for **Nader** because **he** was most aligned with **my** values,” **she** said.*

I	Nader	he	my	she

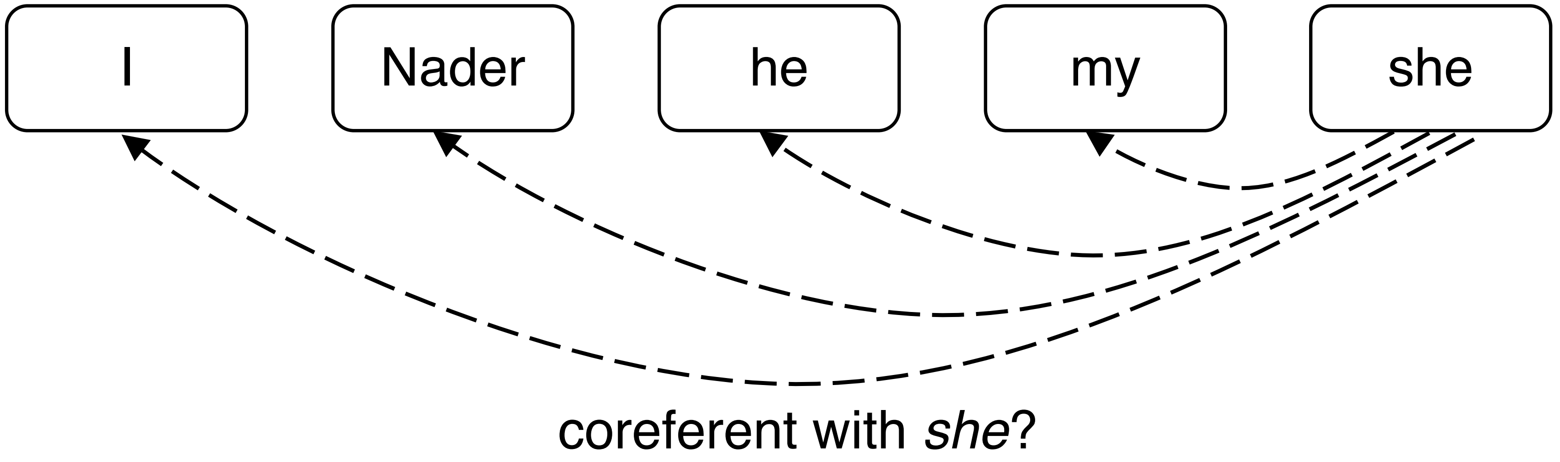
Coreference Cluster 1

Coreference Cluster 2

Coreference Models: Mention Pair

- Train a binary classifier that assigns every pair of mentions a probability of being coreferent: $p(m_i, m_j)$
  - e.g., for "she" look at all **candidate antecedents** (previously occurring mentions) and decide which are coreferent with it

*"**I** voted for **Nader** because **he** was most aligned with **my** values," **she** said.*



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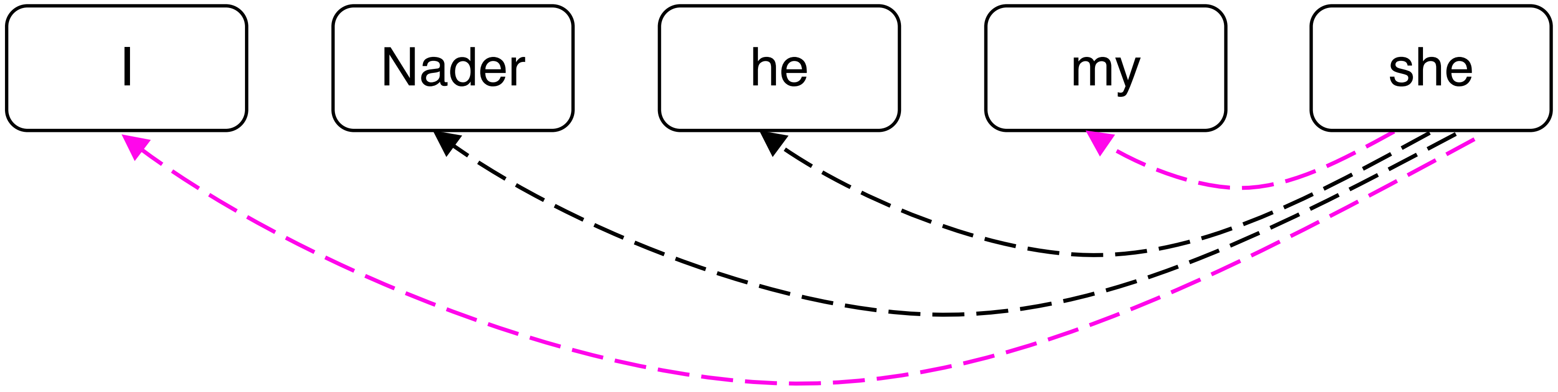

Positive examples: want $p(m_i, m_j)$ to be near 1

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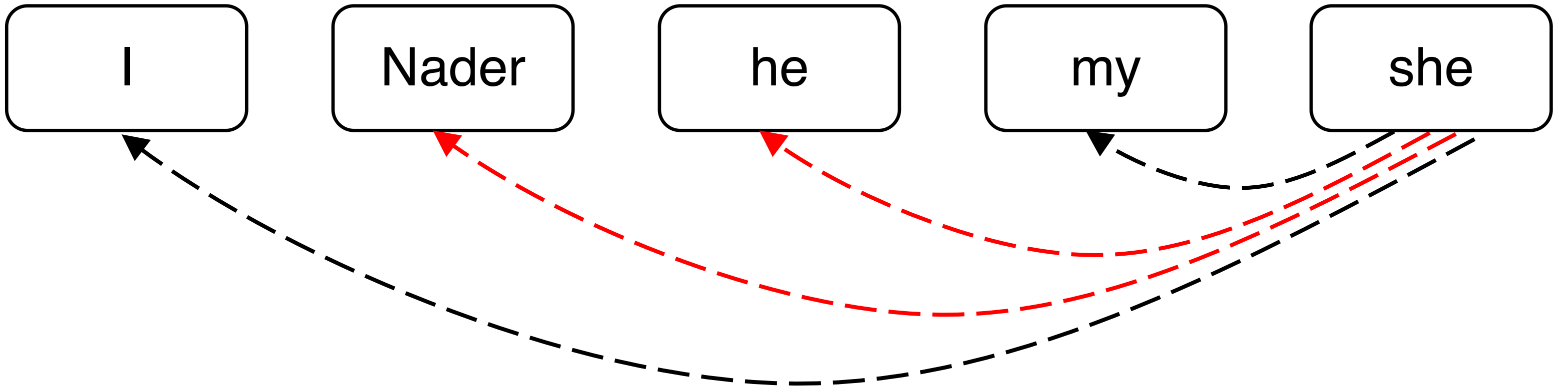


Negative examples: want $p(m_i, m_j)$ to be near 0

Mention Pair Training

- N mentions in a document
- y_{ij} = 1 if mentions m_i and m_j are coreferent, −1 if otherwise
- Just train with regular cross-entropy loss (= binary classification log loss)

$$J = -\sum_{i=2}^{N} \sum_{j=1}^{i} y_{ij} \log p(m_j, m_i)$$

Iterate through mentions

Iterate through candidate antecedents (previously occurring mentions)

Coreferent mentions pairs should get high probability, others should get low probability

Mention Pair Test Time

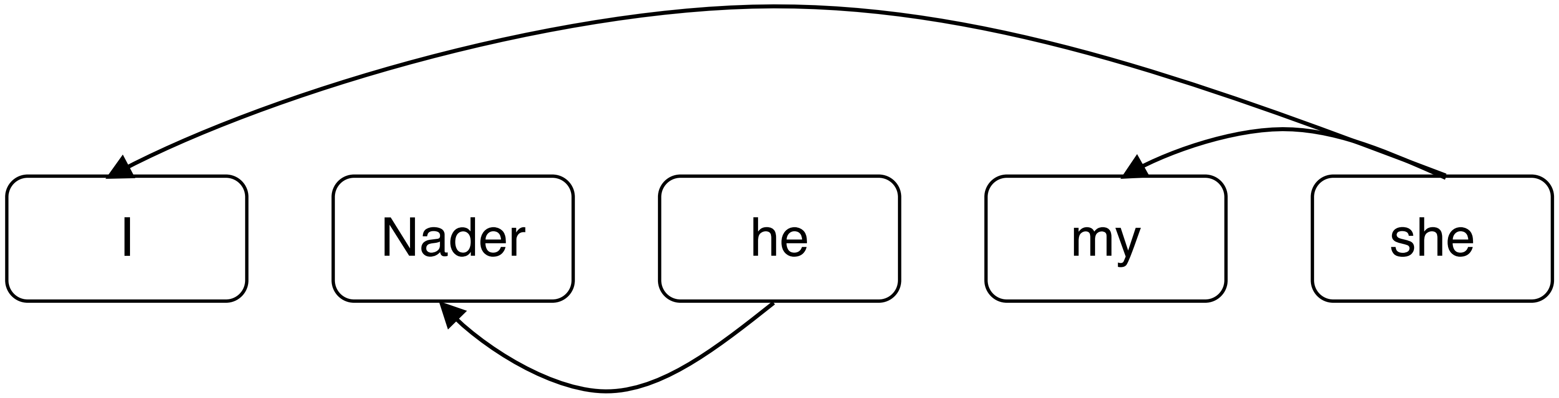
- Coreference resolution is a clustering task, but we are only scoring pairs of mentions… what to do?

I Nader he my she

Mention Pair Test Time

- Coreference resolution is a clustering task, but we are only scoring pairs of mentions… what to do?
- Pick some threshold (e.g., 0.5) and add **coreference links** between mention pairs where $p(m_i, m_j)$ is above the threshold

*“**I** voted for **Nader** because **he** was most aligned with **my** values,” **she** said.*



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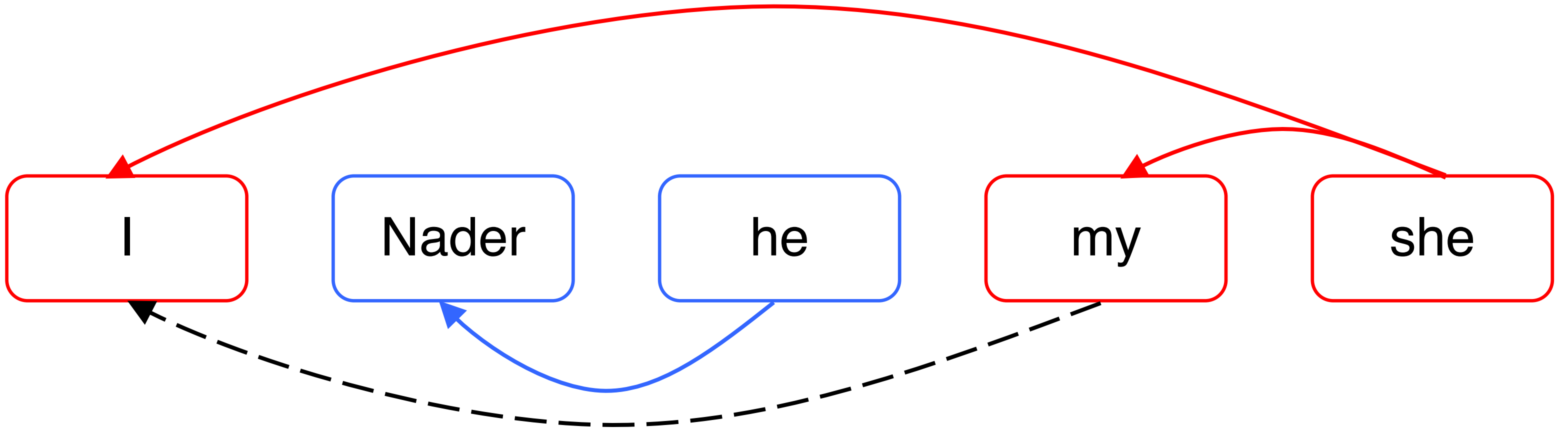
- Coreference resolution is a clustering task, but we are only scoring pairs of mentions… what to do?
- Pick some threshold (e.g., 0.5) and add **coreference links** between mention pairs where $p(m_i, m_j)$ is above the threshold
- Take the transitive closure to get the clustering

*"**I** voted for **Nader** because **he** was most aligned with **my** values," **she** said.*



Even though the model did not predict this coreference link,
I and *my* are coreferent due to transitivity

Mention Pair Test Time

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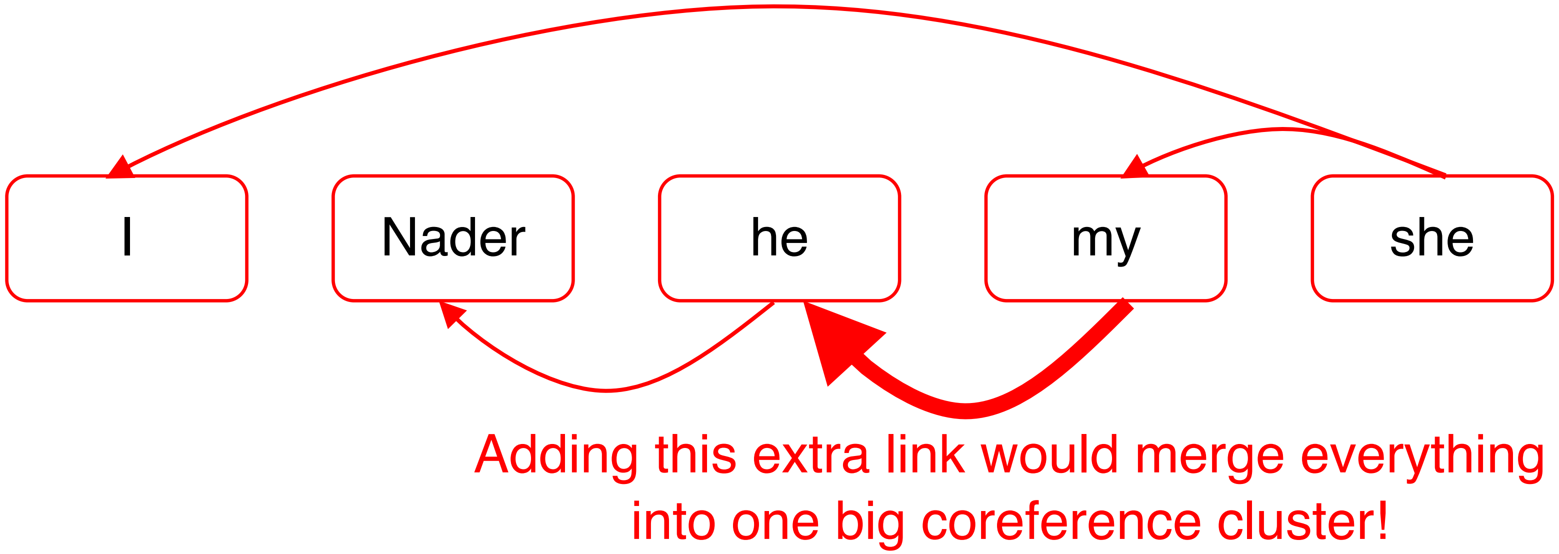
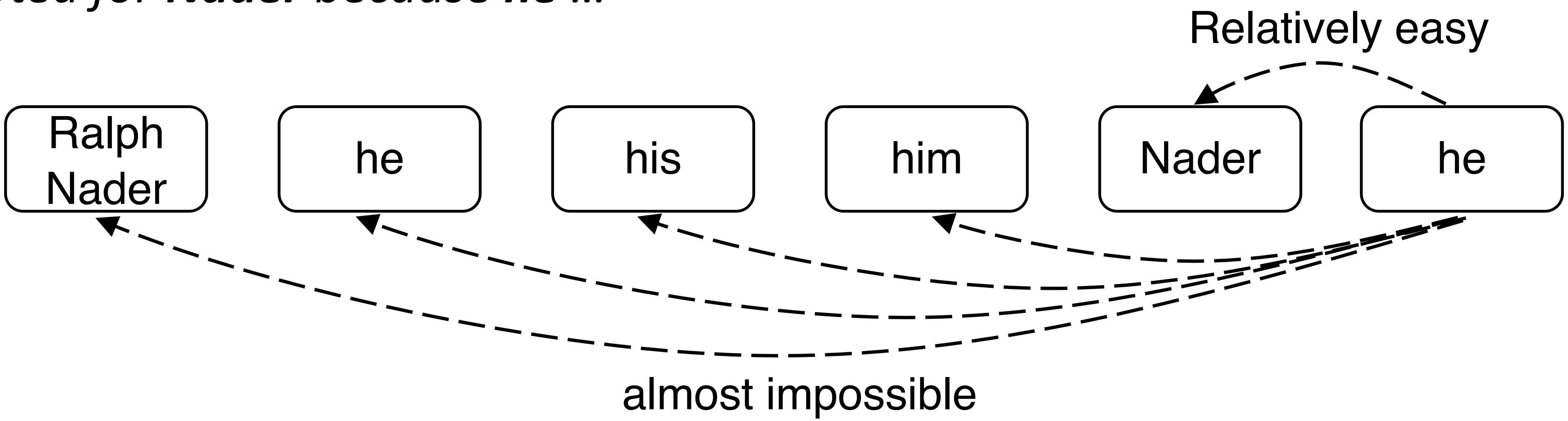


Mention Pair Models: Disadvantage

- Suppose we have a long document with the following mentions
  - **Ralph Nader** … **he** … **his** … **him** … <several paragraphs>
    … *voted for **Nader** because **he** …*



Mention Pair Models: Disadvantage

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  - **Ralph Nader** … **he** … **his** … **him** … <several paragraphs>
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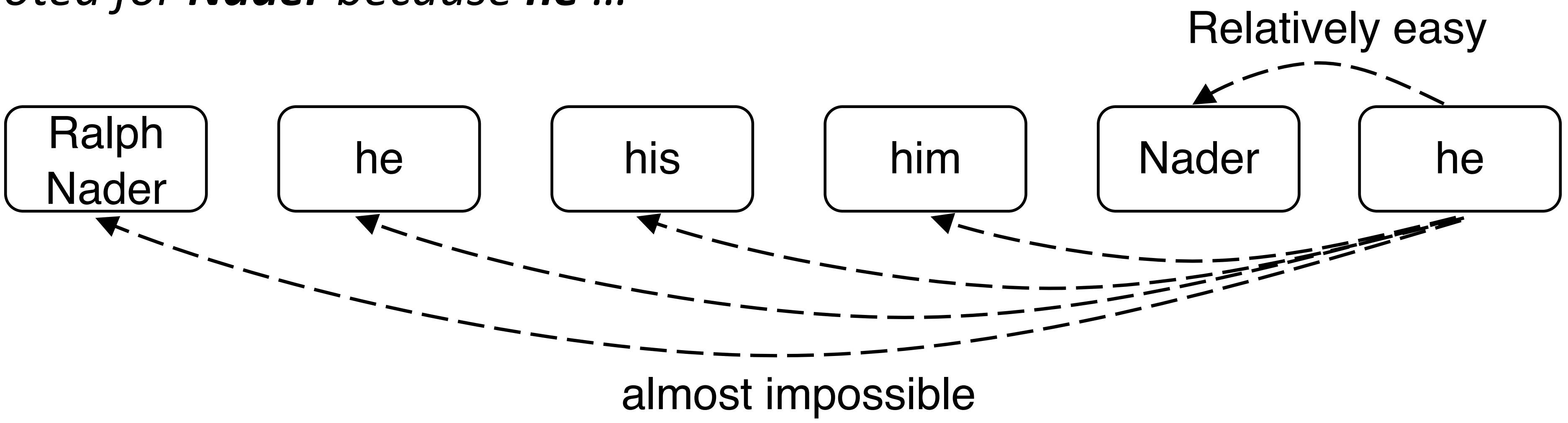
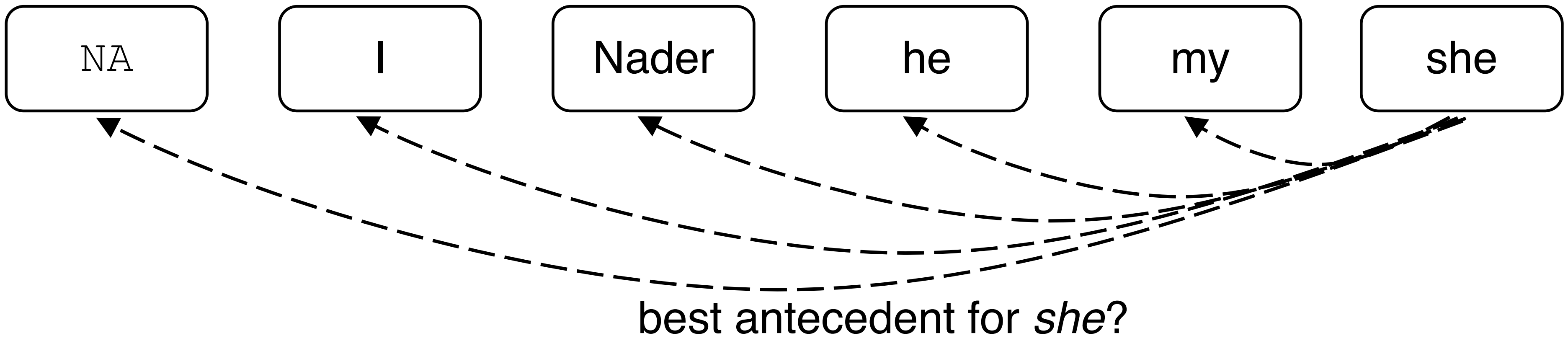


- Many mentions only have one clear antecedent
  - But we are asking the model to predict all of them
- Solution: instead train the model to predict only one antecedent for each mention
  - More linguistically plausible

7. Coreference Models: Mention Ranking

- Assign each mention its highest scoring candidate antecedent according to the model
- Dummy NA mention allows model to decline linking the current mention to anything (“singleton” or “first” mention)



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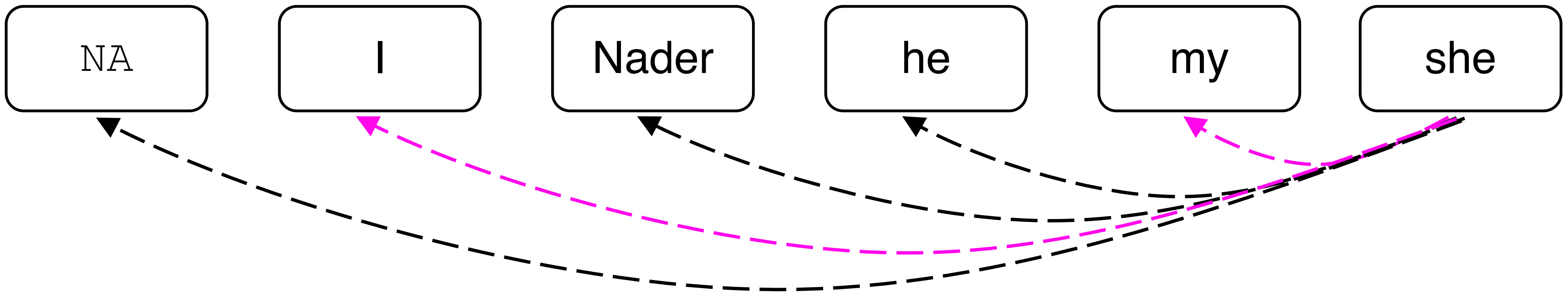

Positive examples: model has to assign a high probability to either one (but not necessarily both)

Coreference Models: Mention Ranking

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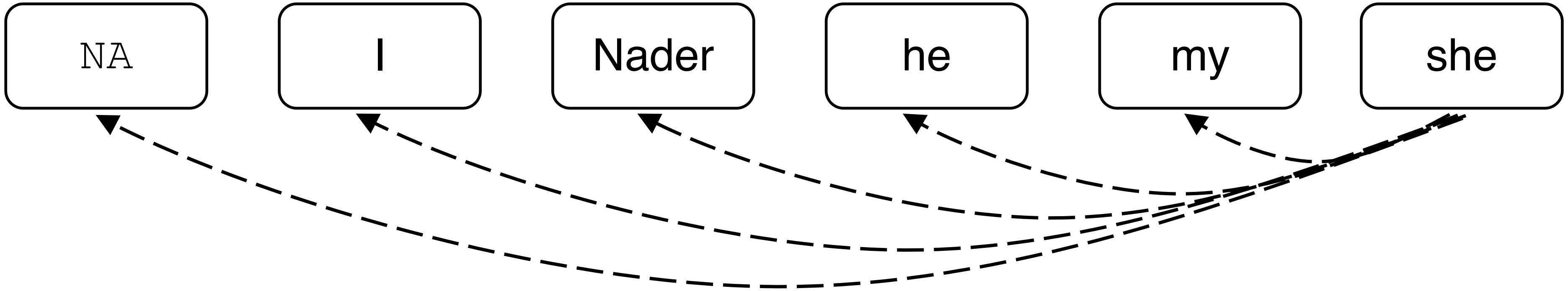

best antecedent for *she*?

p(NA, she) = 0.1
p(I, she) = 0.5
p(Nader, she) = 0.1
p(he, she) = 0.1
p(my, she) = 0.2

Apply a softmax over the scores for candidate antecedents so probabilities sum to 1

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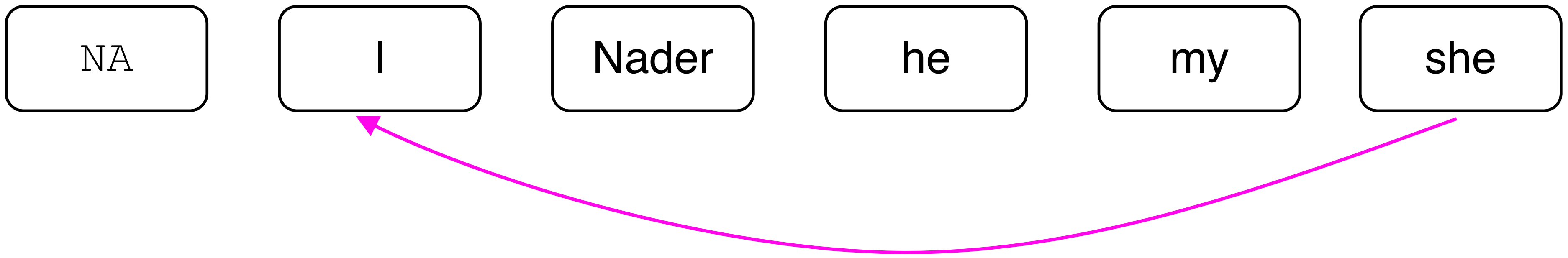

only add highest scoring coreference link

p(NA, she) = 0.1
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Apply a softmax over the scores for candidate antecedents so probabilities sum to 1

Coreference Models: Training

- We want the current mention m_j to be linked to *any one* of the candidate antecedents it's coreferent with.
- Mathematically, we want to maximize this probability:

$$\sum_{j=1}^{i-1} \mathbb{1}(y_{ij} = 1) p(m_j, m_i)$$

Iterate through candidate antecedents (previously occurring mentions)

For ones that are coreferent to m_j…

…we want the model to assign a high probability

- The model could produce 0.9 probability for one of the correct antecedents and low probability for everything else, and the sum will still be large

How do we compute the probabilities?

A. Non-neural statistical classifier

B. Simple neural network

C. More advanced model using LSTMs, attention, transformers

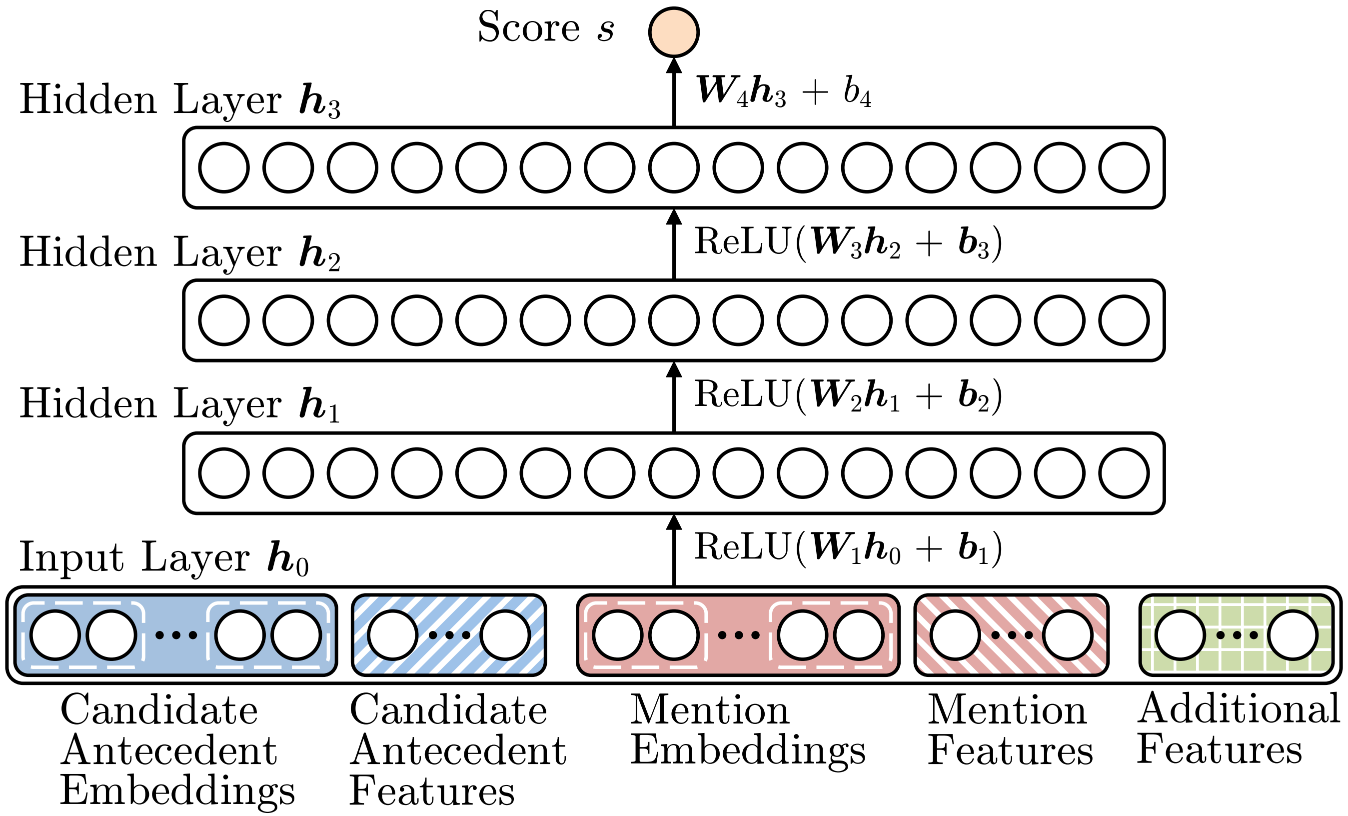
A. Non-Neural Coref Model: Features

- Person/Number/Gender agreement
  - Jack gave Mary a gift. She was excited.
- Semantic compatibility
  - … the mining conglomerate … the company …
- Certain syntactic constraints
  - John bought him a new car. [him can not be John]
- More recently mentioned entities preferred for referenced
  - John went to a movie. Jack went as well. He was not busy.
- Grammatical Role: Prefer entities in the subject position
  - John went to a movie with Jack. He was not busy.
- Parallelism:
  - John went with Jack to a movie. Joe went with him to a bar.
- …

Some changes needed here for singular *they*!

B. Neural Coref Model [Clark and Manning 2016]

- Standard feed-forward neural network
  - Input layer: word embeddings and a few categorical features



Neural Coref Model: Inputs

- Embeddings
  - Previous two words, first word, last word, head word, … of each mention
    - The **head** word is the “most important” word in the mention – you can find it using a parser. e.g., *The fluffy* ***cat*** *stuck in the tree*

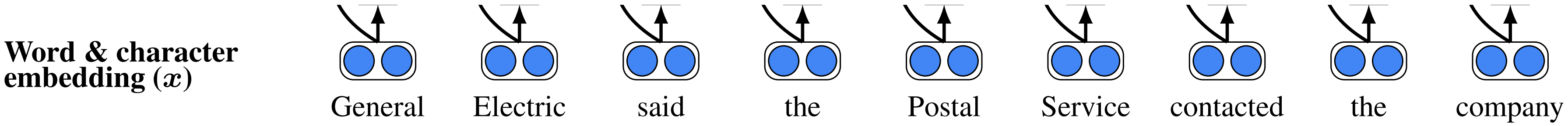
- Still need some other features to get a strongly performing model:
  - Distance
  - Document genre
  - Speaker information

7. End-to-end Neural Coref Model

- Current state-of-the-art models for coreference resolution
  - Kenton Lee et al. from UW (EMNLP 2017) et seq.
- Mention ranking model
- Improvements over simple feed-forward NN
  - Use an LSTM (or more)
  - Use attention
  - Do mention detection and coreference end-to-end
    - No mention detection step!
    - Instead consider every **span** of text (up to a certain length) as a candidate mention
      - a **span** is just a contiguous sequence of words

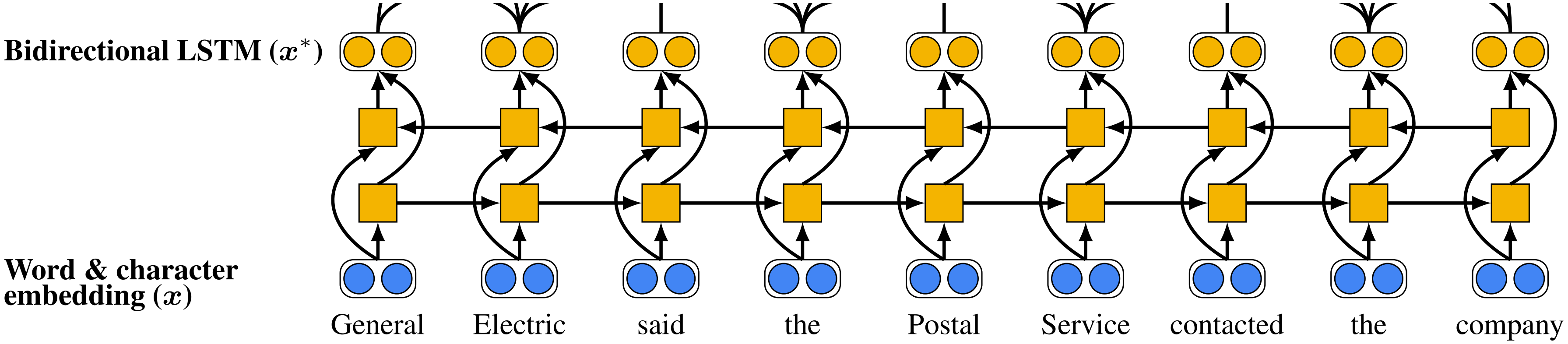
End-to-end Model

- First embed the words in the document using a word embedding matrix and a character-level CNN



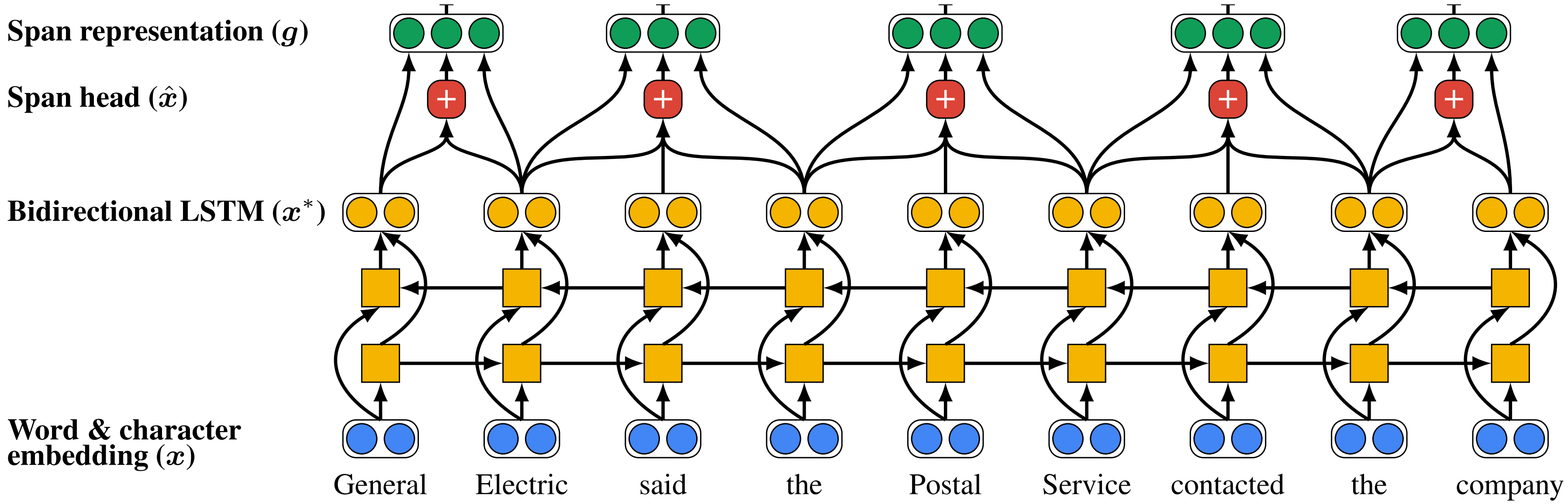
End-to-end Model

- Then run a bidirectional LSTM over the document



End-to-end Model

- Next, represent each span of text *i* going from START(*i*) to END(*i*) as a vector



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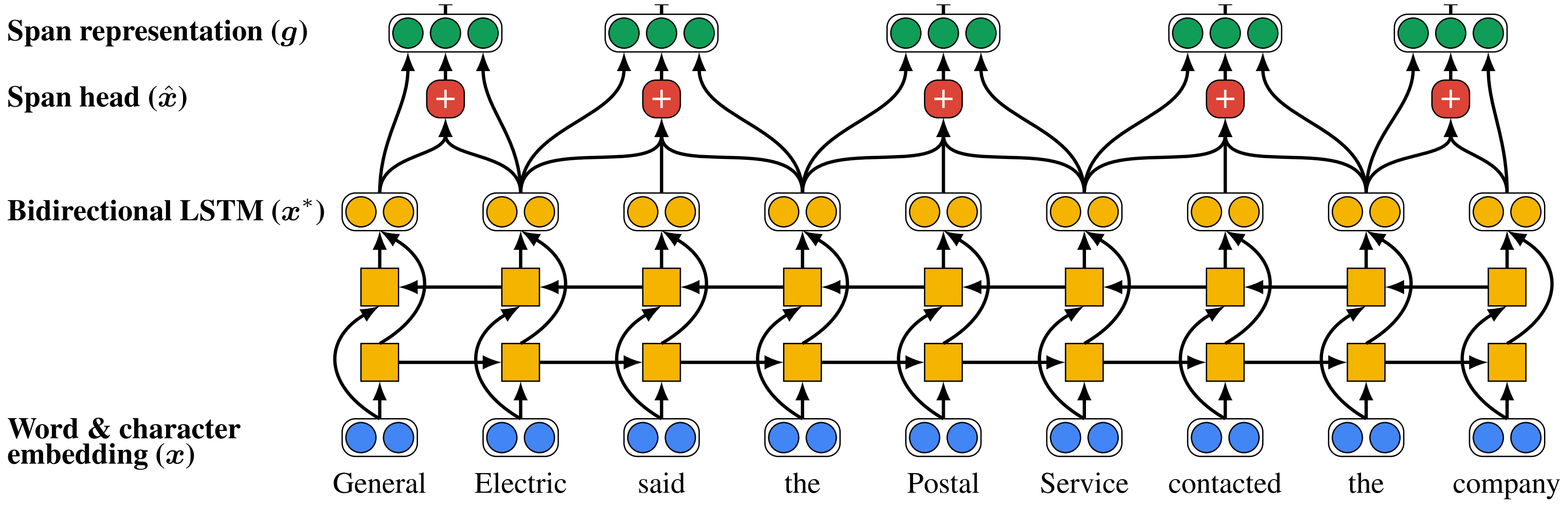
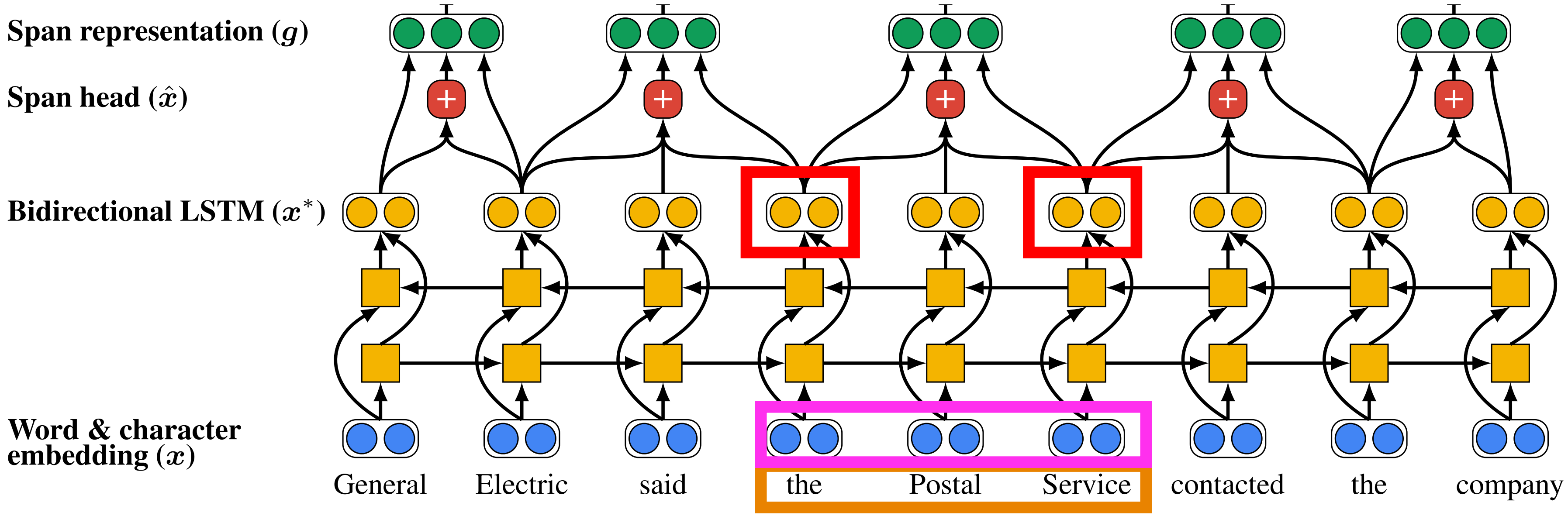


  - *General*, *General Electric*, *General Electric said*, *…*, *Electric*, *Electric said*, *…* will all get its own vector representation

End-to-end Model

- Next, represent each span of text *i* going from START(*i)* to END(*i)* as a vector
- For example, for "the postal service"



Span representation: $\boldsymbol{g}_i = [\boldsymbol{x}^*_{\mathrm{START}(i)}, \boldsymbol{x}^*_{\mathrm{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)]$

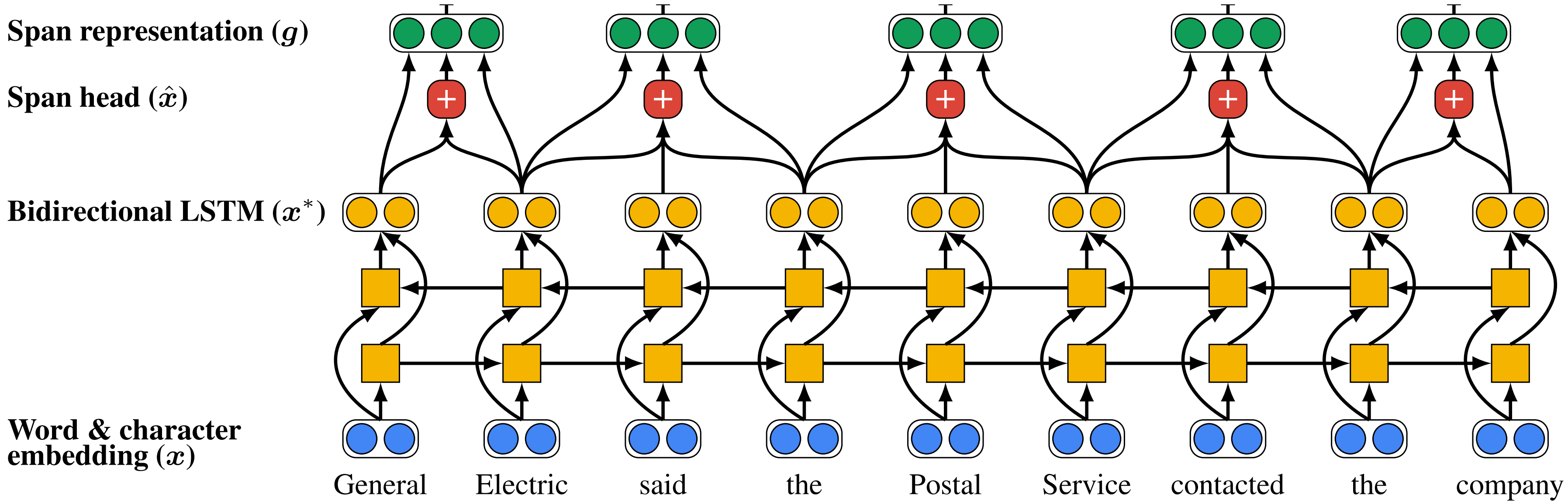
BILSTM hidden states for span's start and end

Attention-based representation (details next slide) of the words in the span

Additional features

End-to-end Model

- $\hat{\boldsymbol{x}}_i$ is an attention-weighted average of the word embeddings in the span



Attention scores

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

dot product of weight vector and transformed hidden state

Attention distribution

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

just a softmax over attention scores for the span

Final representation

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

Attention-weighted sum of word embeddings

End-to-end Model

- Why include all these different terms in the span?

$$\boldsymbol{g}_i = [\boldsymbol{x}^*_{\mathrm{START}(i)}, \boldsymbol{x}^*_{\mathrm{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)]$$

hidden states for span's start and end

Attention-based representation

Additional features

Represents the context to the left and right of the span

Represents the span itself

Represents other information not in the text

End-to-end Model

- Lastly, score every pair of spans to decide if they are coreferent mentions

$$s(i,j) = s_{\mathrm{m}}(i) + s_{\mathrm{m}}(j) + s_{\mathrm{a}}(i,j)$$

Are spans *i* and *j* coreferent mentions?

Is *i* a mention?

Is *j* a mention?

Do they look coreferent?

- Scoring functions take the span representations as input

$$s_{\mathrm{m}}(i) = \boldsymbol{w}_{\mathrm{m}} \cdot \mathrm{FFNN}_{\mathrm{m}}(\boldsymbol{g}_i)$$

$$s_{\mathrm{a}}(i,j) = \boldsymbol{w}_{\mathrm{a}} \cdot \mathrm{FFNN}_{\mathrm{a}}([\boldsymbol{g}_i, \boldsymbol{g}_j, \boldsymbol{g}_i \circ \boldsymbol{g}_j, \phi(i,j)])$$

include multiplicative interactions between the representations

again, we have some extra features

End-to-end Model

- Intractable to score every pair of spans
  - $O(T^2)$ spans of text in a document (T is the number of words)
  - $O(T^4)$ runtime!
  - So have to do lots of pruning to make work (only consider a few of the spans that are likely to be mentions)

- Attention learns which words are important in a mention (a bit like head words)

(**A fire in a Bangladeshi garment factory**) has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee (**the blaze**) in the four-story building.

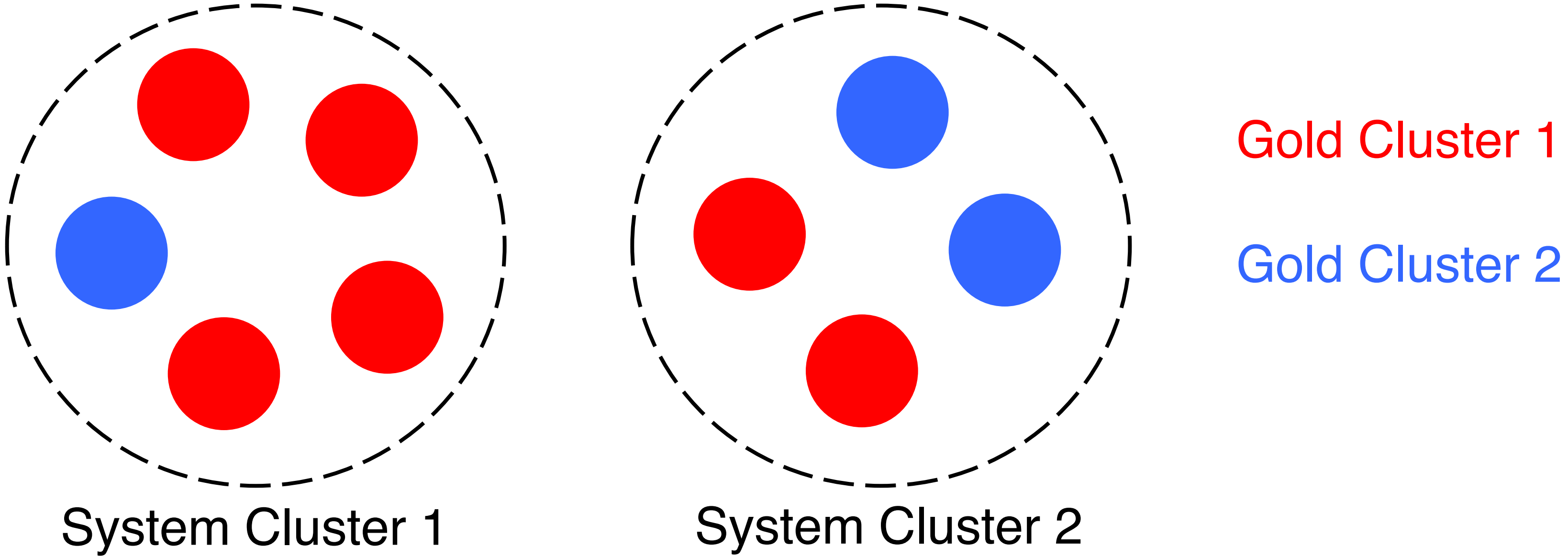
Transformer (*BERT)–based coref: Now the state-of-the-art!*

- Pretrained transformers can learn long-distance semantic dependencies in text.
- Idea 1, SpanBERT: Pretrains BERT models to be better at span-based prediction tasks like coref and QA
- Idea 2, BERT-QA for coref: Treat Coreference like a deep QA task
  - "Point to" a mention, ask "what is its antecedent", answer span is coreference link
- Idea 3: Maybe you don't have to do it with spans after all, and you can represent a mention with a word (maybe the head) and make things $O(T^2)$
  - Dobrovolskii (2021) https://arxiv.org/abs/2109.04127
  - Sort of makes sense given richness of transformers

- *One key exception: Bohnet et al. (2022) currently tops benchmarks https://arxiv.org/abs/2211.12142
  - Still uses a transformer (mT5) but models coreference prediction via a transition-based coreference parsing scheme, reminiscent of our Ass3 dependency parsers!

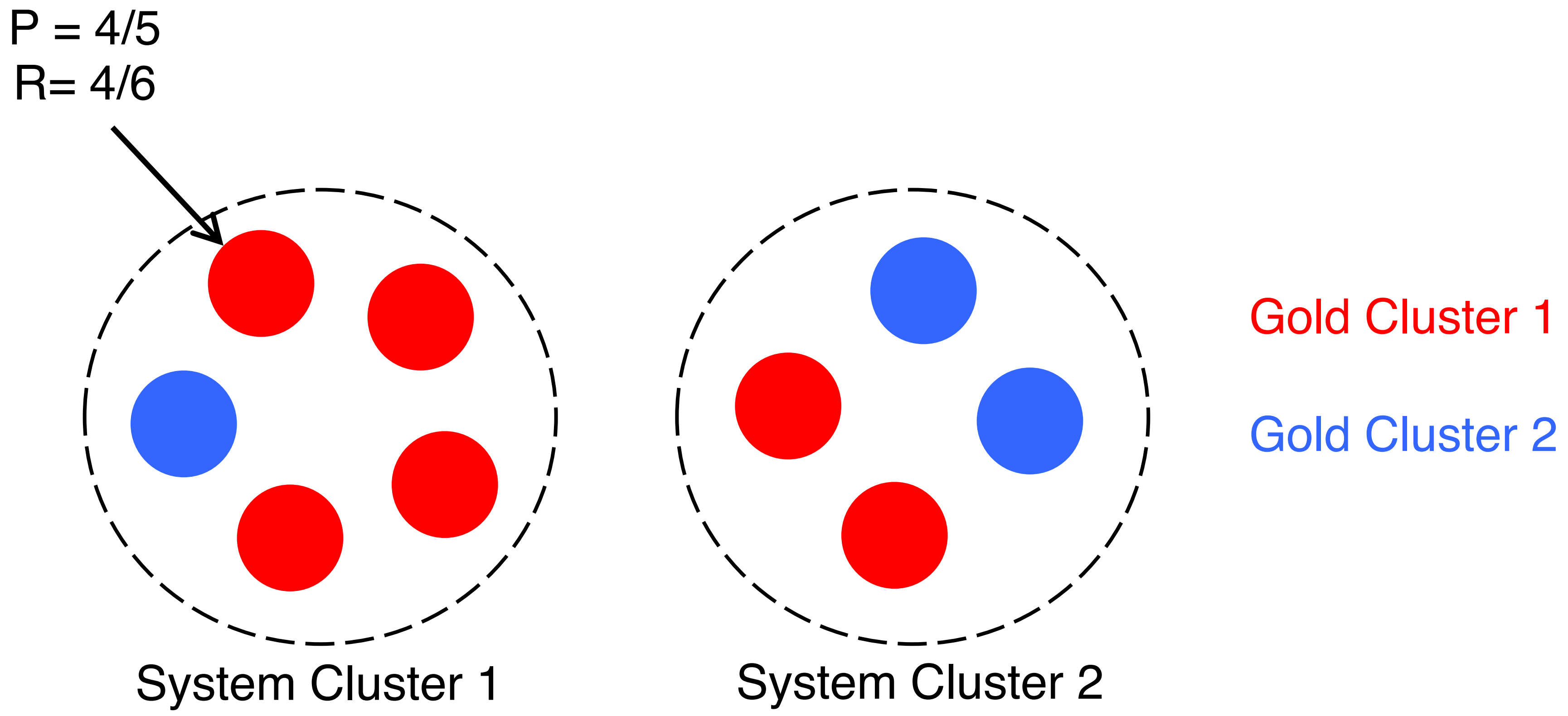
8. Coreference Evaluation

- Many different metrics: MUC, CEAF, LEA, B-CUBED, BLANC
  - People often report the average over a few different metrics
- Essentially the metrics think of coreference as a clustering task and evaluate the quality of the clustering



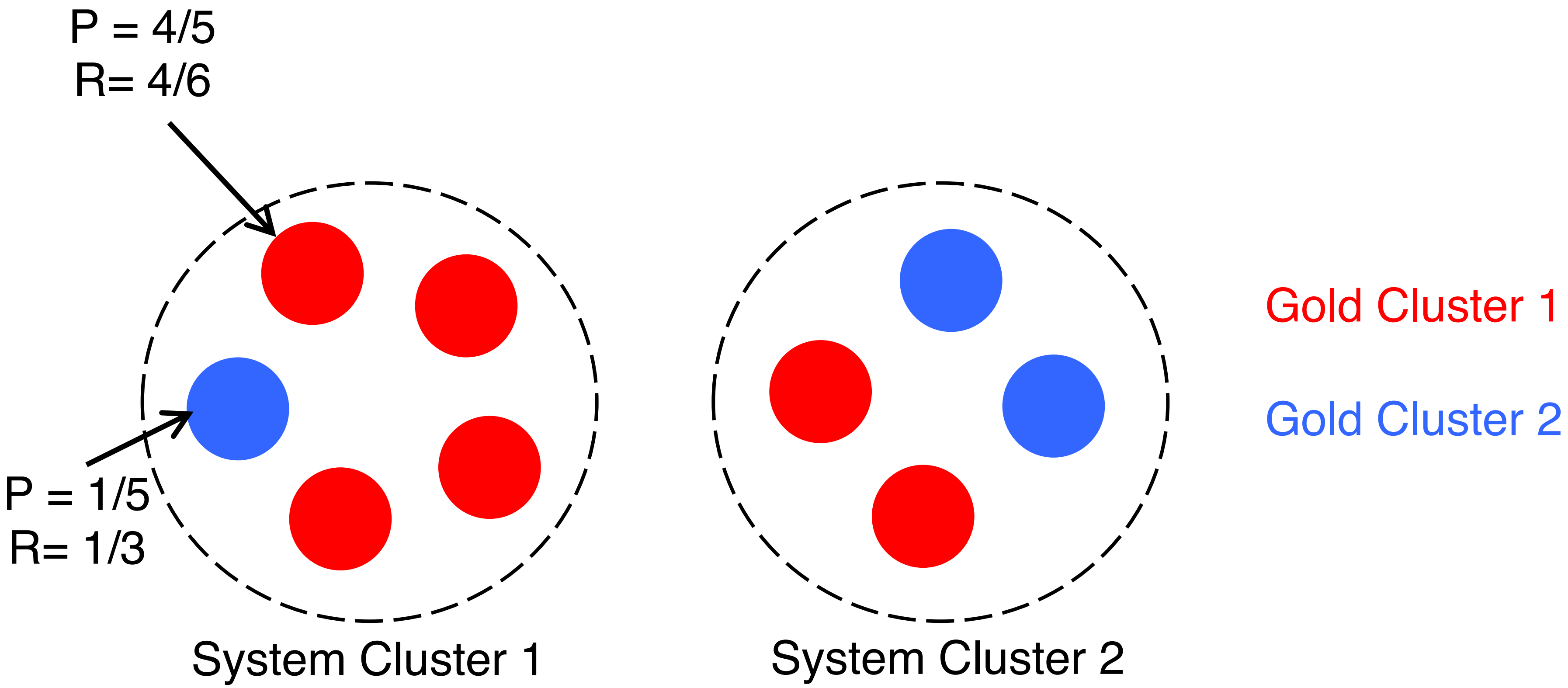
Coreference Evaluation

- An example: B-cubed
  - For each mention, compute a precision and a recall



Coreference Evaluation

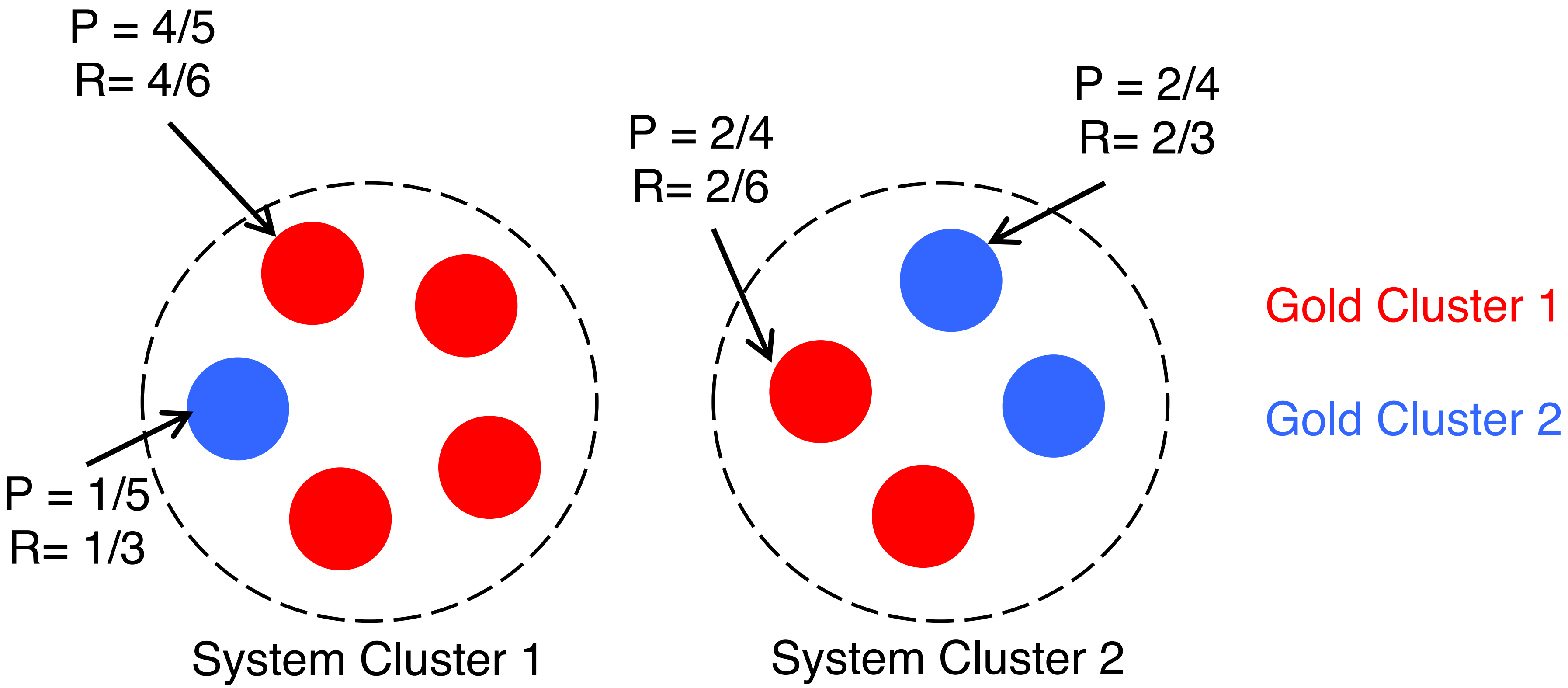
- An example: B-cubed
  - For each mention, compute a precision and a recall



Coreference Evaluation

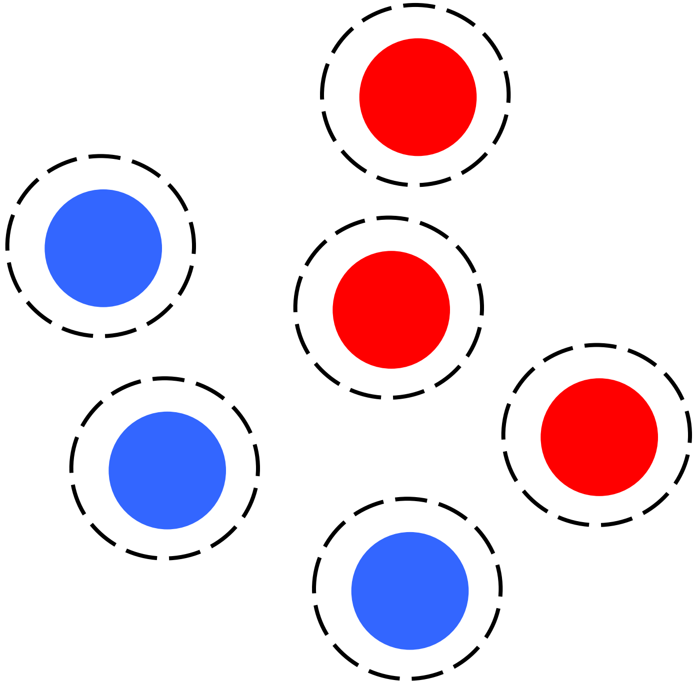
- An example: B-cubed
  - For each mention, compute a precision and a recall
  - Then average the individual Ps and Rs

$$P = [4(4/5) + 1(1/5) + 2(2/4) + 2(2/4)] / 9 = 0.6$$

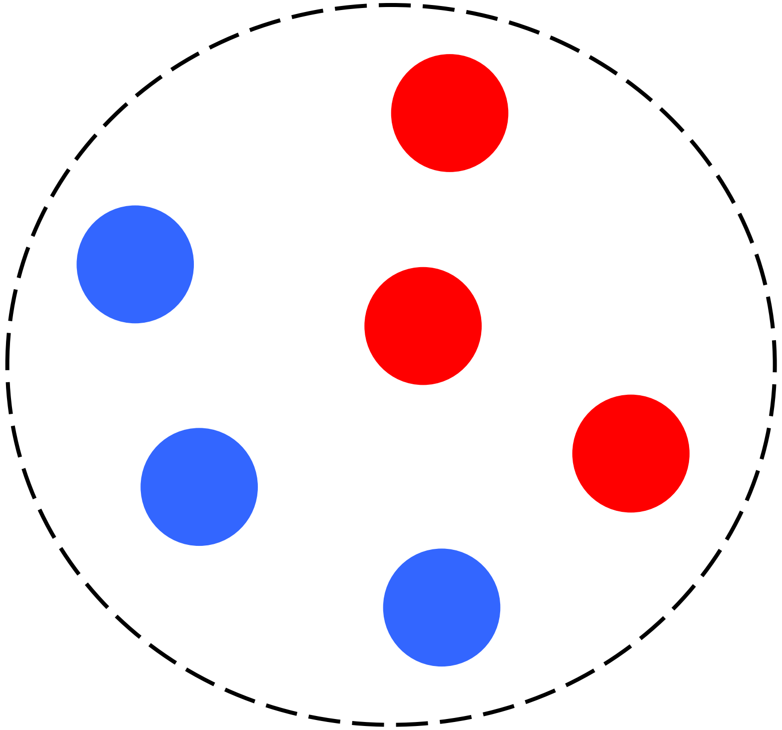


Coreference Evaluation

100% Precision, 33% Recall



50% Precision, 100% Recall,



System Performance

- OntoNotes dataset: ~3000 documents labeled by humans
  - English and Chinese data

- Standard evaluation: an F1 score averaged over 3 coreference metrics

System Performance

Model	English	Chinese
Lee et al. (2010)	~55	~50
Chen & Ng (2012) [CoNLL 2012 Chinese winner]	54.5	57.6
Fernandes (2012) [CoNLL 2012 English winner]	60.7	51.6
Wiseman et al. (2015)	63.3	—
Clark & Manning (2016)	65.4	63.7
Lee et al. (2017)	67.2	—
Joshi et al. (2019)	79.6	—
Wu et al. (2019) [CorefQA]	79.9	—
Xu et al. (2020)	80.2	—
Dobrovolskii (2021)	81.0	—
Alberti et al. (2022)	83.3	74.3

Rule-based system, used to be state-of-the-art!
Non-neural machine learning models

Neural mention ranker

Neural clustering model

End-to-end neural ranker

End-to-end neural mention ranker + **SpanBERT**

CorefQA

CorefQA + SpanBERT rulez

mT5 + transition-based system

Where do neural scoring models help?

- Especially with NPs and named entities with no string matching. Neural vs non-neural scores:

These kinds of coreference are hard and the scores are still low!

Example Wins

Anaphor	Antecedent
the country's leftist rebels	the guerillas
the company	the New York firm
216 sailors from the ``USS cole''	the crew
the gun	the rifle

Conclusion

- Coreference is a useful, challenging, and linguistically interesting task
  - Many different kinds of coreference resolution systems
- Systems are getting better **rapidly**, largely due to better neural models
  - But most models still make many mistakes – OntoNotes coref is easy newswire case

- Try out a coreference system yourself!
  - http://corenlp.run/ (ask for coref in Annotations)
  - https://huggingface.co/coref/