CSEP 517
Natural Language Processing
Autumn 2018

Coreference Resolution

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Slides adapted from Kevin Clark

Lecture Plan:

- What is Coreference Resolution?
- Mention Detection
- Some Linguistics: Types of Reference
- 3 Kinds of Coreference Resolution Models
  - Including the current state-of-the-art coreference system!

What is Coreference Resolution?

- Identify all **mentions** that refer to the same real world entity

Barack Obama nominated Hillary Rodham Clinton as his secretary of state on Monday. He chose her because she had foreign affairs experience as a former First Lady.

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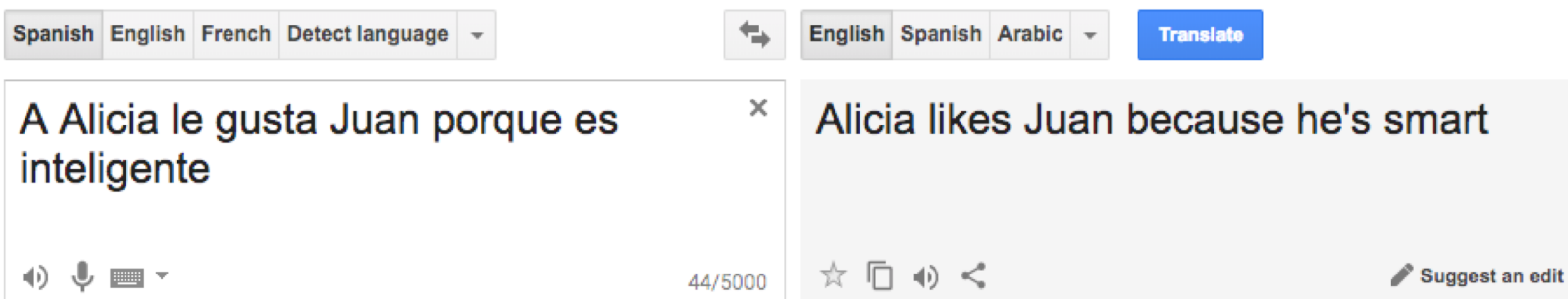
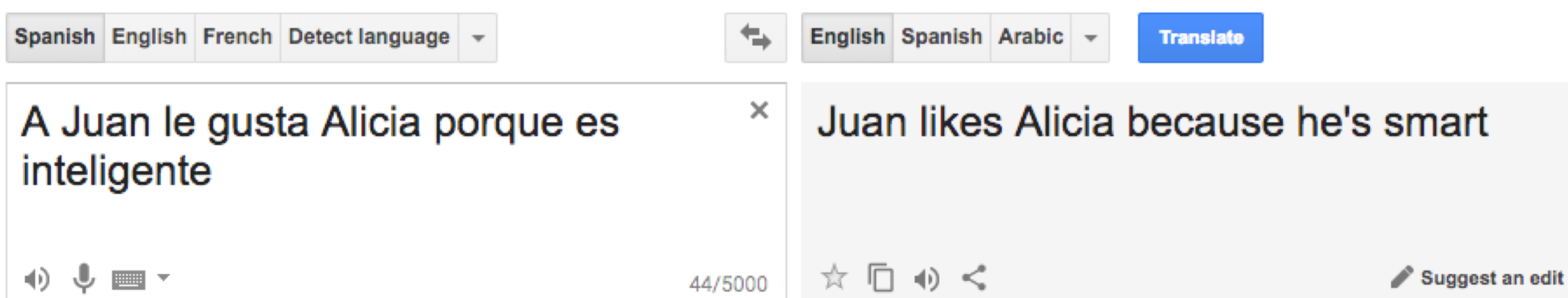
Applications

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

Applications

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





Applications

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

o bir aşçı	she is a cook
o bir mühendis	he is an engineer
o bir doktor	he is a doctor
o bir hemşire	she is a nurse
o bir temizlikçi	he is a cleaner
o bir polis	He-she is a police
o bir asker	he is a soldier
o bir öğretmen	She's a teacher
o bir sekreter	he is a secretary

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 is Really Difficult!

- “She poured water from the pitcher into the cup until it was full”
- Requires reasoning /world knowledge to solve

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Coreference Resolution is Really Difficult!

- "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 trophy would not fit in the suitcase because it was too big.
- The trophy would not fit in the suitcase because it was too small.

- These are called **Winograd Schema**

Coreference Resolution is Really Difficult!

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- The trophy would not fit in the suitcase because it was too small.

- These are called **Winograd Schema**
  - Recently proposed as an alternative to the Turing test
    - Turing test: how can we tell if we've built an AI system? A human can't distinguish it from a human when chatting with it.
    - But requires a person, people are easily fooled
  - If you've fully solved coreference, arguably you've solved AI

Coreference Resolution in Two Steps

1. Detect the mentions (relatively 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

Mention Detection

- Mention: 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.

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

Mention Detection

- Span of text referring to some entity
- For detection: use other NLP systems

1. Pronouns
   - Use a part-of-speech tagger

2. Named entities
   - Use a NER system

3. Noun phrases
   - Use a constituency parser

Mention Detection: Not so Simple

- Marking all pronouns, named entities, and NPs as mentions over-generates mentions
- Are these mentions?
  - It is sunny

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  - It is sunny
  - Every student
  - No student
  - The best donut in the world
  - 100 miles
- Some gray area in defining “mention”: have to pick a convention and go with it

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)

Can we avoid a pipelined system?

- We could instead train a classifier specifically for mention detection instead of using a POS tagger, NER system, and parser.

- Or even jointly do mention-detection and coreference resolution end-to-end instead of in two steps
  - Will cover later in this lecture!

On to Coreference! First, some linguistics

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

- Another kind of reference is **anaphora:** when a term (anaphor) refers to another term (antecedent) and 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

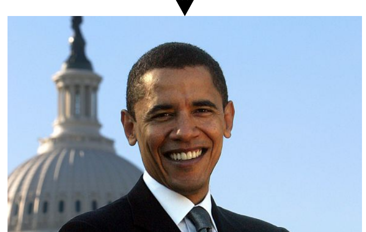
text Barack Obama Obama

world

- Anaphora

text Barack Obama he

world

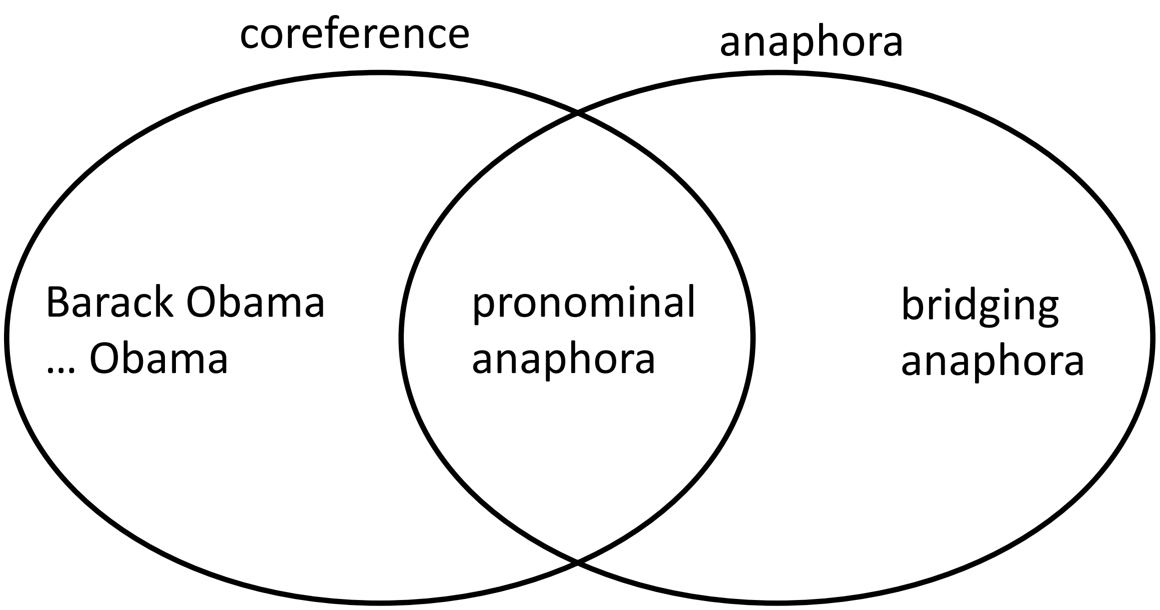


Anaphora vs. Coreference

- 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.



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)

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Next Up: Three Kinds of Coreference Models

- Mention Pair
- Mention Ranking
- Clustering

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

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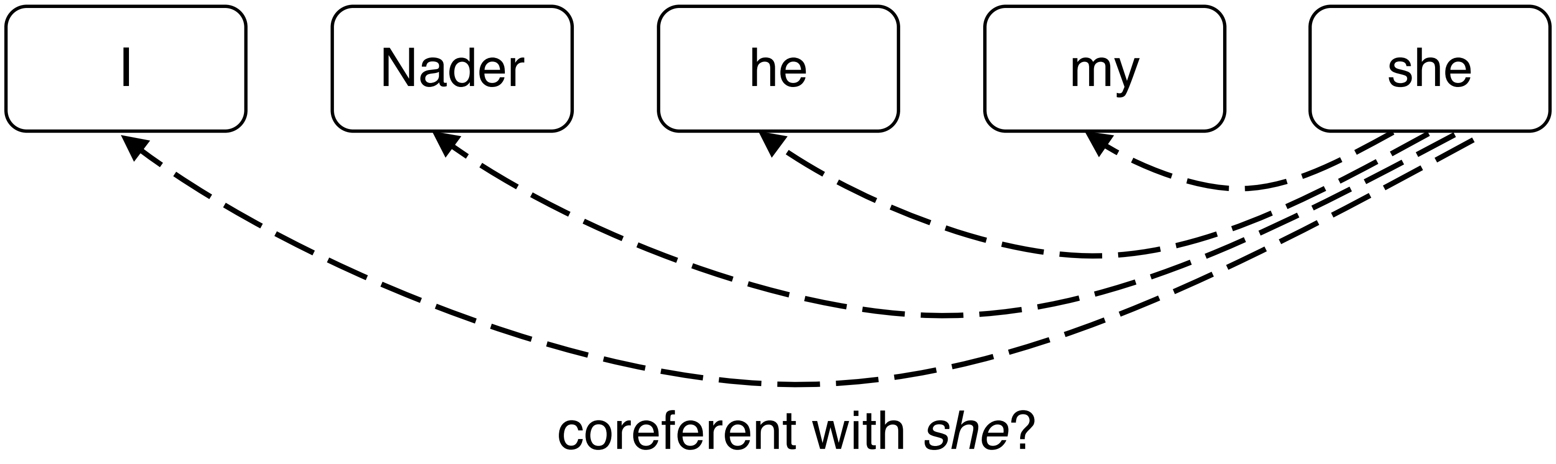

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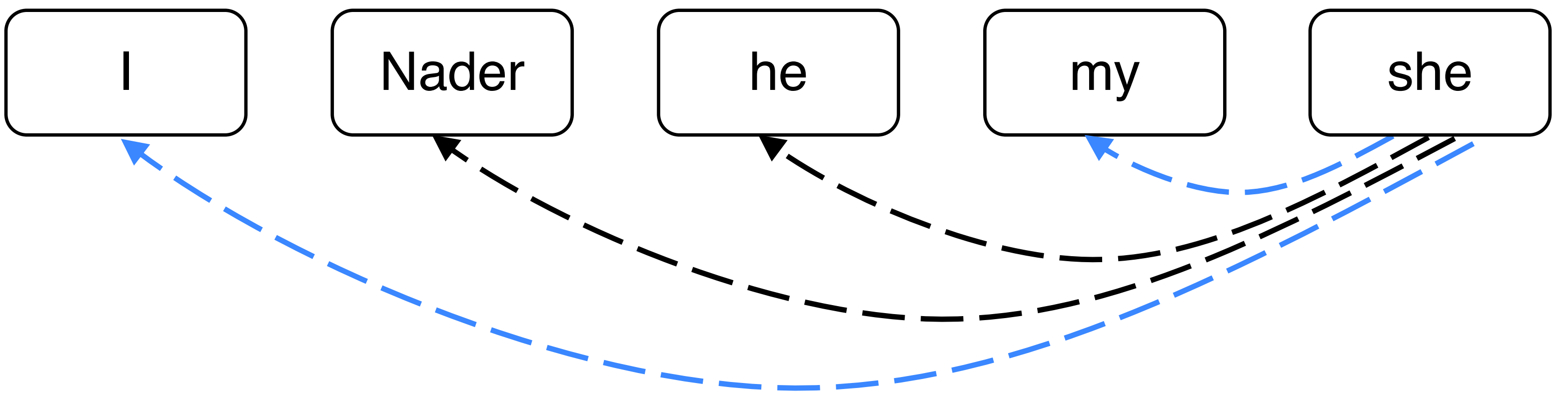

Positive examples: want $p(m_i, m_j)$ to be near 1

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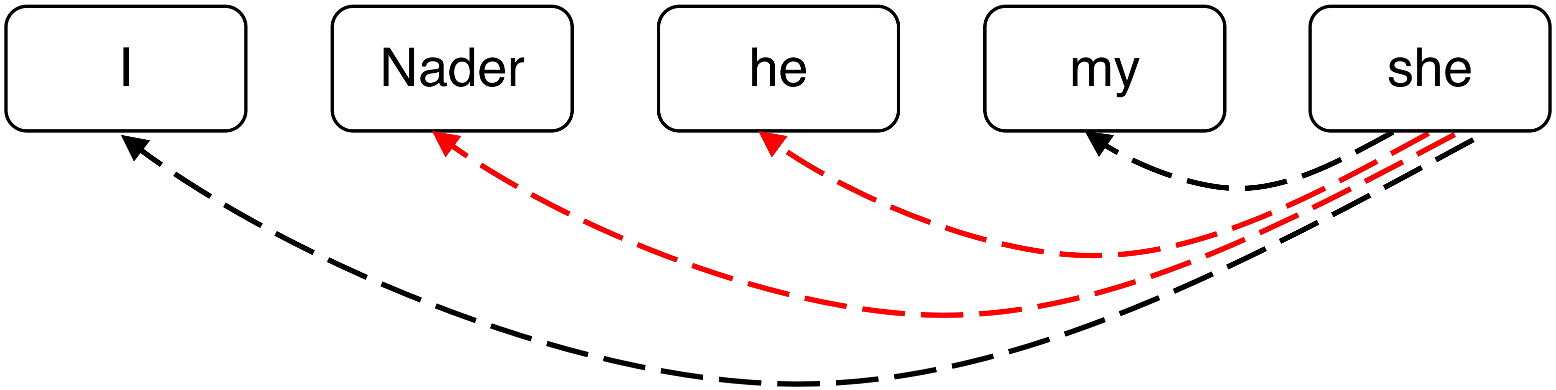


Negative examples: want $p(m_i, m_j)$ to be near 0

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 (looks a bit different because it is binary classification)

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

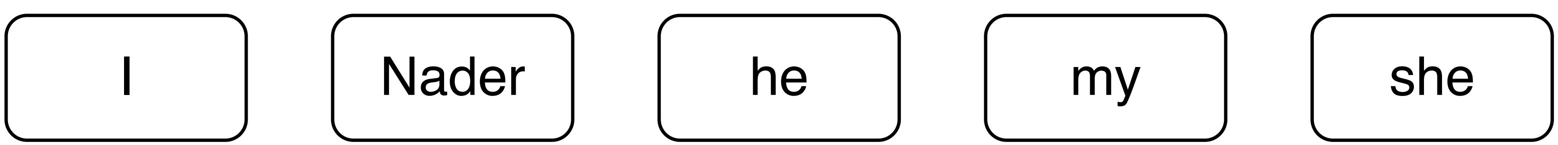
Iterate through mentions

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?



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- Pick some threshold (e.g., 0.5) and add **coreference links** between mention pairs where $p(m_i, m_j)$ is above the threshold

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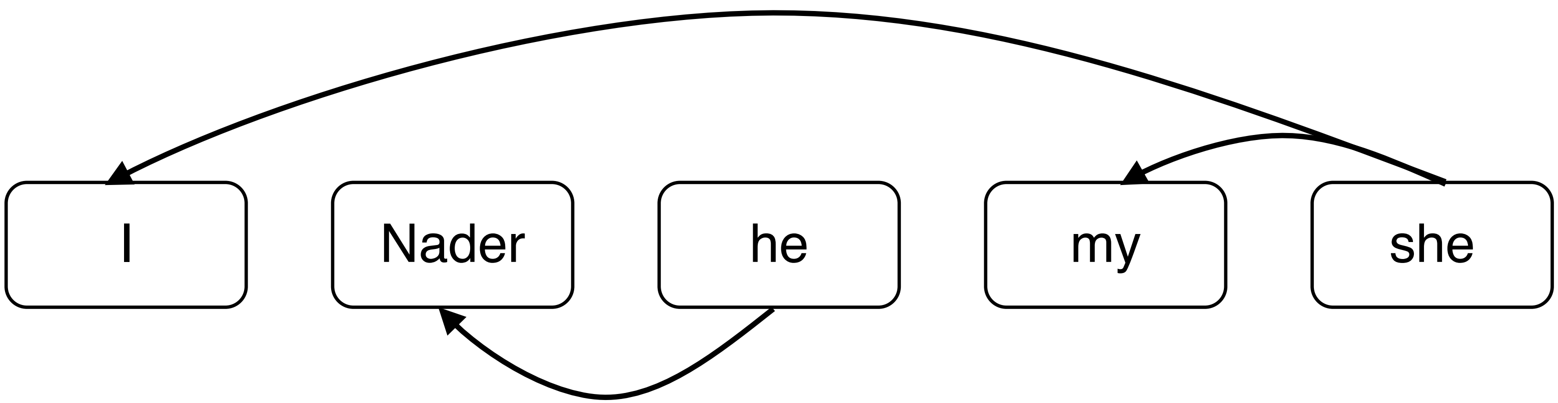

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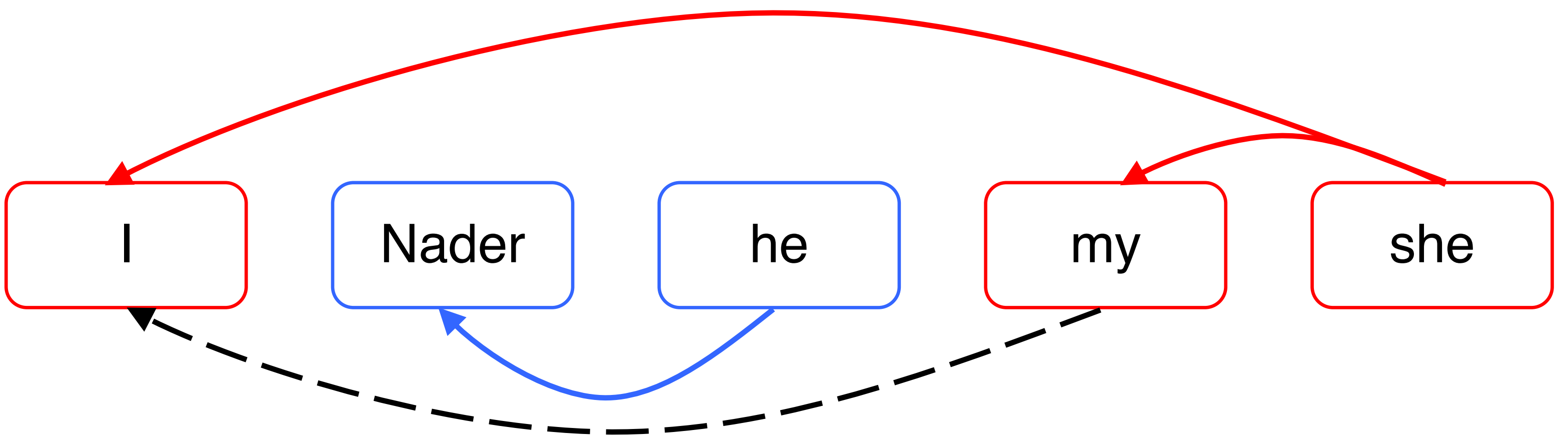

Even though the model did not predict this coreference link, *I* and *my* are coreferent due to transitivity

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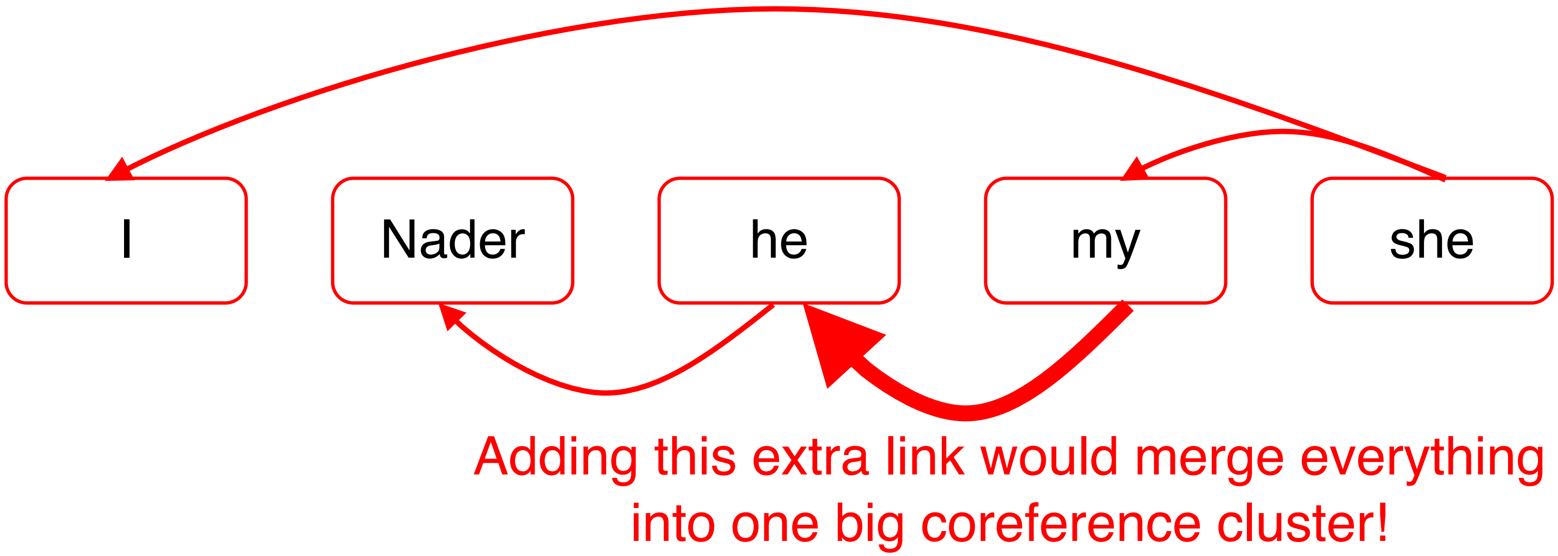
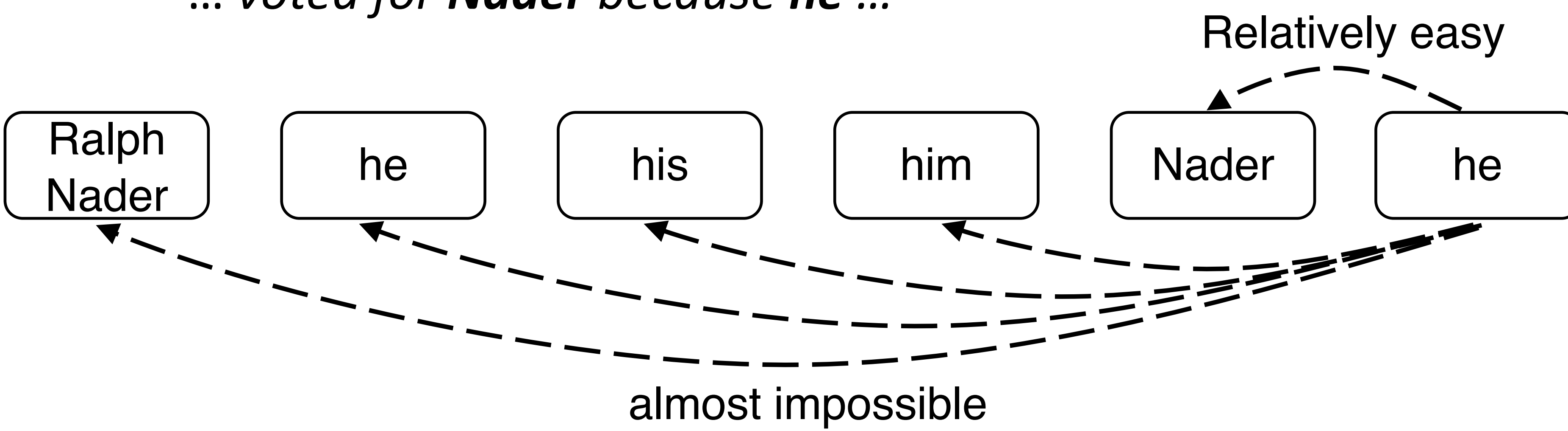


Mention Pair Models: Disadvantage

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



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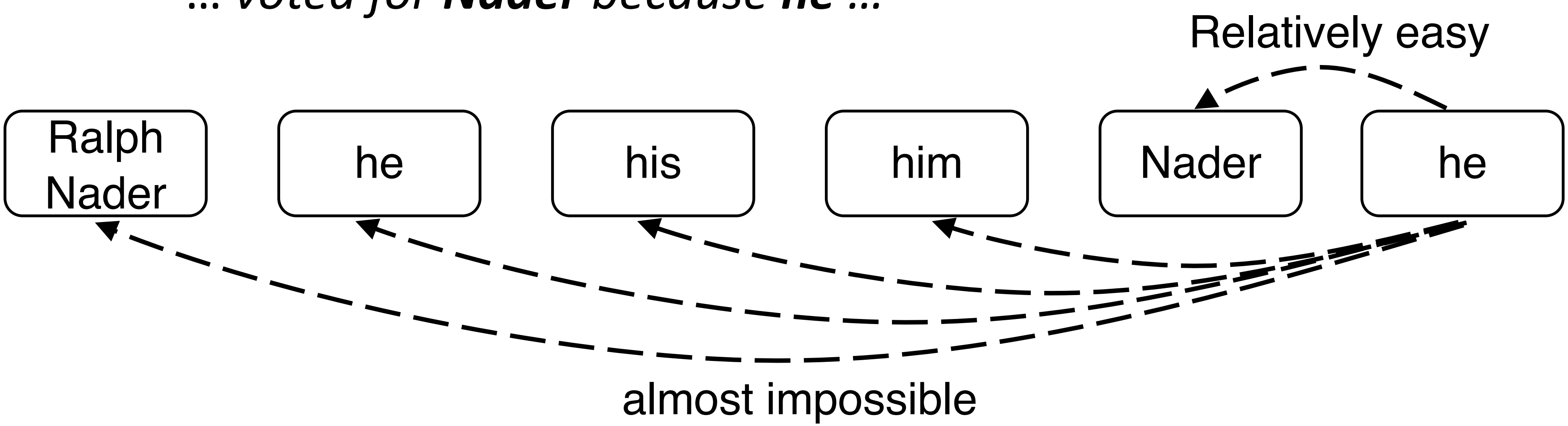
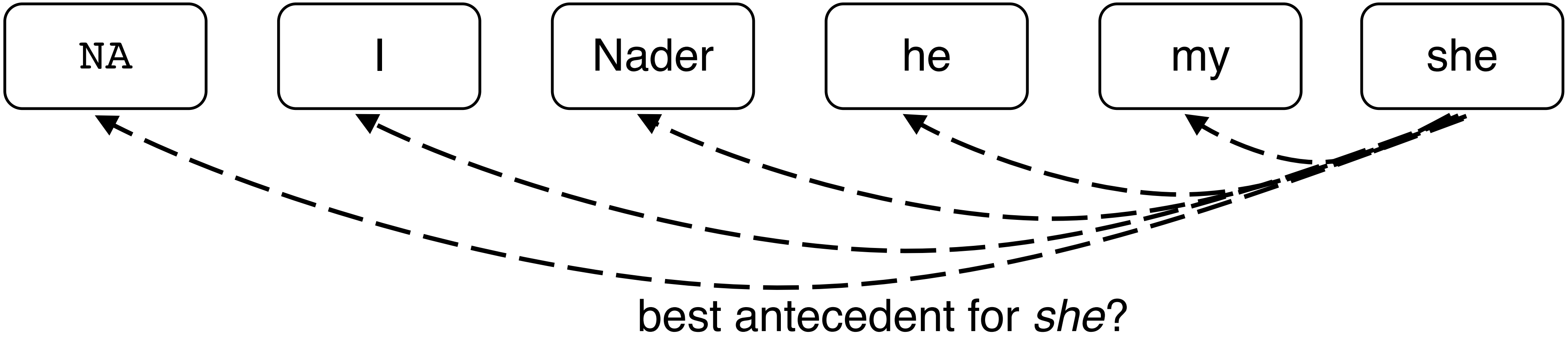


- Many mentions only have one clear antecedent
  - But we are asking the model to predict all of them
- Solution: instead train the model to predict only one antecedent for each mention
  - More linguistically plausible

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



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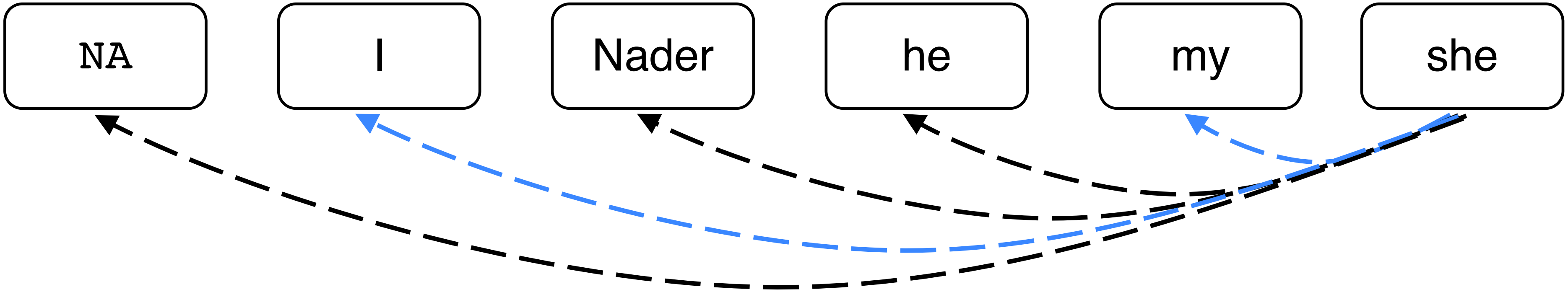

Positive examples: model has to assign a high probability to either one (but not necessarily both)

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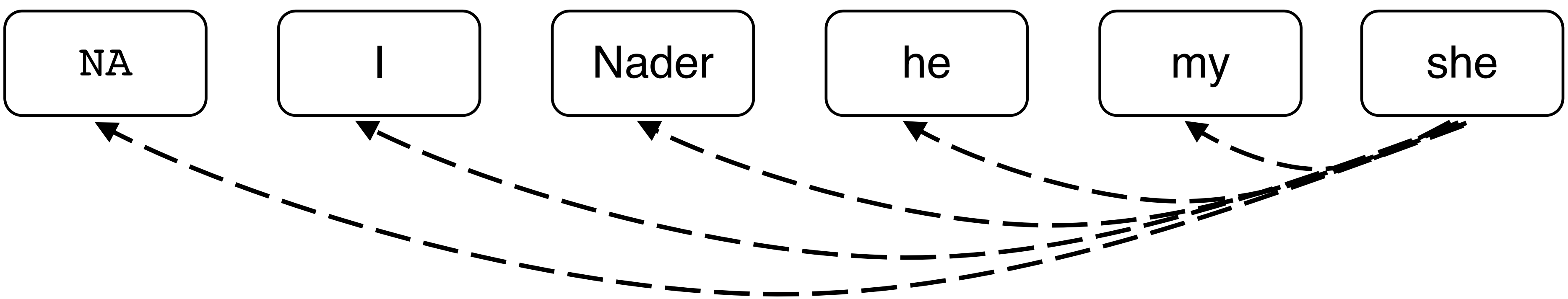

best antecedent for *she*?

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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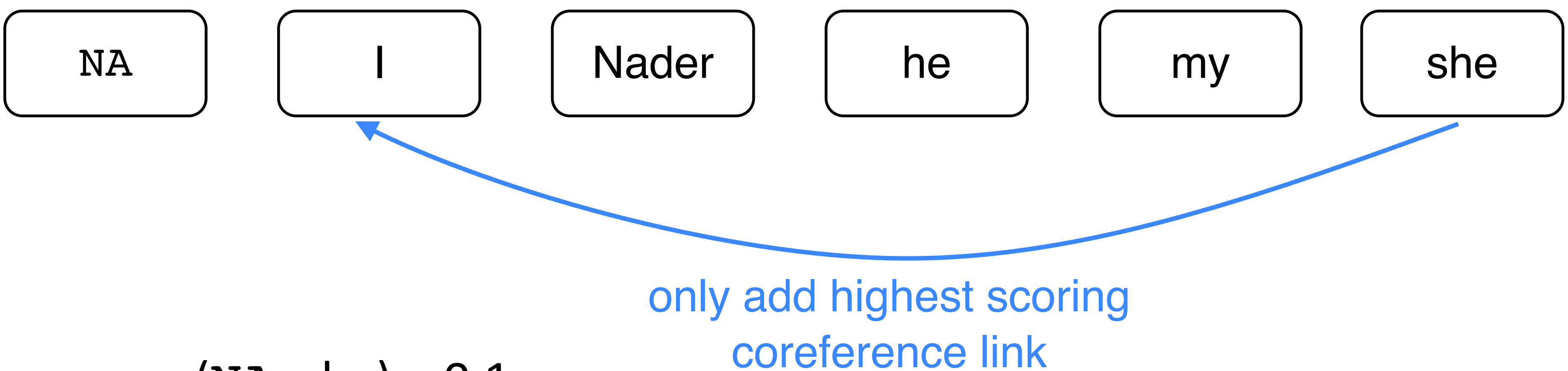

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Coreference Models: Training

- 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

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- 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

Coreference Models: Training

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- Mathematically, we want to maximize this probability:

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

- Turning this into a loss function:

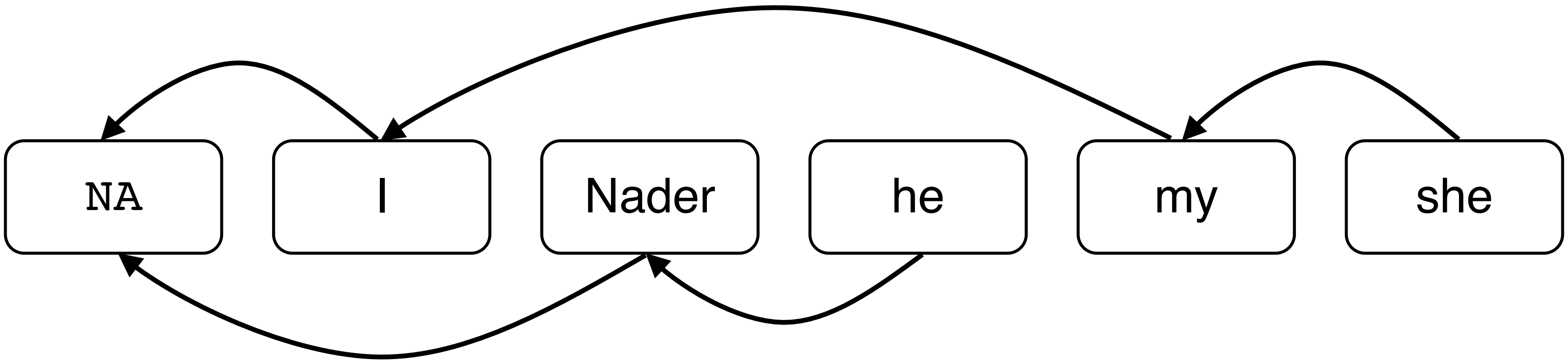
$$J = \sum_{i=2}^{N} -\log \left(\sum_{j=1}^{i-1} \mathbb{1}(y_{ij} = 1)p(m_j, m_i) \right)$$

Iterate over all the mentions in the document

Usual trick of taking negative log to go from likelihood to loss

Mention Ranking Models: Test Time

- Pretty much the same as mention-pair model except each mention is assigned only one antecedent



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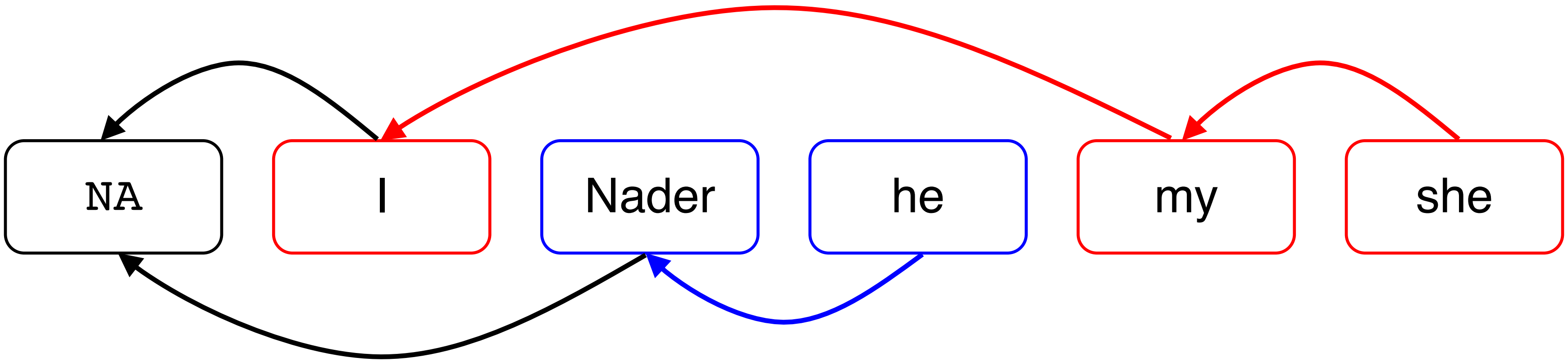


How do we compute the probabilities?

1. Non-neural statistical classifier

2. Simple neural network

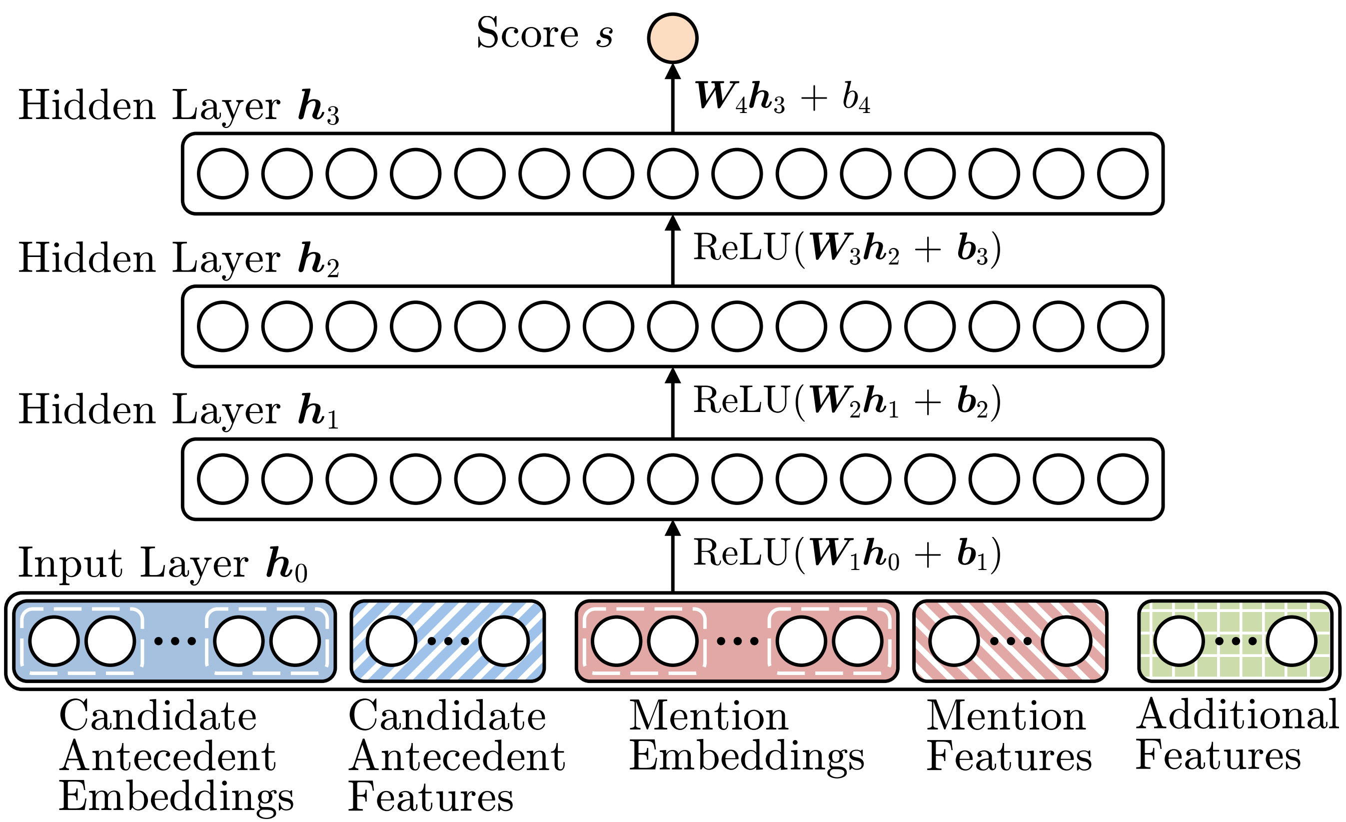
3. More advanced model using LSTMs, attention

1. 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.
- …

2. Neural Coref Model

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



2. 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*

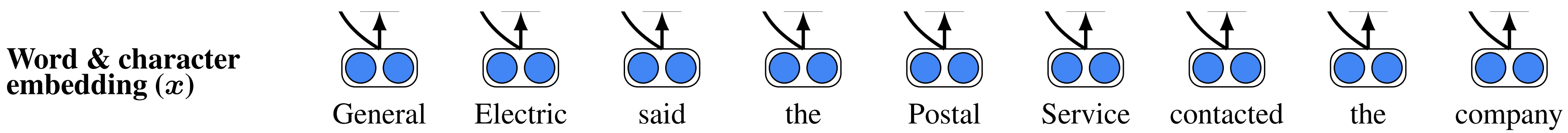
- Still need some other features:
  - Distance
  - Document genre
  - Speaker information

3. End-to-end Model

- Current state-of-the-art model for coreference resolution (Lee et al., EMNLP 2017)
- Mention ranking model
- Improvements over simple feed—forward NN
  - Use an LSTM
  - 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

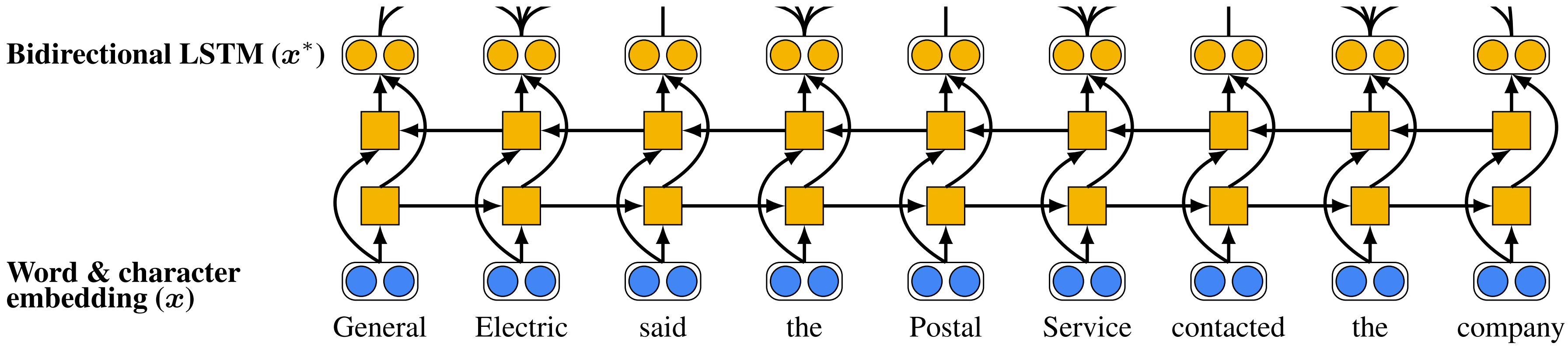
3. End-to-end Model

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



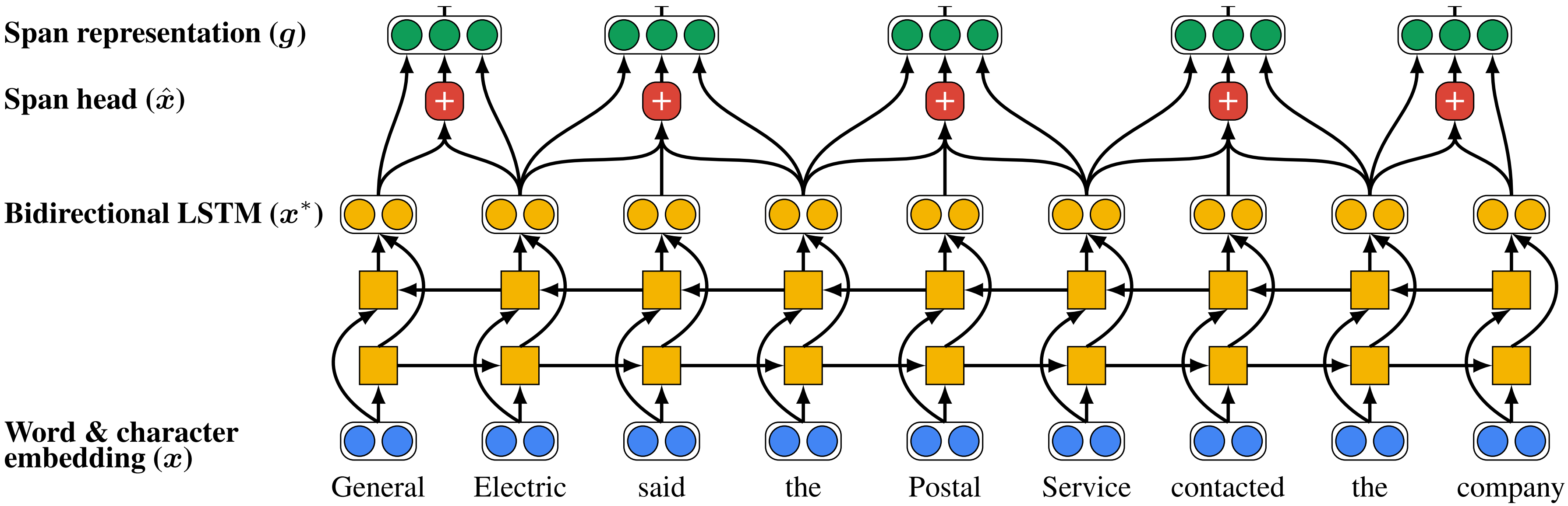
3. End-to-end Model

- Then run a bidirectional LSTM over the document



3. 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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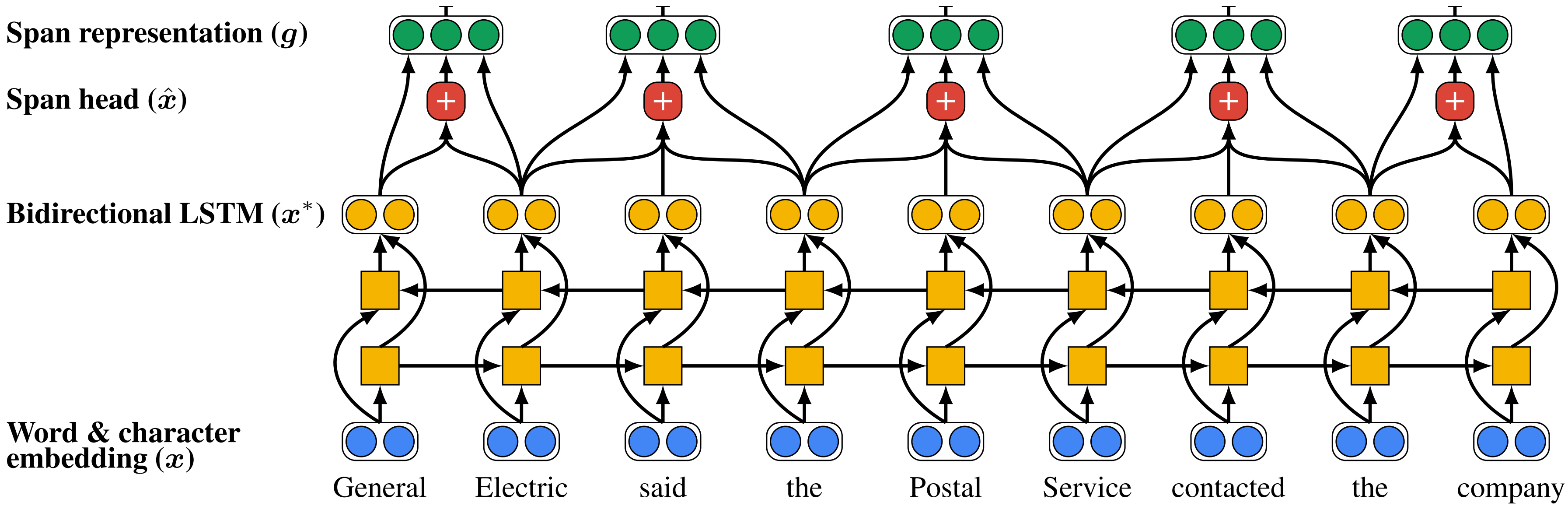

- *General, General Electric, General Electric said, … Electric, Electric said, …* will all get its own vector representation

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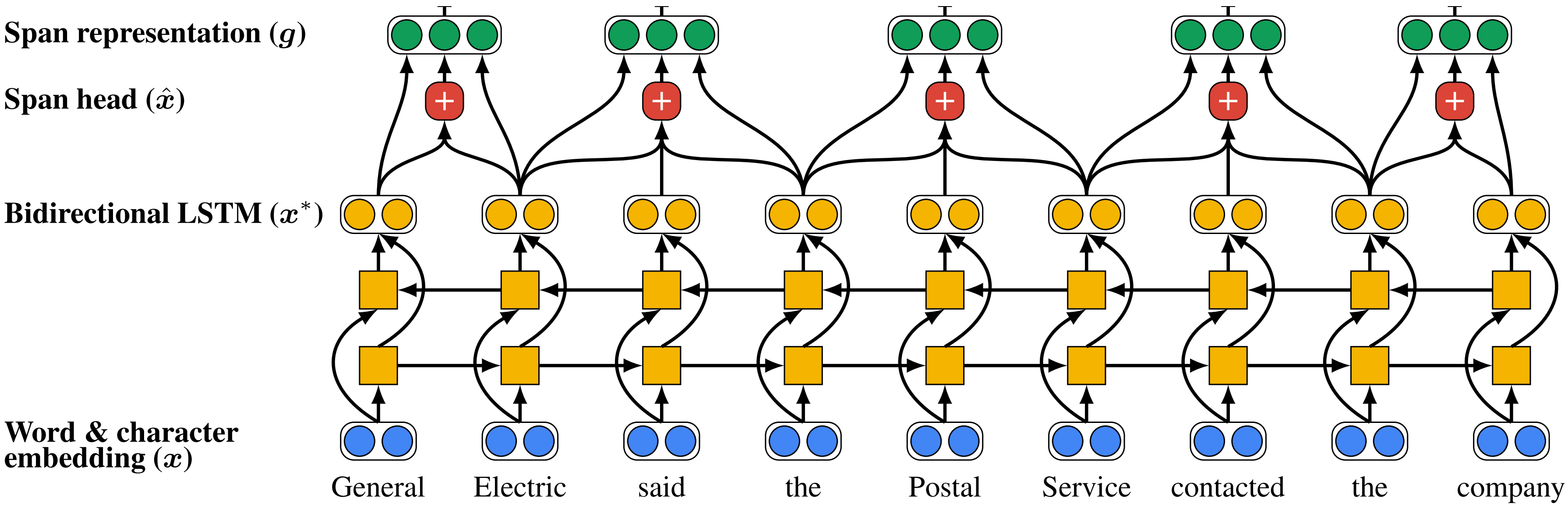

Span representation: $\boldsymbol{g}_i = [\boldsymbol{x}^*_{\mathrm{START}(i)}, \boldsymbol{x}^*_{\mathrm{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)]$

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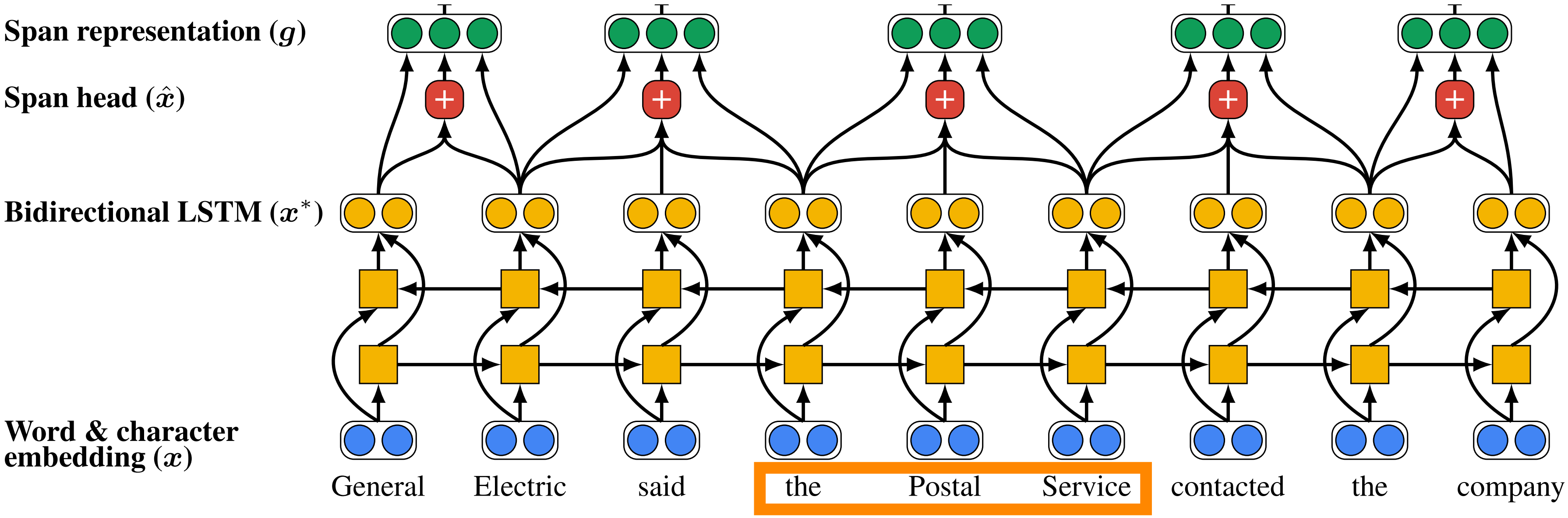

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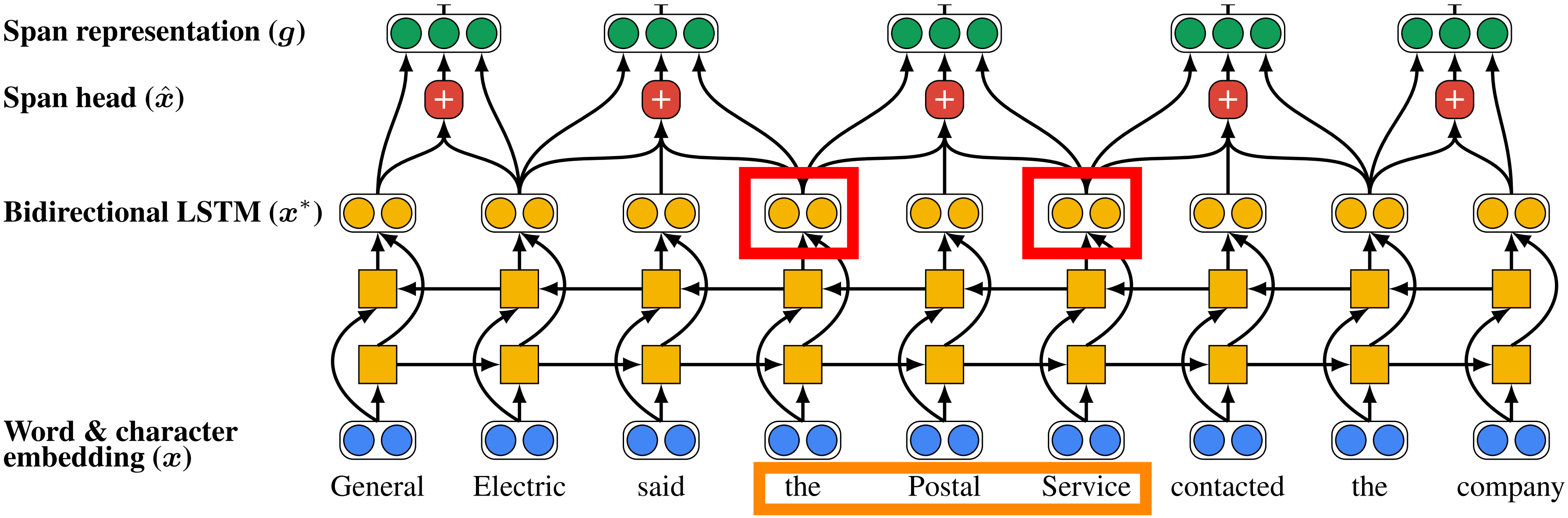

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BILSTM hidden states for span's start and end

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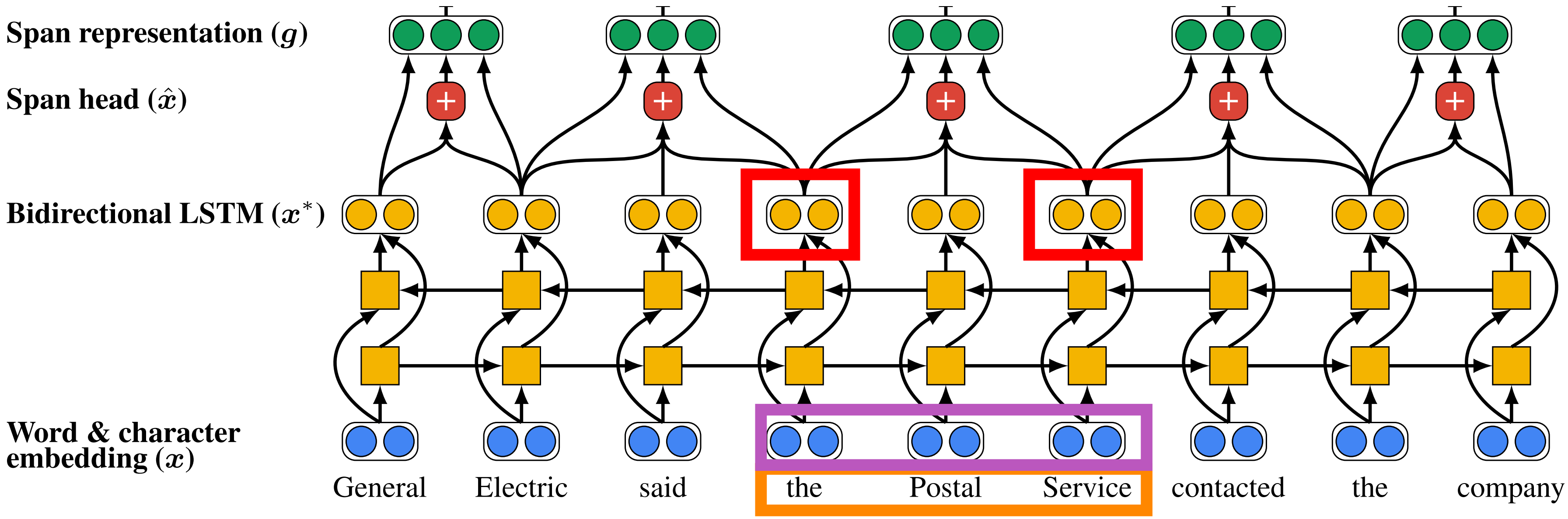

Span representation: $\boldsymbol{g}_i = [\boldsymbol{x}^*_{\mathrm{START}(i)}, \boldsymbol{x}^*_{\mathrm{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)]$

BILSTM hidden states for span's start and end

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

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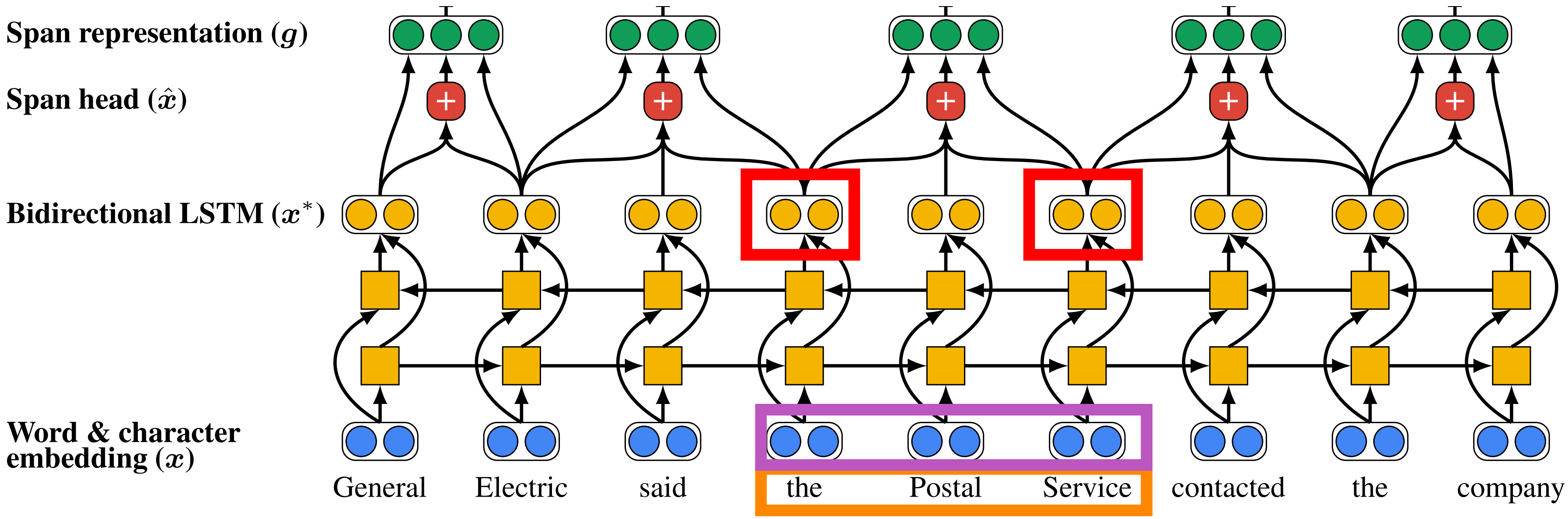

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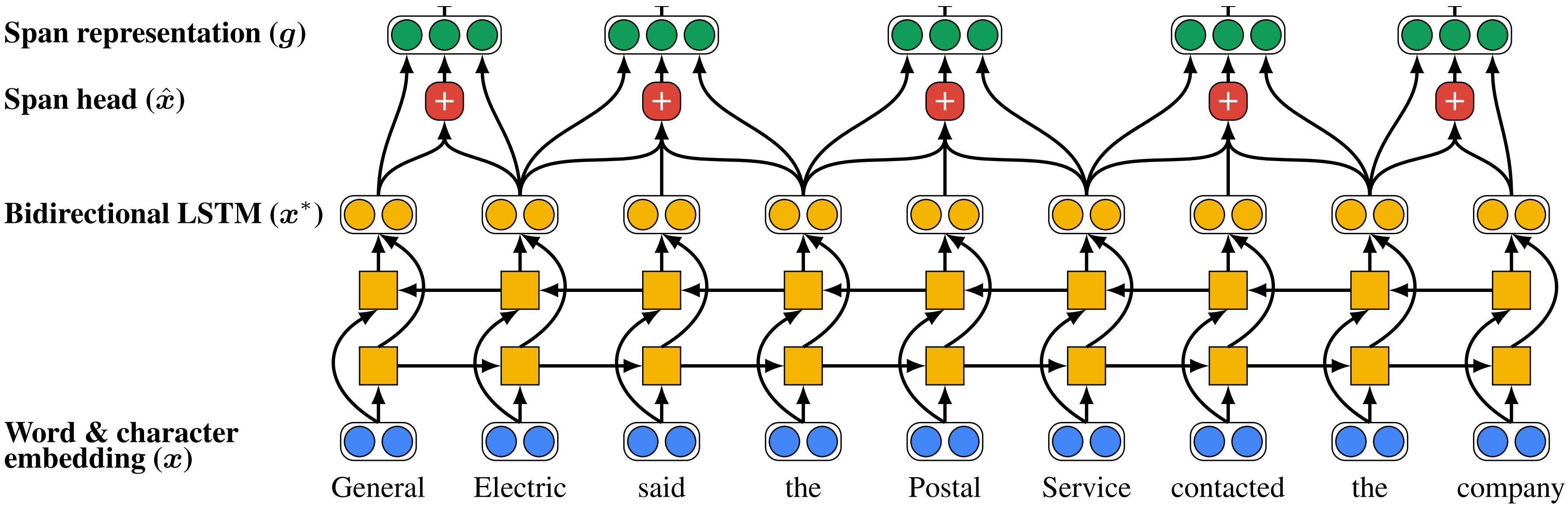
Attention-based representation (details next slide) of the words in the span

Additional features

3. 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

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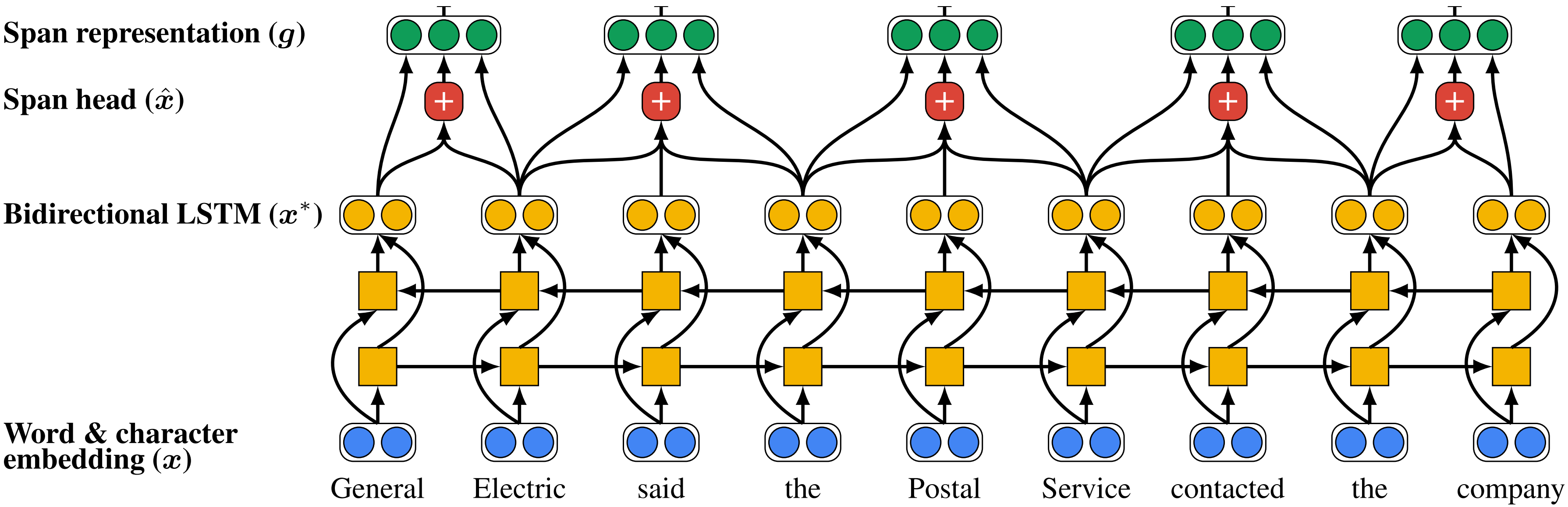

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Attention distribution

$$a_{i,t} = \frac{\exp(\alpha_t)}{\sum\limits_{k=\mathrm{START}(i)}^{\mathrm{END}(i)} \exp(\alpha_k)}$$

just a softmax over attention scores for the span

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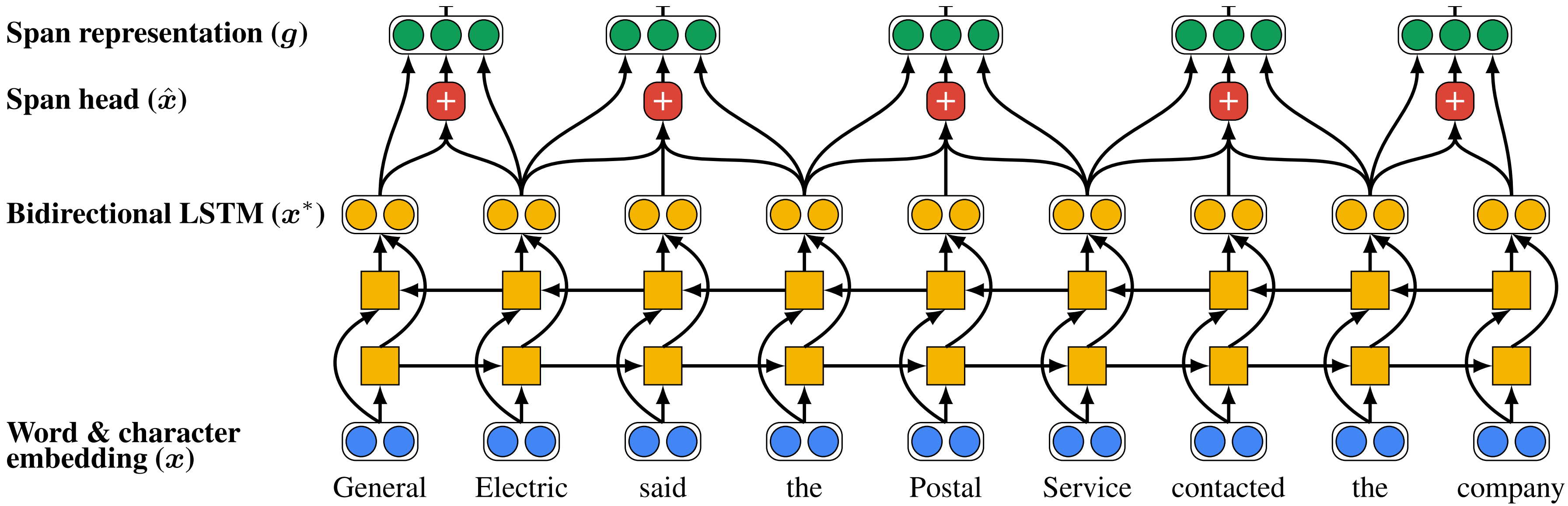

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Final representation

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

Attention-weighted sum of word embeddings

3. End-to-end Model

- Why include all these different terms in the span?

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

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

3. 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?

3. End-to-end Model

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include multiplicative interactions between the representations

again, we have some extra features

3. 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)

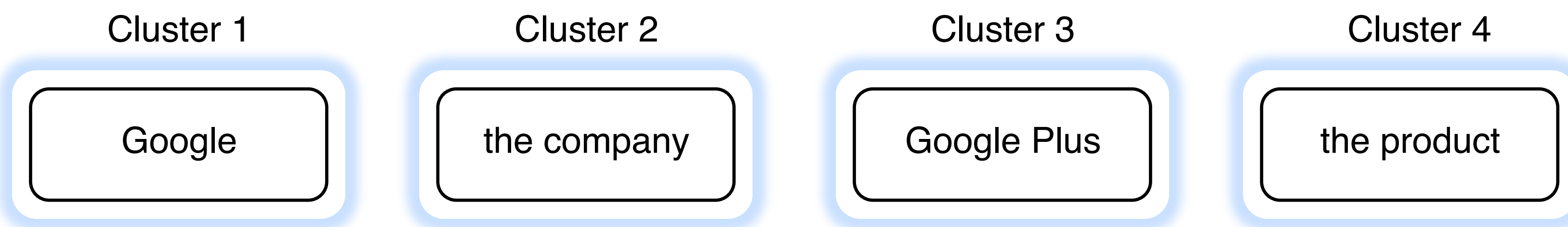
(**A fire in a Bangladeshi garment factory**) has left at least 37 people dead and 100 hospitalized. Most of the deceased were killed in the crush as workers tried to flee (**the blaze**) in the four-story building.

Last Coreference Approach: Clustering-Based

- Coreference is a clustering task, let's use a clustering algorithm!
  - In particular we will use agglomerative clustering
- Start with each mention in it's own singleton cluster
- Merge a pair of clusters at each step
  - Use a model to score which cluster merges are good

Coreference Models: Clustering-Based

Google recently … **the company** announced **Google Plus** … **the product** features …



Coreference Models: Clustering-Based

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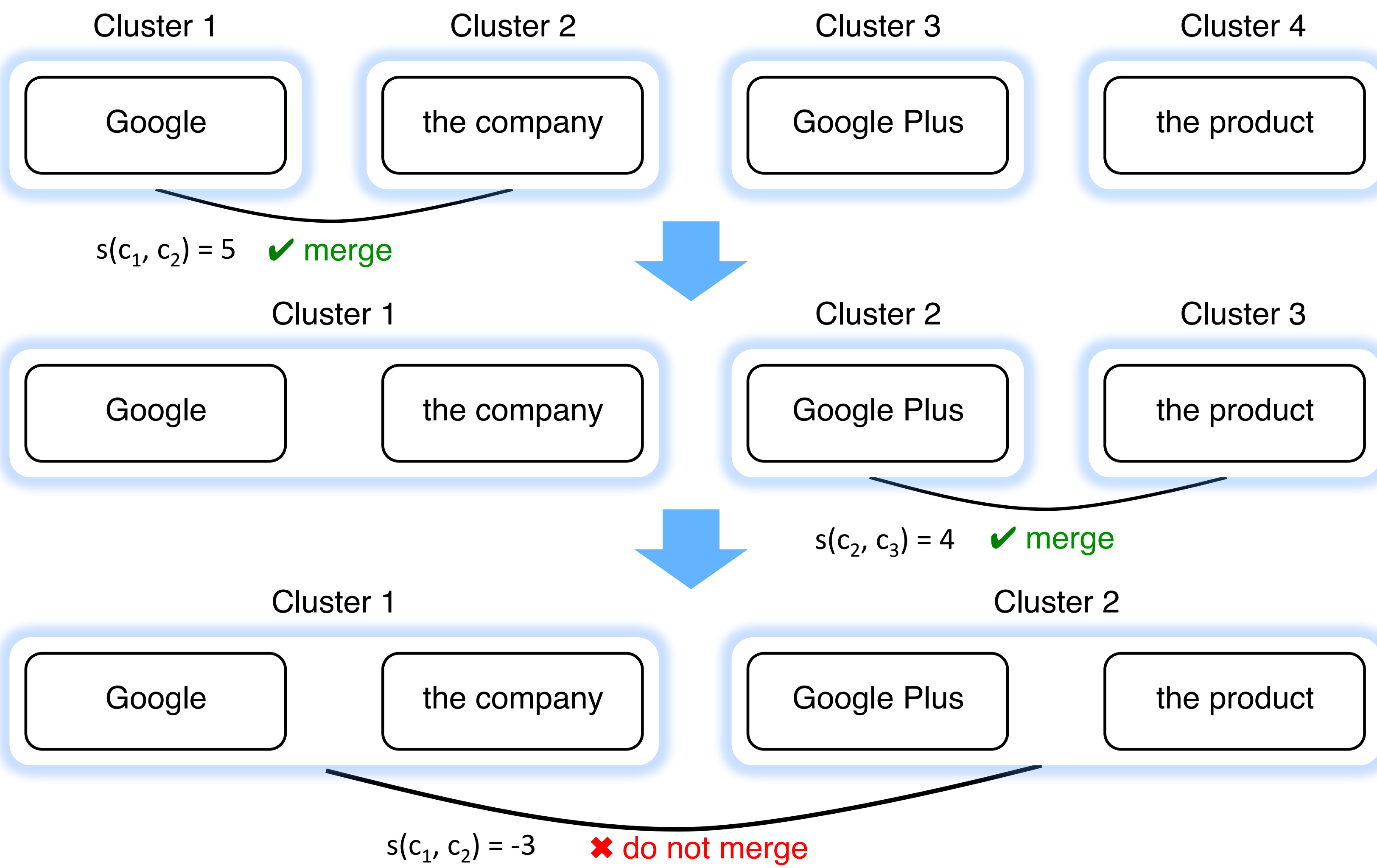
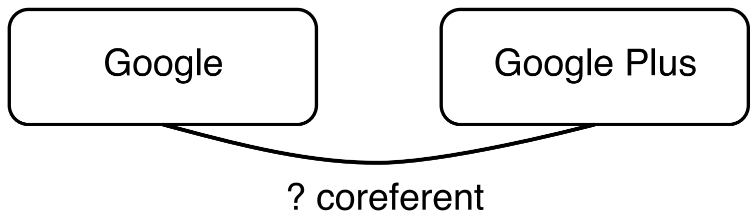
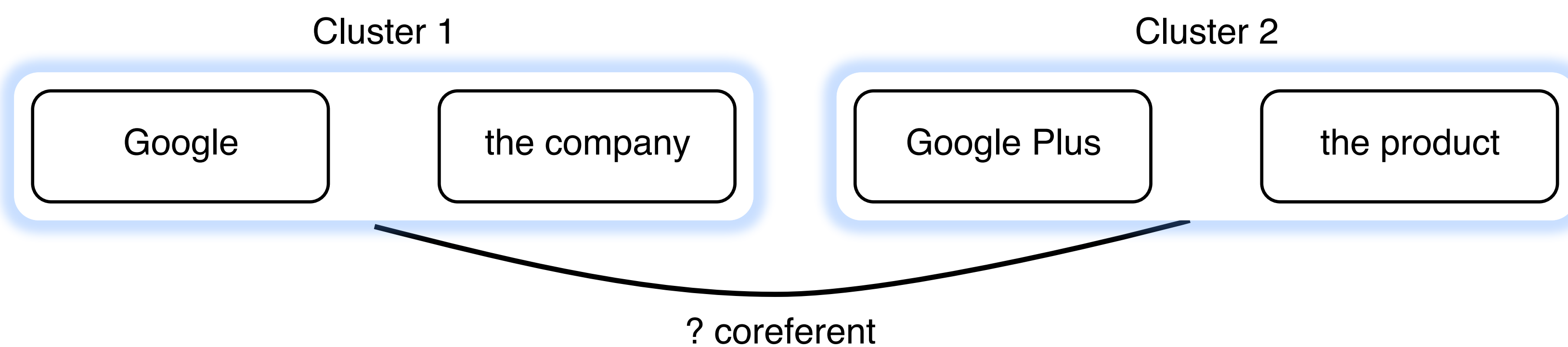


Coreference Models: Clustering-Based

Mention-pair decision is difficult



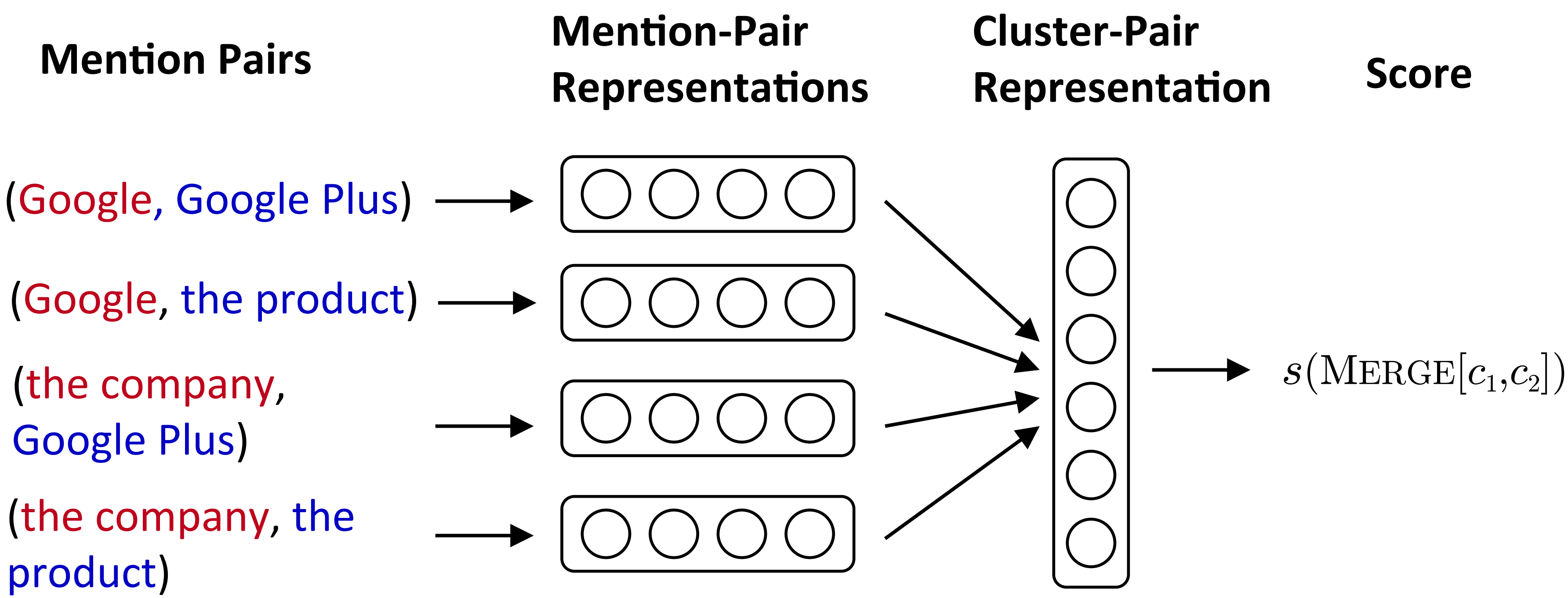
Cluster-pair decision is easier



Clustering Model Architecture

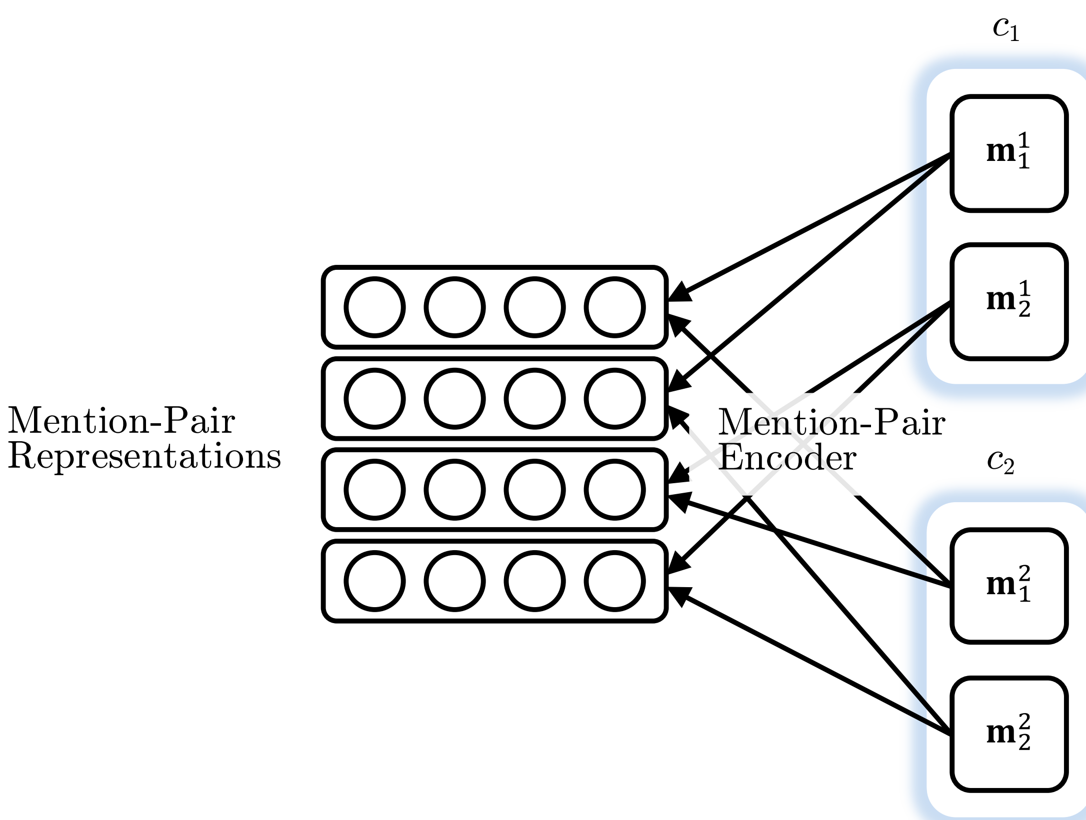
From Clark & Manning, 2016   Me!

Merge clusters c_1 = `{Google, the company}` and c_2 = `{Google Plus, the product}` ?



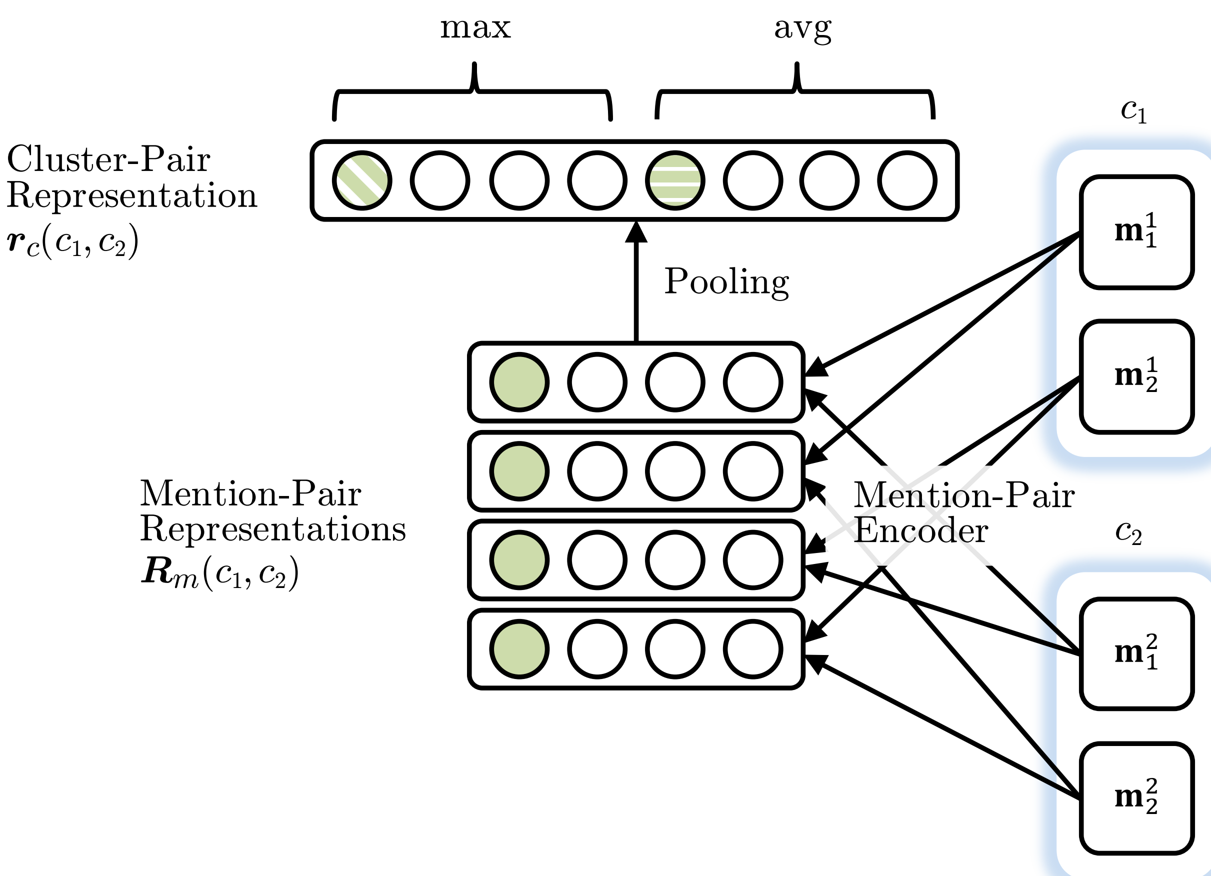
Clustering Model Architecture

- First produce a vector for each pair of mentions
  - e.g., the output of the hidden layer in the feedforward neural network model



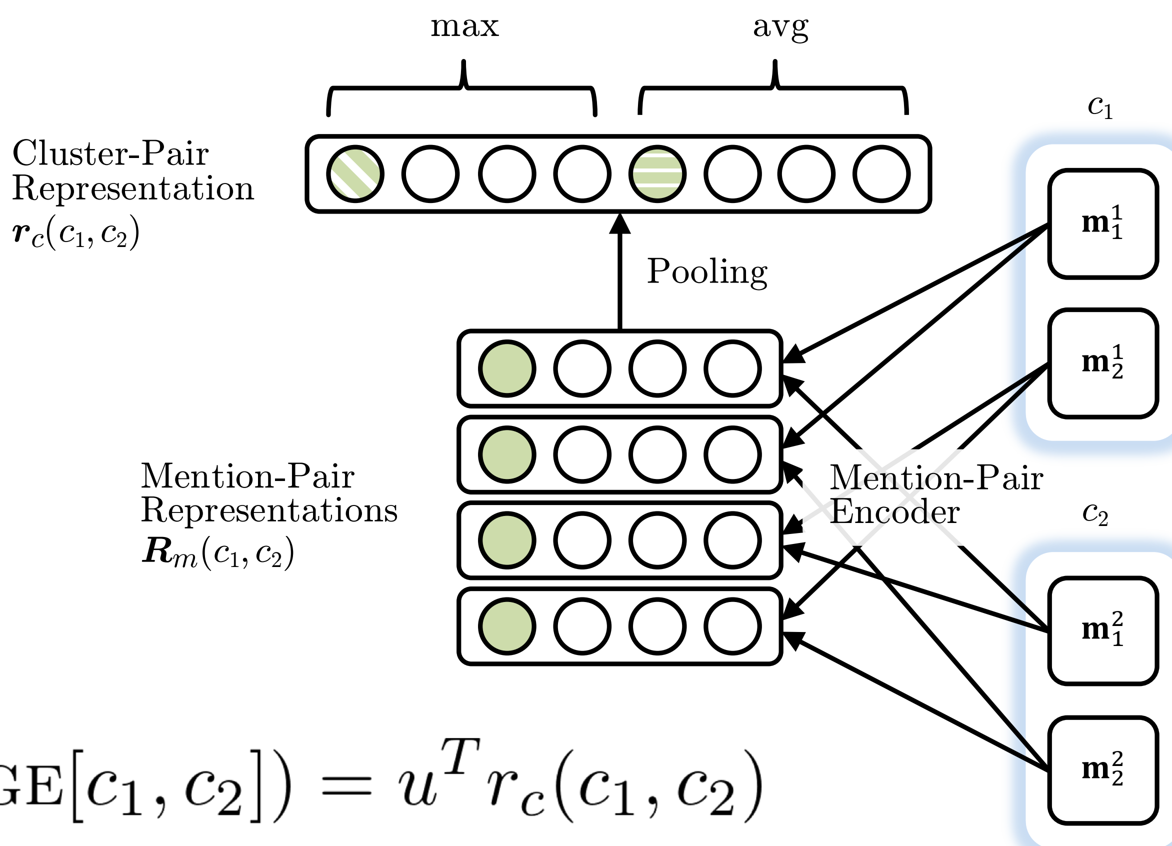
Clustering Model Architecture

- Then apply a pooling operation over the matrix of mention-pair representations to get a cluster-pair representation



Clustering Model Architecture

- Score the candidate cluster merge by taking the dot product of the representation with a weight vector



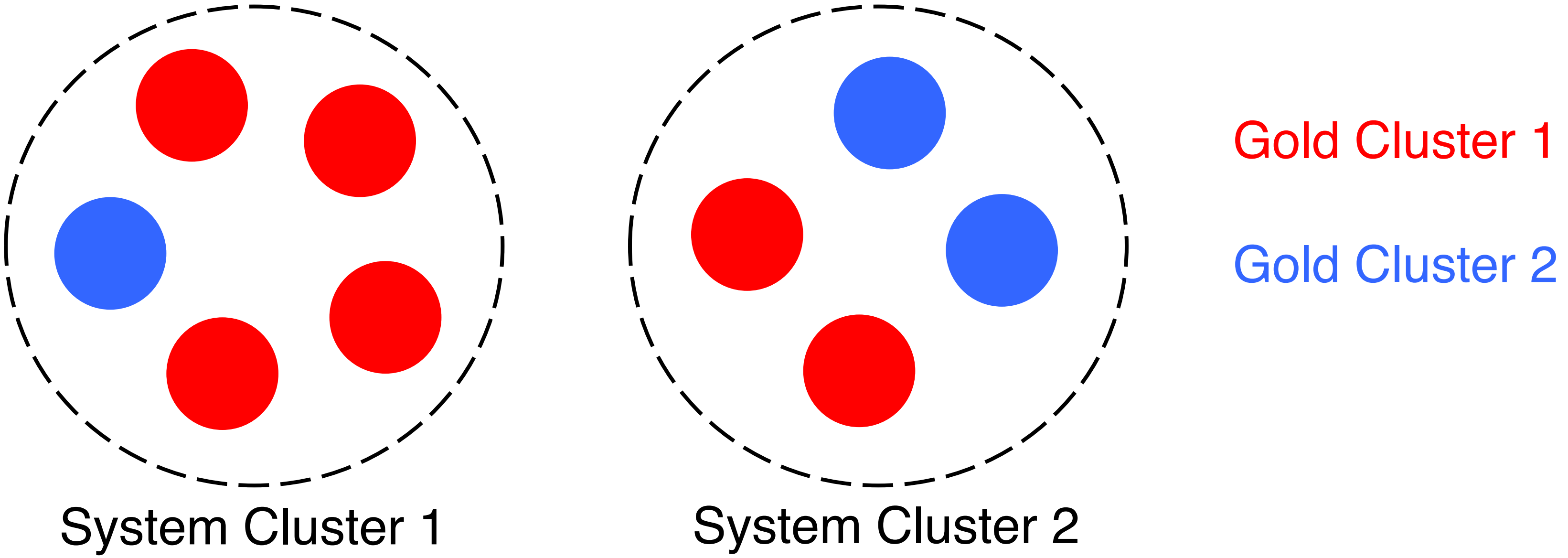
$$s(\textsc{Merge}[c_1, c_2]) = u^T r_c(c_1, c_2)$$

Clustering Model: Training

- Current candidate cluster merges depend on previous ones it already made
  - So can’t use regular supervised learning
  - Instead use something like Reinforcement Learning to train the model
    - Reward for each merge: the change in a coreference evaluation metric

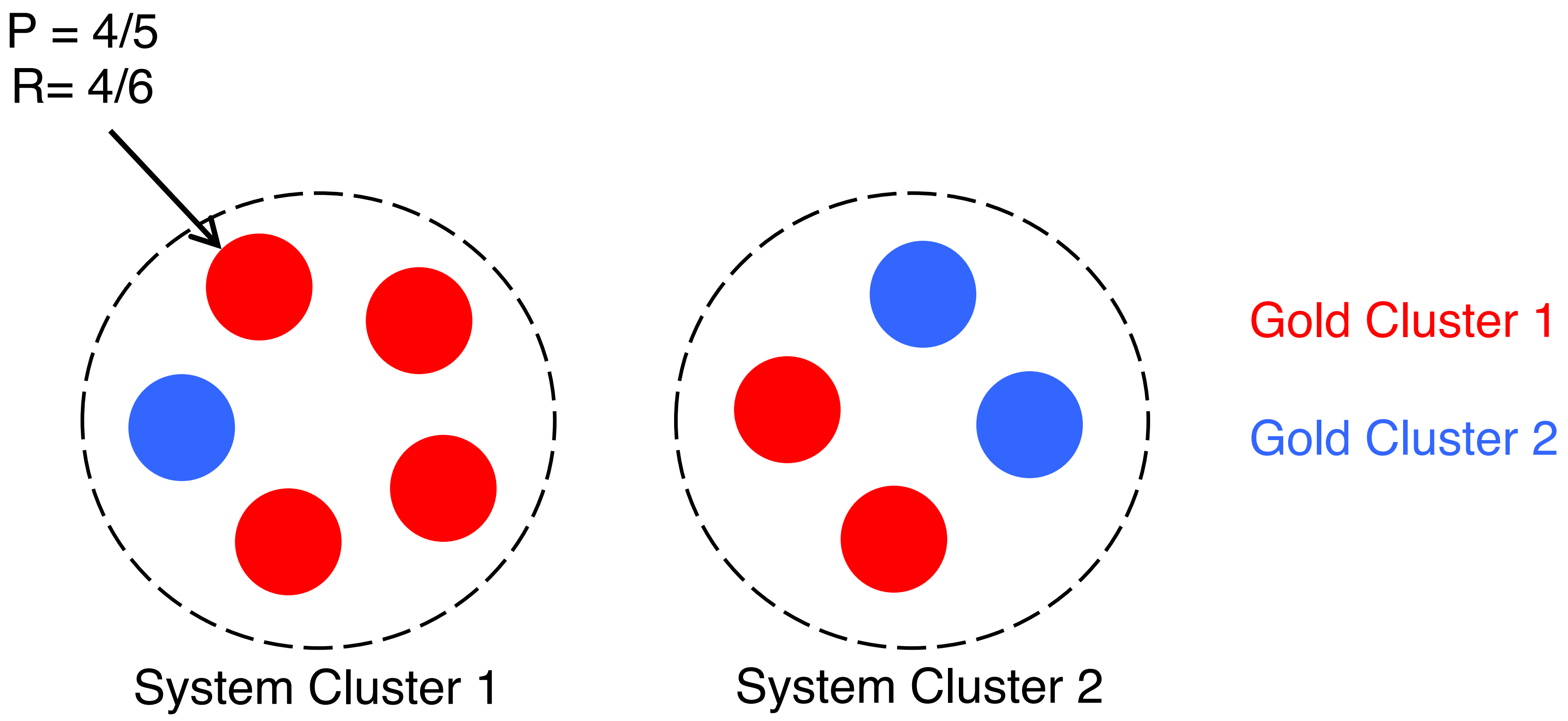
Coreference Evaluation

- Many different metrics: MUC, CEAF, LEA, B-CUBED, BLANC
  - Often report the average over a few different metrics



Coreference Evaluation

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



Coreference Evaluation

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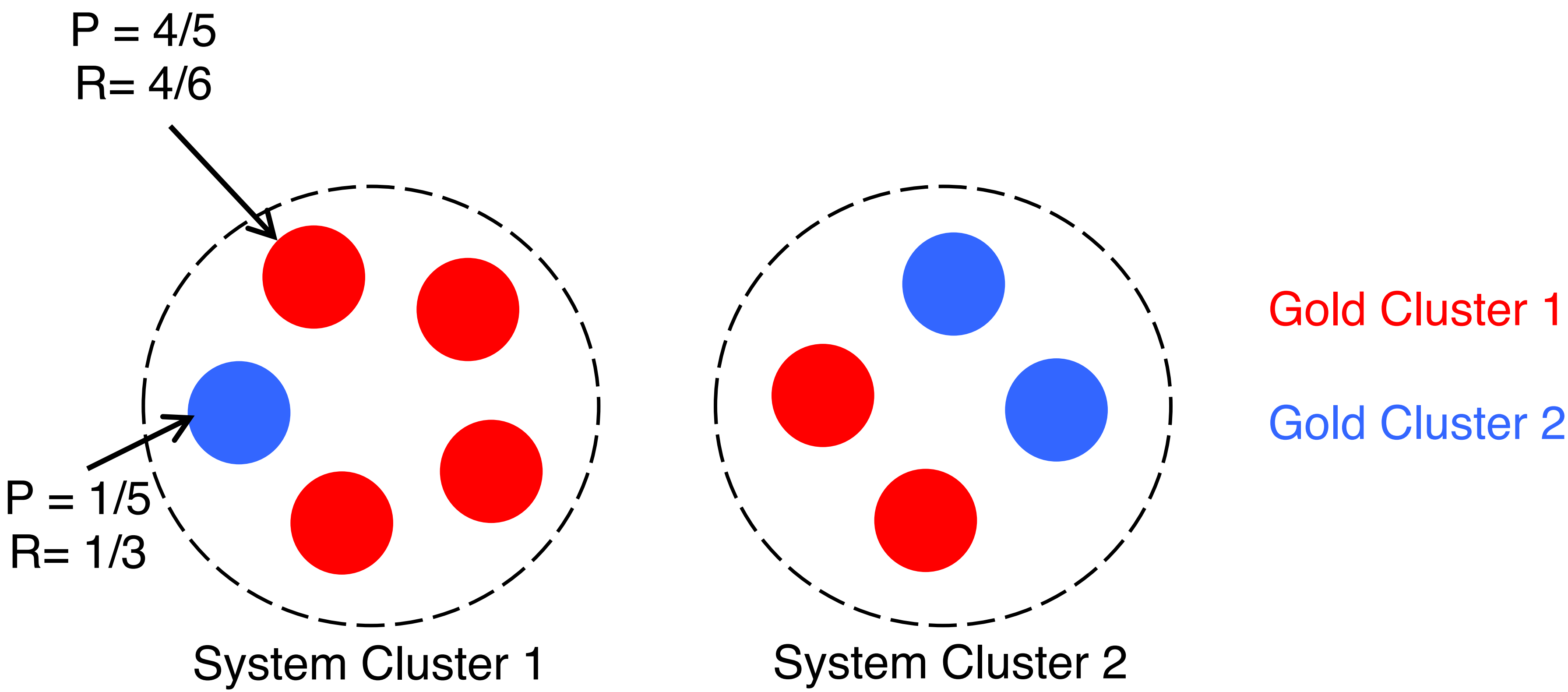
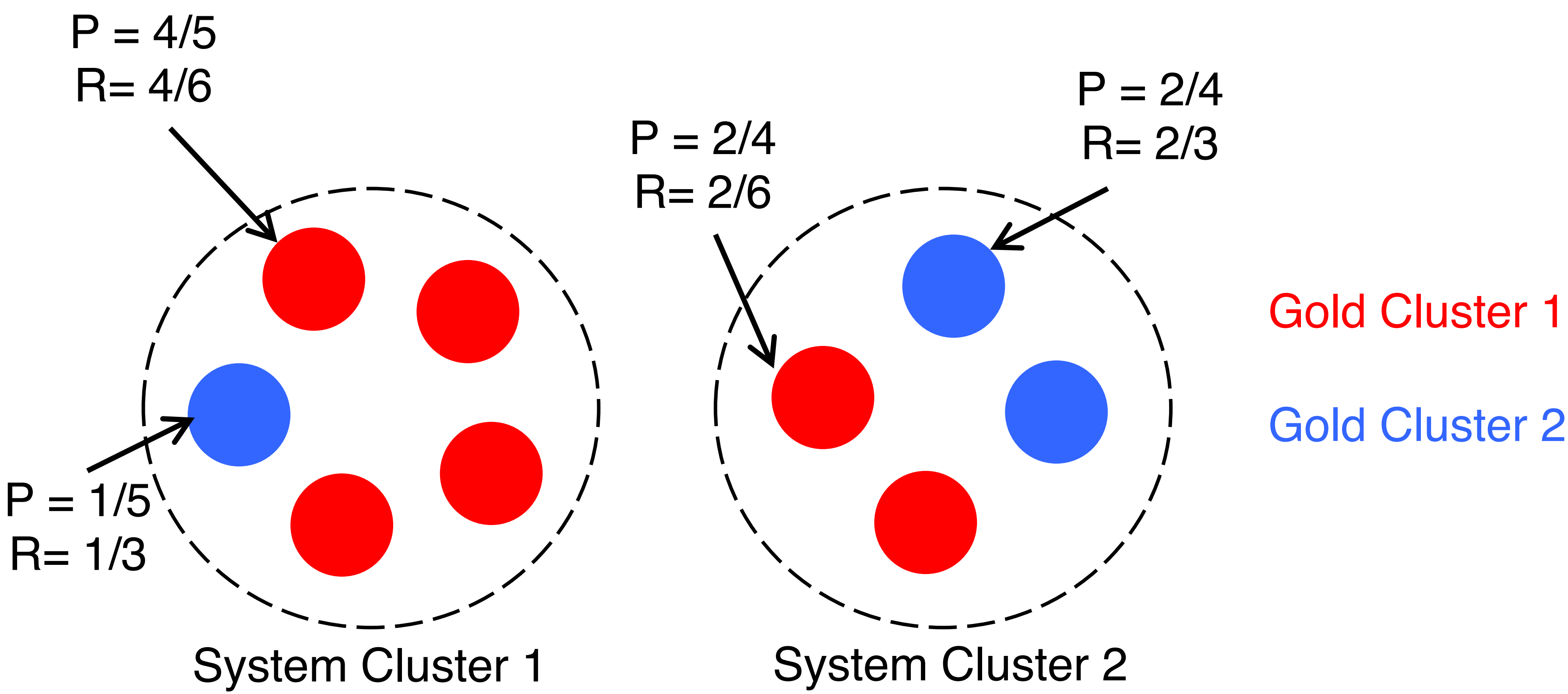


Coreference Evaluation

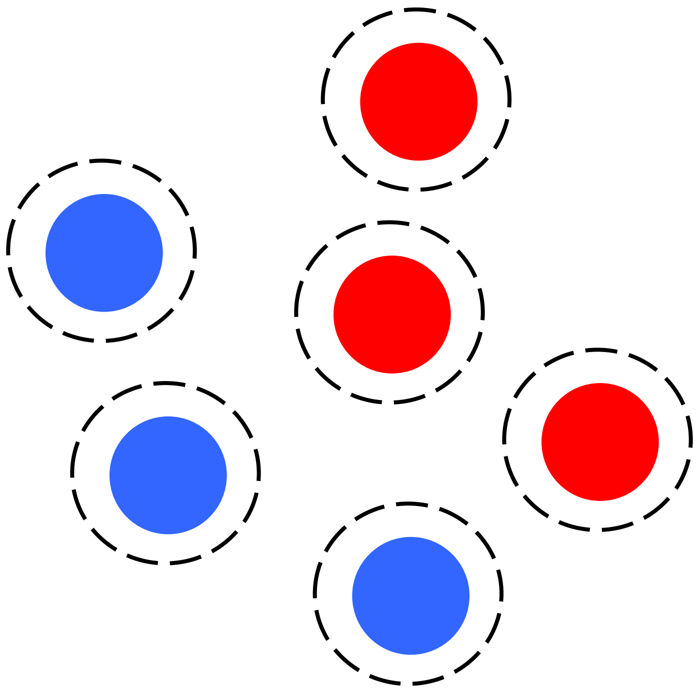
- An example: B-cubed
  - For each mention, compute a precision and a recall
  - Then average the individual Ps and Rs

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

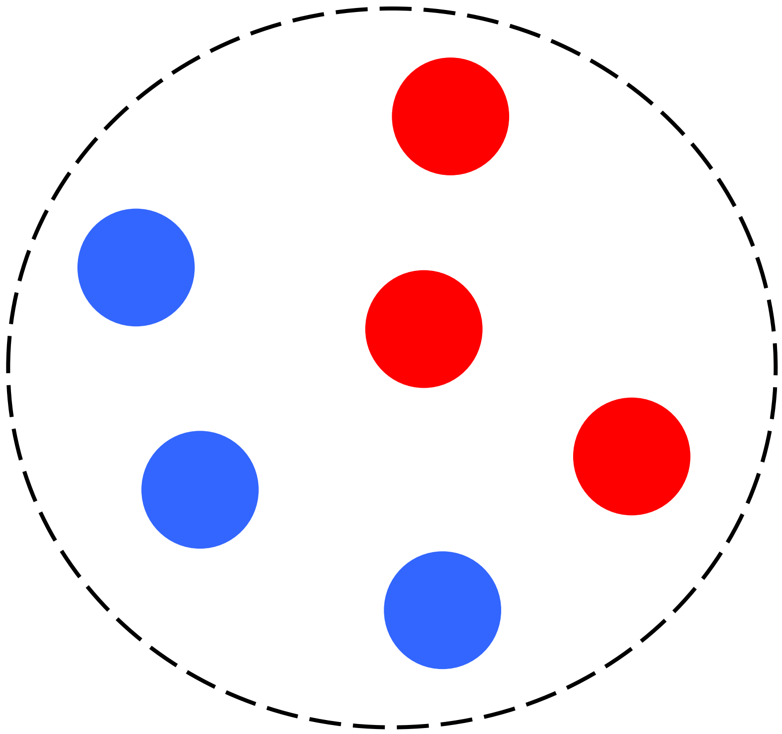


Coreference Evaluation

100% Precision, 33% Recall



50% Precision, 100% Recall,



System Performance

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

- Report 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	--

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 mention ranker

Where do neural scoring models help?

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

  18.9 F_1 vs 10.7 F_1 on this type compared to 68.7 vs 66.1 F_1

  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 overall, results are still not amazing
- Try out a coreference system yourself! https://huggingface.co/coref/