Lecture 16 Coreference Resolution

Lecture Plan

1. What is Coreference Resolution? (15 mins)
2. Applications of coreference resolution (5 mins)
3. Mention Detection (5 mins)
4. Some Linguistics: Types of Reference (5 mins) Four Kinds of Coreference Resolution Models
5. Rule-based (Hobbs Algorithm) (10 mins)
6. Mention-pair models (10 mins)
7. Mention ranking models (15 mins)
    - Including the current state-of-the-art coreference system!
8. Mention clustering model (5 mins – only partial coverage)
9. Evaluation and current results (10 mins)

1. What is Coreference Resolution?

- 识别所有涉及到相同现实世界实体的 **提及**
- He, her 都是实体的提及 mentions of entities

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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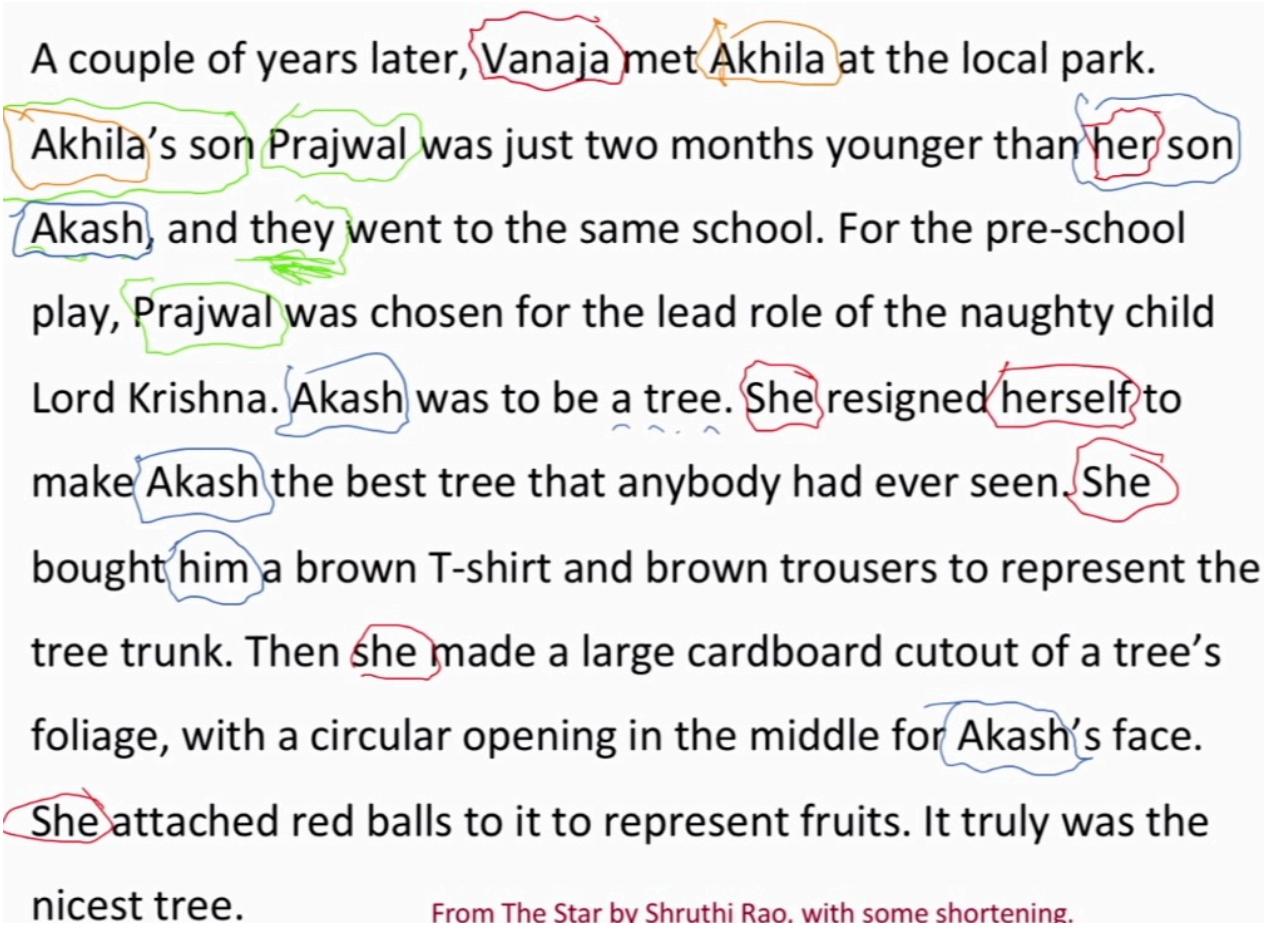
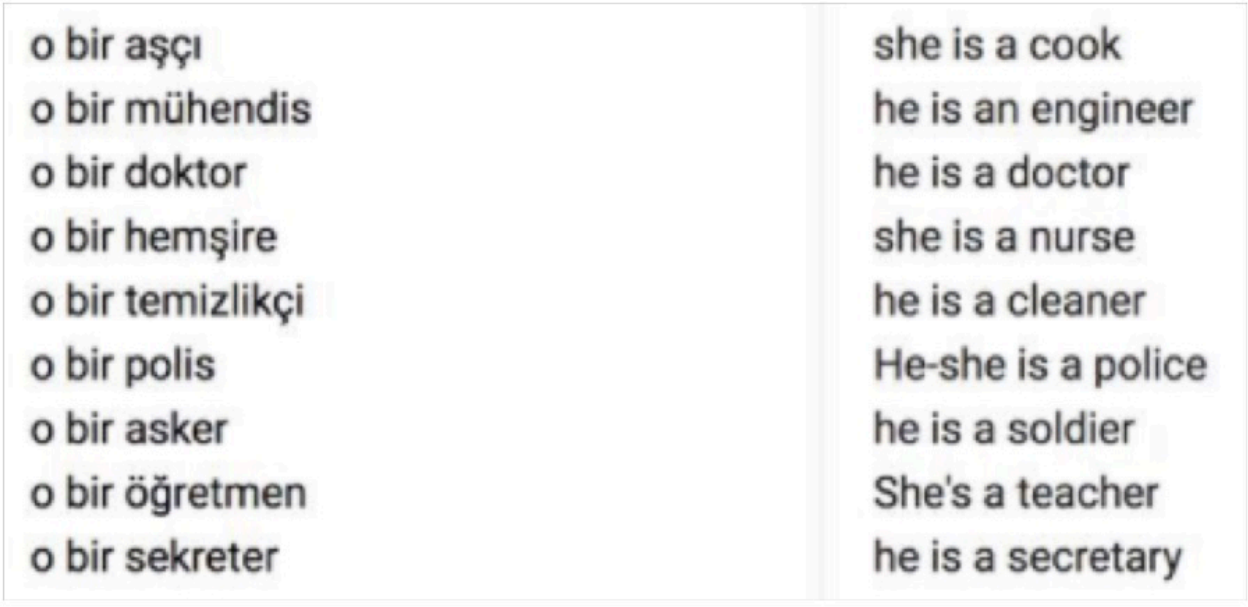


Applications

- 全文理解
  - 信息提取, 回答问题, 总结, ...
  - "他生于1961年"(谁?)
- 机器翻译
  - 语言对性别，数量等有不同的特征



- 对话系统

"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 : 指向某个实体的一段文本
- 三种 mention

1. Pronouns 代词
   - I, your, it, she, him, etc.
   - 因为代词是 POS 检测结果的一种，所以只要使用 POS 检测器即可
2. Named entities 命名实体
   - People, places, etc.
   - Use a NER system (like hw3)
3. Noun phrases 名词短语
   - "a dog," "the big fluffy cat stuck in the tree"
   - Use a parser (especially a 依存解析器 constituency parser – next week!)

- Marking all pronouns, named entities, and NPs as mentions over-generates mentions
- Are these mentions?
  - **It** is sunny
  - **Every student**
  - **No student**
  - **The best donut in the world**
  - **100 miles**

How to deal with these bad mentions?

- 可以训练一个分类器过滤掉 spurious mentions
- 更为常见的：保持所有 mentions 作为 "candidate mentions"
  - 在你的共指系统运行完成后，丢弃所有的单个引用(即没有被标记为与其他任何东西共同引用的)

Can we avoid a pipelined system?

- 我们可以训练一个专门用于 mention 检测的分类器，而不是使用POS标记器、NER系统和解析器。

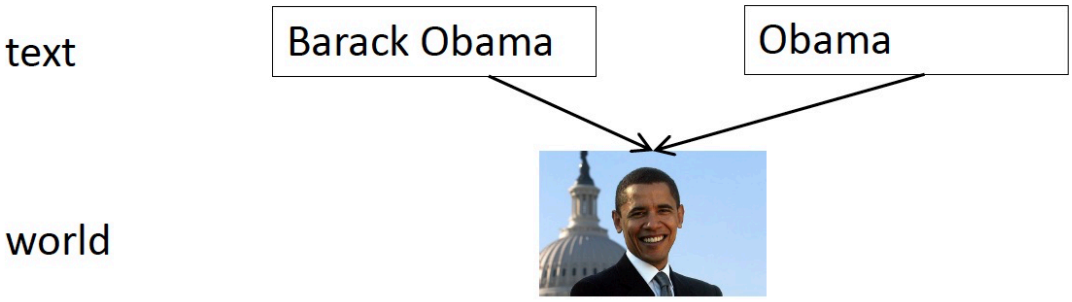
- 甚至端到端共同完成 mention 检测和共指解析，而不是两步

4. On to Coreference! First, some linguistics

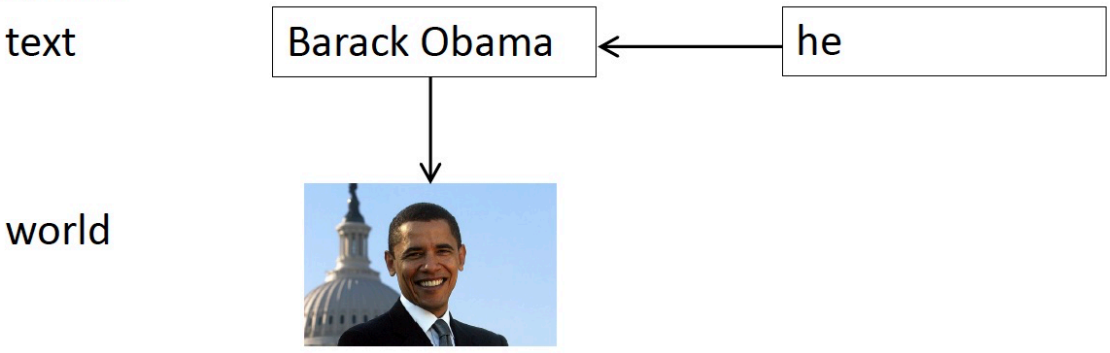
- **Coreference** is when two mentions refer to the same entity in the world 当两个 mention 指向世界上的同一个实体时，被称为共指
  - Barack Obama 和 Obama
- 相关的语言概念是 anaphora 回指：when a term (anaphor) refers to another term (antecedent) 下文的词返指或代替上文的词
  - anaphor 的解释在某种程度上取决于 antecedent 先行词的解释
  - *Barack Obama said he would sign the bill.*
    antecedent anaphor

Anaphora vs Coreference

- Coreference with named entities

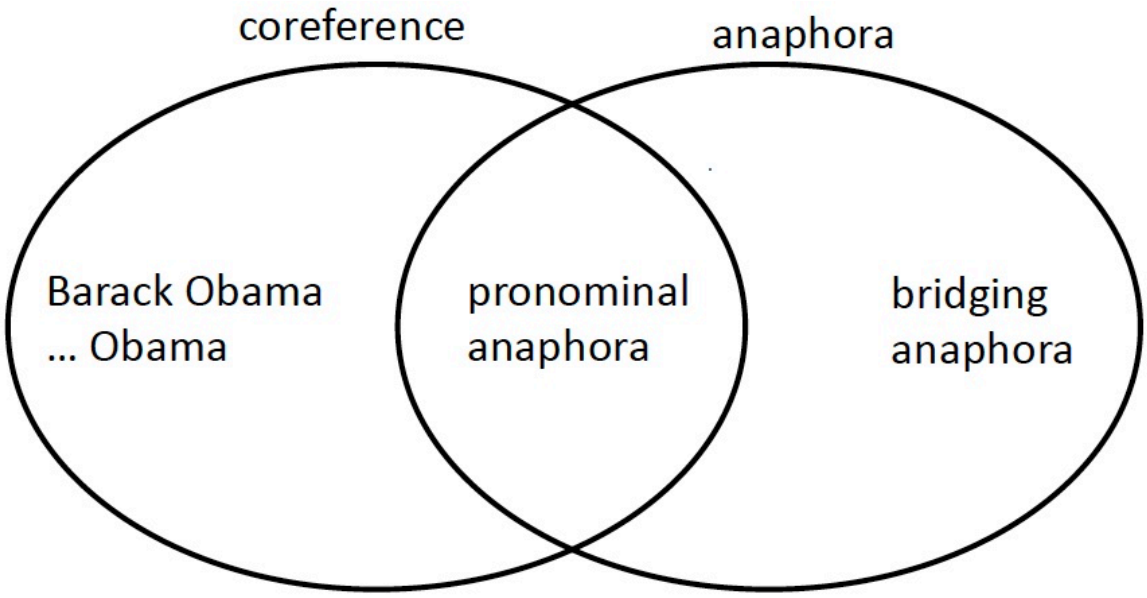


- Anaphora



Not all anaphoric relations are coreferential

- Not all noun phrases have reference 不是所有的名词短语都有指代
  - **Every dancer** twisted **her knee**
  - **No dancer** twisted **her knee**
  - 每一个句子有三个NPs；因为第一个是非指示性的，另外两个也不是
- Not all anaphoric relations are coreferential
  - We went to see a concert last night. The tickets were really expensive.
  - 这被称为桥接回指 bridging anaphora



- 通常先行词在回指（例如代词）之前，但并不总是

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

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Four Kinds of Coreference Models

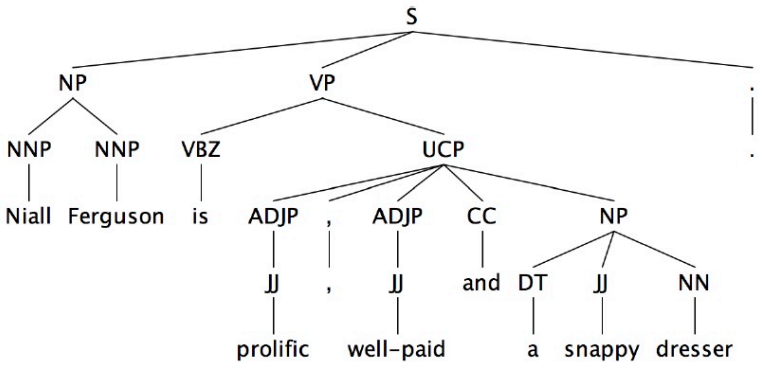
- Rule-based (pronominal anaphora resolution)
- Mention Pair
- Mention Ranking
- Clustering

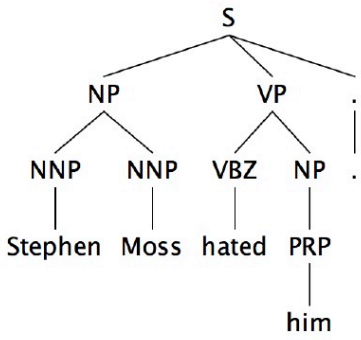
5. Traditional pronominal anaphora resolution:Hobbs' naive algorithm

该算法仅用于寻找代词的参考，也可以延伸到其他案例

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 Sbetween it and X
4. If X is the highest S in the sentence, traverse the parse trees ofthe previous sentences in the order of recency. Traverse eachtree left-to-right, breadth first. When an NP is encountered,propose as antecedent. If X not the highest node, go to step 5.
5. From node X, go up the tree to the first NP or S. Call it X, andthe path p.
6. If X is an NP and the path p to X came from a non-head phraseof X (a specifier or adjunct, such as a possessive, PP, apposition, orrelative clause), propose X as antecedent(The original said “did not pass through the N’ that X immediatelydominates”, but the Penn Treebank grammar lacks N’ nodes....)
7. Traverse all branches below X to the left of the path, in a leftto-right, breadth first manner. Propose any NP encountered asthe antecedent
8. If X is an S node, traverse all branches of X to the right of thepath but do not go below any NP or S encountered. Proposeany NP as the antecedent.9. Go to step 4

Hobbs Algorithm Example

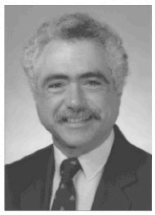




这是一个很简单、但效果很好的共指消解的 baseline

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**
  - Recently 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

- 第一个例子中，两个句子具有相同的语法结构，但是出于外部世界知识，我们能够知道倒水之后，满的是杯子（第一个 it 指向的是 the cup），空的是壶（第二个 it 指向的是 the pitcher）
- **可以将世界知识编码成共指问题**

Hobbs’ algorithm: commentary

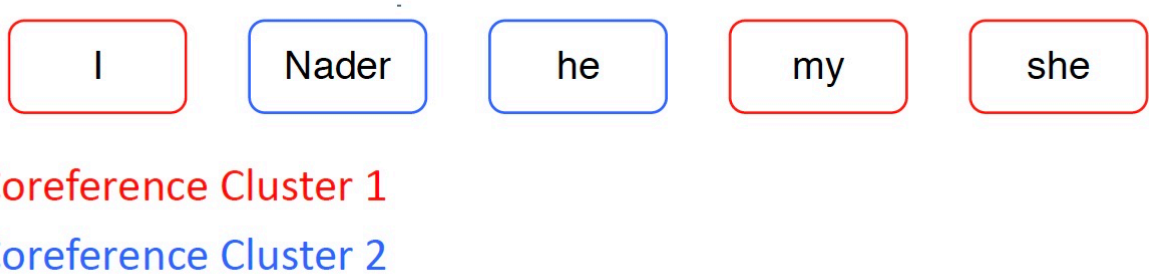
“… the naïve approach is quite good. Computationally speaking, it will be a long time before a semantically based algorithm is sophisticated enough to perform as well, and these results set a very high standard for any other approach to aim for.

“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

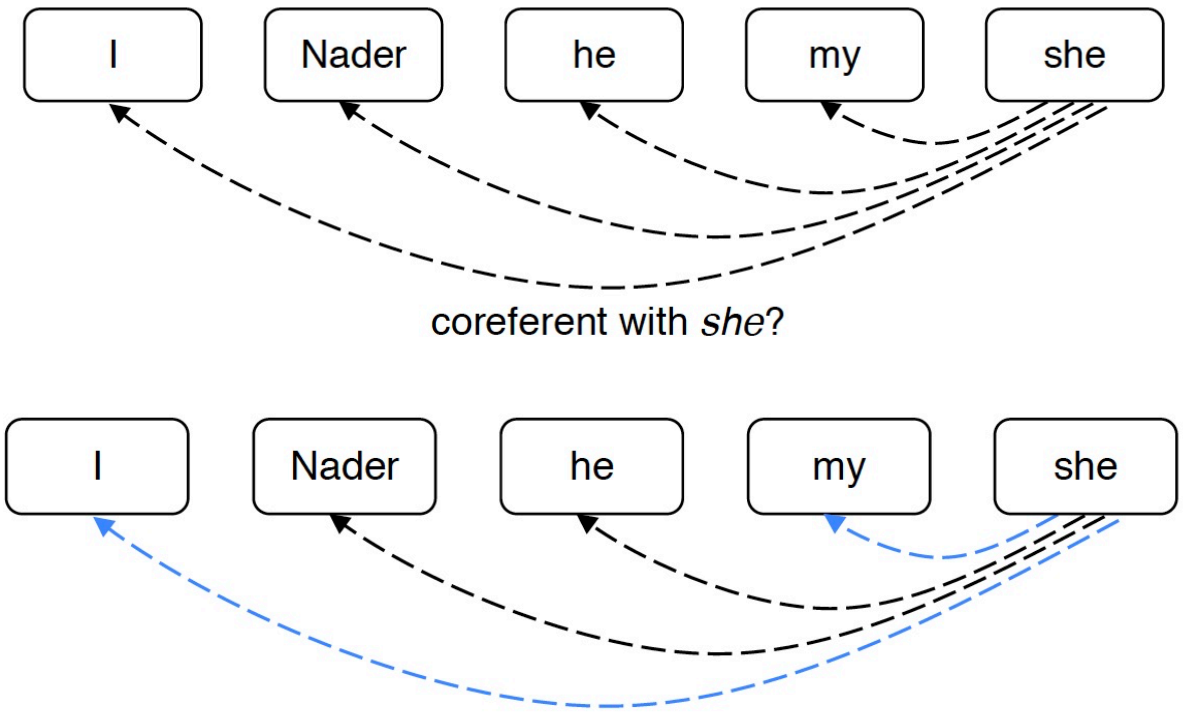
6. Coreference Models: Mention Pair

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

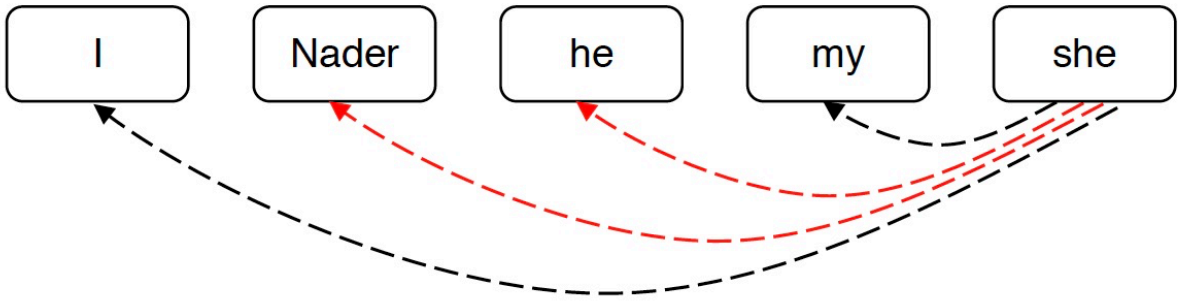


- 训练一个二元分类器，为每一对 mention 的分配共参的概率 $p(m_i, m_j)$
  - 例如，为了寻找 "she" 的共指，查看所有候选先行词(以前出现的 mention)，并确定哪些与之相关

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



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



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

- 文章的 N 个 mention
- 如果 m_i 和 m_j 是共指的，则 $y_{ij} = 1$，否则 $y_{ij} = -1$
- 只是训练正常的交叉熵损失(看起来有点不同，因为它是二元分类)

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

Iterate through mentions

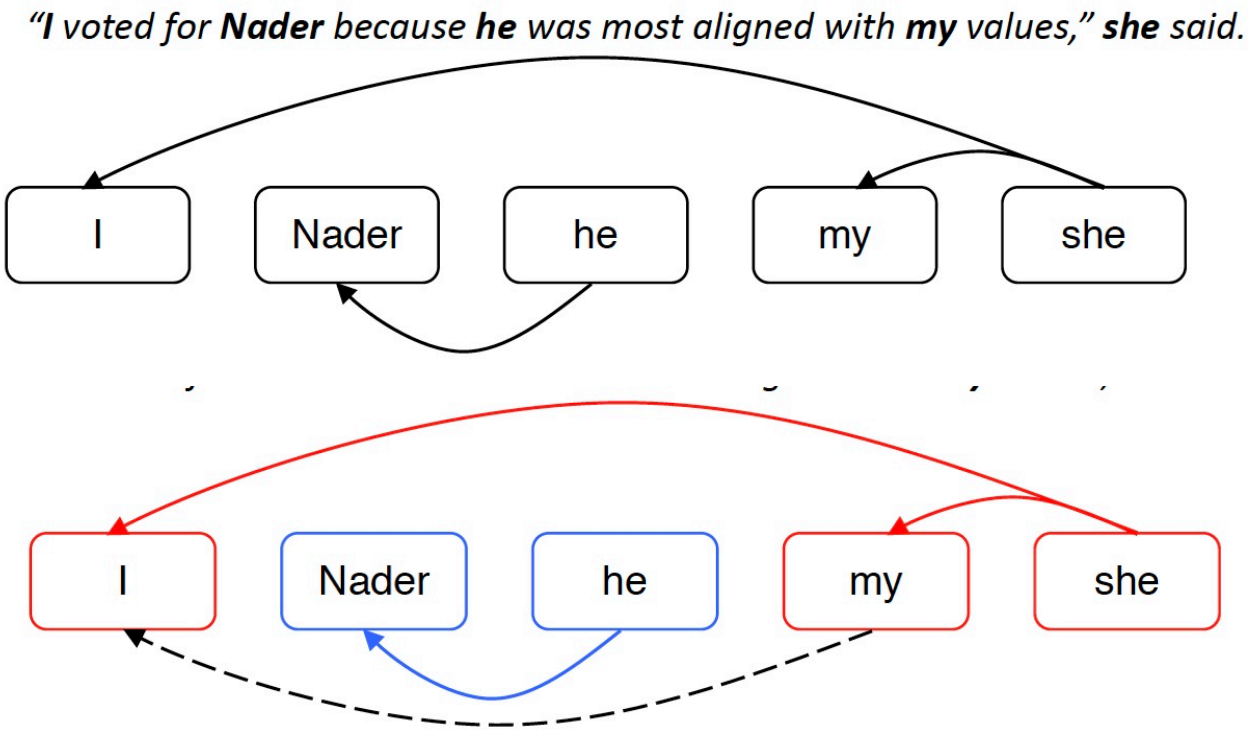
Iterate through candidate antecedents (previously occurring mentions)

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

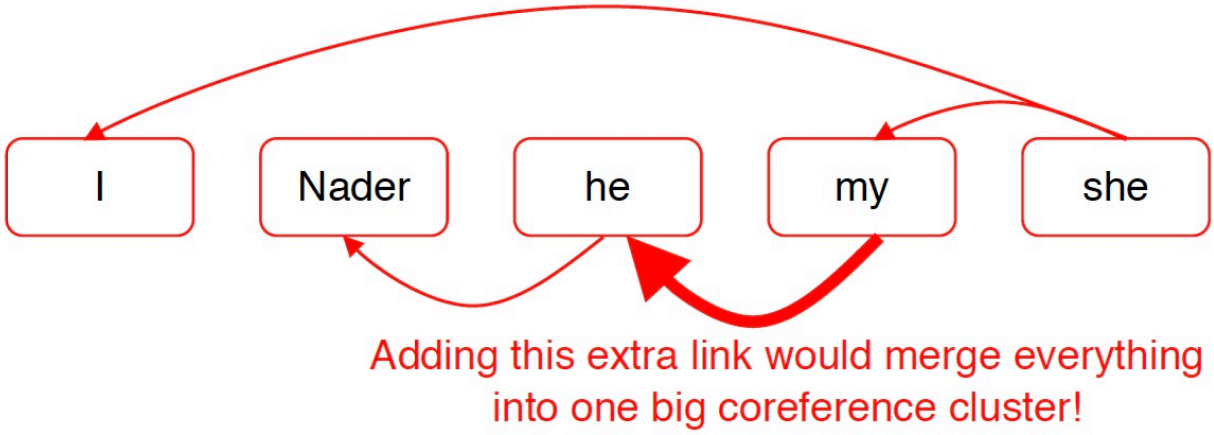
- 遍历 mentions
- 遍历候选先行词(前面出现的 mention)
- 共指 mention 对应该得到高概率，其他应该得到低概率

Mention Pair Test Time

- 共指解析是一项聚类任务，但是我们只是对 mentions 对进行了评分……该怎么办?
- 选择一些阈值(例如0.5)，并将 $p(m_i, m_j)$ 在阈值以上的 mentions 对之间添加共指链接
- 利用传递闭包得到聚类



- 共指连接具有传递性，即使没有不存在 link 的两者也会由于传递性，处于同一个聚类中

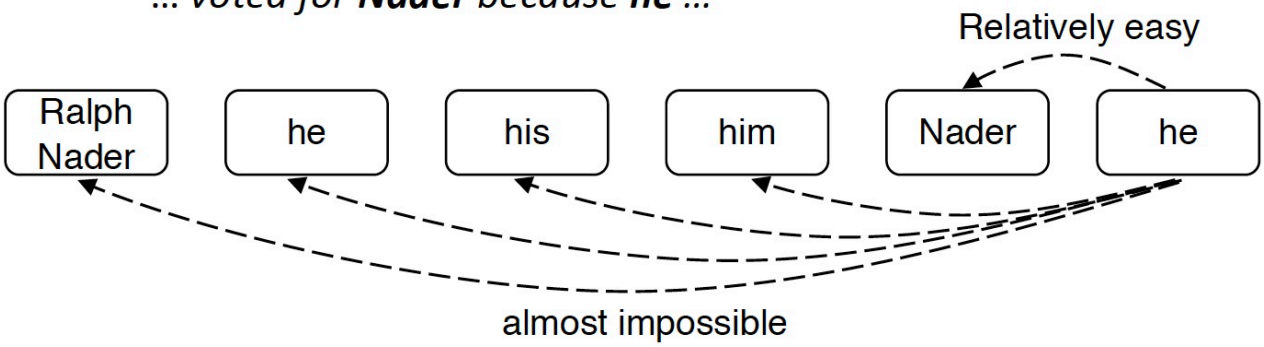


- 这是十分危险的
- 如果有一个共指 link 判断错误，就会导致两个 cluster 被错误地合并了

Mention Pair Models: Disadvantage

- 假设我们的长文档里有如下的 mentions

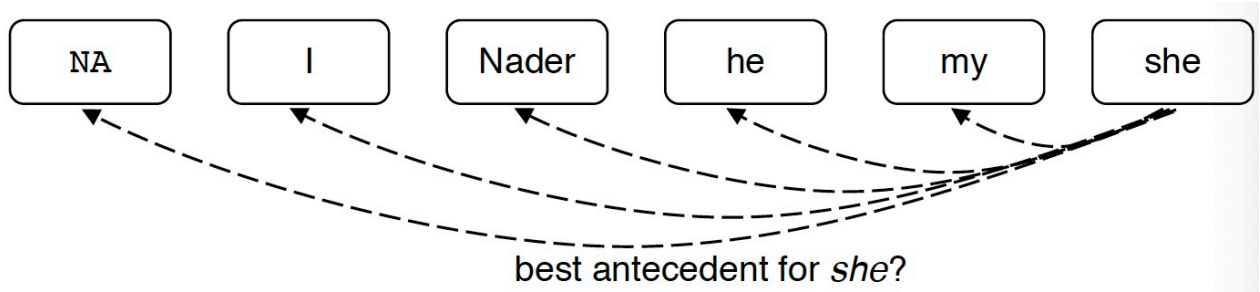
- **Ralph Nader** ... **he** ... **his** ... **him** ... <several paragraphs>
  ... *voted for* ***Nader*** *because* ***he*** ...

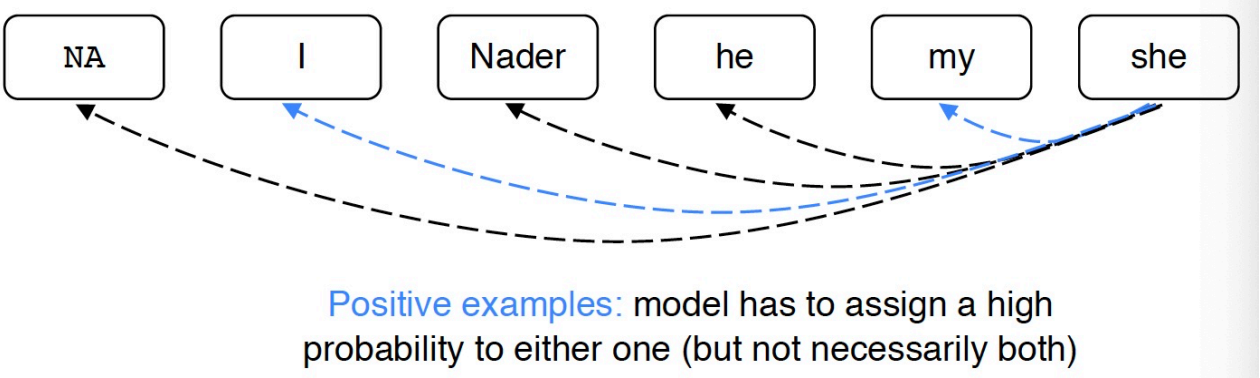


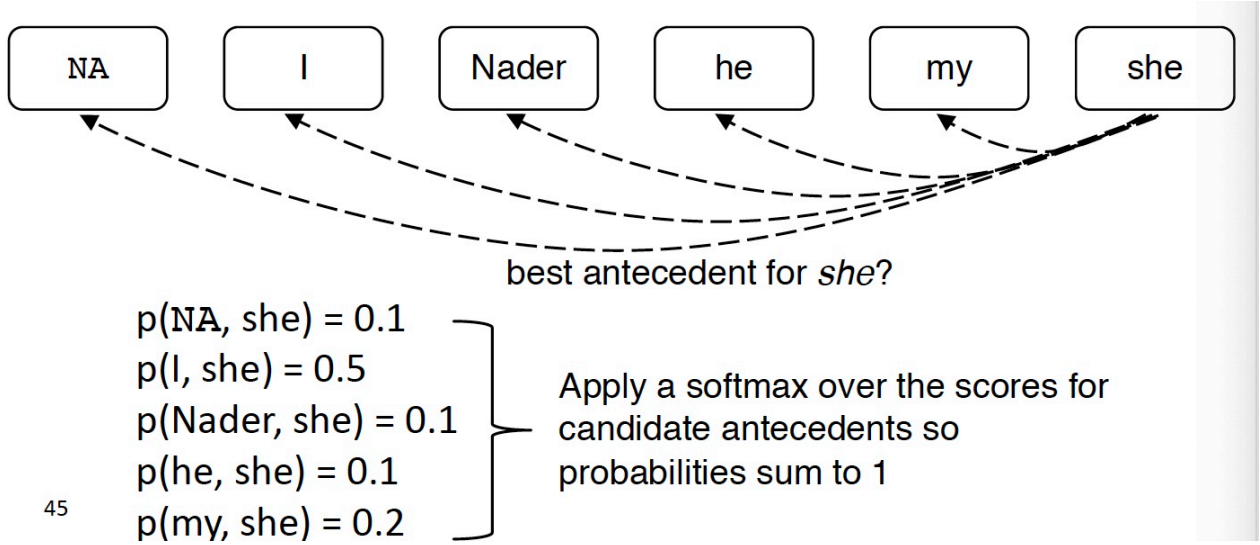
- 许多 mentions 只有一个清晰的先行词
  - 但我们要求模型来预测它们
- 解决方案：相反，训练模型为每个 mention 只预测一个先行词
  - 在语言上更合理

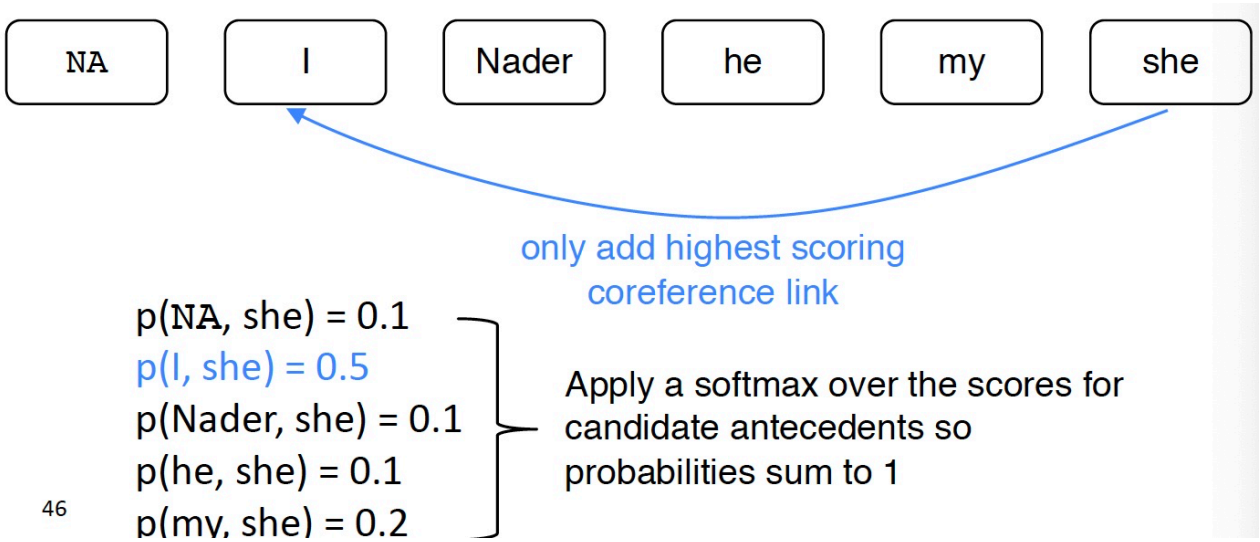
7. Coreference Models: Mention Ranking

- 根据模型把其得分最高的先行词分配给每个 mention
- 虚拟的 NA mention 允许模型拒绝将当前 mention 与任何内容联系起来(“singleton” or “first” mention)
  - first mention： I 只能选择 NA 作为自己的先行词









Coreference Models: Training

- 我们希望当前 mention m_j 与它所关联的任何一个候选先行词相关联。
- 在数学上，我们可能想要最大化这个概率

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

Iterate through candidate antecedents (previously occurring mentions)

For ones that are coreferent to m_j...

...we want the model to assign a high probability

- 公式解析
  - 遍历候选先行词集合
  - 对于 $y_{ij} = 1$ 的情况，即 m_i 与 m_j 是共指关系的情况
  - 我们希望模型能够给予其高可能性
- 该模型可以为一个正确的先行词产生概率 0.9 ，而对其他所有产生较低的概率，并且总和仍然很大

- Turning this into a loss function

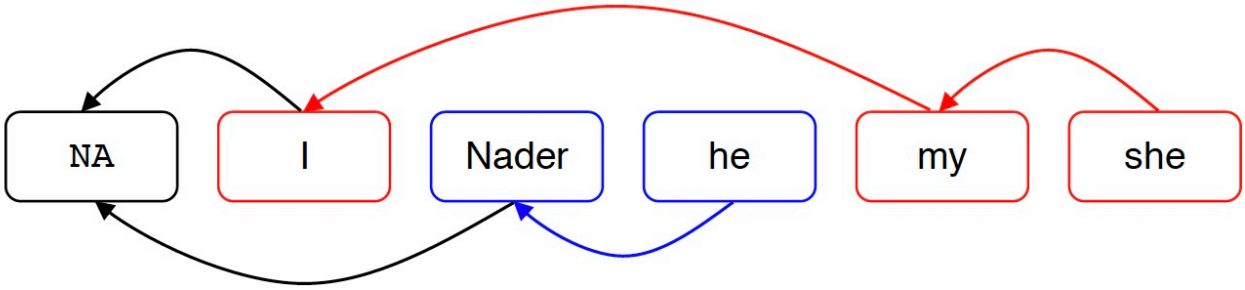
$$J = \sum_{i=2}^{N} -\log \left(\sum_{j=1}^{i-1} \mathbb{1}(y_{ij} = 1) p(m_j, m_i) \right)$$

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

和 mention-pair 模型几乎一样，除了每个 mention 只分配一个先行词



How do we compute the probabilities?

A. Non-neural statistical classifier

B. Simple neural network

C. More advanced model using LSTMs, attention

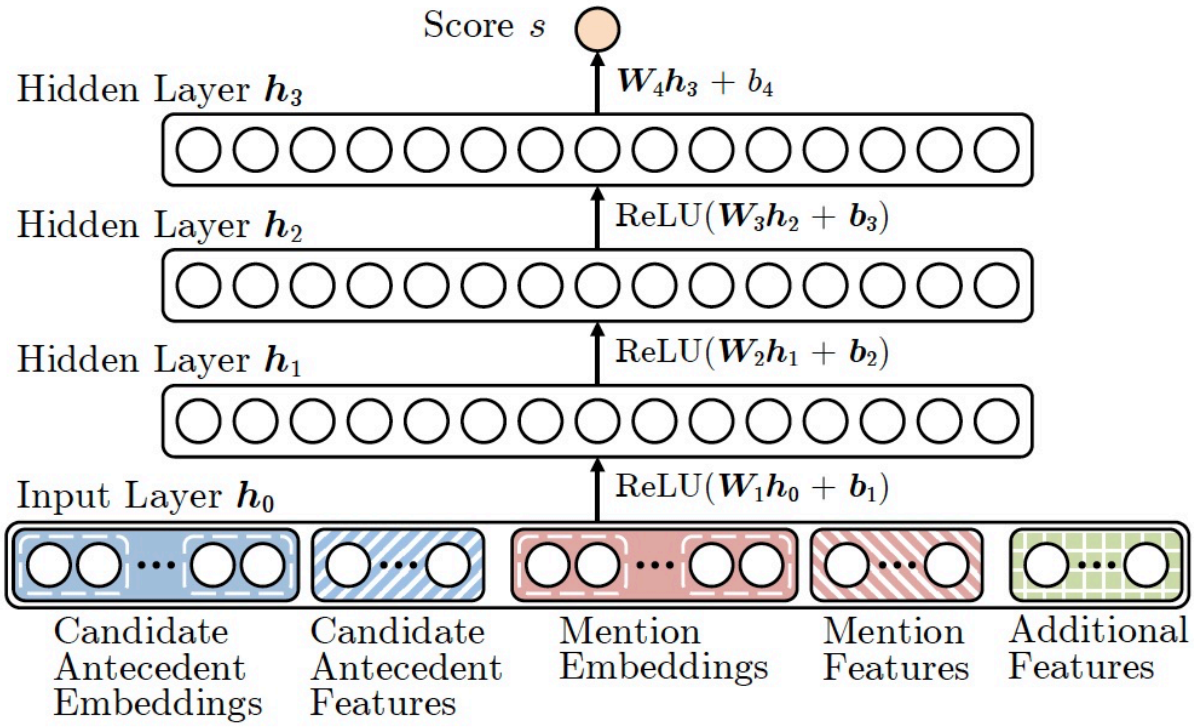
A. Non-Neural Coref Model: Features

- 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.
- …

- 使用如下特征进行分类
  - 人、数字、性别
  - 语义相容性
  - 句法约束
  - 更近的提到的实体是个可能的参考对象
  - 语法角色：偏好主语位置的实体
  - 排比

B. Neural Coref Model

- 标准的前馈神经网络
  - 输入层：词嵌入和一些类别特征



Neural Coref Model: Inputs

- 嵌入
  - 每个 mention 的前两个单词，第一个单词，最后一个单词，head word，...
    - head word是 mention 中“最重要”的单词—可以使用解析器找到它
    - 例如：*The fluffy* **cat** stuck in the tree
- 仍然需要一些其他特征
  - 距离
  - 文档体裁
  - 说话者的信息

C. End-to-end Model

- 当前最先进的模型算法(Kenton Lee et al. from UW, EMNLP 2017)
- Mention 排名模型
- 改进了简单的前馈神经网络
  - 使用LSTM
  - 使用注意力
  - 端到端的完成 mention 检测和共指
    - 没有 mention 检测步骤!
    - 而是考虑每段文本(一定长度)作为候选 mention
      - a **span** 是一个连续的序列

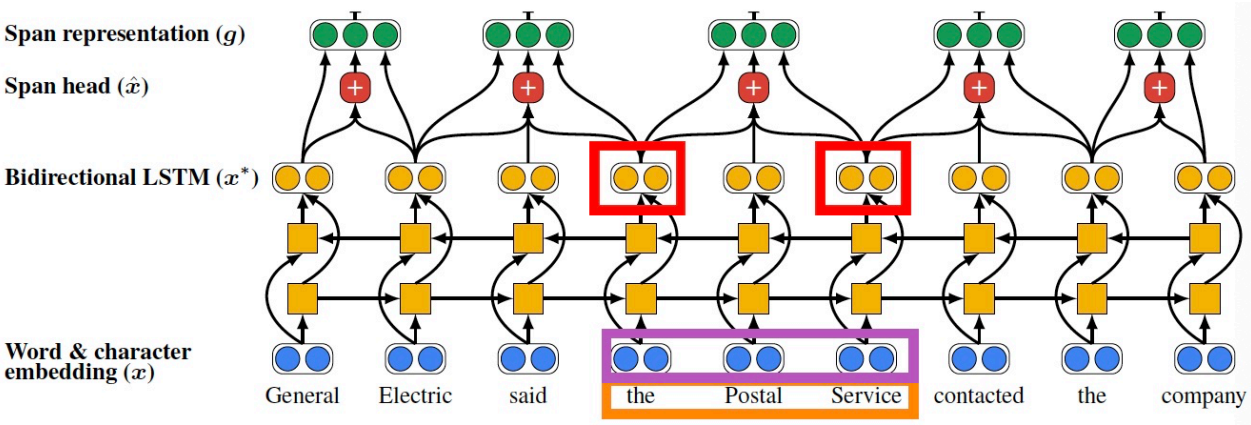
End-to-end Model

- 首先将文档里的单词使用词嵌入矩阵和 charCNN embed 为词嵌入

- 接着在文档上运行双向 LSTM
- 接着将每段文本 i 从 $\text{START}(i)$ 到 $\text{END}(i)$ 表示为一个向量
  - span 是句子中任何单词的连续子句
  - General, General Electric, General Electric said, … Electric, Electric said, …都会得到它自己的向量表示
- span representation

$$\boldsymbol{g}_i = \left[\boldsymbol{x}^*_{\text{START}(i)}, \boldsymbol{x}^*_{\text{END}(i)}, \hat{\boldsymbol{x}}_i, \phi(i)\right] \tag{1}$$

  - 例如 “the postal service”



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

BILSTM hidden states for span's start and end

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

Additional features

- $\hat{\boldsymbol{x}}_i$ 是 span 的注意力加权平均的词向量

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

- 为什么要在 span 中引入所有的这些不同的项

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

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

- 最后，为每个 span 对打分来决定他们是不是共指 mentions

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

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

Is *i* a mention?

Is *j* a mention?

Do they look coreferent?

- 打分函数以 span representations 作为输入

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

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

include multiplicative interactions between the representations

again, we have some extra features

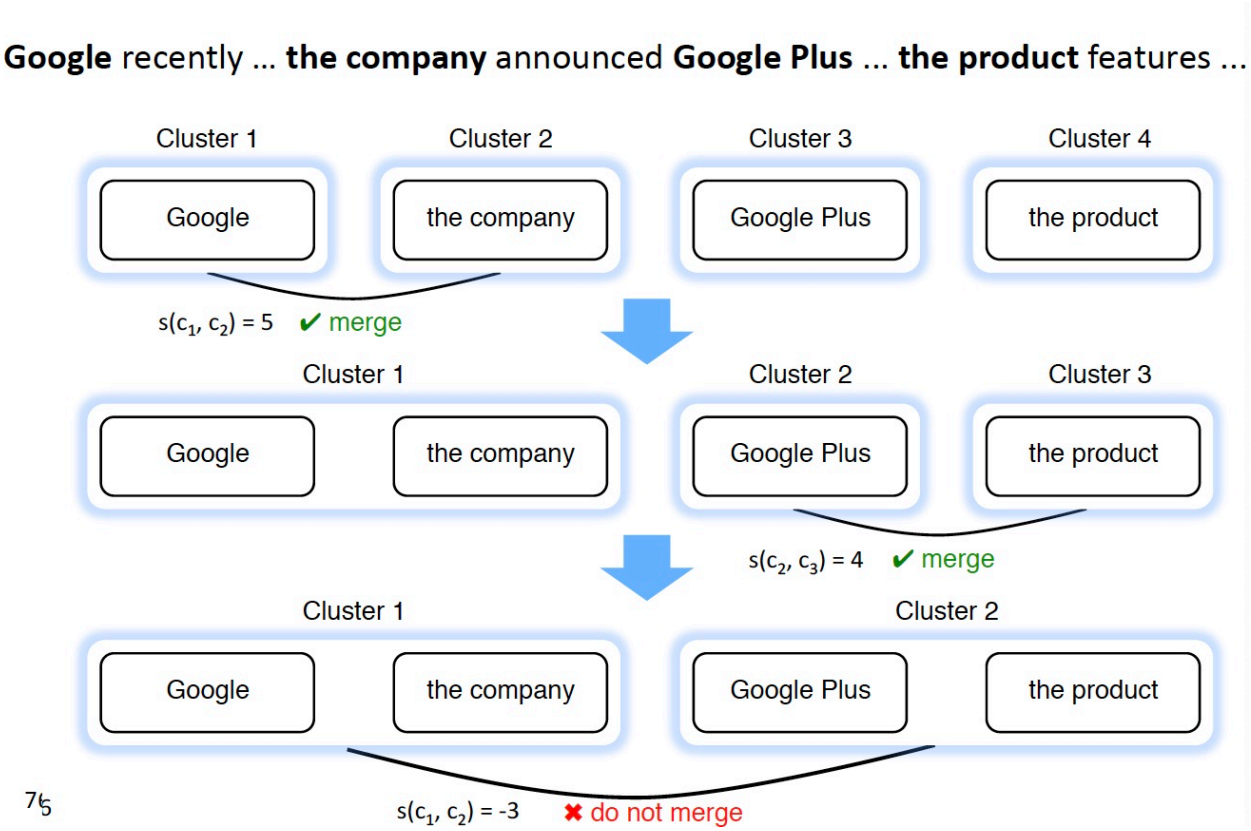
- 为每对 span 打分是棘手的
  - 一个文档中有 $O(T^2)$ spans，T 是词的个数
  - $O(T^4)$ 的运行时间
  - 所以必须做大量的修剪工作(只考虑一些可能是 mention 的span)
- 关注学习哪些单词是重要的在提到(有点像head word)

(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.

8. Last Coreference Approach: Clustering-Bas

- 共指是个聚类任务，让我们使用一个聚类算法吧
  - 特别是我们将使用 agglomerative 凝聚聚类 自下而上的
- 开始时，每个 mention 在它自己的单独集群中
- 每一步合并两个集群

- 使用模型来打分那些聚类合并是好的



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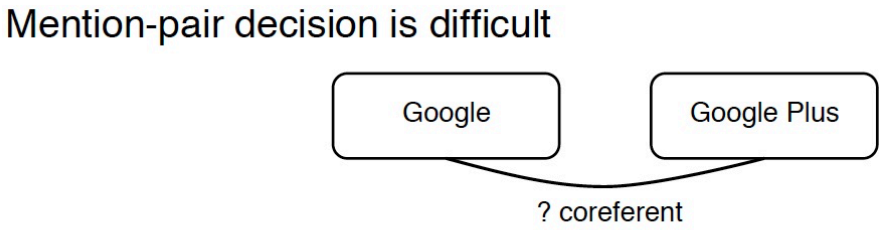
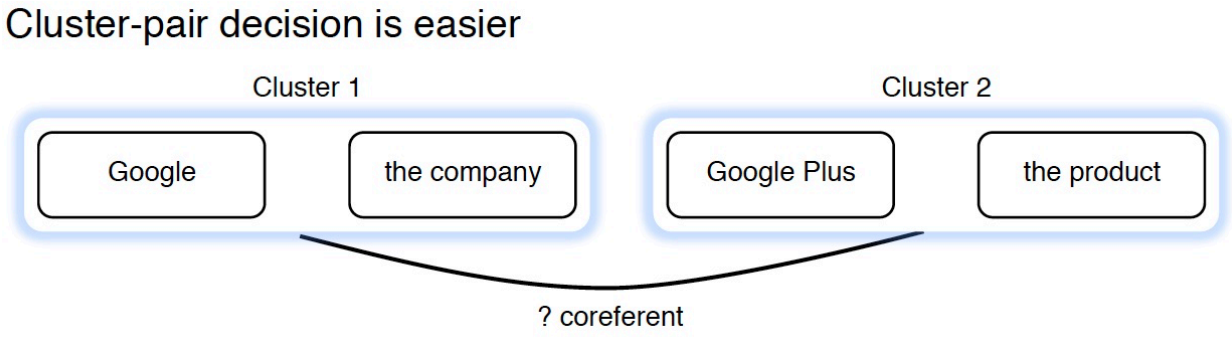
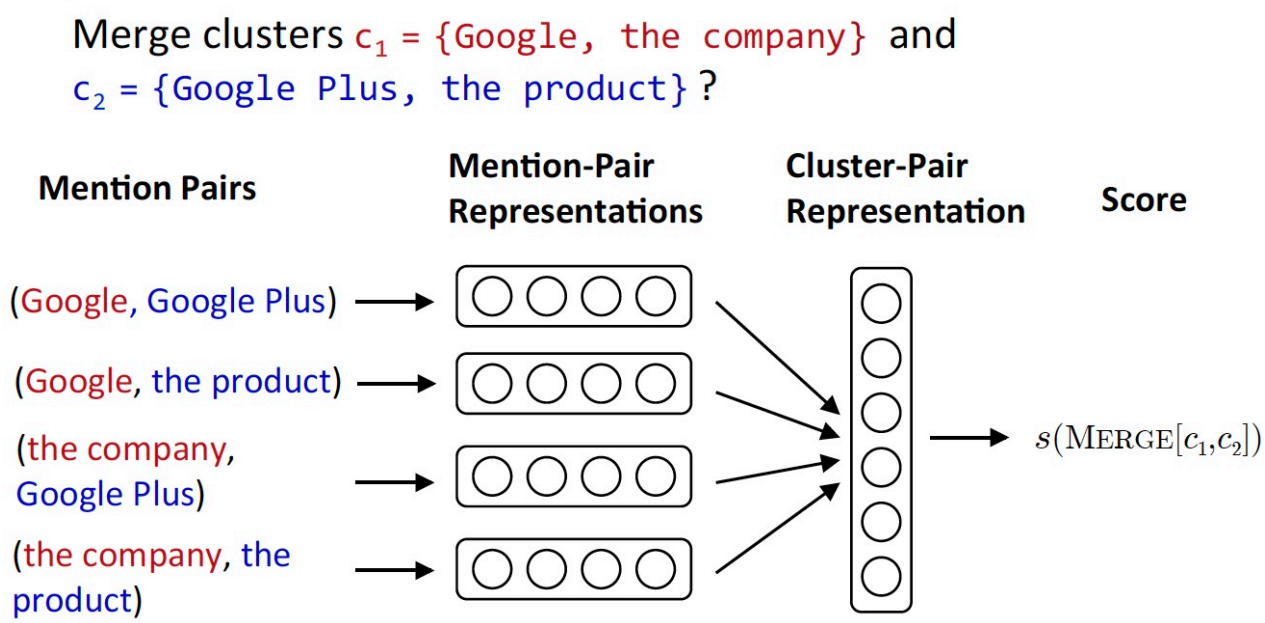


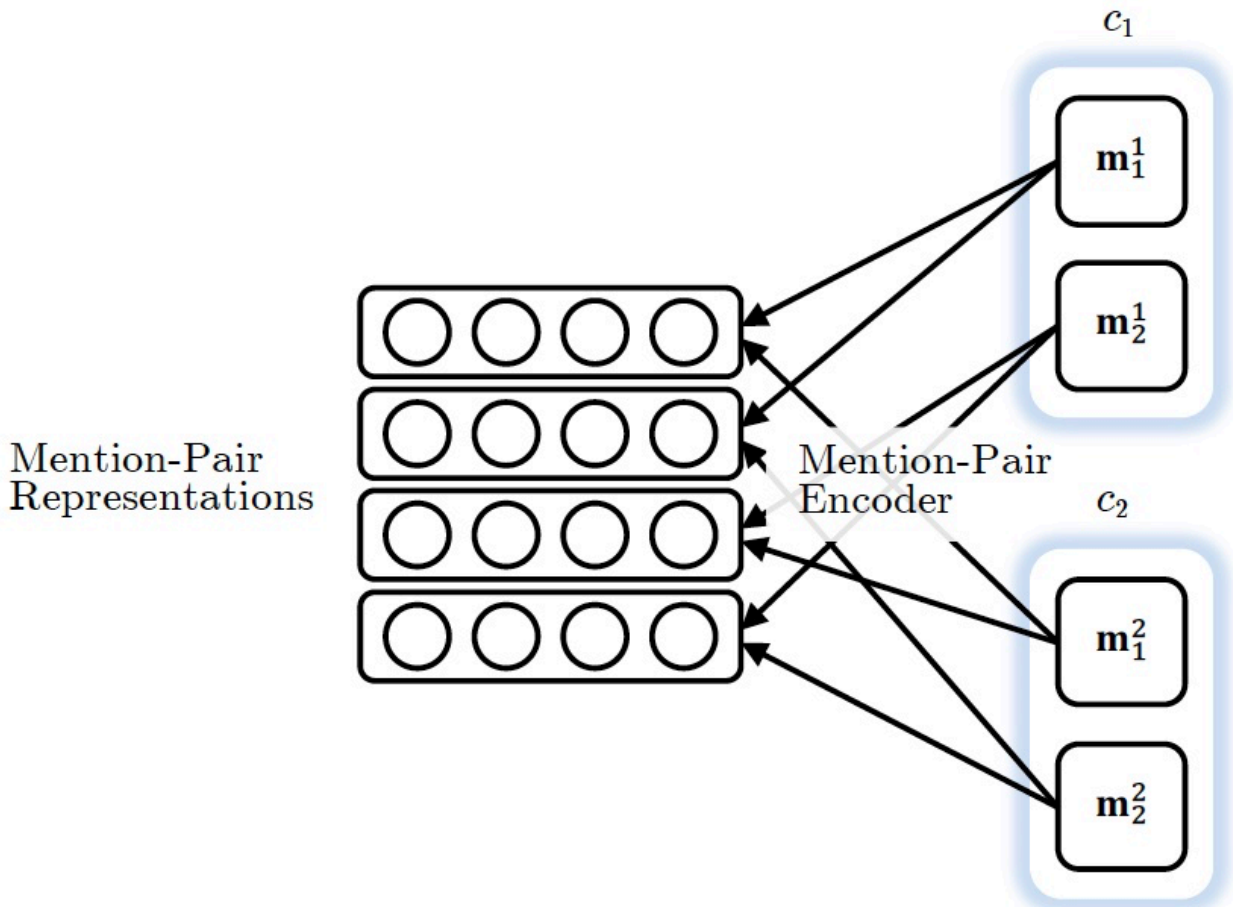


Clustering Model Architecture

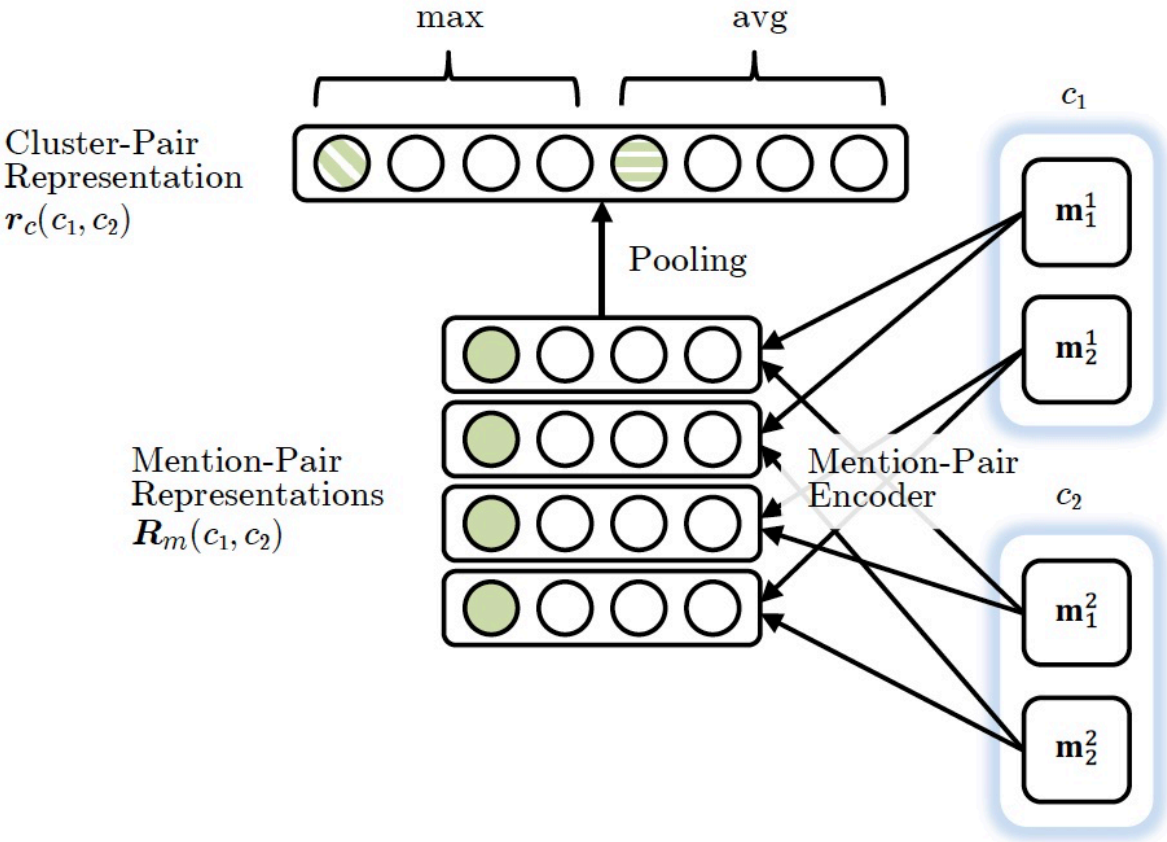
From Clark & Manning, 2016



- 首先为每个 mention 对生成一个向量
  - 例如，前馈神经网络模型中的隐藏层的输出



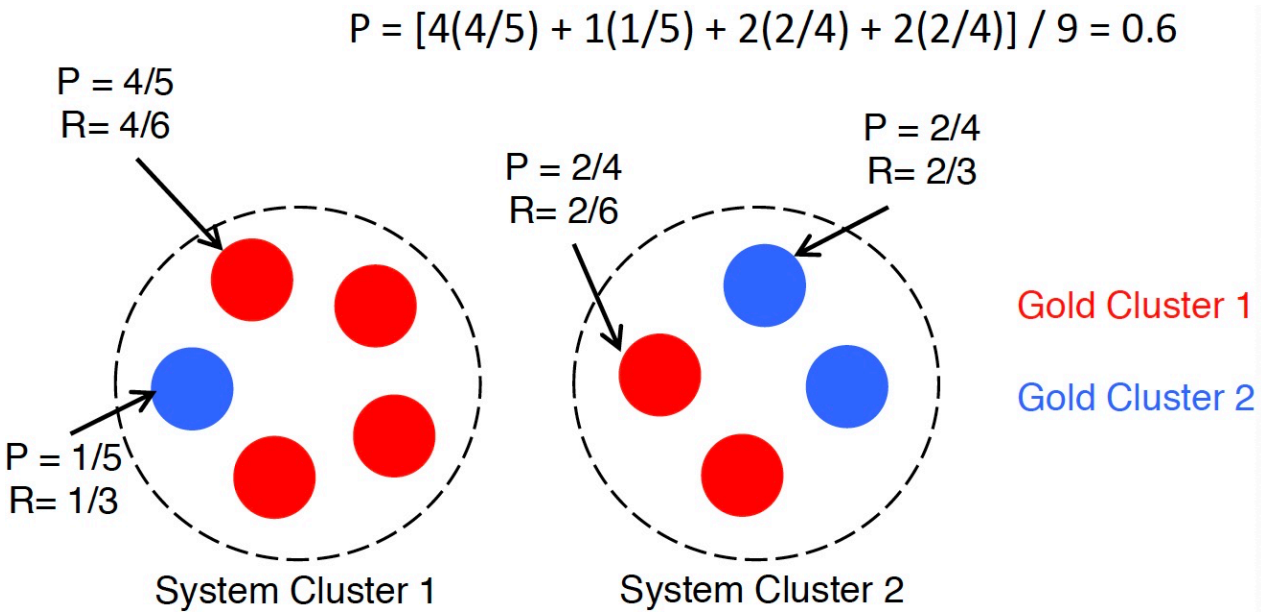
- 接着将池化操作应用于 mentino-pair 表示的矩阵上，得到一个 cluster-pair 聚类对的表示

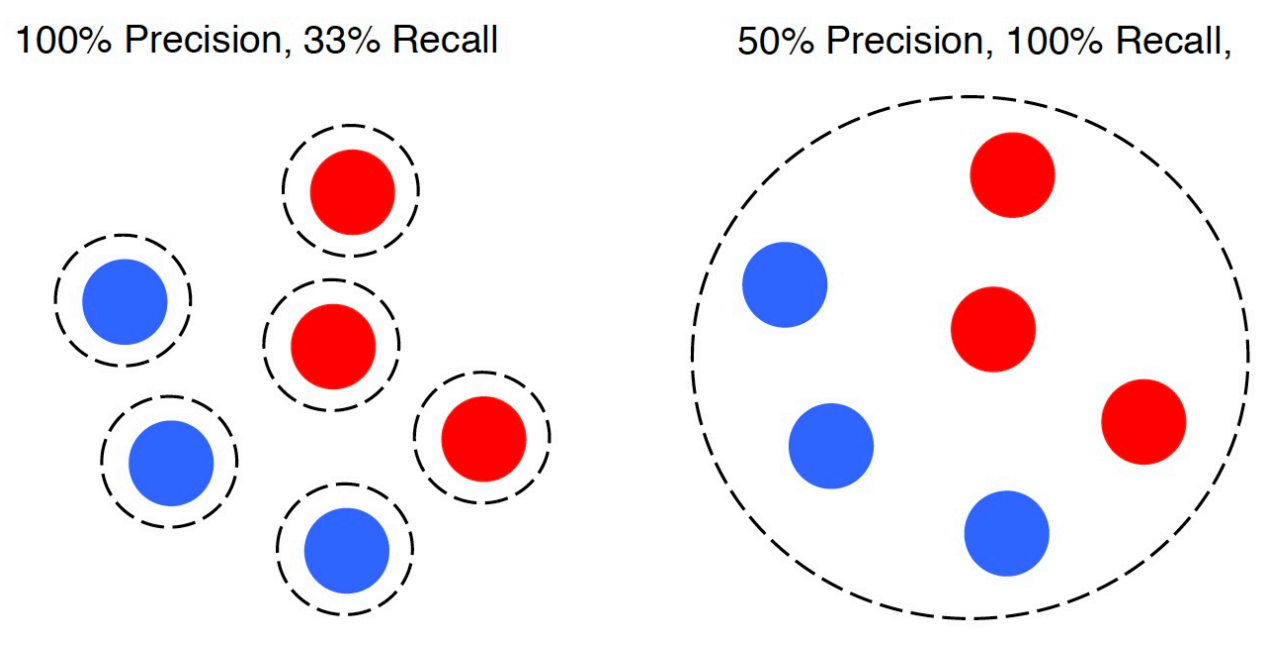


- 通过用权重向量与表示向量的点积，对 candidate cluster merge 进行评分
  - $s\left(\text{MERGE}[c_1, c_2]\right) = u^T r_c\left(c_1, c_2\right)$
- 当前候选簇的合并，取决于之前的合并
  - 所以不能用常规的监督学习
  - 使用类似强化学习训练模型
    - 为每个合并分配奖励：共指评价指标的变化

9. Coreference Evaluation

- 许多不同的评价指标：MUC, CEAF, LEA, B-CUBED, BLANC
  - 经常使用一些不同评价指标的均值
- 例如 B-cubed
  - 对于每个 mention ，计算其准确率和召回率
  - 然后平均每个个体的准确率和召回率





System Performance

- OntoNotes数据集:~ 3000人类标注的文档
  - 英语和中文
- Report an F1 score averaged over 3 coreference metrics

Model	English	Chinese	
Lee et al. (2010)	~55	~50	Rule-based system, used to be state-of-the-art!
Chen & Ng (2012) [CoNLL 2012 Chinese winner]	54.5	57.6	Non-neural machine learning models
Fernandes (2012) [CoNLL 2012 English winner]	60.7	51.6	
Wiseman et al. (2015)	63.3	—	Neural mention ranker
Clark & Manning (2016)	65.4	63.7	Neural clustering model
Lee et al. (2017)	67.2	--	End-to-end neural mention ranker

Where do neural scoring models help?

- 特别是对于没有字符串匹配的NPs和命名实体。神经与非神经评分:

  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

- 共指是一个有用的、具有挑战性和有趣的语言任务
  - 许多不同种类的算法系统
- 系统迅速好转，很大程度上是由于更好的神经模型
  - 但总的来说,还没有惊人的结果
- Try out a coreference system yourself
  - http://corenlp.run/ (ask for coref in Annotations)
  - https://huggingface.co/coref/

Reference

以下是学习本课程时的可用参考书籍:

《基于深度学习的自然语言处理》（车万翔老师等翻译）

《神经网络与深度学习》

以下是整理笔记的过程中参考的博客：

斯坦福CS224N深度学习自然语言处理2019冬学习笔记目录 (课件核心内容的提炼，并包含作者的见解与建议)

斯坦福大学 CS224n自然语言处理与深度学习笔记汇总 {>>这是针对note部分的翻译<<}