

# Natural Language Processing (CS-472) Spring-2023

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### Overview of this week's lecture



### **Coreference Resolution**

- Introduction to Coreference Resolution
- Coreference resolution approaches
  - Using mention-pair
  - Using mention-pair ranking
  - Using clustering
- Coreference resolution evaluation





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  - First identify all mentions.

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# Coreference resolution can be tricky even for humans



The Islamabad High Court on Thursday barred FIA) from arresting Suleman Shehbaz, the son of Prime Minister Shehbaz Sharif, who is expected to return to Pakistan this week after four years of self-exile in London.

Suleman is living in London with his family. He had filed a plea before the IHC a day ago, seeking protective bail that would enable him to surrender before a trial court.

The court took up the plea for hearing today. Suleman's counsel Amjad Pervez appeared before the court.

During the proceedings, IHC Chief Justice Aamer Farooq issued directives for the applicant, asking him to surrender before the court by Dec 13 and barred the FIA from arresting him until then. Justice Farooq said it was necessary for an applicant to be present in the court while seeking protective bail.

Pervez told the court that his client was returning to the country on Sunday. "He wants to appear before the relevant authorities," he added. The counsel said the court had been granting similar protective bails in the past.

Following the arguments, the court granted them relief.





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### **Split Antecedent**







Natural language processing

- To fully understand natural language.
  - Information extraction.

Salman's advocate said that his client was living in London for the last four years and now he wanted to come back to Pakistan.

Who was living in London for the last four years?





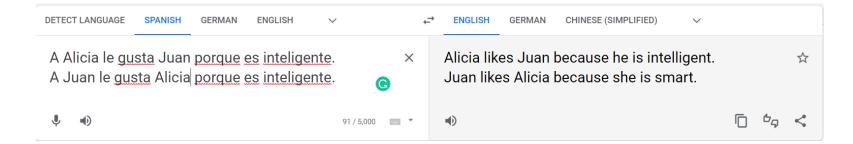
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Machine translation

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NLP Natural language processing

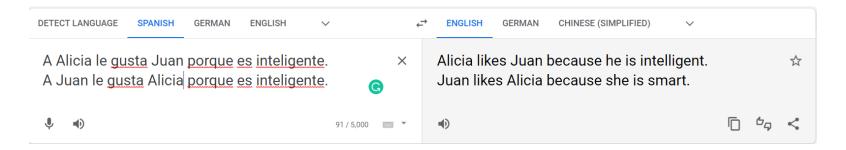
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Machine translation

- Dialogue Generation

Salman's advocate said that his client was living in London for the last four years and now he wanted to come back to Pakistan.

Who was living in London for the last four years?



Human: Book tickets to see James Bond.

Bot: Spectre is playing near you at 02:00 and 05:00.

How many tickets would you like?

Human: Two, for showing at five.





# Coreference resolution is performed in two steps



Detect the mentions.

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



# Coreference resolution is performed in two steps



- Detect the mentions.
  - Mentions can be nested.

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



# Coreference resolution is performed in two steps



- Detect the mentions.
  - Mentions can be nested.
- Cluster the mentions.
  - Which mention is coreferent to what other mention.

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

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







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- There are three types of mentions.

- Pronouns: I, you, it, she, him, etc.

- Named Entities People, Places, Organisations, etc.

- Noun Phrases "A dog", "the big fluffy cat struck in

the tree"





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How to detect them?

- Pronouns: I, you, it, she, him, etc.

- Use Part-of-Speech (POS) taggers

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You can also train a classifier that runs on the text and detects all types of mentions.

You can also perform mention detection and coreference resolution simultaneously in end-to-end manner.

More on this in coming slides.





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- Similarly, are the following words/phrases mention or not mention?

No student got an A Grade.

- Every student got an A Grade.

- The best teacher in the word.

Thousand miles

(Is no student any reference?)

(Is every student a clear and concrete reference?)

(Unclear. May or may not be)

(Not a mention)





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- How to deal with bad mentions?
  - Train a classifier to filter out such spurious mentions.





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Thousand miles (Not a mention)

- How to deal with bad mentions?
  - Train a classifier to filter out such spurious mentions.
    - Keep all mentions as candidate mentions and after clustering remove singletons.





# Let's learn just a tiny bit of linguistics



- Coreference is when two mentions refer to the same entity in the world.
  - "Donald Trump's twitter account reinstated. Trump was banned from twitter in January 2021 after January 6 capitol riots".
    - Both Donald Trump and Trump refer to the same entity but both mentions can be understood and interpreted independently of each other.





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  - "Donald Trump's twitter account reinstated. Trump was banned from twitter in January 2021 after January 6 capitol riots".
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- Anaphora is a related linguistic concept where a term (anaphor) refers to another term (antecedent) for interpretation.
  - **Trump** reacted to reactivation of **his** twitter account by saying **he** wouldn't be quickly returning to twitter.

    Antecedent Anaphor Anaphor





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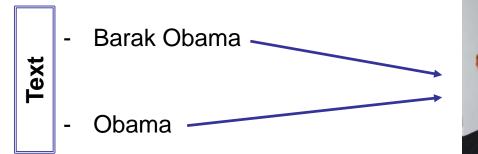
    Antecedent Anaphor Anaphor
- The concept of anaphors (and cataphors, coming soon) is not widely used in NLP.







 Barak Obama visited Florida. During the visit, Obama said his government will increase budget for health.

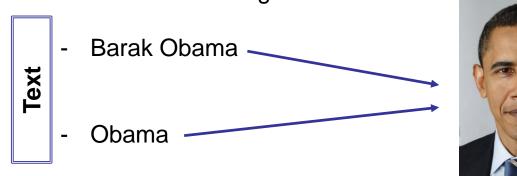


Real World



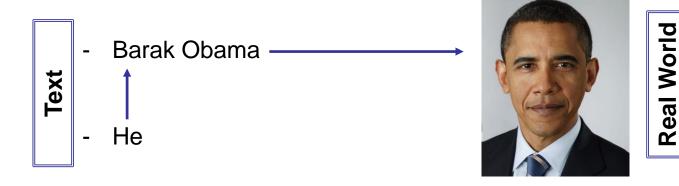


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Natural language processing

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- Barak Obama
- Obama

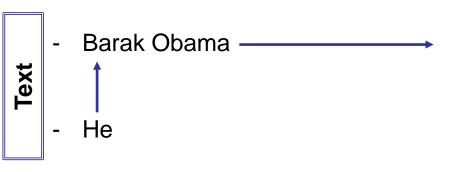
Real World

World

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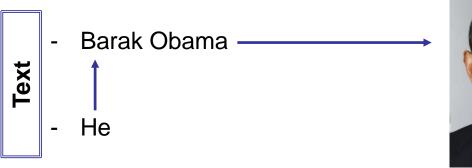
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Real World

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Real World







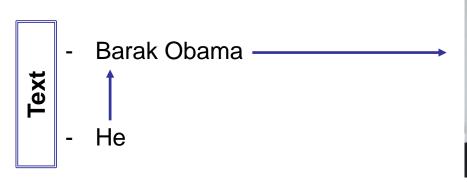
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Real World

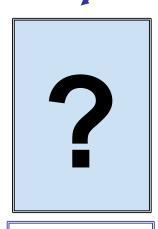
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**Real World** 





# Not all anaphoric relations are coreferential



- Not every noun phrase has reference.
  - No dancer twisted her knee.
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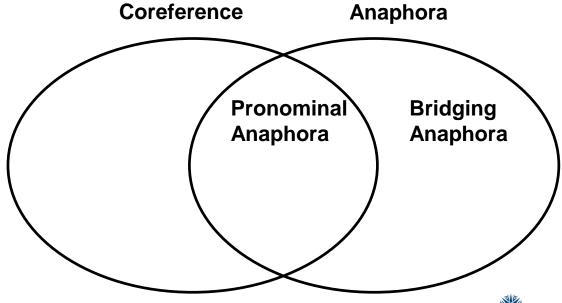
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- We went to see the match. The tickets were already sold.



## Not all anaphoric relations are coreferential

Natural language processing

- Not every noun phrase has reference.
  - No dancer twisted her knee.
  - Every dancer twisted her knee.
- We went to see the match. The tickets were already sold.
  - This is a bridging anaphora.







- Position of antecedent with reference to the dependent term is important, linguistically.

The king, in the first speech after his coronation, freed the prisoners.
 Antecedent Anaphora







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    Antecedent

    Anaphora
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Cataphora Antecedent







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- NLP Natural language processing
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    Antecedent

    Anaphora
  - In the first speech after his coronation, the king freed the prisoners.

Cataphora Antecedent

- In modern linguistics, the term cataphora is completely disused.
- In NLP also, the position of antecedent is not paid much attention to.
  - NLP systems only look back to find the textual reference (antecedent).







- 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.







- 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 protesters a permit because they feared violence.
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P Natural language processing

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Winograd Schema
An alternative to
Turing test





NLP Natural language processing

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https://www.youtube.com/watch?v=fKk9KhGRBdI



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"If you have fully solved coreference, arguably you have fully solved AI."

Hector J. Levesque





https://www.youtube.com/watch?v=fKk9KhGRBdI Levesque, Hector J. "On our best behaviour." Artificial Intelligence 212 (2014): 27-35.





- Take pairs of mentions and train a binary classifier to classify whether the pair is coreferent or not.

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

John Doe

He

My

She







 Take pairs of mentions and train a binary classifier to classify whether the pair is coreferent or not.

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

- The classifier assigns every pair of mentions a probability  $p(m_i, m_i)$ .

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- Read the text from left to right.

- When a mention is encountered, compute its probability will all preceding mentions.
  - For positive examples, the probability should be high.







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Cluster 1
Cluster 2

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 Iterate through previous mentions (candidate antecedents)

What about clustering?







- Pick a threshold, say 0.5, and add reference links between mentions where  $p(m_i, m_j)$  is higher.



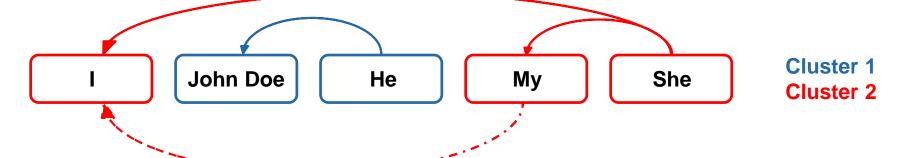




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Linking mentions using into over clustering.

transitive closure may result

Cluster 1 John Doe He She My Cluster 2

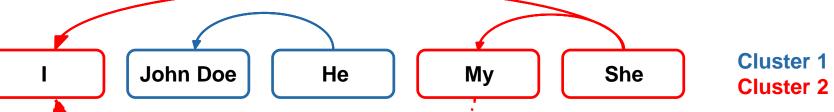
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- Pick a threshold, say 0.5, and add reference links between mentions where  $p(m_i, m_j)$  is higher.

- My is connected to I by transitive closure.
- Linking mentions using transitive closure may result into over clustering.



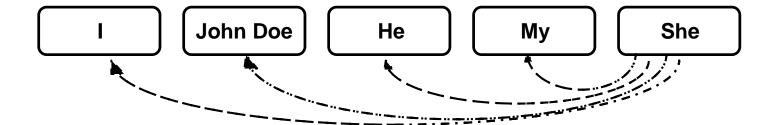
- Some mentions may be coreferent to nothing.
- Disadvantage: The mention-pair model does not work well for longer documents.
  - Many mentions only have one clear antecedent but mention-pair model tries to identify all of them.
    - Solution: Train the model to predict only one antecedent per mention.





NLP Natural language processing

- Assign each mention its highest ranking candidate antecedent.
  - What's the best antecedent for She?



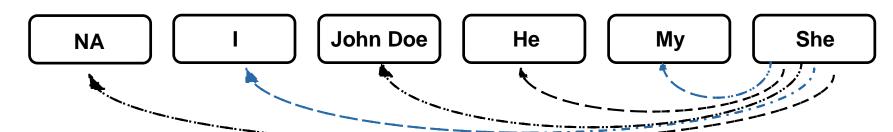




Natural language processing

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- What about singletons?
  - Use dummy antecedent.





Natural language processing

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\_ \_

NA

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John Doe

He

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- Use dummy antecedent.
- During training, the model is only expected to assign high probability to any one of the antecedents (positive examples).

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**John Doe** 

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- Add only the highest scoring coreference link.

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# **Coreference Model: Training Mention Ranking**

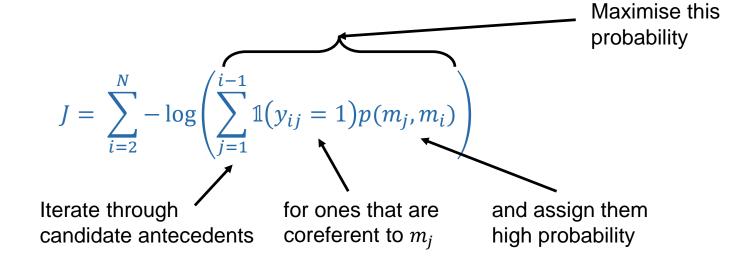


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## **Coreference Model: Training Mention Ranking**

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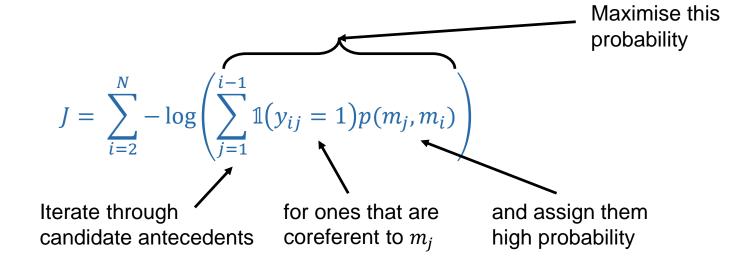


- Producing high probability with any one of candidate antecedents will result in overall high probability.

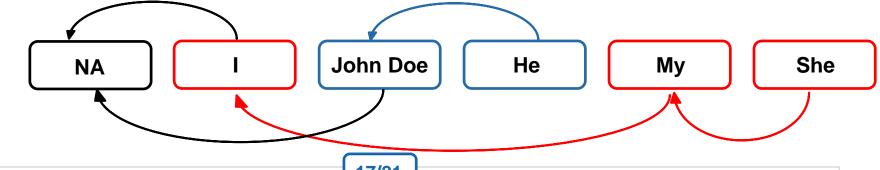


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  - Merge on the basis of what criterion?
    - Euclidian Distance
    - Cosine Similarity
    - Neural Networks



лериш



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Google

The company

**Google Plus** 

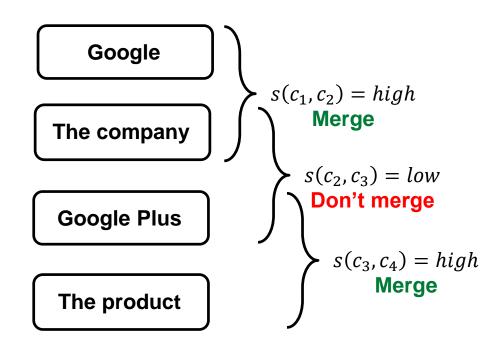
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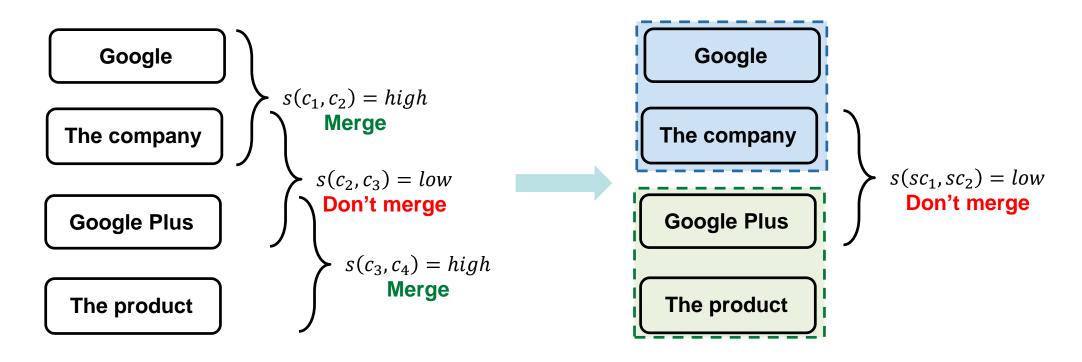








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Ground Truth Red Cluster

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**Ground Truth Blue Cluster** 

B-CUBED algorithms calculates weighted average precision and recall.







MUC, CEAF, LEA, B-CUBED, BLANC are some of the metrics.

**Ground Truth** 

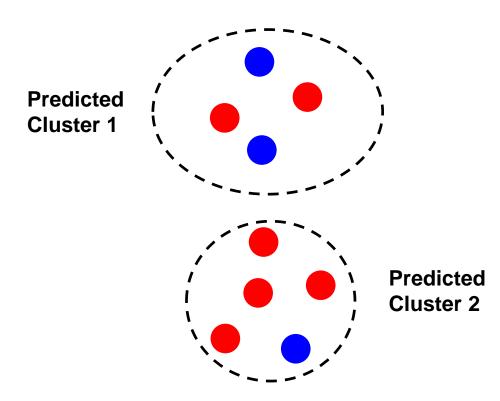
**Red Cluster** 

Often, average over some of the metrics is reported.

International Conference on Computational Linguistics. 1998.

**Ground Truth Blue Cluster** 

B-CUBED algorithms calculates weighted average precision and recall.







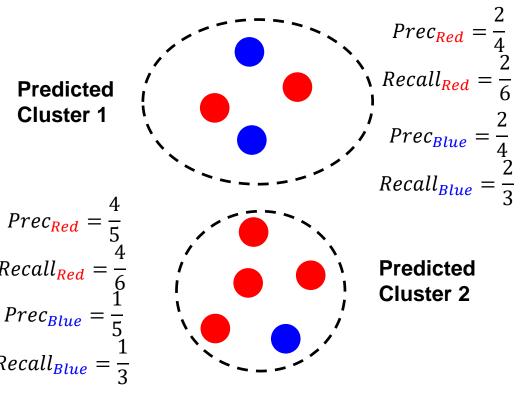
- MUC, CEAF, LEA, B-CUBED, BLANC are some of the metrics.

**Ground Truth Red Cluster** 

- Often, average over some of the metrics is reported.

Ground Truth
Blue Cluster

 B-CUBED algorithms calculates weighted average precision and recall.





Bagga, Amit, and Breck Baldwin. "Entity-based cross-document coreferencing using the vector space model." COLING 1998 Volume 1: The 17th International Conference on Computational Linguistics. 1998.





- MUC, CEAF, LEA, B-CUBED, BLANC are some of the metrics.



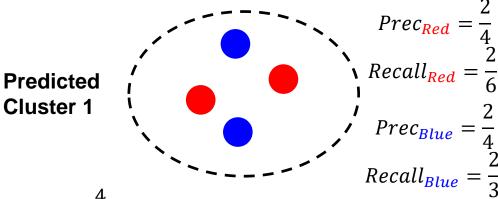
**Ground Truth Red Cluster** 

- Often, average over some of the metrics is reported.

Ground Truth
Blue Cluster

 B-CUBED algorithms calculates weighted average precision and recall.

Weighted Precision = 
$$\frac{\left[4\frac{4}{5} + 1\frac{1}{5} + 2\frac{2}{4} + 2\frac{2}{4}\right]}{9} = 0.6$$



$$Prec_{Red} = \frac{1}{5}$$

$$Recall_{Red} = \frac{4}{6}$$

$$Prec_{Blue} = \frac{1}{5}$$

$$Recall_{Blue} = \frac{1}{3}$$

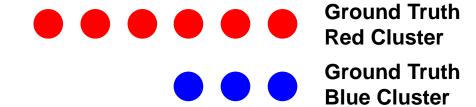
Predicted Cluster 2



Bagga, Amit, and Breck Baldwin. "Entity-based cross-document coreferencing using the vector space model." COLING 1998 Volume 1: The 17th International Conference on Computational Linguistics. 1998.





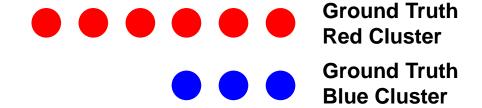






Natural language processing

 Homogeneity: A predicted cluster is homogenous if it all of its members belong to one ground truth cluster.



$$Prec_{Blue} = \frac{1}{1}$$

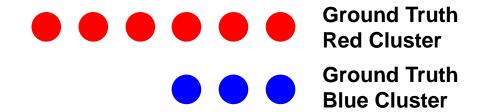
$$Recall_{Blue} = \frac{1}{3}$$





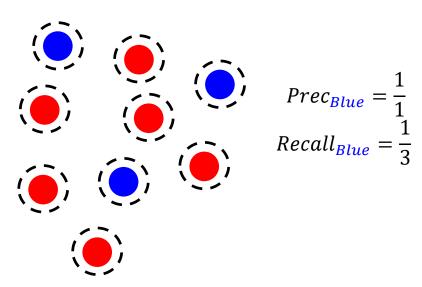
Natural language processing

- **Homogeneity:** A predicted cluster is homogenous if it all of its members belong to one ground truth cluster.
- **Completeness:** A predicted cluster is complete if it contains all members of a ground truth cluster.



$$Prec_{Blue} = \frac{3}{9}$$

$$Recall_{Blue} = \frac{3}{3}$$







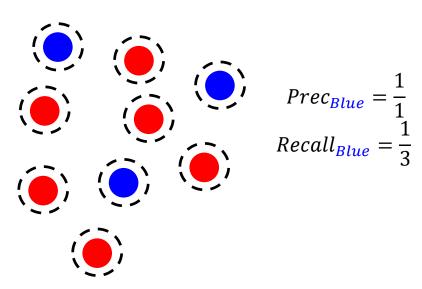
NLP Natural language processing

- Homogeneity: A predicted cluster is homogenous if it all of its members belong to one ground truth cluster.
- Ground Truth
  Red Cluster

  Ground Truth
  Blue Cluster
- Completeness: A predicted cluster is complete if it contains all members of a ground truth cluster.
- Balance between homogeneity and completeness of predicted clusters should be maintained.

$$Prec_{Blue} = \frac{3}{9}$$

$$Recall_{Blue} = \frac{3}{3}$$







### Do you have any problem?



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