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#### Simple premise:

- Given:
  - Pair of mentions (candidate anaphor and candidate antecedent)
- Decide:
  - Whether or not they corefer

#### How does this work?

- Compute coreference probabilities for every plausible pair of mentions
- Goal: High probability for actual coreferring pairs, and low probability for other pairs

The University of Illinois at Chicago is an excellent place to study natural language processing. (UIC) has many faculty currently working in (NLP) including but not limited to Natalie Parde, Barbara Di Eugenia, Cornelia Caragea Bing Liu, and Philip Yu The school is located in bustling downtown Chicago and as a bonustit will be opening a snazzy new (non-brutalist) CS building in 2022.

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## How do we learn these probabilities?

- Select training samples
  - One positive instance  $(m_i, m_j)$  where  $m_i$  is the closest antecedent to  $m_i$
  - A negative instance  $(m_i, m_k)$  for each  $m_k$  between  $m_i$  and  $m_i$
- Extract features
  - Hand-built features, and/or
  - Implicitly learned representations
- Train classification model

## How do we make predictions?

- Apply the trained classifier to each test instance in a clustering step
  - Closest-first clustering
    - For mention i, classifier is run backwards through prior i-1 mentions
    - First antecedent with probability > 0.5 is selected and linked to i
  - Best-first clustering
    - Classifier is run on all possible i-1 antecedents
    - Mention with highest probability is selected as the antecedent for i

- Advantage:
  - Simplest coreference resolution architecture
- Disadvantage:
  - Doesn't directly compare candidate antecedents with one another
  - Considers only mentions, not overall entities

# How can we address these limitations?

- One option: The Mention-Rank Architecture
  - Directly compares antecedents with one another
  - Selects the highest-scoring antecedent for each anaphor
- How does this work?
  - For a mention *i*, we have:
    - Random variable  $y_i$  ranging over the values  $Y(i) = \{1, ..., i 1, \varepsilon\}$ 
      - ε = dummy mention meaning i does not have an antecedent
  - At test time, for i the model computes a softmax over all possible antecedents
  - When training:
    - Use heuristics to determine the best antecedent for an anaphor (e.g., closest = best)
    - Or, learn more optimal ways to model latent antecedents using machine learning