Relation Extraction

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Week 10, Lecture 4

Bootstrapping approaches

- If you don't have enough annotated text to train on ...
- But you do have:
  - some seed instances of the relation
  - (or some patterns that work pretty well)
  - and lots and lots of unannotated text (e.g., the web)
- can you use those seeds to do something useful?
- Bootstrapping can be considered semi-supervised

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“Mark Twain is buried in Elmira, NY.”
→ X is buried in Y
“The grave of Mark Twain is in Elmira”
→ The grave of X is in Y
“Elmira is Mark Twain’s final resting place”
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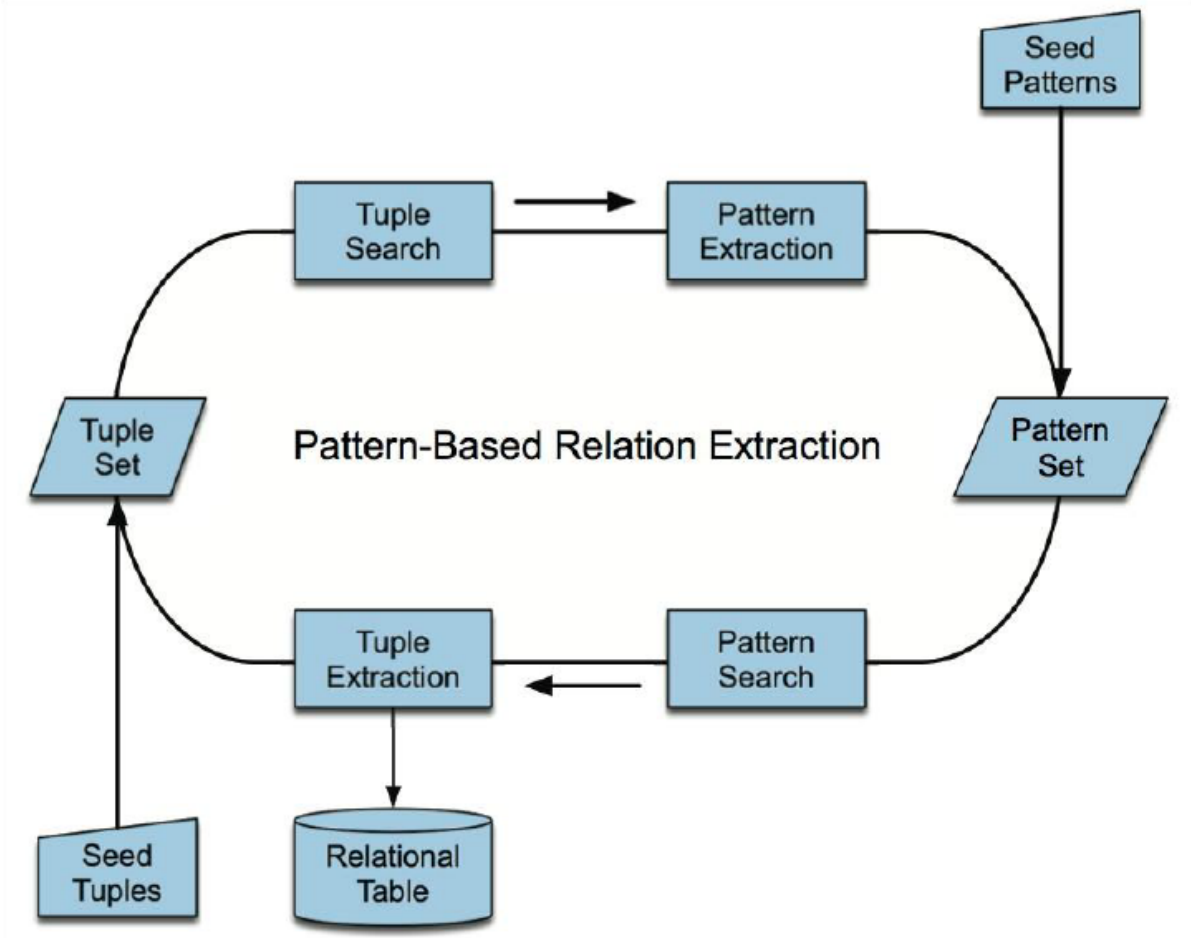
- Use those patterns to search for new tuples

Bootstrapping relations



Bootstrapping problems

- Requires that we have seeds for each relation
  - Sensitive to original set of seeds
- Generally have lots of parameters to be tuned
- No probabilistic interpretation
  - Hard to know how confident to be in each result

Supervised Relation Extraction

- Choose a set of relations you would like to extract

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- Choose a set of relations you would like to extract
- Find and label data
  - Choose a representative corpus
  - Label the named entities in the corpus
  - Hand-label the relations between these entities
  - Break into training, development and test
- Train a classifier on the training set

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- **Extra step:** Build a binary classifier to decide if 2 entities are related
- If yes, use another classifier to classify the relation

Why the extra step?

- Faster classification training by eliminating most pairs
- Can use distinct feature-sets appropriate for each task

Classify the relation between two entities in a sentence

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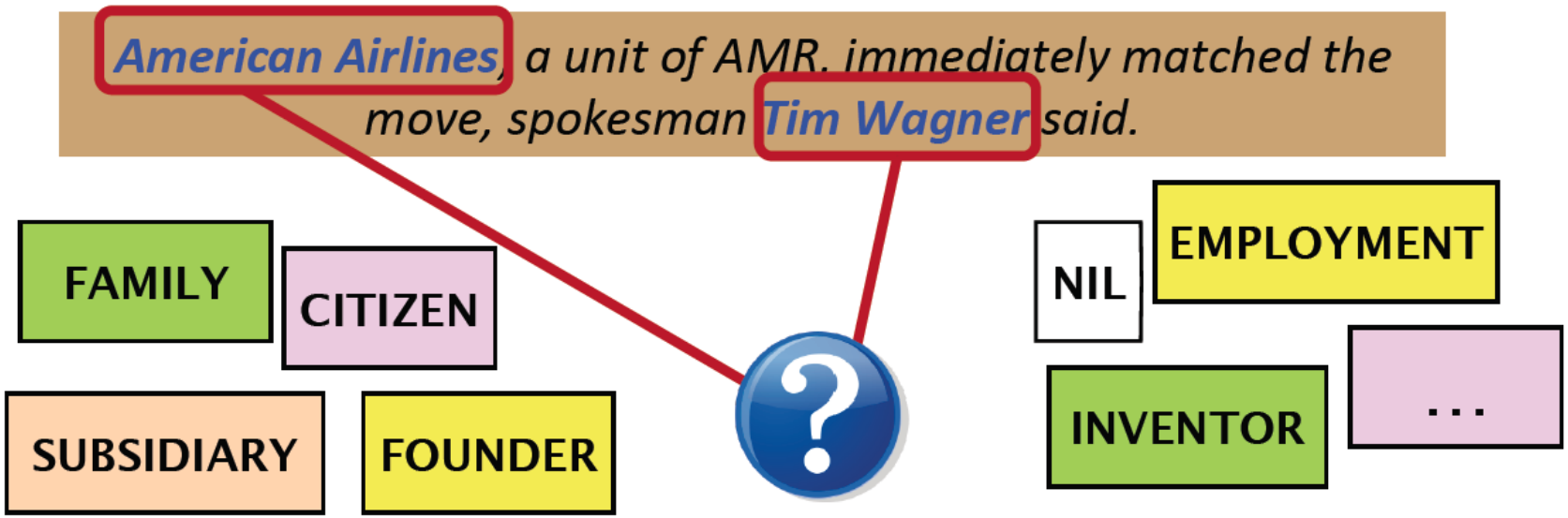

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Head-word features

HM1 = Airlines, HM2 = Wagner, HM12 = Airlines+Wagner

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Bag of words or bigrams between the two entities

{a, AMR, of, immediately, matched, move, spokesman, the, unit}

Named Entity Type and Mention Level Features

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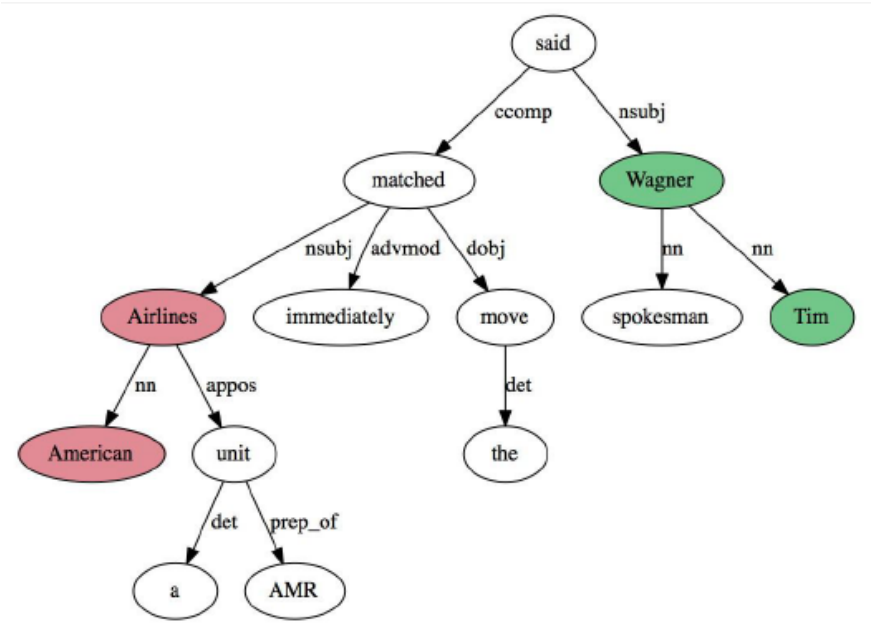
Entity Level of mentions (Name, Nominal, Pronoun)

M1:EL = Name, M2:EL = Name

'it' or 'he' would be pronoun, 'the company' would be nominal

Features: dependency syntax features



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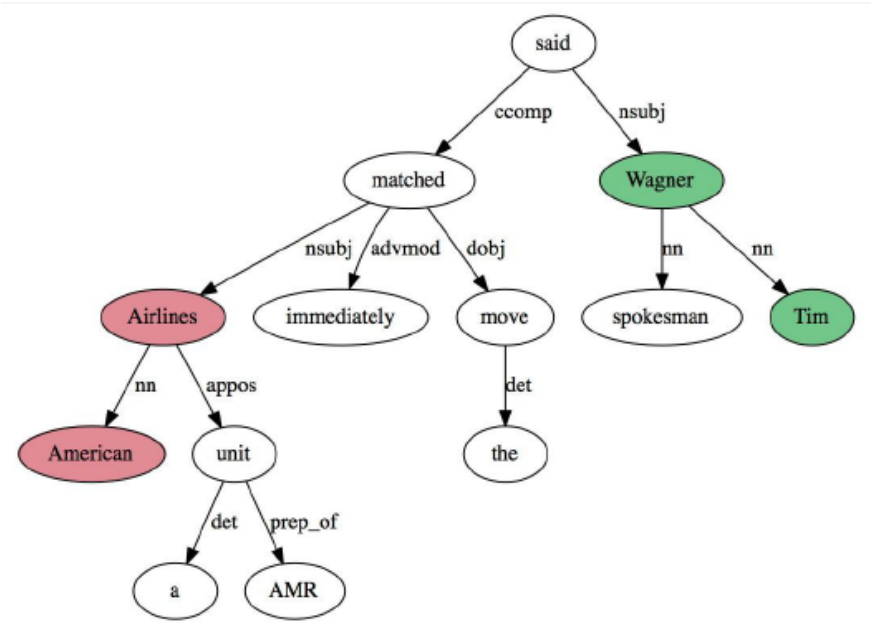

Features of mention dependencies

H1DW1 = matched:Airlines

H2DW2 = said:Wagner

Path = {Airlines, matched, said, Wagner}

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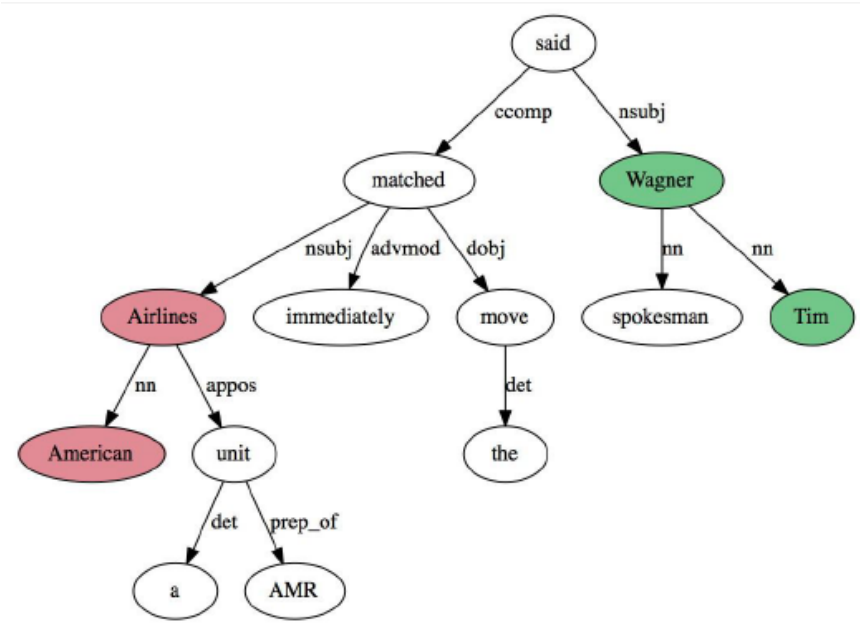

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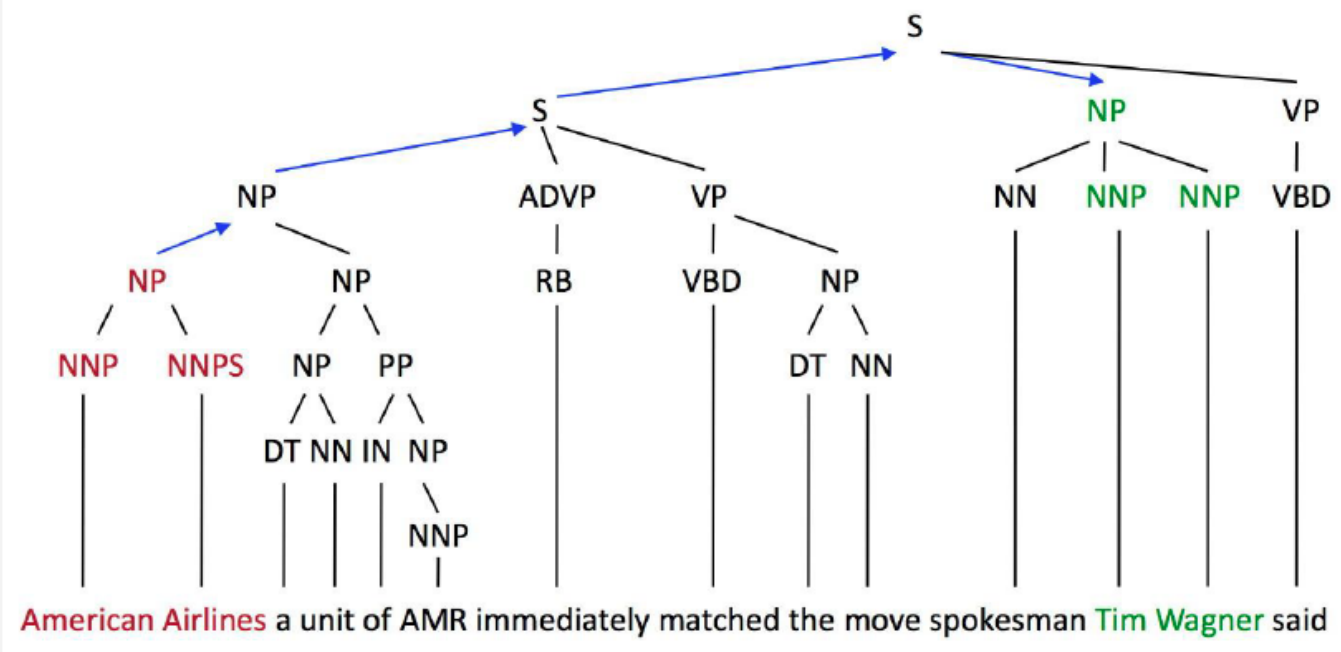
Base Phrase Chunk Features

[$_{NP}$ American Airlines], [$_{NP}$ a unit] [$_{PP}$ of] [$_{NP}$ AMR], [$_{ADVP}$ immediately] [$_{VP}$ matched] [$_{NP}$ the move], [$_{NP}$ spokesman Tim Wagner] [$_{VP}$ said].

Features: constituency parse features



Features for relation extraction: Gazetteer and trigger word features

Trigger list for family: kinship terms

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parent, wife, husband, grandparent etc. [from Wordnet]

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Gazetteer

List of useful geo or geopolitical words

- Country name list
- Other sub-entries

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- SVM
- MaxEnt (multiclass logistic regression)
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Train it on the training set, tune on the development set, test on the test set

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$$F_1 = \frac{2PR}{P+R}$$

Supervised RE : summary

Supervised approach can achieve high accuracy

- At least, for some relations
- If we have lots of hand-labeled training data

But has significant limitations!

- Labeling large training set (+ named entities) is expensive
- Doesn't generalize to different relations

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Beyond supervised relation extraction

- Distantly supervised relation extraction
- Unsupervised relation extraction