Named Entity Disambiguation and Linking

Unlocking the Secrets of the Past: Text Mining for Historical Documents (WS 2008/09)

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Quiz

Who is Michael Jackson?

- a) A British beer guru
- b) A pop star
- c) None of these

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Correct: a). And b). And c).

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Correct: a). And b). And c).
Problem: One name, multiple persons

Overview

1 Introduction

2 Methods
- Bagga/Baldwin 1998: Entity-Based Cross-Document Coreferencing Using the Vector Space Model
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3 Conclusion

Definition Named Entity Disambiguation / Linking

Definition

Named Entity Disambiguation is the task of exploring which real person (e.g. pop star, beer guru), place, event.. is referred to by a certain instance of a name (e.g. Michael Jackson in a certain context).
Named Entity Linking means to connect all references to the correct entity.

What is it good for?

- Basically for all tasks related to Text Mining (Text Summarization, Question Answering..)
- In the historical domain: For example extracting biographical information about one person from a couple of sources
- Named Entity Disambiguation especially necessary when there is more than one source.

Basic Terminology

Michael Jackson released a new album

Michael Jackson (1942-2007) was a beer lover

Basic Terminology

Michael Jackson released a new album

Reference

Michael Jackson (1942-2007) was a beer lover

Reference

?

?

Referent / Entity

Basic Terminology

Instance

Michael Jackson released a new album

Reference

Instance

Michael Jackson (1942-2007) was a beer lover

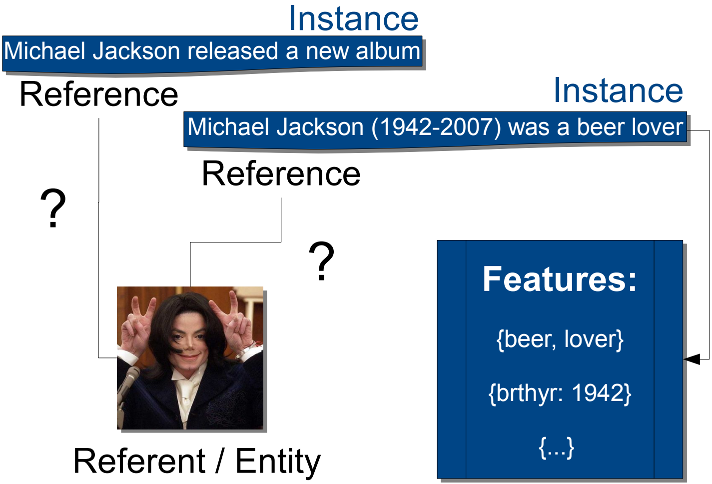
Reference

?

?

Referent / Entity

Basic Terminology



Basic Approach

Given: A set of references together with context (usually the sentence in which they occur. e.g.: „Michael Jackson, the famous British beer guru, ...“, „M.J. has finished a new album..“)

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2. Calculate similarity between two references
3. Create clusters of references that belong to one entity

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Motivation + Source data

- Purpose: **Multi-Document Summarization**: Automatically create a summary of two or more documents
- 173 articles from NYT
- 11 different „John Smiths“ mentioned
- For a single document, create a list of terms that refer to a certain person (e.g. „John Smith“, „he“..) = summary

Example: Two documents

Looking for „John Perry“

Document 1

John Perry, of Weston Golf Club, announced his resignation yesterday. **He** was the President of the Massachusetts Golf Association. During **his** two years in office, **Perry** guided the MGA into a closer relationship with the Women's Golf Association of Massachusetts.

Document 2

Oliver „Biff“ Kelly of Weymouth succeeds **John Perry** as president of the Massachusetts Golf Association. „We will have continued growth in the future,“ said Kelly, who will serve for two years. „There's been a lot of changes and there will be continued changes as we head into the year 2000.“

Example: Extracted Summary

Looking for „John Perry“

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Oliver „Biff“ Kelly of Weymouth succeeds **John Perry** as president of the Massachusetts Golf Association.

Features

- Idea: Assign every word in summaries a weight
- If word occurs often in current summary: Increase weight
- If word occurs seldom in other documents: Increase weight (since it seems to be a specific cue for this summary)
- Example: „president“ => 0.6, „Masachusetts Golf Association“ => 0.8
- Measure called „Term Frequency / Inverse Document Frequency“ (TF/IDF)

Similarity measure

Two summaries are similar if:

- They share many words
- Shared words have a high weight
- Example: „president“ and „Masachusetts Golf Association“ are terms that occur in both summaries
  Their weights are combined (by using „Cosine Distance“) and result in a single output value
  The higher this value, the more similar the summaries are

Finally: Clustering

Calculate the similarity of any two summaries
If value is above a certain threshold => Assume they are referring to the same entity

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Source Data

Sentences extracted from web, containing references. For example:

- „Early in his career, Jim Clark was involved in one of the worst accidents in the history of Formula 1 racing“
- „There’s quite an important debate raging on the Cypherpunks list these days over Netscape CEO Jim Clark [...]“

Convert these extracts to a bundle of features!

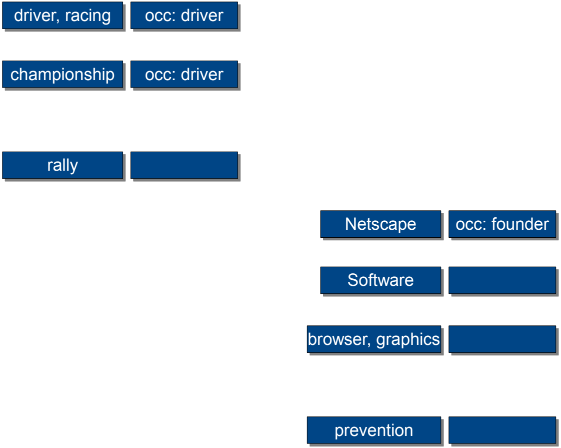
Features

1. Default: A list of words / nouns in the context (ex: „career“, „accident“)
2. Plus: Apply term weights (as seen before) and use only most relevant words (e.g. „accident“)
3. Biographical features: birthdate, occupation..
4. Use these to give higher weight to terms looking like biographical features (e.g. „CEO“ for occupation)

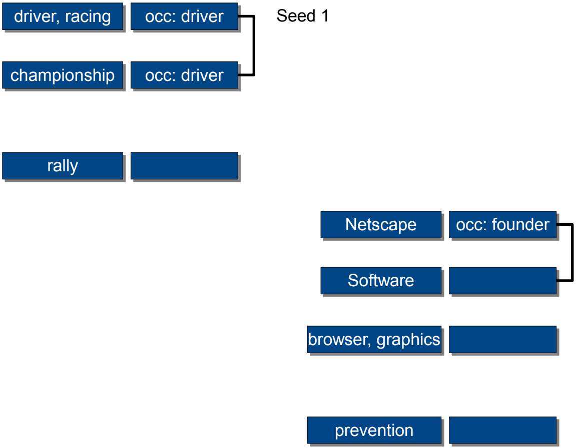
Similarity + Clustering

- Idea: Instances with identical biographical features share probably one referent
  Merge them first
- Next, apply the similarity measure seen before to form bigger clusters
- In later stages of clustering: Few „outlaw“ single instances left, would be merged with random bigger clusters
- „Cluster Refactoring“: After the first few clustering steps, save the clusters formed that far (high quality / accuracy) as „seeds“
- Later on: Assign all remaining instances to the most similar seed

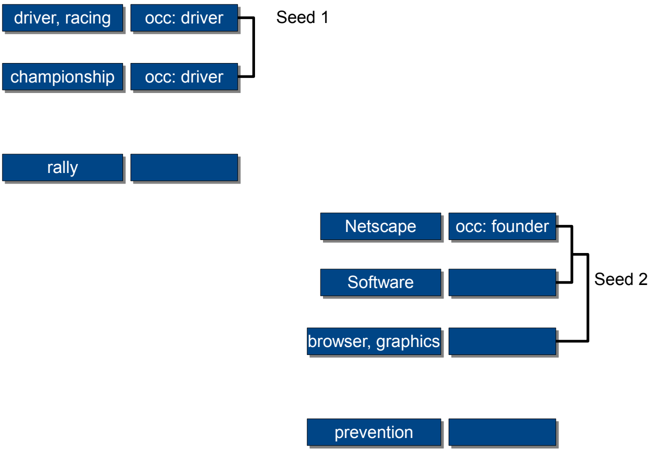
Example: Clustering for name „Jim Clark“



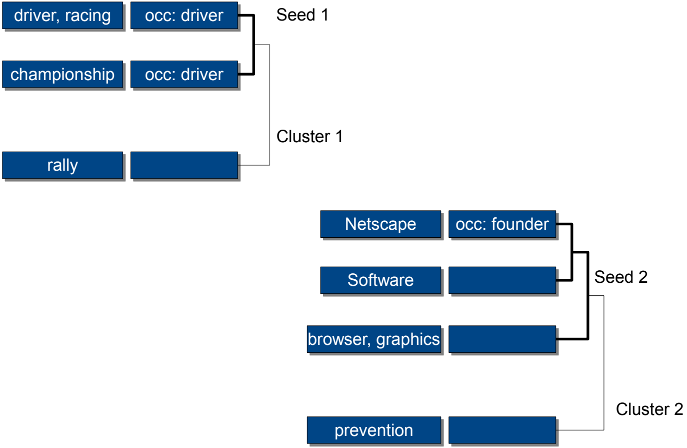
Example: Clustering for name „Jim Clark“



Example: Clustering for name „Jim Clark“



Example: Clustering for name „Jim Clark“



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Fleischman/Hovy: Source data

- Set of 2 million pairs: <Concept [e.g. „beer expert“], Name [e.g. „Michael Jackson“]>
- Originally extracted from a newspaper corpus
- 2675 pairs selected, each one randomly connected to another pair with same name but different concept (e.g. <„beer expert“, „Michael Jackson“> connected to <“King of Pop“, „Michael Jackson“>)

Features

- Name features: commonality, fame
- Overlap (of sentential context): Ratio of words shared between two contexts
- Semantic features: Different semantic measures to grasp the semantic similarity of both concepts (e.g. have „King of Pop“ and „beer guru“ a similar meaning?)
- Statistics features: Several probabilites (likelihood that two instances share the same referent given their concepts, etc.)
- Web features: Web search hits for several queries (e.g. “Michael Jackson +beer expert“)

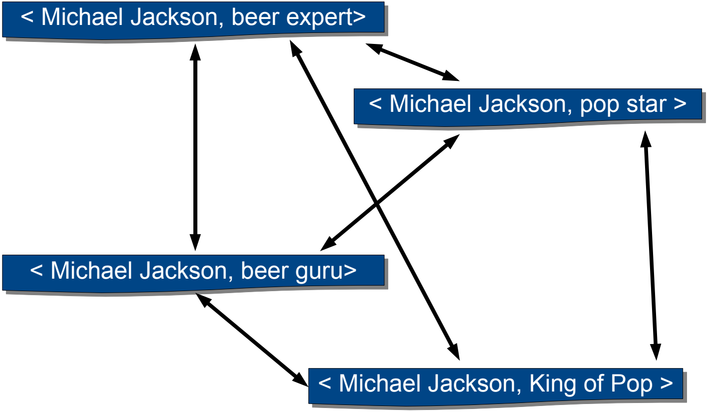
Similarity measure

- A statistical model (Maximum Entropy) is used
- Training process: model should arrange weight of features such that evidence can be explained
- Usage: Feed with created instance pairs, get a probability that both references point to same person

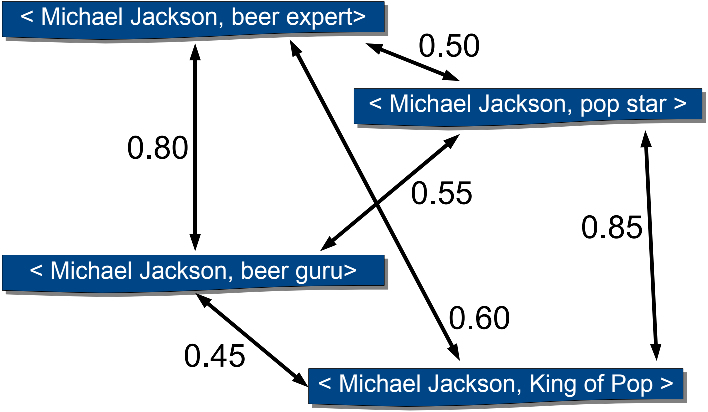
Clustering

- Imagine: Each instance is connected to each other by edges specifying their similarity
- As long as maximum similarity above a threshold (e.g. 70%): Merge two instances with max. similarity into one
- Result: one or more clusters with max. inter-cluster similarity less than threshold

Example: Clustering for name „Michael Jackson“

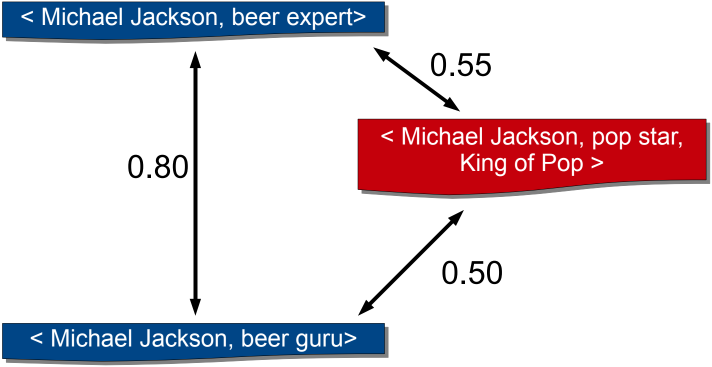


Example: Clustering for name „Michael Jackson“



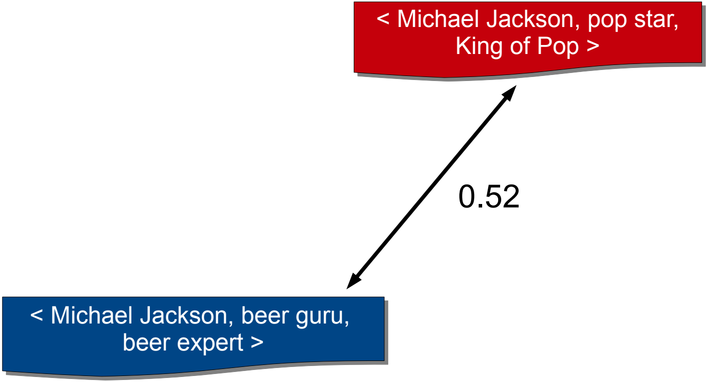
0.85 > 0.7: CLUSTER

Example: Clustering for name „Michael Jackson“



0.80 > 0.7: CLUSTER

Example: Clustering for name „Michael Jackson“



0.52 < 0.7: STOP

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Comparison between methods is hard. Differences in:

- ... used data (newspaper articles, hand-annotated and preprocessed data set, web pages...)
- ... evaluation methods („Pseudonames", match against hand-annotated „gold standard"..)
- ... evaluation measures (General „Accuracy", F-Measure, example clusterings..)

Conclusion, cont.

Several features have been proven useful:

- Biographical features
- Statistics features
- Web search hits (e.g. Google page count)
- Term weight
- etc. pp.

Text mining in historical domain: Biographical features of special importance?

References

- Amit Bagga; Breck Baldwin. Entity-Based Cross-Document Coreferencing Using the Vector Space Model. ACL-COLING-1998. 1998
- Gideon Mann; David Yarowsky. Unsupervised Personal Name Disambiguation. CoNLL-03. 2003
- Michael Fleischman; Eduard Hovy. Multi-Document Person Name Resolution. Proceedings of the ACL-2004 Workshop on Reference Resolution and Its Applications. 2004

The End

Thanks for your attention!