Information Extraction

MPRI 2.26.2: Web Data Management

Antoine Amarilli Friday, January 11th



Idea of Information Extraction (IE)

• Going from unstructured text... Elvis Presley

Elvis Aaron Presley^[a] (January 8, 1935 – August 16, 1977) was an American singer and actor. Regarded as one of the most significant cultural icons of the 20th century, he is often referred to as the "**King of Rock and Roll**" or simply "**the King**".

... to structured data



Detour: Natural Language Processing (NLP)

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 Word-sense disambiguation (WSD): choose the right meaning: bass/1: a type of fish bass/2: a music instrument • Part-of-speech (POS) tagging: annotate each word with its grammatical nature

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- Word-sense disambiguation (WSD): choose the right meaning: bass/1: a type of fish bass/2: a music instrument
- Coreference resolution:

Trump told Macron that \rd{he} was not a spying t

Detour: Natural Language Processing (NLP), cont'd



• **Parsing:** figuring out the **structure** of the sentence:

Detour: Natural Language Processing (NLP), cont'd

- NP-SBJ VP ADJP NP MD VP NNP NNP NP VB NP PP-CLR NP-TMP Pierre Vinken CD NNS old ioin DT NN IŇ NP NNP CD 61 vears the board 34 DT ĴĴ NN Nov. 29 nonexecutive director
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- Preprocessing, e.g.:
 - Stop-word removal: "the", "is", "at"
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- Preprocessing, e.g.:
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 - Stemming: "suffixed" \rightarrow "suffix"
- \rightarrow All these tasks are **related** to information extraction
- ightarrow But we will often try to do IE without solving these problems

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- Possibly classify names in a simple **type hierarchy**: person, address, date, organization, etc.
- Difficulties:
 - Nested entities: "Bank of America", "Carnegie Hall"
 - Boundaries: "All England Lawn Tennis and Croquet Club"

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- Implemented, e.g., in Spacy, NLTK, OpenNLP, or Stanford NER http://nlp.stanford.edu:8080/ner/process

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- To avoid **overfitting**, evaluate the system on a **validation dataset** different from the one on which the system was designed/trained

- Disambiguate which entity is being used
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Entity Disambiguation

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- Several **signals**:
 - Prior:
 - How well-known the entity is
 - How well the name **fits** the entity
 - \rightarrow She went to Paris.
 - Similarity between the **context** of the word in the text and that of the entity in the knowledge base
 - Consistency with other disambiguated entities

https://gate.d5.mpi-inf.mpg.de/webaida/

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 - Disambiguation, and semantic drift
- Taxonomy induction: cleaning up the resulting taxonomy

Evample: NELL http://mtr.ml.amu.adu/mtr./hhhparraam/mmad.himd

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- General technique: Wrapper induction (see next slide)









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- Course structure inspired by the class by Fabian Suchanek https: //suchanek.name/work/teaching/inf344-2018/index.html
- Slide 4: https://www.nltk.org/_images/tree.gif