

# 10 – Automatic relation extraction

## IA161 Advanced Techniques of Natural Language Processing

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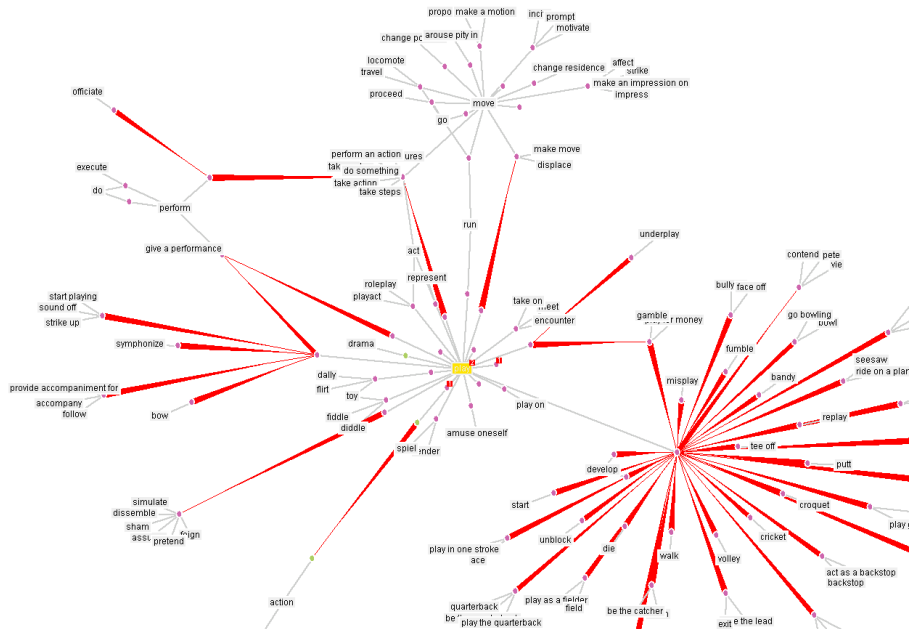
## 1 Introduction

## 2 Extraction

- Pattern-based approach
- Distributional approach
- Neural networks

## 3 Evaluation

# Automatic relation extraction



# Semantic Networks

- network representing *relations between concepts*
- *knowledge graph*
- WordNet – lexical database of English
  - ▶ synsets, main relation hyponymy/hypernymy, meronymy, synonymy, antonymy. . .
  - ▶ Multilingual Wordnet network

## Why would you do that?

- semantic analysis (house → home, music, MD?)
- query expansion (dog → poodle, terrier...)
- lexical substitution (match → game)
- machine translation
- question answering
- domain classification (lemon, apple, banana → fruit)
- summarization
- paraphrase

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## Example

Human illuminates Document

AG[bird:1] VERB sezobnout SUBS[feed:1]

# What do we need?

- morphological tags
- syntactic analysis (phrases)
- dataset (dictionary, corpus, Wikipedia...)

# Pattern recognition

regular expression to match Part-of-Speech and text



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...most *European countries*, especially *France*, *England*, and *Spain*.

European country >France

European country >England

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e.g. {NP,}\* {and |or} NP.

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## Example

e.g. {NP,}\* {and |or} NP.

...e.g. apples, bananas, or pears.

related terms

## Example

NP such as  $\{NP, \}^* \{and \mid or\} NP$

## Example

NP such as {NP, }\* {and |or} NP

common *domestic animals* such as the *ferret* and the *fancy rat*

domestic animal >ferret

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in areas with a long history of *mining* such as *South-west England*

mining >South-west England

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in areas with a long history of *mining* such as *South-west England*

mining >South-west England

in *areas* (with a long history of mining) such as *South-west England*

area >South-west England

- remove stopwords
- detect optional adjunct phrases
- detect named entities



No.	Pattern	Number of occurrences	Number of relevant occurrences	Intermediary precision (%)
1.	other than	168	164	97.6
2.	especially	120	90	75
3.	principally	11	6	54.5
4.	usually	18	14	77.8
5.	such as	2470	1950	78.9
6.	in particular	78	48	61.5
7.	e(.)g(.)	280	216	77.1
8.	become	780	510	66.7
9.	another	92	72	78.3
10.	notably	76	42	55.3
11.	particularly	130	80	61.5
12.	except	13	4	30.8
13.	called	270	220	81.5
14.	like	1600	1300	81.3
15.	including	670	430	64.2

## Corpus query

- special case of pattern recognition, CQL query
- bigger data at hand, less options

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### Example

je/jsou

```
2: [k="k1"&c="c1"] ([lc=","] [k="k1"])*  
([lc="a"|lc="i"|lc="nebo"|lc="či" ] [k="k1"])?  
[lemma_lc="být"&tag="k5eAaImIp3.*"&lc!="ne.*"]  
([k="k1"&c="c[1246]" ] [k="k2"]{0,2})?  
1: [k="k1"&c="c[1246]" ]
```

experiment on domain dictionary: precision 40%, when limited to dictionary terms 52%

# Multilingual translation

using translation equivalents from multilingual dictionary to provide synonyms

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## Example

stůl = table

table = stůl, stolek

stůl = stolek

# Synonym transitivity

- expanding relations based on existing relations (transitive closure)

## Example

city = town, town = municipality

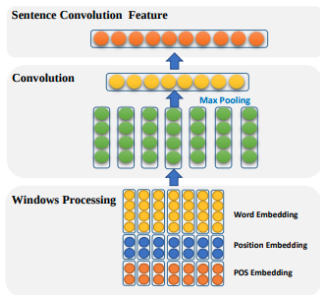
⇒ city = municipality

# Distributional approach

- vector space model
- word-context frequency matrix
- clustering
- similar context  $\neq$  synonym
- e.g. Sketch Engine thesaurus

# Neural networks

- word embeddings
- position embeddings – relative distance between words
- part of speech embeddings – tag PoS for each word
- WordNet information may help
- combine properties to get relations between entities in sentence



Relation	Representation of Word Attention Weight
Instrument-Agency	The <b>author</b> of a keygen uses a <b>disassembler</b> to look at the raw <b>assembly</b> code
Message-Topic	The Pulitzer Committee <b>issues</b> an <b>official citation</b> explaining the <b>reasons</b> for the award
Cause-Effect	The <b>burst</b> has been <b>caused</b> by water <b>hammer pressure</b>
Instrument-Agency	Even <b>commercial networks</b> have <b>moved</b> into high-definition <b>broadcast</b>
Component-Whole	The girl showed a <b>photo of</b> apple tree <b>blossom</b> on a <b>fruit tree</b> in the Central Valley
Member-Collection	They tried an assault of their <b>OWN</b> an hour later, <b>with</b> two columns of sixteen <b>tanks backed</b> by a <b>battalion</b> of Panzer grenadiers



# TOEFL test evaluation

- evaluation by solving TOEFL synonym test
- Choose synonym for *fabricate*.
  - ▶ construct, alter, select, demonstrate
- build synonym set for each word
- detect overlap
- success rate 88 %

- various tasks evaluating computational semantic analysis systems
- human annotators provide *gold standards*
- NLP systems are evaluated
- tasks include Word Sense Disambiguation, Machine Translation, Information Extraction, Learning Semantic Relations. . .

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