# Lecture 12: Figurative language processing

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Literal and figurative language

Statistical modelling of metaphor

Metaphor interpretation

Literal and figurative language

# Lecture 12: Figurative language processing

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### Figurative language

Semantic shift: words do not appear in their default meanings, some semantic incongruity is evident

- Metaphor (Inflation has eaten up all my savings.)
- Metonymy (He played Bach. He bought a Picasso.)
- Irony (November... my favourite month!)
- Humor (Exaggeration is a billion times worse than understatement!)

Interpretation of figurative language and humor is very challenging for NLP.

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Statistical modelling of metaphor

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Statistical modelling of metaphor

### What is metaphor?



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#### What is metaphor?

"A political machine"

"The wheels of the regime were well oiled and already turning"

"Time to mend our foreign policy"

*"20 Steps towards a Modern, Working Democracy"* 



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# How does it work?

Conceptual Metaphor Theory (Lakoff and Johnson, 1980. *Metaphors we live by*.)



Metaphorical associations between concepts <u>POLITICALSYSTEM</u> is a <u>MECHANISM</u> target source

#### Cross-domain knowledge projection and inference

Reasoning about the target domain in terms of the properties of the source

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# Metaphor influences our decision-making

Thibodeau and Boroditsky, 2011. *Metaphors We Think With: The Role of Metaphor in Reasoning* 

- investigated how metaphor influences decision-making
- subjects read a text containing metaphors of either
  - 1. CRIME IS A VIRUS
  - 2. CRIME IS A BEAST
- then they were asked a set of questions on how to tackle crime in the city
  - 1. preventive measures
  - 2. punishment, restraint



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## Metaphor processing tasks

- Learn metaphorical associations from corpora "POLITICAL SYSTEM is a MECHANISM"
- 2. Identify metaphorical language in text

"mend the policy"

3. Interpret the metaphorical language

"*mend the policy*" means "improve the policy; address the downsides of the policy"

## Example feature vectors (verb-object relations)

N: game	N: politics
1170 play	31 dominate
202 win	30 play
99 miss	28 enter
76 watch	16 discuss
66 lose	13 leave
63 start	12 understand
42 enjoy	8 study
22 finish	6 explain
	5 shape
20 dominate	4 influence
18 quit	4 change
17 host	4 analyse
17 follow	
17 control	2 transform

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NEED TO FIND A WAY TO PARTITION THE SPACE

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### Soft clustering



 Hard clustering: each data point assigned to one cluster only (as in our k-means experiment)

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 Soft clustering: each data point is associated with multiple clusters with a membership probability

# Soft clustering for metaphor identification

Shutova and Sun, 2013. Unsupervised metaphor identification using hierarchical graph factorization clustering



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# Creating the graph

- ALGORITHM: Hierarchical graph factorization clustering (Yu, Yu and Tresp, 2006. Soft clustering on graphs)
- DATASET: 2000 most frequent nouns in the BNC
- FEATURES: subject, direct and indirect object relations; verb lemmas indexed by relation type (extracted from the Gigaword corpus)

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# Hierarchical clustering using graph factorization





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# Hierarchical clustering using graph factorization

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# Hierarchical clustering using graph factorization



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# Hierarchical clustering using graph factorization



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# Hierarchical clustering using graph factorization



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# Identifying metaphorical associations in the graph

- start with the source concept, e.g. "fire"
- output a ranking of potential target concepts

#### SOURCE: fire

TARGET: sense hatred emotion passion enthusiasm sentiment hope interest **feeling** resentment optimism hostility excitement anger TARGET: coup **violence** fight resistance clash rebellion battle drive fighting riot revolt war confrontation volcano row revolution struggle

#### SOURCE: disease

TARGET: fraud outbreak offence connection leak count **crime** violation abuse conspiracy corruption terrorism suicide TARGET: **opponent** critic rival

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## Identifying metaphorical expressions



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## Identifying metaphorical expressions



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#### Metaphorical expressions retrieved

#### FEELING IS FIRE

anger *blazed* (Subj), passion *flared* (Subj), interest *lit* (Subj), *fuel* resentment (Dobj), anger *crackled* (Subj), *light* with hope (lobj) etc.

#### CRIME IS A DISEASE

*cure* crime (Dobj), abuse *transmitted* (Subj), *suffer from* corruption (lobj), *diagnose* abuse (Dobj) etc.

#### Output sentences from the BNC

EG0 275 In the 1930s the words "means test" was a curse, **fuelling the resistance** against it both among the unemployed and some of its administrators.

HL3 1206 [..] he would strive to **accelerate progress** towards the economic integration of the Caribbean.

HXJ 121 [..] it is likely that some **industries will flourish** in certain countries as the **market widens**.

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# Multilingual metaphor processing

- Statistical methods are portable to other languages
- Metaphor identification systems for Russian and Spanish:
  - work!
  - reveal a number of interesting cross-cultural differences

#### Cross-cultural differences identified by the system

Spanish: stronger metaphors for poverty ("*fight* poverty, *eradicate* poverty" -> POVERTY IS AN ENEMY, PAIN etc.)

English: stronger metaphors for immigration (IMMIGRATION IS A DISEASE, FIRE etc.)

Russian: sporting events / competitions associated with WAR

Metaphor interpretation

# Lecture 12: Figurative language processing

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-Metaphor interpretation

## Metaphor interpretation as paraphrasing

Derive literal paraphrases for single-word metaphors

#### Phrases

All of this *stirred* an uncontrollable excitement in her. a carelessly *leaked* report

#### Paraphrases

All of this *provoked* an uncontrollable excitement in her. a carelessly *disclosed* report

Shutova 2010. Automatic metaphor interpretation as a paraphrasing task.

Metaphor interpretation

# Paraphrasing system overview

"carelessly leaked report" -> "carelessly ... report"

- 1. Paraphrase selection model: meaning retention
- 2. WordNet similarity filtering
- 3. Selectional preference model: quantifying literalness

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Metaphor interpretation

# Context-based paraphrase ranking model

#### Example

carelessly *leaked* report  $\rightarrow$  carelessly ( $w_1$ ) ... (*i*) report ( $w_2$ )

$$P(i, w_1, w_2) \approx P(i)P(w_1|i)P(w_2|i) = \frac{f(w_1, i) \cdot f(w_2, i)}{f(i) \cdot \sum_k f(i_k)}$$
$$P(i) = \frac{f(i)}{\sum_k f(i_k)} \qquad P(w_n|i) = \frac{f(w_n, i)}{f(i)}$$

where f(i) is the frequency of the interpretation on its own

 $f(w_n, i)$  - the frequency of the co-occurrence of the interpretation with the context word  $w_n$ .

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Metaphor interpretation

### Shared features in WordNet

- The paraphrasing model overgenerates
- Thus we need to filter out unrelated verbs
- Metaphor is based on similarity
- We define similarity as sharing a common hypernym in WordNet

#### Example

How can I *kill* a process? How can I *terminate* a process? *Kill* and *terminate* share a common hypernym.

Metaphor interpretation

#### Example output

#### Candidate paraphrases

stir excitement:

-14.28	create
-14.84	provoke
-15.53	make
-15.53	elicit
-15.53	arouse
-16.23	stimulate
-16.23	raise
-16.23	excite
-16.23	conjure

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Metaphor interpretation

#### Selectional preference model

Selectional preference strength (Resnik, 1993)

$$S_R(v) = D(P(c|v)||P(c)) = \sum_c P(c|v)\lograc{P(c|v)}{P(c)}$$

Selectional association (Resnik, 1993)

$$A_R(v,c) = rac{1}{S_R(v)} P(c|v) \log rac{P(c|v)}{P(c)}$$

P(c) is the prior probability of the noun class, P(c|v) its posterior probability given the verb; R is the GR

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Metaphor interpretation

#### Paraphrasing system output

#### Initial ranking

stir excitement:

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-15.53	make
-15.53	elicit
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-16.23	stimulate
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#### SP reranking

stir excitement: 0.0696 provoke 0.0245 elicit 0.0194 arouse 0.0061 conjure 0.0028 create 0.0001 stimulate  $\approx 0$ raise  $\approx 0$ make  $\approx 0$ excite

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