Outline of today's lecture

Literal and figurative language

Statistical modelling of metaphor

Multimodal distributional semantics

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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Literal and figurative language

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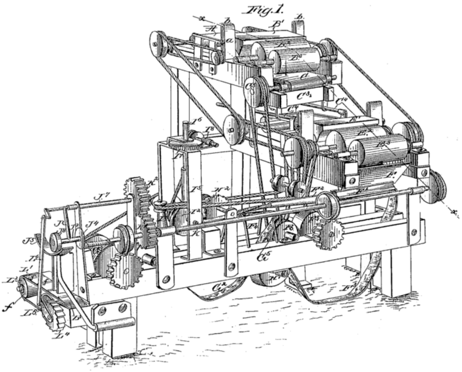
What is metaphor?



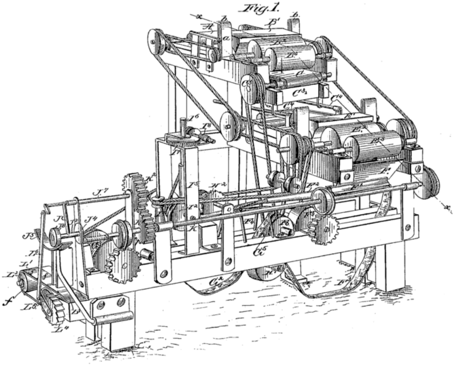
What is metaphor?

"*A political machine*"

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

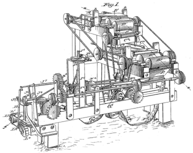
"*Time to mend our foreign policy*"

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



How does it work?

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



Metaphorical associations between concepts

$\underbrace{\textit{POLITICALSYSTEM}}_{\textit{target}}$ is a $\underbrace{\textit{MECHANISM}}_{\textit{source}}$

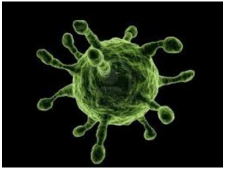
Cross-domain knowledge projection and inference

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

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



Metaphor processing tasks

1. 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

1170 play
202 win
99 miss
76 watch
66 lose
63 start
42 enjoy
22 finish
...
20 dominate
18 quit
17 host
17 follow
17 control
...

N: politics

31 dominate
30 play
28 enter
16 discuss
13 leave
12 understand
8 study
6 explain
5 shape
4 influence
4 change
4 analyse
...
2 transform
...

Example feature vectors (verb–object relations)

N: game	N: politics
1170 **play**	31 **dominate**
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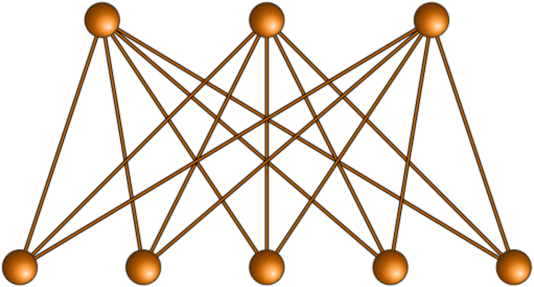
NEED TO FIND A WAY TO PARTITION THE SPACE

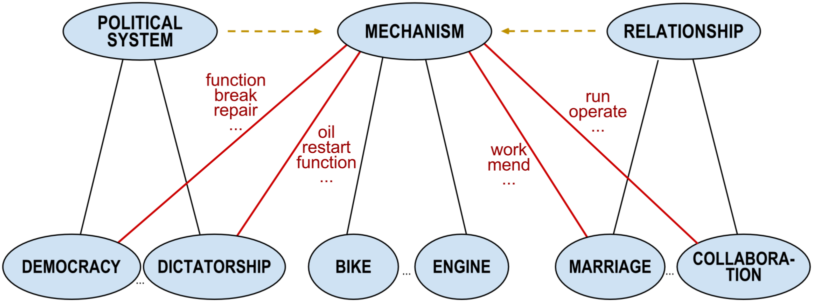
Hierarchical soft clustering



- Hard clustering: each data point assigned to one cluster only (as in our k-means experiment)
- Soft clustering: each data point is associated with multiple clusters with a membership probability

Soft clustering for metaphor identification

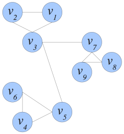
Shutova and Sun, 2013. *Unsupervised metaphor identification using hierarchical graph factorization clustering*



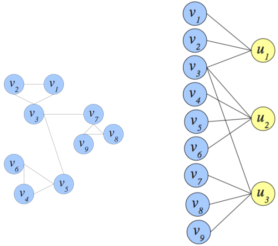
Creating the graph

- 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)
- LEVELS: 10

Hierarchical clustering using graph factorization



Hierarchical clustering using graph factorization



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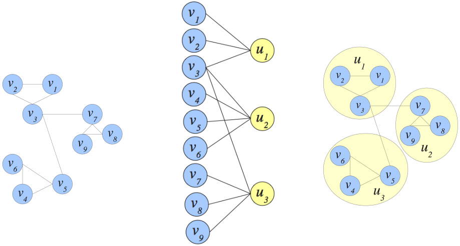

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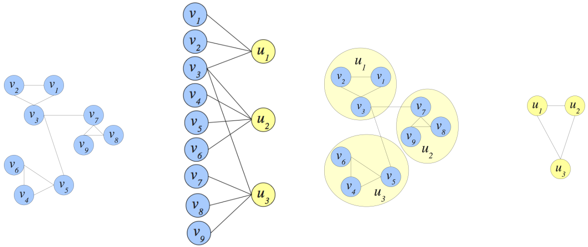

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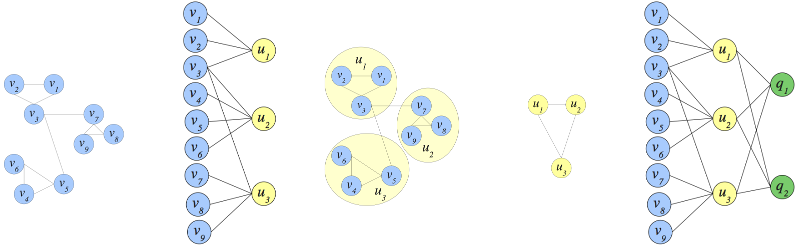


Identifying metaphorical associations in the graph

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

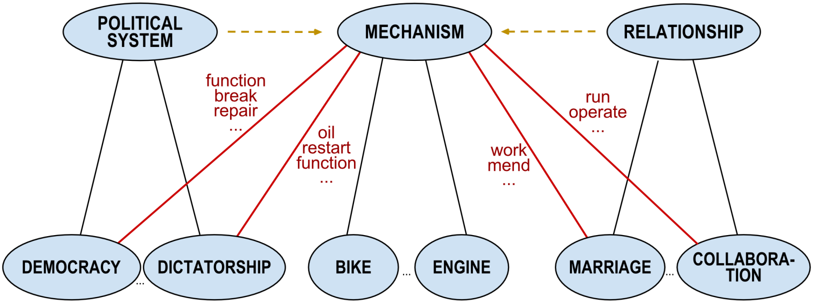
SOURCE: fire

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

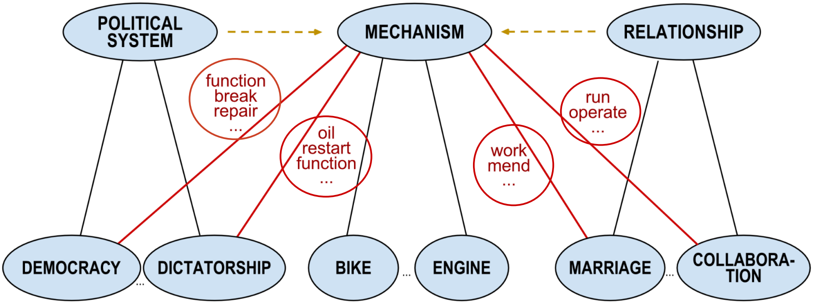
SOURCE: disease

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

Identifying metaphorical expressions



Identifying metaphorical expressions



Metaphorical expressions retrieved

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

CRIME IS A DISEASE
cure crime (Dobj), abuse *transmitted* (Subj), *suffer from* corruption (Iobj), *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**.

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 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*.

Literal and figurative language

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Multimodal distributional semantics

Multimodal semantics

Intuition: Humans learn word meanings from both linguistic and perceptual experience

This includes:

- linguistic input (text or speech)
- visual input (images and videos)
- other sensory modalities: taste, smell, touch etc.
- motor activity and simulation

Multimodal semantics in NLP today mainly focuses on building word representations from text, images and (recently) videos.

Combining linguistic and visual information

Bag-of-visual-words models:

- extract image descriptor features from the images
  - colour histogram
  - SIFT keypoints
- add them to distributional vectors of words

Image caption based models:

- extract word co-occurrences from image captions
- build separate linguistic and visual models
- interpolate the models

Though the line between the two is becoming blurry due to automatic caption generation techniques

Bag-of-visual-words models

Elia Bruni, Nam Khanh Tran and Marco Baroni (2014).
Multimodal distributional semantics.

- Extract images for a given word, e.g. *bike*
- Identify keypoints in the images
- Cluster keypoints to obtain visual words
- Bag of visual words – ignore the location

Combining text and visual words

Relations between words are computed by similarity estimation, e.g. *cosine*

1. Feature level fusion:
   - concatenate textual and visual feature vectors
   - dimensionality reduction (some approaches) – map the features into the same low dimensional space, e.g. using SVD or NMF
   - estimate similarity of the vectors
2. Scoring level fusion:
   - estimate similarity for textual and visual vectors separately
   - take a mean of the similarity scores

Datasets and performance

- Visual datasets:
  - ImageNet
  - ESP-game dataset
  - use Google image search
- Evaluation:
  - typically evaluated in semantic similarity / relatedness tasks, e.g. *cathedral – church, dog – race, boat – fishing*
  - MEN and WordSim datasets
  - beat purely text-based models (word windows)
  - work quite well for noun pairs
  - more difficult to extract visual features for verbs

Using image tags and captions

- Extract word co-occurrence information from image descriptions: natural language tags or captions
  - e.g. Yahoo! Webscope Flickr-100M dataset
  - contains tagged images and videos
  - videos tagged frame by frame
- map the visual features into the same semantic space as the text-based model
- combine linguistic and visual information by model interpolation

A tagged image from Yahoo! Webscope dataset

dog, road, pavement, street, play

Selectional preference acquisition from visual data

Build a joint model of SPs from text, images and videos

- extract verb and noun co-occurrences in image and video descriptions
- extract verb-subject and verb-object relations from text
- estimate $P(c)$ and $P(c|v)$ from visual and textual data separately
- interpolate the two models using linear interpolation techniques

Selectional preferences of ***cut*** (Dobj) from text

0.2845 expenditure cost risk expense emission budget spending
0.1527 dividend price rate premium rent rating salary wages
0.0832 employment investment growth supplies sale import export production consumption traffic input spread supply flow
0.0738 potato apple slice food cake meat bread fruit
0.0407 stitch brick metal bone strip cluster coffin stone piece tile fabric rock layer remains block
0.0379 excess deficit inflation unemployment pollution inequality poverty delay discrimination symptom shortage
0.0366 tree crop flower plant root leaf seed rose wood grain stem forest garden
0.0330 tail collar strand skirt trousers hair curtain sleeve
0.0244 rope hook cable wire thread ring knot belt chain string
...

Selectional preference model

Phillip Resnik, 1997. *Selectional Preference and Sense Disambiguation*

Selectional preference strength

$$S_R(v) = D_{KL}(P(c|v)||P(c)) = \sum_c P(c|v) \log \frac{P(c|v)}{P(c)}$$

D_{KL} is Kullback–Leibler divergence

Selectional association

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

$P(c)$ is the prior probability of the noun class;
$P(c|v)$ its posterior probability given the verb; R is the grammatical relation

Linguistic and visual model interpolation

- Simple linear interpolation

$$p^{\mathrm{LI}}(c) = \lambda_{\mathsf{LM}} p_{\mathsf{LM}}(c) + \lambda_{\mathsf{VM}} p_{\mathsf{VM}}(c)$$

$$p^{\mathrm{LI}}(c|v) = \lambda_{\mathsf{LM}} p_{\mathsf{LM}}(c|v) + \lambda_{\mathsf{VM}} p_{\mathsf{VM}}(c|v)$$

- Predicate-driven linear interpolation derives predicate-specific interpolation weights from the data

$$\lambda_{\mathsf{LM}}(v) = \frac{\mathrm{rel}_{\mathsf{LM}}(v)}{\mathrm{rel}_{\mathsf{LM}}(v) + \mathrm{rel}_{\mathsf{VM}}(v)}, \quad \lambda_{\mathsf{VM}}(v) = \frac{\mathrm{rel}_{\mathsf{VM}}(v)}{\mathrm{rel}_{\mathsf{LM}}(v) + \mathrm{rel}_{\mathsf{VM}}(v)}$$

  where *rel* is the relevance function of model i for verb v: $\mathrm{rel}_i(v) = \frac{f_i(v)}{\sum_V f_i(v)}$.

SP acquisition from visual data: Example

Top three direct object classes for *cut* and their association scores, assigned by different models

LSP:
(1) 0.284 expenditure cost risk expense emission budget spending;
(2) 0.152 dividend price rate premium rent rating salary wages;
(3) 0.083 employment investment growth supplies sale import export production [..]

ISP predicate-driven $\lambda_{\mathrm{LM}} = 0.65$
(1) 0.346 expenditure cost risk expense emission budget spending;
(2) 0.211 dividend price rate premium rent rating salary wages;
(3) 0.126 tail collar strand skirt trousers hair curtain sleeve

---

VSP:
(1) 0.224 tail collar strand skirt trousers hair curtain sleeve;
(2) 0.098 expenditure cost risk expense emission budget spending;
(3) 0.090 management delivery maintenance transport service housing

How is visual data different from linguistic data?

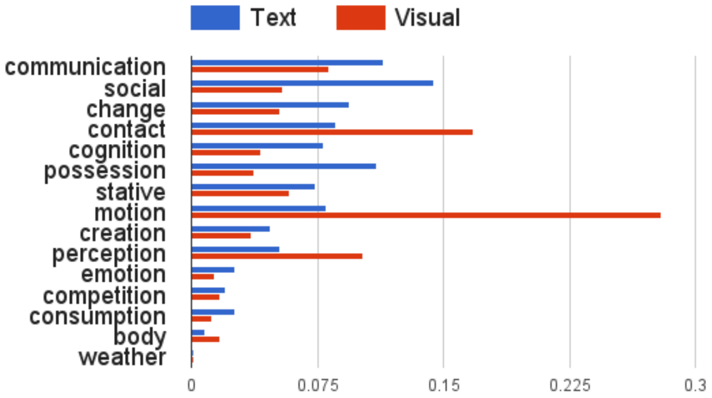
Clusters obtained using linguistic features:

desire hostility anxiety passion doubt fear curiosity enthusiasm impulse instinct emotion feeling suspicion
official officer inspector journalist detective constable police policeman reporter
book statement account draft guide advertisement document report article letter

Clusters obtained using visual features:

pilot aircraft plane airline landing flight wing arrival departure airport
concert festival music guitar alternative band instrument audience event performance rock benjamin
cost benefit crisis debt credit customer consumer

How is visual data different from linguistic data?



Biases in the data

- Textual corpora: abstract events and topics
- Image corpora: concrete events / actions, also topic bias
- Videos: extended actions, states