Natural Language Processing 1

Lecture 5: Distributional semantics

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Distributional hypothesis

You shall know a word by the company it keeps (Firth)

The meaning of a word is defined by the way it is used (Wittgenstein).

it was authentic scrumpy, rather sharp and very strong

we could taste a famous local product — scrumpy

spending hours in the pub drinking scrumpy

Cornish Scrumpy Medium Dry. £19.28 - Case

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Scrumpy


WESTONS
CIDERS INSPIRED BY TRADITION
SCRUMPY
CLOUDY CIDER
Alc 7.5% Vol

Distributional hypothesis

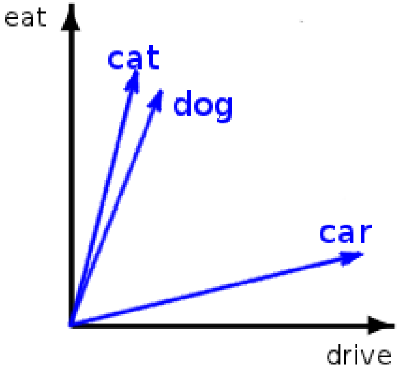
This leads to the distributional hypothesis about word meaning:

- the context surrounding a given word provides information about its meaning;
- words are similar if they share similar linguistic contexts;
- semantic similarity $\approx$ distributional similarity.

The general intuition

- **Distributions** are vectors in a multidimensional semantic space.
- The **semantic space** has dimensions which correspond to possible contexts – features.
- For our purposes, a distribution can be seen as a point in that space (the vector being defined with respect to the origin of that space).
- *scrumpy* [...pub 0.8, drink 0.7, strong 0.4, joke 0.2, mansion 0.02, zebra 0.1...]

Vectors



Feature matrix

	feature$_1$	feature$_2$	...	feature$_n$
word$_1$	$f_{1,1}$	$f_{2,1}$		$f_{n,1}$
word$_2$	$f_{1,2}$	$f_{2,2}$		$f_{n,2}$
...				
word$_m$	$f_{1,m}$	$f_{2,m}$		$f_{n,m}$

The notion of context

1 Word windows (unfiltered): *n* words on either side of the lexical item.
Example: n=2 (5 words window):

> | *The prime **minister** acknowledged the* |
> *question.*

minister [the 2, prime 1, acknowledged 1, question 0]

Context

2 Word windows (filtered): *n* words on either side removing some words (e.g. function words, some very frequent content words). Stop-list or by POS-tag.
Example: n=2 (5 words window), stop-list:

> | *The prime* ***minister*** *acknowledged the* |
> *question.*

minister [prime 1, acknowledged 1, question 0]

Context

3 Lexeme window (filtered or unfiltered); as above but using stems.
Example: n=2 (5 words window), stop-list:

> *| The prime* ***minister*** *acknowledged the | question.*

minister [prime 1, acknowledge 1, question 0]

Context

4 Dependencies (directed links between heads and dependents). Context for a lexical item is the dependency structure it belongs to (various definitions).
Example:

*The prime **minister** acknowledged the question.*

minister [prime_a 1, acknowledge_v 1]

minister [prime_a_mod 1, acknowledge_v_subj 1]

minister [prime_a 1, acknowledge_v+question_n 1]

Parsed vs unparsed data: examples

word (unparsed)	word (parsed)
meaning_n	or_c+phrase_n
derive_v	and_c+phrase_n
dictionary_n	syllable_n+of_p
pronounce_v	play_n+on_p
phrase_n	etymology_n+of_p
latin_j	portmanteau_n+of_p
ipa_n	and_c+deed_n
verb_n	meaning_n+of_p
mean_v	from_p+language_n
hebrew_n	pron_rel_+utter_v
usage_n	for_p+word_n
literally_r	in_p+sentence_n

Dependency vectors

word (Subj)	**word (Dobj)**
come_v	use_v
mean_v	say_v
go_v	hear_v
speak_v	take_v
make_v	speak_v
say_v	find_v
seem_v	get_v
follow_v	remember_v
give_v	read_v
describe_v	write_v
get_v	utter_v
appear_v	know_v
begin_v	understand_v
sound_v	believe_v
occur_v	choose_v

Context weighting

- Binary model: if context c co-occurs with word w, value of vector $\vec{w}$ for dimension c is 1, 0 otherwise.

  ... [a long long long ***example*** *for a distributional semantics] model... (n=4)*

  ... {a 1} {dog 0} {long 1} {sell 0} {semantics 1}...
- Basic frequency model: the value of vector $\vec{w}$ for dimension c is the number of times that c co-occurs with w.

  ... [a long long long ***example*** *for a distributional semantics] model... (n=4)*

  ... {a 2} {dog 0} {long 3} {sell 0} {semantics 1}...

Characteristic model

- Weights given to the vector components express how *characteristic* a given context is for word w.
- Pointwise Mutual Information (PMI)

$$PMI(w,c) = \log \frac{P(w,c)}{P(w)P(c)} = \log \frac{P(w)P(c|w)}{P(w)P(c)} = \log \frac{P(c|w)}{P(c)}$$

$$P(c) = \frac{f(c)}{\sum_k f(c_k)}, \qquad P(c|w) = \frac{f(w,c)}{f(w)},$$

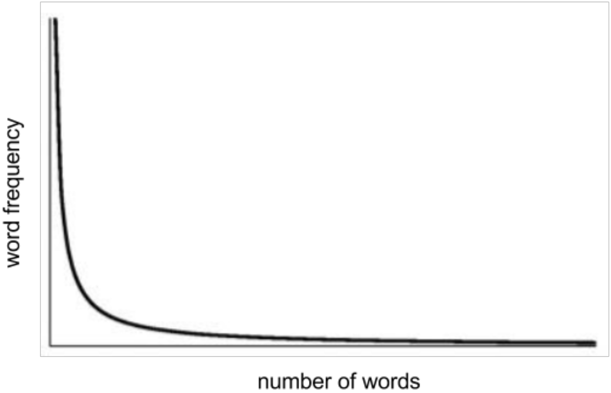
$$PMI(w,c) = \log \frac{f(w,c)\sum_k f(c_k)}{f(w)f(c)}$$

$f(w,c)$: frequency of word w in context c
$f(w)$: frequency of word w in all contexts
$f(c)$: frequency of context c

What semantic space?

- Entire vocabulary.
  - + All information included – even rare contexts
  - - Inefficient (100,000s dimensions). Noisy (e.g. *002.png|thumb|right|200px|graph_n*). Sparse
- Top *n* words with highest frequencies.
  - + More efficient (2000-10000 dimensions). Only ‘real’ words included.
  - - May miss out on infrequent but relevant contexts.

Word frequency: Zipfian distribution



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  - - Inefficient (100,000s dimensions). Noisy (e.g. *002.png|thumb|right|200px|graph_n*). Sparse.
- Top *n* words with highest frequencies.
  - + More efficient (2000-10000 dimensions). Only ‘real’ words included.
  - - May miss out on infrequent but relevant contexts.

What semantic space?

- Singular Value Decomposition (SVD): the number of dimensions is reduced by exploiting redundancies in the data.
  - + Very efficient (200-500 dimensions). Captures generalisations in the data.
  - - SVD matrices are not interpretable.
- Non-negative matrix factorization (NMF)
  - Similar to SVD in spirit, but performs factorization differently

Our reference text

Douglas Adams, *Mostly harmless*

The major difference between a thing that might go wrong and a thing that cannot possibly go wrong is that when a thing that cannot possibly go wrong goes wrong it usually turns out to be impossible to get at or repair.

- **Example:** Produce distributions using a word window, PMI-based model

The semantic space

Douglas Adams, *Mostly harmless*

The major difference between a thing that might go wrong and a thing that cannot possibly go wrong is that when a thing that cannot possibly go wrong goes wrong it usually turns out to be impossible to get at or repair.

- Assume only keep open-class words.
- **Dimensions:**

difference	impossible	thing
get	major	turns
go	possibly	usually
goes	repair	wrong

Frequency counts...

Douglas Adams, *Mostly harmless*

The major difference between a thing that might go wrong and a thing that cannot possibly go wrong is that when a thing that cannot possibly go wrong goes wrong it usually turns out to be impossible to get at or repair.

- **Counts:**

difference 1	impossible 1	thing 3
get 1	major 1	turns 1
go 3	possibly 2	usually 1
goes 1	repair 1	wrong 4

Conversion into 5-word windows...

Douglas Adams, *Mostly harmless*

The major difference between a thing that might go wrong and a thing that cannot possibly go wrong is that when a thing that cannot possibly go wrong goes wrong it usually turns out to be impossible to get at or repair.

- ∅ ∅ **the** major difference
- ∅ the **major** difference between
- the major **difference** between a
- major difference **between** a thing
- ...

Distribution for *wrong*

Douglas Adams, *Mostly harmless*

The major difference between a thing that [might go wrong and a] thing that cannot [possibly go wrong is that] when a thing that cannot [possibly go [wrong goes wrong] it usually] turns out to be impossible to get at or repair.

- **Distribution (frequencies):**

difference 0	impossible 0	thing 0
get 0	major 0	turns 0
go 3	possibly 2	usually 1
goes 2	repair 0	wrong 2

Distribution for *wrong*

Douglas Adams, *Mostly harmless*

The major difference between a thing that [might go wrong and a] thing that cannot [possibly go wrong is that] when a thing that cannot [possibly go [wrong goes wrong] it usually] turns out to be impossible to get at or repair.

- **Distribution (PPMIs):**

difference 0	impossible 0	thing 0
get 0	major 0	turns 0
go 0.70	possibly 0.70	usually 0.70
goes 1	repair 0	wrong 0.40

Experimental corpus

- Dump of entire **English Wikipedia**, parsed with the English Resource Grammar producing dependencies.
- Dependencies include:
  - **For nouns**: head verbs (+ any other argument of the verb), modifying adjectives, head prepositions (+ any other argument of the preposition).
    cat: *chase_v+mouse_n, black_a, of_p+neighbour_n*
  - **For verbs**: arguments (NPs and PPs), adverbial modifiers.
    eat: *cat_n+mouse_n, in_p+kitchen_n, fast_a*
  - **For adjectives**: modified nouns; head prepositions (+ any other argument of the preposition)
    angry: *cat_n, at_p+dog_n*

System description

- Semantic space: top 100,000 contexts.
- Weighting: pointwise mutual information (PMI).

An example noun

- *language*:

0.54::other+than_p+English_n
0.53::English_n+as_p
0.52::English_n+be_v
0.49::english_a
0.48::and_c+literature_n
0.48::people_n+speak_v
0.47::French_n+be_v
0.46::Spanish_n+be_v
0.46::and_c+dialects_n
0.45::grammar_n+of_p
0.45::foreign_a
0.45::germanic_a
0.44::German_n+be_v

0.44::of_p+instruction_n
0.44::speaker_n+of_p
0.42::pron_rel_+speak_v
0.42::colon_v+English_n
0.42::be_v+English_n
0.42::language_n+be_v
0.42::and_c+culture_n
0.41::arabic_a
0.41::dialects_n+of_p
0.40::percent_n+speak_v
0.39::spanish_a
0.39::welsh_a
0.39::tonal_a

An example adjective

- *academic*:

0.52::Decathlon_n
0.51::excellence_n
0.45::dishonesty_n
0.45::rigor_n
0.43::achievement_n
0.42::discipline_n
0.40::vice_president_n+for_p
0.39::institution_n
0.39::credentials_n
0.38::journal_n
0.37::journal_n+be_v
0.37::vocational_a
0.37::student_n+achieve_v
0.36::athletic_a
0.36::reputation_n+for_p
0.35::regalia_n
0.35::program_n
0.35::freedom_n
0.35::student_n+with_p
0.35::curriculum_n
0.34::standard_n
0.34::at_p+institution_n
0.34::career_n
0.34::Career_n
0.33::dress_n
0.33::scholarship_n
0.33::prepare_v+student_n
0.33::qualification_n

Corpus choice

- As much data as possible?
  - British National Corpus (BNC): 100 m words
  - Wikipedia: 897 m words
  - UKWac: 2 bn words
  - ...
- In general preferable, *but*:
  - More data is not necessarily the data you want.
  - More data is not necessarily realistic from a psycholinguistic point of view. We perhaps encounter 50,000 words a day. BNC = 5 years' text exposure.

Data sparsity

- Distribution for *unicycle*, as obtained from Wikipedia.

0.45::motorized_a
0.40::pron_rel_+ride_v
0.24::for_p+entertainment_n
0.24::half_n+be_v
0.24::unwieldy_a
0.23::earn_v+point_n
0.22::pron_rel_+crash_v
0.19::man_n+on_p
0.19::on_p+stage_n
0.19::position_n+on_p
0.17::slip_v
0.16::and_c+1_n
0.16::autonomous_a
0.16::balance_v
0.13::tall_a
0.12::fast_a
0.11::red_a
0.07::come_v
0.06::high_a

Polysemy

- Distribution for *pot*, as obtained from Wikipedia.

0.57::melt_v
0.44::pron_rel_+smoke_v
0.43::of_p+gold_n
0.41::porous_a
0.40::of_p+tea_n
0.39::player_n+win_v
0.39::money_n+in_p
0.38::of_p+coffee_n
0.33::amount_n+in_p
0.33::ceramic_a
0.33::hot_a

0.32::boil_v
0.31::bowl_n+and_c
0.31::ingredient_n+in_p
0.30::plant_n+in_p
0.30::simmer_v
0.29::pot_n+and_c
0.28::bottom_n+of_p
0.28::of_p+flower_n
0.28::of_p+water_n
0.28::food_n+in_p

Polysemy

- Some researchers incorporate word sense disambiguation techniques.
- But most assume a single space for each word: can perhaps think of subspaces corresponding to senses.
- Graded rather than absolute notion of polysemy.

Idiomatic expressions

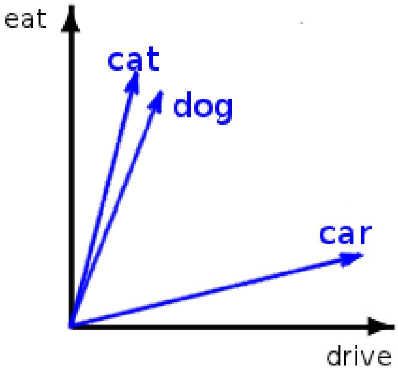
- Distribution for *time*, as obtained from Wikipedia.

0.46::of_p+death_n
0.45::same_a
0.45::1_n+at_p(temp)
0.45::Nick_n+of_p
0.42::spare_a
0.42::playoffs_n+for_p
0.42::of_p+retirement_n
0.41::of_p+release_n
0.40::pron_rel_+spend_v
0.39::sand_n+of_p
0.39::pron_rel_+waste_v

0.38::place_n+around_p
0.38::of_p+arrival_n
0.38::of_p+completion_n
0.37::after_p+time_n
0.37::of_p+arrest_n
0.37::country_n+at_p
0.37::age_n+at_p
0.37::space_n+and_c
0.37::in_p+career_n
0.37::world_n+at_p

Calculating similarity in a distributional space

- Distributions are vectors, so distance can be calculated.



Measuring similarity

- Cosine:

$$cos(\theta) = \frac{\sum v1_k * v2_k}{\sqrt{\sum v1_k^2} * \sqrt{\sum v2_k^2}} \quad (1)$$

- The cosine measure calculates the angle between two vectors and is therefore length-independent. This is important, as frequent words have longer vectors than less frequent ones.
- Other measures include Jaccard, Euclidean distance etc.

The scale of similarity: some examples

house – building 0.43
gem – jewel 0.31
capitalism – communism 0.29
motorcycle – bike 0.29
test – exam 0.27
school – student 0.25
singer – academic 0.17
horse – farm 0.13
man –accident 0.09
tree – auction 0.02
cat –county 0.007

Words most similar to *cat*

as chosen from the 5000 most frequent nouns in Wikipedia.

1 cat	0.29 human	0.25 woman	0.22 monster
0.45 dog	0.29 goat	0.25 fish	0.22 people
0.36 animal	0.28 snake	0.24 squirrel	0.22 tiger
0.34 rat	0.28 bear	0.24 dragon	0.22 mammal
0.33 rabbit	0.28 man	0.24 frog	0.21 bat
0.33 pig	0.28 cow	0.23 baby	0.21 duck
0.31 monkey	0.26 fox	0.23 child	0.21 cattle
0.31 bird	0.26 girl	0.23 lion	0.21 dinosaur
0.30 horse	0.26 sheep	0.23 person	0.21 character
0.29 mouse	0.26 boy	0.23 pet	0.21 kid
0.29 wolf	0.26 elephant	0.23 lizard	0.21 turtle
0.29 creature	0.25 deer	0.23 chicken	0.20 robot

But what is similarity?

- In distributional semantics, very broad notion: synonyms, near-synonyms, hyponyms, taxonomical siblings, antonyms, etc.
- Correlates with a psychological reality.
- Test via correlation with human judgments on a test set:
    - Miller & Charles (1991)
    - WordSim
    - MEN
    - SimLex

Miller & Charles 1991

3.92 automobile-car	3.05 bird-cock	0.84 forest-graveyard
3.84 journey-voyage	2.97 bird-crane	0.55 monk-slave
3.84 gem-jewel	2.95 implement-tool	0.42 lad-wizard
3.76 boy-lad	2.82 brother-monk	0.42 coast-forest
3.7 coast-shore	1.68 crane-implement	0.13 cord-smile
3.61 asylum-madhouse	1.66 brother-lad	0.11 glass-magician
3.5 magician-wizard	1.16 car-journey	0.08 rooster-voyage
3.42 midday-noon	1.1 monk-oracle	0.08 noon-string
3.11 furnace-stove	0.89 food-rooster	
3.08 food-fruit	0.87 coast-hill	

- Distributional systems, reported correlations 0.8 or more.

TOEFL synonym test

Test of English as a Foreign Language: task is to find the best match to a word:

Prompt:		levied
Choices:	(a)	imposed
	(b)	believed
	(c)	requested
	(d)	correlated
Solution:	(a)	imposed

- Non-native English speakers applying to college in US reported to average 65%
- Best corpus-based results are 100%

Distributional methods are a usage representation

- Distributions are a good conceptual representation if you believe that ‘the meaning of a word is given by its usage’.
- Corpus-dependent, culture-dependent, register-dependent.
  Example: similarity between *policeman* and *cop*: 0.23

Distribution for *policeman*

policeman
0.59::ball_n+poss_rel
0.48::and_c+civilian_n
0.42::soldier_n+and_c
0.41::and_c+soldier_n
0.38::secret_a
0.37::people_n+include_v
0.37::corrupt_a
0.36::uniformed_a
0.35::uniform_n+poss_rel
0.35::civilian_n+and_c
0.31::iraqi_a
0.31::lot_n+poss_rel
0.31::chechen_a
0.30::laugh_v
0.29::and_c+criminal_n
0.28::incompetent_a
0.28::pron_rel_+shoot_v
0.28::hat_n+poss_rel
0.28::terrorist_n+and_c
0.27::and_c+crowd_n
0.27::military_a
0.27::helmet_n+poss_rel
0.27::father_n+be_v
0.26::on_p+duty_n
0.25::salary_n+poss_rel
0.25::on_p+horseback_n
0.25::armed_a
0.24::and_c+nurse_n
0.24::job_n+as_p
0.24::open_v+fire_n

Distribution for *cop*

cop

0.45::crooked_a
0.45::corrupt_a
0.44::maniac_a
0.38::dirty_a
0.37::honest_a
0.36::uniformed_a
0.35::tough_a
0.33::pron_rel_+call_v
0.32::funky_a
0.32::bad_a
0.29::veteran_a
0.29::and_c+robot_n
0.28::and_c+criminal_n
0.28::bogus_a
0.28::talk_v+to_p+pron_rel_
0.27::investigate_v+murder_n
0.26::on_p+force_n
0.25::parody_n+of_p
0.25::Mason_n+and_c
0.25::pron_rel_+kill_v
0.25::racist_a
0.24::addicted_a
0.23::gritty_a
0.23::and_c+interference_n
0.23::arrive_v
0.23::and_c+detective_n
0.22::look_v+way_n
0.22::dead_a
0.22::pron_rel_+stab_v
0.21::pron_rel_+evade_v

The similarity of synonyms

- Similarity between *egglant/aubergine*: 0.11
  Relatively low cosine. Partly due to frequency (222 for *eggplant*, 56 for *aubergine*).
- Similarity between *policeman/cop*: 0.23
- Similarity between *city/town*: 0.73

In general, true synonymy does not correspond to higher similarity scores than near-synonymy.

Similarity of antonyms

- Similarities between:
  - cold/hot 0.29
  - dead/alive 0.24
  - large/small 0.68
  - colonel/general 0.33

Identifying antonyms

- Antonyms have high distributional similarity: hard to distinguish from near-synonyms purely by distributions.
- Identification by heuristics applied to pairs of highly similar distributions.
- For instance, antonyms are frequently coordinated while synonyms are not:
  - a selection of cold and hot drinks
  - wanted dead or alive

Distributions and knowledge

What kind of information do distributions encode?

- lexical knowledge
- world knowledge
- boundary between the two is blurry
- no perceptual knowledge

Distributions are partial lexical semantic representations, but useful and theoretically interesting.

Acknowledgement

Some slides were adapted from Aurelie Herbelot