IN5550: Neural Methods in Natural Language Processing
Sub-lecture 5.1
Distributional and distributed

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Bag-of-words problems

Simple Bag-of-Words approaches (without representation learning) do not take into account semantic relationships between linguistic entities.



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It means we need more sophisticated semantically-aware methods.

Like distributional word embeddings.

Distributional and Distributed



Distant memory from the last lecture

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Distributional and Distributed



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How come that we can get good word embeddings without any manually annotated data?

Distributional and Distributed



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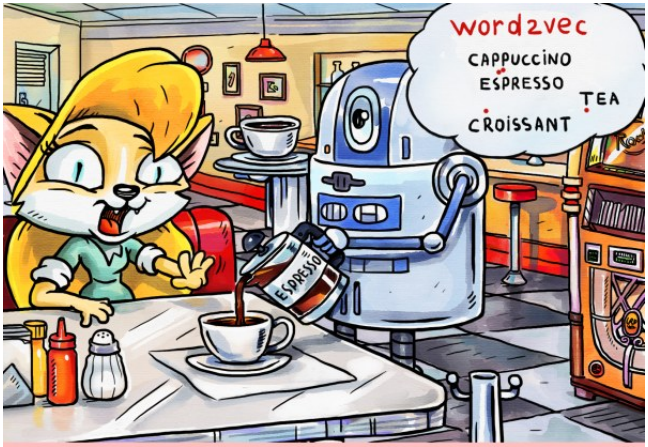
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- Commonly used in research and large-scale industry projects (web search, opinion mining, tracing events, plagiarism detection, document collections management, etc.)
- All this is based on their ability to efficiently predict semantic similarity between linguistic entities (in particular, words).
- Semantic information is distributed across word vectors, making them non-interpretable.

Distributional and Distributed



- Espresso? But I ordered a cappuccino!
- Don't worry, the cosine distance between them is so small that they are almost the same thing.

(by Dmitry Malkov)

Distributional hypothesis



OK, why does it work at all?

Distributional hypothesis



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Tiers of linguistic analysis

Distributional hypothesis



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Tiers of linguistic analysis

Computational linguistics models various tiers of language:

- graphematics – how words are spelled,

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Computational linguistics models various tiers of language:

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- phonetics – how words are pronounced,
- morphology – how words inflect,
- syntax – how words interact in sentences.

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Question

Are these representations discrete or continuous?

Distributional hypothesis

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- ...even though their surface form suggests the opposite.

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- *'Judge'* must be similar to *'court'* but not to *'kludge'*...
- ...even though their surface form suggests the opposite.
- Why so?

Distributional hypothesis



Arbitrariness of a linguistic sign

Distributional hypothesis



Arbitrariness of a linguistic sign

Unlike in road signs, there's no direct link between form and meaning in words [Saussure, 1916]

Distributional hypothesis

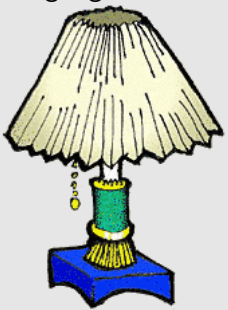
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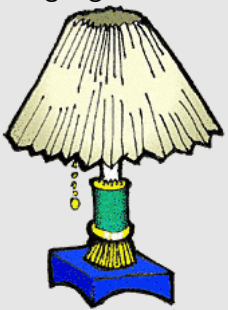


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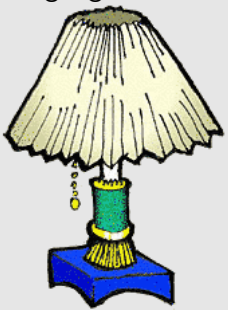


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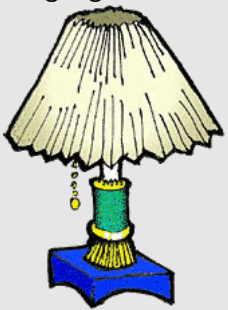


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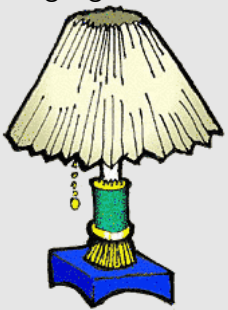


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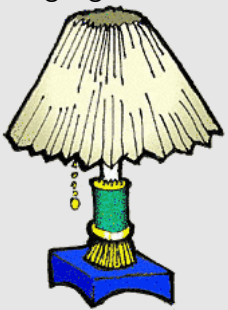


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The second approach is behind 'word embeddings' (and most modern NLP).

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Hypothesis: meaning is actually a sum of contexts.

Distributional differences will always be enough to explain semantic differences:

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- *'You shall know a word by the company it keeps'* [Firth, 1957]

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- *'You shall know a word by the company it keeps'* [Firth, 1957]
- Distributional semantics models (DSMs) get information from lexical co-occurrences in large natural corpora.

Distributional hypothesis

Contexts for '*tea*':

establishments, besides two livery stables, a	tea They never boasted of Robert Acton, nor indulg
en things, because their methods of family to	tea at once. pose, which you carry so well
, as, indeed, A waiter comes in with the	tea. He places the tray on the table. Jasper
let me always remain here.' "I prefer weak	tea!" cried Daisy, and she went off with the
hell. I should think you had drunk enough	tea in Chin a. life; it is a failure,
. Not a bit. Come in and have some	tea. Stay to dinner. every year. Don't persist
responsibility. And greatly as we enjoyed our	tea Crusoe island. Then there's the religious diff
your naturally liking me. (She is and had	tea in the evening. Afraid though as he was
] Tell them I shan't be home to	tea, will you, LADY BRITOMART. I must get the
, that was Mr. McComas will not come to	tea, ma'am: he has gone to call upon
, or asked you to have a cup of	tea. It's not human. ugly woman must have
woman can hardly know one places Gilbey's	tea on the table before him]. The lady that
of my — my hopes.' BROADBENT. He'll want	tea. Let us have some. BURGE-LUBIN [_resolutely ge
: THE MANAGER. Can I take any order? Some	tea? would THE SHE-ANCIENT. Speak, Arjillax: you w
to Tramp.} Will you drink a sup of	tea with myself and the the happiest person in
are trying to sleep." the evening after your	tea. "Better still—then there you are!" And Streth
GUINNESS. I'll go get you some fresh	tea, ducky. [She takes up the its burden, is
sional men, artists, and even with laborers	tea services out and made the people who had
the Lutches and Mrs. Rance the attendance at	tea just in the right place on the west
she came over to the great house to	tea. She had let the proposal that she should
. The Baroness found it amusing to go to	tea; she dressed as if for dinner. The tea-
tea; she dressed as if for dinner. The	tea-table offered an anomalous and picturesque rep
would be dead in two years, as the	tea-table. Be serious, Felix. You forget that I

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Contexts for '*coffee*':

prompt his an incident in my life as	coffee for breakfast. Of course, hes too _Two fig
ek her out all courteously, PETKOFF (over his	coffee and cigaret). I don't believe in going
could be done, too,' he remarked, sipping his	coffee. 'Bury him in some sort,' I explained. 'One
, of us. I should like a cup of	coffee. MICHAEL. If you'd come in better hours,
UKA (innocently). Perhaps you would like some	coffee, sir? DISCOVERY ANTICIPATED BY DIVINATION s
her in public because he has fallen head	coffee-colored heathens and pestilential white agi
manners for he was novels, broken backed,	coffee stained, torn and '''This was the last time
stretches her hand across the table for the	coffee pot.) welcome, an expression which drops in
ittle sitting-room, and cigarettes, after the	coffee, had been permitted by the ladies, and in
had just given me a pannikin of hot	coffee....Slapped it down there, on my chest—bange
a heavy roll coming; tried to save my	coffee, burnt my fingers....and fell out of my
I'll have a claret cup instead of	coffee. Put some first night that we've come
t of trouble travelling. And then, with fresh	coffee, a clean cup, and a brandy bottle on
. Your word had such weight with me!" fresh	coffee? He gave his friend a glance as to
wont press you. `Try a weed with your	coffee. Local tobacco. The black coffee you get at

Representing words with vectors



- Your neural classifiers in Obligatory 1 implicitly learned vector representations for words (embeddings).
- In practice, representing word meaning with vectors was first popularized in psychology by [Osgood et al., 1964]...
- ...then developed by many others.

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- Word vectors can be created manually...
- ...but in most cases corpus-driven distributional methods are much more efficient.

Representing words with vectors

Componential analysis: manual creation of word vectors

Kinship terms	[MALE]	[ASCEND]	[DESCEND]	[LINEAL]
Father	+	+	-	+
Mother	-	+	-	+
Uncle	+	+	-	-
Aunt	-	+	-	-
Brother	+	-	-	+
Sister	-	-	-	+
Son	+	-	+	+
Daughter	-	-	+	+
Nephew	+	-	+	-
Niece	-	-	+	-
Causin	+/-	-	-	-

[Widyastuti, 2010]

We will not do this. We will use distributional vector models *(next sub-lecture 5.2)*.

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