

Build your own Semantle-clone

Stuts 72. Hamburg

Luuk Suurmeijer



What is Semantle?

- Semantle: <https://semantle.com/>
- Pedantle: <https://cemantle.herokuapp.com/>
- Workshop materials: https://github.com/LuukSuurmeijer/semantle_workshop

Why Semantle?



Representations under the hood of Semantle are everywhere in NLP



Good illustration for the question: How to approximate meaning with computers?



It's just fun! :-)

How does Semantle work?

- We need some way to compare words based on their meaning
- Needs to be computable by a machine

Distributional Hypothesis (Firth/Harris):
“You shall know a word by the company it keeps”

Thought experiment

- What is a *bardiwac* ?
 - He handed her a glass of *bardiwac*
 - After drinking too much South African *bardiwac*, John woke up with a massive headache
 - *Bardiwac* turns out scarlet red if the grapes are exposed to a lot of sunlight

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Bardiwac seems to be a red wine!

Count Matrices

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An automobile is a wheeled motor vehicle used for transporting passengers.

A car is a form of transport, usually with four wheels and the capacity to carry around five passengers.

Transport for the London games is limited, with spectators strongly advised to avoid the use of cars.

The London 2012 soccer tournament began yesterday, with plenty of goals in the opening matches.

Giggs scored the first goal of the football tournament at Wembley, North London.

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Term vocab: $\langle wheel, transport, passenger, tournament, London, goal, match \rangle$

	<i>wheel</i>	<i>transport</i>	<i>passenger</i>	<i>tournament</i>	<i>London</i>	<i>goal</i>	<i>match</i>
<i>automobile</i>	1	1	1	0	0	0	0
<i>car</i>	1	2	1	0	1	0	0
<i>soccer</i>	0	0	0	1	1	1	1
<i>football</i>	0	0	1	1	1	2	1

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What design choices
are made in this
example?

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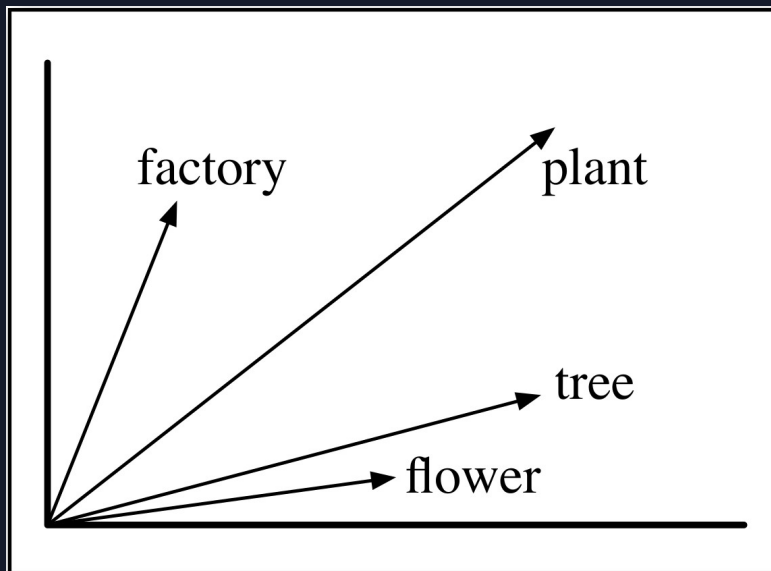
	Ever tried. Ever failed.	No matter. Try again.	Fail again. Fail better.
Ever	2	0	0
tried	1	0	0
failed	1	0	0
No	0	1	0
matter	0	1	0
Try	0	1	0
again	0	1	1
Fail	0	0	2
better	0	0	1

And here?

Vector Space Models

What's the point?

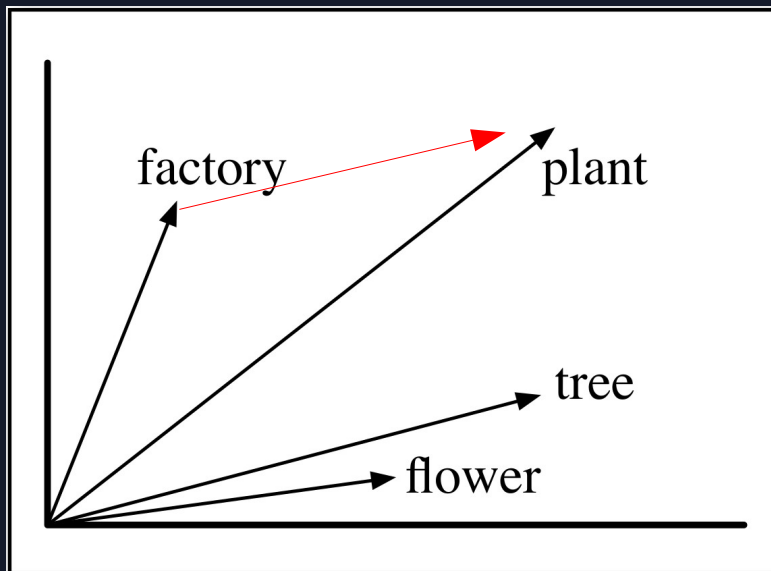
- This matrix encodes a *Vector Space*
- Vector Spaces have very attractive mathematical properties!



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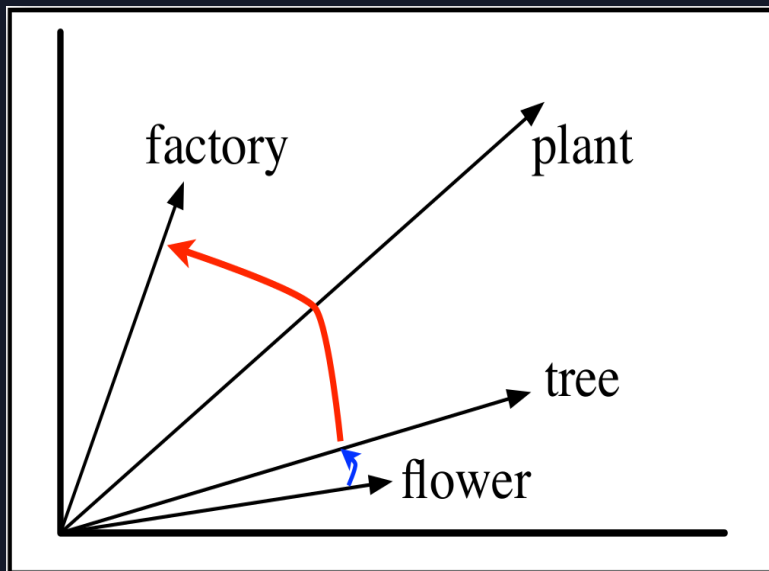


Adding/Subtracting vectors
 $\text{factory} + \text{flower} = \text{plant}$

Vector Space Models

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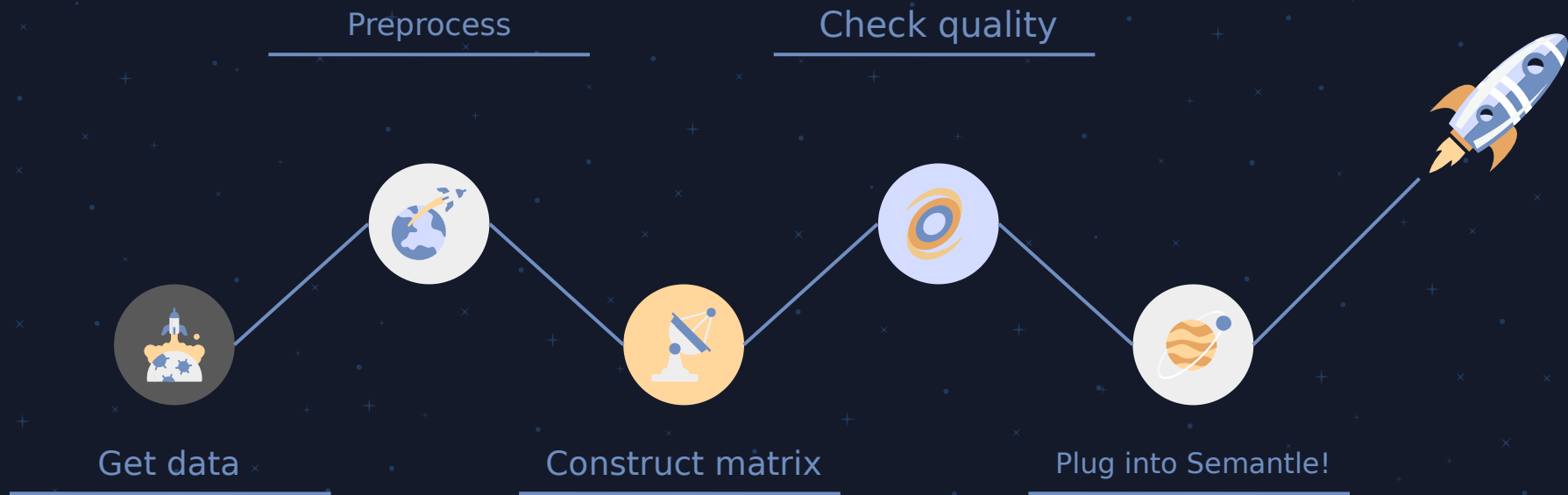
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Adding/Subtracting vectors
 $\text{factory} + \text{flower} = \text{plant}$

Computing angles between
vectors (more on that later)

Steps



Preprocessing

- Tokenization
 - Split text into sensible word units
- Lemmatizing
 - Worse, worst => bad
- Stemming
 - Cried, cries => cri
- Stopword removal
 - Punctuation, function words, etc.
- Annotation
 - POS tags, semantic roles, etc.

Drawbacks of count matrices

- Language is Zipfian! → Most words never occur in most contexts
 - 1) Surprising (rare) occurrences contribute very little to the vector representation
 - 2) Matrix becomes very sparse (almost all entries are zero)

Boosting rare events: PMI

- Pointwise Mutual Information: How dependent is a word on a particular context?

$$\text{pmi}(x; y) \equiv \log \frac{p(x, y)}{p(x)p(y)}.$$

Boosting rare events: PMI

- Pointwise Mutual Information: How dependent is a word on a particular context?

$$p_{ij} = \frac{f_{ij}}{\sum_{i=1}^{n_r} \sum_{j=1}^{n_c} f_{ij}} \quad (1)$$

$$p_{i*} = \frac{\sum_{j=1}^{n_c} f_{ij}}{\sum_{i=1}^{n_r} \sum_{j=1}^{n_c} f_{ij}} \quad (2)$$

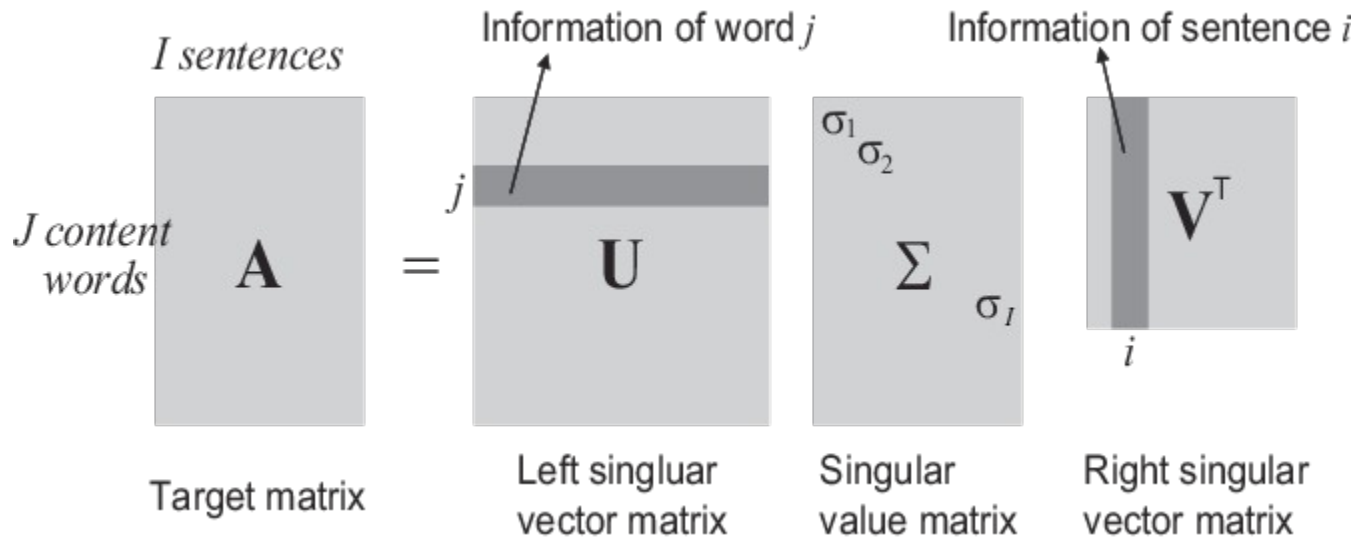
$$p_{*j} = \frac{\sum_{i=1}^{n_r} f_{ij}}{\sum_{i=1}^{n_r} \sum_{j=1}^{n_c} f_{ij}} \quad (3)$$

$$\text{pmi}_{ij} = \log \left(\frac{p_{ij}}{p_{i*} p_{*j}} \right) \quad (4)$$

$$x_{ij} = \begin{cases} \text{pmi}_{ij} & \text{if } \text{pmi}_{ij} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Data Sparsity

- In order to make the matrix less sparse, we can use dimensionality reduction measure like *Singular Value Decomposition*, *Principal Component Analysis* (won't talk about the details here)



Comparing vectors

- We can compare vectors by calculating the angle between them. This is known as the *cosine similarity*
 - Number between -1 and 1
 - $\cos(a,b) = 1 \rightarrow a$ and b point in the same direction
 - $\cos(a,b) = -1 \rightarrow a$ and b point in opposite directions
 - $\cos(a,b) = 0 \rightarrow a$ and b are orthogonal (perpendicular)

$$\cos(\mathbf{x}, \mathbf{y}) = \frac{\sum_{i=1}^n x_i \cdot y_i}{\sqrt{\sum_{i=1}^n x_i^2 \cdot \sum_{i=1}^n y_i^2}} \quad (10)$$

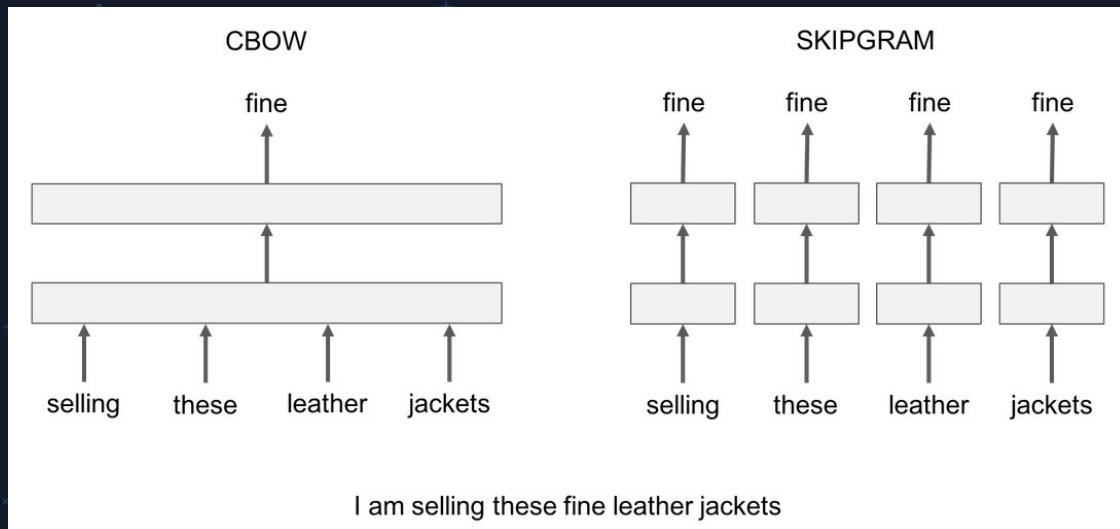
$$= \frac{\mathbf{x} \cdot \mathbf{y}}{\sqrt{\mathbf{x} \cdot \mathbf{x}} \cdot \sqrt{\mathbf{y} \cdot \mathbf{y}}} \quad (11)$$

$$= \frac{\mathbf{x}}{\|\mathbf{x}\|} \cdot \frac{\mathbf{y}}{\|\mathbf{y}\|} \quad (12)$$

Beyond counts: Word Embeddings

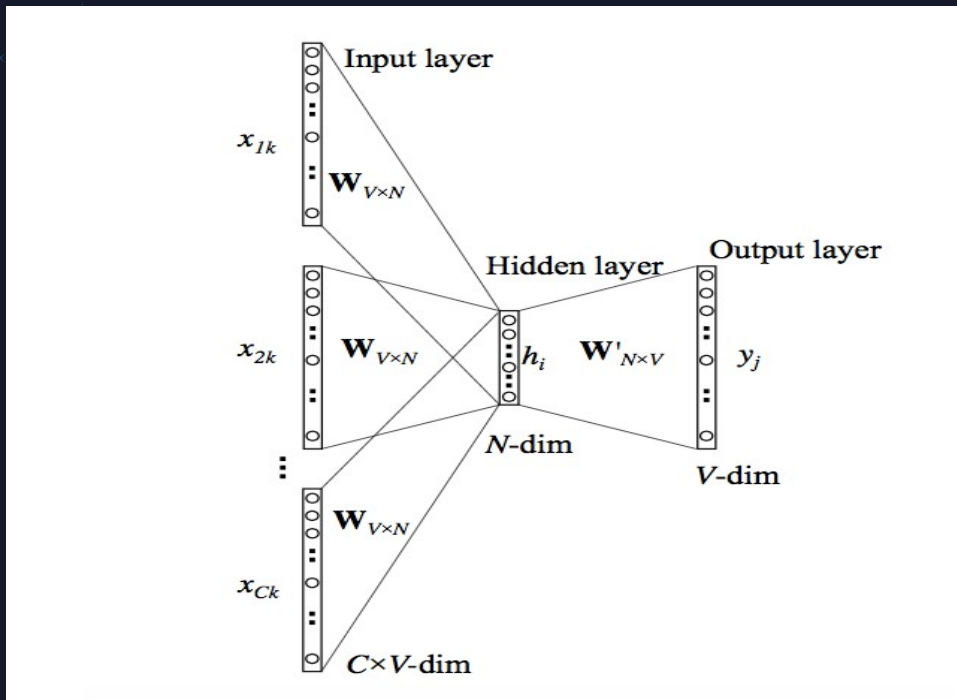
Idea: Train a neural network to predict words from contexts and use the hidden representations as “embeddings”

- Popular algorithm: Word2Vec



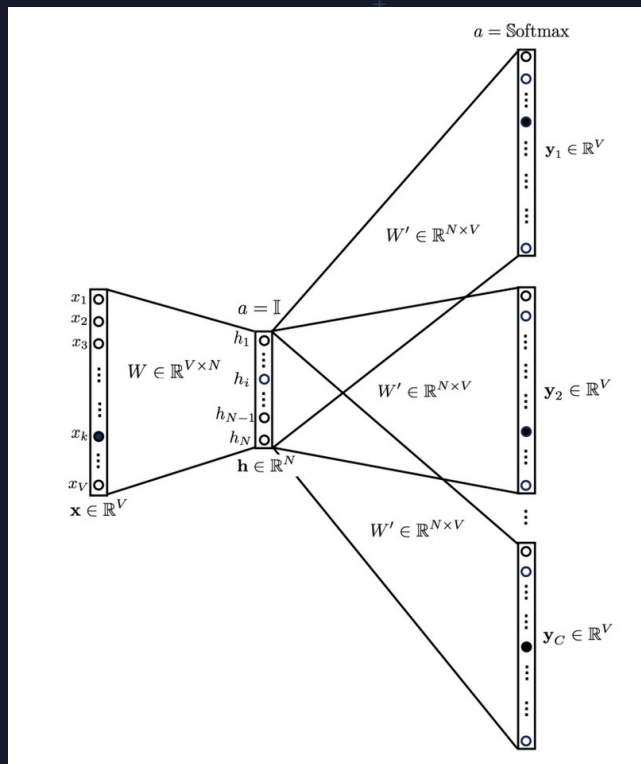
Beyond counts: Word Embeddings

Example of CBOW (Continuous bag of words)



Beyond counts: Word Embeddings

Example of Skipgram



Beyond counts: Word Embeddings

Skipgram:

- Better for small amount of data
- Better vectors for rare words

CBOW:

- Faster algorithm
- Better with large amount of data

Python implementation of word2vec:

https://github.com/LakheyM/word2vec/blob/master/word2vec_SGNS_git.ipynb

Other popular algorithm: FastText (uses 'subword' information):

fasttext.cc

Evaluating Word Embeddings

How can we tell our vectors/embeddings are 'good'?

- Word analogy tasks

$$V(\text{king}) - V(\text{man}) + V(\text{woman}) = ?$$

$$V(\text{france}) - V(\text{paris}) + V(\text{rome}) = ?$$

$$V(\text{Cu}) - V(\text{copper}) + V(\text{gold}) = ?$$

Evaluating Word Embeddings

How can we tell our vectors/embeddings are 'good'?

- Word analogy tasks

$$V(\text{king}) - V(\text{man}) + V(\text{woman}) = V(\text{queen})$$

$$V(\text{france}) - V(\text{paris}) + V(\text{rome}) = V(\text{italy})$$

$$V(\text{Cu}) - V(\text{copper}) + V(\text{gold}) = V(\text{Au})$$

The vector is 'correct' if the predicted word has the highest cosine similarity to the intended vector (or if its in the top N closest)

Some resources

These slides + some papers + exercises

https://github.com/LuukSuurmeijer/semantle_workshop

Algorithm for playing Codenames using word2vec

<https://github.com/thomasahle/codenames>

Algorithm for playing Semantle using word2vec

<https://github.com/womogenes/semantle-bot>

Python package with pretrained word2vec embeddings

<https://pypi.org/project/gensim/>



Ready to launch your own
Vector Space Rocket?



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