

We develop Individual Software & **Artificial Intelligence** Solutions



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Our algorithms and solutions have been awarded multiple times











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Literally Recommendable

Using Text Embedding Algorithms in Recommendation Systems

- Natural Language Processing (NLP)
- Recommendation Systems (RecSys)
- 3 Hybrid Filtering RecSys powered by word2vec



Natural Language Processing (NLP)





Big Leaps Forward

How come **machines** have become decent at **understanding humans** recently?













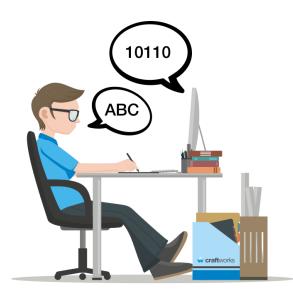
It's Complicated

"Communication is key to a healthy relationship"

... well, it's complicated.

Humans communicate using natural languages (German, English, ...)

Nondeterministic



Machines communicate using

artificial languages (binary, C++, ...)

Deterministic

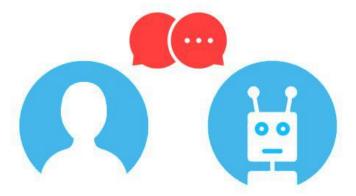




The Translator

Natural Language Processing is the translator.

NLP is a collection of **methods** from **linguistics**, **statistics** and **computer science** that aims to make *computers "understand" natural language.*







The Translation Process

Computers excel at **Maths**. So let's turn **text into numbers**:

- 1. Intelligent humans control machines.
- Intelligent machines control humans.
- 3. Be careful with machines.

"Bag of Words"



	be	careful	control	human	intelligent	machine	with
Sentence 1	0	0	1	1	1	1	0
Sentence 2	0	0	1	1	1	1	0
Sentence 3	1	1	0	0	0	1	1





Natural Language is Complex

The **bag of words** method is **ignorant**. For instance, it fails to model:

- word order
- context
- grammar

We lost any information about what truly matters for humans:

The relationship between words/phrases and symbols, constituting *meaning*. We lack Semantics.





Company is Key

We need to **preserve semantics** when converting text to a numerical, **machine-readable** form.

HOW?

"You shall know a word by the company it keeps"
J. R. Firth, linguist, 1957







An Old Hypothesis in New Clothes

Distributional Hypothesis:

Words that appear in similar contexts are similar in meaning.

e.g. father \leftrightarrow dad

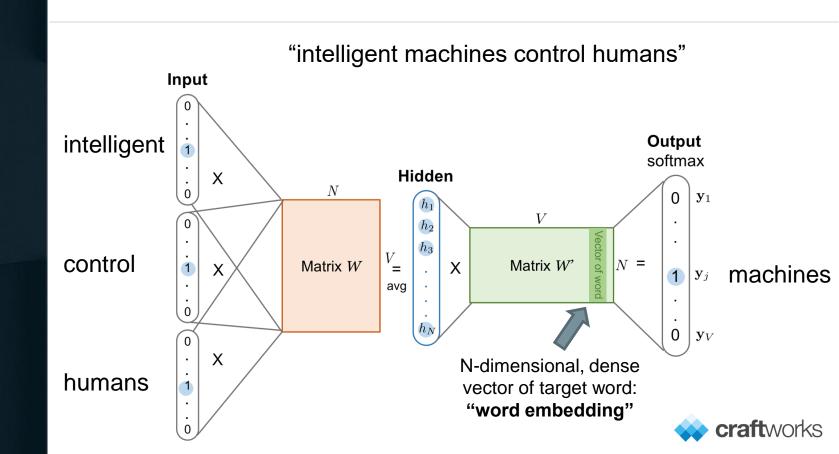
Modern Text Embedding Algorithms make use of this idea.

Most notably: word2vec by Mikolov et al.





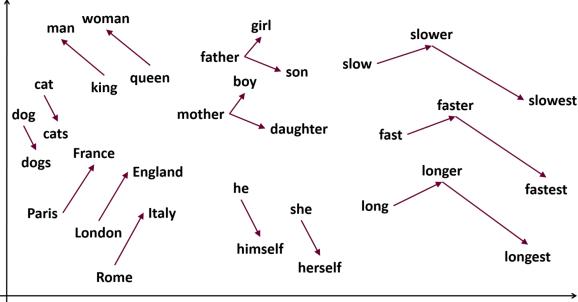
word2vec - CBOW Model in Action





Semantics in a Nutshell: Dense Vectors

- w2v generates dense N-dimensional numeric word vectors
- similar words ← similar vectors (cosine similarity)



Projection of vectors into 2-dimensional space using t-SNE



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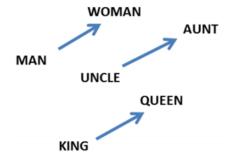


Similarity

Remember:

word2vec is excellent at extracting the meaning of words.

similar context \rightarrow similar meaning \rightarrow similar vectors



Similarity is not only important when it comes to words ...





You are the Average of the Five People you Spend the Most Time with

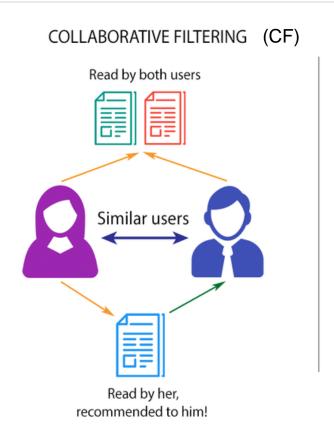
- Similarity also plays a key role in our social relationships
- Typically, our friends are highly similar to ourselves and we often like the same things

Also **Recommendation Systems** often use **similarity measures** to find out what we like.

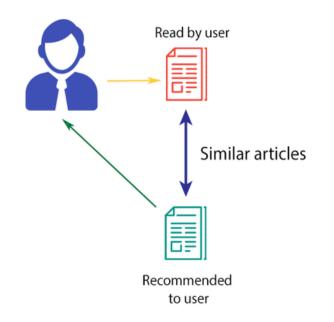




Traditional Filtering Methods in Recommendation Systems



CONTENT-BASED FILTERING (CBF)





Traditional Filtering Methods have significant Weaknesses

Problems of Collaborative Filtering

- Cold Start problem
- Synonyms
- Gray Sheep

Problems of Content-based Filtering

- Entirely relies on quality of metadata
- "boring" recommendations





Hybrid Filtering

Both Collaborative and Content-based Filtering suffer from significant weaknesses.

→ Overcome by **combining both techniques**.

f Collaborative Content-based Filtering , Filtering





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An Enlightening Analogy

"What do **news articles** and **website visitors** have in common?"







Both are **sequences**!





A Matter of Perspective

For a website visitor, online news articles are **sequences of words**.

 \longleftrightarrow

For a news website, visitors are sequences of articles they read.

news article

= ["intelligent", "machines", "control", "humans"]

 \longleftrightarrow

news website visitor = ["ArticleID_1", "ArticleID_2", "ArticleID_3"]





Putting it together: word2vec in Hybrid Filtering

For a news website ...

• <u>users</u> are sequences of articles

For a news website visitor (user) ...

• <u>articles</u> are sequences of words



users are sequences of sequences of words



Putting it together: word2vec in Hybrid Filtering

Training word2vec on our corpus of articles (sequences of words) provides us with N-dimensional **vectors for each word i**.

Aggregation on article level:

$$article_vector_j = \frac{1}{N} \sum_{i \in K=1}^{N} word_vector_i$$

Aggregation on user level:

$$user_vector_c = \frac{1}{N} \sum_{j \in P=1}^{N} article_vector_j$$





Practical Example

You can find the Jupyter Notebook on the craftworks github account:

https://github.com/craftworksgmbh/wad





Putting it together: word2vec in Hybrid Filtering

What do we get from this?

- Mapping of items and users into shared vector space brings flexibility
- Computation of similarities and making recommendations:
 - User-to-User
 - Item-to-Item
 - Item-to-User
- Overcoming problems of traditional methods





Text Embedding Algorithms in Hybrid Filtering are powerful

Problems of Collaborative Filtering

- Cold Start problem
- Synonyms
- Gray Sheep

Solved!

Problems of Content-based Filtering

- Entirely relies on quality of metadata
- "boring" recommendations





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