





**185.A83** Machine Learning for Health Informatics 2016S, VU, 2.0 h, 3.0 ECTS Week 25 - 22.06.2016 17:00-20:00

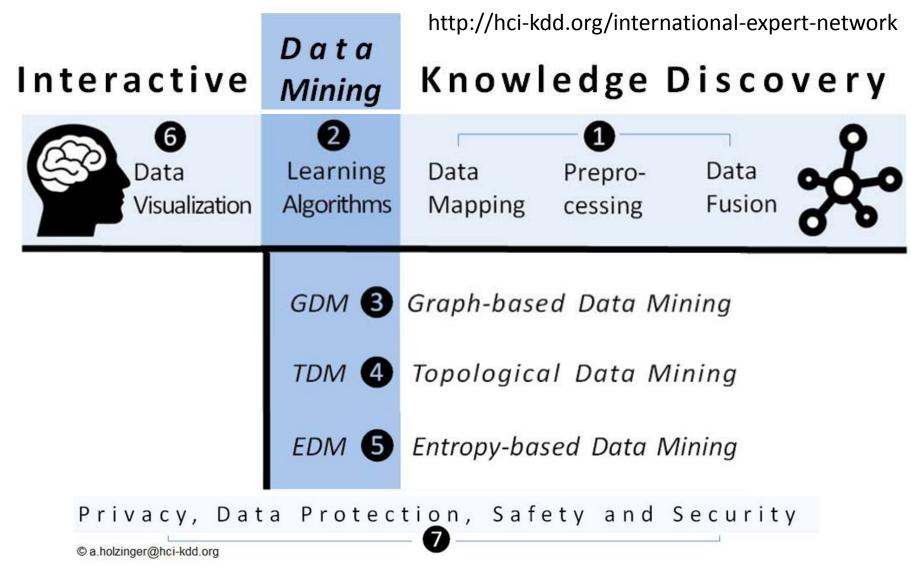
## Introduction to word embeddings word-vectors (Word2Vec/GloVe) Tutorial

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http://hci-kdd.org/machine-learning-for-health-informatics-course







Holzinger, A. 2014. Trends in Interactive Knowledge Discovery for Personalized Medicine: **Cognitive Science meets Machine Learning.** IEEE Intelligent Informatics Bulletin, 15, (1), 6-14.

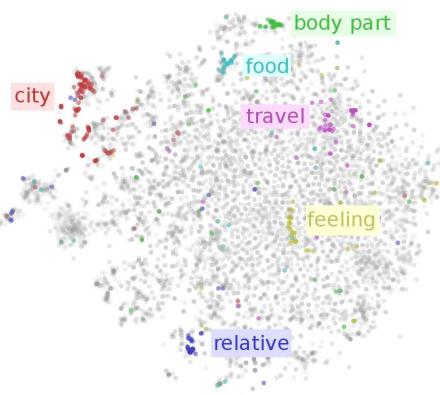




- 1. What does Word embedding mean?
- 2. Three main ideas (take home message)
- 3. Word vector general assumptions
- 4. Advantages
- 5. Applications
- 6. Word vector operations
- 7. Methods (W2V, GloVe)
- 8. DEMO



Any technique mapping a word (or phrase) from it's original high-dimensional input space (the body of all words) to a lower-dimensional numerical vector space - so one *embeds* the word in a different space



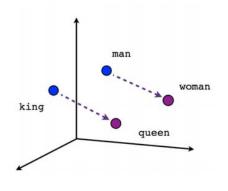
Points: original word space

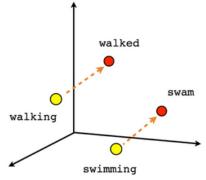
Colored points / clusters: Word embedding





"Word representations are a critical component of many natural language processing systems. It is common to represent words as indices in a vocabulary, but this fails to capture the rich relational structure of the lexicon. Vector-based models do much better in this regard. They encode continuous similarities between words as distance or angle between word vectors in a high-dimensional space [1]".





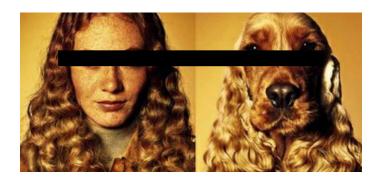
https://www.tensorflow.or g/versions/r0.7/tutorials/ word2vec/index.html

[1] Maas, A. L., Daly, R. E., Pham, P. T., Huang, D., Ng, A. Y. & Potts, C. Learning word vectors for sentiment analysis. Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, 2011. Association for Computational Linguistics, 142-150.

[2] Petz, G., Karpowicz, M., Fürschuß, H., Auinger, A., Stříteský, V. & Holzinger, A. 2015. Computational approaches for mining user's opinions on the Web 2.0. Information Processing & Management, 51, (4), 510-519, doi:http://dx.doi.org/10.1016/j.ipm.2014.07.011.







- 1) Similarity in **meaning** ⇔ similarity in **vectors** 
  - ⇒ Mathematics should be able to encode meaning
- 2) You shall know a word by the company it keeps;)
  - ⇒ The environment of a word gives meaning to it
- 3) Use BIG datasets (millions of billions to words)
  - ⇒ Especially neural models require lots of data!



 The more often two words co-occur, the closer their vectors will be

 Two words have close meanings if their local neighborhoods are similar

 Maps of words (trained on the same dataset) should be similar for each language => can build translators!



 Depending on the model, we do not infer meaning only from global statistics, but local contexts with are more precise

 Computers can "grasp" the meaning of words by looking at the distance between vectors / vector components

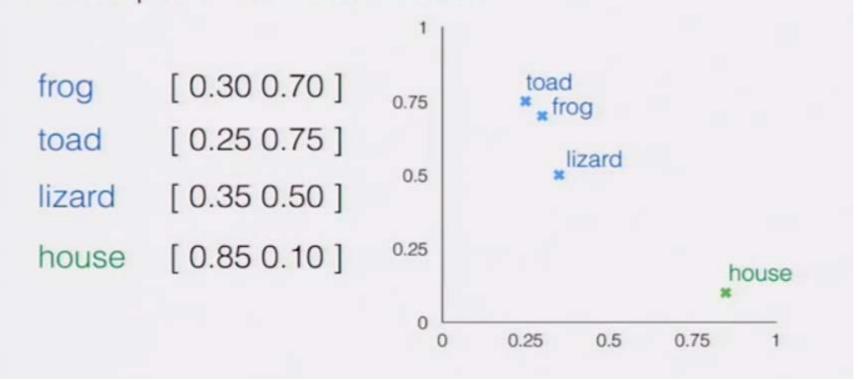
 Can apply mathematical operations translating to actual meaning within semantic models





## Distributed representations

Word vectors aren't guaranteed to encode any linguistic relationships between words, but many models produce vectors that do



Source: https://www.youtube.com/watch?v=RyTpzZQrHCs

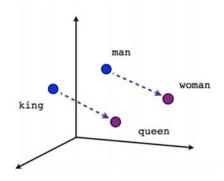


- Machine translation (word maps)
- Sentiment analysis
  - e.g. via Vector averaging
- Any NER task (seeking to locate and classify elements in text into pre-defined categories)
  - Topics
  - Goals
- Innovative search engine (ThisPlusThat), where we can subtract queryies, e.g.: "pizza + Japan - Italy => sushi"
- Thus: recommendation system for online shops





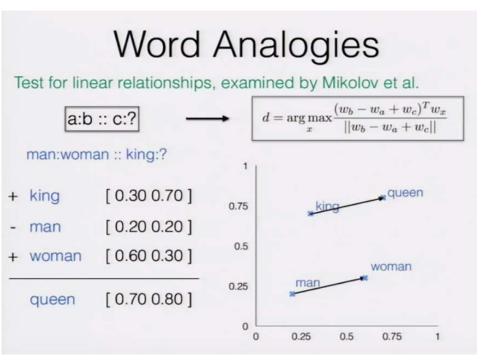
#### Arithmetic



"king - man + woman = queen"

#### 2. Nearest Neighbours

• frog: toad, litoria, lizard, ...



Source: https://www.youtube.com/watch?v=RyTpzZQrHCs

- works even with numbers (given certain context, like gene sequence)
- 3. Find words that do not belong
  - dog, cat, mouse, fruit basket



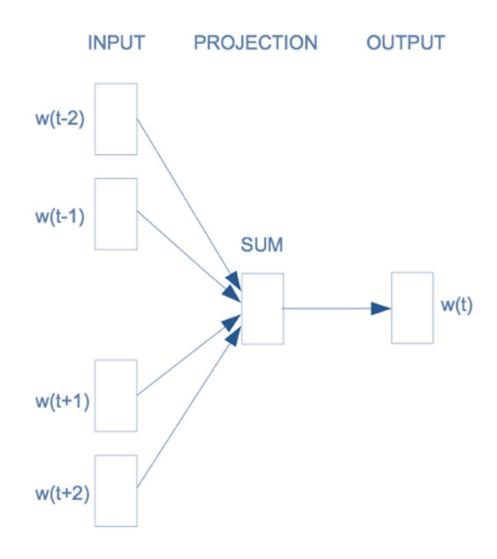
 Uses neural networks to train word / context classifiers (feed-forward neural net)

 Uses local context windows (environment around any word in a corpus) as inputs to the NN

- Two main models:
  - 1. Continuous bag-of-words (CBOW)
  - 2. Skip-gram (SG)



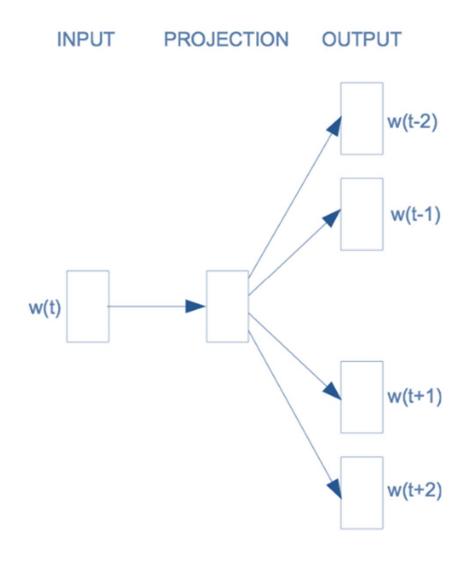




CBOW uses the context given by a local window to predict a (known) center word







Skip-gram
works exactly
the other way
around, using a
given center
word to predict
it's context





- 1. Generate Co-occurrence matrix X (symmetric)
  - Take a context window (distance around a word, e.g. 10)
  - X(i,j) = # of times 2 words lie in the same context window

#### 2. Factorize X

- Extract vectors: X(i,j) = <vi,vj> | v el R^d (d is a hyperparamter)
- 3. Ratio of co-occurrences between 3 words => the ratio of the C/O of similar words will be closer to 1 = > this is how meaning is captured in this model



### Encoding meaning in vector differences

Crucial insight: Ratios of co-occurrence probabilities can encode meaning

	x = solid	x = gas	x = water	x = random
P(x ice)	large	small	large	small
P(x steam)	small	large	large	small
$\frac{P(x \text{ice})}{P(x \text{steam})}$	large	small	~1	~1





## !!! DEMO!!!





# Thank you!

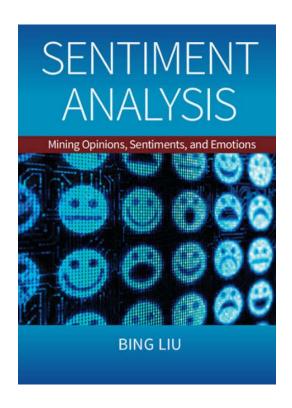




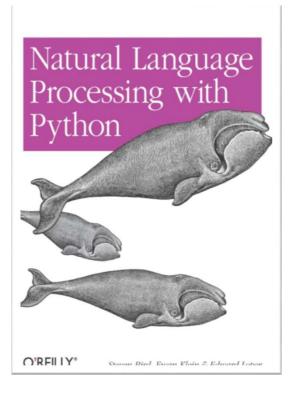
- Principal question: Why is natural language important for health informatics?
- What are the key problems involved in NLP?
- Side Question: What makes NLP in the biomedical domain so difficult?
- What does word embedding mean?
- What are the three main ideas?
- Describe the advantages of this approach!
- Provide some examples for applications!



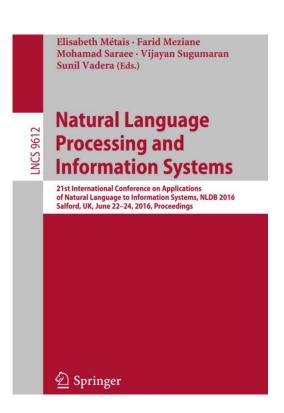




Liu, B. 2015. Sentiment analysis: Mining opinions, sentiments, and emotions, Cambridge University Press.



Bird, S., Klein, E. & Loper, E. 2009. Natural language processing with Python, "O'Reilly Media







- 1. associate with each word in the vocabulary a distributed word feature vector a real valued vector in  $\mathbb{R}^m$
- 2. express the joint probability function of word sequences in terms of the feature vectors of these words in the sequence; and
- 3. learn simultaneously the word feature vectors and the parameters of that probability function

Bengio, Y., Ducharme, R., Vincent, P. & Jauvin, C. 2003. A neural probabilistic language model. Journal of machine learning research (JMLR), 3, (2), 1137-1155.

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