Technische Universität München

sebis

Literature Study: Use Case Analysis for Word Embeddings

Bachelor Thesis – Kickoff Presentation

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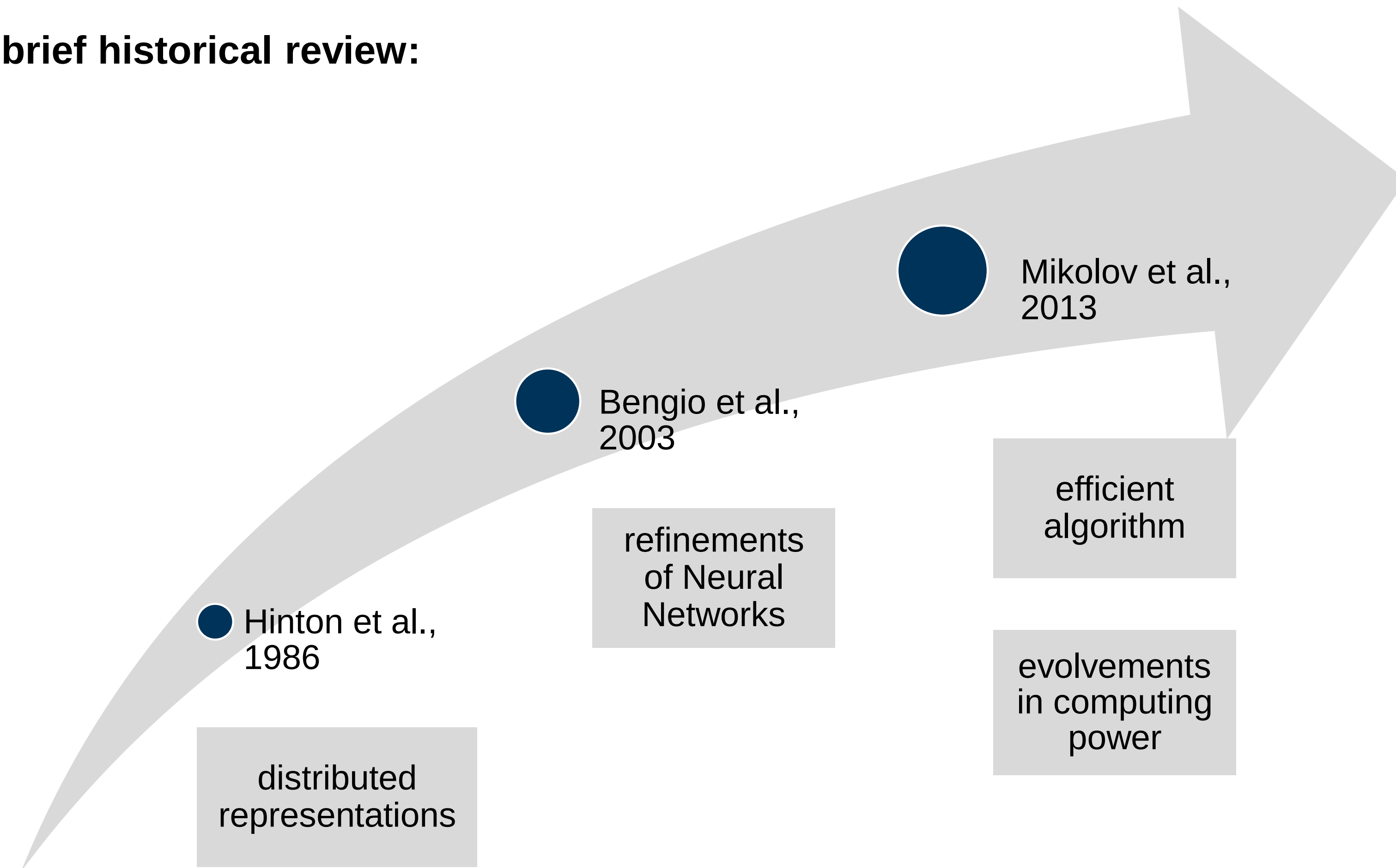
A brief historical review:



Similar terms for word embeddings:
- distributional semantics
- distributed word representations
- semantic vectors

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Traditional NLP

The best university in Germany.

Vocabulary

1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

Sparse one-hot representation

Vector length = size of vocabulary

Easy to use

Does not store context

Word Embeddings

The best university in Germany.

2,34	4,87	1.01	8,34	3,22
-1,30	3,22	0.01	0.23	5.67
0.23	-1.0	2.44	2.34	0.01
1.33	3.9	3.84	1.04	-1.2
1.0	3.8	-2.08	4,55	2,66

Manually chosen size

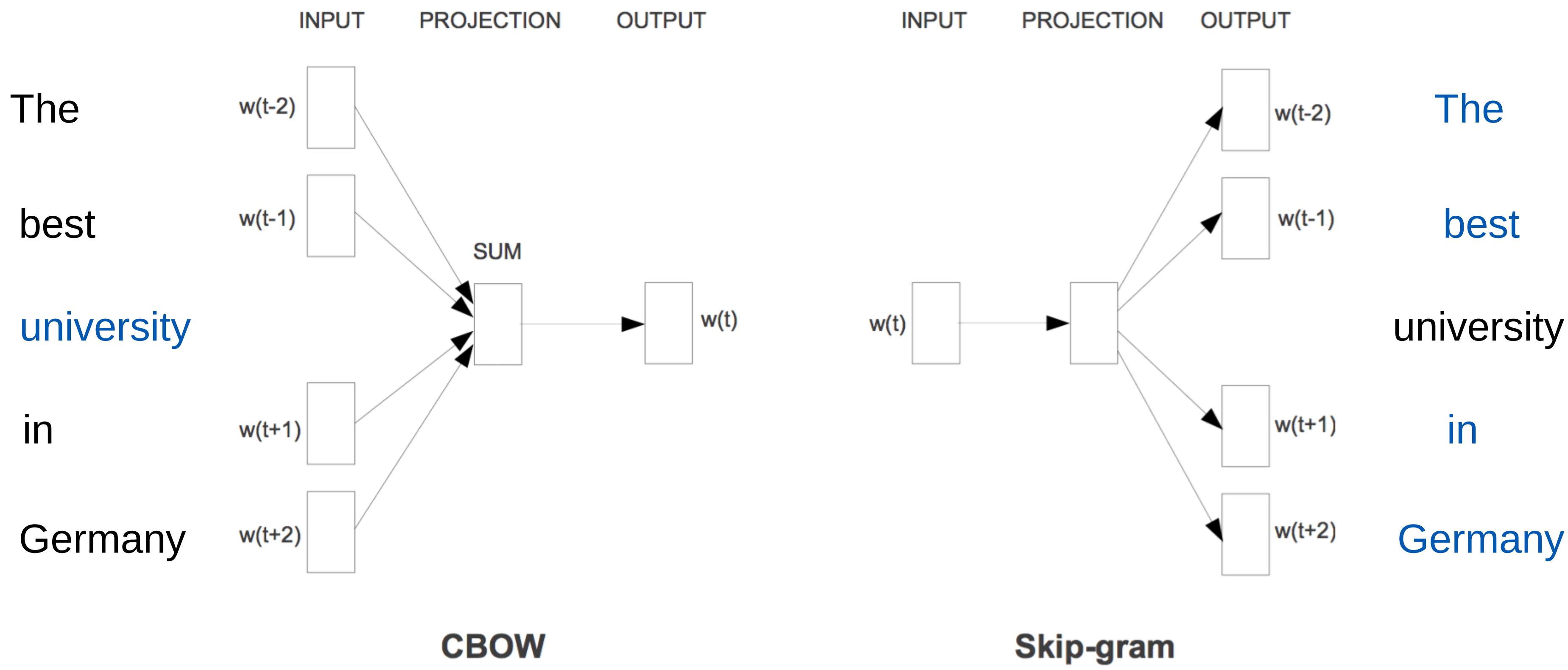
Dense representation

Every word represented as a vector of fixed length (e.g. 300)

Unsupervised learning

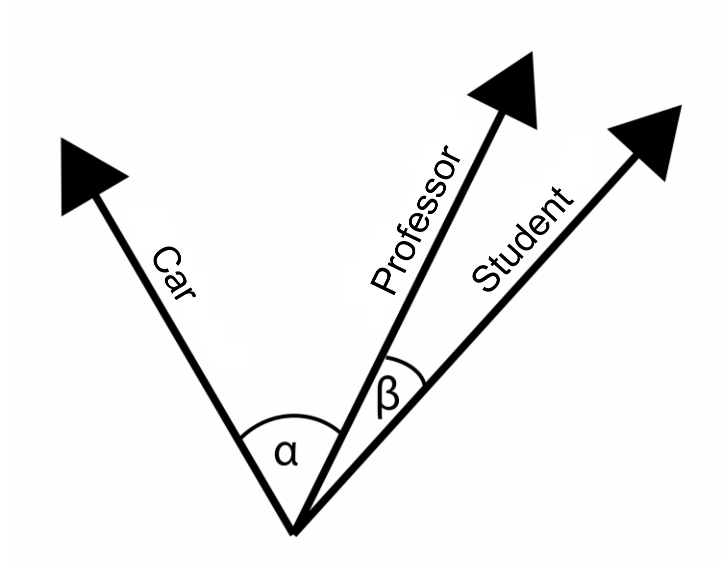
Frequent context of words is encoded in the vectors

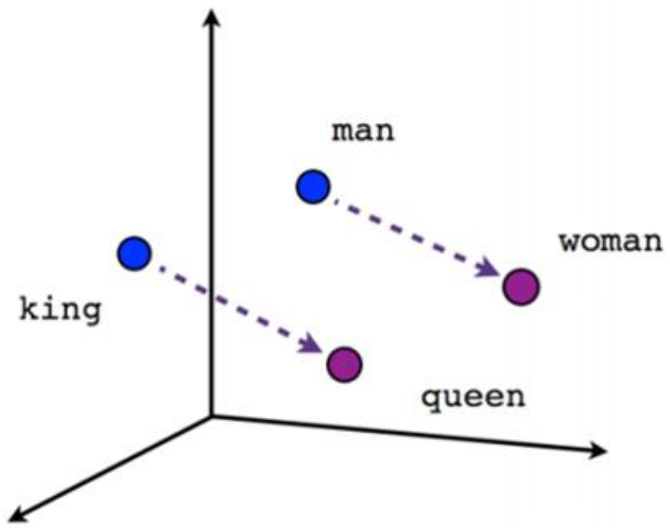
2 possible classification models with word2vec:



Mikolov et al., 2013

Illustration of the characteristics of Word Embeddings (in 2D/3D)





Simple mathematical operations, e.g. addition and substraction lead to interesting results:

Vec(„King“) – Vec („Man“) + Vec(„Woman“) -> Vec(„Queen“)

Mikolov et al., 2013b

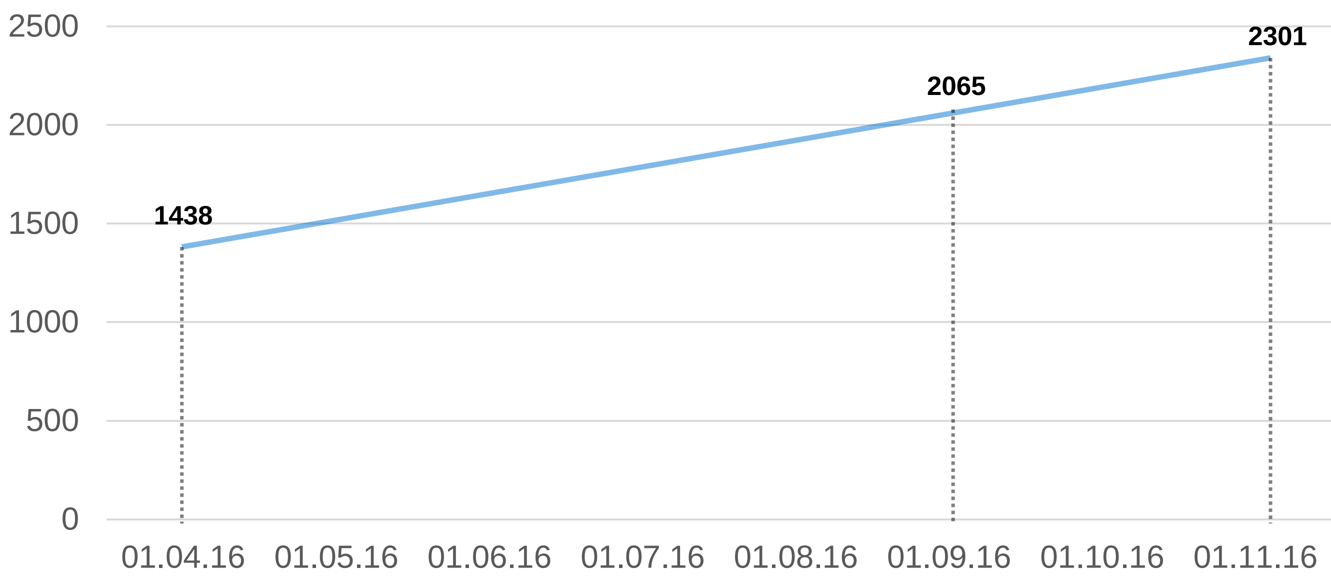
2. Motivation

Efficient estimation of word representations in vector space

T **Mikolov**, K Chen, G Corrado, J Dean - arXiv preprint arXiv:1301.3781, 2013 - arxiv.org

Abstract: We propose two novel model architectures for computing continuous vector representations of words from very large data sets. The quality of these representations is measured in a word similarity task, and the results are compared to the previously best ...

Zitiert von: 1438 Ähnliche Artikel Alle 8 Versionen Zitieren Speichern



=> no literature survey (esp. use cases) available

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3. Research Questions

?

Which Use Cases that apply to organizational contexts can be identified in the existing body of literature?

?

How can Use Cases for Word Embeddings be categorized?

?

What are the most frequent use cases?

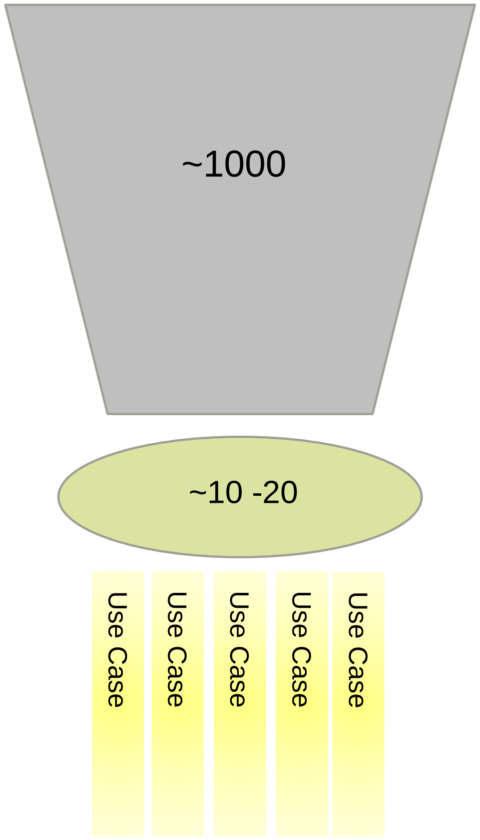
?

What further technological developments of Word2Vec can be identified in the body of literature?

?

For the most interesting Use Cases: How do they work technically?

4. Approach



1) Mikolov Cites Analysis

2) Use Case Selection
(in coordination with Prof. Matthes)

3) Focused Use Case Analysis

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5. Preliminary Results

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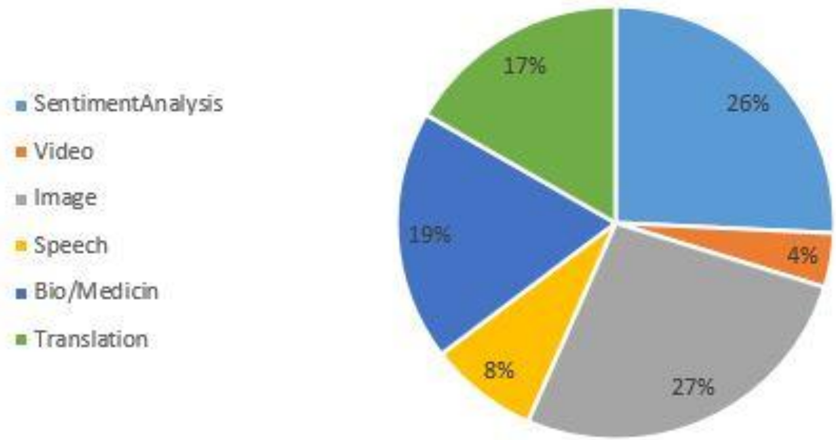
Use Cases by Research Area:

- Sentiment Analysis
- Video: Annotation
- Image: Object Classification
- Speech Recognition
- Bio/Medicine:
  Genome Sequence Analysis
- Translation



Current baseline: 198 paper

1	title	authors	abstract	link	cites	categories	SubCategories
2	Distributed representations of words and phrases and the	T Mikolov, I Sutskever, K C	Abstract The	http://papers.	2271	Explanation	Other
3	Imagenet large scale visual recognition challenge	O Russakovsky, J Deng, I	Abstract The	http://link.spri	1268	UseCase	Image
4	Glove: Global Vectors for Word Representation.	R Socher, CD Manning	Theatre or th	http://llcao.ne	899	Advancement	Other
5	Distributed Representations of Sentences and Document	QV Le, T Mikolov	Abstract Man	http://www.jm	631	Advancement	Other
6	Show and tell: A neural image caption generator	O Vinyals, A Toshev, S Be	Abstract Auto	http://www.cv	500	UseCase	Image
7	Deep Learning	L Deng, D Yu	Abstract This	http://citeseer	303	Explanation	Other
8	Knowledge vault: A web-scale approach to probabilistic kr	X Dong, E Gabrilovich, G I	Abstract Rec	http://dl.acm.	270	UseCase	Other
9	Devise: A deep visual-semantic embedding model	A Frome, GS Corrado, J S	Abstract Mod	http://papers.	264	UseCase	Image
10	Intriguing properties of neural networks	C Szegedy, W Zaremba, I	Abstract: Dee	http://arxiv.or	236	UseCase	Image
11	Neural word embedding as implicit matrix factorization	O Levy, Y Goldberg	Abstract We	http://papers.	210	Explanation	Other
12	Exploiting similarities among languages for machine trans	T Mikolov, QV Le, I Sutske	Abstract: Dic	http://arxiv.or	206	UseCase	Translation
13	Unifying visual-semantic embeddings with multimodal neu	R Kiros, R Salakhutdinov,	Abstract: Insp	http://arxiv.or	174	UseCase	Image
14	Dependency-Based Word Embeddings.	O Levy, Y Goldberg	Abstract Whi	http://www.ac	169	Advancement	Other
15	Learning word embeddings efficiently with noise-contrasti	A Mnih, K Kavukcuoglu	Abstract Con	http://papers.	133	Advancement	Other
16	Bilingual Word Embeddings for Phrase-Based Machine T	WY Zou, R Socher, DM C	Abstract We	http://jan.stan	133	UseCase	Translation
17	Tailoring Continuous Word Representations for Depender	M Bansal, K Gimpel, K Liv	Abstract Wor	http://ttic.uchi	121	Advancement	Other
18	Multimodal Neural Language Models.	R Kiros, R Salakhutdinov,	Abstract We	http://www.jm	130	UseCase	Image

Benton et al., 2016

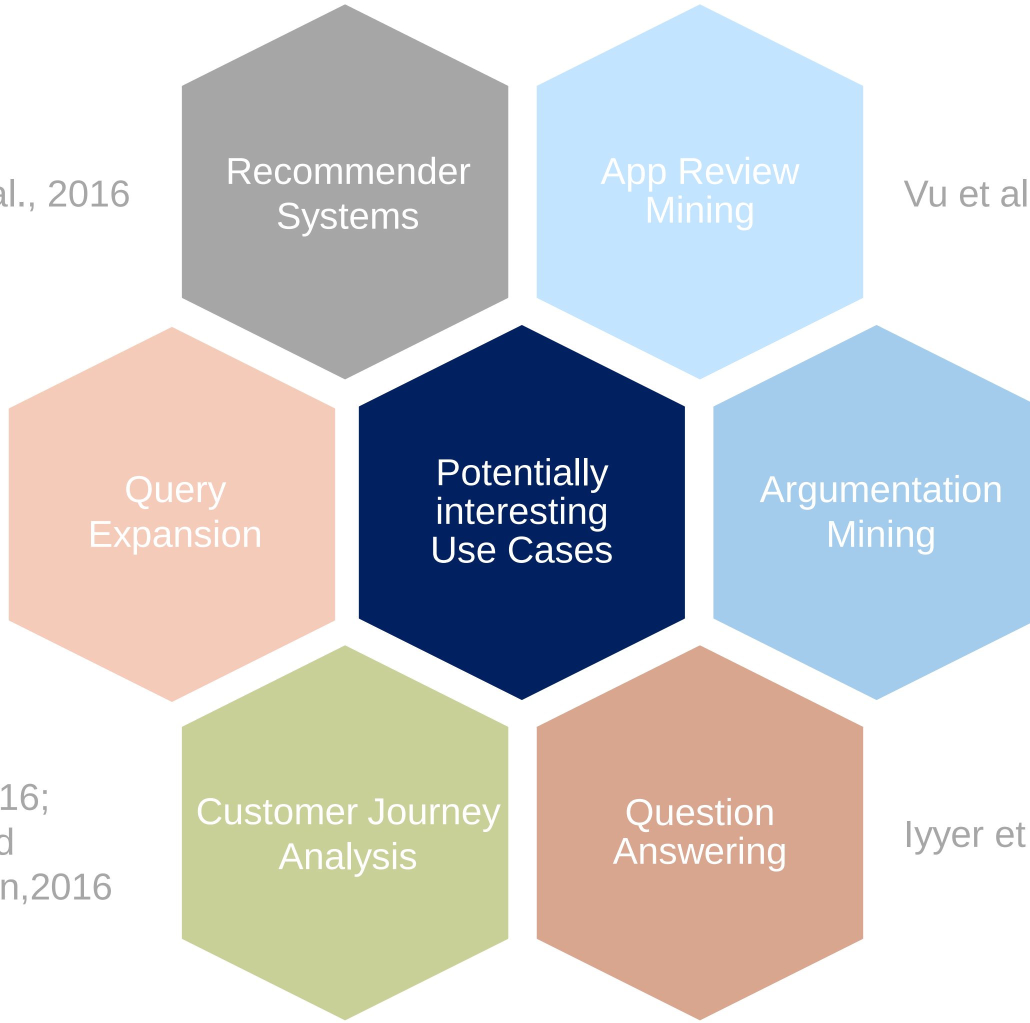
Vu et al., 2015

Ganguly et al., 2015;
Amer et al., 2016

Naderi and Hirst, 2015;
Rinott et al., 2015

Ozsow, 2016;
Barkan and
Koenigstein,2016

Iyyer et al., 2014



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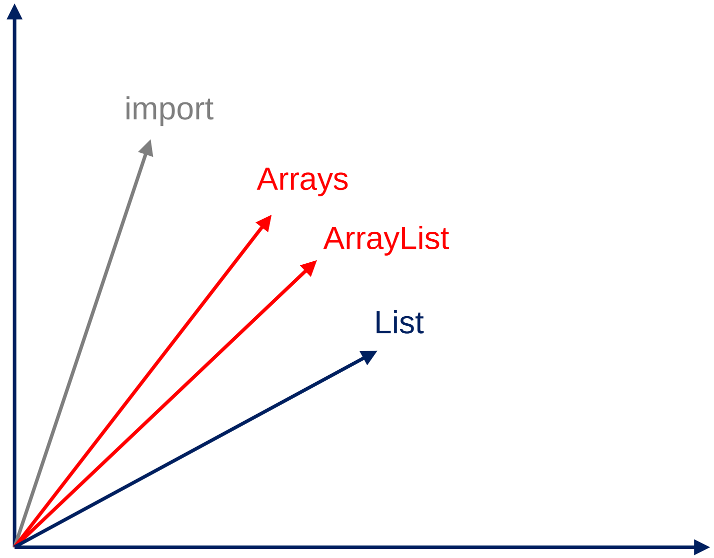
Source Code Recommendation:

```
import java.util.Arrays;
import java.util.ArrayList;
import java.util.List;
```

```
[import, java, util, Arrays]
[import, java, util, ArrayList]
[import, java, util, List]
```




```
>>> closest_words('Array's, n=5)

[('Arrays'),
('equals()'),
('sort()'),
('toString()'),
('ArrayList')]
```

Gude, 2016

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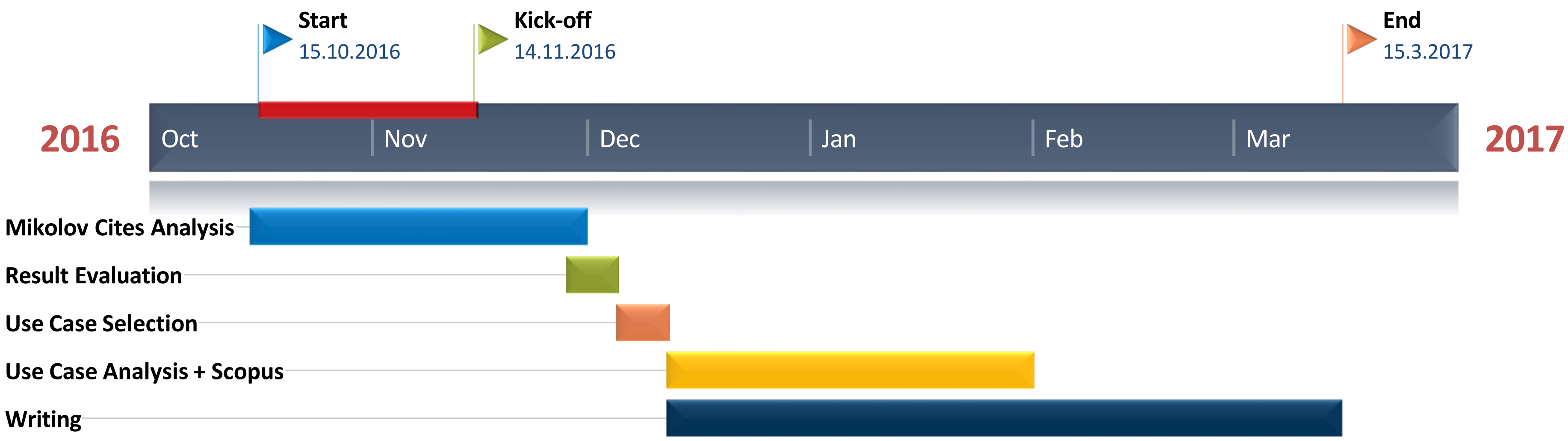
7. Timeline



Start
15.10.2016
Kick-off
14.11.2016
End
15.3.2017
2016
Oct
Nov
Dec
Jan
Feb
Mar
2017
Mikolov Cites Analysis
Result Evaluation
Use Case Selection
Use Case Analysis + Scopus
Writing

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8. Sources

Recommended readings:

Natural Language Processing:

- COLLOBERT, Ronan, et al. Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 2011, 12. Jg., Nr. Aug, S. 2493-2537.

Artificial Neural Networks:

- HAYKIN, Simon; NETWORK, Neural. A comprehensive foundation. *Neural Networks*, 2004, 2. Jg., Nr. 2004.
- SCHMIDHUBER, Jürgen. Deep learning in neural networks: An overview. *Neural Networks*, 2015, 61. Jg., S. 85-117.

Word Embeddings:

- PENNINGTON, Jeffrey; SOCHER, Richard; MANNING, Christopher D. Glove: Global Vectors for Word Representation. In: *EMNLP*. 2014. S. 1532-43.

Word2Vec:

- MIKOLOV, Tomas, et al. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.
- https://deeplearning4j.org/word2vec
- https://rare-technologies.com/word2vec-tutorial/

8. Sources

- MIKOLOV, Tomas; LE, Quoc V.; SUTSKEVER, Ilya. Exploiting similarities among languages for machine translation. *arXiv preprint arXiv:1309.4168*, 2013.
- BENGIO, Yoshua, et al. A neural probabilistic language model. *journal of machine learning research*, 2003, 3. Jg., Nr. Feb, S. 1137-1155.
- MELAMUD, Oren, et al. A simple word embedding model for lexical substitution. In: *Proceedings of the 1st Workshop on Vector Space Modeling for Natural Language Processing*. 2015. S. 1-7.
- https://gab41.lab41.org/python2vec-word-embeddings-for-source-code-3d14d030fe8f#.dw78fmh1h
- COLLOBERT, Ronan; WESTON, Jason. A unified architecture for natural language processing: Deep neural networks with multitask learning. In: *Proceedings of the 25th international conference on Machine learning*. ACM, 2008. S. 160-167.
- ALLAMANIS, Miltiadis, et al. Suggesting accurate method and class names. In: *Proceedings of the 2015* 10th Joint Meeting on Foundations of Software Engineering. ACM, 2015. S. 38-49.
- ALLAMANIS, Miltiadis; PENG, Hao; SUTTON, Charles. A Convolutional Attention Network for Extreme Summarization of Source Code. arXiv preprint arXiv:1602.03001, 2016.
- IYER, Srinivasan, et al. Summarizing Source Code using a Neural Attention Model. 2016
- https://www.tensorflow.org/versions/r0.11/tutorials/word2vec/index.html
- http://blog.aylien.com/overview-word-embeddings-history-word2vec-cbow-glove/
- HINTON, Geoffrey E.; MCCLELLAND, James L.; RUMELHART, David E. Distributed representations, Parallel distributed processing: explorations in the microstructure of cognition, vol. 1: foundations. 1986.
- Gude A., Lab41, 2016: https://gab41.lab41.org/python2vec-word-embeddings-for-source-code-3d14d030fe8f#.dw78fmh1h

8. Sources

- VU, Phong Minh, et al. Mining User Opinions in Mobile App Reviews: A Keyword-Based Approach (T). In: *Automated Software Engineering (ASE), 2015 30th IEEE/ACM International Conference on*. IEEE, 2015. S. 749-759.
- NADERI, Nona; HIRST, Graeme. Argumentation Mining in Parliamentary Discourse. 2015
- RINOTT, Ruty, et al. Show Me Your Evidence–an Automatic Method for Context Dependent Evidence Detection. In: *Proceedings of the 2015 Conference on Empirical Methods in NLP (EMNLP), Lisbon, Portugal*. 2015. S. 17-21.
- IYYER, Mohit, et al. A Neural Network for Factoid Question Answering over Paragraphs. In: *EMNLP*. 2014. S. 633-644.
- OZSOY, Makbule Gulcin. From Word Embeddings to Item Recommendation. *arXiv preprint arXiv:1601.01356*, 2016.
- BARKAN, Oren; KOENIGSTEIN, Noam. Item2Vec: Neural Item Embedding for Collaborative Filtering. *arXiv preprint arXiv:1603.04259*, 2016.
- GANGULY, Debasis, et al. Word embedding based generalized language model for information retrieval. In: *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval*. ACM, 2015. S. 795-798.
- AMER, Nawal Ould; MULHEM, Philippe; GÉRY, Mathias. Toward Word Embedding for Personalized Information Retrieval. In: *Neu-IR: The SIGIR 2016 Workshop on Neural Information Retrieval*. 2016.
- ZAMANI, Hamed; CROFT, W. Bruce. Embedding-based query language models. In: *Proceedings of the 2016 ACM on International Conference on the Theory of Information Retrieval*. ACM, 2016. S. 147-156.
- BENTON, Adrian; ARORA, Raman; DREDZE, Mark. Learning multiview embeddings of twitter users. In: *The 54th Annual Meeting of the Association for Computational Linguistics*. 2016. S. 14.

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Thank you for your attention!
Questions?

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