Information Retrieval (IN4325)

Lecture 15: Intro to Word Embeddings

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Review paper 12

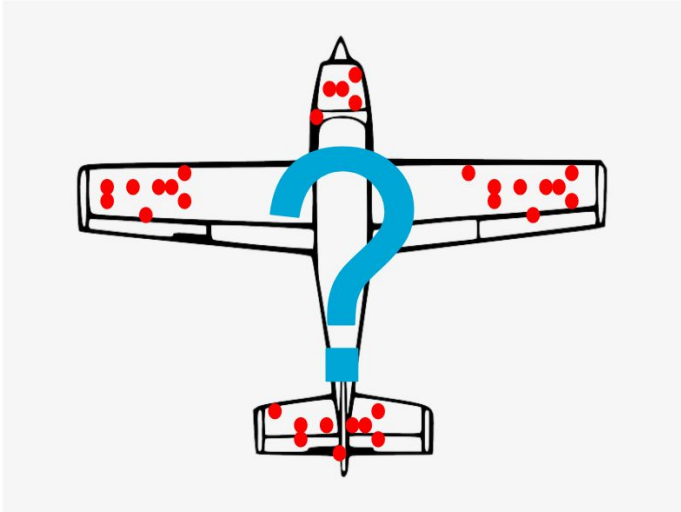
Tintarev, Nava, et al. "MinkApp: Generating spatio-temporal summaries for nature conservation volunteers." Proceedings of the Seventh International Natural Language Generation Conference. Association for Computational Linguistics, 2012.

TIRA - existing teams

Admin

- Interview
  - Why is BLEU more suitable than precision in this NLP project compared to an IR project?
  - What is a suitable classifier for small amounts of training data?
  - When might you use PMI in sentiment analysis?
  - Can you model sentiment analysis as a regression problem?

Yesterday



NLP bias

- Selection bias
- Annotation bias
  - Inter-annotator agreement
  - Bias in feature learning
- Model bias
- System/evaluation bias

		Coder B	
		Treats	No Treats
Coder A	Treats	12	5
	No Treats	8	20

Today

- Why word embeddings
- Word Embeddings
  - Dimensionality reduction, e.g., SVD
  - Word2Vec
    - Skipgrams
    - Continuous Bag of Words (CBoW)
  - GloVe
- Example: Analogies
  - Limitations
  - Data limitations

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To compare pieces of text

- We need effective representation of :
  - Words
  - Sentences
  - Text
- **Approach 1:** Use existing thesauri or ontologies like WordNet and Snomed CT (for medical). Drawbacks:
  - Manual
  - Not context specific
- **Approach 2:** Use co-occurrences for word similarity. Drawbacks:
  - Quadratic space needed
  - Relative position and order of words not considered

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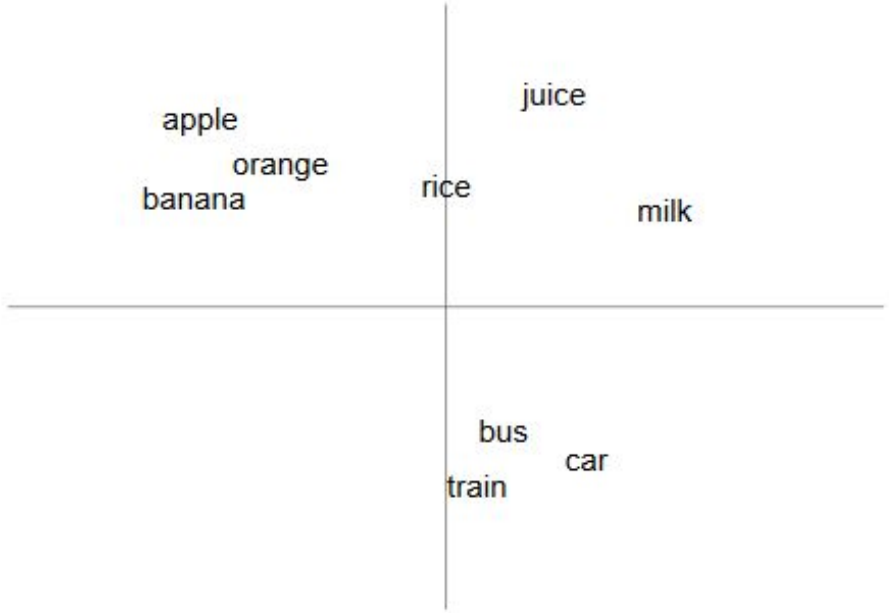
Approach 3: low dimensional vectors

- Store only “important” information in fixed, low dimensional vector.

Word embeddings

"A word is known by the company it keeps"

Distributional semantics



Reference Materials

- Deep Learning for NLP by Richard Socher (http://cs224d.stanford.edu/)
- Word2vec in Gensim by Radim Řehůřek (http://rare-technologies.com/deep-learning-with-word2vec-and-gensim/)

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Word Representations

Traditional Method - Bag of Words Model	Word Embeddings
• Uses one hot encoding • Each word in the vocabulary is represented by one bit position in a HUGE vector. • For example, if we have a vocabulary of 10000 words, and "Hello" is the 4th word in the dictionary, it would be represented by: 0 0 0 **1** 0 0 . . . . . 0 0 0 0 • Context information is not utilized	• Stores each word in as a point in space, where it is represented by a vector of fixed number of dimensions (generally 300) • Unsupervised, built just by reading huge corpus • For example, "Hello" might be represented as : **[0.4, -0.11, 0.55, 0.3 . . . 0.1, 0.02]** • Dimensions are basically projections along different axes, more of a mathematical concept.

Power of Word Vectors

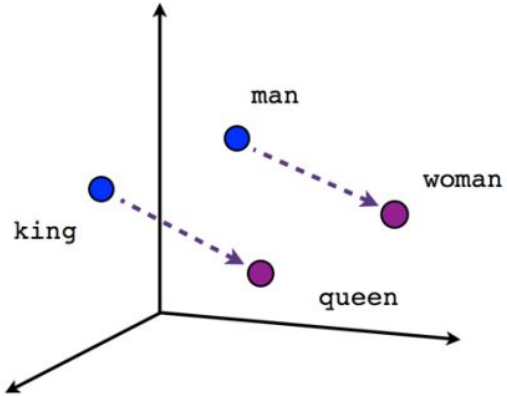
- They provide a fresh perspective to ***MANY*** problems in NLP, and not just solve one problem.

- Technological Improvement
  - Rise of deep learning since 2006 (Big Data + GPUs + Work done by Andrew Ng, Yoshua Bengio, Yann Lecun and Geoff Hinton)

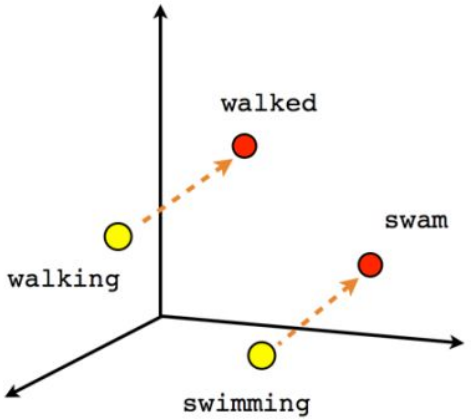
  - Application of Deep Learning to NLP – led by Yoshua Bengio, Christopher Manning, Richard Socher, Tomas Mikalov

- The need for unsupervised learning . (Supervised learning tends to be excessively dependant on hand-labelled data and often does not scale)

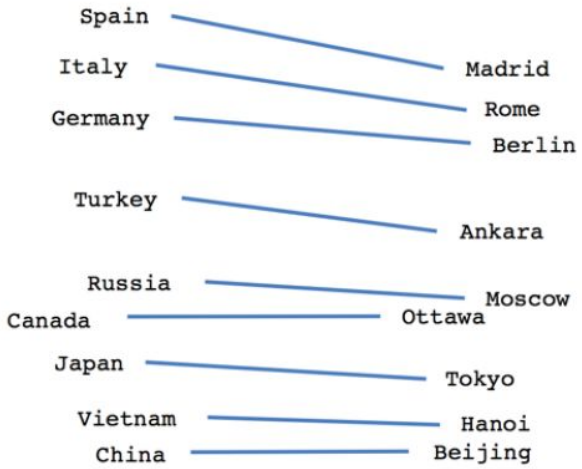
Examples



Male-Female



Verb tense



Country-Capital

vector[Queen] = vector[King] - vector[Man] + vector[Woman]

Examples

Expression	*Nearest token*
Paris - France + Italy	Rome
bigger - big + cold	colder
sushi - Japan + Germany	bratwurst
Cu - copper + gold	Au
Windows - Microsoft + Google	Android
Montreal Canadiens - Montreal + Toronto	Toronto Maple Leafs

So, how does Word Embedding ‘solve problems in NLP’?

Applications of Word Vectors

Word Similarity

Classic Methods : Edit Distance, WordNet, Porter's Stemmer, Lemmatization using dictionaries

- Easily identifies similar words and synonyms since they occur in similar contexts
- Stemming (thought -> think)
- Inflections, Tense forms
- *E.g., Think, thought, ponder, pondering,*
- *E.g., Plane, Aircraft, Flight*

Applications of Word Vectors

Sentiment Analysis

Classic Methods : Naive Bayes, Random Forests/SVM

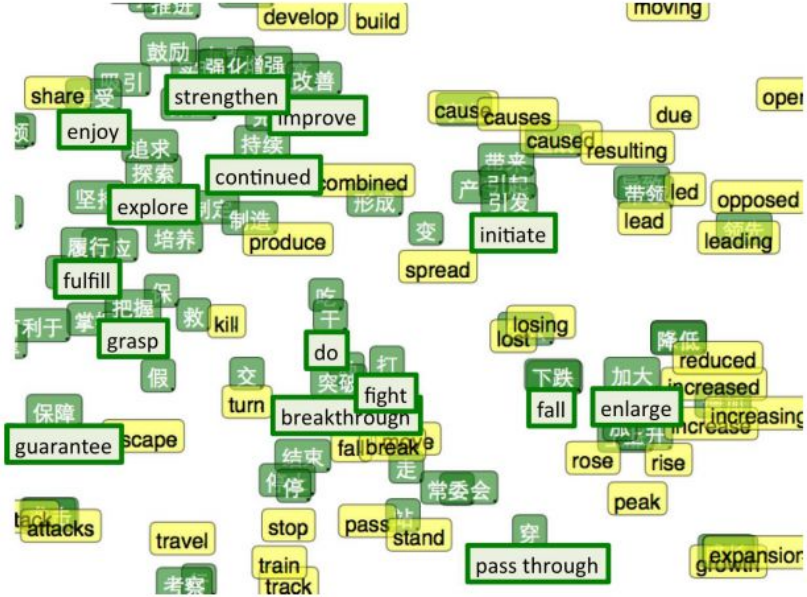
- Classifying sentences as positive and negative
- Building sentiment lexicons using seed sentiment sets
- No need for classifiers, we can just use cosine distances to compare unseen reviews to known reviews.

```
Enter word or sentence (EXIT to break): sad

Word: sad  Position in vocabulary: 4067

                                             Word       Cosine distance
--------------------------------------------------------------------------
                                        saddening                 0.727309
                                              Sad                 0.661083
                                         saddened                 0.660439
                                    heartbreaking                 0.657351
                                    disheartening                 0.650732
                                    Meny_Friedman                 0.648706
                               parishioner_Pat_Patello            0.647586
                                       saddens me                 0.640712
```

Applications of Word Vectors

Machine Translation

Classic Methods : Rule-based machine translation, morphological transformation



Applications of Word Vectors

Part-of-Speech and Named Entity Recognition

Classic Methods : Sequential Models (MEMM, Conditional Random Fields), Logistic Regression

	POS WSJ (acc.)	NER CoNLL (F1)
State-of-the-art*	97.24	89.31
Supervised NN	**96.37**	**81.47**
Unsupervised pre-training followed by supervised NN**	**97.20**	**88.87**
+ hand-crafted features***	97.29	89.59

Applications of Word Vectors

Relation Extraction

Classic Methods : OpenIE, Linear programing models, Bootstrapping

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Building these `magical' vectors . . .

- How do we actually build these super-intelligent vectors, that seem to have such magical powers?
- How to find a word's friends?
- We will discuss the most common methods to build such lower-dimension vector representations for words based on their context
  1. Co-occurrence Matrix with SVD
  2. word2vec (*Google)*
  3. Global Vector Representations (GloVe) (*Stanford)*

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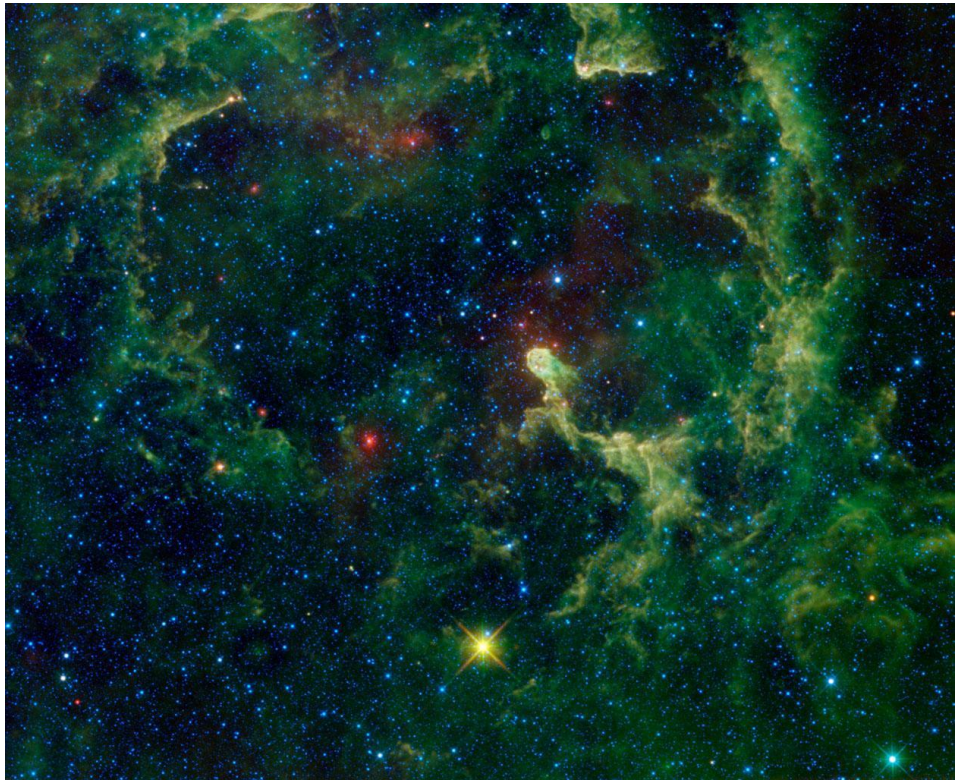
Singular Value Decomposition (SVD)

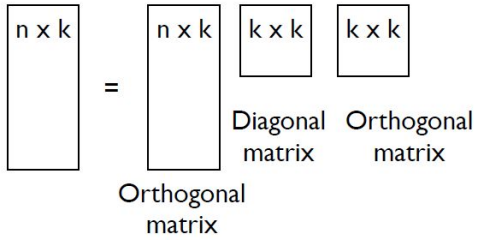
Elephant's Trunk nebula from NASA's Wide-field Survey Explorer (WISE)



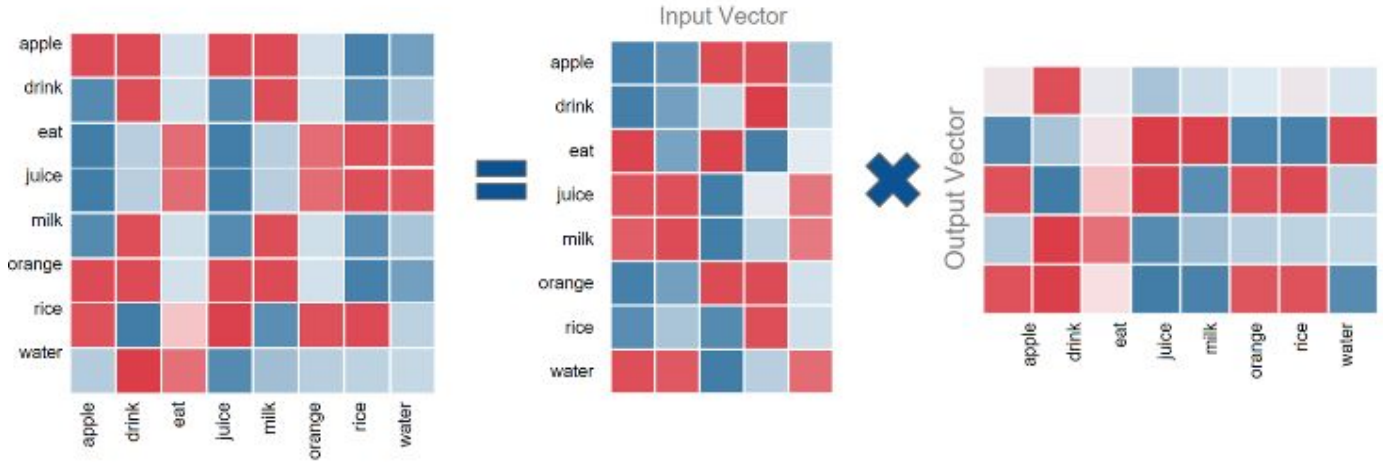
Approach 3: low dimensional vectors

- Store only “important” information in fixed, low dimensional vector.
- Single Value Decomposition (SVD) on co-occurrence matrix
- k = n = size of vocabulary

$$\mathbf{X} = \mathbf{U}\mathbf{D}\mathbf{V}^{\mathsf{T}}$$



Singular Value Decomposition



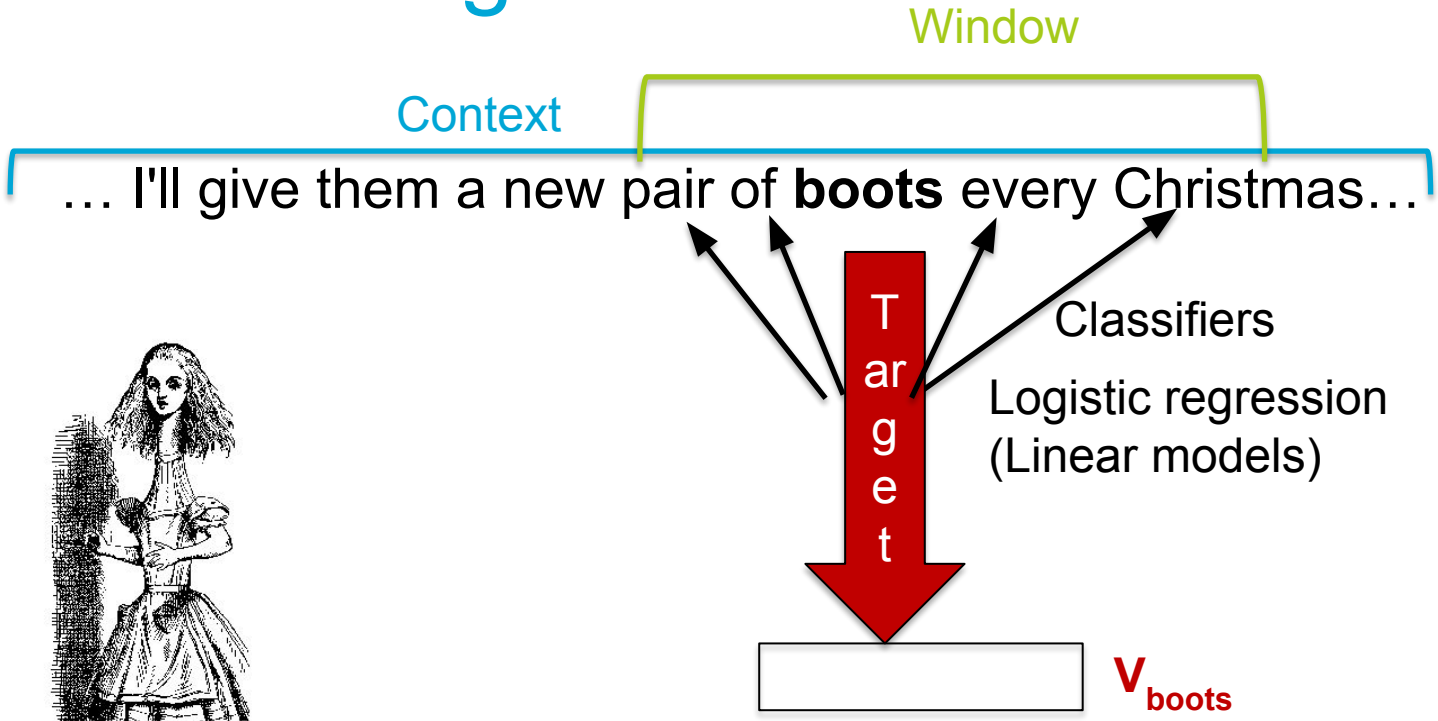
The problem with this method, is that we may end up with matrices having billions of rows and columns, which makes SVD computationally restrictive.

Problems with SVD

- Computational cost scales quadratically for n x k matrix
- Hard to incorporate new words or documents
- Does not consider order of words

Word2Vec

Embedding overview



word2vec Approach to represent the meaning of word

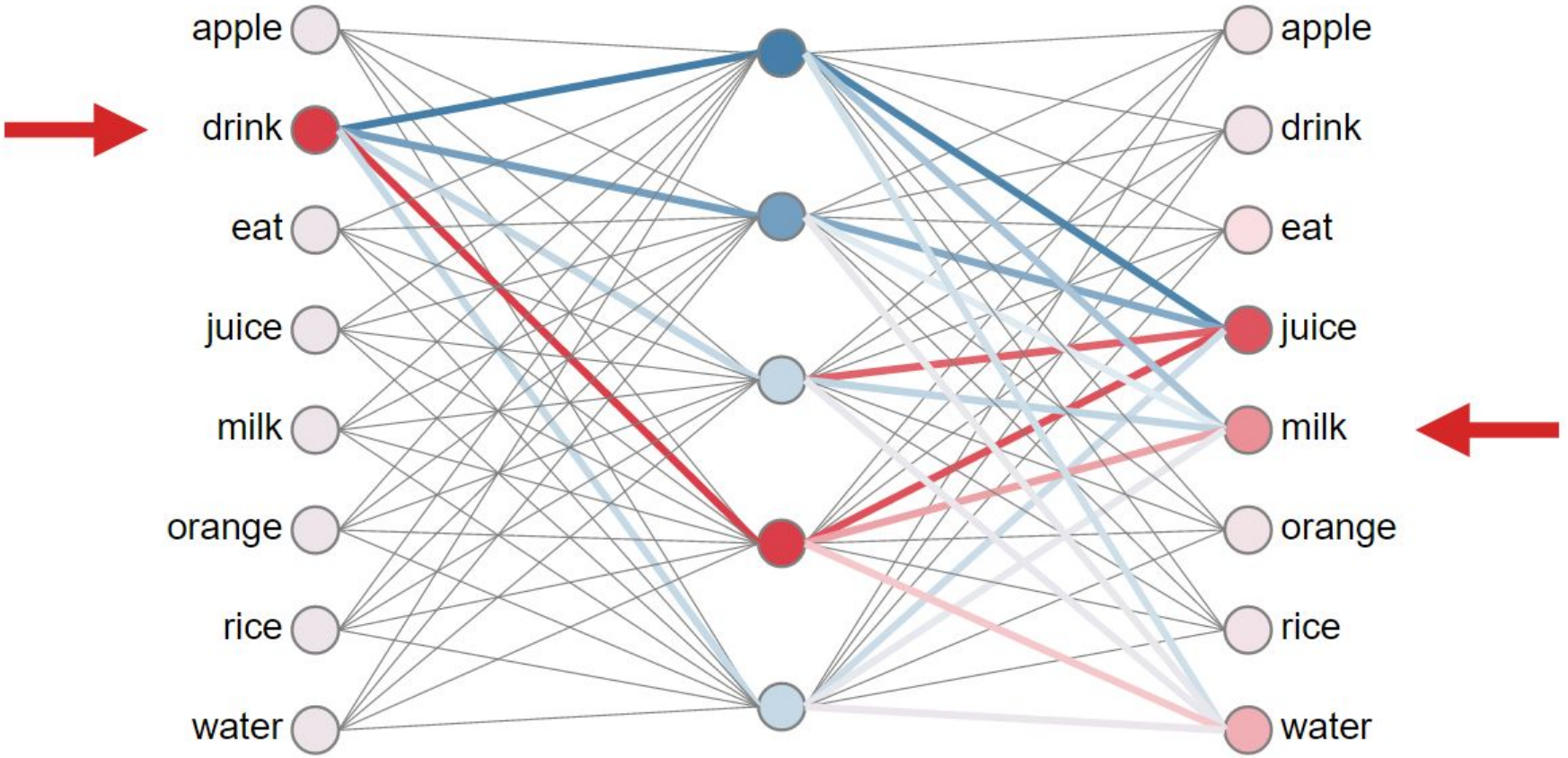
- Represent each word with a low-dimensional vector
- Word similarity = vector similarity
- **Key idea**: Predict surrounding words of every word
- Faster and can easily incorporate a new sentence/document or add a word to the vocabulary

Training Data

1. eat|apple
2. eat|orange
3. eat|rice
4. drink|juice
5. drink|milk
6. orange|juice
7. apple|juice
8. rice|milk

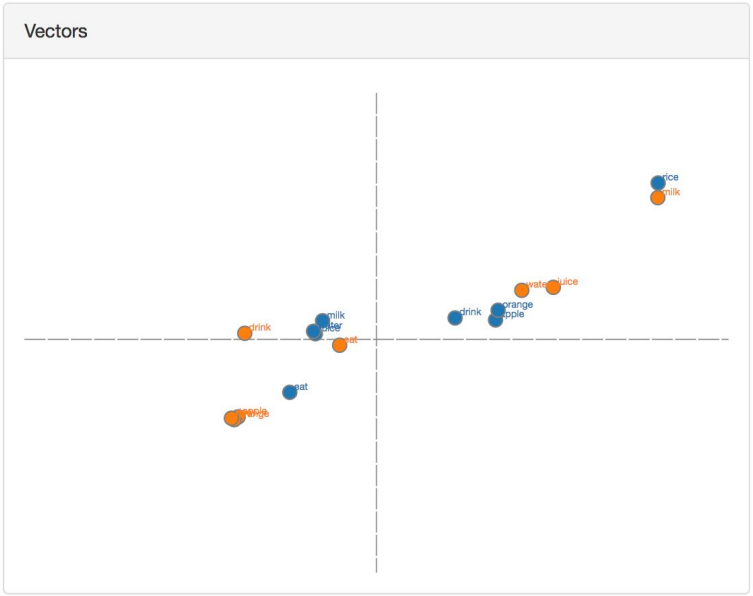
Concept :

1. Milk and Juice are drinks
2. Apples, Oranges and Rice can be eaten
3. Apples and Orange are also juices
4. Rice milk is a actually a type of milk!

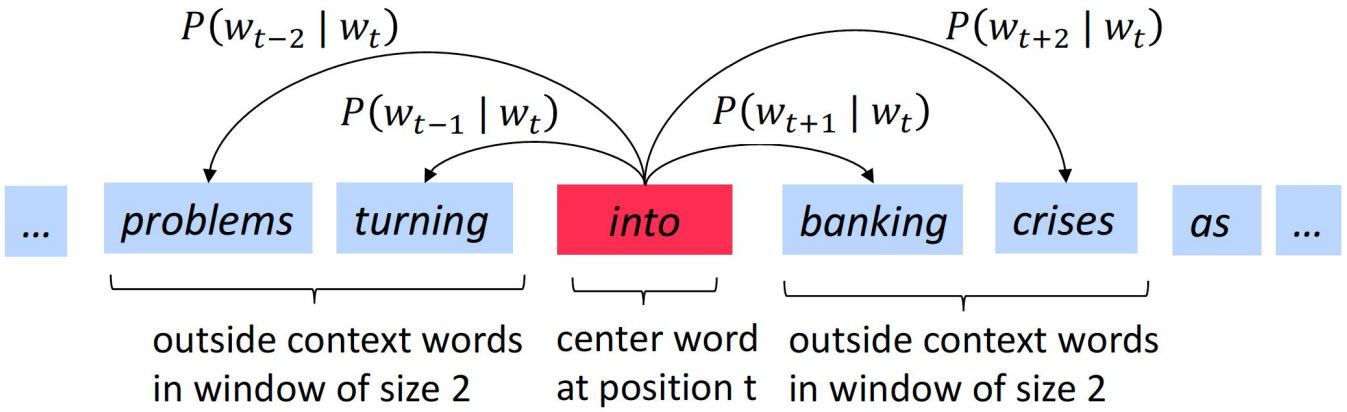

apple
drink
eat
juice
milk
orange
rice
water
apple
drink
eat
juice
milk
orange
rice
water

Word Embedding Visualization

http://ronxin.github.io/wevi/

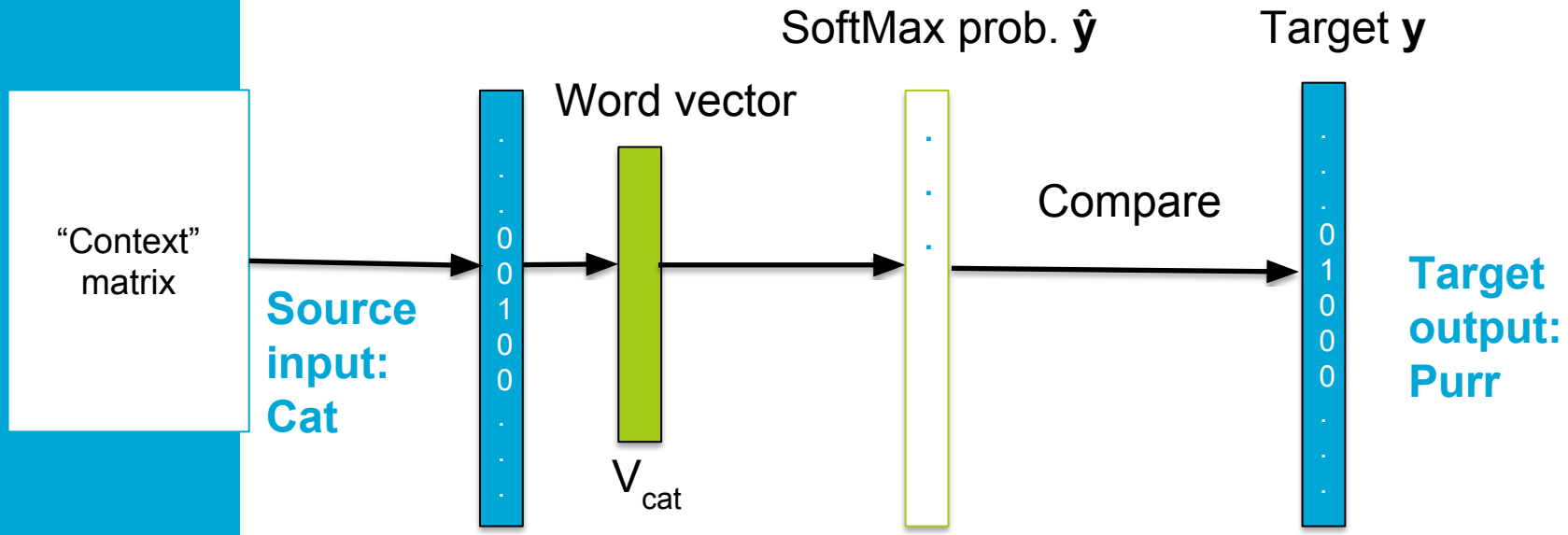


Context window



Context can be anything. E.g., a surrounding n-gram, a randomly sampled set of words from a fixed size window around word….

Architecture



Softmax

W_O- target
W_I - source
v' - “output” vector
v - “input” vector

Target output

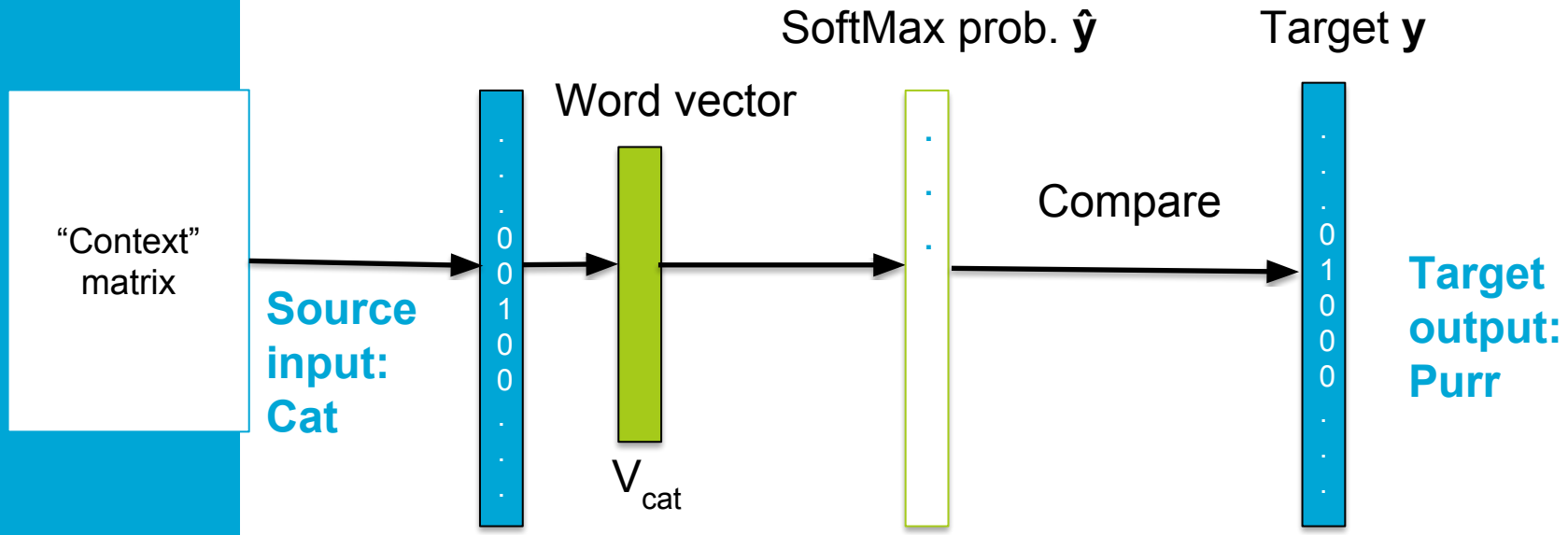
Source input

$$p(w_O|w_I) = \frac{\exp\left(v'_{w_O}{}^{\top} v_{w_I}\right)}{\sum_{w=1}^{W} \exp\left(v'_{w}{}^{\top} v_{w_I}\right)}$$

[0,1]

- Minimize error using e.g, gradient descent:
  - $L(\hat{y},y)= \sum(y_i * \log \hat{y}_i)$

Architecture



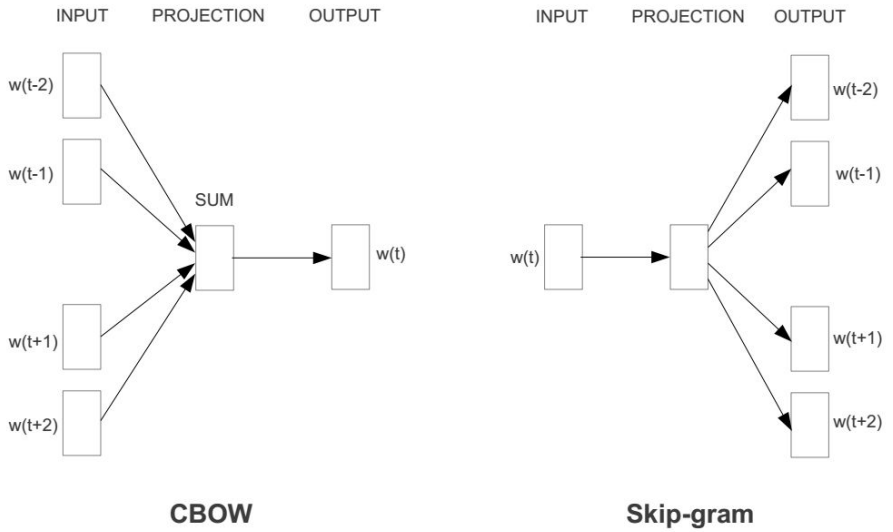
Some other concepts

- Known as neural embedding
- Often optimized using two methods
  1. Hierarchical Softmax
  2. Negative Sampling

- CBOW(continuous bag-of-words) and Skip-gram based training
- Down Sampling of Frequent words
- Phrasal and paragraph vectors

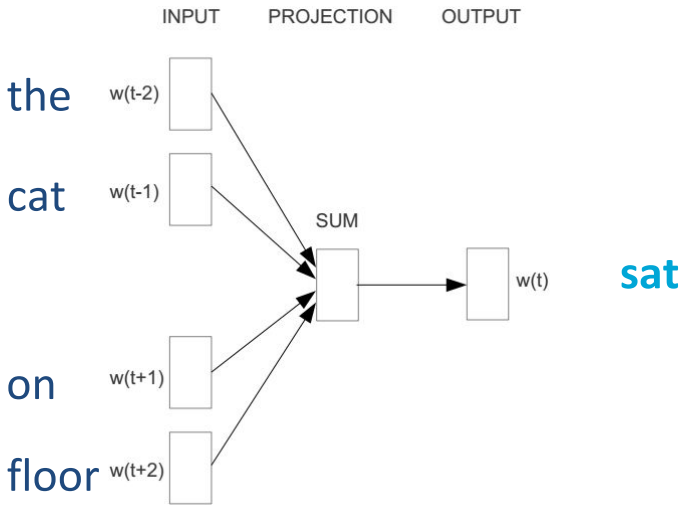
Word2vec - 2 neural models

- **Continuous Bag of Word** (CBOW): use a window of word to predict the middle word
- **Skip-gram** (SG): use a word to predict the surrounding ones in window.



Word2vec – Continuous Bag of Word

- E.g. “The cat sat on floor”
  - Window size = 2



Review Paper 13

- Sensitive to position
  - Structured skip-gram model
  - Continuous Window BoW model
- Used an understanding of language!
- Tasks
  - PoS tagging
  - Dependency Parsing
- UNK
  - Word type with 50 parameters

Questions?

Using word2vec in your research . . .

- Easiest way to use it is via the Gensim library for Python (tends to be slowish, even though it tries to use C optimizations like Cython, NumPy)

https://radimrehurek.com/gensim/models/word2vec.html

- Original word2vec C code by Google

https://code.google.com/archive/p/word2vec/

Not necessarily suitable for Twitter data!

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Global Vectors for Word Representation (GloVe)

https://nlp.stanford.edu/projects/glove/

Main Idea

- Uses ratios of co-occurrence probabilities, rather than the co-occurrence probabilities themselves

Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	1.36	0.96

GloVe

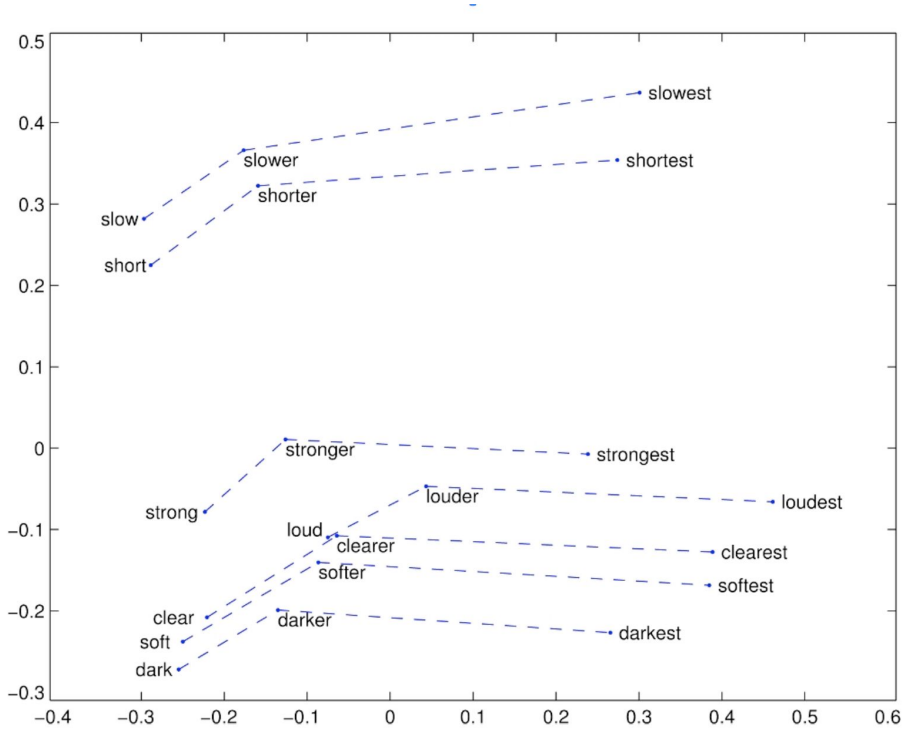
- Fast training
- Scalable to huge corpora
- Good performance even with small corpus, and small vectors
- By Pennington, Socher, Manning (2014)

Least Squares Problem

- Often used for data fitting
- Several equations, set models toward a solution
- Solution **minimizes** sum of the squares of the residual

Residual: the difference between an observed value, and the fitted value provided by a model.

Examples


slowest
slower
shortest
shorter
slow
short
stronger
strongest
strong
louder
loudest
loud
clearer
clearest
softer
softest
clear
darker
darkest
soft
dark
0.5
0.4
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
−0.4
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0
0.1
0.2
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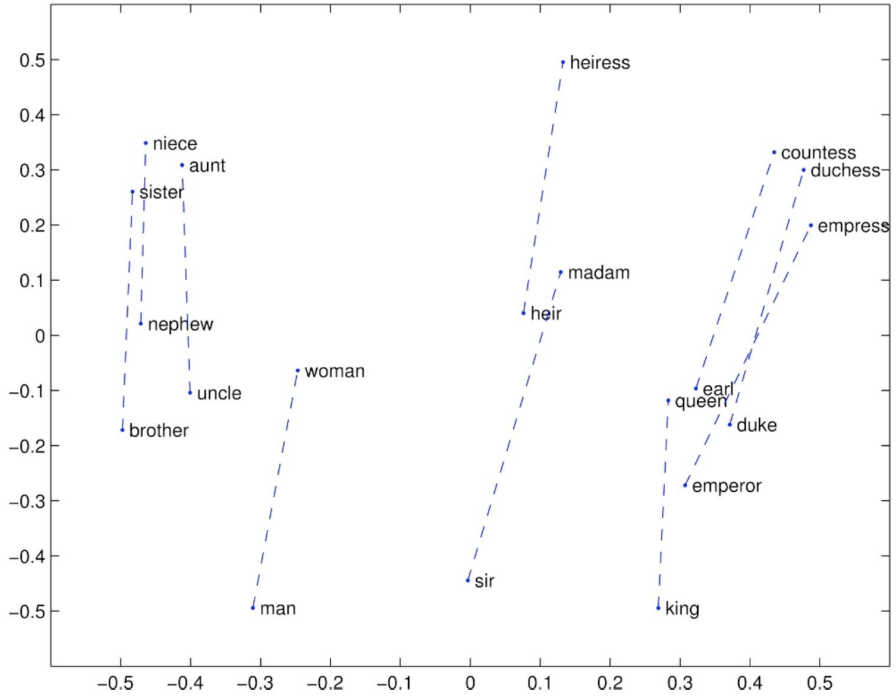
0.4
0.5
0.6

Examples


0.5
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0
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−0.5
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−0.4
−0.3
−0.2
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0
0.1
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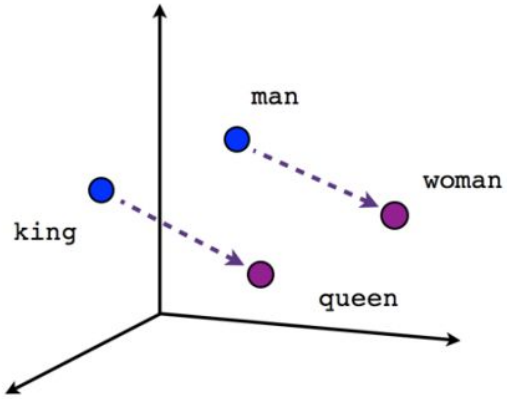
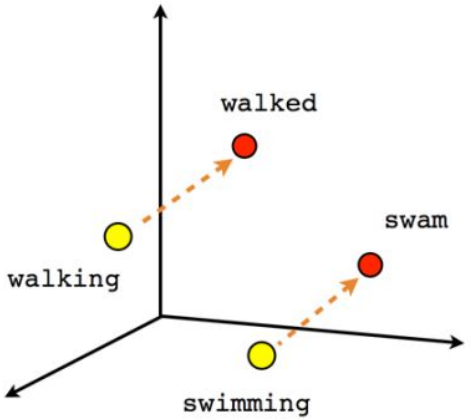
niece
aunt
sister
nephew
uncle
brother
woman
man
heiress
madam
heir
sir
countess
duchess
empress
earl
queen
duke
emperor
king

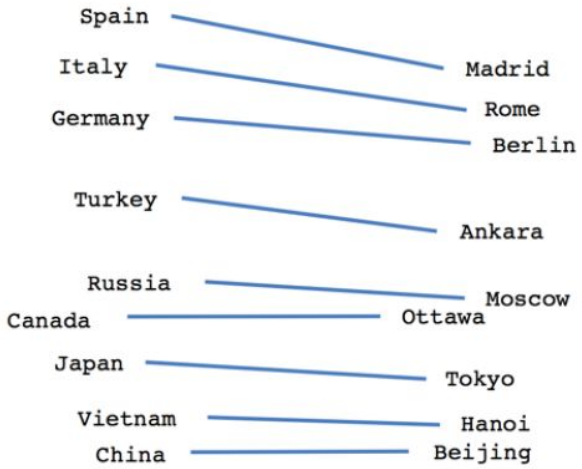
Examples



Male-Female



Verb tense



Country-Capital

vector[Queen] = vector[King] - vector[Man] + vector[Woman]

Word Analogies

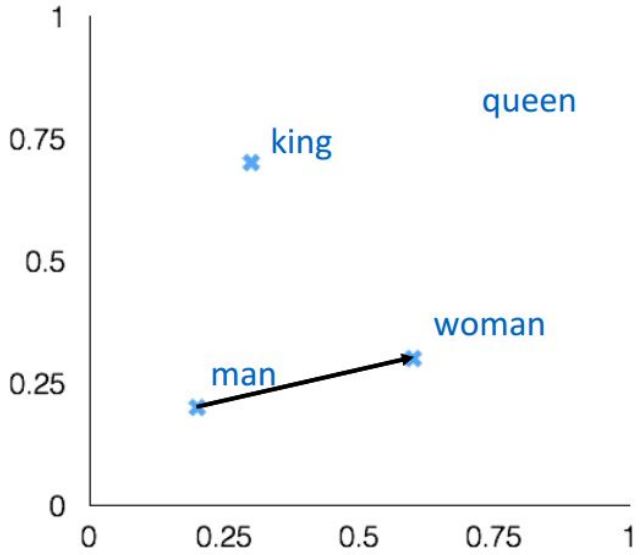
Test for linear relationships, examined by Mikolov et al. (2014)

a:b :: c:?

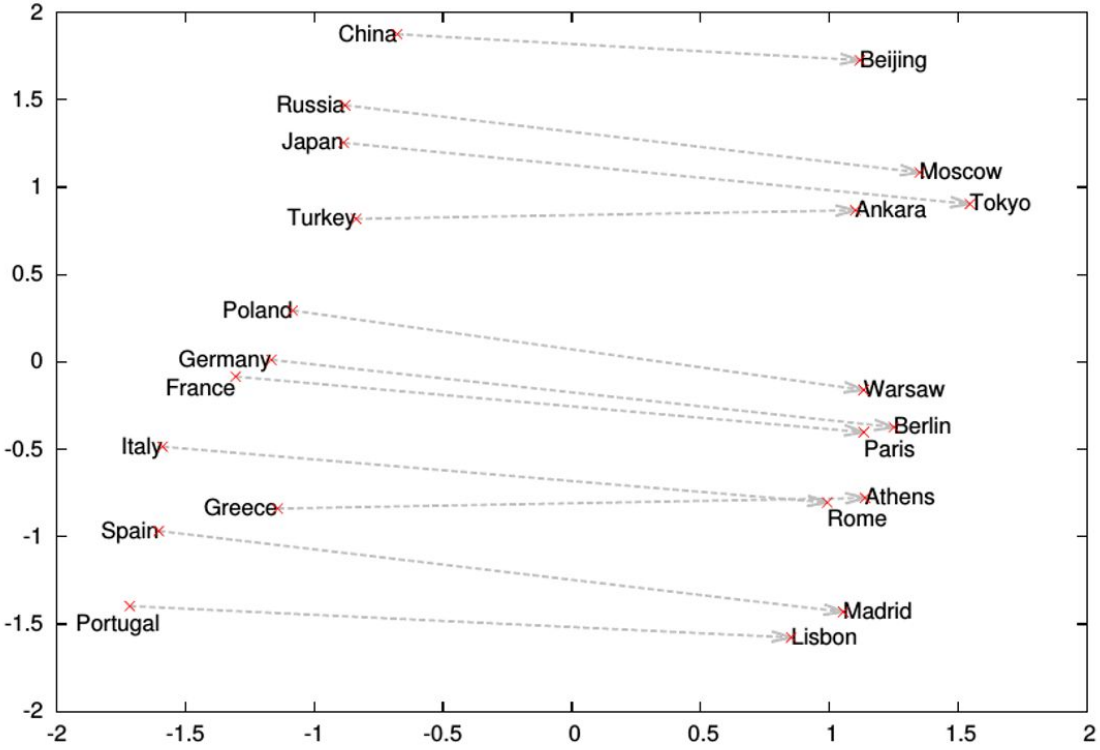
$$d = \arg\max_x \frac{(w_b - w_a + w_c)^T w_x}{||w_b - w_a + w_c||}$$

man:woman :: king:?

+	king	[0.30 0.70]
-	man	[0.20 0.20]
+	woman	[0.60 0.30]
	queen	[0.70 0.80]



Word analogies

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GOT THE STAR TO
PROVE IT!
ICANHASCHEEZBURGER.COM

Limitations Embeddings

Limitations 1

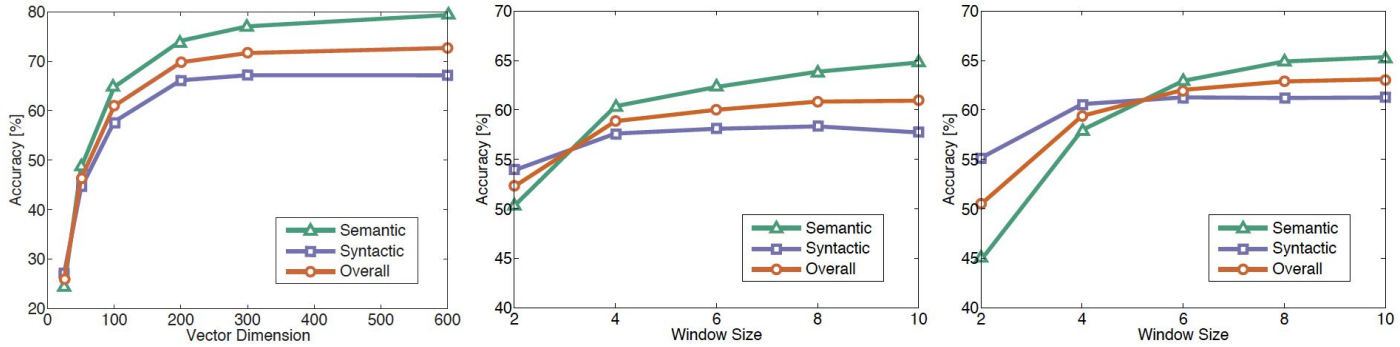
- Very vulnerable, and not a robust concept
- Can take a long time to train
- Non-uniform results
- Hard to understand and visualize

Limitations 2

- Inability to handle unknown or OOV words
- No shared representations at sub-word levels
- Scaling to new languages requires new embedding matrices

Data limitations

- Asymmetric context (only words to the left) are not as good



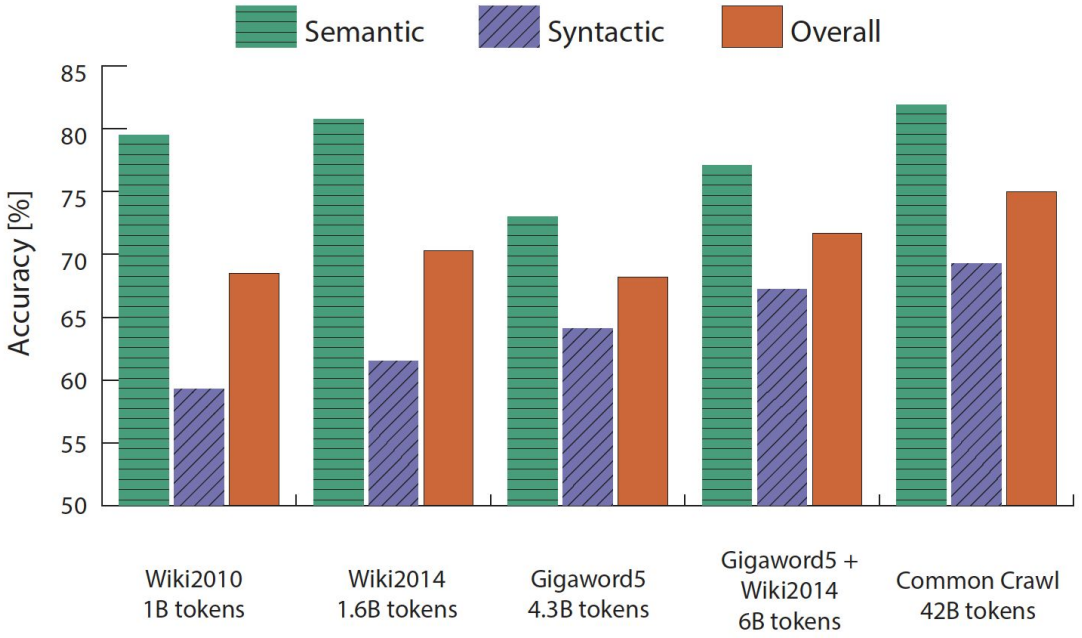
(a) Symmetric context (b) Symmetric context (c) Asymmetric context

- Best dimensions ~300, slight drop-off afterwards
- But this might be different for downstream tasks!

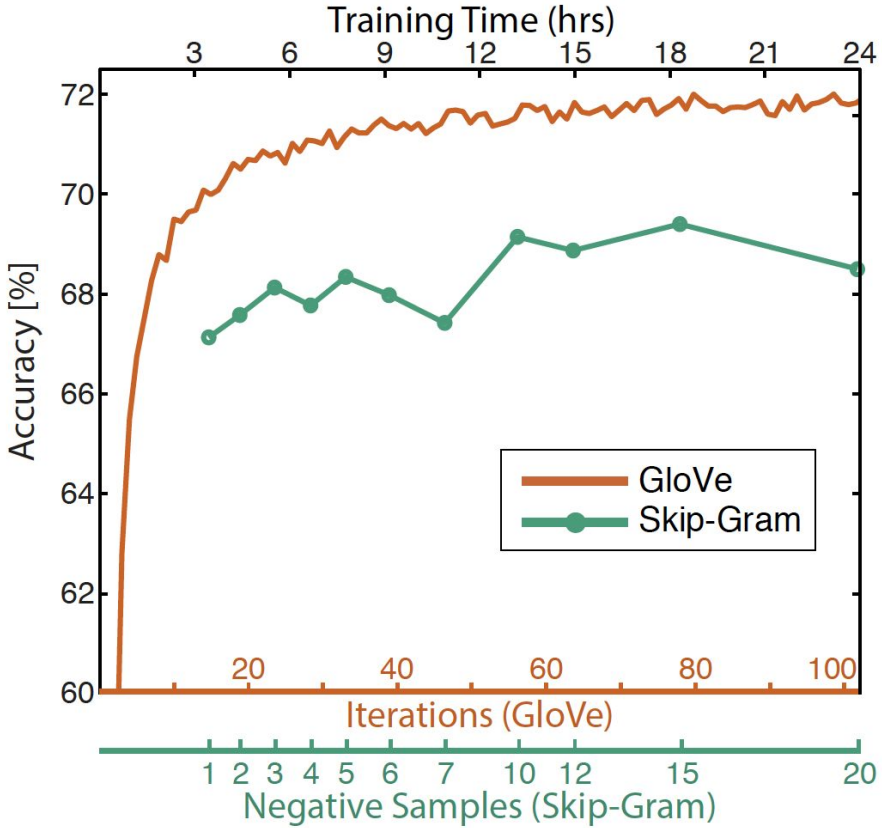
- Window size of 8 around each center word is good for Glove vectors

More data!

- More data helps, Wikipedia is better than news text!

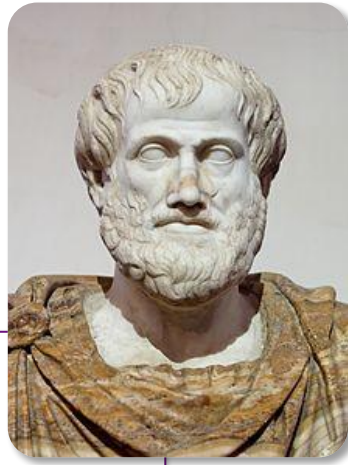


More training!



Towards Analogy-Enabled Recommendation

- **Towards human-level communication…**
  - Main tool between humans: **analogies**
    - “Core of human cognition”
    - “The thing that makes us smart”
  - Does this also work for recommendation?
    - **Querying and Explaining**



Analogy (from Greek ἀναλογία, "proportion") is a cognitive process of transferring information or meaning from a particular subject (*the source*) to another particular subject (*the target*), and a linguistic expression corresponding to such a process.[…]

Towards Analogy-Queries

- **Explain complex concepts intuitively**
- Describe concepts **not using the respective domain vocabulary** or domain knowledge
- **Communicate a lot of semantics in only a few words**

Analogy Semantics for Recommendations

- – **Completion query**:

  $?: [a_1, a_2] :: [b_1, ?]$

::

?

Analogy Semantics for Recommendations

- Completion: $?: [a_1, a_2] :: [b_1, ?]$

Analogies from an Algorithmic Point of View

- **Multiple Choice:**
- $?: [a_1, a_2] :: ?\{[b_1, b_2], \ldots, [z_1, z_2]\}$



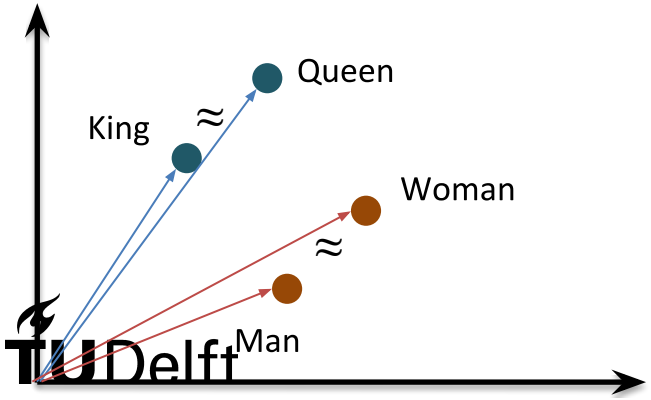


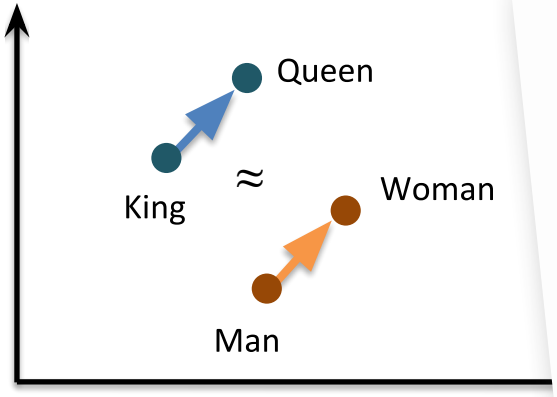





Solving Analogy Queries

- **Word Embeddings**: Current peak of distributional semantics research based on Neural Networks (e.g., Word2Vec)
  - Has many surprising applications…
  - Learn a semantic vector representation of words
  - **Claim**: Word Embeddings are good at analogy processing! TRUE?






Distributed Representations of Words and Phrases and their Compositionality

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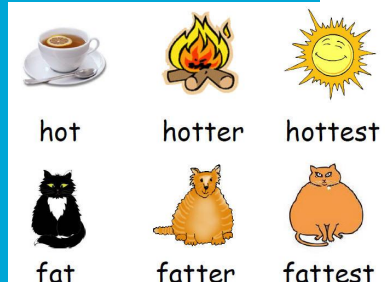
Abstract

The recently introduced continuous Skip-gram model is an efficient method for learning high-quality distributed vector representations that capture a large number of precise syntactic and semantic word relationships. In this paper we present several extensions that improve both the quality of the vectors and the training speed. By subsampling of the frequent words we obtain significant speedup and also learn more regular word representations. We also describe a simple alternative to the hierarchical softmax called negative sampling.

An inherent limitation of word representations is their indifference to word order and their inability to represent idiomatic phrases. For example, the meanings of "Canada" and "Air" cannot be easily combined to obtain "Air Canada". Motivated

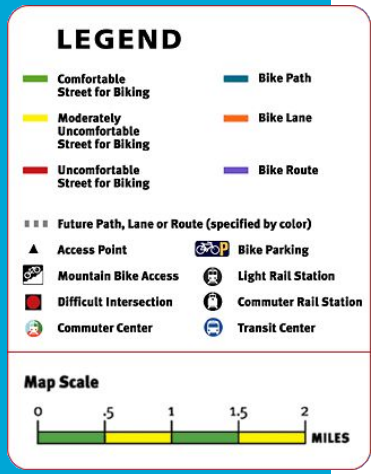
Benchmark Sets

- Word Embeddings are usually evaluated using “weak” analogies, only 25 relationship types: These analogies are near useless!
  - [hot, hotter] :: [fat, fatter] : **Superlative relationship**
  - [Delft, Netherlands] :: [Rome, Italy] : **City-In Relationship**
  - [petal, flower] :: [tire, car] **: Part-Of relationship**



Better Benchmark Sets

SAT®



- **SAT analogy challenges**
  - Hand-crafted set used in US-college admission test
    - **College students get around <u>55%</u> of these challenges right**
  - Multiple-choice challenges with clear and undisputable "correct" answers
    - 5 choices per challenge
  - 353 challenges
  - Many domains
  - **Difficulty comes from using rare words**

? <u>legend :: map</u>

a) subtitle :: translation
b) bar :: graph
c) figure: blueprint
d) key :: chart
e) footnote :: information

AGS Benchmark Set

- **Multi-Step Crowdsourcing Process**
  - **Multiple-Steps == Easier quality control**
  - Start with **seed word pairs** which are “somehow” related
    - Mined from SimLex-999 or WordSim-353
  - Used **crowdsourcing** to classify each seed word pair into one of 14 categories
  - Based on the categories**, generate new word pairs** sharing the same relationship
    - (Good examples, but also bad examples)
  - Obtain **aggregated analogy ratings** for each pair

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The AGL Testset - Domains

Categories	#chall.	#analog.	Categories	#chall.	#analog.
Animals /Plants	10	128	House/Furniture/Clothing	17	169
Automobiles/Transportation	5	41	Humans/Human relations	3	28
Electrical/Electronics	4	42	Medicine/Healthcare	3	28
English grammar	11	121	Movies/Music	4	61
Food/Beverages	11	92	People/Profession	12	151
Geography/Architecture	9	144	Sports	4	33

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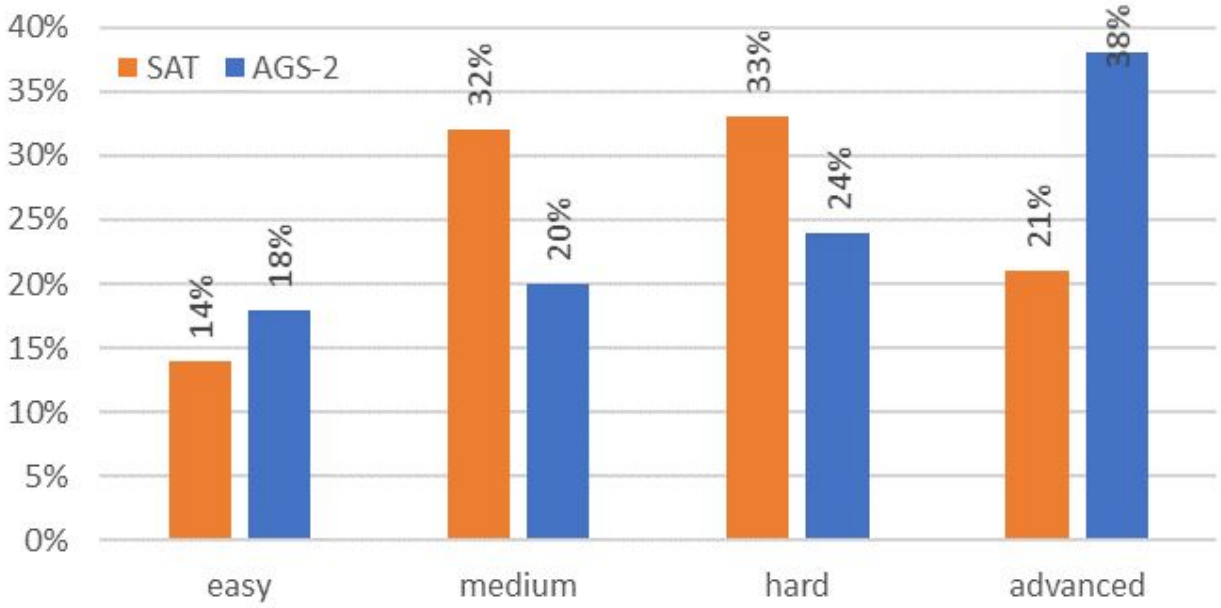
Our AGS-2 Benchmark Set

- New concept: **Analogy Rating**
  - Based the definiteness of the analogy, and its overall “quality”
    - **This is subjective, needs to be based on human judgement!**
  - Good example: [Bordeaux Area, France] :: [Napa Valley, US] : **famous-for-good-wine relationship**
  - **Subjective: Use crowdsourcing consensus**

Our AGS-2 Benchmark Set

- New concept: **Difficulty**
  - Analogies imply a reasoning process, which may be easier or harder to follow
  - Difficulty depends on abstractness of reasoning, rareness of vocabulary
  - Again: Subjective, Crowdsourcing consensus necessary

Difficulty of challenges in Analogy datasets



Our AGS-2 Benchmark Set

- Design goal of new AGS Benchmark set
  - **Include a wide variety of analogy semantics**
    - Cover different relationship types
    - Cover some defining analogies, but also some less defining ones
  - Allow for benchmarking all three query types
    - Confirmation, Completion, Multiple Choice
  - Include **analogy rating, difficulty rating** judging the quality of analogon combinations
    - Include analogon with high analogy rating, but also include some with a low rating
    - **Judgments by humans**

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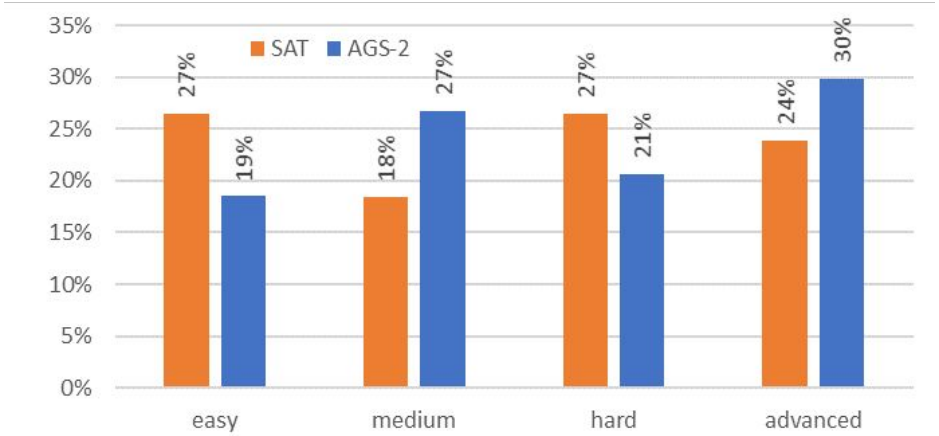
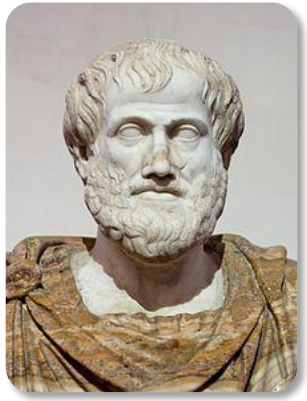
Word-Embeddings: How well do they do?

- Setup: Word2Vec using Wikipedia dumps
  - Multiple Choice: Find the best answer from given collection
- Result: Accuracy between 18-30%
  - Word2Vec does not perform well for easy challenges (humans have ≥80%)
  - Better for hard ones (humans ≤20%)



Summary and Outlook



- Human-Centered Information Systems are a big challenge for the future
  - Analogies are likely a central part
  - But: Analogies are hard to process, and hard to evaluate
    - Lot of subjectivity and common-sense consensus
    - Current benchmark datasets are not suitable
- Our AGS dataset is large step towards more semantic evaluation
  - Still, many improvements can be made…
  - Improve dataset covering more aspects of analogies
  - Better and stronger classification of challenges
  - Evaluations with a wider selection of approaches
- Toward analogy-based explanations!

This week

- Why word embeddings
- Word Embeddings
  - Relation to other dimension. reduction, e.g., SVD
  - Word2Vec
    - Skipgrams
    - Continious Bag of Words (CBoW)
  - GLOVE
- Example: Analogies
  - Limitations
  - Data limitations

This course...

- Intro
- Syntax
- Semantics
- Evaluation
- Machine learning
- NLG
- Annotation
- Embeddings

- NLU
  - Syntax
  - Semantics
  - Embeddings
- NLG
- Evaluation
  - Annotation
  - With people
  - Offline (ML)

Questions?

Final report due April 10

- 7-8 pages SIGCHI
- Title, authors
- Abstract
- **Introduction:** problem statement, motivation for the problem, overall plan to tackle the problem
- **Background:** what important works does this project build on
- **Approach:** what methods/algorithms did you use (**justify** why these are suitable)
- **Experiments:** describe your evaluation/experiments (**justify** experimental methodology), the results and discuss them (comparisons and critical discussion will be considered in the grading)
- **Conclusions:** describe what you learnt/found and what avenues for future work you see
- References

Milestones

- Signing up for an interview slot

Credits

- Natural Language Processing Lab, Texas A&M University
- Vagelis Hristidis, prepared with the help of Nhat Le
- Richard Socher, Stanford CS224d: Deep Learning for NLP

- Paper reference:
  - Christoph Lofi and Nava Tintarev. "Towards analogy-based recommendation: benchmarking of perceived analogy semantics". In *Complex-Rec workshop at Recsys'17*. 2017