Vector Embeddings

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TA: Omkar Kulkarni (he)

https://laramartin.net/NLP-class/

Slides modified from Dr. Frank Ferraro

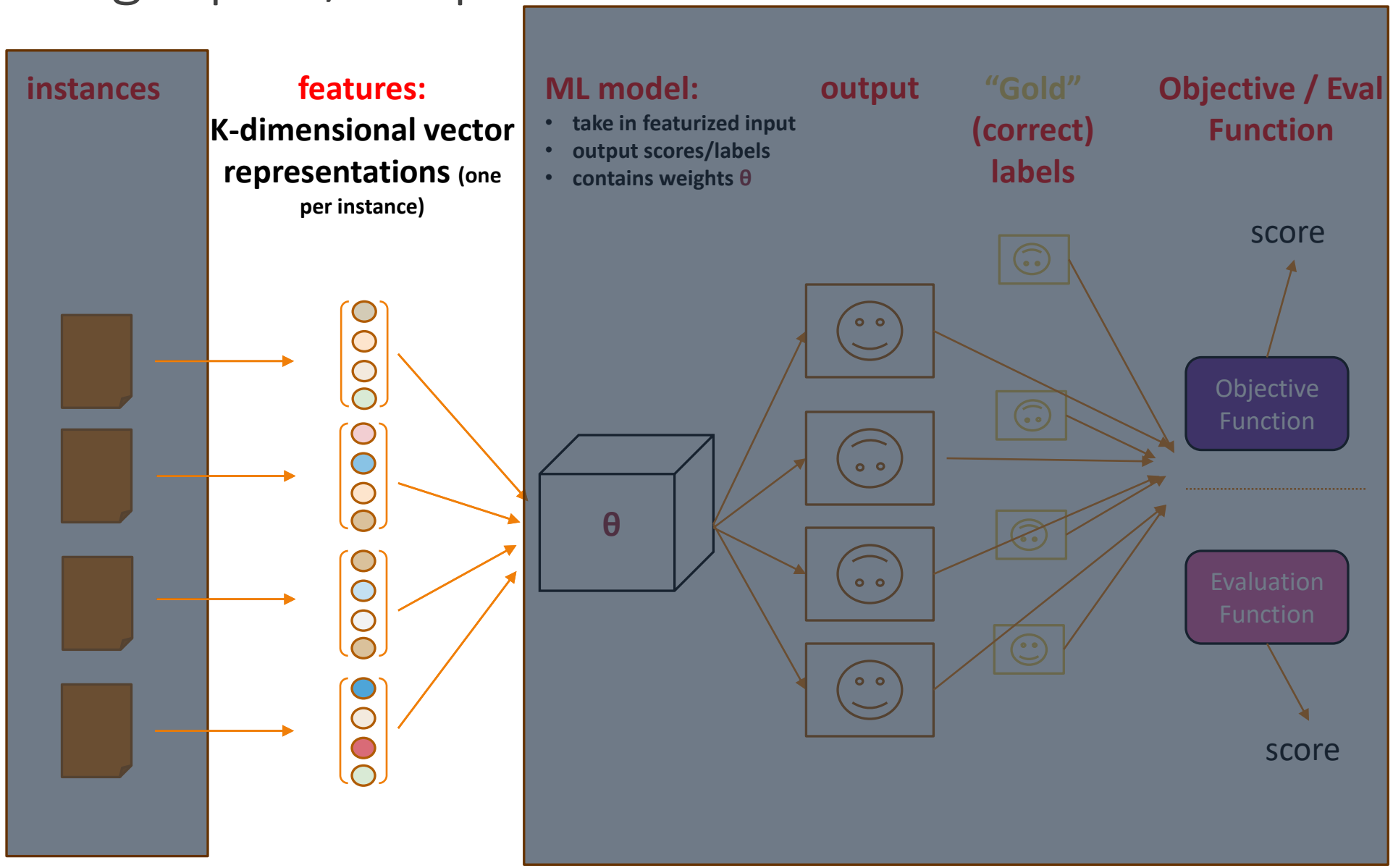
Learning Objectives

Understand the use & creation of dense vector embeddings

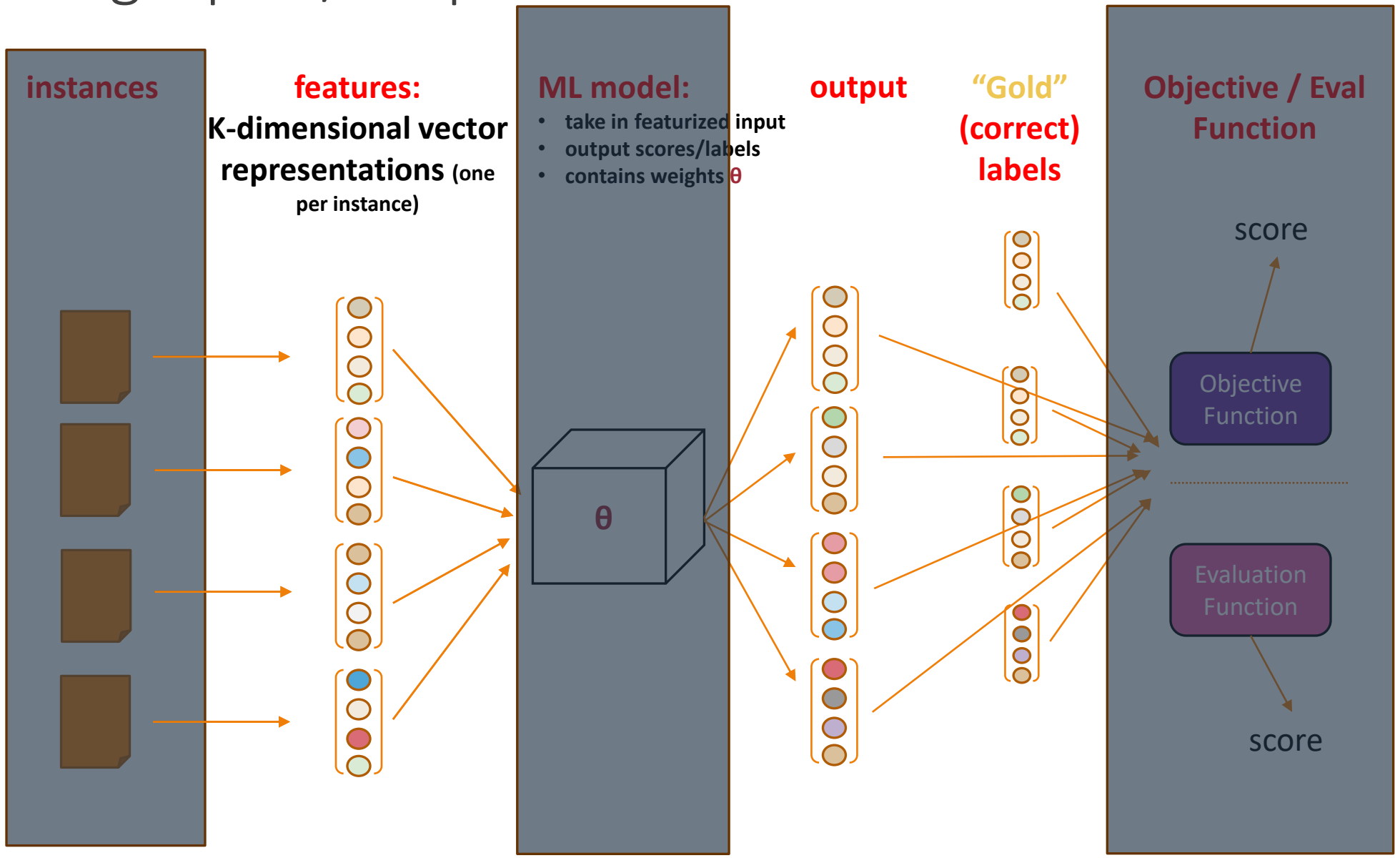
Calculate the distance between vector embeddings

Recognize popular vector embeddings

Representing Inputs/Outputs



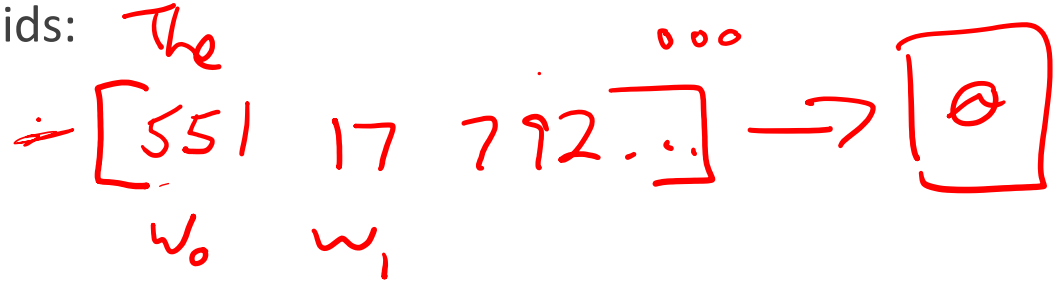
Representing Inputs/Outputs



How have we represented words?

Each word is a distinct item

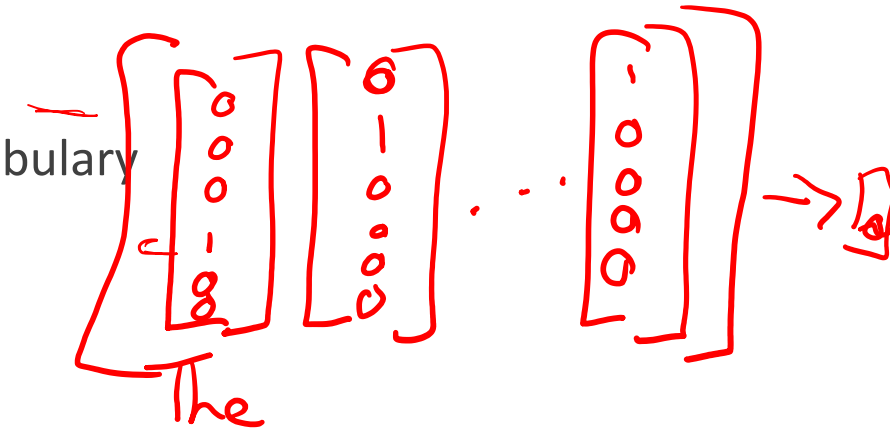
- Bijection between the strings and unique integer ids:
- "cat" --> 3, "kitten" --> 792 "dog" --> 17394



- Are "cat" and "kitten" similar?

Equivalently: "One-hot" encoding

- Represent each word type w with a vector the size of the vocabulary
- This vector has V-1 zero entries, and 1 non-zero (one) entry



Review: One-Hot Encoding Example

Let our vocab be {a, cat, saw, mouse, happy}

V = # types = 5

Assign:

a	4
cat	2
saw	3
mouse	0
happy	1

How do we represent "cat?"

$$e_{\text{cat}} = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}$$

How do we represent "happy?"

$$e_{\text{happy}} = \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

The Fragility of One-Hot Encodings
Case Study: Maxent Plagiarism Detector

Given two documents x_1, x_2, predict y = 1 (plagiarized) or y = 0 (not plagiarized)

What is/are the:

- Method/steps for predicting?
- General formulation?
- Features?

Image: http://3.bp.blogspot.com/_MWJDzvrnu7Y/TTcXpCWZerI/AAAAAAAAAWY/zxu1GwrIBz0/s1600/excellent-mr-burns.gif

Case Study: Maxent Plagiarism Detector (Feature Example)

Given two documents x_1, x_2, predict y = 1 (plagiarized) or y = 0 (not plagiarized)

Intuition: documents are more likely to be plagiarized if they have words in common

$$f_{\text{any-common-word,Plag.}}(x_1, x_2) = ???$$
$$f_{\text{<word v>,Plag.}}(x_1, x_2) = ???$$

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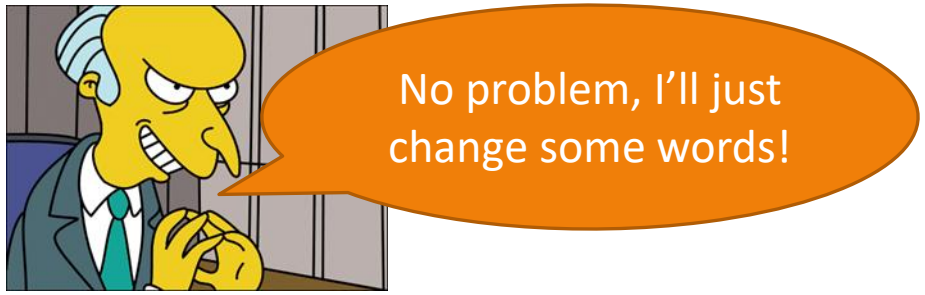

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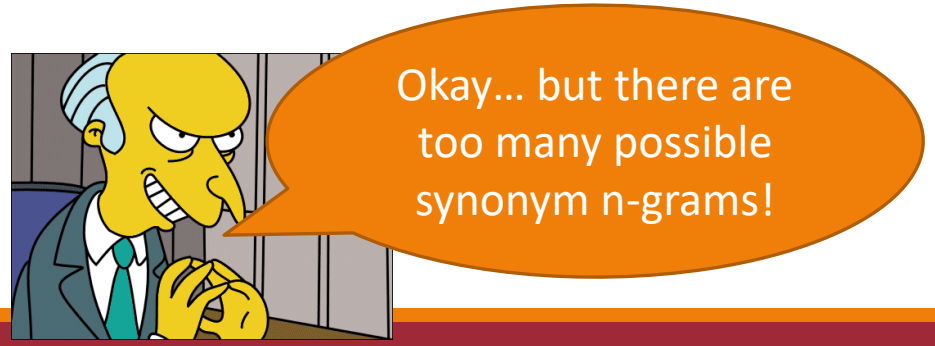

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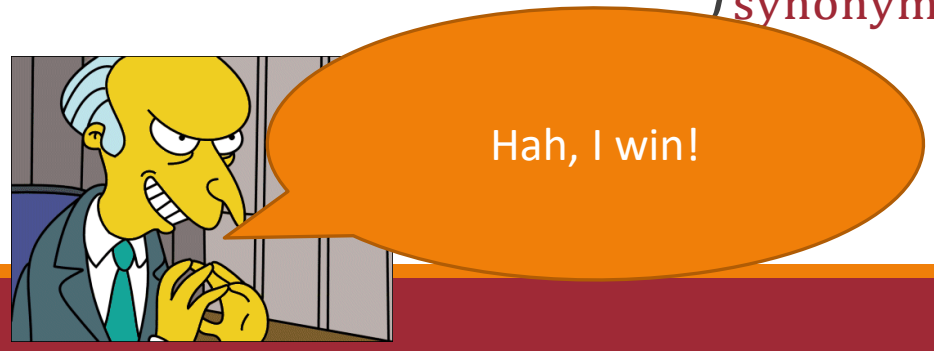

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Plagiarism Detection: Word Similarity?

MAINFRAMES

Mainframes are primarily referred to large computers with rapid, advanced processing capabilities that can execute and perform tasks equivalent to many Personal Computers (PCs) machines networked together. It is characterized with high quantity Random Access Memory (RAM), very large secondary storage devices, and high-speed processors to cater for the needs of the computers under its service.

Consisting of advanced components, mainframes have the capability of running multiple large applications required by many and most enterprises and organizations. This is one of its advantages. Mainframes are also suitable to cater for those applications (programs) or files that are of very high demand by its users (clients). Examples of such organizations and enterprises using mainframes are online shopping websites such as

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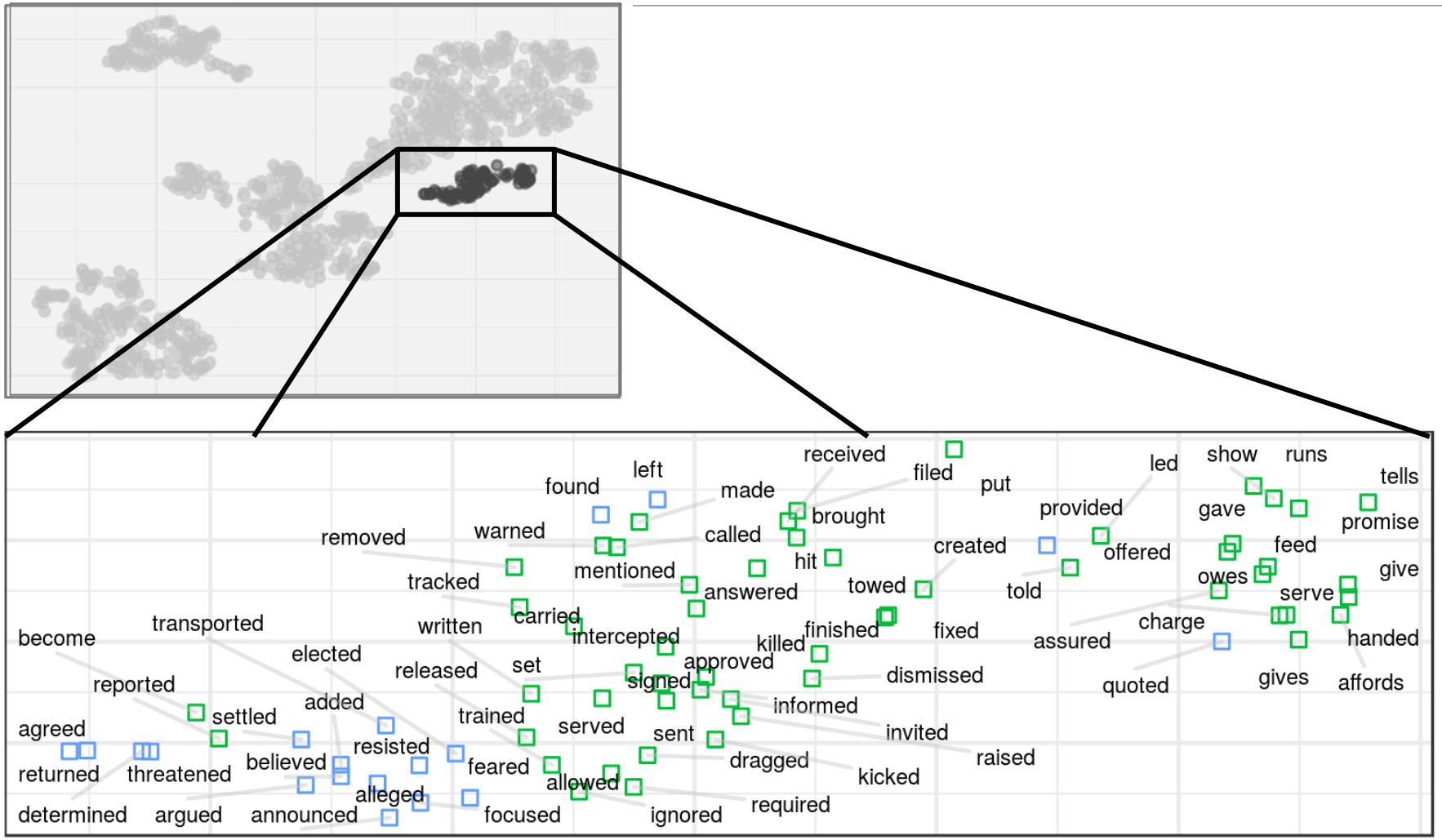
A Dense Representation (E=2)



Distributional Representations

A dense, "low"-dimensional vector representation

Many values are not 0 (or at least less sparse than one-hot)

Up till ~2013: E could be any size
2013-present: E << vocab

An E-dimensional vector, often (but not always) real-valued

These are also called

- **embeddings**
- **Continuous representations**
- **(word/sentence/…) vectors**
- **Vector-space models**

Continuous Meaning

The paper reflected the truth.

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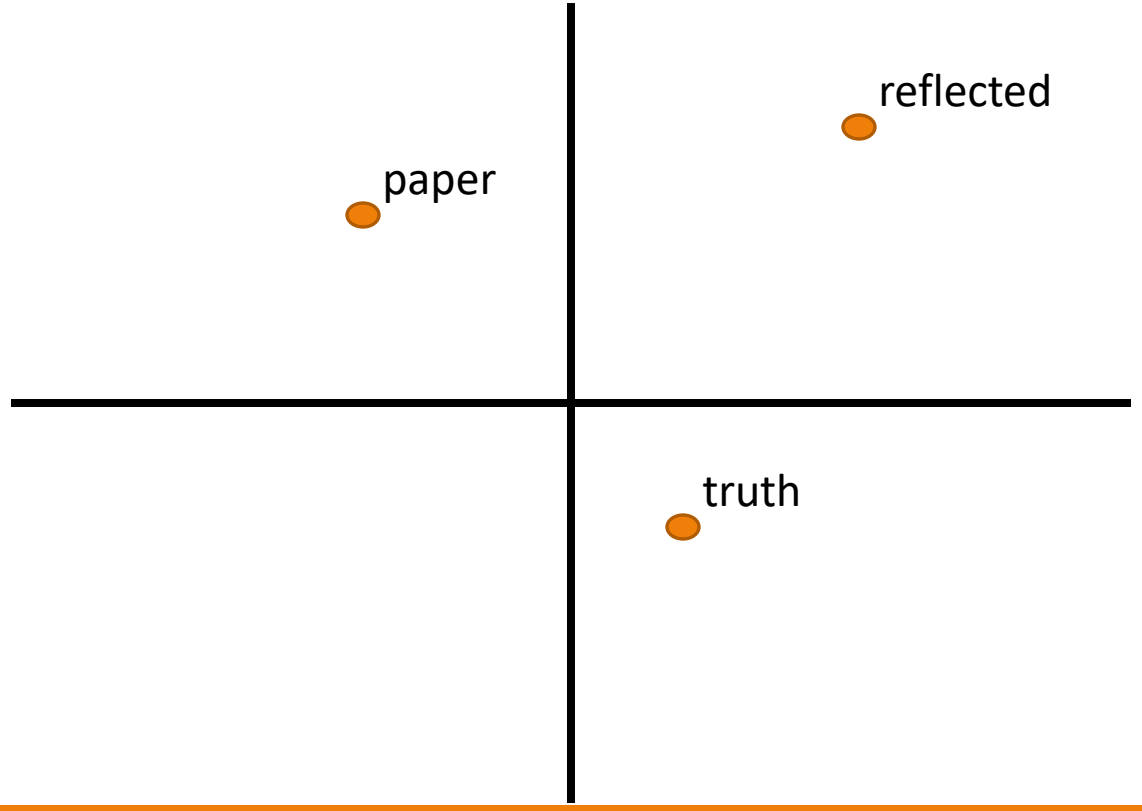

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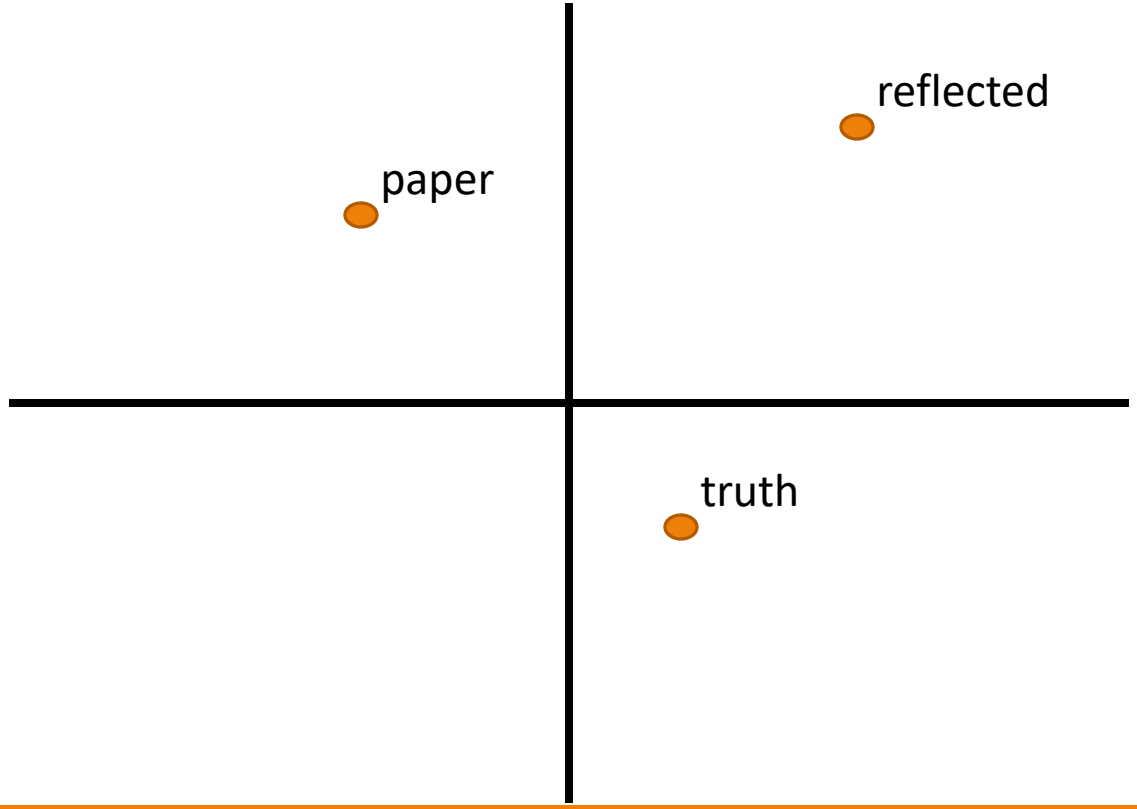

glean

hide

falsehood

where might these go in this space?

Continuous Meaning

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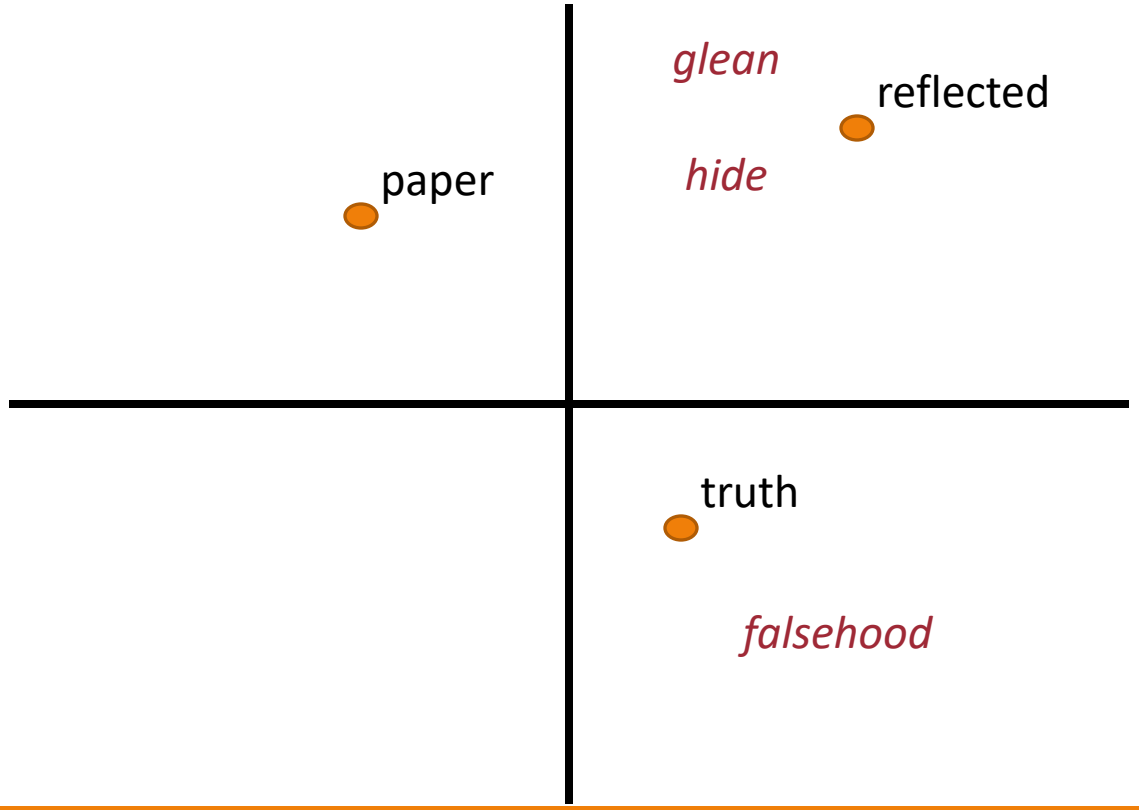

One option

Continuous Meaning

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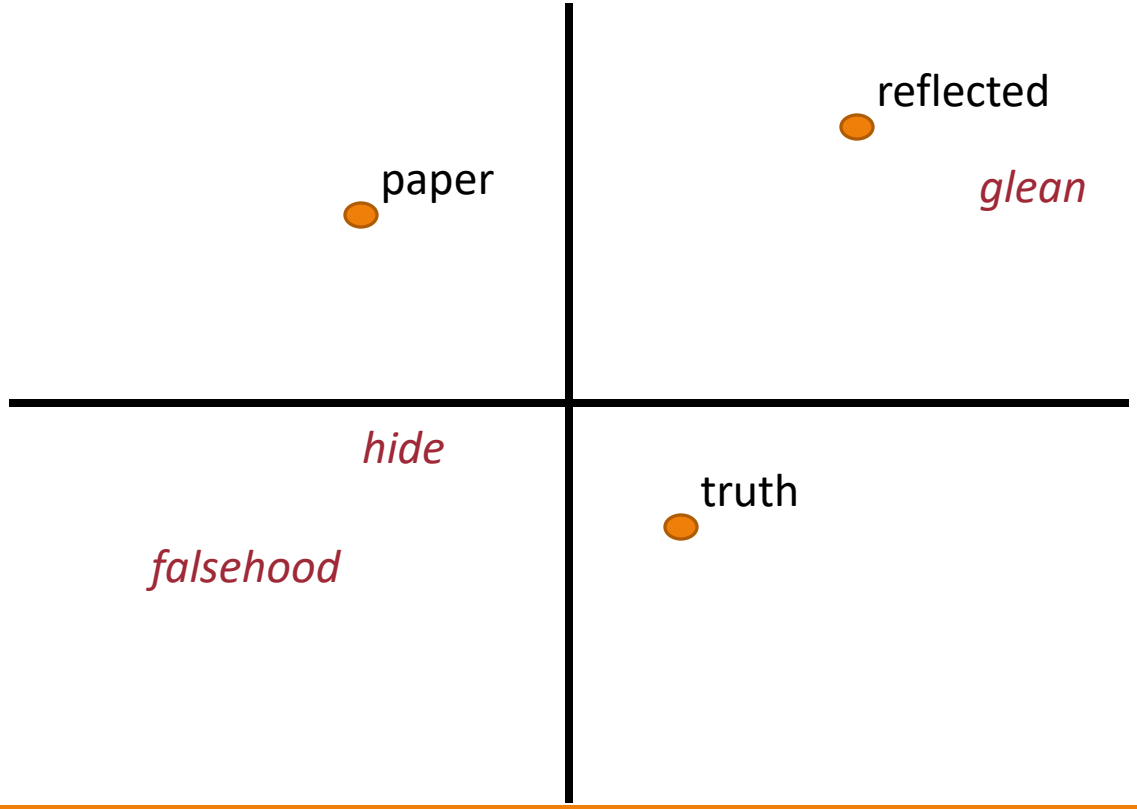

Another option

(Some) Properties of Embeddings

https://media3.giphy.com/media/3orif0M8U1E7NfpFzq/200_s.gif

Capture “like” (similar) words

target:	Redmond	Havel	ninjutsu	graffiti	capitulate
	Redmond Wash.	Vaclav Havel	ninja	spray paint	capitulation
	Redmond Washington	president Vaclav Havel	martial arts	grafitti	capitulated
	Microsoft	Velvet Revolution	swordsmanship	taggers	capitulating

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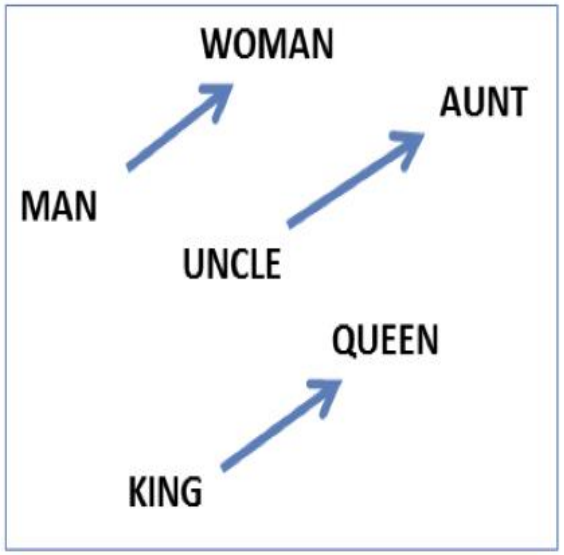
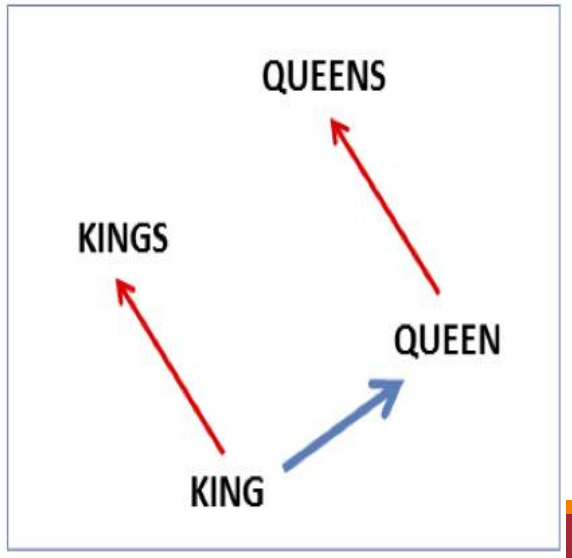
Capture relationships





vector(*'king'*) – vector(*'man'*) + vector(*'woman'*) ≈ vector('queen')

vector(*'Paris'*) - vector(*'France'*) + vector(*'Italy'*) ≈ vector('Rome')

Mikolov et al. (2013)

https://projector.tensorflow.org/

Play around with the word embeddings.

What patterns do you see in the data?

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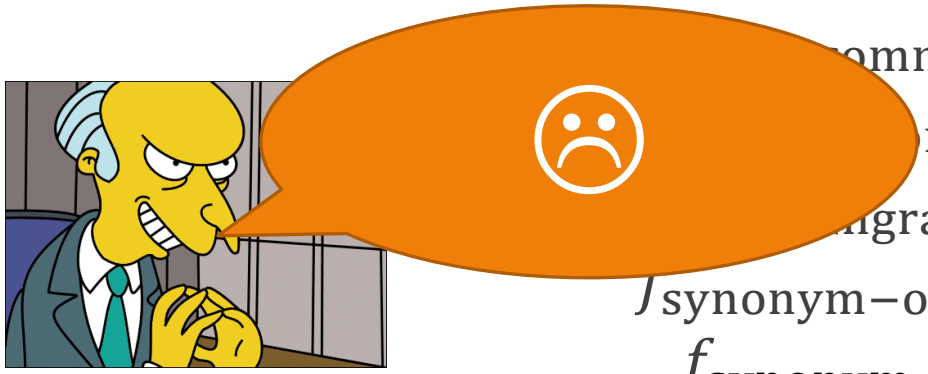

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get_similarity_with_embeddings()

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Dense Embeddings: Key Ideas

Vector embeddings can be used for phrases, paragraphs, or even whole documents!

1. Acquire basic contextual statistics (often counts) for each word type v

2. Extract a real-valued vector e_v for each word v from those statistics

[0.00315225, 0.00315225, 0.00547597, 0.00741556, 0.00912817, 0.01068435, 0.01212381, 0.01347162, 0.01474487, 0.0159558]

3. Use the vectors to represent each word in later tasks

Vector from https://www.tensorflow.org/text/tutorials/word2vec

Common Continuous Representations

Shared Intuition

Model the meaning of a word by “embedding” in a vector space

The meaning of a word is a vector of numbers

Contrast: word meaning is represented in many computational linguistic applications by a vocabulary index (“word number 545”) or the string itself

Three Common Kinds of Embedding Models

1. Co-occurrence matrices
2. Matrix Factorization: Singular value decomposition/Latent Semantic Analysis, Topic Models
3. Neural-network-inspired models (skip-grams, CBOW)

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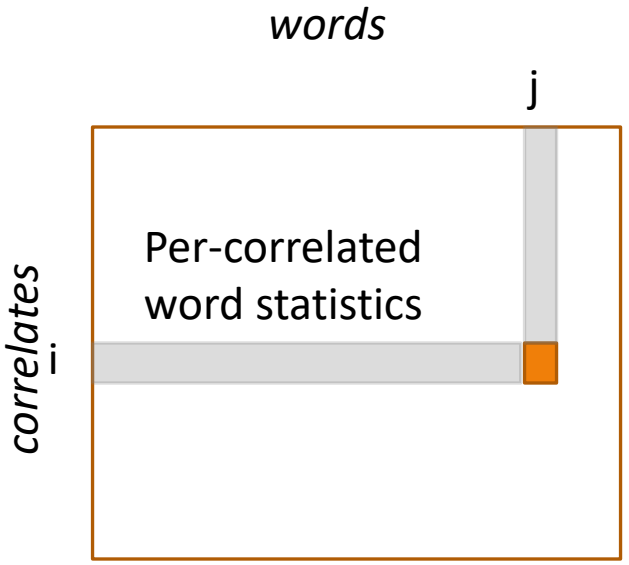
Co-occurrence matrices can be used in their own right, but they're most often used as inputs (directly or indirectly) to the matrix factorization or neural approaches

Co-occurrence Matrix

Acquire basic contextual statistics (often counts) for each word type v via *correlate*.



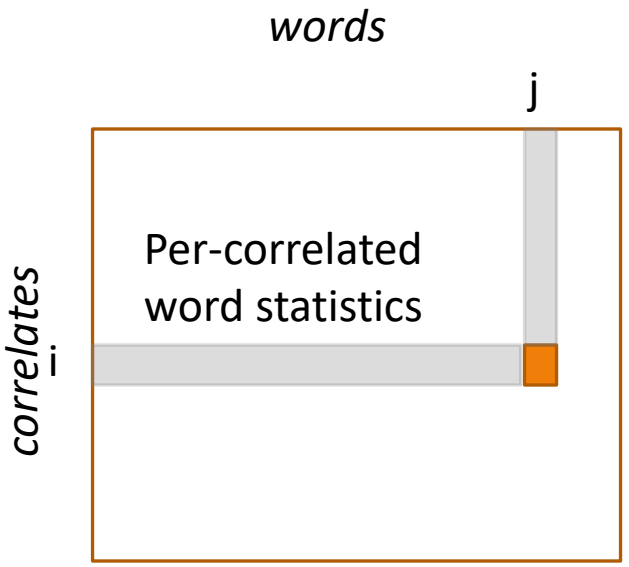
Co-occurrence Matrix

Acquire basic contextual statistics (often counts) for each word type v via *correlate*:

For example:

documents

- Record how often a word occurs in each document



correlates =
documents

Co-occurrence Matrix

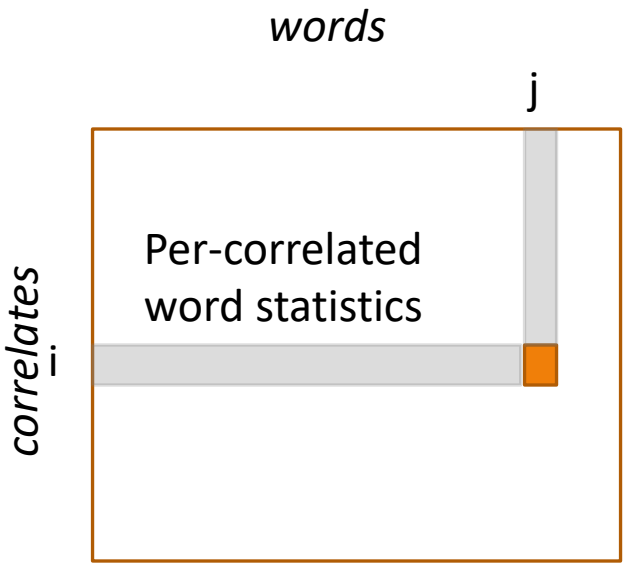
Acquire basic contextual statistics (often counts) for each word type v via *correlate*:

For example:

documents

surrounding context words

- Record how often v occurs with other word types u



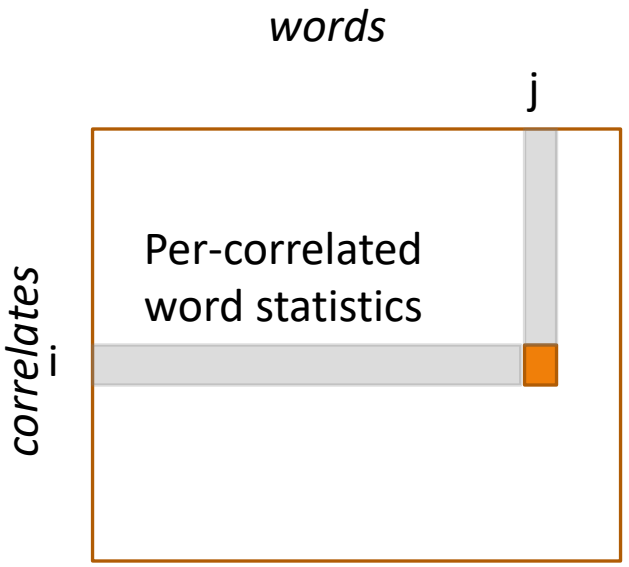
correlates =
word types

Co-occurrence Matrix

Acquire basic contextual statistics (often counts) for each word type v via *correlate*:

For example:

- documents
- surrounding context words
- linguistic annotations (POS tags, syntax)
- …



Assumption: Two words are similar if their vectors are similar

“Acquire basic contextual statistics (often counts) for each word type v”

Two basic, initial counting approaches

- Record which words appear in which documents
- Record which words appear together

These are good first attempts, but with some large downsides

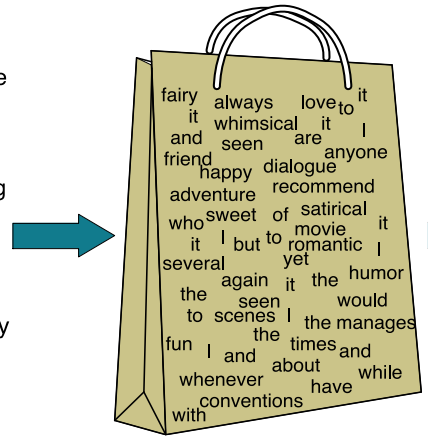
“You shall know a word by the company it keeps!” Firth (1957)

document (↓)-word (→) count matrix

	battle	soldier	fool	clown
As You Like It	1	2	37	6
Twelfth Night	1	2	58	117
Julius Caesar	8	12	1	0
Henry V	15	36	5	0

basic bag-of-words counting

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!



it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
would	1
whimsical	1
times	1
sweet	1
satirical	1
adventure	1
genre	1
fairy	1
humor	1
have	1
great	1
…	…

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Issue: Count word vectors are very large, sparse, and skewed!

“You shall know a word by the company it keeps!” Firth (1957)

context (↓)-word (→) count matrix

	apricot	pineapple	digital	information
aardvark	0	0	0	0
computer	0	0	2	1
data	0	10	1	6
pinch	1	1	0	0
result	0	0	1	4
sugar	1	1	0	0

Context: those other words within a small “window” of a target word

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a cloud [computer stores digital data on] a remote computer

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The size of windows depends on your goals

The shorter the windows , the more **syntactic** the representation

± 1-3 more “syntax-y”

The longer the windows, the more **semantic** the representation

± 4-10 more “semantic-y”

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Pointwise Mutual Information (PMI): Dealing with Problems of Raw Counts

Raw word frequency is not a great measure of association between words

- It's very skewed: "the" and "of" are very frequent, but maybe not the most discriminative

We'd rather have a measure that asks whether a context word is **particularly informative** about the target word.

- (Positive) Pointwise Mutual Information ((P)PMI)

Pointwise mutual information:

Do events x and y co-occur more than if they were independent?

probability words x and y occur together (in the same context/window)

$$\text{PMI}(x, y) = \log \frac{p(x, y)}{p(x)p(y)}$$

probability that word x occurs

probability that word y occurs

Advanced: Equivalent PMI Computations

Intuition: Do words x and y co-occur more than if they were independent?

$$\text{PMI}(x, y) = \log \frac{p(x, y)}{p(x)p(y)} = \log \frac{p(y \mid x)}{p(y)} = \log \frac{p(x \mid y)}{p(x)}$$

“Noun Classification from Predicate-Argument Structure,” Hindle (1990)

“drink it” is more common than “drink wine”

“wine” is a better “drinkable” thing than “it”

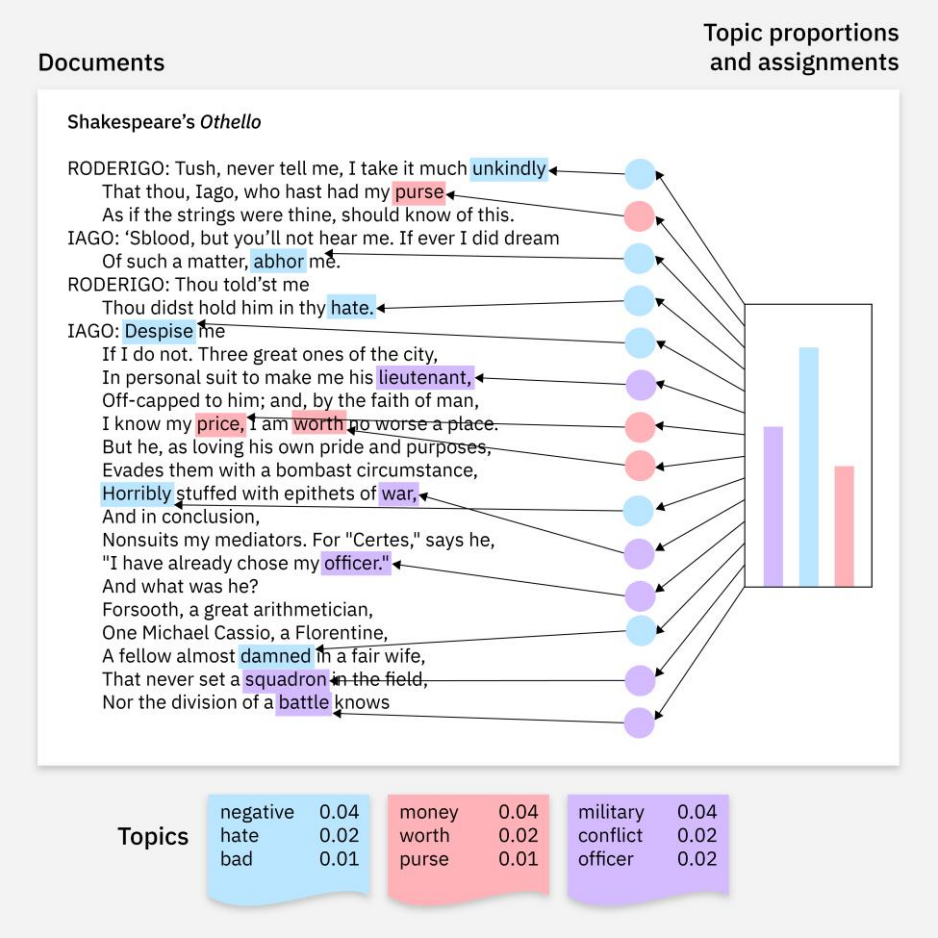
Object of “drink”	Count	PMI
it	3	1.3
anything	3	5.2
wine	2	9.3
tea	2	11.8
liquid	2	10.5

Three Common Kinds of Embedding Models

Learn more in:
- Grad assignment (potentially, if you choose to do the paper)
- Other classes (478/678)

1. Co-oc
2. Matrix Factorization: Singular value decomposition/Latent Semantic Analysis, Topic Models
3. Neural-network-inspired models (skip-grams, CBOW)

Topic Modeling Teaser – Latent Dirichlet Allocation (LDA)



In-depth LDA tutorial:

https://people.eecs.berkeley.edu/~cjrd/static/pdfs/lda_tutorial.pdf

https://www.ibm.com/think/topics/latent-dirichlet-allocation

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Word2Vec

Mikolov et al. (2013; NeurIPS): “Distributed Representations of Words and Phrases and their Compositionality”

Revisits the context-word approach

Learn a model p(c | w) to predict a context word from a target word

Learn two types of vector representations

- $h_c \in \mathbb{R}^E$: vector embeddings for each context word
- $v_w \in \mathbb{R}^E$: vector embeddings for each target word

$$p(c \mid w) \propto \exp(h_c^T v_w)$$

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result	0	0	1	4
sugar	1	1	0	0

Context: those other words within a small "window" of a target word

$$\max_{h,v} \sum_{c,w \text{ pairs}} \text{count}(c,w) \log p(c \mid w)$$

Word2Vec

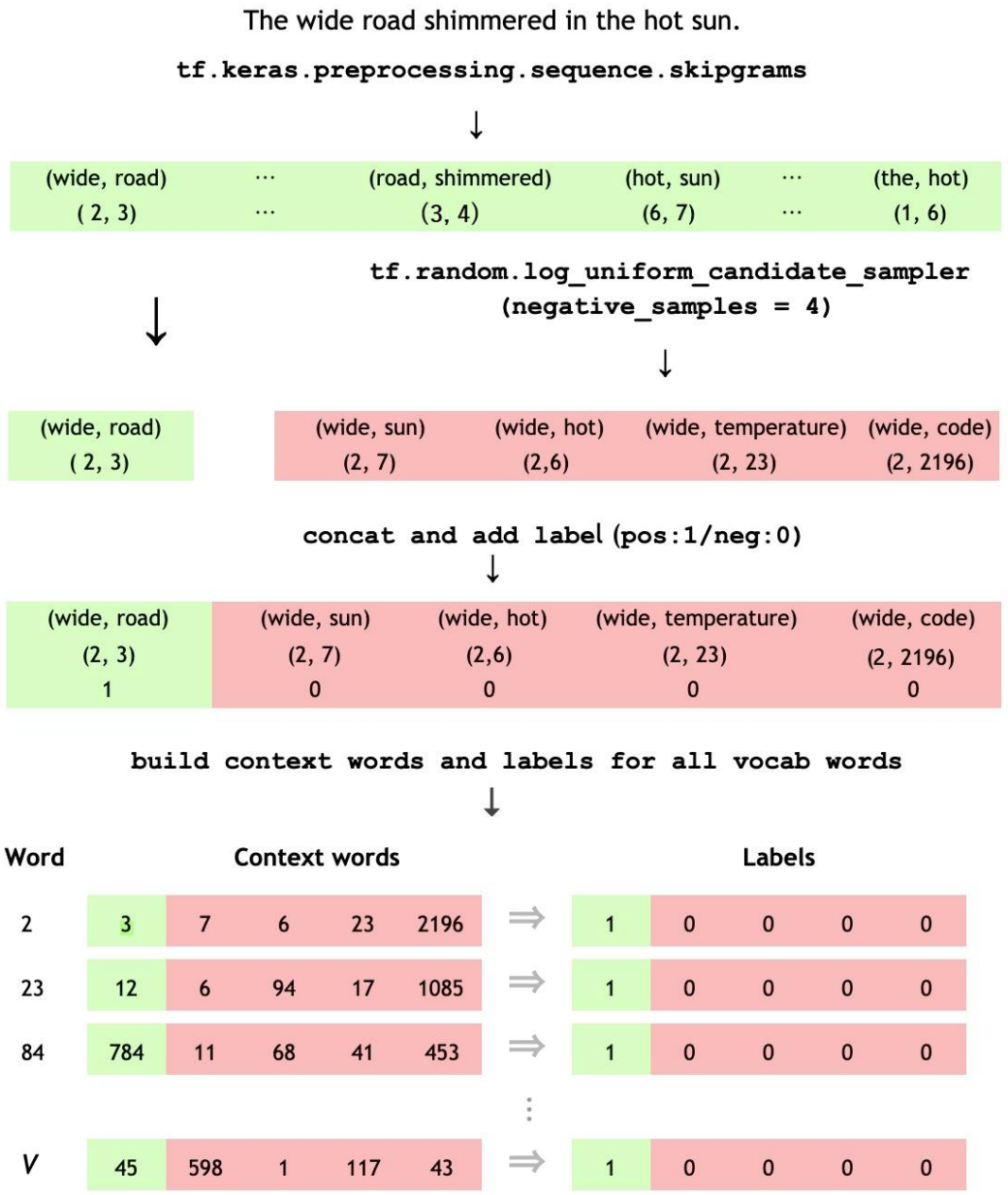
context (↓)-word (→) count matrix

	apricot	pineapple	digital	information
aardvark	0	0	0	0
computer	0	0	2	1
data	0	10	1	6
pinch	1	1	0	0
result	0	0	1	4
sugar	1	1	0	0

Context: those other words within a small "window" of a target word

$$\max_{h,v} \sum_{c,w \text{ pairs}} \text{count}(c,w) \left[h_c^T v_w - \log\left(\sum_u \exp(h_u^T v_w) \right) \right]$$

Example (Tensorflow)



https://www.tensorflow.org/text/tutorials/word2vec

Word2Vec has Inspired a Lot of Work

Off-the-shelf embeddings

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

Off-the-shelf implementations

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

Follow-on work

- J. Pennington, R. Socher, and C. D. Manning, "**GLoVe: Global Vectors for Word Representation**," in *Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Doha, Qatar, 2014, pp. 1532–1543. doi: 10.3115/v1/D14-1162.
  - https://nlp.stanford.edu/projects/glove/
- Many others
- 15000+ citations

FastText

P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, "**Enriching Word Vectors with Subword Information**," *Transactions of the Association for Computational Linguistics*, vol. 5, pp. 135–146, 2017, doi: 10.1162/tacl_a_00051.

Main idea: learn **character n-gram embeddings** for the target word (not context) and modify the word2vec model to use these

Pre-trained models in 150+ languages

- https://fasttext.cc