Vector Embeddings

CMSC 473/673 - NATURAL LANGUAGE PROCESSING

Slides modified from Dr. Frank Ferraro

Learning Objectives

Correct common misconceptions about machine learning

Define a language model

Understand the use & creation of dense vector embeddings

Calculate the distance between vector embeddings

Recognize popular vector embeddings

Misconceptions

Continual/Lifelong Learning vs “Regular” Machine Learning

Baselines

Determining a goal vs evaluation metrics

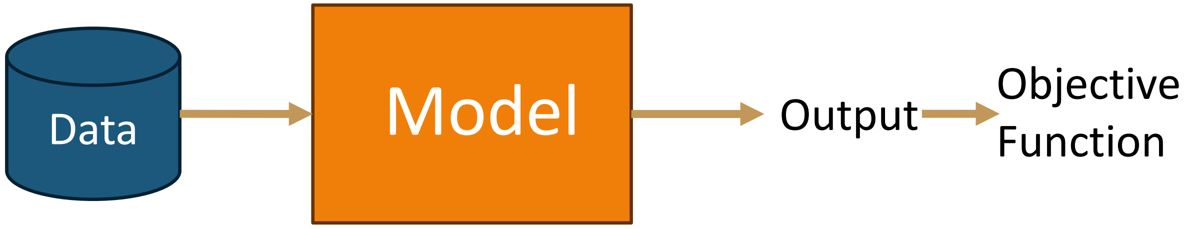
Language Models

Continual Learning vs Machine Learning

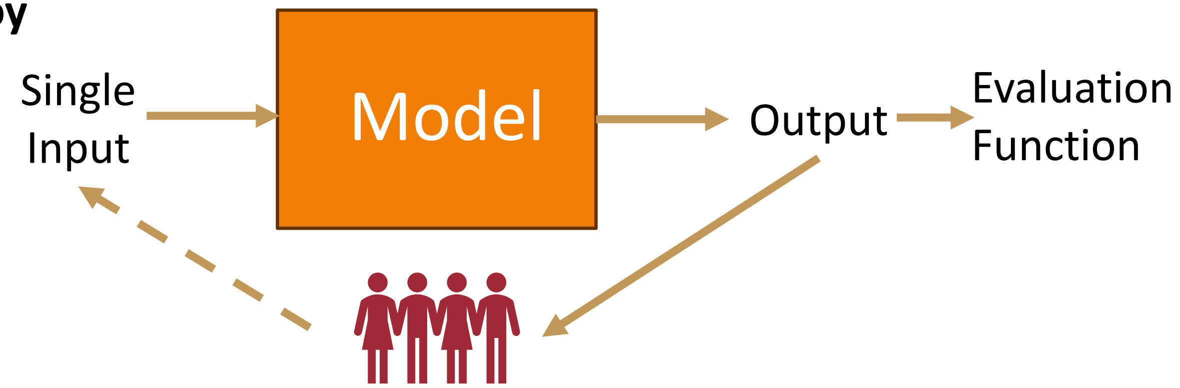
“STATIC” MACHINE LEARNING

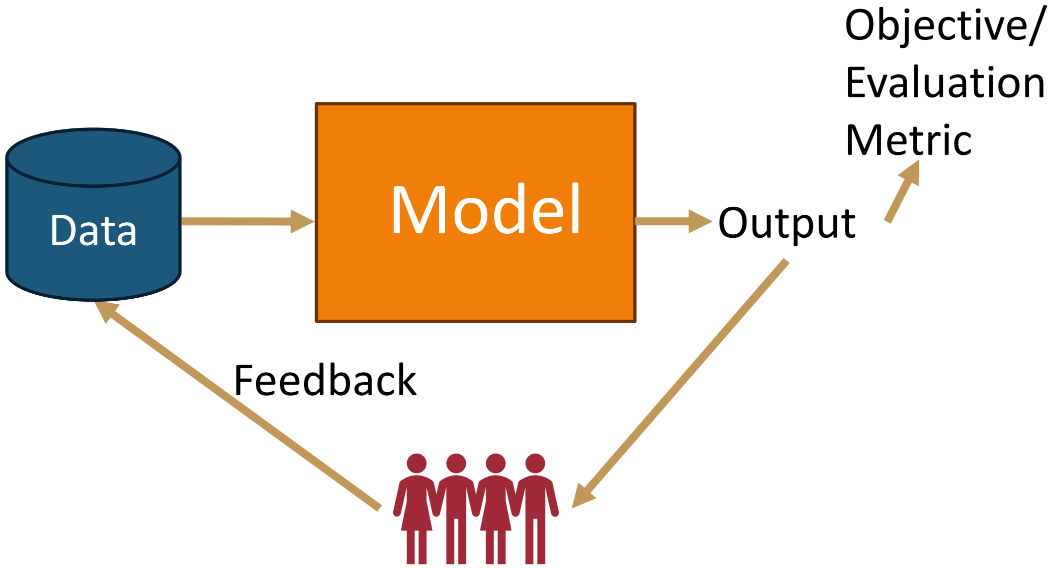
CONTINUAL MACHINE LEARNING

1) Train



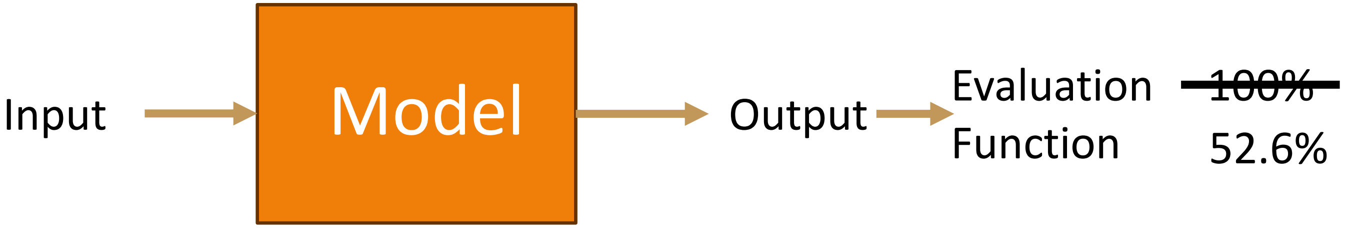
2) Test/Deploy



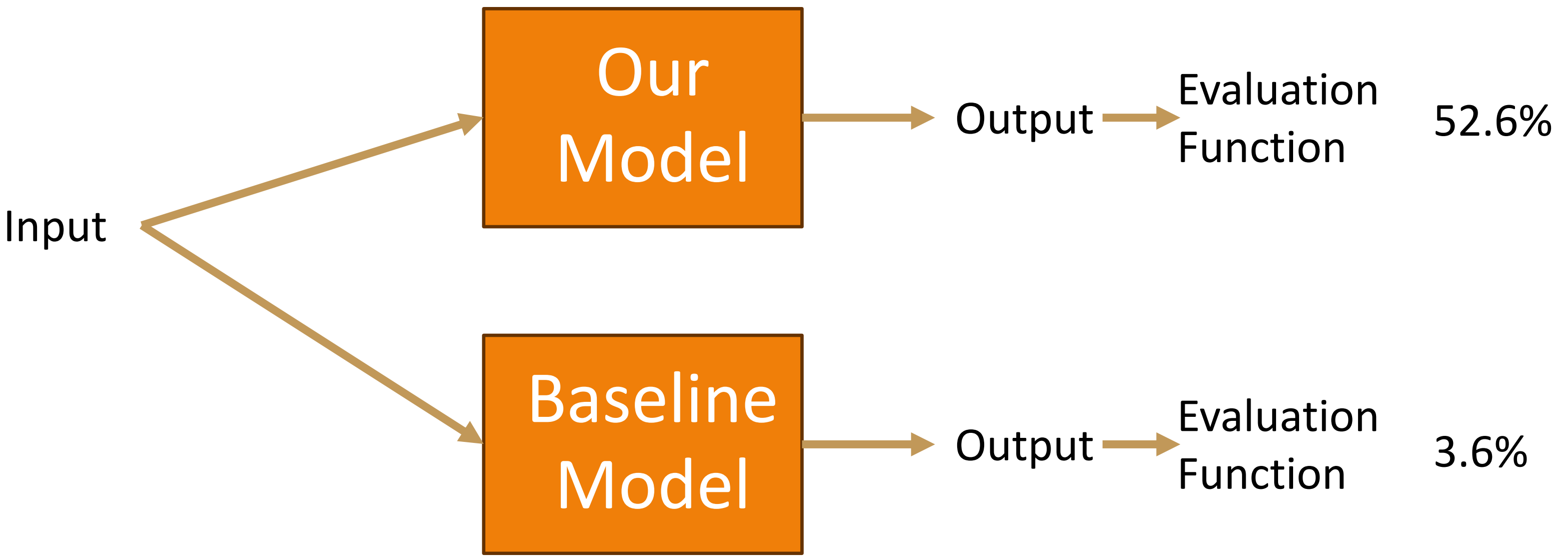


Determining how good a model is

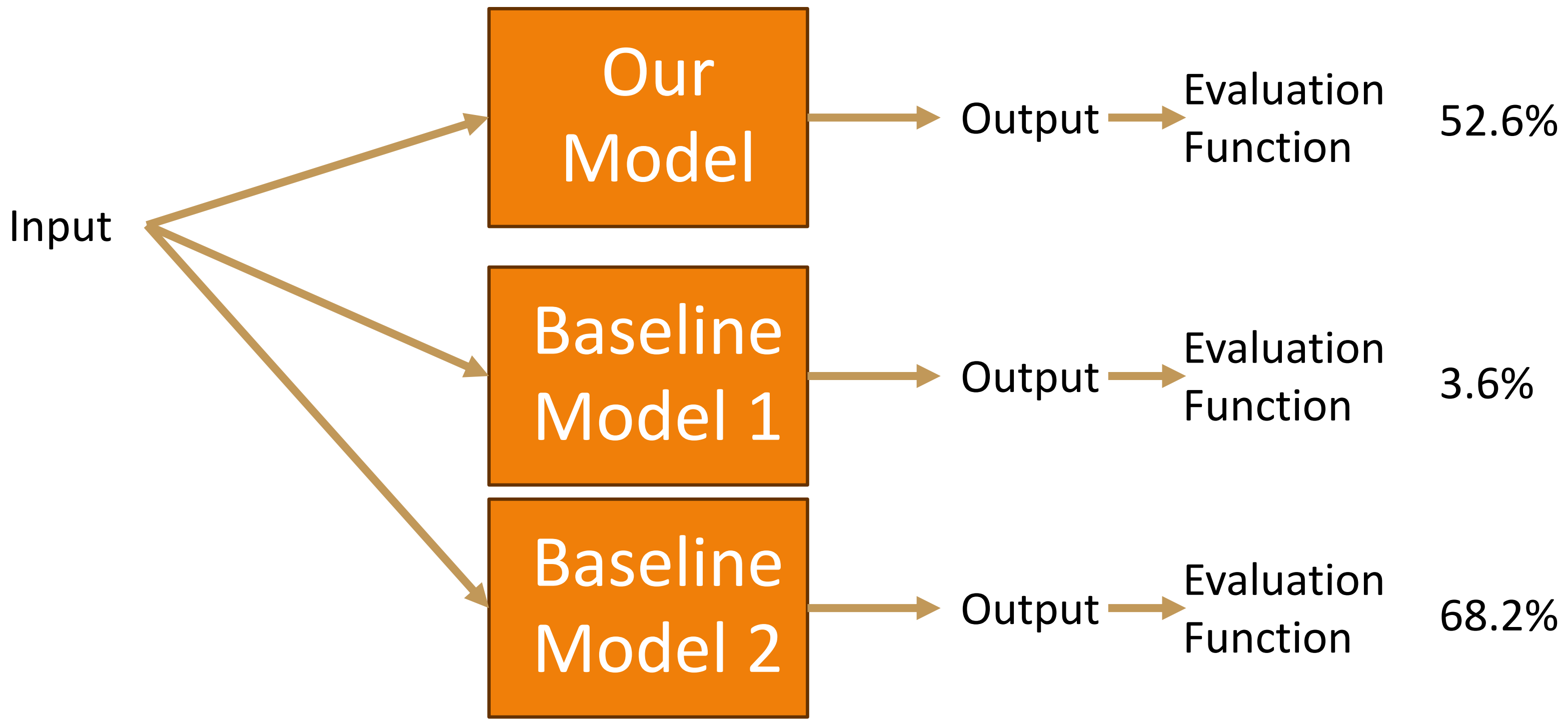
2) Test



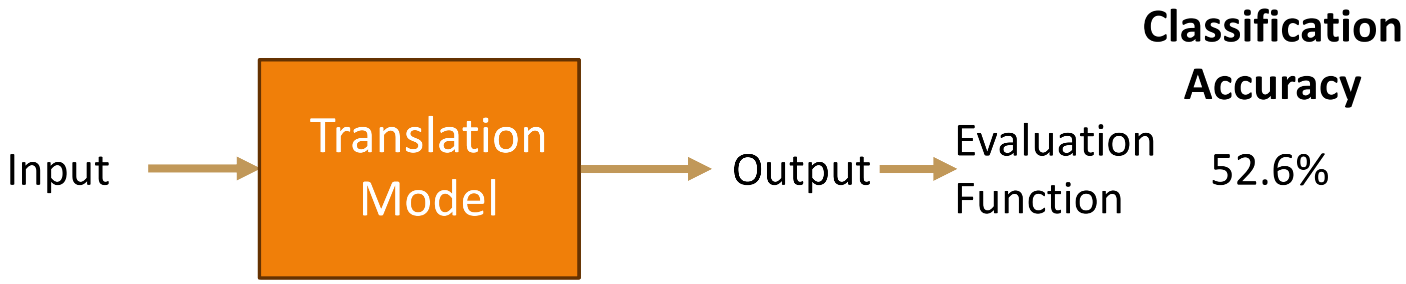
Determining how good a model is: Baselines



Determining how good a model is: Baselines



Determining how good a model is: Evaluation Metric vs Goal



What are you evaluating?

- How good is the model at translating from Mandarin to Twi?
- How accurate is the model at translating the word “potato” across languages?

- [Your questions here]

Bonus Misconception: Data References

If it’s cited in a paper:

In Text

In this paper, we use ROC Stories (Mostafazadeh et al., 2016), which is a dataset…

Reference

Mostafazadeh, N., Chambers, N., He, X., Parikh, D., Batra, D., Vanderwende, L., Kohli, P., & Allen, J. (2016). A Corpus and Cloze Evaluation for Deeper Understanding of Commonsense Stories. *Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL)*, 839–849. http://www.aclweb.org/anthology/N16-1098

Bonus Misconception: Data References

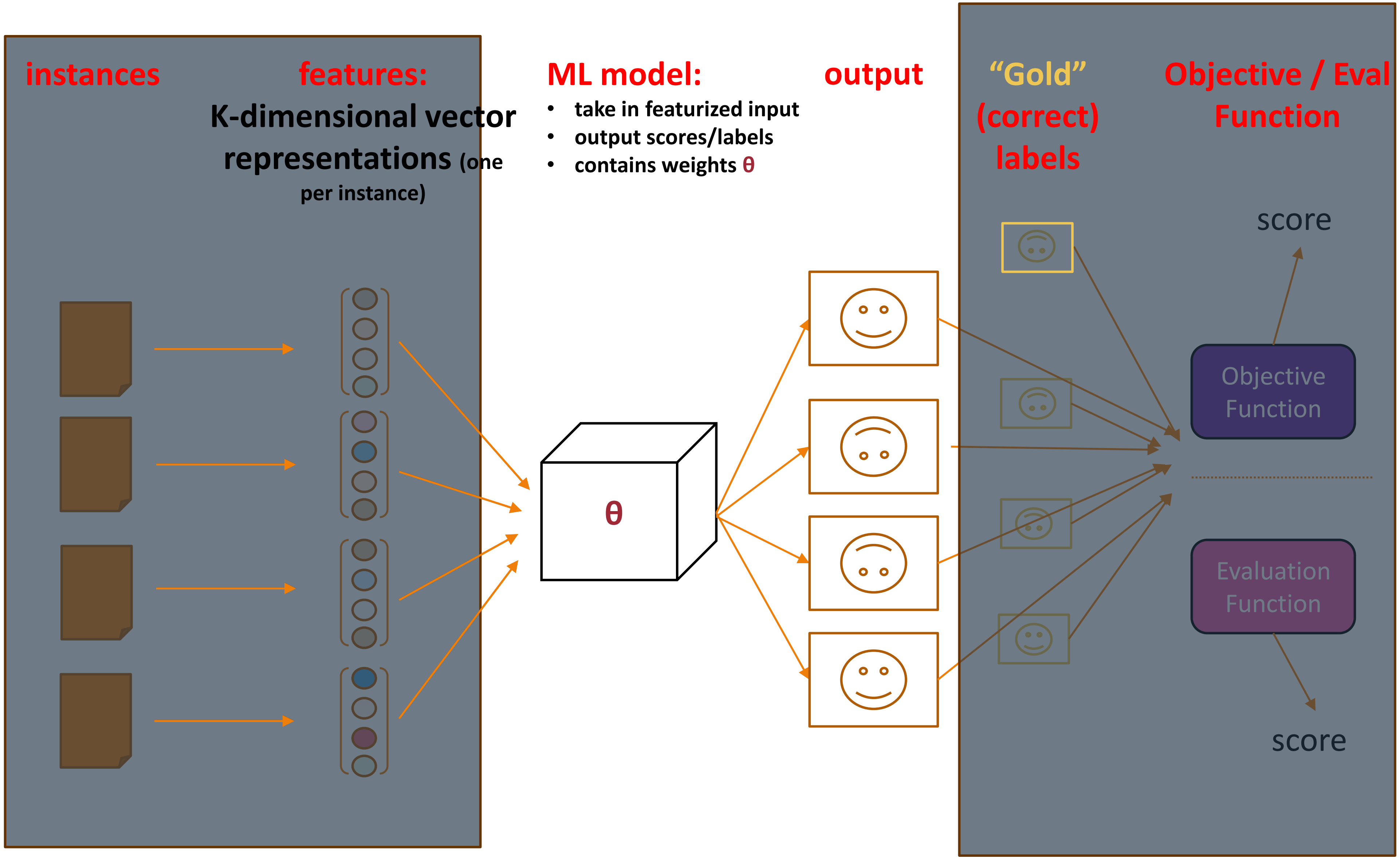
If it's not cited in a paper (i.e., just online/on Github/on 🤗):

In Text

We scraped story plots from Fandom wikis[1]

<u>Footnote</u>

[1] https://www.fandom.com/


instances
features:
K-dimensional vector representations (one per instance)
ML model:
take in featurized input
output scores/labels
contains weights θ
θ
output
"Gold" (correct) labels
Objective / Eval Function
score
Objective Function
Evaluation Function
score

Modeling

Classification

$$P(y \mid x)$$

Language Model (LM)

$$P(w_t | w_{t-1}, w_{t-2} \cdots)$$

A language model is used to **generate** the next word(s) given a history of words.

Knowledge Check

When poll is active respond at

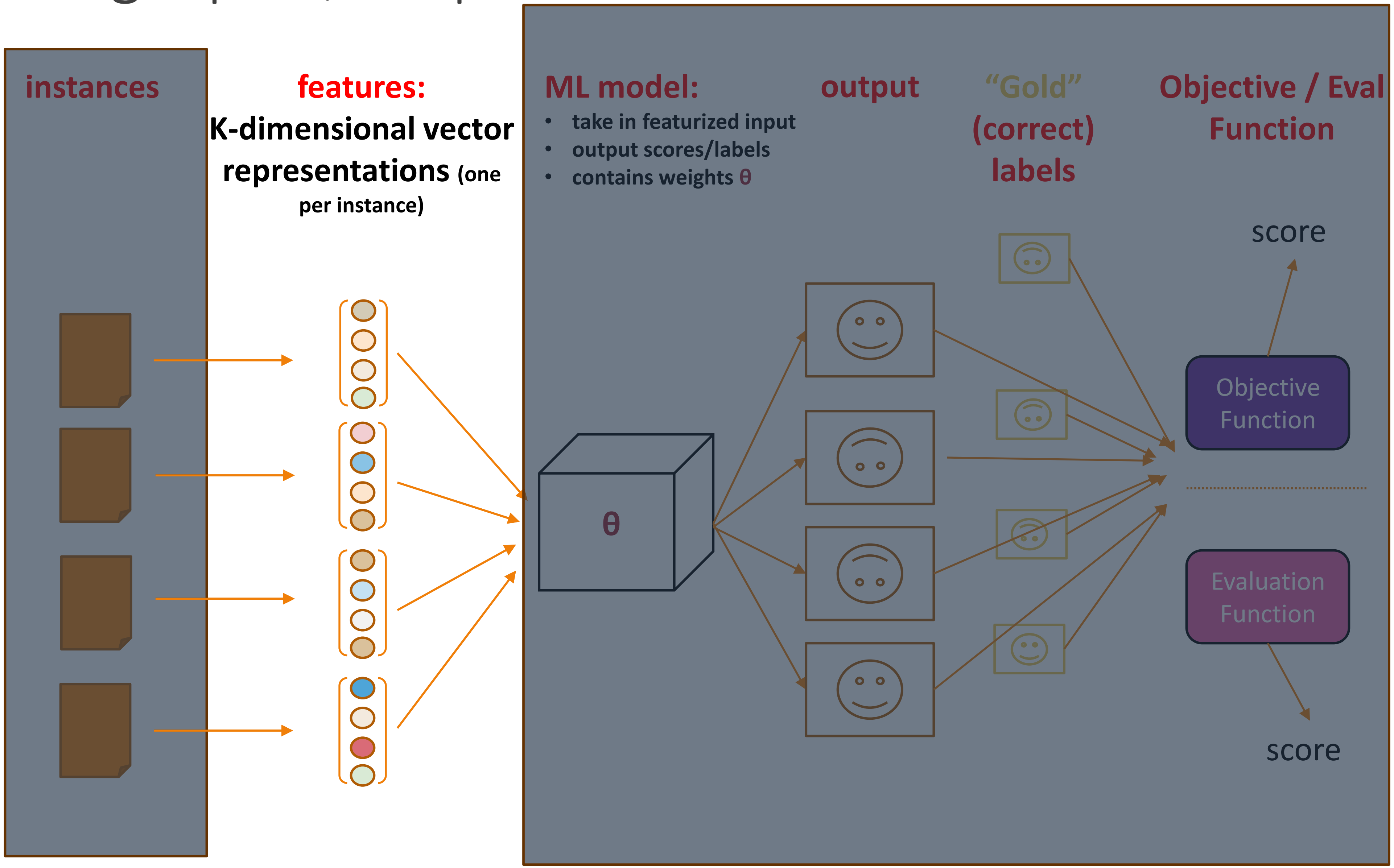
PollEv.com/laramartin527

or

Send laramartin527 and your message to 22333

Embeddings

Representing Inputs/Outputs



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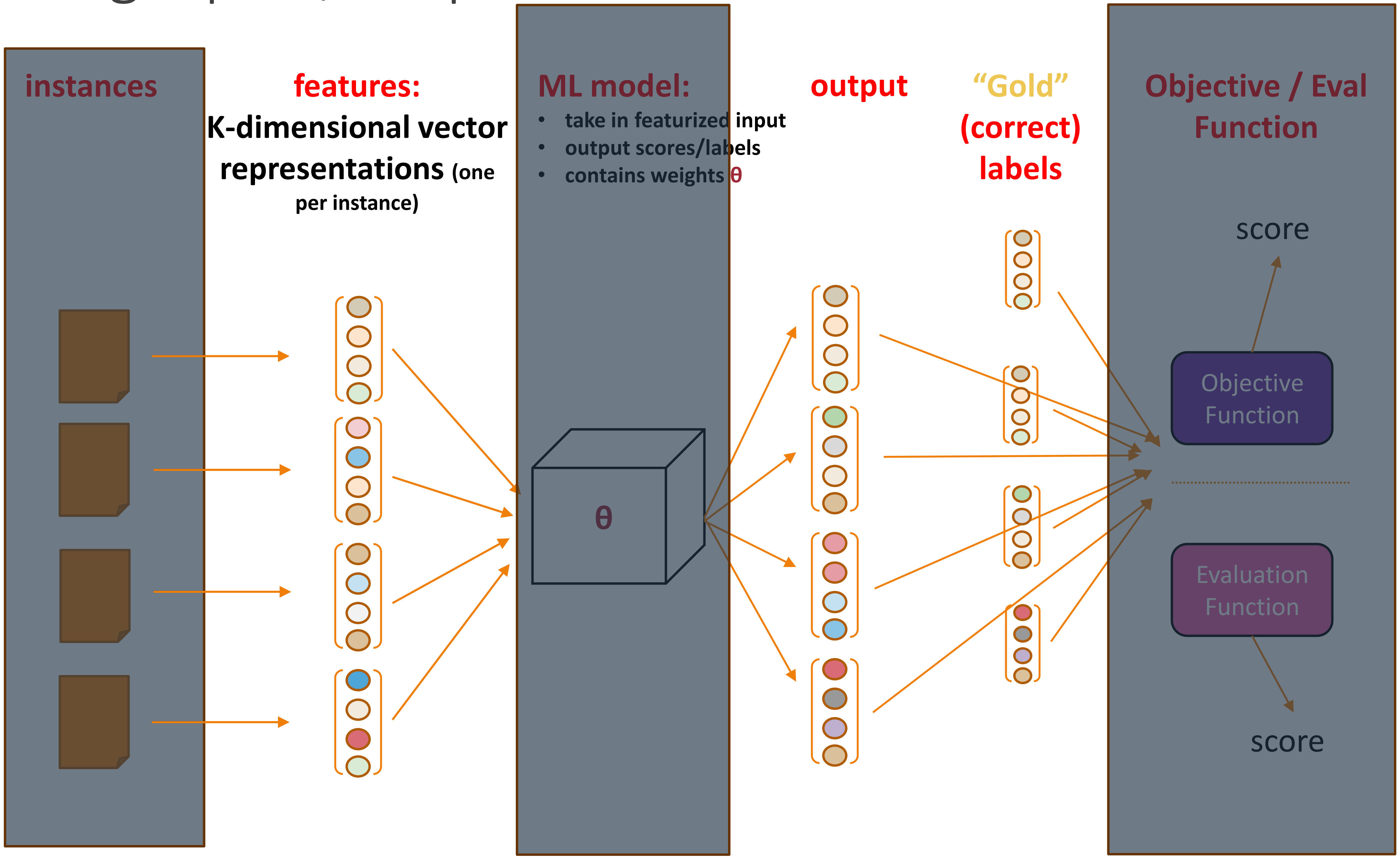

How have we represented words?

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

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?

There's no way you'll catch me!

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

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

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

Yes, but surely some words will be in common… these features won't catch phrases!

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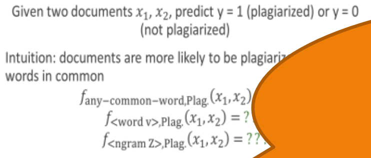

No problem, I'll just change some words!

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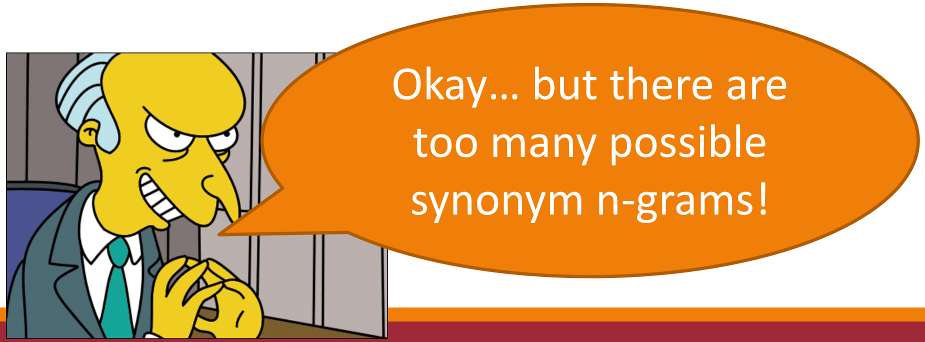

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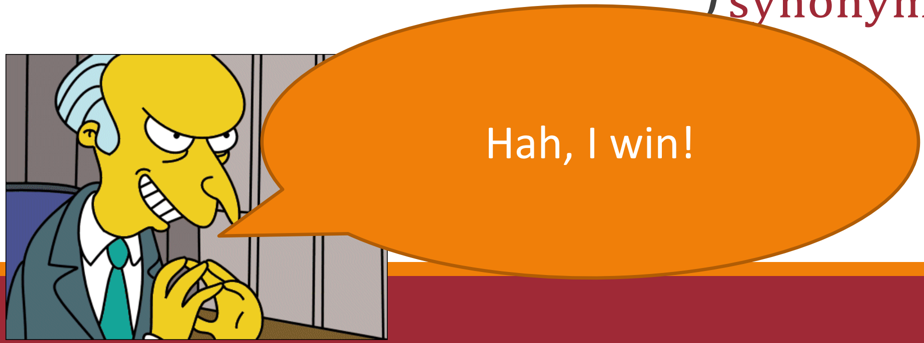

Plagiarism Detection: Word Similarity?

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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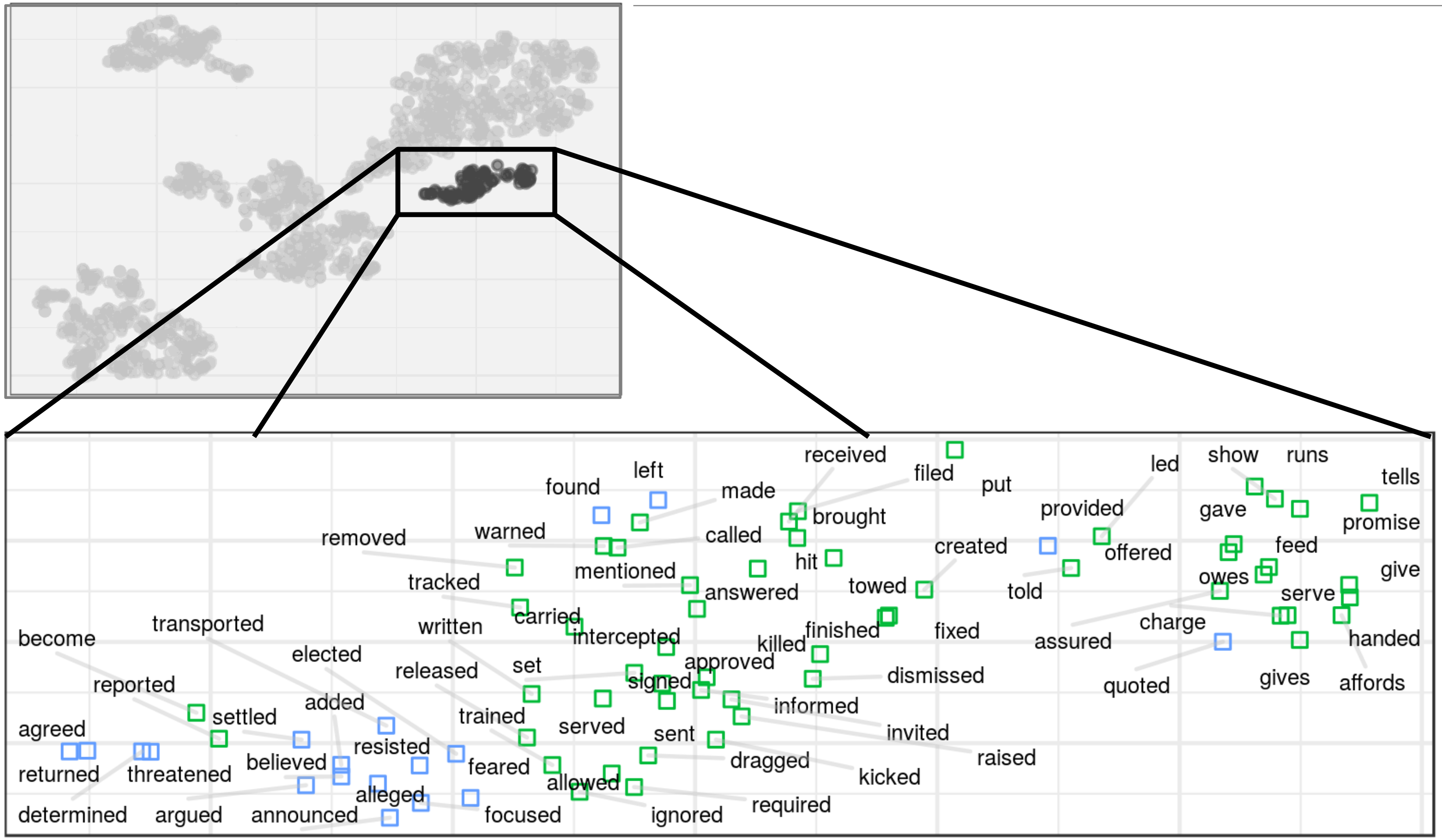
Due to the advanced components mainframes have, these computers have the capability of running multiple large applications required by most enterprises, which is one of its advantage. Mainframes are also suitable to cater for those applications or files that are of very large demand by its users (clients). Examples of these include the large online shopping websites -i.e. : Ebay, Amazon, Microsoft, etc.

A Dense Representation (E=2)



Review: 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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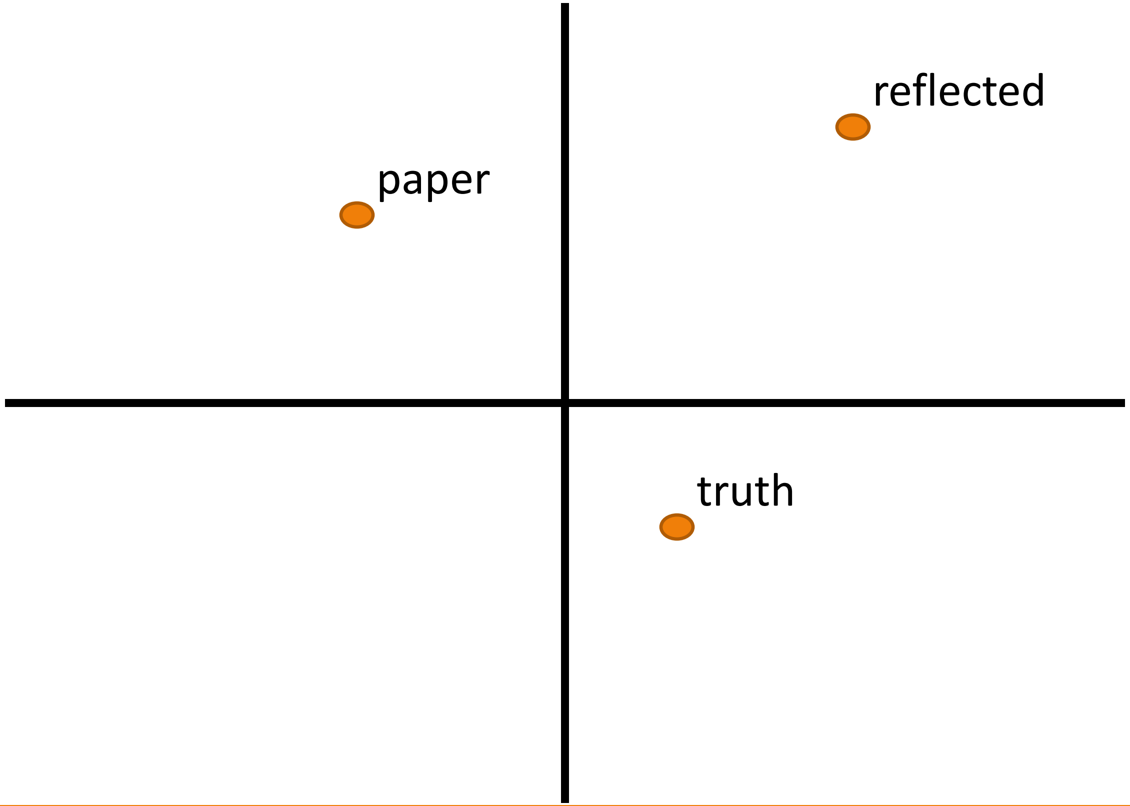

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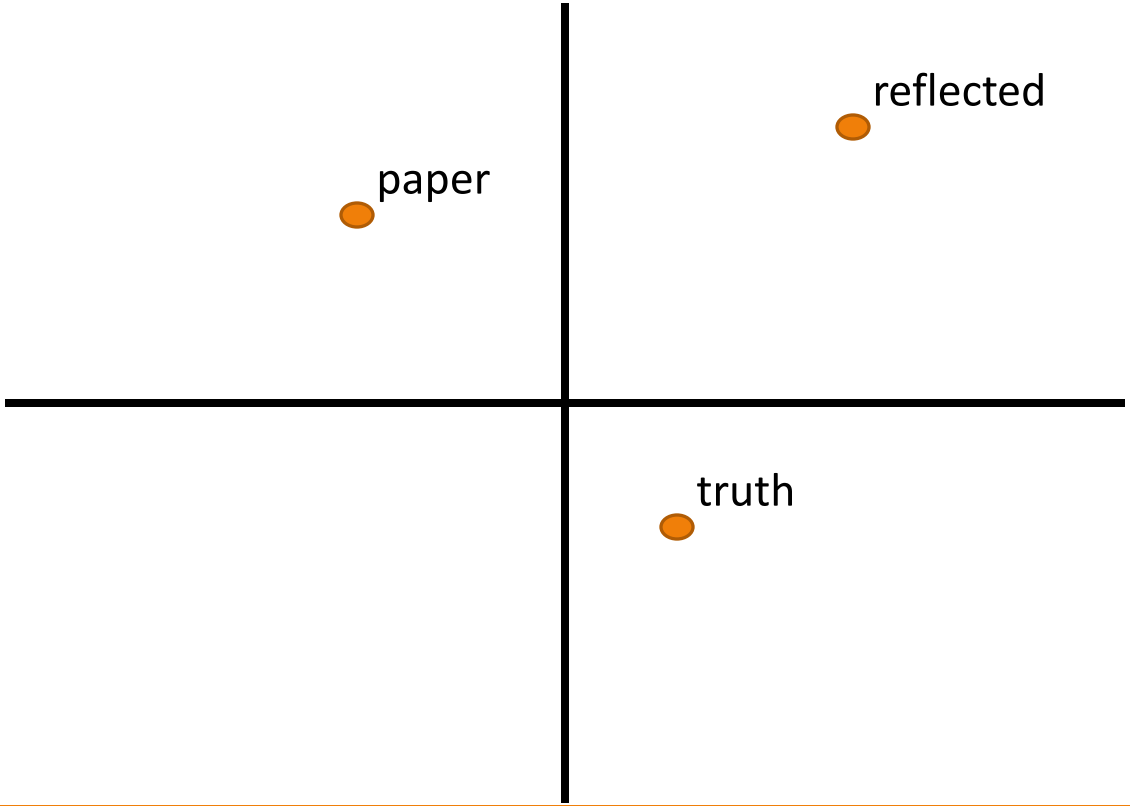


glean

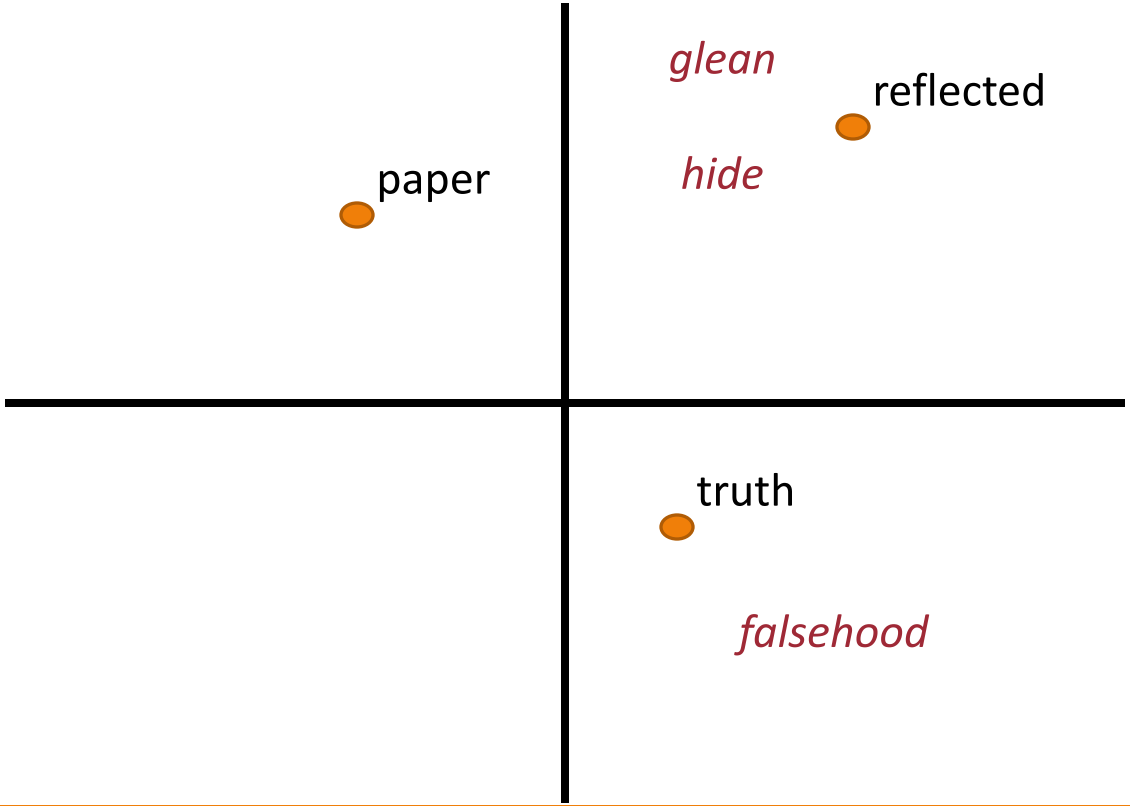
hide

falsehood

where might these go in this space?

Continuous Meaning

The paper reflected the truth.



One option

Continuous Meaning

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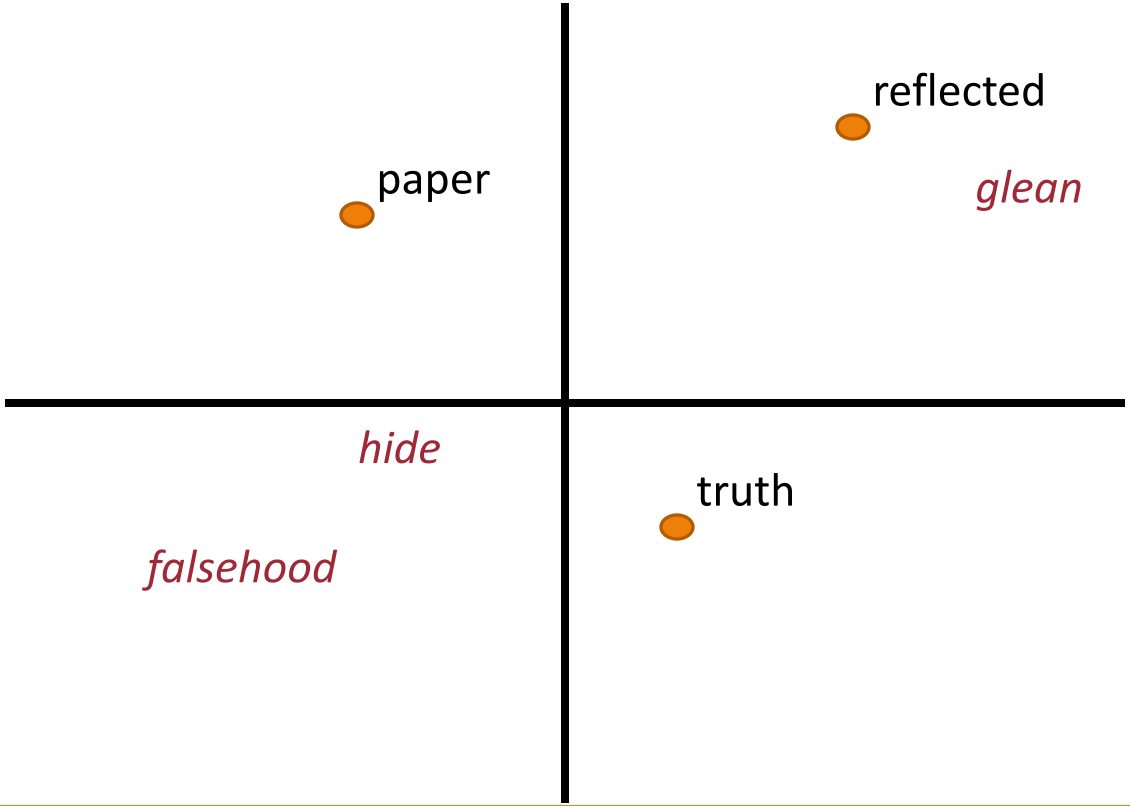

Another option

(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

Mikolov et al. (2013)

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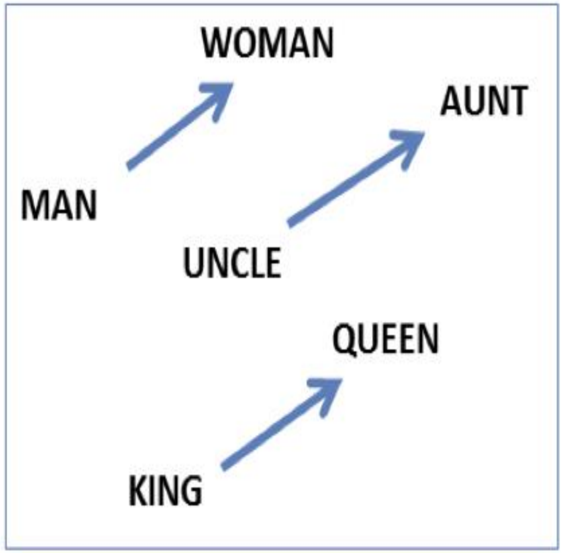
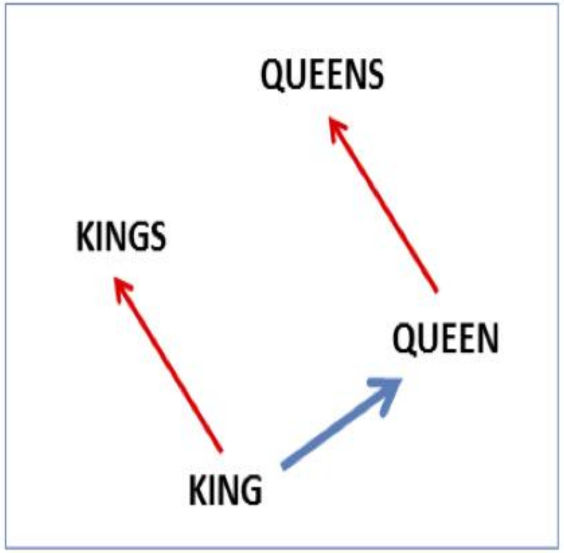
Capture relationships





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

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

Mikolov et al. (2013)

https://projector.tensorflow.org/

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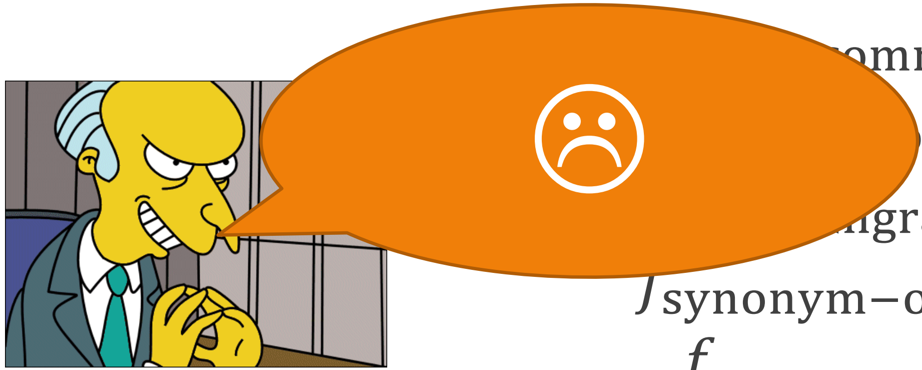

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$$\text{ngram Z>,Plag.}(x_1, x_2) = ???$$

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

$$f_{\text{synonym}-\text{of}-\text{<ngram Z>,Plag.}}(x_1, x_2) =$$

get_similarity_with_embeddings()

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

Vector Representations

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

Evaluating Vector Embeddings

Evaluating Similarity

Extrinsic (task-based, end-to-end) Evaluation:

- Question Answering
- Spell Checking
- Essay grading

Common Evaluation: Correlation between similarity ratings

Input: list of N word pairs $\{(x_1, y_1), \dots, (x_N, y_N)\}$

- Each word pair (x_i, y_i) has a human-provided similarity score h_i

Use your embeddings to compute an embedding similarity score $s_i = \mathrm{sim}(x_i, y_i)$

Compute the correlation between human and computed similarities

$$\rho = \mathrm{Corr}((h_1, \dots, h_N), (s_1, \dots, s_N))$$

Wordsim353: 353 noun pairs rated 0-10

Cosine: Measuring Similarity

Given 2 target words v and w how similar are their vectors?

Dot product or inner product from linear algebra

$$\text{dot-product}(\vec{v},\vec{w}) = \vec{v}\cdot\vec{w} = \sum_{i=1}^{N} v_i w_i = v_1 w_1 + v_2 w_2 + \ldots + v_N w_N$$

- High when two vectors have large values in same dimensions, low for orthogonal vectors with zeros in complementary distribution

Correct for high magnitude vectors

$$\frac{\vec{a}\cdot\vec{b}}{|\vec{a}||\vec{b}|}$$

Cosine Similarity

Divide the dot product by the length of the two vectors

$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|}$$

This is the cosine of the angle between them

$$\vec{a} \cdot \vec{b} \;=\; |\vec{a}||\vec{b}|\cos\theta$$

$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} \;=\; \cos\theta$$

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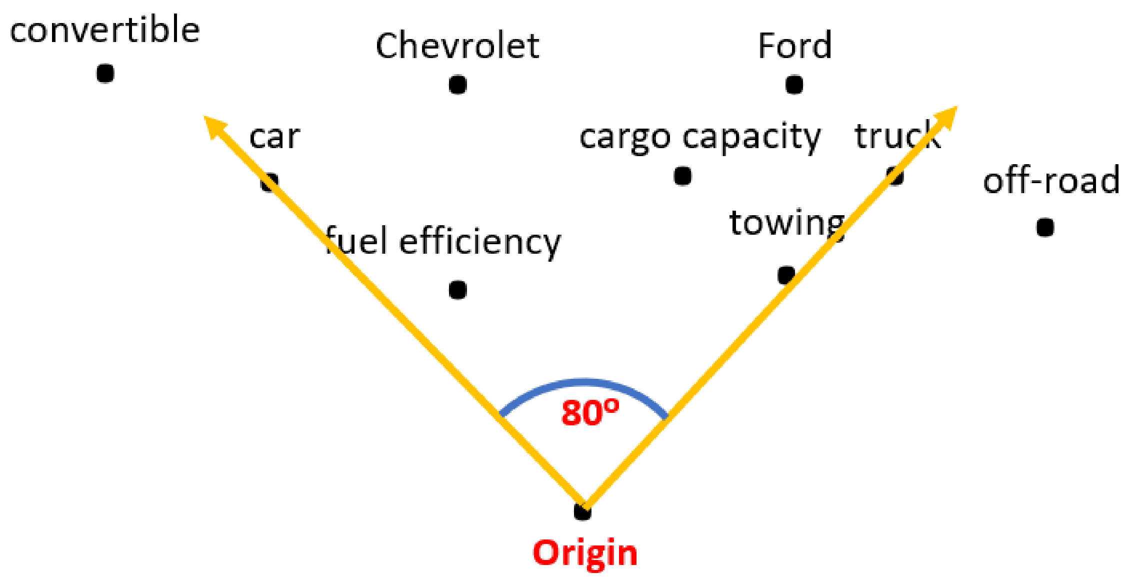
$$\vec{a}\cdot\vec{b} = |\vec{a}||\vec{b}|\cos\theta$$

$$\frac{\vec{a}\cdot\vec{b}}{|\vec{a}||\vec{b}|} = \cos\theta$$



https://upload.wikimedia.org/wikipedia/commons/2/23/CosineSimilarity.png

Example: Word Similarity

$$\cos(x, y) = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2}\sqrt{\sum_i y_i^2}}$$

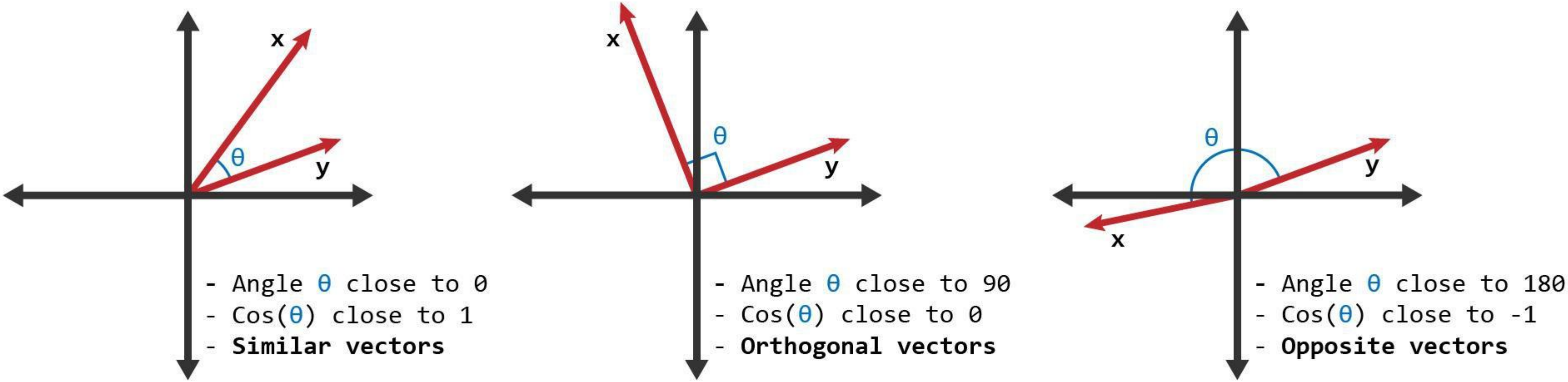
	Dim. 1	Dim. 2	Dim. 3
apricot	2	0	0
digital	0	1	2
information	1	6	1

cosine(apricot,information) = $\frac{2+0+0}{\sqrt{4+0+0}\sqrt{1+36+1}} = 0.1622$

cosine(digital,information) = $\frac{0+6+2}{\sqrt{0+1+4}\sqrt{1+36+1}} = 0.5804$

cosine(apricot,digital) = $\frac{0+0+0}{\sqrt{4+0+0}\sqrt{0+1+4}} = 0.0$

Cosine Similarity Range



https://www.learndatasci.com/glossary/cosine-similarity/

Other Similarity Measures

$$\text{sim}_{\text{cosine}}(\vec{v},\vec{w}) = \frac{\vec{v}\cdot\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\sum_{i=1}^{N} v_i \times w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

$$\text{sim}_{\text{Jaccard}}(\vec{v},\vec{w}) = \frac{\sum_{i=1}^{N} \min(v_i,w_i)}{\sum_{i=1}^{N} \max(v_i,w_i)}$$

$$\text{sim}_{\text{Dice}}(\vec{v},\vec{w}) = \frac{2\times\sum_{i=1}^{N} \min(v_i,w_i)}{\sum_{i=1}^{N} (v_i+w_i)}$$

$$\text{sim}_{\text{JS}}(\vec{v}||\vec{w}) = D(\vec{v}|\frac{\vec{v}+\vec{w}}{2}) + D(\vec{w}|\frac{\vec{v}+\vec{w}}{2})$$

Adding Morphology, Syntax, and Semantics to Embeddings

- Lin (1998): “Automatic Retrieval and Clustering of Similar Words”
- Padó and Lapata (2007): “Dependency-based Construction of Semantic Space Models”
- Levy and Goldberg (2014): “Dependency-Based Word Embeddings”
- Cotterell and Schütze (2015): “Morphological Word Embeddings”
- Ferraro et al. (2017): “Frame-Based Continuous Lexical Semantics through Exponential Family Tensor Factorization and Semantic Proto-Roles”
- and many more…

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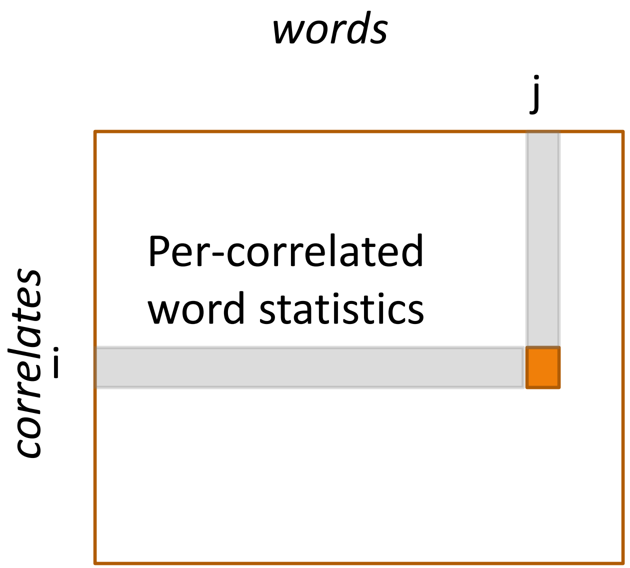
1. Co-occurrence matrices
2. Matrix Factorization: Singular value decomposition/Latent Semantic Analysis, Topic Models
3. Neural-network-inspired models (skip-grams, CBOW)

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*.



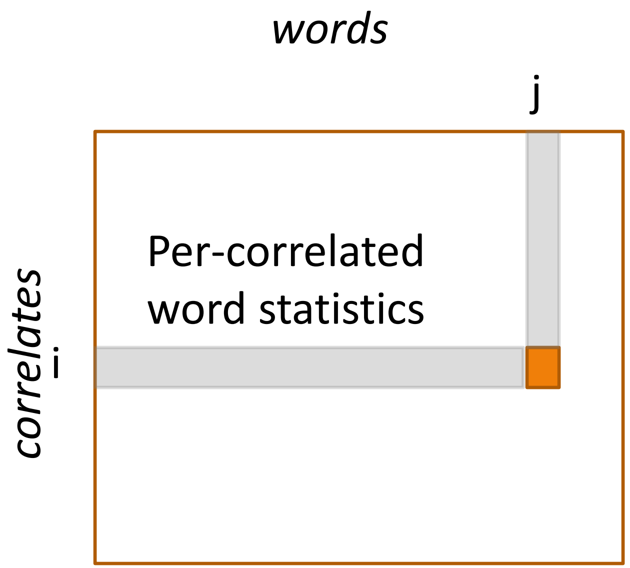
Co-occurrence Matrix

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



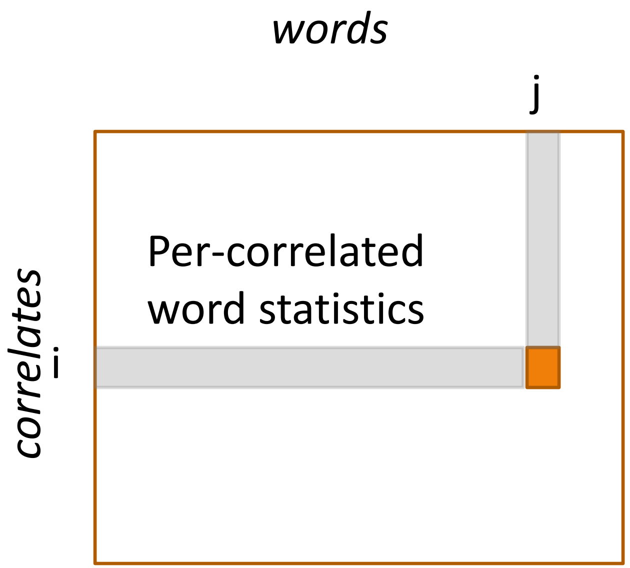
correlates =
documents

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



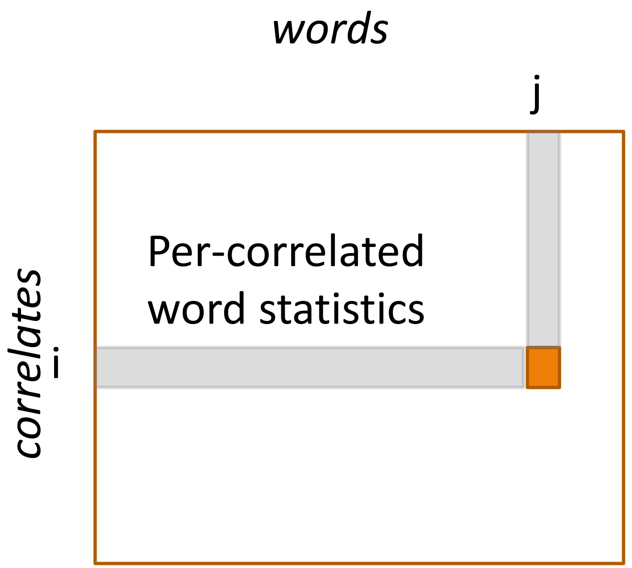
\# correlates =
\# word types

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

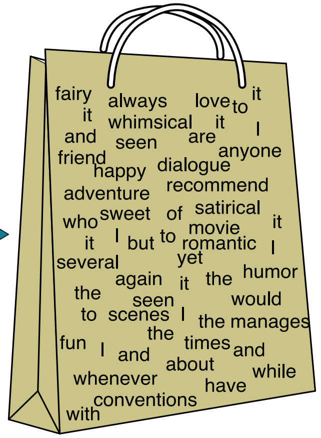
“You shall know a word by the company it keeps!” Firth (1957)

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
…	…

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

document (↓)-word (→) count matrix

	battle	soldier	fool	clown
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Assumption: Two documents are similar if their vectors are similar

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Assumption: Two words are similar if their vectors are similar

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

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

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	apricot	**pineapple**	**digital**	**information**
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Context: those other words within a small “window” of a target word

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

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

context (↓)-word (→) count matrix

	apricot	pineapple	digital	information
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result	0	0	1	4
sugar	1	1	0	0

The size of windows depends on your goals
- The shorter the windows , the more **syntactic** the representation
  - $\pm$ 1-3 more "syntax-y"
- The longer the windows, the more **semantic** the representation
  - $\pm$ 4-10 more "semantic-y"

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

context (↓)-word (→) count matrix

	apricot	**pineapple**	**digital**	**information**
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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)

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

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?

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

“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:
- Your project
- Paper (673)
- Other classes (478/678)

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

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)

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

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

Word2Vec

context (↓)-word (→) count matrix

	apricot	pineapple	digital	information
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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
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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)

The wide road shimmered in the hot sun.

`tf.keras.preprocessing.sequence.skipgrams`

↓

(wide, road)	⋯	(road, shimmered)	(hot, sun)	⋯	(the, hot)
(2, 3)	⋯	(3, 4)	(6, 7)	⋯	(1, 6)

`tf.random.log_uniform_candidate_sampler`
`(negative_samples = 4)`

↓

(wide, road)
(2, 3)

(wide, sun)	(wide, hot)	(wide, temperature)	(wide, code)
(2, 7)	(2,6)	(2, 23)	(2, 2196)

`concat and add label (pos:1/neg:0)`

↓

(wide, road)	(wide, sun)	(wide, hot)	(wide, temperature)	(wide, code)
(2, 3)	(2, 7)	(2,6)	(2, 23)	(2, 2196)
1	0	0	0	0

`build context words and labels for all vocab words`

↓

Word	Context words						Labels				
2	3	7	6	23	2196	⇒	1	0	0	0	0
23	12	6	94	17	1085	⇒	1	0	0	0	0
84	784	11	68	41	453	⇒	1	0	0	0	0
						⋮					
V	45	598	1	117	43	⇒	1	0	0	0	0

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

FastText Details

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

Original word2vec:

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

FastText:

$$p(c \mid w) \propto \exp\left(h_c^T \left(\sum_{\text{n-gram } g \text{ in } w} z_g\right)\right)$$

FastText Details

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

$$p(c \mid w) \propto \exp\left(h_c^T\left(\sum_{\text{n-gram } g \text{ in } w} z_g\right)\right)$$

decompose

`fluffy` → `fl flu luf uff ffy fy`

Sub-word units like this have become an important part of today's NLP work!

FastText Details

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

$$p(c \mid w) \propto \exp\left(h_c^T \left(\sum_{\text{n-gram } g \text{ in } w} z_g\right)\right)$$

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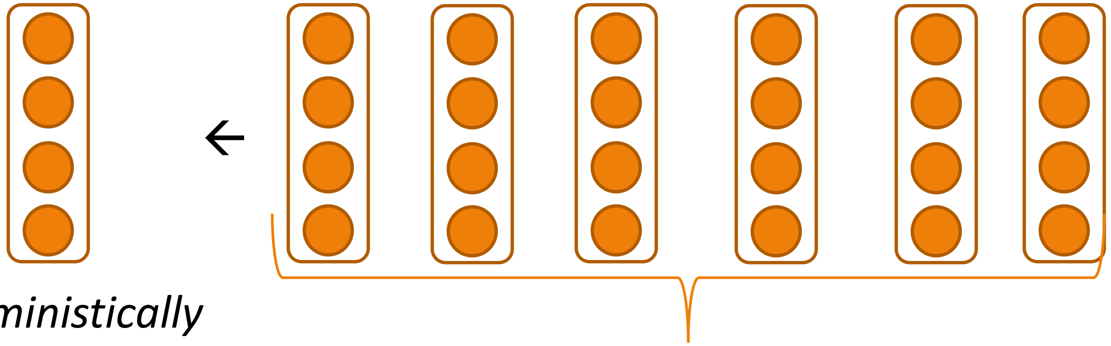

To deterministically compute word embeddings

Learn n-gram embeddings


123
SESAME STREET

Contextual Word Embeddings

Word2vec-based models are not context-dependent

- Single word type → single word embedding

If a single word type can have different meanings…

- bank, bass, plant,…

… why should we only have one embedding?

Entire task devoted to classifying these meanings:
Word Sense Disambiguation

Contextual Word Embeddings

Growing interest in this

Off-the-shelf is a bit more difficult

- Download and run a model
- Can't just download a file of embeddings

Two to know about (with code):

- ELMo: "Deep contextualized word representations" Peters et al. (2018; NAACL)
- https://allennlp.org/elmo
- BERT: "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding" Devlin et al. (2019; NAACL)
  - https://github.com/google-research/bert