Natural Language Processing

NLP | Lecture 4

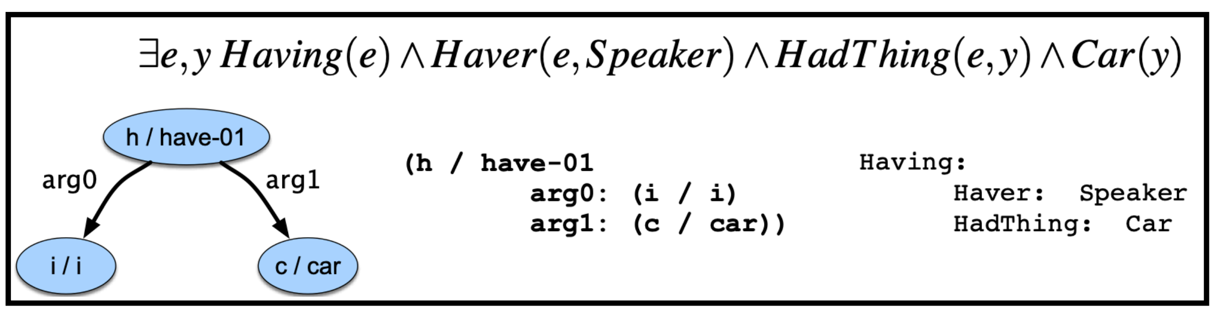
Word Embeddings and Language Models

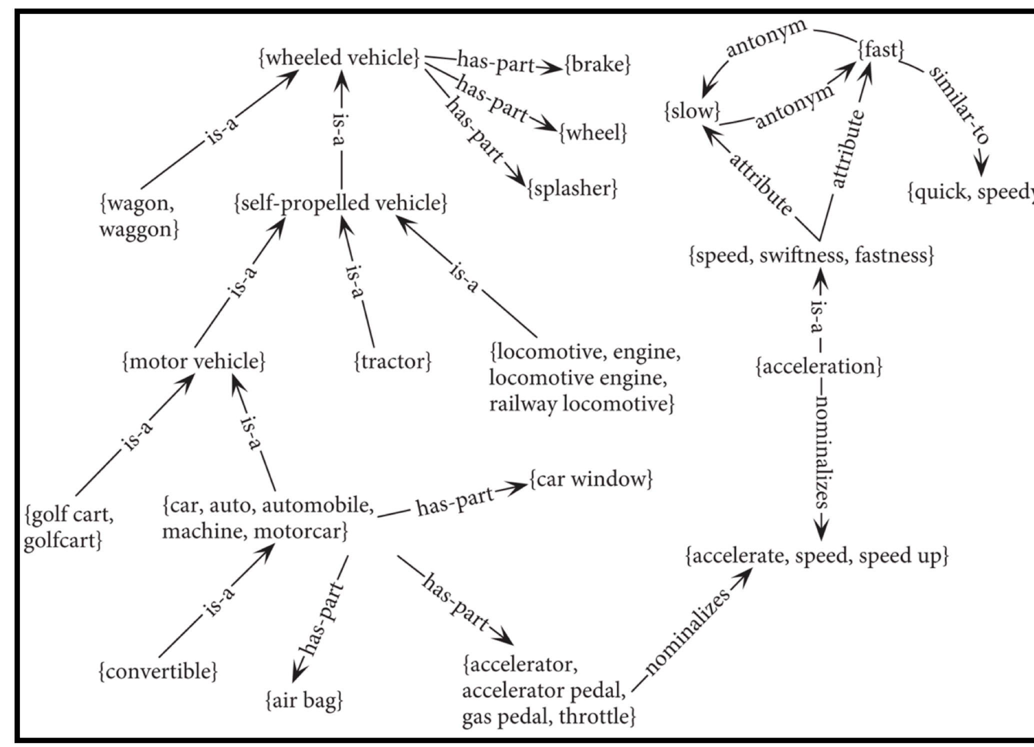
Aron Henriksson

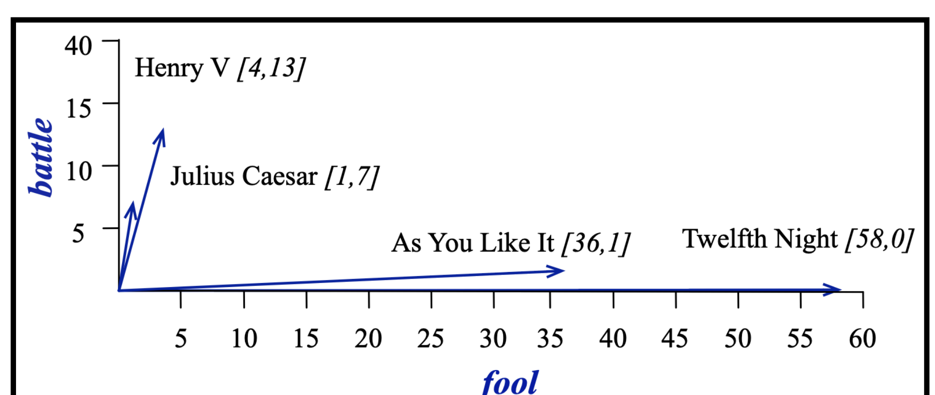
Semantics in Natural Language Processing

NLP systems must account for semantics, i.e. linguistic meaning

- Many different approaches to semantics in NLP
  - Computational semantics
  - Frame semantics
  - Distributional semantics







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Lexical Semantics

The linguistic study of word meaning

- The meaning of a text can be derived from the meaning of words: **semantic composition**
- How should we **represent** the **meaning** of a word?
- Lexical semantics can help us to formulate **desiderata** of **word representations**
  - Lemmas and wordforms
  - Senses and polysemy
  - Semantic and taxonomic relationships
  - Word similarity
  - Word relatedness
  - Connotations

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Lemmas and Wordforms

mouse (N)

1. any of numerous small rodents...
2. a hand-operated device that controls a cursor...

'mouse' is the **lemma**

- Also lemma for 'mice'
- 'sing' is the lemma for 'sing', 'sang', 'sung'
- Lemma for verbs: infinitive form

The specific forms are called **wordforms**

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Senses and Polysemy

mouse (N)

1. any of numerous small rodents...
2. a hand-operated device that controls a cursor...

Each lemma can have multiple meanings

- Each of these aspects of the meaning of mouse is a **word sense**
- Lemmas with multiple meanings are **polysemous**
- Can make interpretation difficult — language is ambiguous

Word sense disambiguation: which sense is used in a particular context?

Semantic Relations

Synonyms

- A sense of a word whose meaning is (nearly) identical to a sense of another word (couch/sofa — vomit/throw up — car/automobile)
- Substitutable in any sentence without changing its truth condition: same **propositional meaning**
- **Principle of contrast**: a difference in linguistic form is always associated with some difference in meaning

Antonyms

- Words with opposite meanings (bad/good — hard/easy — fast/slow)
- Define binary opposition or at opposite ends of some scale (long/short)
- **Reversives** describe change/movement in opposite directions (up/down)

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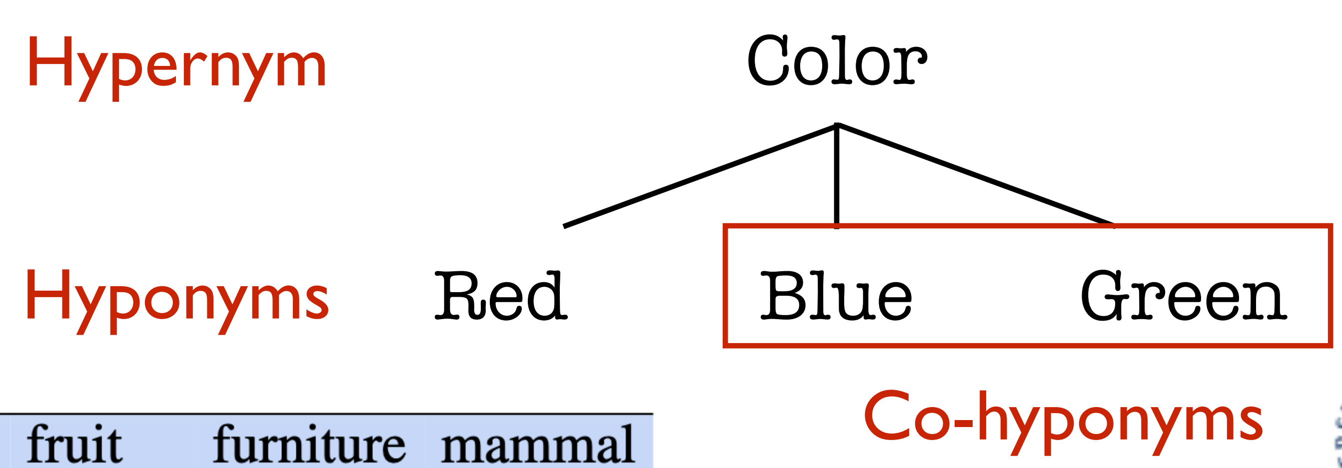
Taxonomic Relations

Taxonomic relations

- A word is a **hyponym** of another word if it is more specific, denoting a subclass of the other (car/vehicle — dog/animal)
- A word is a **hypernym** of another word if it is more general, denoting a superclass of the other (vehicle/car — animal/dog)
- Also known as **superordinate/subordinate** or **IS-A hierarchy**
- Hypernymy useful for **textual entailment** and **question answering**
- Other taxonomic relations: meronymy, metonymy etc.



Superordinate	vehicle	fruit	furniture	mammal
Subordinate	car	mango	chair	dog

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Word Similarity

Synonymy is rare, but words often have many similar words

- 'cat' and 'dog' are not synonymous, but they are similar words
- Notion of **word similarity** is very useful in larger semantic tasks
- Word similarity helps compute similarity between phrases or sentences
- Important for **question answering**, **paraphrasing** and **summarization**

vanish	disappear	9.8
belief	impression	5.95
muscle	bone	3.65
modest	flexible	0.98
hole	agreement	0.3

Examples from SimLex-999: human judgment of word similarity on a scale from 0 to 10

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Word Relatedness

Words can be related in ways other than similarity

- One such class of connections is called **word relatedness**
- ‘coffee’ and ‘cup' are not similar but clearly related — associated by co-participating in an the event of drinking coffee out of a cup
- Some related words belong to the same **semantic field**, i.e. a set of words encompassing a particular semantic domain
  - **Hospitals**: ‘surgeon’, ‘scalpel’, ‘nurse’, ‘anesthetic’, ‘hospital’
  - **Restaurants**: ‘waiter’, ‘menu’, ‘plate’, ‘food’, ‘chef’
  - **Houses**: ‘door’, ‘roof’, ‘kitchen’, ‘family’, ‘bed’
- Semantic fields related to **topic models**

Connotation

Words have affective meanings or connotations

- Aspects of a word's meaning related to emotions, sentiment, opinions, or evaluations
- Some words have positive ('happy') or negative ('sad) connotations
- Similar words can have different connotations: 'innocent' vs. 'naive'
- Positive or negative evaluation language is called **sentiment** (positive: 'great', 'love' — negative: 'terrible', 'hate')
- Word sentiment important in **sentiment analysis** and **stance detection**

Representing the Meaning of Words

Representing words as a string of letters

- Or an index in a **vocabulary**
- Convert symbols to numbers

V = {'files', 'find', 'my'}

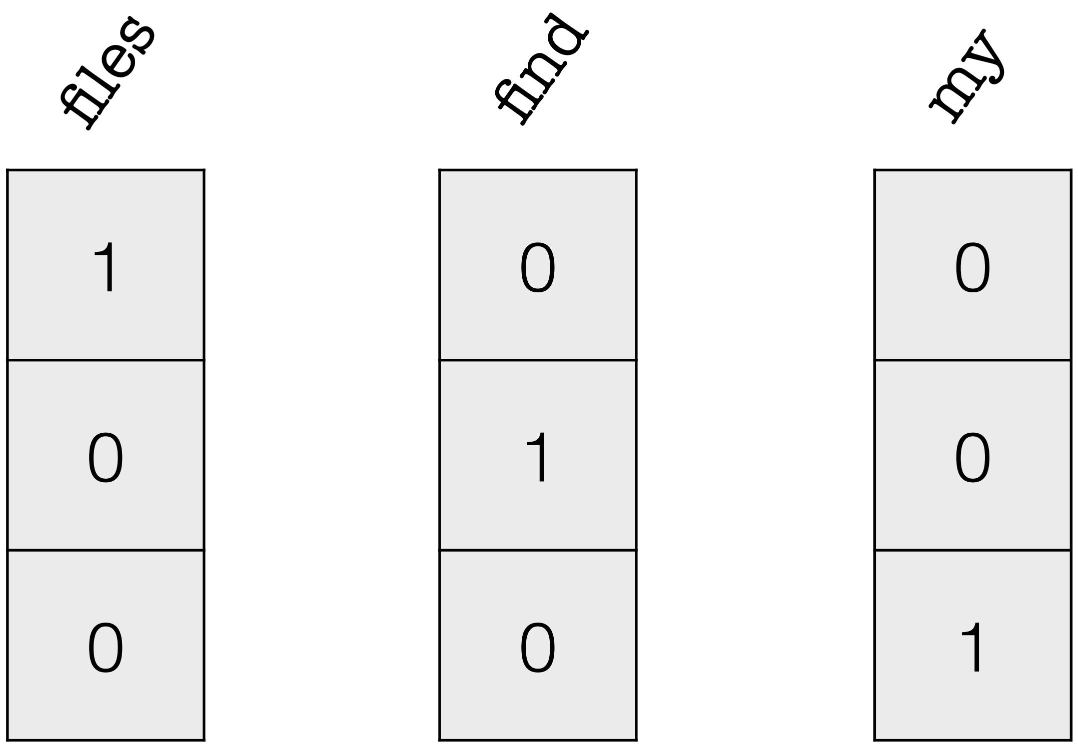
'files' = 1
'find' = 2
'my' = 3

'find my file' —> ['find', 'my', ['file'] —> [2, 3, 1]

One Hot Encoding

Representing words as vectors

- Symbol represented by an array of the same length as the vocabulary size
- All zeros except a single element with a value of one
- Each element corresponds to a separate symbol



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Dot Product

How can we calculate the similarity between words?

$$
\begin{array}{ccccc}
\boxed{0} & \times & \boxed{1} & = & 0 \\
\boxed{1} & \times & \boxed{0} & = & 0 \\
\boxed{1} & \times & \boxed{1} & = & 1 \\
\boxed{2} & \times & \boxed{2} & = & 4 \\
 & & & + & \overline{} \\
 & & & & 5
\end{array}
$$

Dot Product

The dot product of any one-hot vector with itself is one

$$
\begin{array}{|c|}\hline 0 \\ \hline 1 \\ \hline 0 \\ \hline 0 \\ \hline \end{array}
\begin{array}{c} \times \\ \times \\ \times \\ \times \end{array}
\begin{array}{|c|}\hline 0 \\ \hline 1 \\ \hline 0 \\ \hline 0 \\ \hline \end{array}
\begin{array}{l} = 0 \\ = 1 \\ = 0 \\ = 0 \end{array}
$$

$$
\begin{array}{r} + \\ \hline 1 \end{array}
$$

Dot Product

The dot product of any one-hot vector with any other one-hot vector is zero

$$
\begin{array}{ccccc}
\boxed{0} & \times & \boxed{0} & = & 0 \\
\boxed{1} & \times & \boxed{0} & = & 0 \\
\boxed{0} & \times & \boxed{0} & = & 0 \\
\boxed{0} & \times & \boxed{1} & = & 0 \\
 & & & + & \overline{} \\
 & & & & 0
\end{array}
$$

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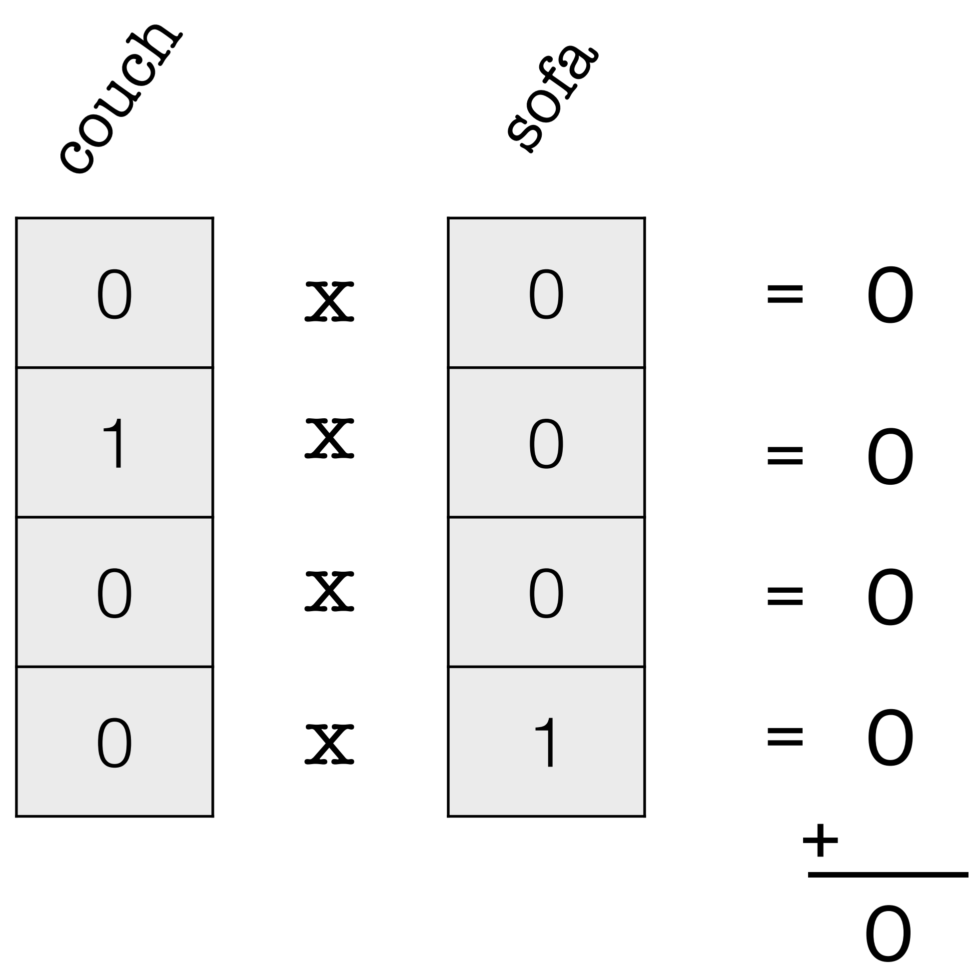
Dot Product

No notion of semantic similarity between words represented

- Synonyms have orthogonal representations with one-hot encoding!



Vector Semantics

Representing words as vectors

- The standard way to represent word meaning in NLP
- Representing word meaning as a vector goes back to 1950s and Osgood's idea to use a point in 3-dimensional space to represent word connotation
- Ideas in 1950 to define word meaning by its **distribution in language use**

	Valence	Arousal	Dominance
courageous	8.05	5.5	7.38
music	7.67	5.57	6.5
heartbreak	2.45	5.65	3.58
cub	6.71	3.95	4.24

Words represented in a 3-dimensional space

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Desiderata of Word Representations

We want a model of word meaning to account for many aspects of semantics

- ❖ Some words have similar meanings, others have unrelated meanings
- ❖ Some words are synonyms, others are antonyms
- ❖ Some word pairs have taxonomic relations, e.g hypernym-hyponym
- ❖ Words are polysemous and have ambiguous, context-dependent meanings
- ❖ Some words have positive connotations, others have negative connections

Allow us to make inferences to address meaning-related tasks

Distributional Hypothesis

Words that appear in **similar contexts** tend to have **similar meanings**

- The meaning of a word can be derived from the contexts in which it appears — **Z. Harris** (1954)

Meaning is use

L. Wittgenstein

You shall know a word by the company it keeps

J.R. Firth

What is there to watch on the television tonight?

I want to watch TV!

We must watch the news on the telly.

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Distributional Hypothesis

What is ‘ongchoi’?

Ongchoi is delicious sautéed with garlic.

Ongchoi is superb over rice.

...**ongchoi** leaves with salty sauces...

...**spinach** sautéed with garlic over rice...

...**chard stems** and leaves are delicious...

...**collard greens** and other salty leafy greens

A leafy green similar to these other leafy greens?

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Distributional Semantics

Exploits **distributional hypothesis** and **large corpora** to model word meaning

- A word is represented as a point (vector) in a multidimensional **semantic space**
- Derived from the distributions of contexts (word neighbors)
- Offers enormous power to NLP applications

A two-dimensional (t-SNE) projection of 60-dimensional semantic representations for words and phrases

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Models of Distributional Semantics

An evolution of models of distributional semantics

- Counting-based vs. prediction-based models
- Sparse vs. dense word vectors (or embeddings)
- Static vs. dynamic (context-specific) word vectors

All learned automatically from large corpora without supervision

- No need for manually labeled data!

Term-Document Matrix

The vector space model of information retrieval

- Each **row** represents a word in the vocabulary
- Each **column** represents a document from a document collection
- Each **cell** represents the number of times a particular word occurs in a particular document
- A document is represented as a **count vector**
- Document vectors of **dimension** |V| = vocabulary size (= 4 in example)

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

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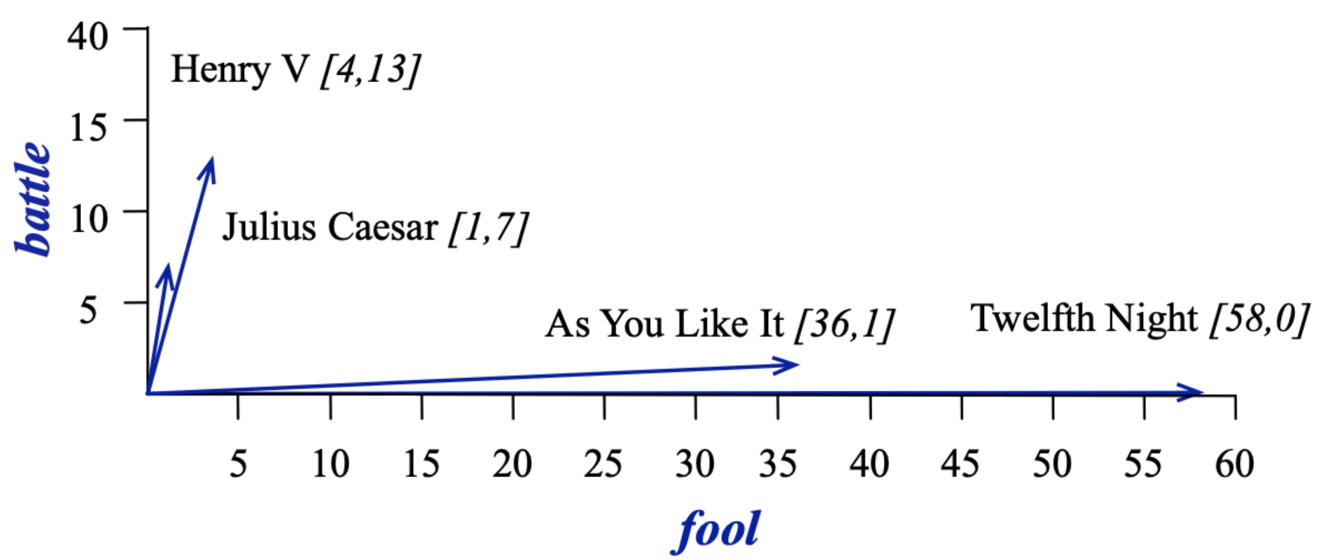
As You Like It —> [1,114,36,20]

Term-Document Matrix

The vector space model of information retrieval

- Originally defined as means of finding similar documents
- Two documents that are similar will have similar words
- Documents with similar words will have similar column vectors
- As You Like It [1,114,36,20] and Twelfth Night [0,80,58,15] more similar to each than to Julius Caesar [7,62,1,2] or Henry V [13,89,4,3]
- The term-document matrix has |V| rows and D columns



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Words as Vectors: Document Dimensions

Vector semantics to represent the meaning of words

- Each word is associated with a word vector (a row vector)
- Dimensions correspond to documents (here: Shakespeare plays)
- Similar words have similar vectors because they tend to occur in similar context
- The **term-document matrix** lets us represent word meaning by the documents it occurs in

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

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'battle' —> [1,0,7,13]

Words as Vectors: Word Dimensions

Vector semantics to represent the meaning of words

- Represent words as vectors of document counts
- Columns labeled by words rather than documents
- This is a **term-term matrix** of dimensionality |V| × |V|
- Each cell records the number of times the row (target) word and the column (context) word **co-occur** in some **context** in a given corpus

Words as Vectors: Word Dimensions

Vector semantics to represent the meaning of words

- Different **context definitions** exist:
  - A document
  - Words in a window surrounding the target word (most common)
  - Syntactic dependencies

is traditionally followed by	**cherry**	pie, a traditional dessert
often mixed, such as	**strawberry**	rhubarb pie. Apple pie
computer peripherals and personal	**digital**	assistants. These devices usually
a computer. This includes	**information**	available on the internet

A context window of 4 words to the left and 4 words to the right of the target word

	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	...
strawberry	0	...	0	0	1	60	19	...
digital	0	...	1670	1683	85	5	4	...
information	0	...	3325	3982	378	5	13	...

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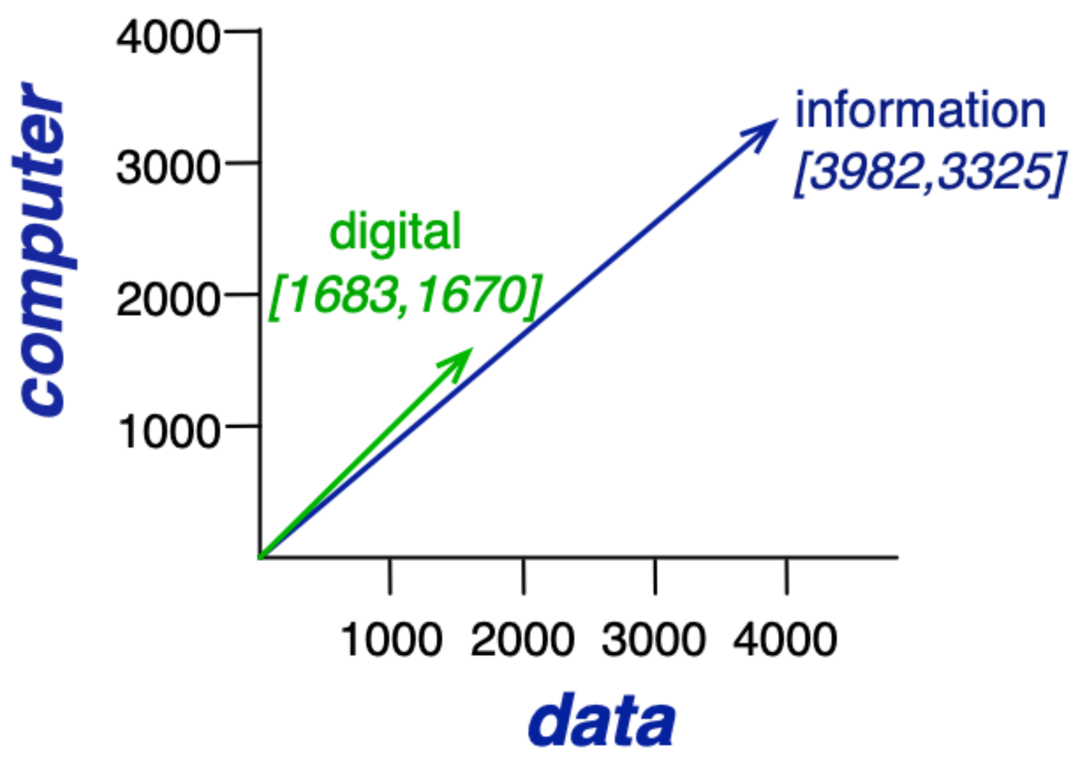
Words as Vectors: Word Dimensions

Vector semantics to represent the meaning of words

- A spatial visualization of word vectors for ‘digital’ and ‘information’, showing just two of the dimensions: ‘computer’ and ‘data’



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Measuring Semantic Similarity

How can we calculate the similarity between words?

- Need metric that takes two vectors (of same dimensionality) and returns a measure of their **similarity**
- How about using the **dot product**?
  - High when large values in same dimensions
  - Orthogonal vectors (zeros in different dimensions) will return 0

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

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Problem: favors long vectors!

- More frequent words have longer vectors
- We want a similarity metric that is not affected by term frequency!

$$\boxed{|\mathbf{v}| = \sqrt{\sum_{i=1}^{N} v_i^2}}$$

Measuring Semantic Similarity

How can we calculate the similarity between words?

- Solution: modify dot product to normalize for vector length
- This **normalized dot product** is the same as the **cosine** of the angle between the two vectors

$$\boxed{\begin{aligned} \mathbf{a} \cdot \mathbf{b} &= |\mathbf{a}||\mathbf{b}| \cos\theta \\ \frac{\mathbf{a} \cdot \mathbf{b}}{|\mathbf{a}||\mathbf{b}|} &= \cos\theta \end{aligned}}$$

Cosine similarity — the most common similarity metric

- 1 for vectors in the same direction, 0 for orthogonal vectors, -1 for vectors in opposite directions
- Since raw frequency values are non-negative: cosine ranges from 0-1

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

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Measuring Semantic Similarity

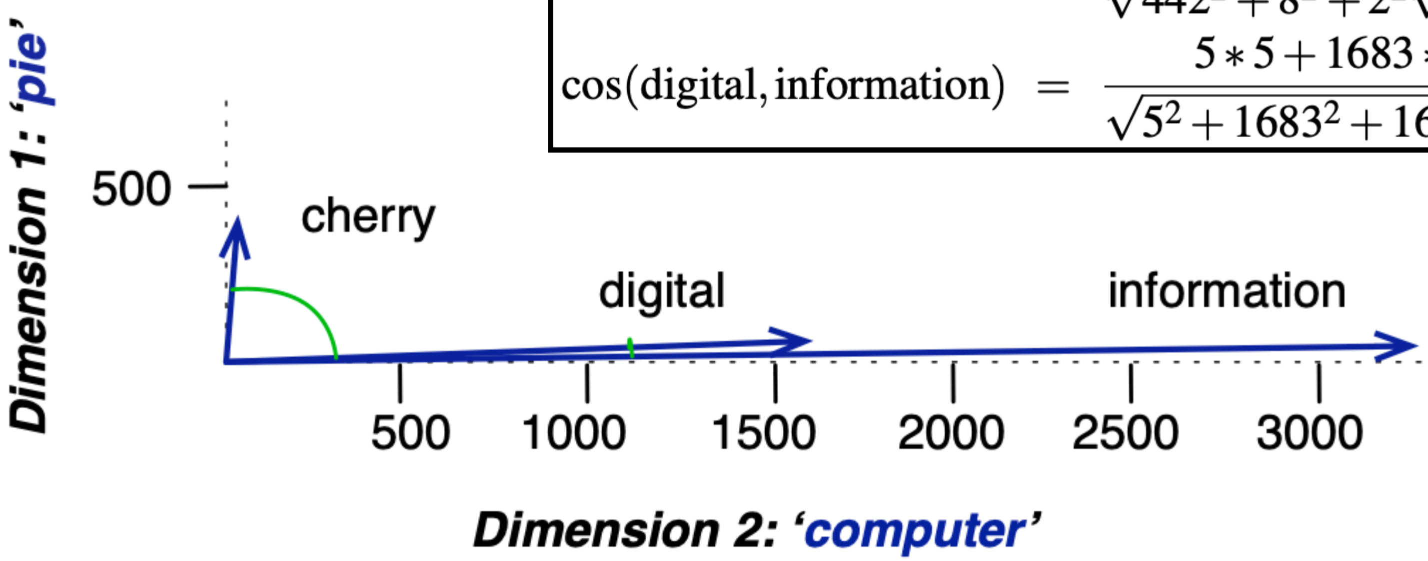
How can we calculate the similarity between words?

- Calculating cosine similarity between ‘cherry’ and ‘information’ vs. ‘digital’ and ‘information’
- 2D visualization of three vectors

	pie	data	computer
cherry	442	8	2
digital	5	1683	1670
information	5	3982	3325

$$\cos(\text{cherry}, \text{information}) = \frac{442*5+8*3982+2*3325}{\sqrt{442^2+8^2+2^2}\sqrt{5^2+3982^2+3325^2}} = .018$$

$$\cos(\text{digital}, \text{information}) = \frac{5*5+1683*3982+1670*3325}{\sqrt{5^2+1683^2+1670^2}\sqrt{5^2+3982^2+3325^2}} = .996$$



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Weighting Co-Occurrences

Not all co-occurrence events are equally significant!

- Raw frequency not the best measure of word association
- Raw frequency is skewed and not very discriminative
- To discriminate 'cherry' and 'strawberry' from 'digital' and 'information'
  - Words like 'the', 'it' and 'they' will not provide good discrimination
  - Occur frequently will all words and therefore not informative
- **Paradox**: words that appear nearby frequently are important, but words that are too frequent are unimportant

How can we balance these two conflicting constraints?

- Two common solutions: **tf-idf** and **PPMI** weighting

Weighting Co-Occurrences

tf-idf

- Used when the dimensions are documents
- **Term frequency × inverse document frequency**
  - tf: the frequency of word t in document d
  - idf: give a higher weight to words that occur only in a few documents (N/df_t — N = total # of docs, df_t = # of docs in which term t occurs)
- **Intuition**: words appearing in few documents have a high discriminative power!

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	0.074	0	0.22	0.28
good	0	0	0	0
fool	0.019	0.021	0.0036	0.0083
wit	0.049	0.044	0.018	0.022

A tf-idf weighted term-document matrix

Jurafsky &. Martin, 2022. Speech and Language Processing.

Weighting Co-Occurrences

PPMI

- Used when dimensions are words (term-term matrices)
- Positive Pointwise Mutual Information
- **Intuition**: weigh association between two words according to how much more the words co-occur than expected
- PMI values range from negative to positive infinity
  - Negative PMI values tend to be unreliable — PPMI often used instead (replaces negative PMI values with 0)

$$\boxed{\text{PMI}(w,c) = \log_2 \frac{P(w,c)}{P(w)P(c)}}$$

$$\boxed{\text{PPMI}(w,c) = \max(\log_2 \frac{P(w,c)}{P(w)P(c)},0)}$$

	computer	data	result	pie	sugar
cherry	0	0	0	4.38	3.30
strawberry	0	0	0	4.10	5.51
digital	0.18	0.01	0	0	0
information	0.02	0.09	0.28	0	0

PPMI matrix

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High-Dimensional and Sparse Vectors

Context-counting vectors are high-dimensional and sparse

- The dimensionality of the vector is the size of the vocabulary: |V|
- The vocabulary of a corpus can be > 1M
  - Common to limit vocabulary to 10,000-50,000 most frequent words
- Co-occurrences between all word pairs are rare events!
  - Most cells are 0
  - Sparse vectors
- Dimensionality reduction

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Sparse vs. Dense Vector Representations

Sparse vectors

- Dimensions corresponding to words in the vocabulary

Dense vectors

- Dimensions ranging from 50–1000, difficult to interpret
- Dense vectors are often referred to as **word embeddings**

Dense vectors work better for most NLP tasks — why?

- Smaller parameter space helps with generalization and avoiding overfitting
- Dense vectors better at capturing synonymy? Sparse vectors have distinct dimensions for synonymous context words

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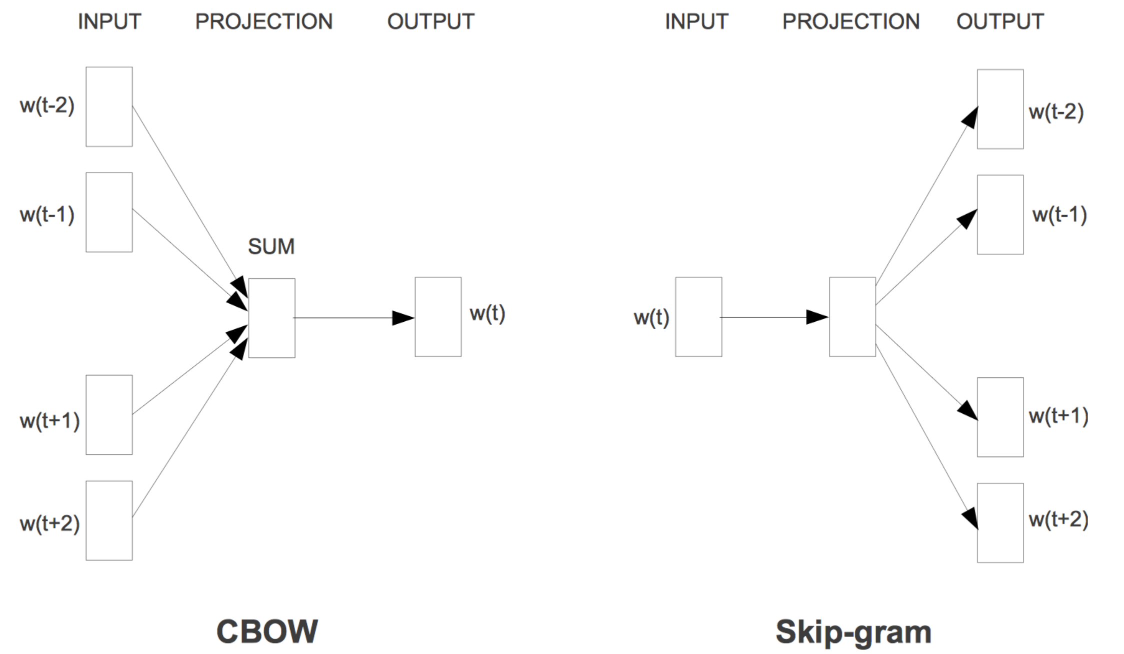
word2Vec

Prediction-based model for creating word embeddings

- Instead of counting how often each word w occurs in different contexts, we train a classifier on one of two binary prediction tasks
  - Predict target word based on an neighboring context words (CBOW)
  - Predict neighboring context words based on target word (Skip-gram)
- **The prediction task itself is uninteresting** — we use the learned classifier weights as the word embeddings



Mikolov et al., 2013. Efficient estimation of word representation in vector space.

Self-Supervision

Use unlabeled data in a supervised learning setting

- Use running text as implicitly supervised training data for the classifier
- Words that occurs near a target word provide positive examples
- Words that do not occur near a target word provide negative examples

Self-supervision was first proposed in neural language modeling task

- A neural network that learned to predict the next word
- Used the next word as its supervision signal
- word2vec is much simpler model
  - Simpler task: binary classification instead of word prediction
  - Simpler architecture: logistic regression instead of multi-layer NN

Skip-gram with Negative Sampling

The intuition of SGNS

1. Treat the target word and a neighboring context word as positive examples
2. Randomly sample other words in the vocabulary to get negative samples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights as the embeddings

Skip-gram with Negative Sampling

The classification task

- Train classifier such that:
  - Given a tuple (w,c) of a target word w paired with a candidate context word c — e.g. (‘apricot’, ’jam’) or (‘apricot', ‘aardvark’)
  - It will return the probability that c is a real context word (true for ‘jam’, false for ‘aardvark’)

```
... lemon,  a [tablespoon of apricot jam,     a] pinch ...
               c1          c2     w     c3        c4
```

Jurafsky &. Martin, 2022. Speech and Language Processing.

- Probabilities computed based on **embedding similarity**: a word is likely to occur near target word if its embedding is similar to target embedding
  - Apply sigmoid function to dot product of embeddings of target word with each context word

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Skip-gram with Negative Sampling

Learning skip-gram embeddings

- Learning algorithm takes as input a corpus and vocabulary size N
- First, assigns random embedding to each word
- Then, proceeds to iteratively shift embeddings of each word w to be more likely embeddings of context words and less like non-context words
- Negative examples: randomly sampled ‘noise words’

```
... lemon,  a [tablespoon of apricot jam,     a] pinch ...
               c1          c2     w     c3       c4
```

positive examples +

w	c_{pos}
apricot	tablespoon
apricot	of
apricot	jam
apricot	a

negative examples -

w	c_{neg}	w	c_{neg}
apricot	aardvark	apricot	seven
apricot	my	apricot	forever
apricot	where	apricot	dear
apricot	coaxial	apricot	if

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Skip-gram with Negative Sampling

Given training data — and an initial set of embeddings — the goal of the learning algorithm is to adjust those embeddings to:

- Maximize the similarity of the target word, context word pairs (w,c_{pos}) drawn from the positive examples
- Minimize the similarity of the (w,c_{neg}) pairs from the negative examples

In other words, we want to:

- Maximize the dot product of the word with the actual context words
- Minimize the dot products of the word with the k negative sampled non-neighbor words.

Loss function minimized using stochastic gradient descent

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Other Static Embeddings

fasttext

- An extension of word2vec
- Addresses the inability to deal with **unknown words** — words in a test corpus that were not seen in the training corpus
- Also deals with **word sparsity**, e.g. in languages with rich morphology
- Uses **subword models**, representing each word as itself + bag of constituent **character n-grams**, with special boundary symbols <>
- Example: with n=3, 'where' — <where> + <wh, whe, her, ere, re>
- Skipgram embedding learned for each constituent n-gram and the word is represented by sum of embeddings
- Unknown words represented only by sum of of constituent n-grams

Other Static Embeddings

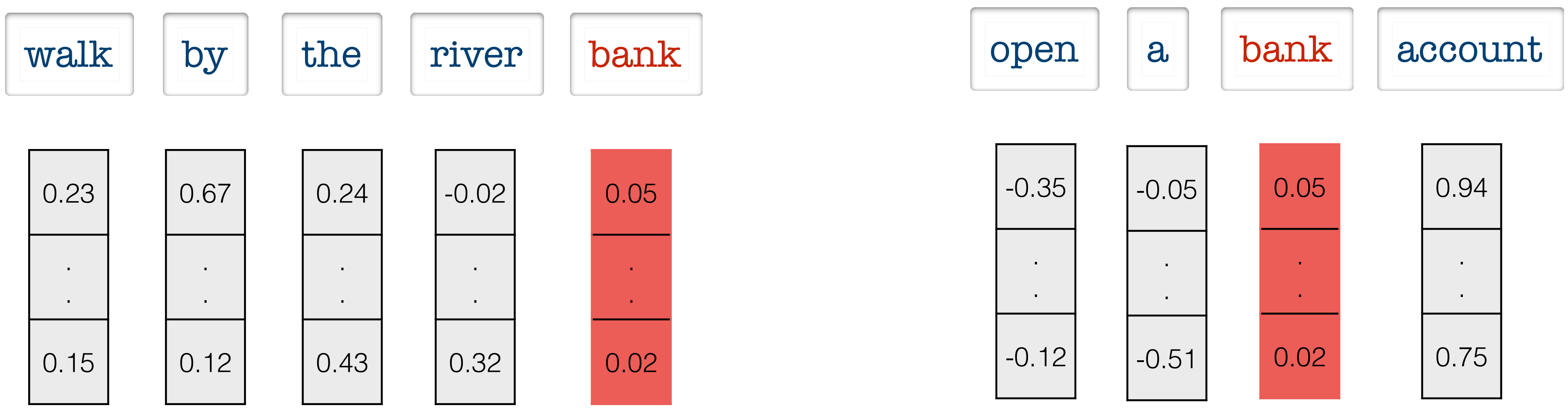
GloVe

- Short for **Global Vectors**
- Captures global **corpus statistics**
- Based on ratios of probabilities from word-word co-occurrence matrix
- Combines the intuitions of count-based sparse vector models while capturing linear structures by prediction-based dense vector models

Static vs. Dynamic Word Embeddings

Static Embeddings

- A single vector for each unique word w in the vocabulary (types)



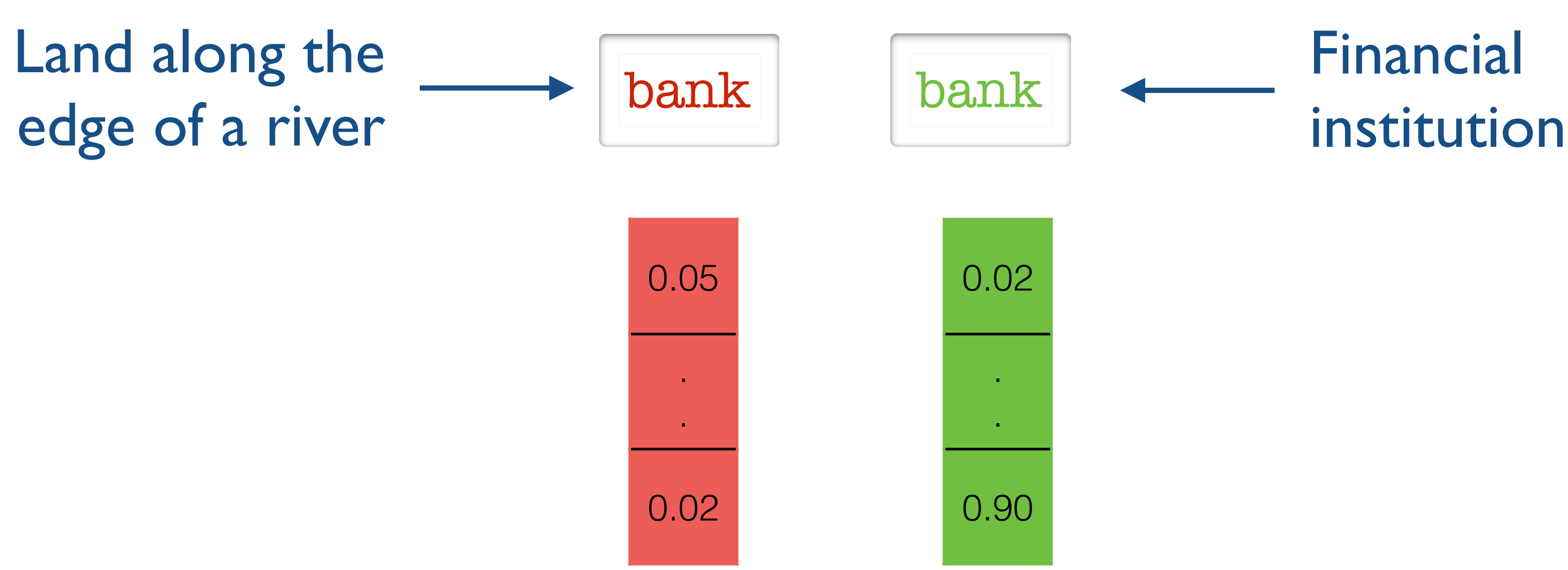
Dynamic Embeddings

- Representations for words in context (tokens)
- Each word w represented by a different vector each time it appears in a different context
- Also known as **contextual word embeddings**

Contextual Word Embeddings

Sense-specific and context-aware word representations

- A function of the entire sentence/sequence containing that word
- Different word vectors under different contexts
- Helps with polysemy!



Language Models

Language modeling — assign probabilities to word sequences and predicting upcoming words

- An important task in itself
- Plays a role in many NLP applications

Can also be used for learning contextual word embeddings

- ELMo
- BERT

Pre-trained language models

- Pre-training and fine-tuning paradigm
- Transfer learning

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BERT Overview

Bidirectional Encoder Representations from Transformers

- One of the biggest leaps in NLP

Applies bidirectional training of **Transformer** — an **attention** model — to language modeling

- In contrast to single-direction language models, where a text sequence is processed left to right or right to left (or combination)
- Bidirectionally trained language model leads to a deeper sense of language context and flow
- Introduced **masked language modeling** for bidirectional training

Transformer Encoder of BERT

BERT is based on the transformer

- An **attention mechanism**
- Learns contextual relations between words — contextual word embeddings

Transformer includes two separate mechanisms

- An **encoder** that reads input text
- A **decoder** that produces the prediction for the task
- BERT goal is to create a language model — only encoder needed

Reads entire sequence of words at once

- Bidirectional (or non-directional)
- Learns contextual word embeddings

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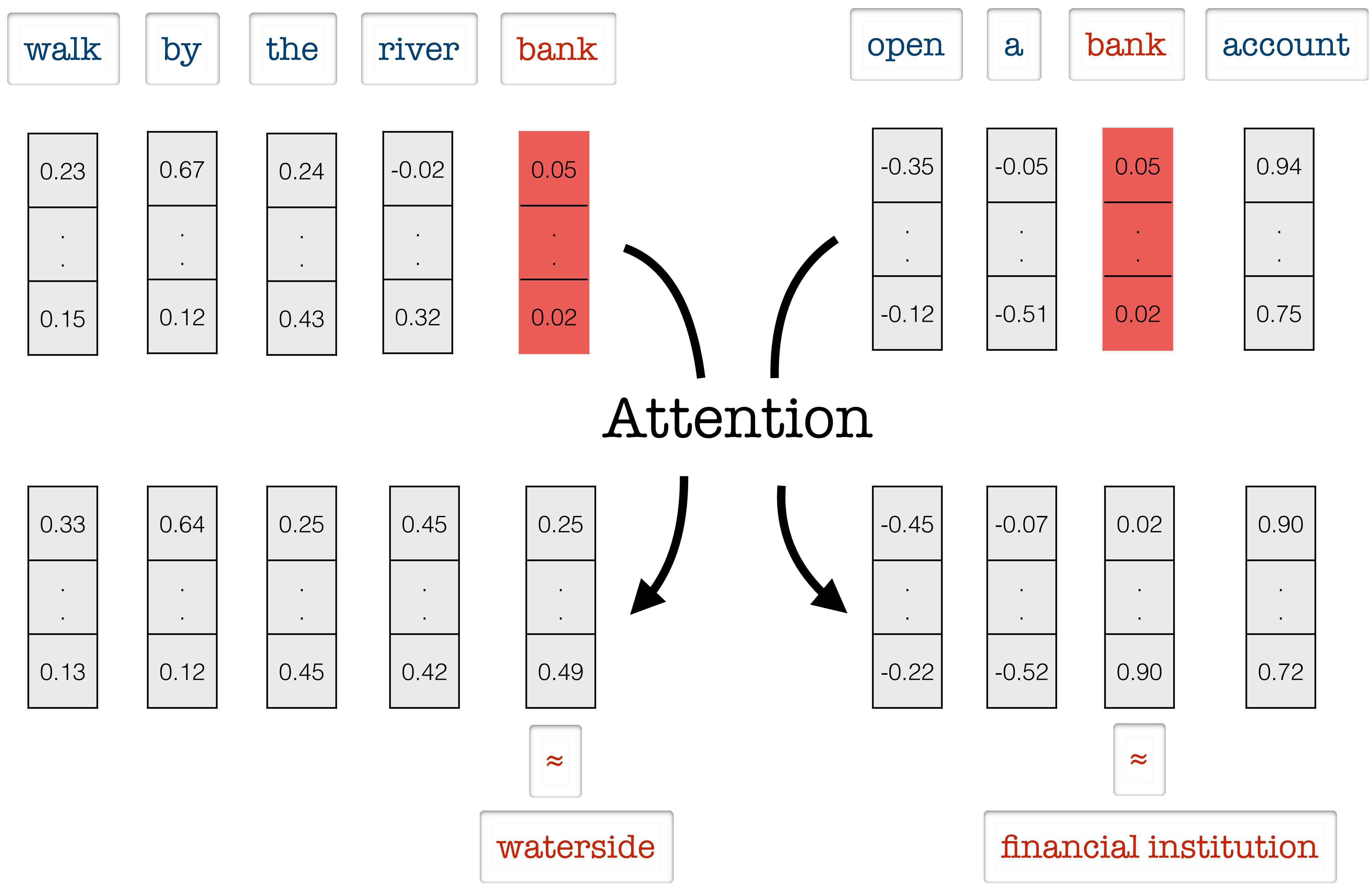
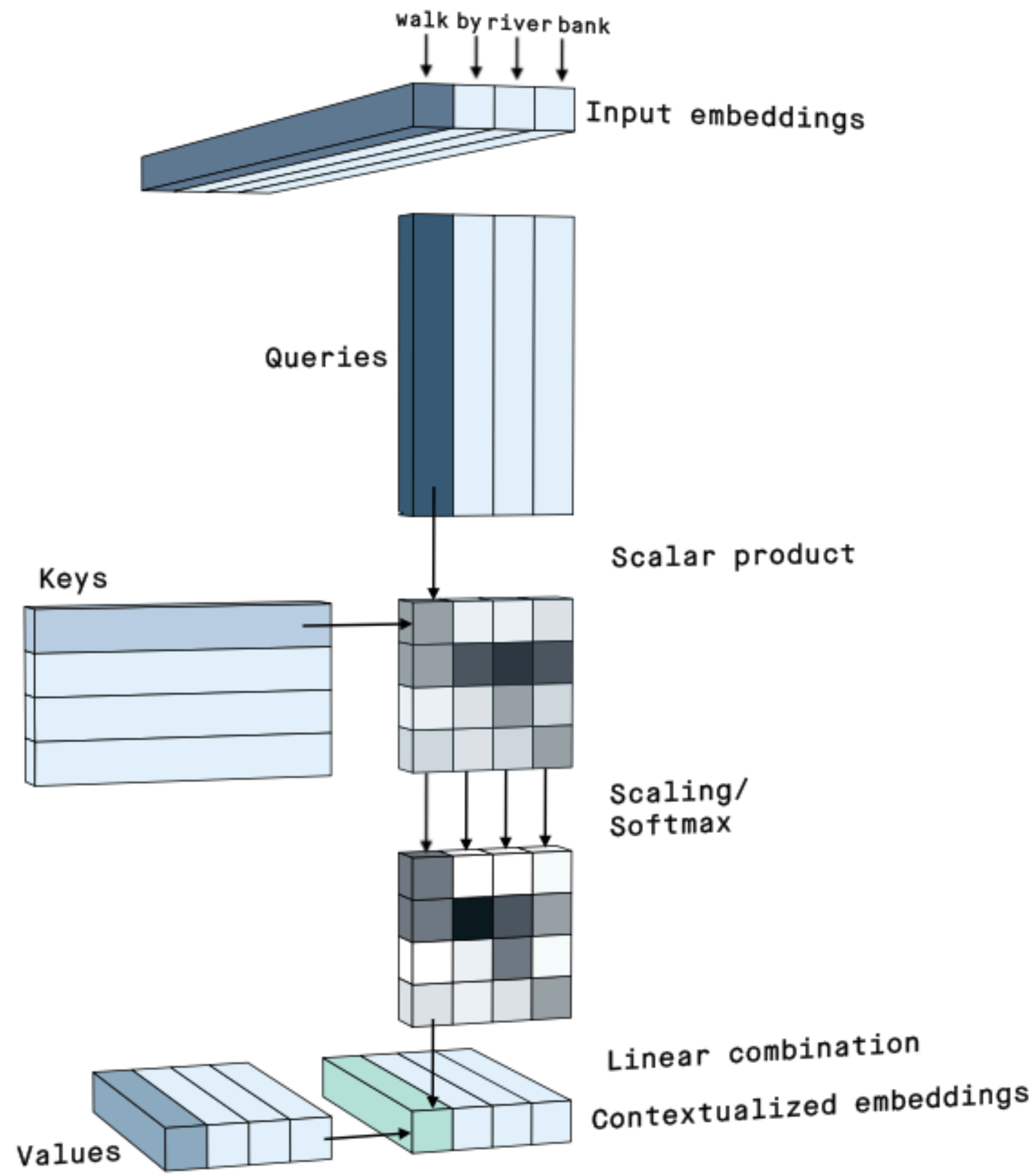
Contextual Word Embeddings in BERT



Contextual Word Embeddings in BERT

1. Each token replaced with default, **context-independent embedding**
2. Calculate **scalar product** between pairs of embeddings in input sequence
   - High when similar
   - Low when dissimilar
3. Scalar values are passed to a **softmax** activation function column by column
   - Amplifies large values
   - Crushes low and negative values
4. **Contextualized embedding** created for each token through a linear combination of input embeddings in proportion to softmax results

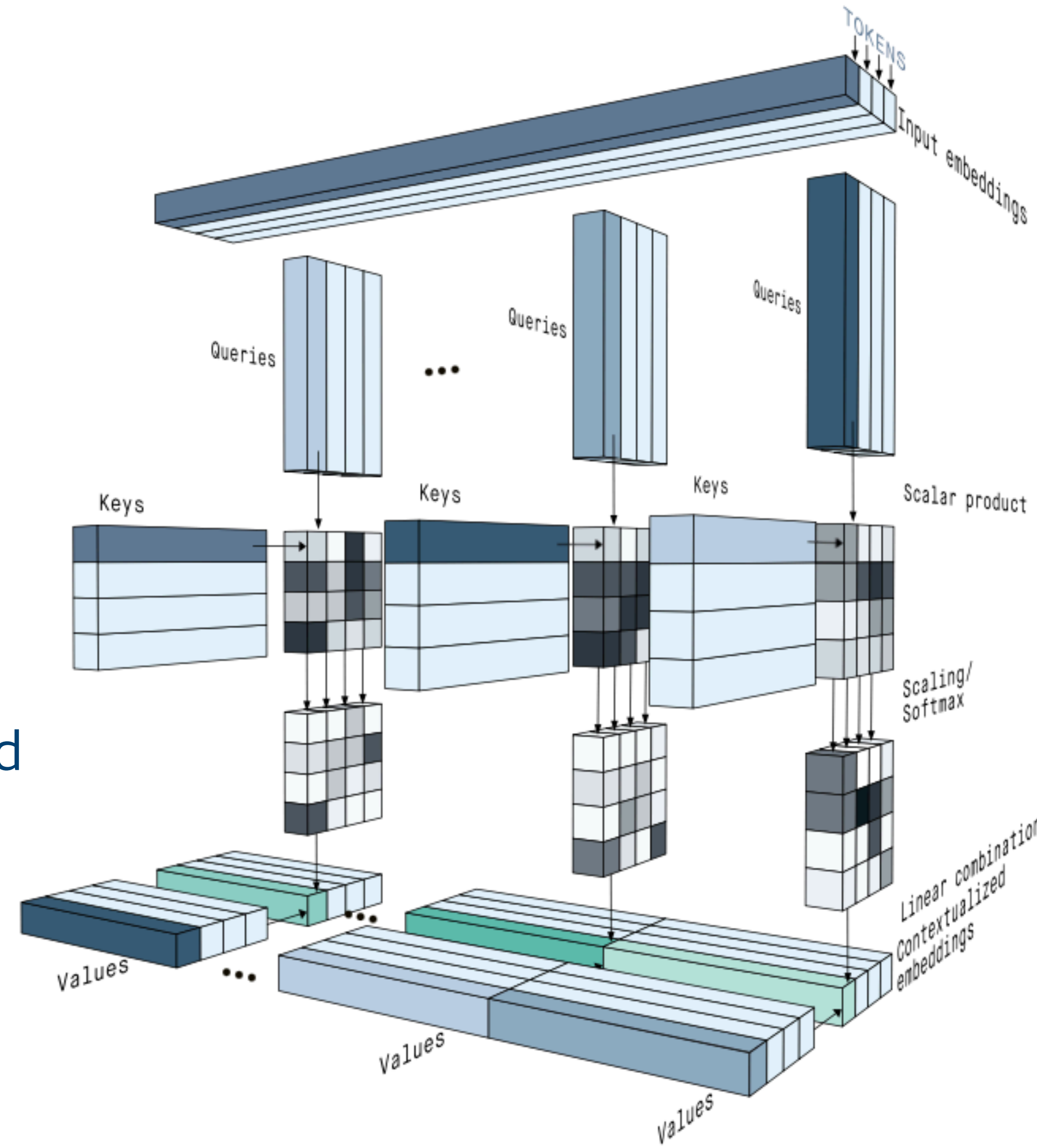


https://peltarion.com/blog/data-science/self-attention-video

Multi-head Attention and BERT

BERT uses multi-head attention

- Sequence of input embeddings projected using many different sets of **key**, **query**, and **value** projections
- Each focus on different types of relationships between tokens
- Specific contextualized embeddings
- Contextualized embeddings from different attention heads concatenated

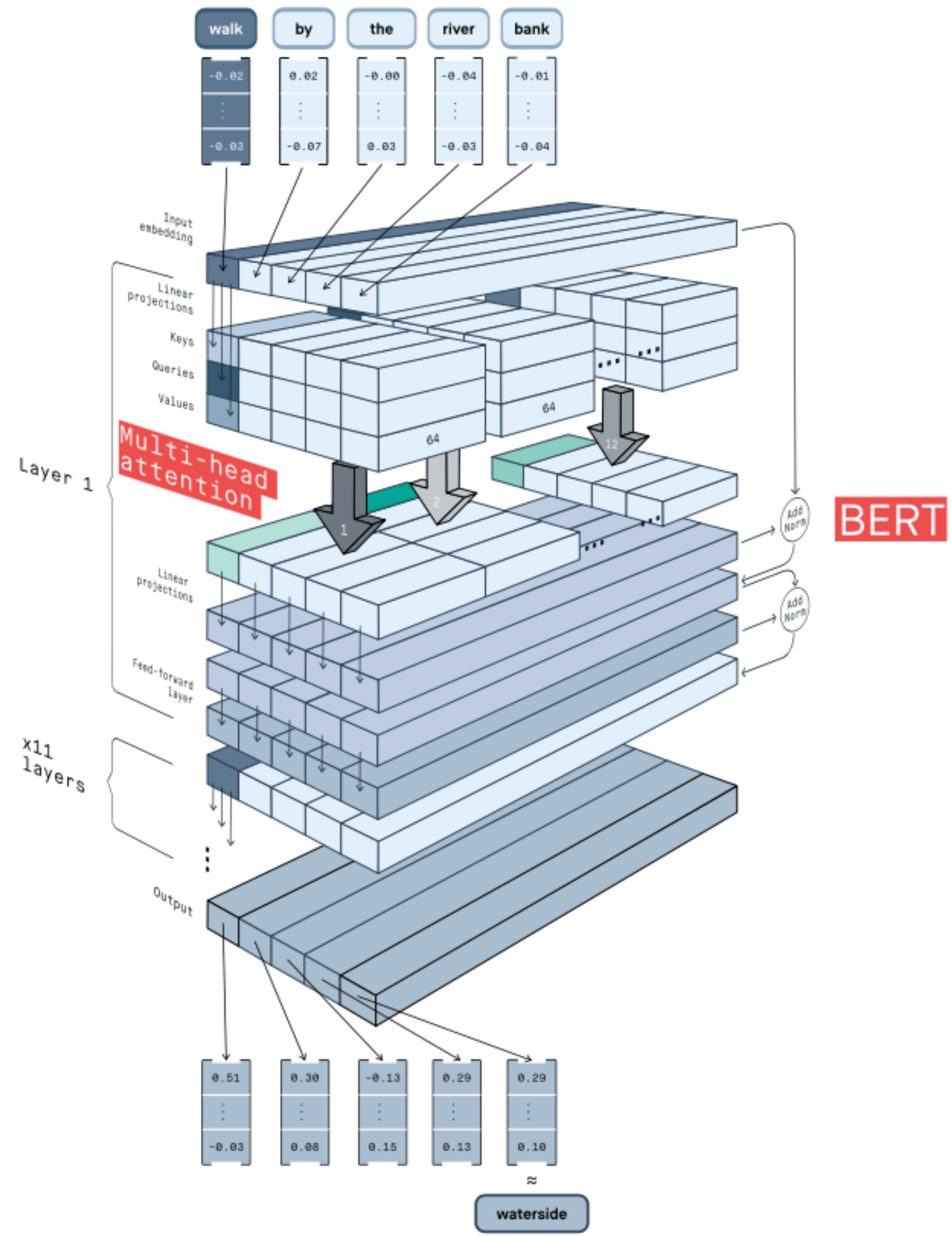


https://peltarion.com/blog/data-science/self-attention-video

BERT Architecture

Many layers of multi-head attention

- BERT encoder uses WordPiece embeddings of tokens
- Begins by adding them to **positional embeddings** — provides information about the order of tokens
- Additional linear projections, normalization and feed-forward layers add flexibility and stability



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BERT Pre-training

Self-supervision — what prediction task to use?

- Predict the next word in a sequence?
- “The child came home from ____”
- A directional approach limits context learning

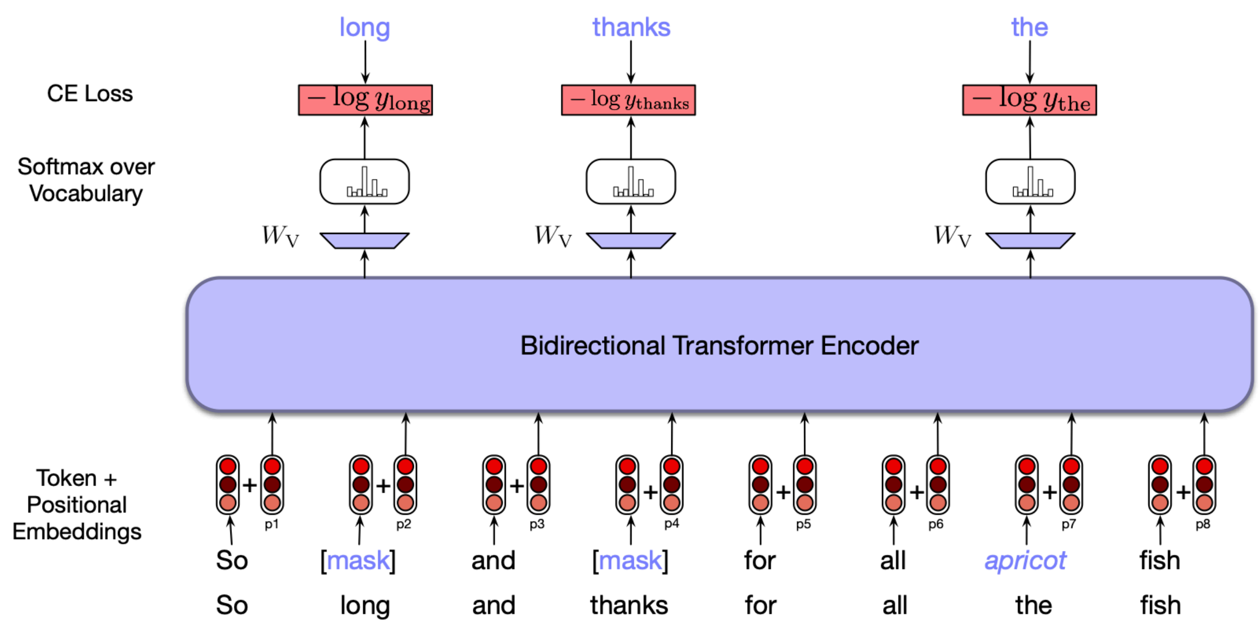
BERT uses two training strategies

- Masked language modeling
- Next sentence prediction

Masked Language Modeling

MLM — a Cloze task

- 15% of words replaced by [MASK] token — actually, of the 15%:
  - 80% replaced by [MASK] token
  - 10% by random word
  - 10% use the original word
- Predict original value of masked words based on the context
- BERT loss function takes into account only prediction of masked values



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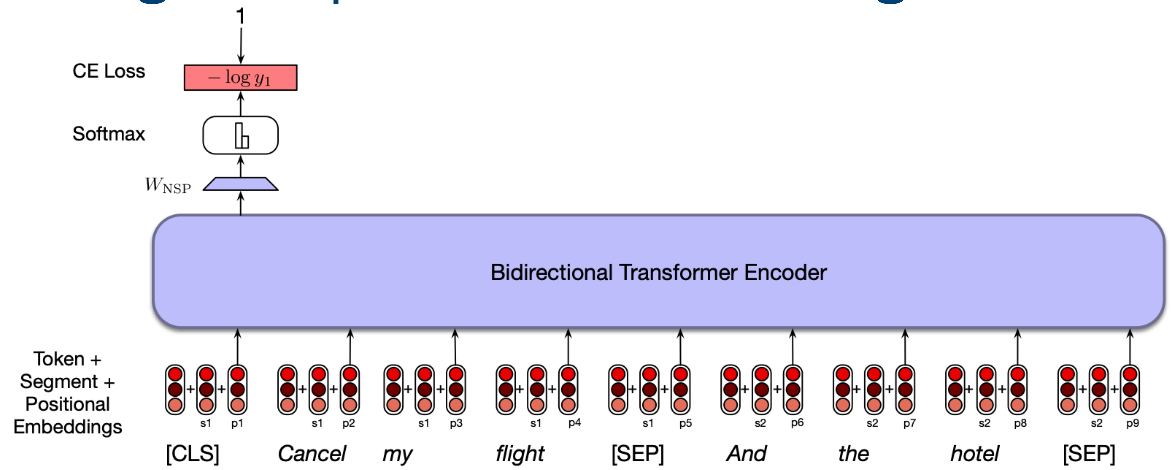
Next Sentence Prediction

NSP

- Model receives pairs of sentences
- Learns to predict if the second sentence is the subsequent sentence
- 50% original sentence sequence, 50% random sequences

Input is processed as follows

- A [CLS] token at beginning of first sentence
- A [SEP] token at the of each sentence
- Sentence embeddings and positional embeddings added to each token



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BERT Fine-tuning

Fine-tuning a pre-trained language model is the process of further training the model to perform some **downstream task**

- Relatively cheap compared to pre-training
- Relatively straightforward, only adding a small layer to the core model

BERT can be fine-tuned to perform a variety of NLP tasks

- **Classification**: add classification layer for the [CLS] token
- **QA**: learn two extra vectors marking beginning/end of answer
- **Named Entity Recognition**: feed output vector of each token into a classification layer that predicts the NER label (e.g. Person, Organization)

During fine-tuning, **most hyper-parameters stay the same** — BERT paper gives guidance on the hyper-parameters that require tuning

BERT Performance

Pre-training data

- BooksCorpus — 800M words
- English Wikipedia — 2,500M words

Two architectures

- $\text{BERT}_{\text{BASE}}$ — 12 layers, 110M parameters
- $\text{BERT}_{\text{LARGE}}$ — 24 layers, 340M parameters

Evaluated on 11 downstream tasks — GLUE test results shown here

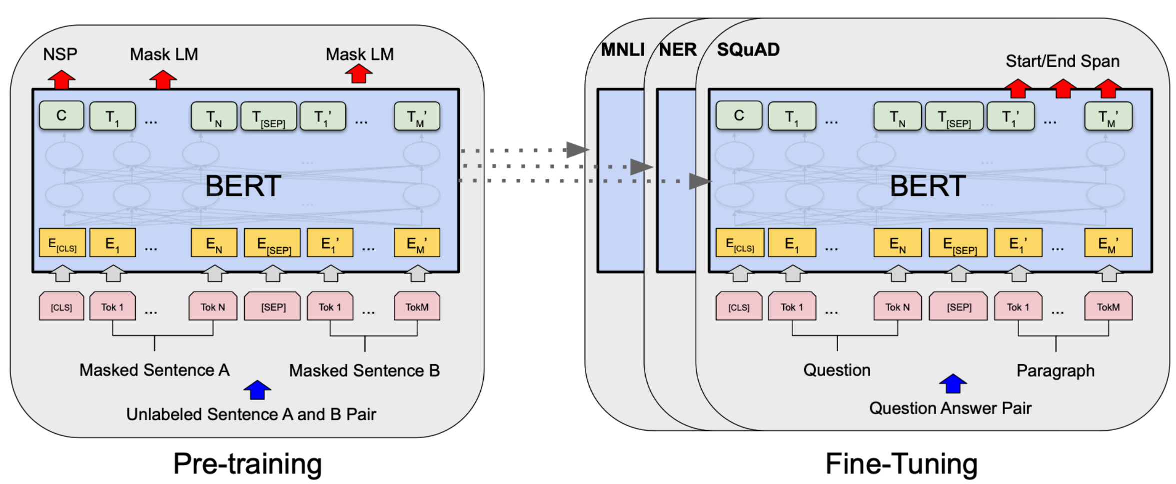
System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Devlin et al., 2019.BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Paradigm of Pre-training & Fine-tuning

Transfer learning

- Value shown in computer vision
- Has also led to a **paradigm shift in NLP**
- **Pre-training phase**: learns language model with rich representations of word meaning
- **Fine-tuning phase**: enables the model to learn the requirements of a downstream task
- Fine-tuning relatively **cheap** in terms of **computation** and **data**



Devlin et al., 2019.BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Visualizing Embeddings

How can we visualize embeddings in high-dimensional semantic space?

- Important for understanding, applying and improving models of word meaning
- How can we visualize, e.g., a 100-dimensional vector?

Nearest neighbors

- List the most similar words according to cosine similarity

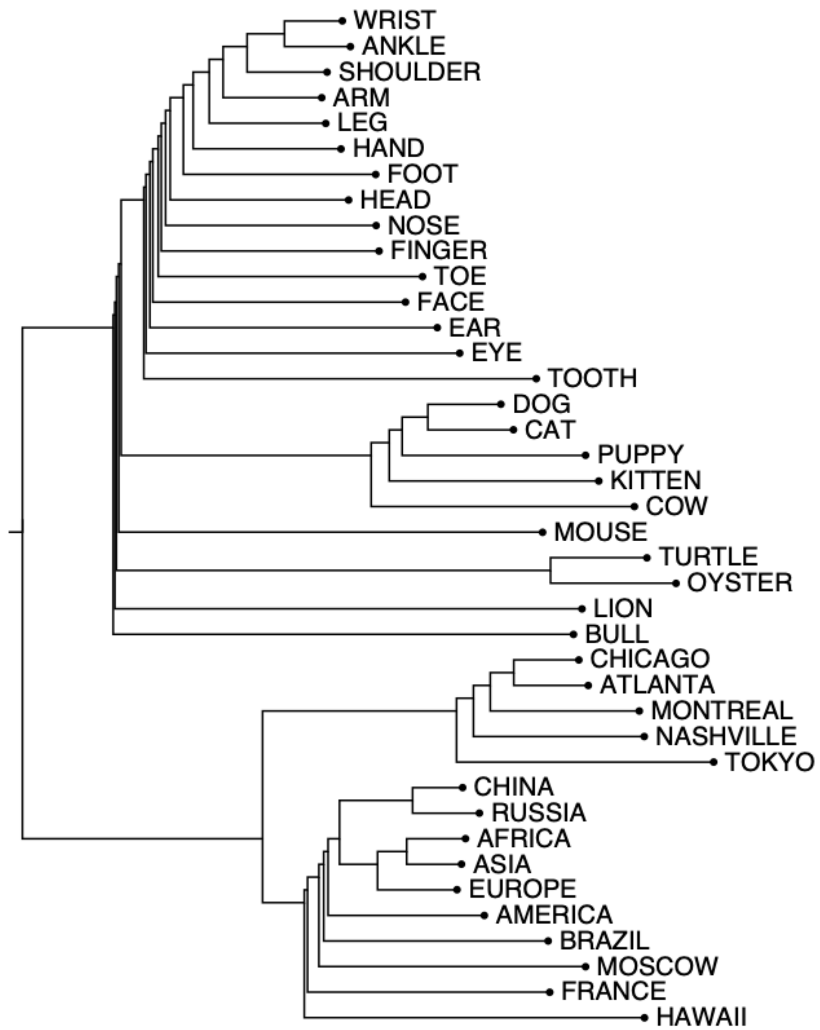
Example **frog** :

- frogs, toad, Vitoria, leptodactylidae, rana, lizard, eleutherodactylus

Visualizing Embeddings

Hierarchical clustering

- Hierarchical representation of which words are similar to others in embedding space
- Example: hierarchical clustering of embedding vectors for nouns



Jurafsky &. Martin, 2022. Speech and Language Processing.

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Visualizing Embeddings

Projects high-dimensional space down to two dimensions

- Using a projection method called **t-SNE**

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Semantic Properties of Embeddings

Different types of similarity or association

- Affected by the **size of the context window**
  - Choice depends on goals of the representation
- Smaller context windows yields more **syntactic representations**
  - Similar words tend to be semantically similar words with same PoS
- Larger context windows yields more **topical representations**
  - Similar words tend to be topically related but not similar words
- **First-order co-occurrence**
  - Words typically near each other (‘wrote’ and ‘book’)
  - **Syntagmatic association**
- **Second-order co-occurrence**
  - Two words with similar neighbors (‘wrote’ and ‘said’)
  - **Paradigmatic association**

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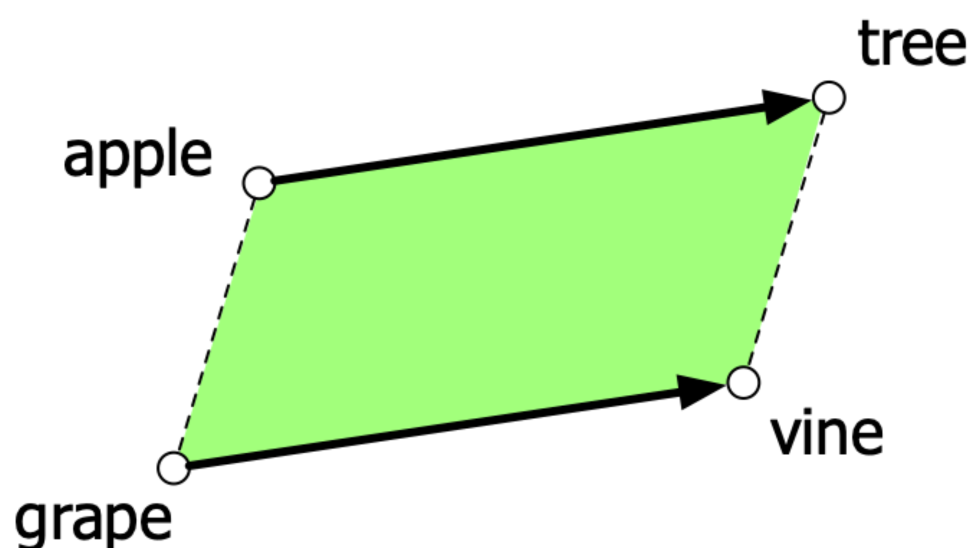
Semantic Properties of Embeddings

Analogy / Relational Similarity

- Embeddings can capture relational meanings

vector(“King”) - vector(“Man”) + vector(“Woman”) ≈ vector(“Queen”)

vector(“Paris”) - vector(“France”) + vector(“Italy”) ≈ vector(“Rome”)



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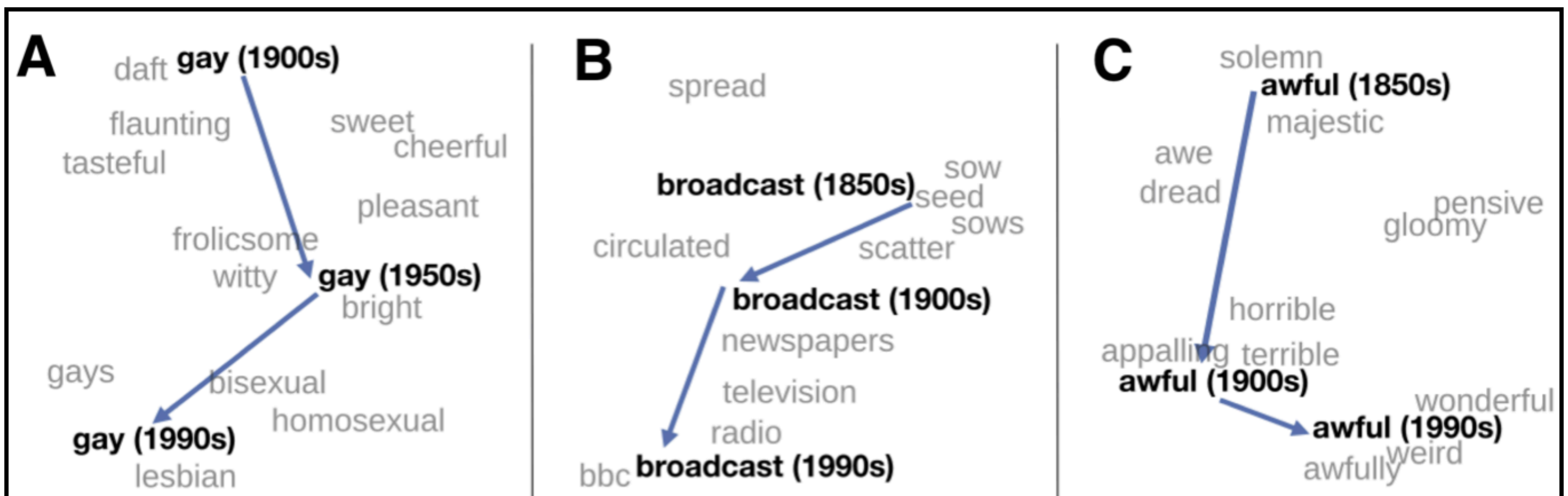
Semantic Shift

Embeddings and historical semantics

- Visualizing changes in meaning in English words over last two centuries
- Computed by building separate embedding spaces for each decade using historical corpora (here: Google n-grams and the Corpus of Historical American English)



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Bias in Embeddings

Allocational harm

Word embeddings reproduce implicit biases and stereotypes

- **Gender stereotypes** in word2vec embeddings trained on news text
  - Closest occupation to ‘man’ – ‘computer programmer’ + ‘woman’ is ‘homemaker’
  - Analogy: ‘father’ is to ‘doctor’ as ‘mother’ is to ‘nurse’
- Could result in **allocational harm**: a system allocates resources unfairly to different groups

Bias in Embeddings

Bias amplification

- Embeddings do not just reflect input statistics, they also **amplify bias**
- Gendered terms more gendered in embedding space than in input text statistics
- Biases more exaggerated than in actual labor employment statistics

Bias in Embeddings

Representational harm

Embeddings also encode implicit associations

- Implicit Association Test: measures people's associations between concepts and attributes by differences in latency when labeling words in various categories
- People in the U.S. shown to associate:
  - African-American and old people's names with unpleasant words
  - Male names more with mathematics; female names with the arts
- Findings replicated using **GloVe vectors** and **cosine similarity** instead of human latency
- **Representational harm** caused by a system demeaning or ignoring social groups

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Bias in Embeddings

Debiasing

- Recent research focuses on ways to remove biases from embeddings
- Developing a transformation of embedding space that removes gender stereotypes but preserves definitional gender
- Changing the training procedure to remove biases
- Shown to reduce but not eliminate bias in embeddings

Evaluating Vector Semantic Models

Extrinsic evaluations

- Most important evaluation metric
- Use word vectors in an NLP task and evaluate model performance compared to baseline model
- Language models fine-tuned and evaluated on downstream tasks

Intrinsic evaluations

- Most common metric is performance on **similarity tasks**, i.e. computing correlation between algorithm's word similarity score and ratings assigned by humans
- Similarity tasks that include context are more realistic
- Analogy tasks

Summary

Lexical Semantics & Distributional Hypothesis

- Deriving word meaning based on context
- Representing word meaning in high-dimensional vector space

Models of Distributional Semantics

- Sparse vs. dense word vectors
- Static vs. dynamic word vectors
- word2vec: skip-gram with negative sampling

Language Models

- BERT for learning contextual word embeddings
- Pre-training & fine-tuning paradigm

Other Aspects of Embeddings

- Visualization, biases and evaluation

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