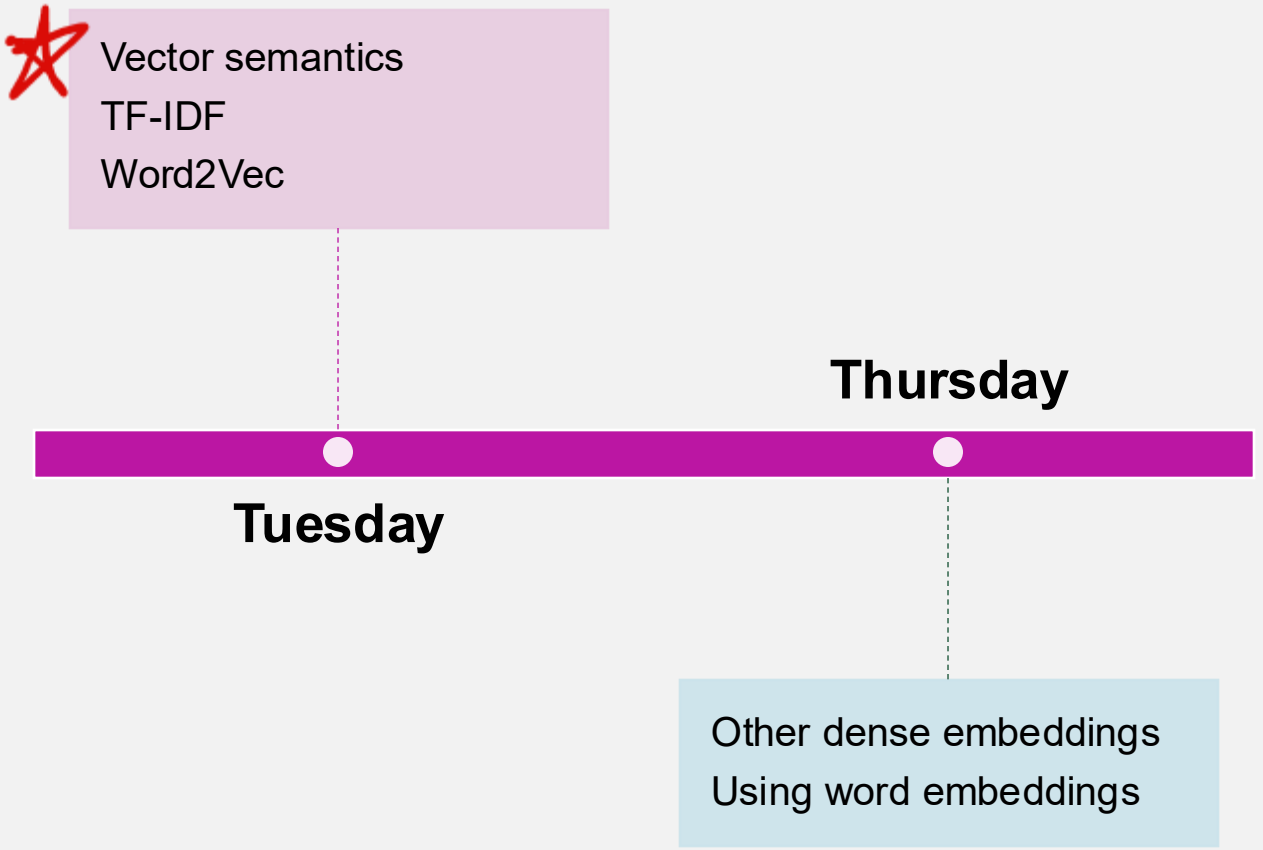
Vector Semantics

Natalie Parde
UIC CS 421

This Week's Topics



Vector Semantics

- Facilitates a form of **representation learning** based on the notion that similar words tend to occur in similar environments
  - This notion is known as the distributional hypothesis, which was first formulated by linguists in the 1950s
    - Joos (1950)
    - Harris (1954)
    - Firth (1957)
- Self-supervised

DISTRIBUTIONAL STRUCTURE

ZELLIG S. HARRIS

1. Does language have a distributional structure? For the purposes of the present discussion, the term structure will be used in the following non-rigorous sense: A set of phonemes or a set of data is structured in respect to some feature, to the extent that we can form in terms of that feature some organized system of statements which describes the members of the set and their interrelations (at least up to some limit of complexity). In this sense, language can be structured in respect to various independent features. And whether it is structured (to more than a trivial extent) in respect to, say, regular historical change, social intercourse, meaning, or distribution—or to what extent it is structured in any of these respects—is a matter decidable by investigation. Here we will discuss how each language can be described in terms of a distributional structure, i.e. in terms of the occurrence of parts (ultimately sounds) relative to other parts, and how this description is complete without intrusion of other features such as history or meaning. It goes without saying that other studies of language—historical, psychological, etc.—are also possible, both in relation to distributional structure and independently of it.

The distribution of an element will be understood as the sum of all its environments. An environment of an element A is an existing array of its co-occurrents, i.e. the other elements, each in a particular position, with which A occurs to yield an utterance. A's co-occurrents in a particular position are called its selection for that position.

1.1. Possibilities of structure for the distributional facts.

To see that there can be a distributional structure we note the following: First, the parts of a language do not occur arbitrarily relative to each other: each element occurs in certain positions relative to certain other elements. The perennial man in the street believes that when he speaks he freely puts together whatever elements have the meanings he intends; but he does so only by choosing members of those classes that regularly occur together, and in the order in which these classes occur.

Second, the restricted distribution of classes persists for all their occurrences; the restrictions are not disregarded arbitrarily, e.g. for semantic needs. Some logicians, for example, have considered that an exact distributional description of natural languages is impossible because of their inherent vagueness. This is not quite the case. All elements in a language can be grouped into classes whose relative occurrence can be stated exactly. However, for the occurrence of a particular member of one class relative to a particular member of another class it would be necessary to speak in terms of probability, based on the frequency of that occurrence in a sample.

Third, it is possible to state the occurrence of any element relative to any other element, to the degree of exactness indicated above, so that distributional state-

Vector Semantics

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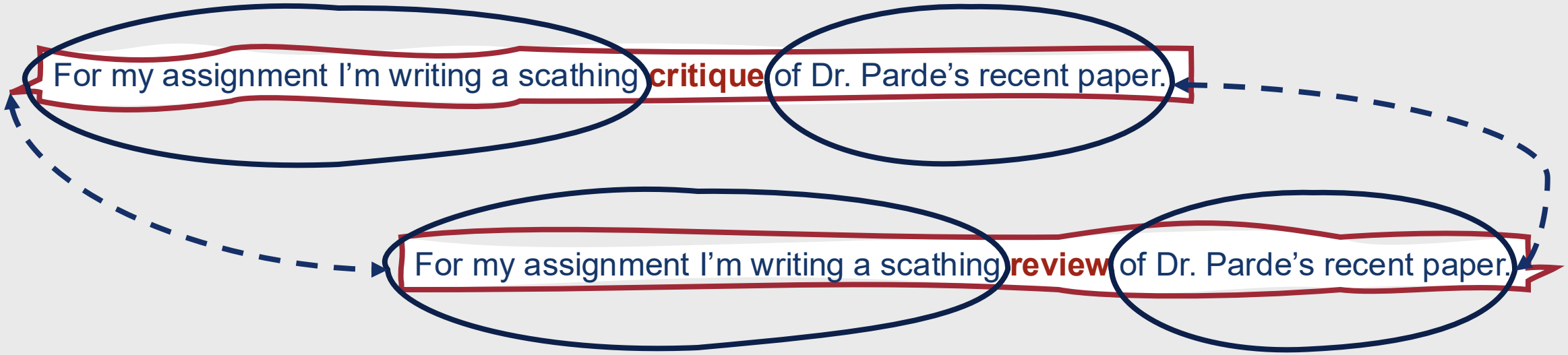
Vector Semantics



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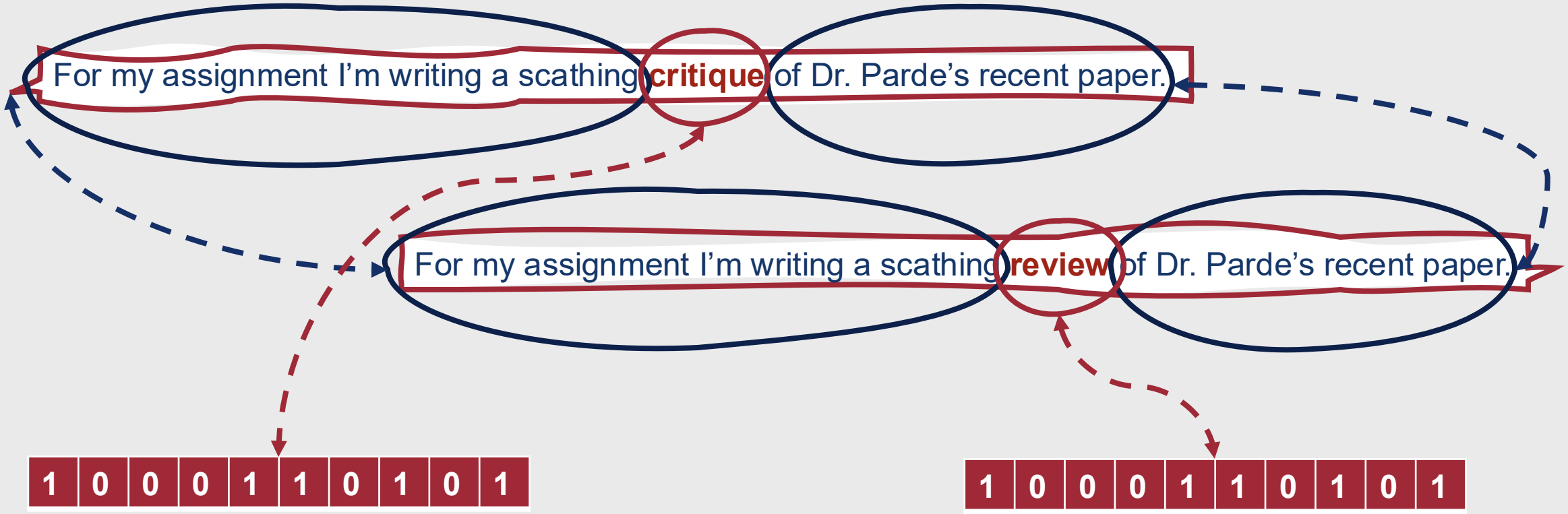
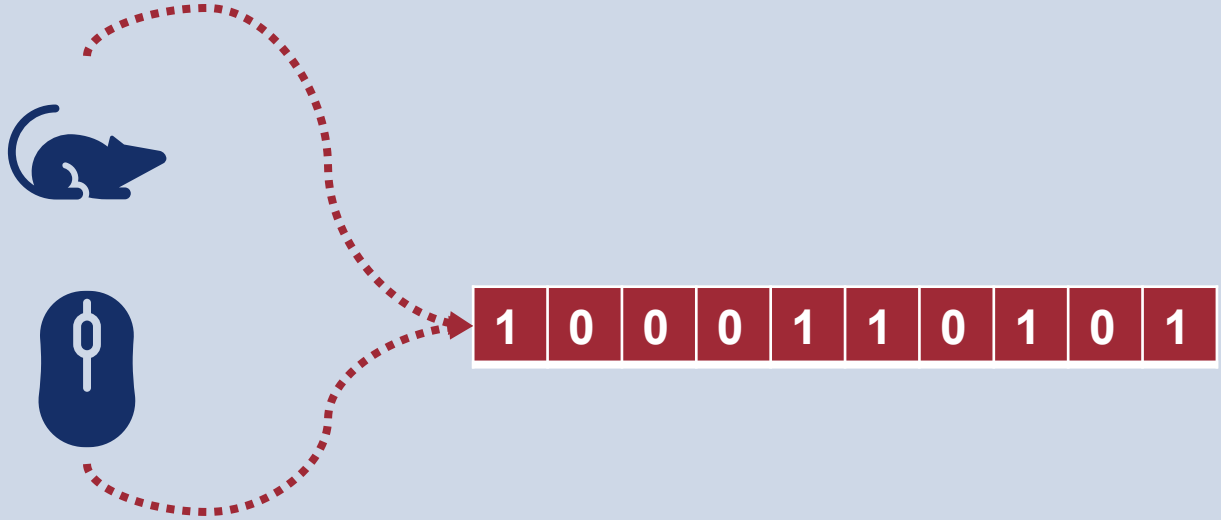


There are many ways to make use of the distributional hypothesis!

- **Classical word vectors**
  - Bag of words representations and their variations
- **Implicitly learned word vectors**
  - Word2Vec
  - GloVe
- All of these approaches seek to encode the same linguistic phenomena observed in studies of lexical semantics

Lemmas and Senses

- **Lemma:** The base form of a word
  - Papers → paper
  - Mice → mouse
- **Word Sense:** Different aspects of meaning for a word
  - Mouse (1): A small rodent
  - Mouse (2): A device to control a computer cursor
- Words with the same lemma should (hopefully!) reside near one another in vector space
- Words with the same sense might also reside near one another in vector space, depending on the representation learning technique



Synonymy

- When a word sense for one word is (nearly) identical to the word sense for another word
- **Synonymy:** Two words are synonymous if they are substitutable for one another in any sentence without changing the situations in which the sentence would be true
  - This means that the words have the same **propositional meaning**

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Word Similarity and Relatedness

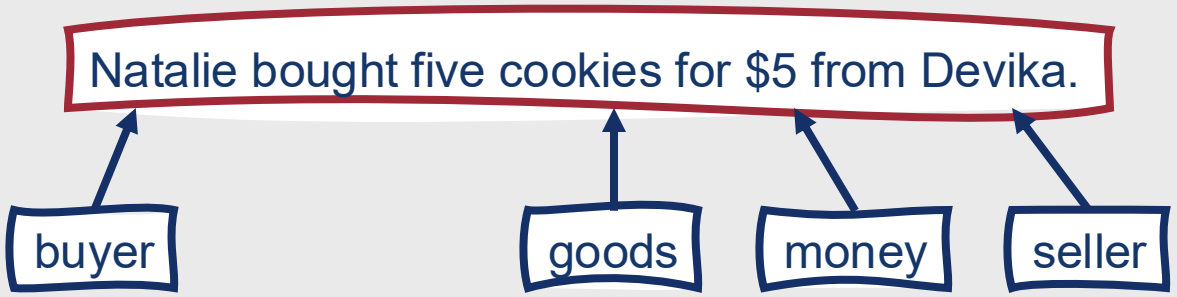
- **Word similarity:** Words are not synonyms, but they can be used in the same contexts as one another
- **Word Relatedness:** Words are associated with one another based on their shared participation in an event

Natalie grabbed the **purple** coffee mug.

Natalie grabbed the **green** coffee mug.

Semantic Frames

- **Semantic Frame:** A set of words that denote perspectives or participants in a particular type of event
  - Commercial Transaction = {buyer, seller, goods, money}
- **Semantic Role:** A participant's underlying role with respect to the main verb in the sentence



Connotation

- Also referred to as **affective meaning**
- The aspects of a word's meaning that are related emotions, sentiment, opinions, or evaluations
  - **Valence:** Positivity
    - High: Happy, satisfied
    - Low: Unhappy, annoyed
  - **Arousal:** Intensity of emotion
    - High: Excited, frenzied
    - Low: Relaxed, calm
  - **Dominance:** Degree of control
    - High: Important, controlling
    - Low: Awed, influenced

	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
life	6.68	5.59	5.89

Word vector! (Osgood et al., 1957)

How, then, should we represent meaning?

- Many, many approaches!
- Two classic strategies:
  - **Bag of words representations:** A word is a string of letters, or an index in a vocabulary list
  - **Logical representation:** A word defines its own meaning (“dog” = DOG)

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Bag of words features implement a simple form of vector semantics.

- **Two words with very similar sets of contexts (i.e., similar distributions of neighboring words) are assumed to have very similar meanings**
- We represent this context using vectors
- For bag of words:
  - Define a word as a single vector point in an *n*-dimensional space, where *n* = vocabulary size
  - The value stored in a dimension corresponds to the presence of a context word in the same sample as the target word

Example: Context-Based BOW Vector

To earn a Bachelor of Science in Computer Science degree from UIC, students need to complete university, college, and department degree requirements. The Department of Computer Science **degree** requirements are outlined below. Students should consult the College of Engineering section for additional degree requirements and college academic policies.

Context Window = 4

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Context Window = 4

bachelor	of	science	in	computer	department	requirements	are	…	students	need	complete	outlined	college	below	consult	engineering
0	1	1	0	1	1	1	1	…	0	0	0	1	0	1	0	0

Example: Context-Based BOW Vector

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Context Window = 8

bachelor	of	science	in	computer	department	requirements	are	…	students	need	complete	outlined	college	below	consult	engineering
0	1	1	0	1	2	2	1	…	1	0	0	1	0	1	1	0

The goal is for the values in these vector representations to correspond with dimensions of meaning.

- Assuming this is the case, we should be able to:
  - Cluster vectors into semantic groups
  - Perform operations that are semantically intuitive

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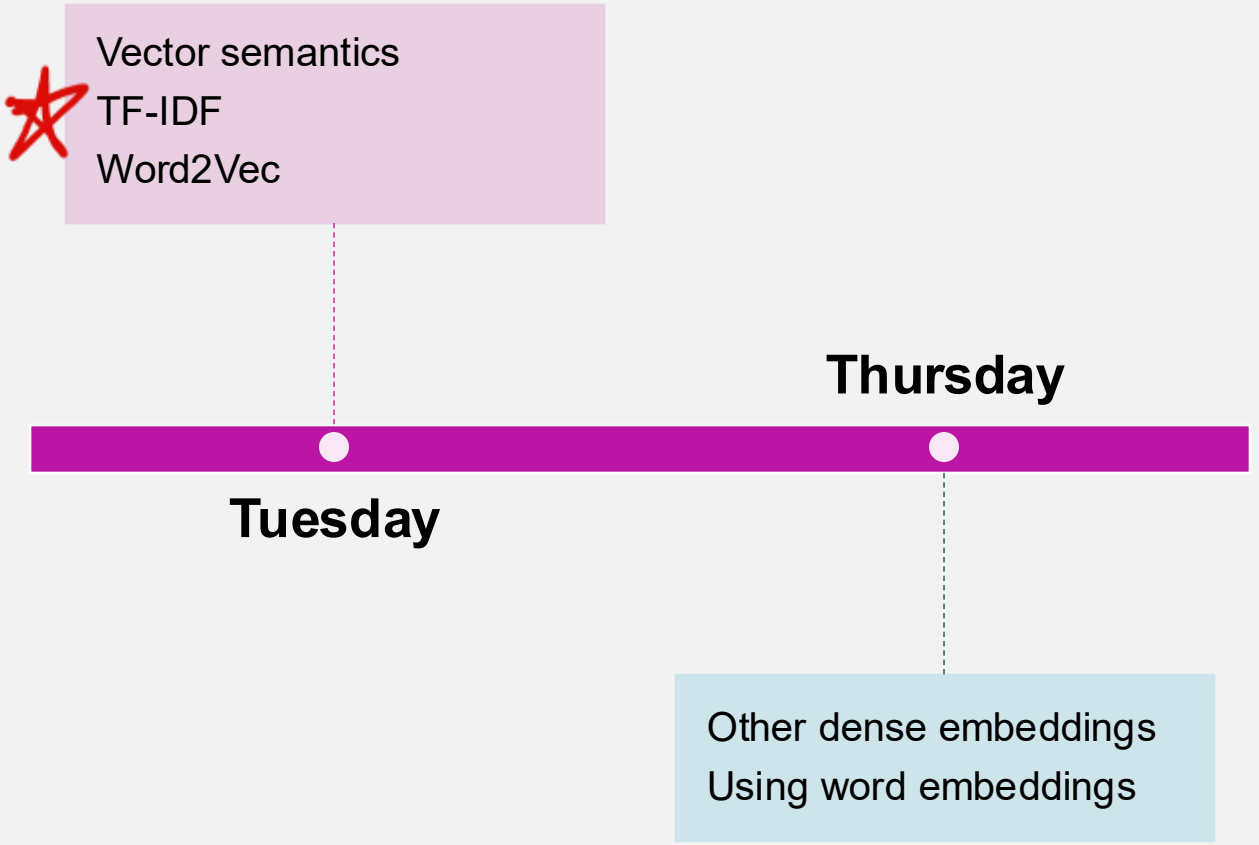
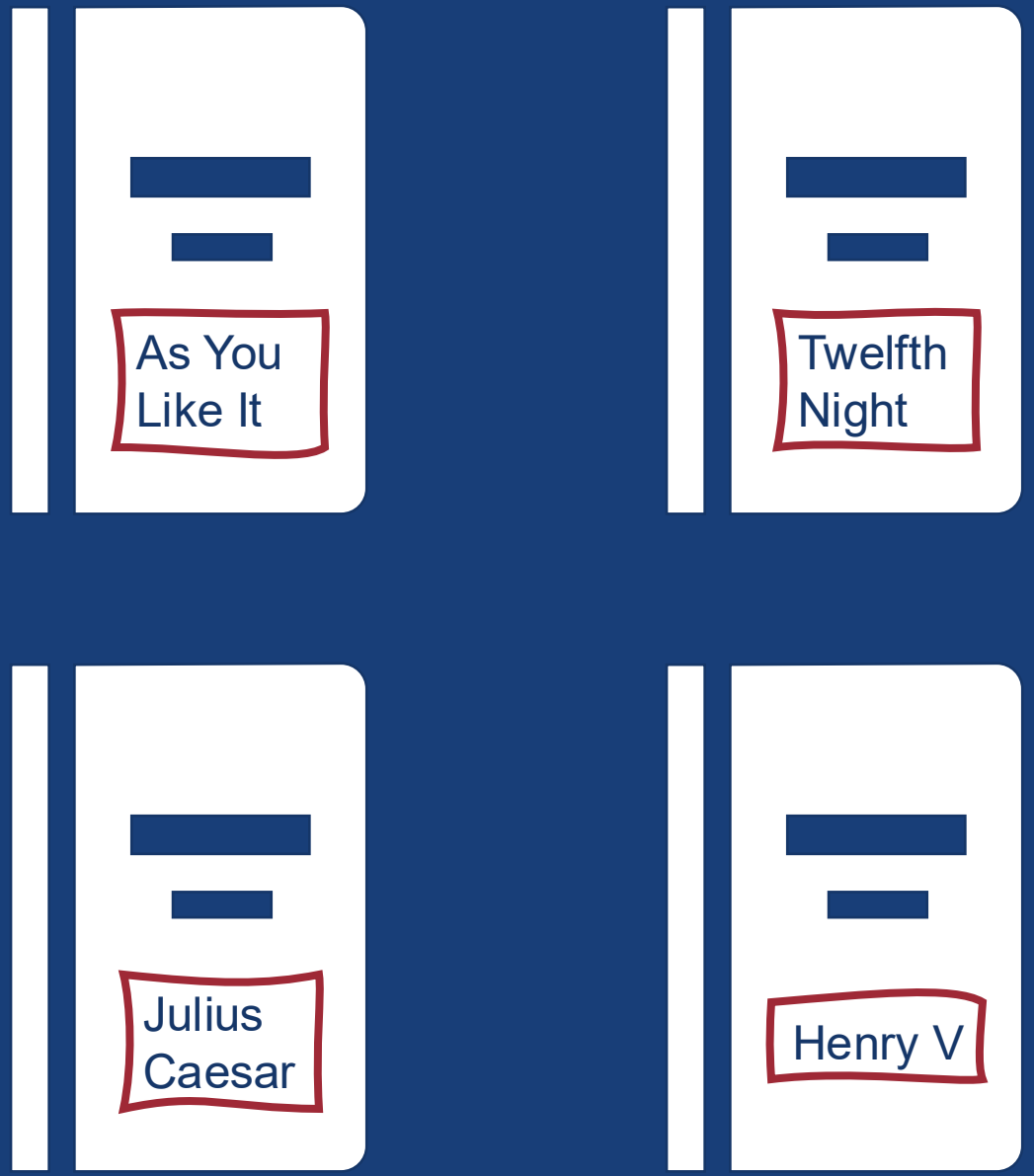


Are there alternatives to using frequency in bag-of-words representations?

- TF-IDF:
  - Term Frequency * Inverse Document Frequency
  - Meaning of a word is defined by the counts of words in the *same* document, as well as *overall*

TF-IDF originated as a tool for information retrieval.

- Rows: Words in a vocabulary
- Columns: Documents in a corpus



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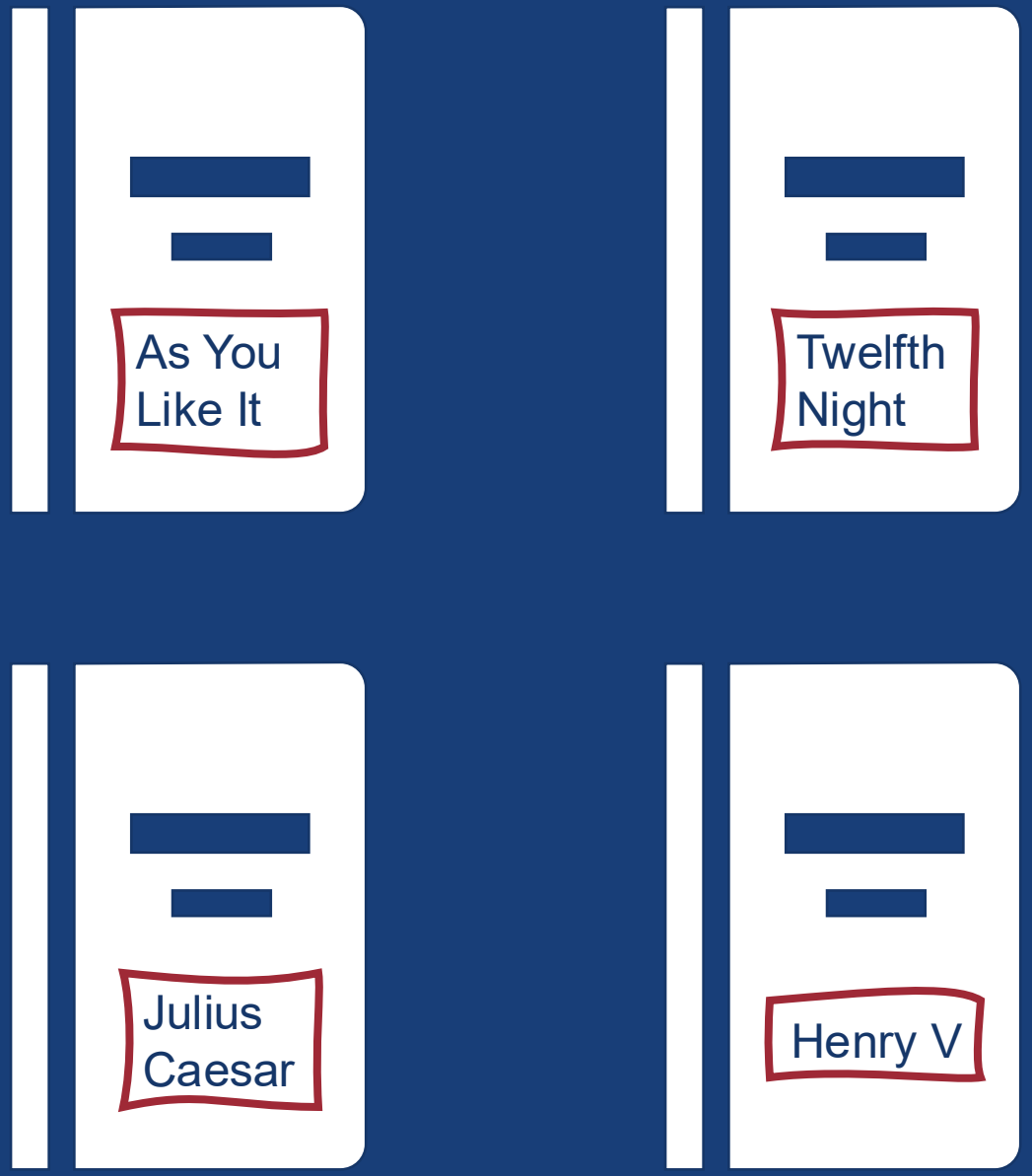
	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

"wit" appears 3 times in Henry V



Why information retrieval?

- A common goal in web search is to find documents that are similar to the search query
- These documents are likely to have information that is of interest to the person performing the search

In a term-document matrix, rows can be viewed as word vectors.

- Each dimension corresponds to a document
- Words with **similar vectors** occur in **similar documents**
- This is one way to define **term frequency** vectors

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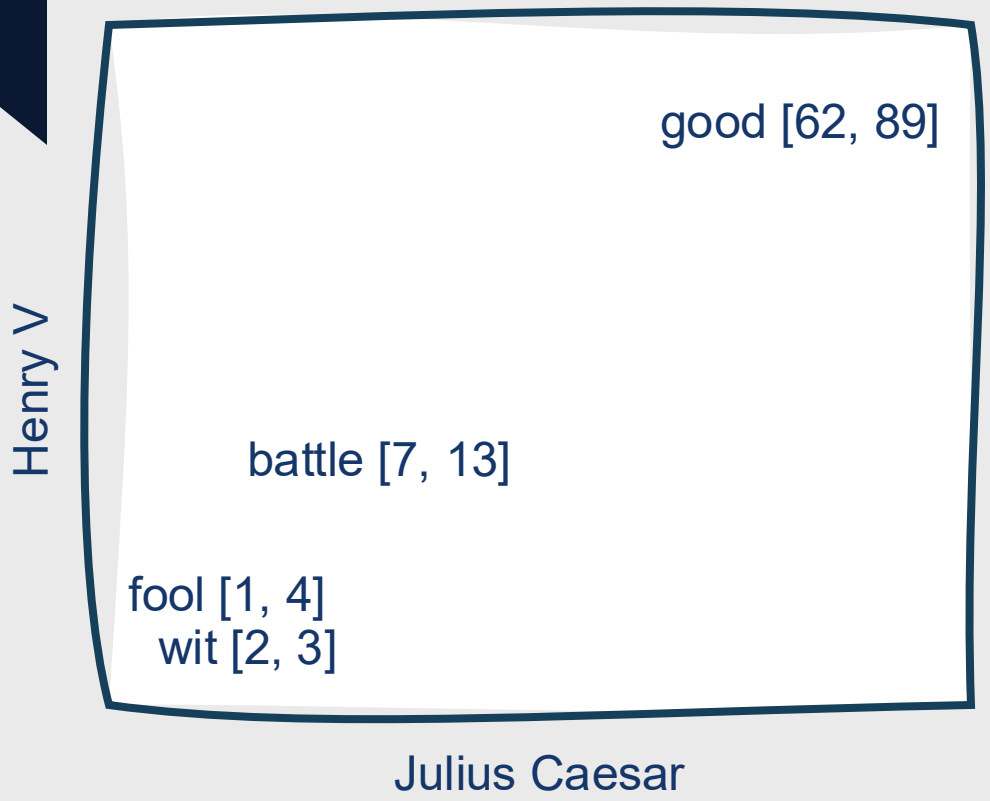

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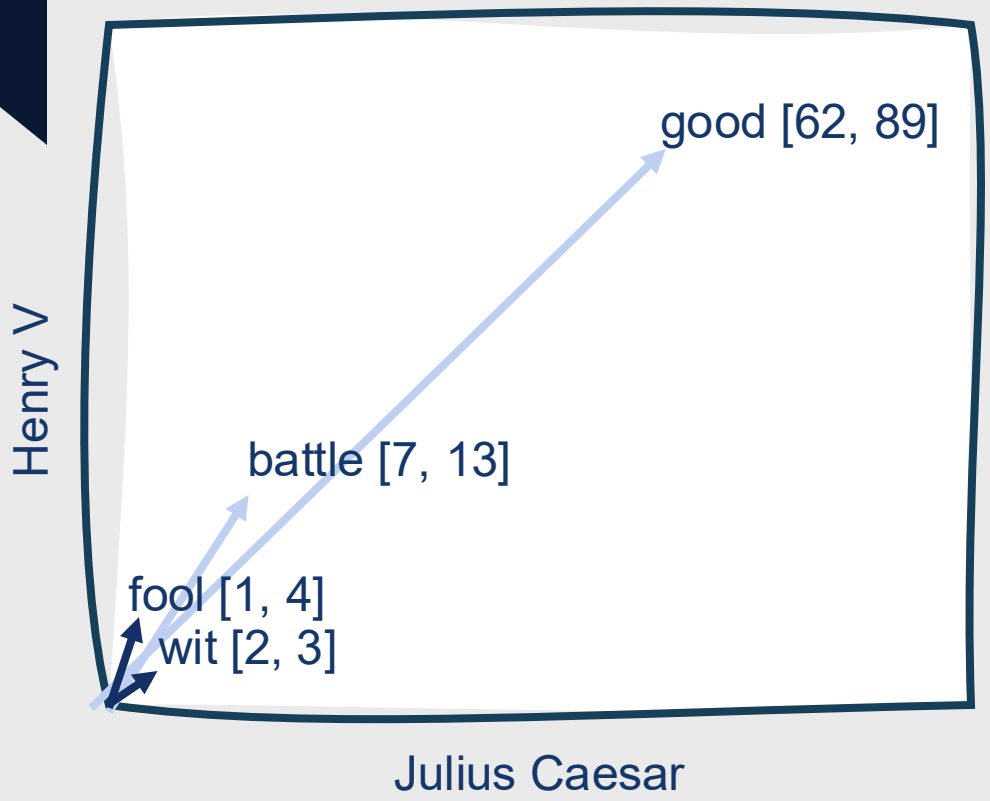

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How does this relate to more global word frequency?

- Some words co-occur frequently with many words, so won't be very informative
  - *the*, *it*, *they*
- We want to know about **words that co-occur frequently with one another, but less frequently across all texts**

TF-IDF

- **Term Frequency:** The frequency of the word t in the document d
  - $tf_{t,d} = \text{count}(t, d)$
- **Document Frequency:** The number of documents in which the word t occurs

Computing TF-IDF

- **Inverse Document Frequency:** The inverse of document frequency, where *N* is the total number of documents in the collection
  - $idf_t = \frac{N}{df_t}$
- IDF is higher when the term occurs in fewer documents
  - Document = Whatever is considered an instance or context in your dataset
- It is often useful to perform these computations in log space
  - TF: $\log_{10}(tf_{t,d}+1)$ → Make sure to smooth so you don't try to take the log of 0!
  - IDF: $\log_{10} idf_t$

Assume we're looking at a subset of a 37-document corpus of Shakespearean plays….

Example: Computing TF-IDF

- **TF-IDF(battle, d_1) = ?**

	d_1	d_2	d_3	d_4
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

Example: Computing TF-IDF

- TF-IDF(battle, d_1) = ?
- **TF(battle, d_1) = 1**

	d_1	d_2	d_3	d_4
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Example: Computing TF-IDF

- TF-IDF(battle, d_1) = ?
- TF(battle, d_1) = 1
- **IDF(battle) = N/DF(battle) = 37/21 = 1.76**

	d_1	d_2	d_3	d_4
battle	1	0	7	13
good	114	80	62	89
fool	36	58		
wit	20	15		

Overall document frequencies from our 37 plays

Example: Computing TF-IDF

- TF-IDF(battle, d_1) = ?
- TF(battle, d_1) = 1
- IDF(battle) = N/DF(battle) = 37/21 = 1.76
- **TF-IDF(battle, d_1) = 1 * 1.76 = 1.76**

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- TF-IDF(battle, d_1) = 1 * 1.76 = 1.76
- **Alternately, TF-IDF(battle, d_1) = $log_{10}(1+1) * log_{10} 1.76 =$ 0.074**

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	d_1	d_2	d_3	d_4
battle	0.074	0	7	13
good	114	80	62	89
fool	36	58	1	4
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To convert our entire term frequency matrix to a TF-IDF matrix, we need to repeat this calculation for each element.

	d_1	d_2	d_3	d_4
battle	0.074	0.000	0.220	0.280
good	0.000	0.000	0.000	0.000
fool	0.019	0.021	0.004	0.008
wit	0.049	0.044	0.018	0.022

How does the TF-IDF matrix compare to the original term frequency matrix?

	d_1	d_2	d_3	d_4
battle	1	0	7	13
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Occurs in every document …not important in the overall scheme of things!

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Increases the importance of seeing rarer words like “battle”

Note that TF-IDF vectors are sparse.

- Many (usually most) cells have values of 0
- This can make learning difficult

	d_1	d_2	d_3	d_4	d_5	d_6	d_7
battle	0.1	0.0	0.0	0.0	0.2	0.0	0.3
good	0.0	0.0	0.0	0.0	0.0	0.0	0.0
fool	0.0	0.0	0.0	0.0	0.0	0.0	0.0
wit	0.0	0.0	0.0	0.0	0.0	0.0	0.0

What we know so far….

- **Word vectors:** Vectors of numbers used to encode language
  - Each vector represents a point in an n-dimensional semantic space
- Simple techniques to create word vectors:
  - Co-occurrence frequency (**bag of words**)
  - **TF-IDF**

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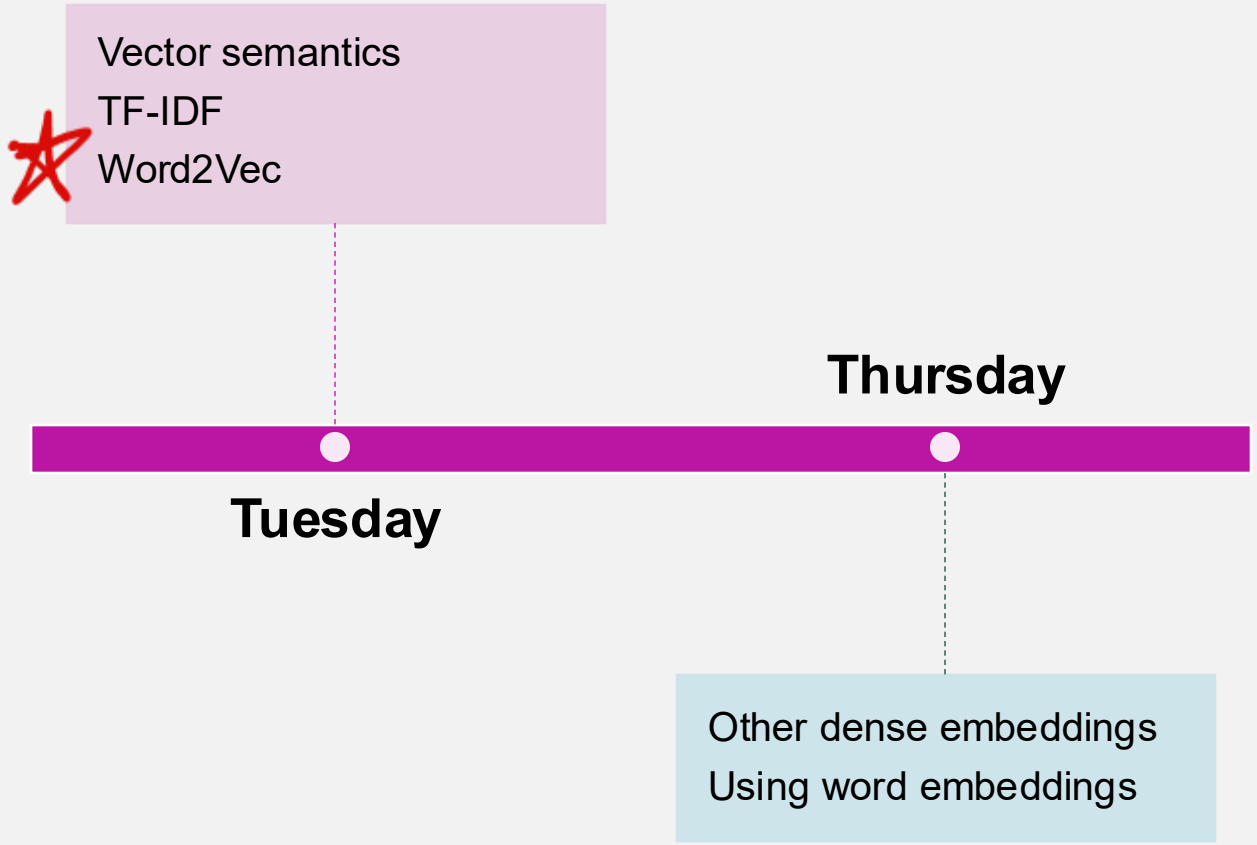


Limitations of Bag-of-Words Style Vectors

- Very **high-dimensional**
- Lots of **empty** (zero-valued) cells
- Struggle with inferring deeper semantic content:
  - Synonyms
  - Antonyms
  - Positive/negative connotations
  - Related contexts

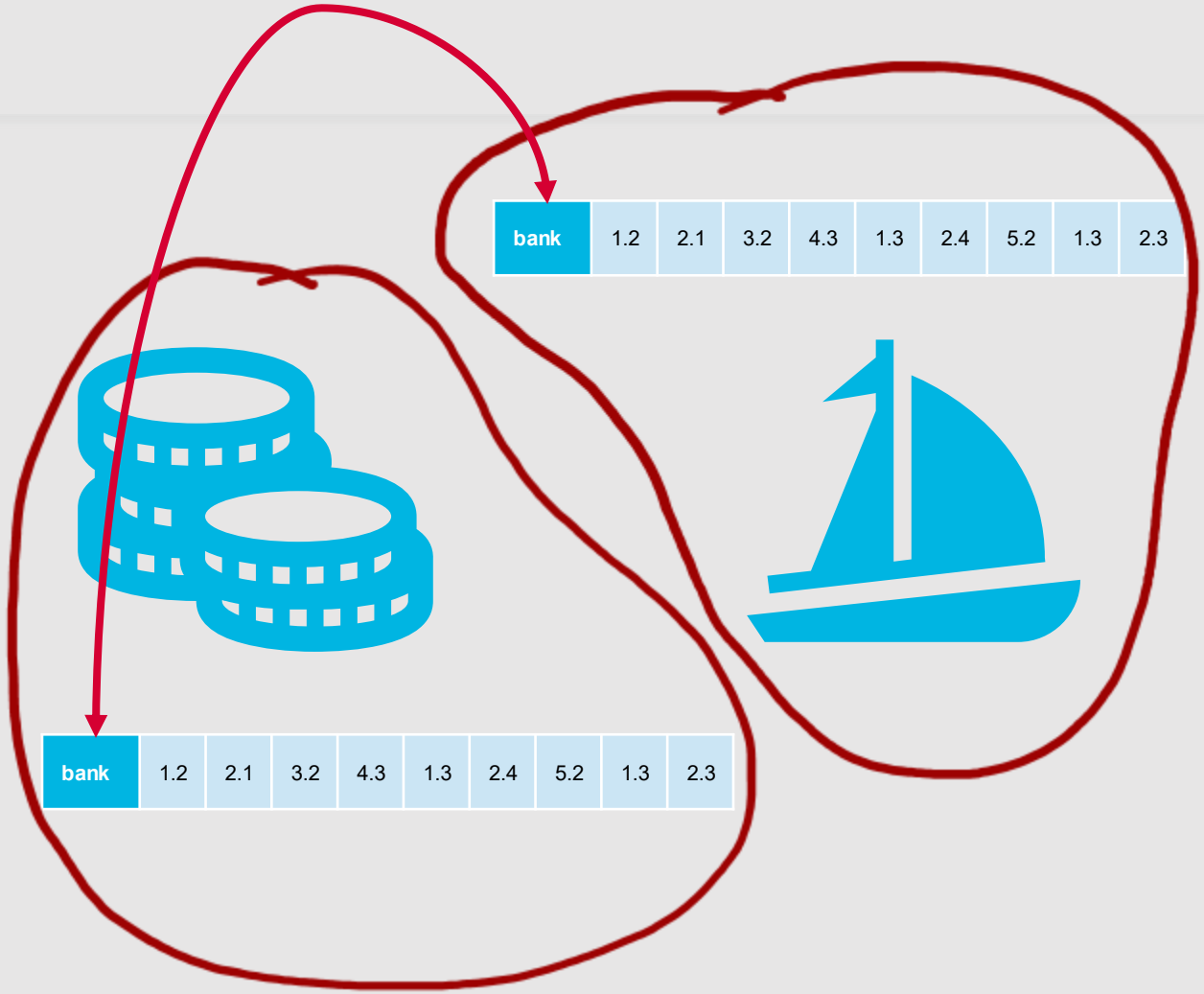
What would our "dream vector" look like?

- **Lower-dimensional** (~ 50-1000 cells)
  - Easier to include as **features**
    - Classifiers have to learn ~100 weights instead of ~50,000
  - Fewer **parameters** → lower chance of overfitting
    - May generalize better to new data
- Most dimensions with **non-zero** values

- We'd also prefer to be able to encode other semantic dimensions of meaning
  - *Good* should be:
    - Far from *bad*
    - Close to *great*
  - For this, we need vector dimensions to correspond to meaning directly, rather than specific words

Enter Word2Vec....

- **Word2Vec:** A method for automatically learning dense word representations from large text corpora
  - Fast
  - Efficient to train
- Not *quite* a dream vector: Word2Vec embeddings are static (homonyms have the same representations)



Word2Vec

- Technically a tool for implementing word vectors:
  - https://code.google.com/archive/p/word2vec
- The algorithm that people usually refer to as *Word2Vec* is the **skip-gram** model with **negative sampling**

Word2Vec Intuition

- Instead of counting how often each word occurs near each context word, train a classifier on a **binary prediction task**
  - Is word *w* likely to occur near context word *c*?
- The twist: **We don't actually care about the classifier!**
- We use the **learned classifier weights** from this prediction task as our word embeddings

None of this requires manual supervision.

- Text (without any other labels) is framed as **implicitly supervised** training data
  - Given the question: Is word *w* likely to occur near context word *c*?
    - If *w* occurs near *c* in the training corpus, the gold standard answer is “yes”
- Similar setup to **neural language modeling** (neural networks that predict the next word based on prior words), but simpler:
  - Fewer layers
  - Makes **binary yes/no predictions** rather than predicting words

What does the classification task look like?

- **Goal:** Train a classifier that, given a tuple (*t*, *c*) of a target word *t* paired with a context word *c* (e.g., (super, bowl) or (super, laminator)), will return the probability that *c* is a real context word
  - P(+ | t,c)
- Context is defined by our context window (in this case, ± 2 words)

this	sunday,	watch	the	super	bowl	at	5:30	p.m.
		c1	c2	t	c3	c4		

High-Level Overview: How Word2Vec Works

- Treat the target word *w* and a neighboring context word *c* as positive samples

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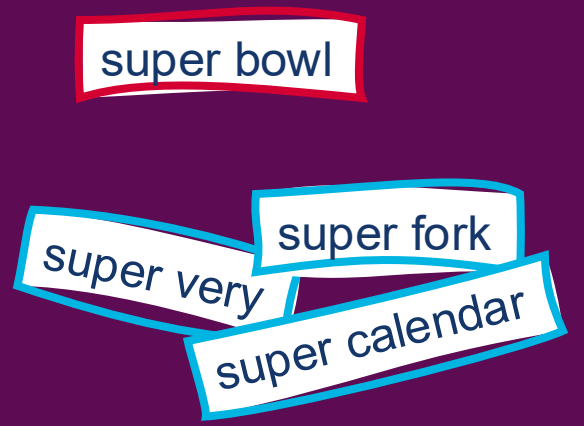

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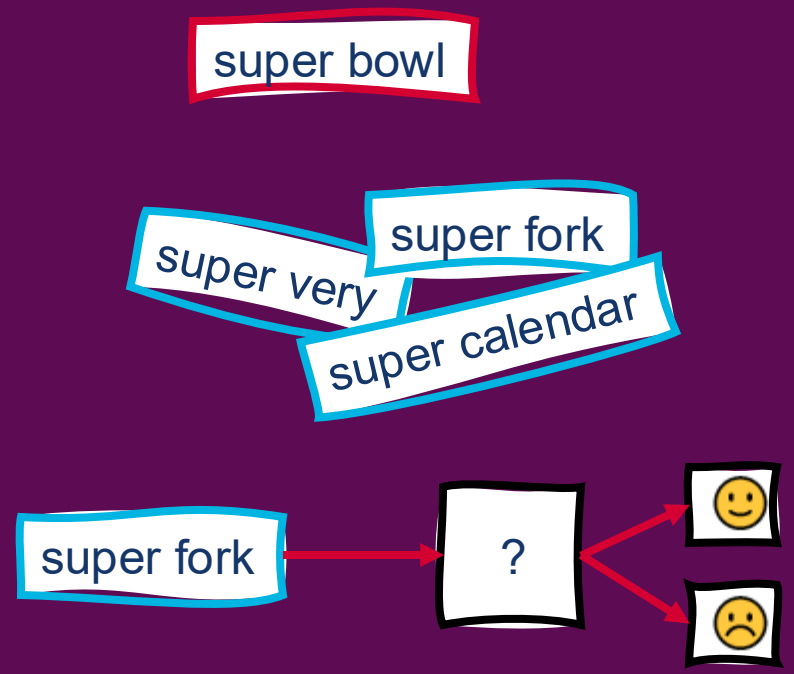
- Train a classifier to distinguish between those two cases



High-Level Overview: How Word2Vec Works

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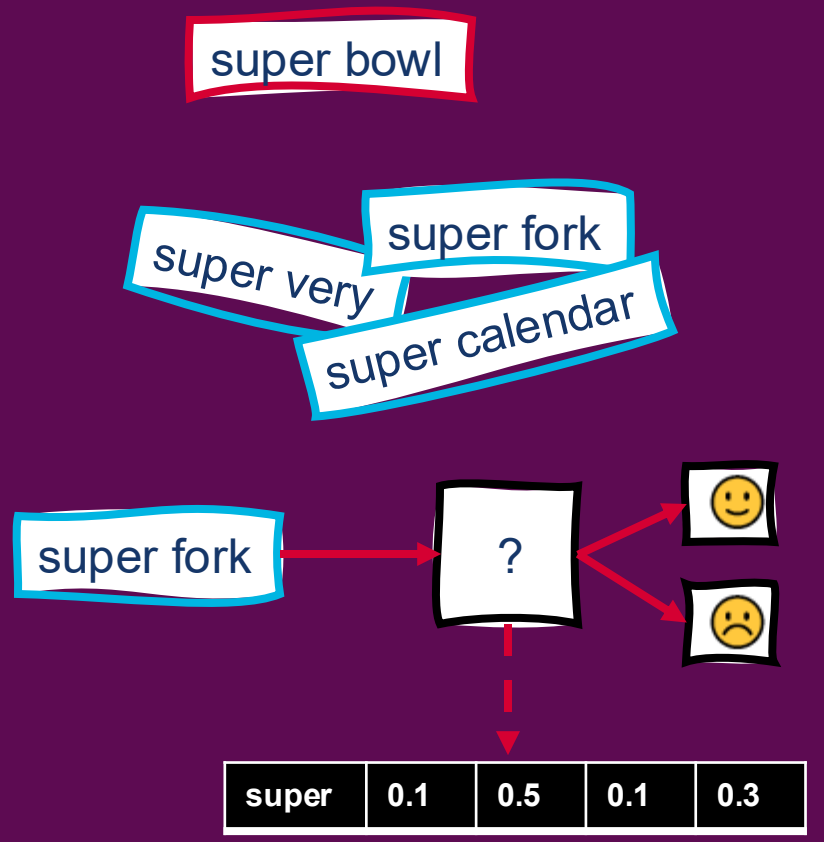
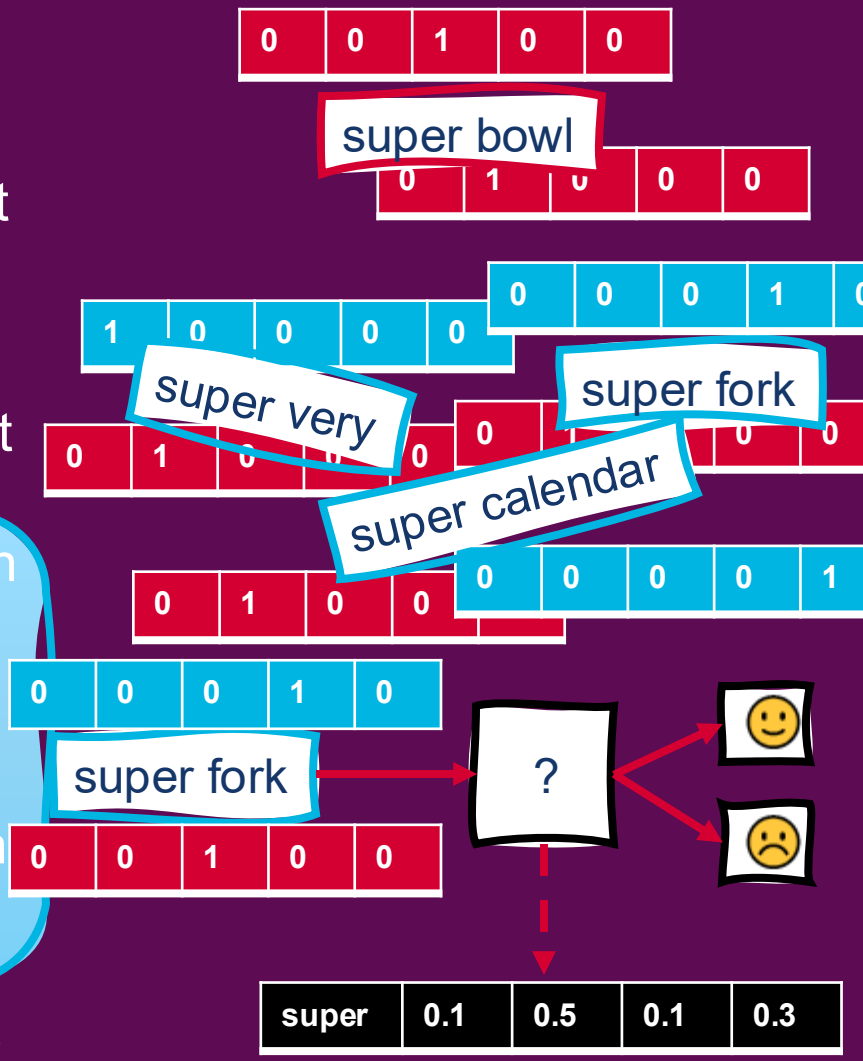
- Use the weights from that classifier as the word embeddings



High-Level Overview: How Word2Vec Works

- Represent all words in a vocabulary as a vector
- Treat the target word *w* and a neighboring context word *c* as positive samples
- Randomly sample other words in the lexicon to get negative samples
- Find the similarity for each (t,c) pair and use this to calculate P(+|(t,c))
- Train a classifier to maximize these probabilities to distinguish between positive and negative cases
- Use the weights from that classifier as the word embeddings



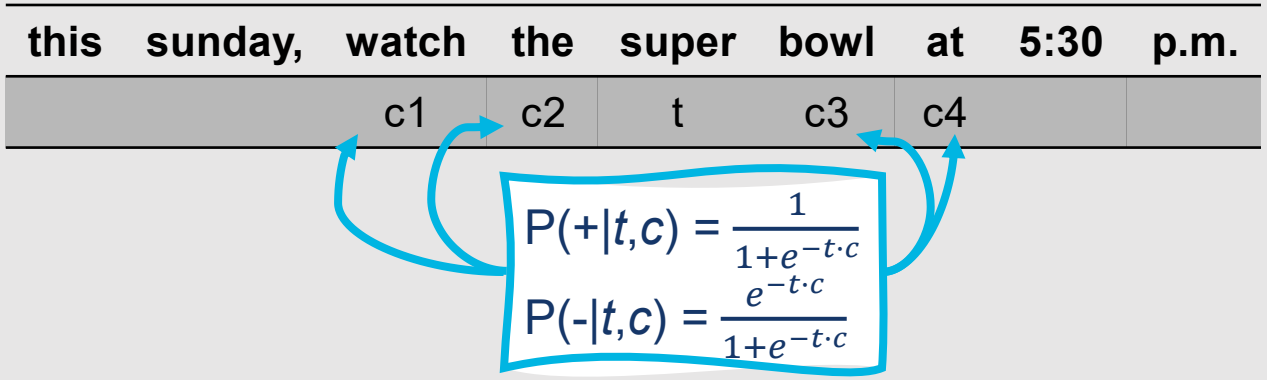
How do we *compute* P(+ | *t*,*c*)?

- This is based on vector similarity
- We can assume that vector similarity is proportional to the dot product between two vectors
  - Similarity(*t*,*c*) $\propto t \cdot c$
- More similar vectors → more likely that *c* occurs near *t*

A dot product gives us a number, not a probability.

- How do we turn it into a probability?
  - **Sigmoid function** (just like we did with logistic regression!)
  - We can set:
    - $P(+|t,c) = \frac{1}{1+e^{-t \cdot c}}$
- Then:
  - $P(+ \mid t,c) = \frac{1}{1+e^{-t \cdot c}}$
  - $P(- \mid t,c) = 1 - P(+ \mid t,c) = \frac{e^{-t \cdot c}}{1+e^{-t \cdot c}}$

What if we want to know the probability that a span of text occurs in the context of the target word?



- Simplifying assumption: **All context words are independent**
- So, we can just multiply their probabilities:
  - $P(+|t,c_{1:k}) = \prod_{i=1}^{k} \frac{1}{1+e^{-t \cdot c_i}}$, or
  - $\log P(+|t,c_{1:k}) = \sum_{i=1}^{k} \log \frac{1}{1+e^{-t \cdot c_i}}$

With this in mind….

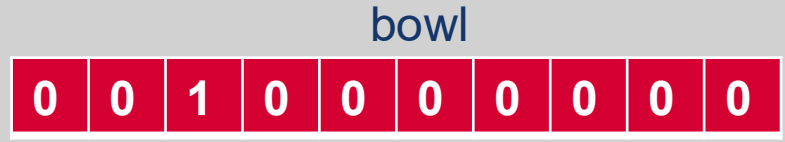
this	sunday,	watch	the	super	bowl	at	5:30	p.m.
		c1	c2	t	c3	c4		
		P(+|*super*, *watch*) = .7	P(+|*super*, *the*) = .5		P(+|*super*, *bowl*) = .9	P(+|*super at*) = .5		

$P(+|t,c_{1:k}) = .7 * .5 * .9 * .5 = .1575$

- Given *t* and a context window of *k* words $c_{1:k}$, we can assign a probability based on how similar the context window is to the target word
- However, we still have some unanswered questions….
  - **How do we determine our input vectors?**
  - **How do we learn word embeddings** throughout this process (this is the real goal of training our classifier in the first place)?

Input Vectors

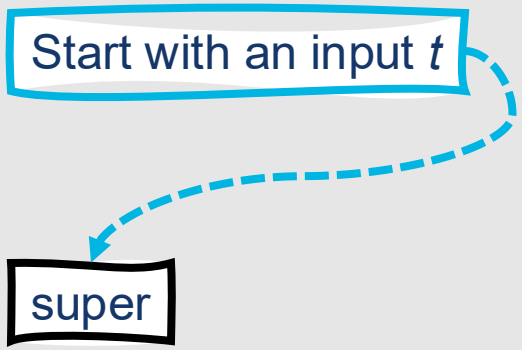
- Typically represented as **one-hot vectors**
  - **Binary bag-of-words approach:** Place a “1” in the position corresponding to a given word, and a “0” in every other position



Learned Embeddings….

- Embeddings are the weights learned for a two-layer classifier that predicts P(+ | *t*,*c*)
- Recall from our discussion of logistic regression:
  - $y = \sigma(z) = \frac{1}{1+e^{-z}} = \frac{1}{1+e^{-w \cdot x+b}}$
- This is quite similar to the probability we're trying to optimize:
  - P(+ | *t*,*c*) = $\frac{1}{1+e^{-t \cdot c}}$

What does this look like?



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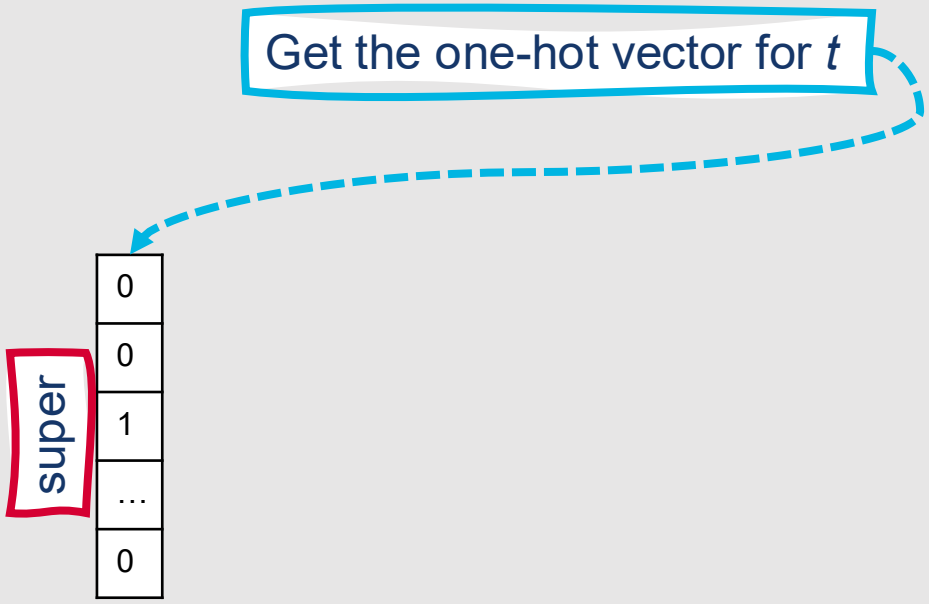

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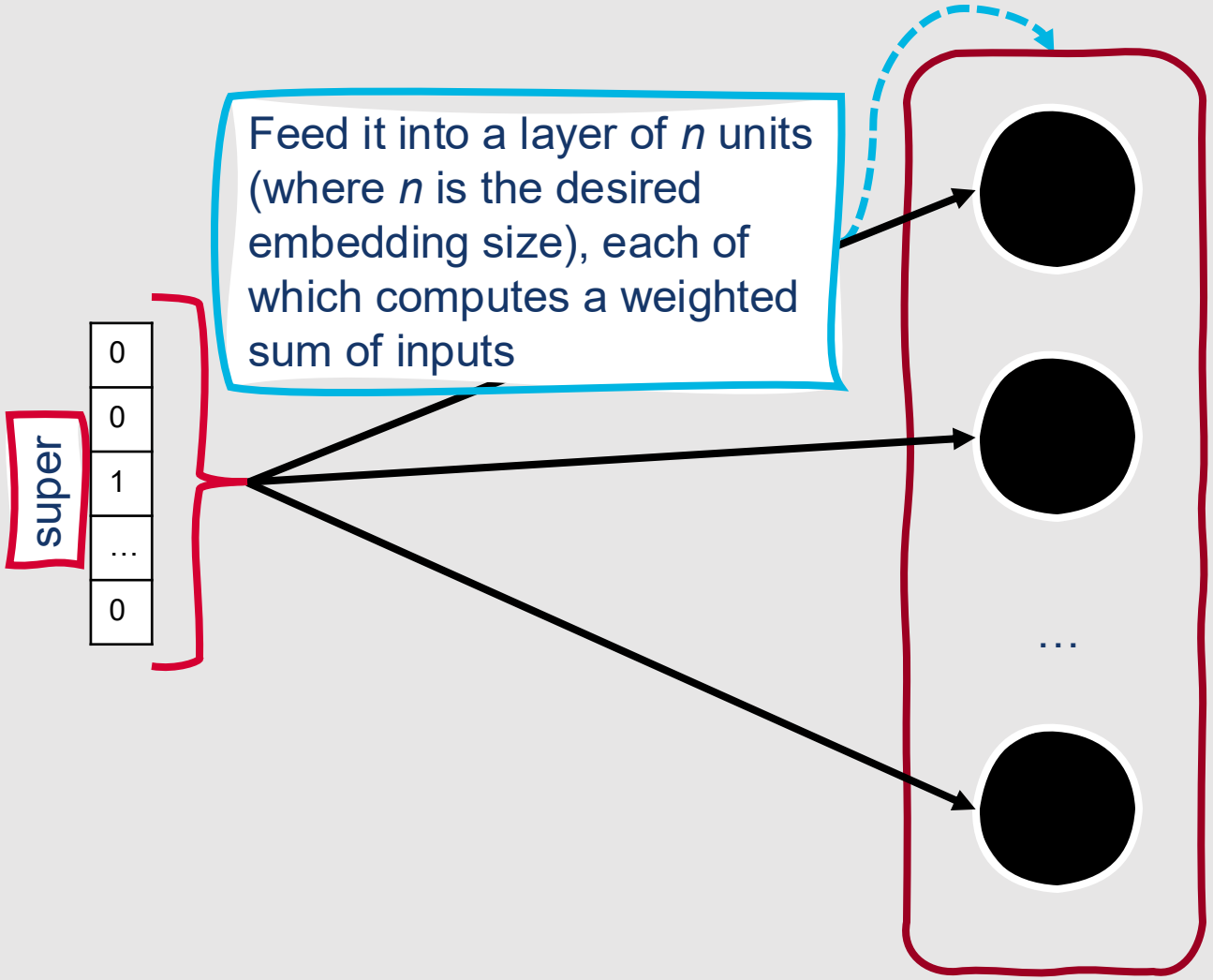

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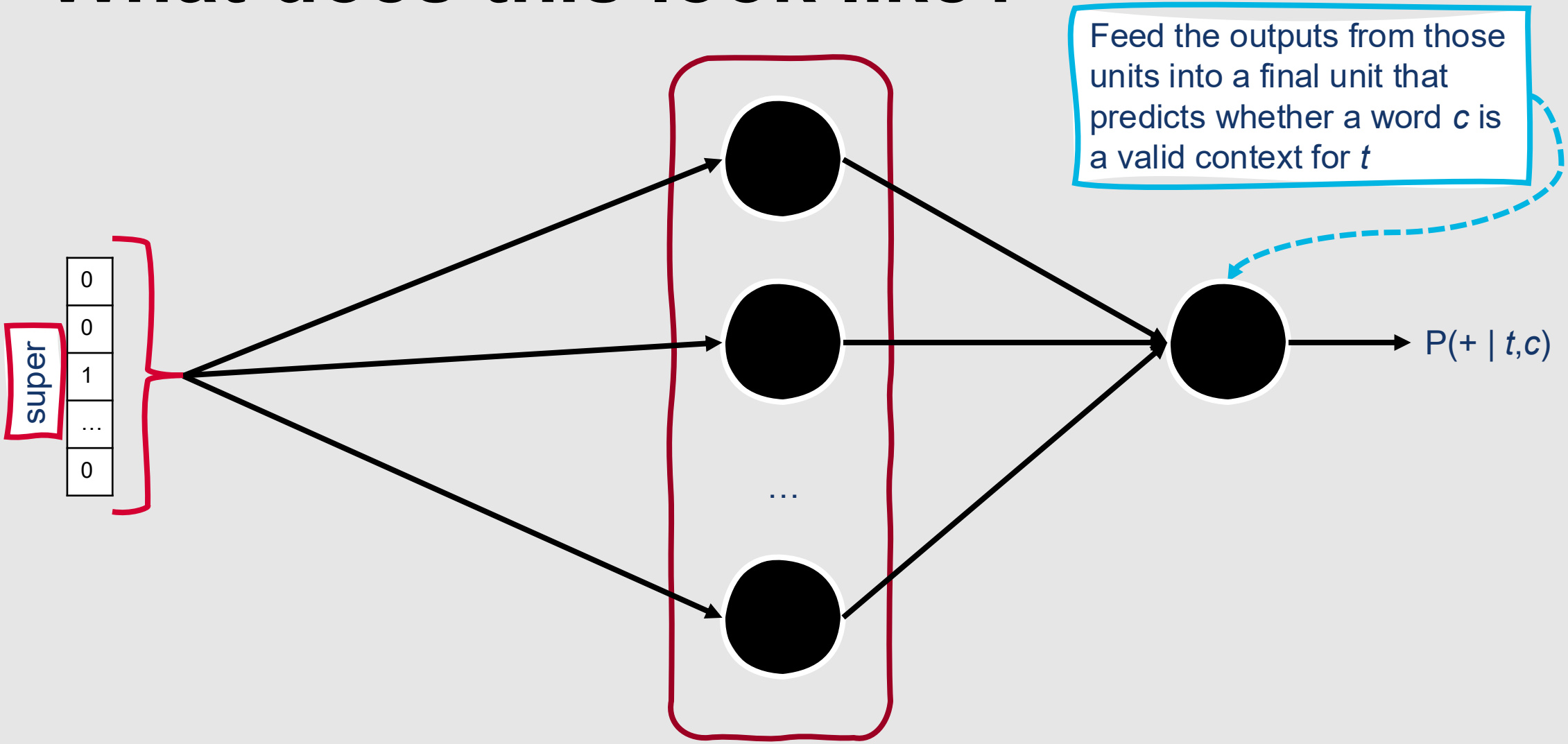

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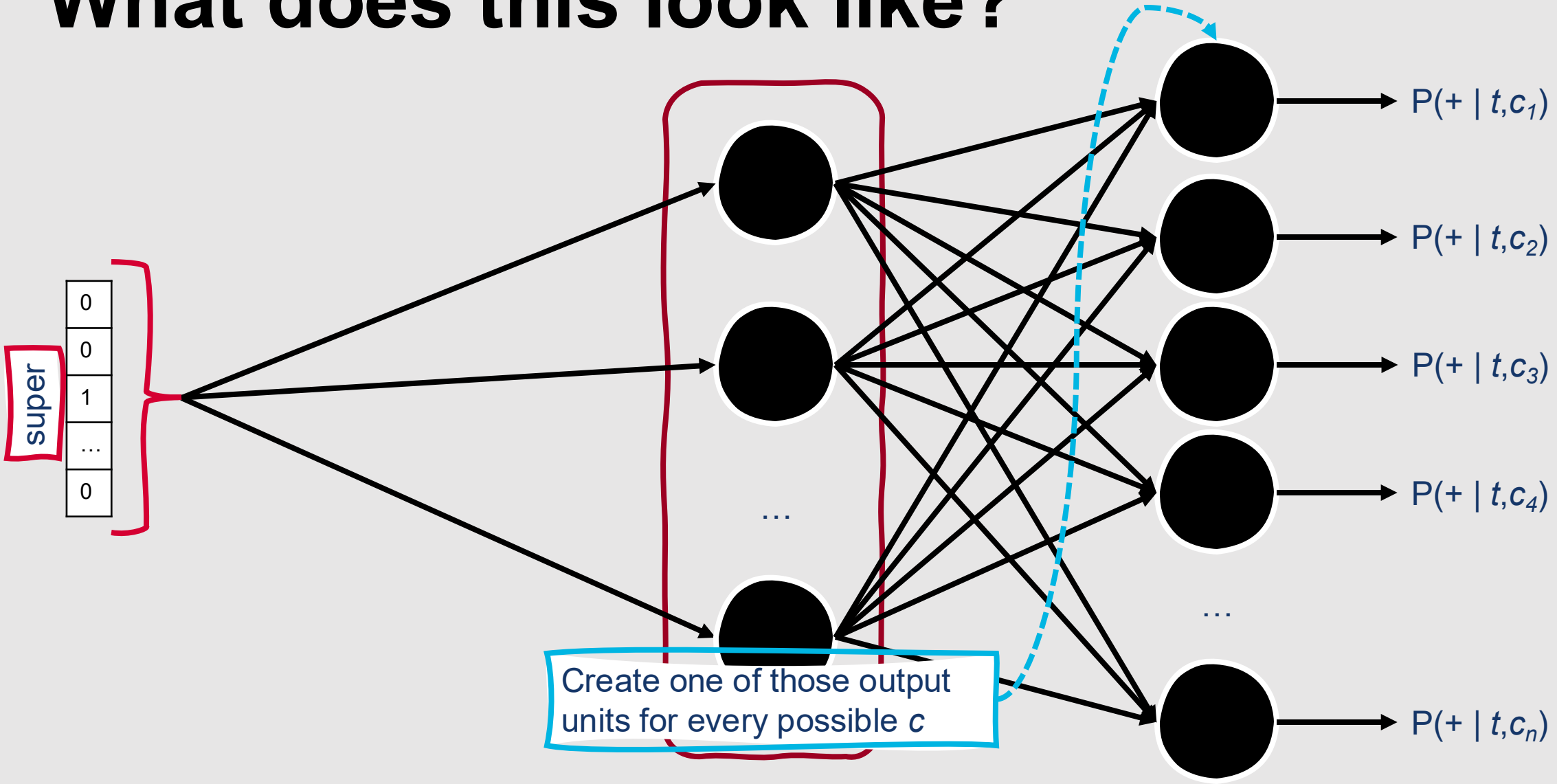
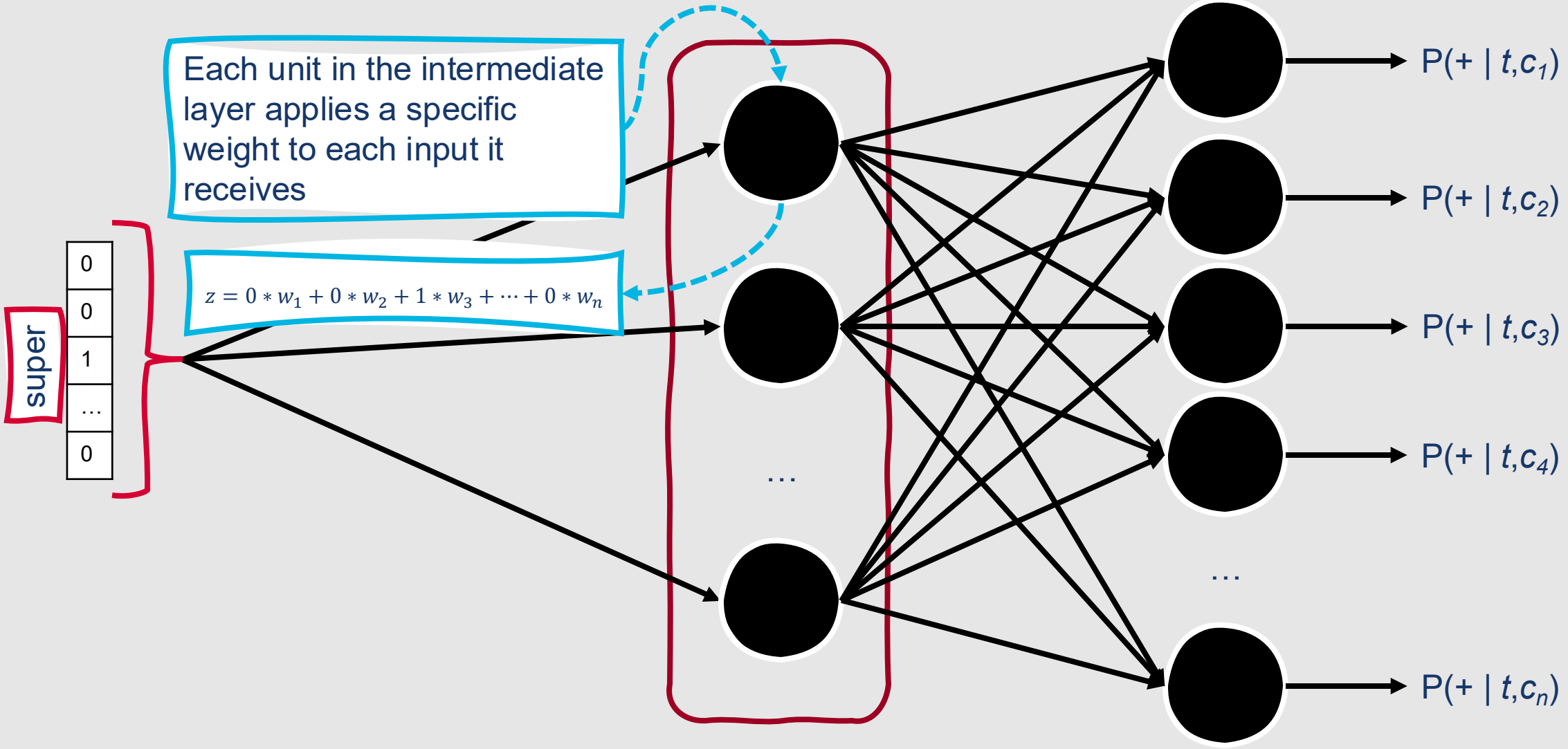


Behind the scenes….



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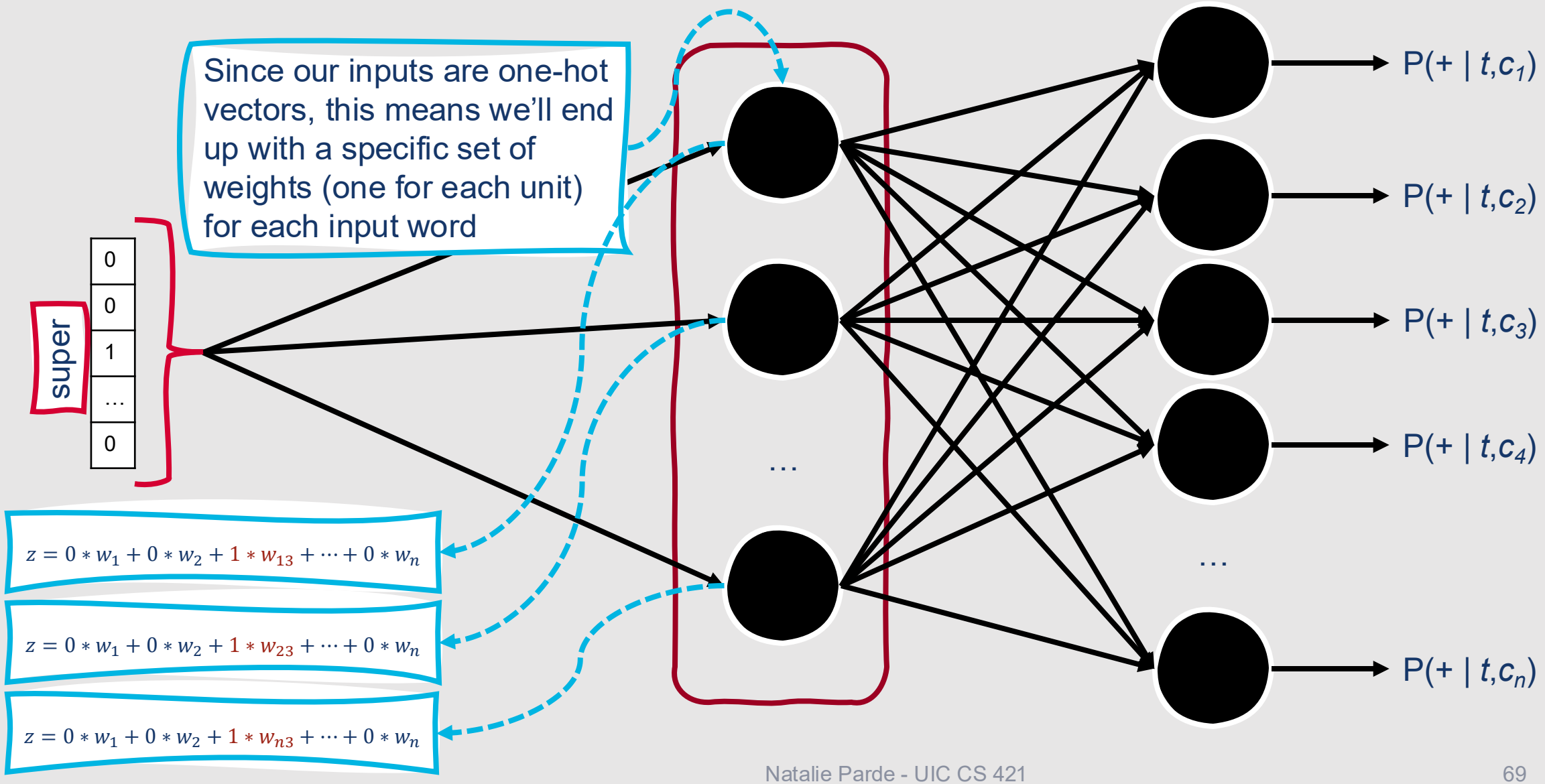
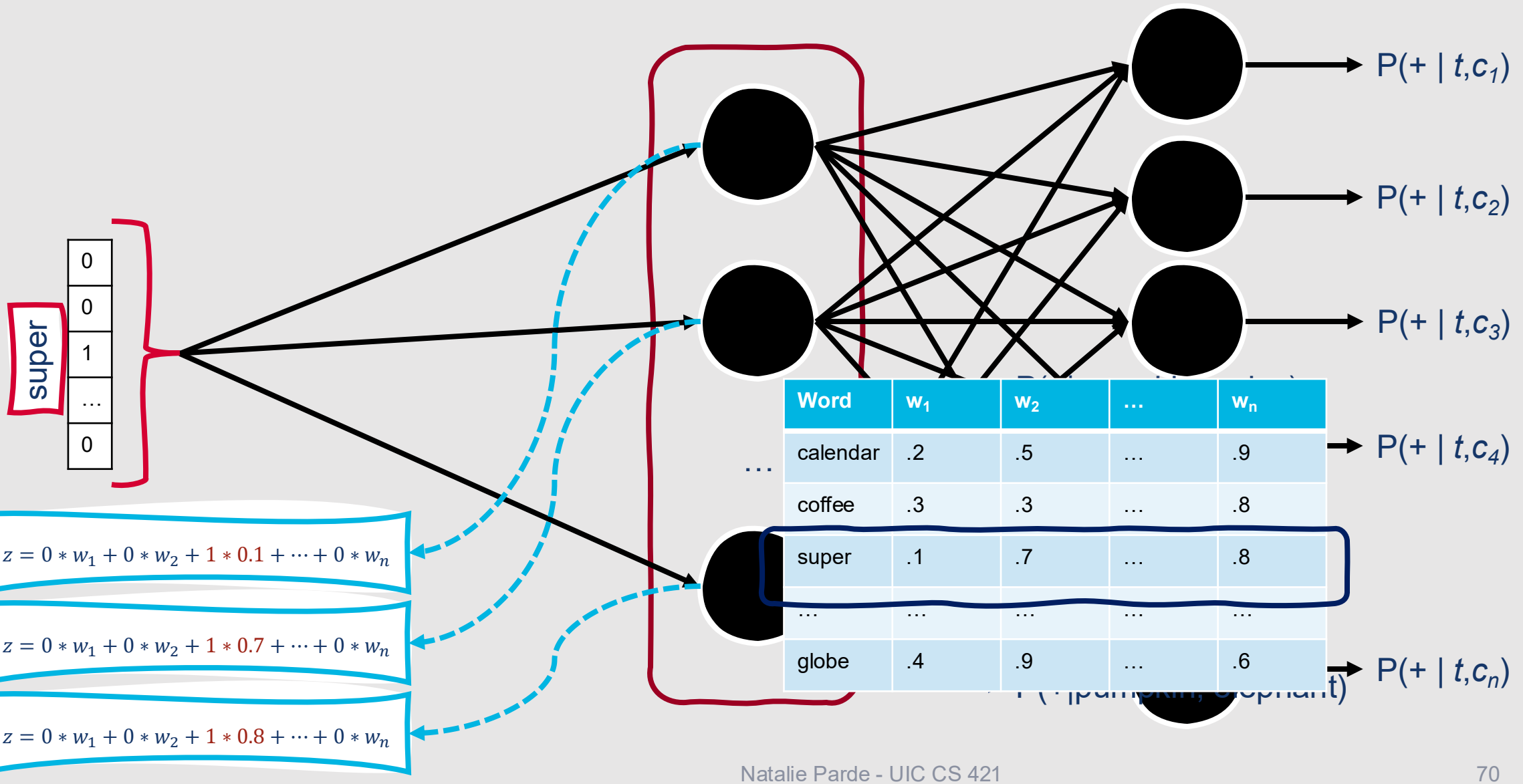


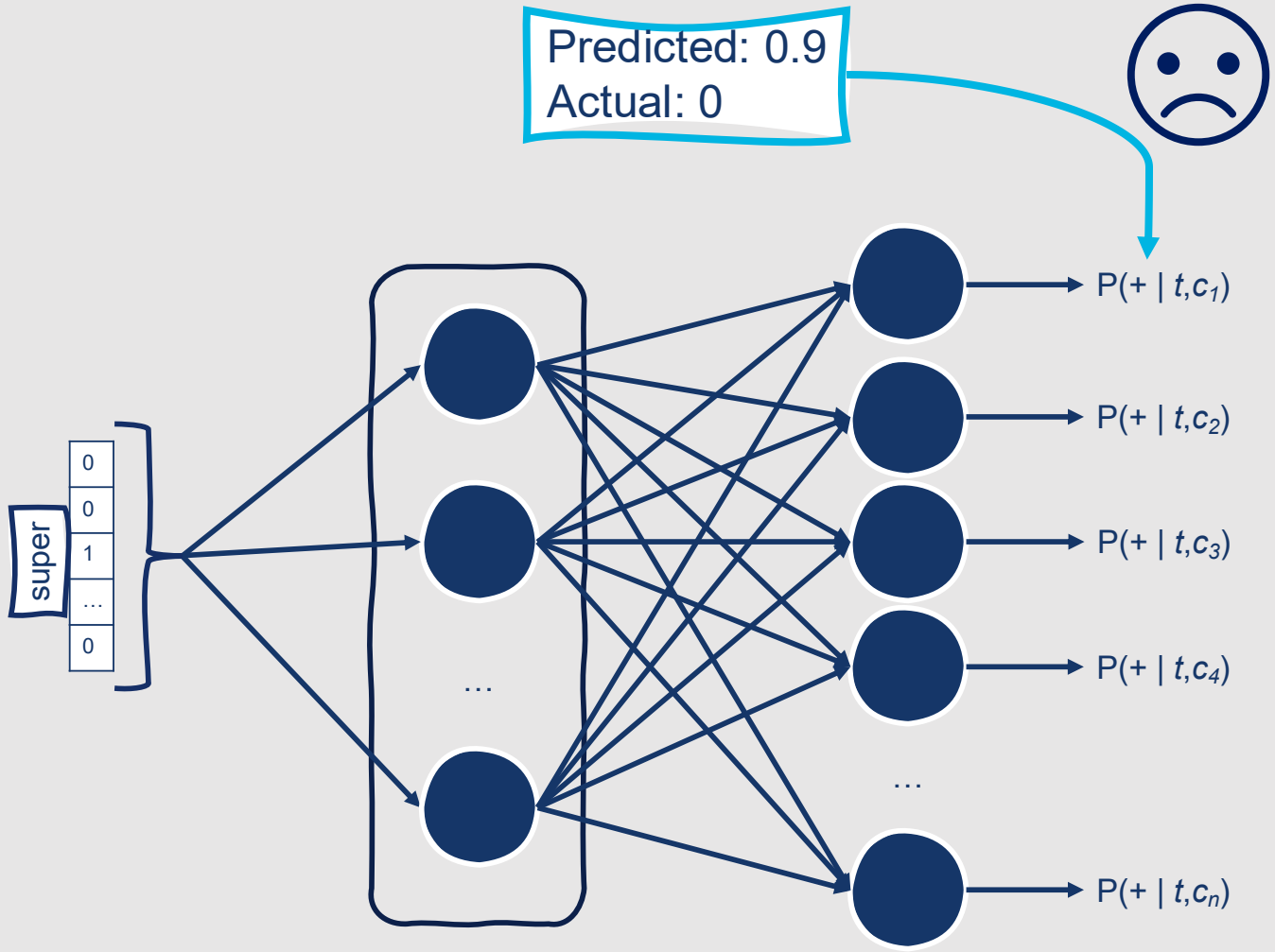
These are the weights we're interested in!



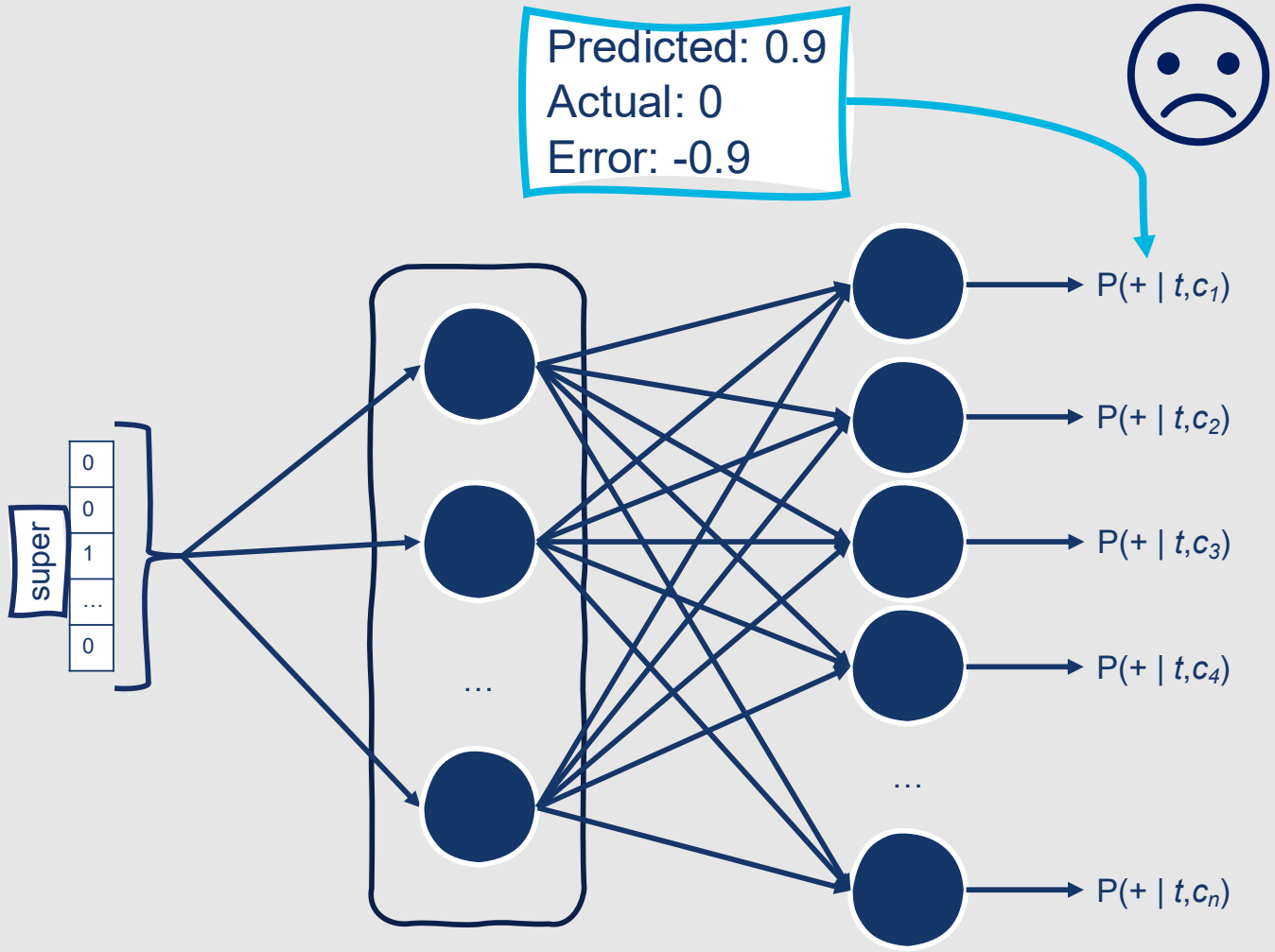
How do we optimize word embeddings over time?

- Weights are **initialized to some random value** for each word
- They are then iteratively updated to be more similar for words that occur in similar contexts in the training set, and less similar for words that do not
  - Specifically, in Word2Vec we want to find weights that maximize P(+|*t*,*c*) for words that occur in similar contexts and minimize P(+|*t*,*c*) for words that do not, given the information we have at the time

Since we initialize our weights randomly, the classifier's first prediction will almost certainly be wrong.



However, the error values from our incorrect guesses are what allow us to improve our embeddings over time.



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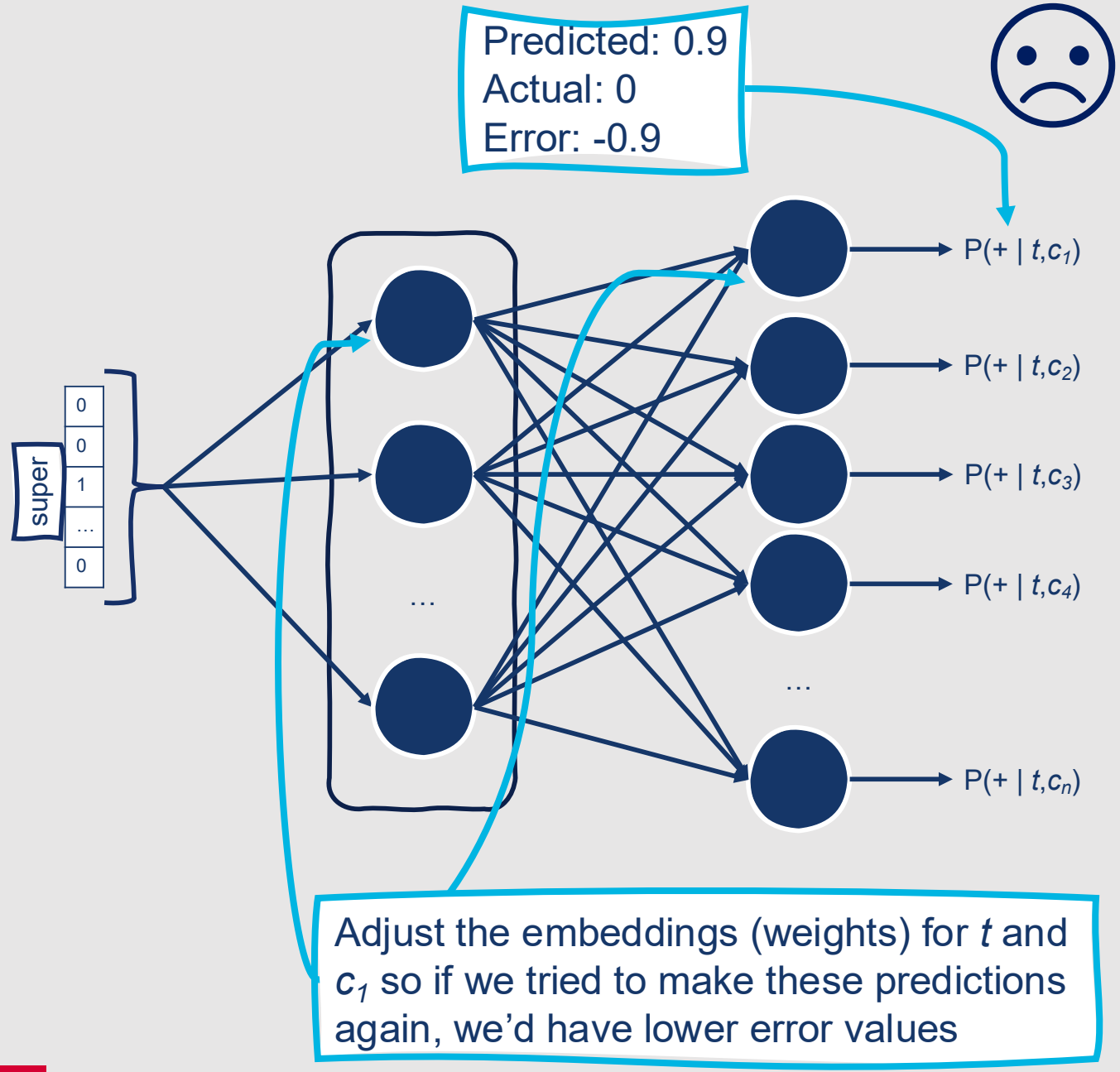

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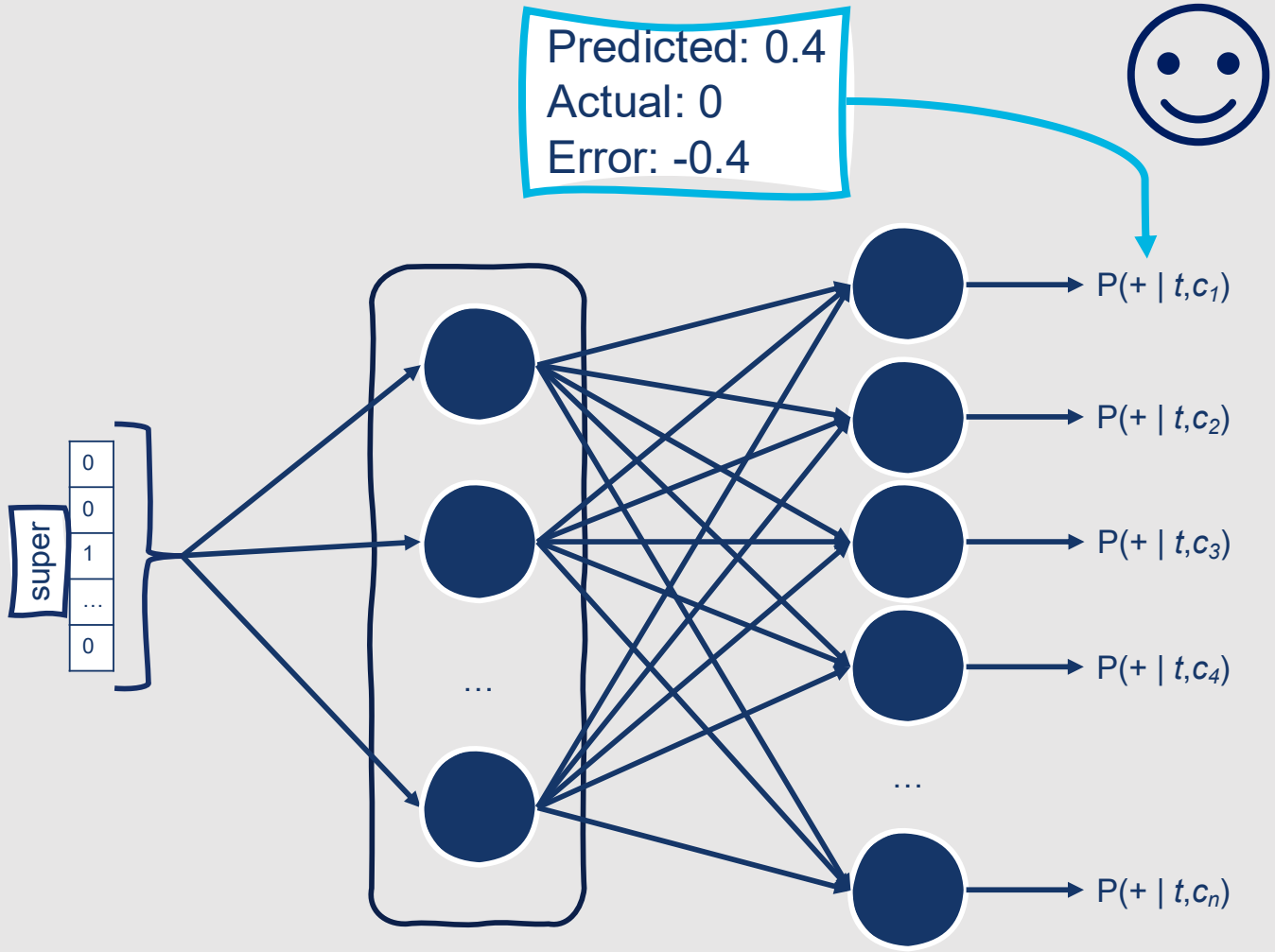


What is our training data?

this	sunday,	watch	the	super	bowl	at	5:30
		c1	c2	t	c3	c4	

Positive Examples

t	c
super	watch
super	the
super	bowl
super	at

- We assume that all occurrences of words in similar contexts in our training corpus are **positive samples**

What is our training data?

this	sunday,	watch	the	super	bowl	at	5:30
		c1	c2	t	c3	c4	

Positive Examples

t	c
super	watch
super	the
super	bowl
super	at

- However, we also need negative samples!
- In fact, Word2Vec uses more negative than positive samples (the exact ratio can vary)
- We need to create our own negative examples

What is our training data?

this	sunday,	watch	the	super	bowl	at	5:30
		c1	c2	t	c3	c4	

Positive Examples

t	c
super	watch
super	the
super	bowl
super	at

Negative Examples

t	c
super	calendar
super	exam
super	loud
super	bread
super	cellphone
super	enemy
super	penguin
super	drive

- How to create negative examples?
  - Target word + "noise" word that is sampled from the training set
  - Noise words are chosen according to their weighted unigram frequency $p_\alpha(w)$, where α is a weight:
    - $p_\alpha(w) = \frac{\text{count}(w)^\alpha}{\sum_{w'} \text{count}(w')^\alpha}$
    - Often, $\alpha = 0.75$ to give rarer noise words slightly higher probability of being randomly sampled
- Randomly select noise words according to weighted unigram frequency

Learning Skip-Gram Embeddings

- The model uses these positive and negative samples to:
  - Maximize the vector similarity of the (target, context) pairs drawn from positive examples
  - Minimize the vector similarity of the (target, context) pairs drawn from negative examples
- Parameters (target and context weight vectors) are fine-tuned by:
  - Applying stochastic gradient descent
  - Optimizing a cross-entropy loss function

What if we want to predict a target word from a set of context words instead?

- **Continuous Bag of Words (CBOW)**
  - Another variation of Word2Vec
- Very similar to skip-gram model!

In general, skip-gram embeddings are good with:

- Small datasets
- Rare words and phrases

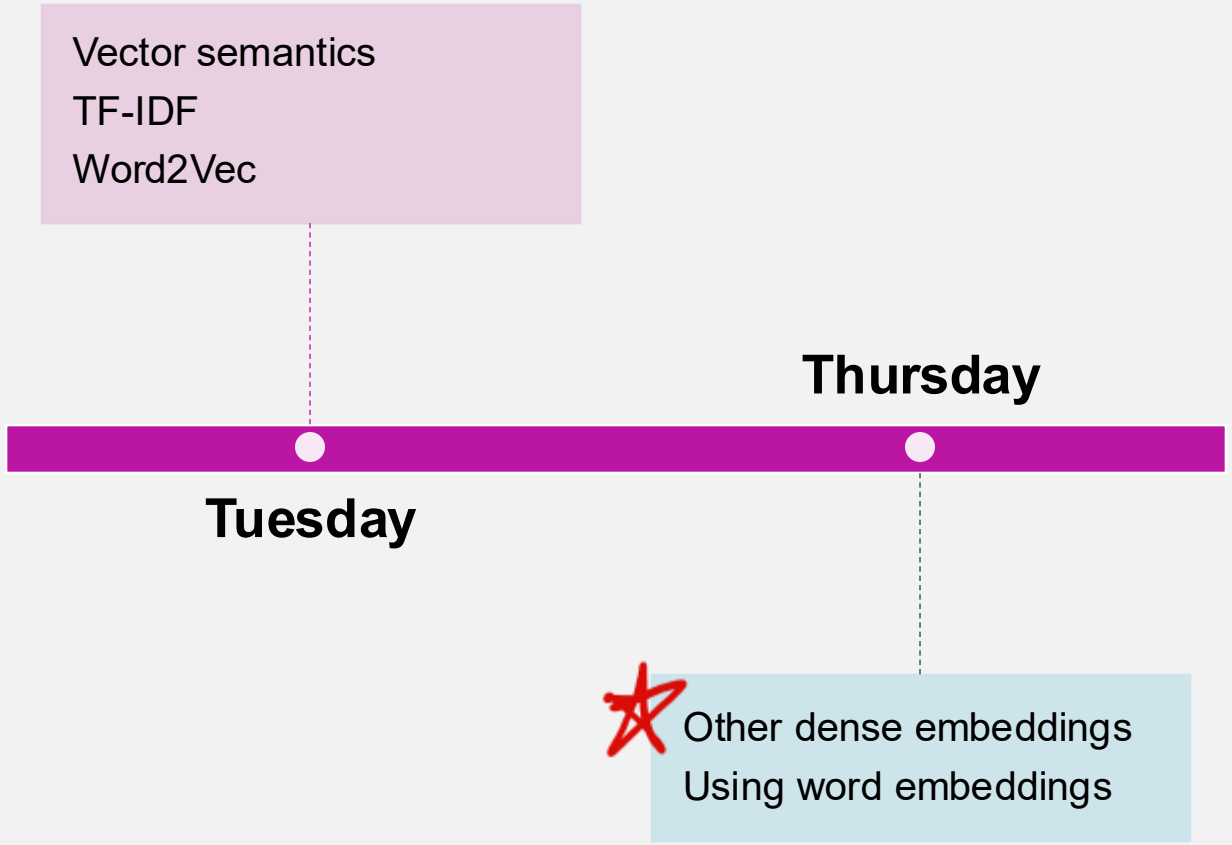
CBOW embeddings are good with:

- Larger datasets (faster to train)
- Frequent words

Summary: Introduction to Vector Semantics

- **Word vectors** are based on **the distributional hypothesis**
- Bag-of-words representations are one form of word vector, and so far **TF-IDF representations**
- TF-IDF representations combine simple term frequency with **inverse document frequency** to minimize the impact of words that occur more frequently in general
- **Word2Vec** allows us to learn dense word vectors that are more closely tied to semantic relationships

This Week's Topics



Are there any other variations of Word2Vec?

- **fastText**
  - An extension of Word2Vec that also incorporates **subwords**
  - Designed to better handle unknown words and sparsity in language

fastText

- Each word is represented as:
  - Itself
  - A bag of constituent n-grams

fastText

- Skip-gram embedding is learned for each constituent n-gram
- Word is represented by the sum of all embeddings of its constituent n-grams

- Key advantage of this extension?
  - Allows embeddings to be predicted for unknown words based on subword constituents alone

Source code available online:
https://fasttext.cc/

Other Types of Dense Word Embeddings

- Word2Vec is an example of a **predictive** word embedding model
  - Learns to predict whether words belong in a target word's context
- Other models are **count-based**
  - Remember co-occurrence matrices?
- **GloVE** combines aspects of both predictive and count-based models

Global Vectors for Word Representation (GloVe)

- Co-occurrence matrices quickly grow extremely large
- GloVe learns to predict weights in a lower-dimensional space that correspond to the co-occurrence probabilities between words
- Why is this useful?
  - Predictive models → black box
    - They work, but why?
  - GloVe models are easier to interpret

Local versus Global Context

- Word2Vec: Captures local context via prediction
- GloVe: Leverages global co-occurrence statistics across the entire corpus
  - (Along with learning local context)

How does GloVe work?

	c_1	…	c_n
t_1	123	…	456
…	…	…	…
t_n	0	…	789

Build a huge word-context co-occurrence matrix

Step #1

Ratios Encode Meaning

- Raw word co-occurrence counts will create similar issues to what we observed with bag of words-style vectors
- More informative alternative: ratios
  - Given a word *k*, what is the ratio of *k* given one word versus another?

k = “solid” → $\frac{P(\text{“solid”}|\text{”ice”})}{P(\text{“solid”}|\text{”steam”})}$

High value: “ice” relates strongly to “solid”

Low value: “steam” relates strongly to “solid”

How does GloVe work?

	c_1	…	c_n
t_1	123	…	456
…	…	…	…
t_n	0	…	789

Build a huge word-context co-occurrence matrix

Step #1

Step #2

Find word vectors w_i and w_j such that their dot product encodes co-occurrence info

Scaler biases for t_i and c_j

$$w_i^T w_j + b_i + b_j = \log X_{ij}$$

Vector for t_i Vector for c_j Co-occurrence count for $t_i c_j$

How does GloVe work?

	c_1	…	c_n
t_1	123	…	456
…	…	…	…
t_n	0	…	789

Build a huge word-context co-occurrence matrix

Step #1

Step #2

Find word vectors w_i and w_j such that their dot product encodes co-occurrence info

$$w_i^T w_j + b_i + b_j = \log X_{ij}$$

Define a cost function

$$J = \sum_{i=1}^{V} \sum_{j=1}^{V} f(X_{ij})(w_i^T w_j + b_i + b_j - \log X_{ij})^2$$

Weighting function:

$$f(X_{ij}) = \begin{cases} (\frac{X_{ij}}{x_{max}})^{\alpha}, & X_{ij} < XMAX \\ 1, & \text{otherwise} \end{cases}$$

Why this cost function?

- Same intuition as TFIDF
  - Very frequent words dominate the corpus
- By adding a weighting function to the loss function, we can increase the importance of rarer words
  - $f(X_{ij}) = \begin{cases} (\frac{X_{ij}}{x_{max}})^{\alpha}, & X_{ij} < XMAX \\ 1, & \text{otherwise} \end{cases}$
- Common to set α=0.75 and XMAX=100

How does GloVe work?

	c_1	…	c_n
t_1	123	…	456
…	…	…	…
t_n	0	…	789

Build a huge word-context co-occurrence matrix

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Step #3

Minimize the cost function to learn ideal embedding values for w_i and w_j

How does GloVe work?

	c_1	…	c_n
t_1	123	…	456
…	…	…	…
t_n	0	…	789

Build a huge word-context co-occurrence matrix

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$$w_i^T w_j + b_i + b_j = \log X_{ij}$$

Define a cost function

$$J = \sum_{i=1}^{V} \sum_{j=1}^{V} f(X_{ij})(w_i^T w_j + b_i + b_j - \log X_{ij})^2$$

0.4	0.7	1.2	4.3	0.9	6.7	1.3	0.5	0.7	5.3

Step #3

Minimize the cost function to learn ideal embedding values for w_i and w_j

Training Process

- Similar to other algorithms we've examined!
  - Minimize cost function using stochastic gradient descent
- Standard context window size: 5-10 words
- Store co-occurrence matrix as a sparse matrix (only non-zero counts) and thus iterate over only non-zero counts during training

Final Vector

- Each word technically has two roles during the training process
  - As a target word: w_i
  - As a context word: $\widetilde{w_i}$
    - (Represented as w_j in the equation earlier)
- After training, to get a single embedding per word, we merge these two roles
  - $v_i = w_i + \widetilde{w_i}$

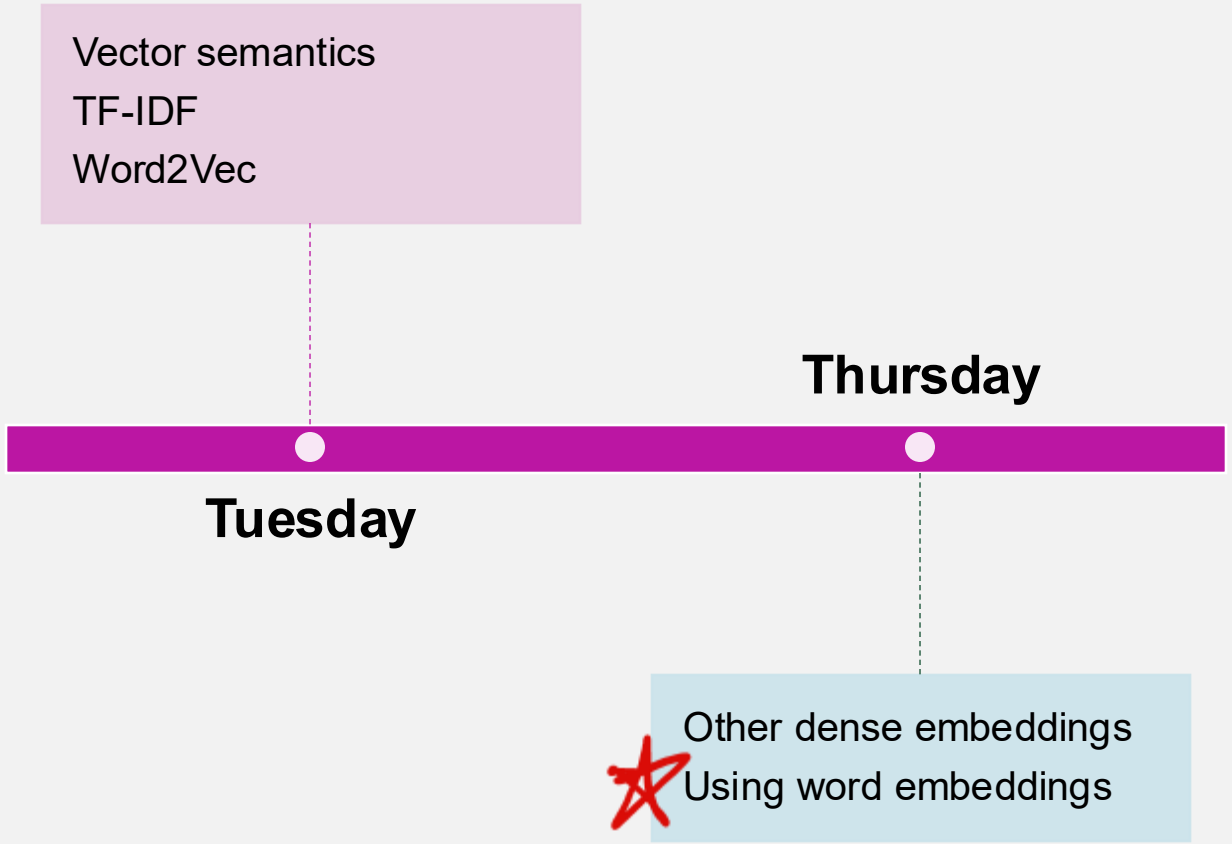
Why does GloVe work?

- Ratios of co-occurrence probabilities have the potential to encode word similarities and differences
- These similarities and differences are useful components of meaning
  - GloVe embeddings perform particularly well on analogy tasks

Which is better …Word2Vec or GloVe?

- In general, Word2Vec and GloVe produce similar embeddings
- Word2Vec → slower to train but less memory intensive
- GloVe → faster to train but more memory intensive
- Word2Vec and Glove both produce context-independent embeddings
- Contextual embeddings:
  - ELMo (Peters et al., 2018; https://www.aclweb.org/anthology/N18-1202/)
  - BERT (Devlin et al., 2019; https://www.aclweb.org/anthology/N19-1423/)

This Week's Topics



Evaluating Vector Models

- Extrinsic Evaluation
  - Add the vectors as features in a downstream NLP task, and see whether and how this changes performance relative to a baseline model
  - Most important evaluation metric for word embeddings!
    - Word embeddings are rarely needed in isolation
    - They are almost solely used to boost performance in downstream tasks

Evaluating Vector Models

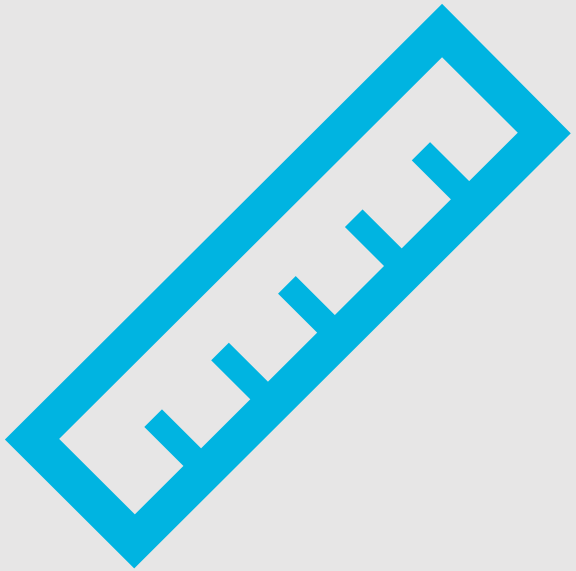
- Intrinsic Evaluation
  - Performance at predicting:
    - Word similarity
    - Text similarity
    - Analogy

Evaluating Performance at Predicting Word Similarity

- Compute the **cosine similarity** between vectors for pairs of words
- Compute the **correlation** between those similarity scores and word similarity ratings for the same pairs of words manually assigned by humans
- Corpora for doing this:
  - WordSim-353
  - SimLex-999
  - TOEFL Dataset
    - *Levied* is closest in meaning to: (a) imposed, (b) believed, (c) requested, (d) correlated

Cosine Similarity

- Based on the **dot product** from linear algebra
  - $\mathbf{v} \cdot \mathbf{w} = \sum_{i=1}^{N} v_i w_i = v_1 w_1 + v_2 w_2 + \cdots + v_N w_N$
- Intuition:
  - Similar vectors (e.g., large values in the same dimensions) will have high cosine similarity
  - Dissimilar vectors (e.g., zeros or low values in different dimensions) will have low cosine similarity



Normalized Dot Product = Cosine Similarity

- We compute a **normalized dot product** to avoid issues related to word frequency
  - Non-normalized dot product will be higher for frequent words, regardless of how similar they are
  - We normalize by dividing the dot product by the lengths of the two vectors
- The cosine similarity metrics between two vectors **v** and **w** can thus be computed as:
  - $\text{cosine}(\mathbf{v}, \mathbf{w}) = \frac{\mathbf{v} \cdot \mathbf{w}}{|\mathbf{v}||\mathbf{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2} \sqrt{\sum_{i=1}^{N} w_i^2}}$
- This value ranges between:
  - 0 (dissimilar) and 1 (similar) for frequency or TF-IDF vectors
  - -1 (dissimilar) and 1 (similar) for embedding vectors that may have negative values

Example: Computing Cosine Similarity

	glitter	data	computer
unicorn	442	8	2
digital	5	1683	1670
information	5	3982	3325

cos(unicorn, information) = ?

Example: Computing Cosine Similarity

	glitter	data	computer
unicorn	442	8	2
digital	5	1683	1670
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$$\cos(\text{unicorn, information}) = \frac{[442,8,2]\cdot[5,3982,3325]}{\sqrt{442^2+8^2+2^2}\sqrt{5^2+3982^2+3325^2}}$$

Example: Computing Cosine Similarity

	glitter	data	computer
unicorn	442	8	2
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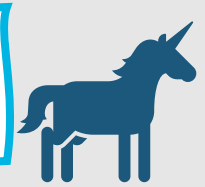
$$\cos(\text{unicorn, information}) = \frac{442*5+8*3982+2*3325}{\sqrt{442^2+8^2+2^2}\sqrt{5^2+3982^2+3325^2}}$$



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$$\cos(\text{digital, information}) = \frac{5*5+1683*3982+1670*3325}{\sqrt{5^2+1683^2+1670^2}\sqrt{5^2+3982^2+3325^2}} = 0.996$$

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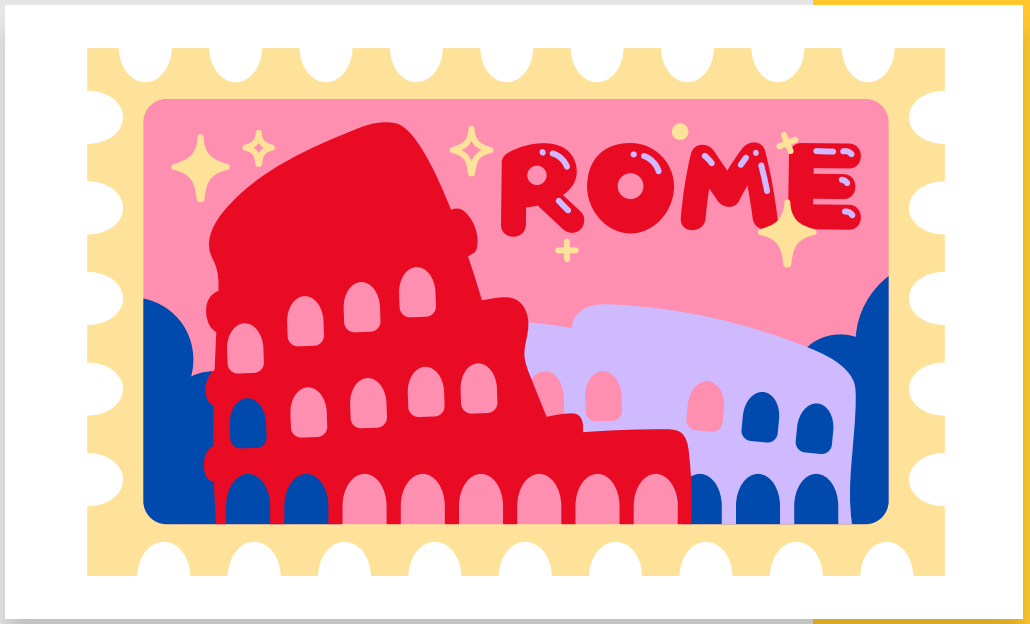
$$\cos(\text{digital, information}) = \frac{5*5+1683*3982+1670*3325}{\sqrt{5^2+1683^2+1670^2}\sqrt{5^2+3982^2+3325^2}} = 0.996$$

Result: *information* is way closer to *digital* than it is to *unicorn*!

More about Word Embeddings

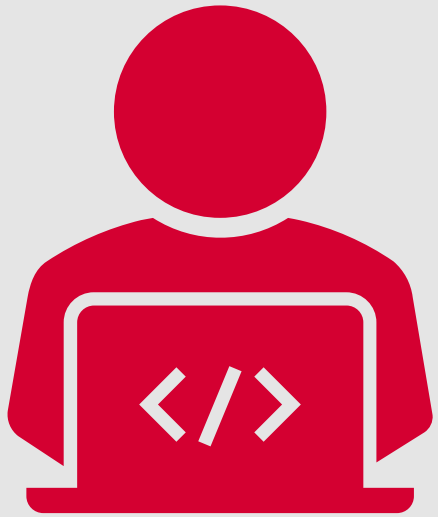
- We can capture **relational meanings** in word embeddings by computing the offsets between values in the same columns for different vectors
- Famous examples (Mikolov et al., 2013; Levy and Goldberg, 2014):
  - king - man + woman = queen
  - Paris - France + Italy = Rome



Context window size influences what you learn!

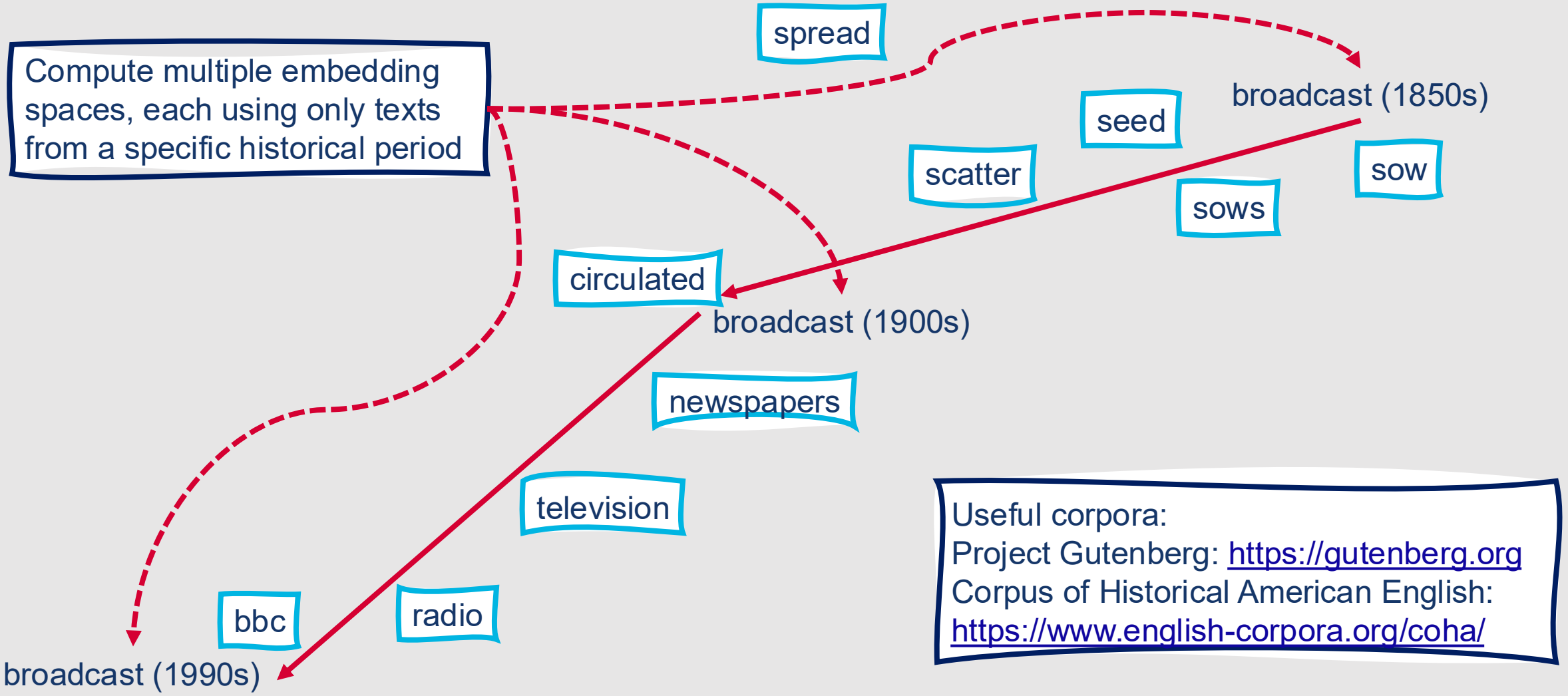
- Shorter context window → more **syntactic representations**
  - Information is from immediately nearby words
  - Most similar words tend to be semantically similar words with the same parts of speech
- Longer context window → more **topical representations**
  - Information can come from longer-distance dependencies
  - Most similar words tend to be topically related, but not necessarily similar (e.g., *diner* and *eats*, rather than *spoon* and *fork*)

Word embeddings have many practical applications.



- Features for text classification tasks
- Representations for computational social science studies
  - Studying word meaning over time
  - Studying implicit associations between words

Embeddings and Historical Semantics

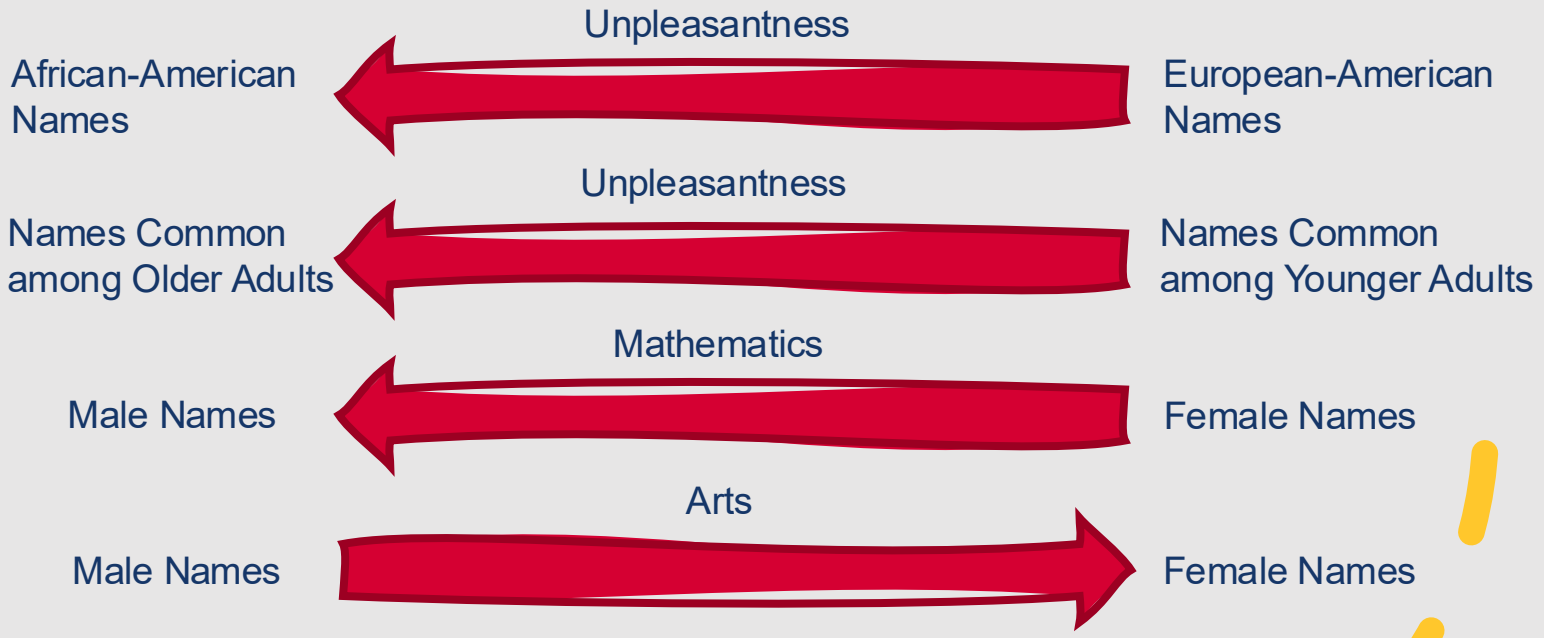


Unfortunately, word embeddings can also end up reproducing implicit biases and stereotypes latent in text.

- Recall: king - man + woman = queen
- Word embeddings trained on news corpora also produce:
  - man - computer programmer + woman = homemaker
  - doctor - father + mother = nurse
- Very problematic for real-world applications (e.g., CV/resume scoring models)

Bias and Embeddings

- Caliskan et al. (2017) identified known, harmful implicit associations in GloVe embeddings



How do we keep the useful associations present in word embeddings, but get rid of the harmful ones?

- Recent research has begun examining ways to **debias** word embeddings by:
  - Transforming embedding spaces to remove gender stereotypes but preserve definitional gender
  - Changing training procedures to eliminate these issues before they arise
- Increasingly active area of study:
  - https://facctconference.org

Visualizing Embeddings

- Word embeddings typically represent words in high-dimensional space
  - Hard to interpret directly!
- Effectively visualizing embeddings helps us understand issues pertaining to language change and bias
  - Also helps us more broadly understand semantic structure

How do we visualize embeddings?

- Reduce dimensionality so that they can be plotted in 2D or 3D space
- Common techniques:
  - **Principle component analysis** (PCA)
  - **t-Distributed Stochastic Neighbor Embedding** (t-SNE)
  - **Uniform Manifold Approximation and Projection** (UMAP)

Principle Component Analysis

- Goal:
  - Find axes (principle components) that capture the most variance in the data
    - Eigenvectors of the data's covariance matrix
  - Project the high-dimensional data to the new principle components space
- Fast, interpretable, linear method
- Limitation: May not capture non-linear clusters

t-Distributed Stochastic Neighbor Embedding

- Goal:
  - Preserve local neighborhoods (words close in high-dimensional space) by converting distances into probabilities of being neighbors
- Non-linear-method that produces visually appealing clusters
- Limitation: Computationally expensive, and global distances between clusters may be misleading

Uniform Manifold Approximation and Projection

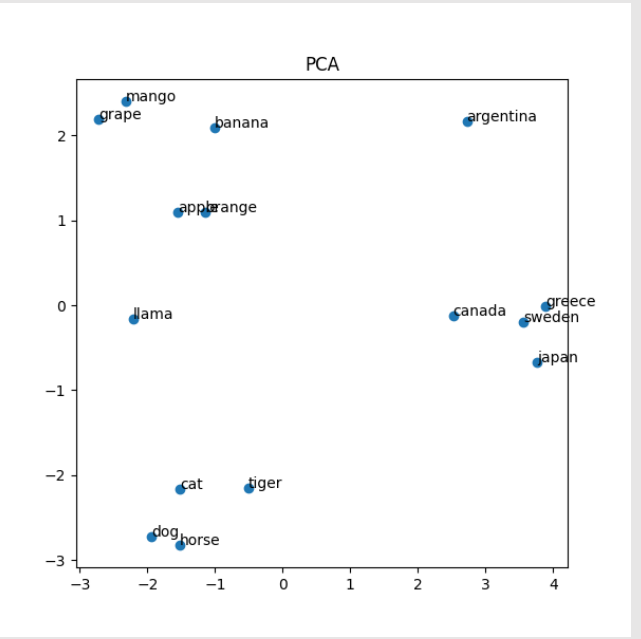
- Goal:
  - Construct a high-dimensional graph representation of the data and then optimize a low-dimensional graph to be as structurally similar as possible
- More equipped to balance local and global structure
- Fast and scalable

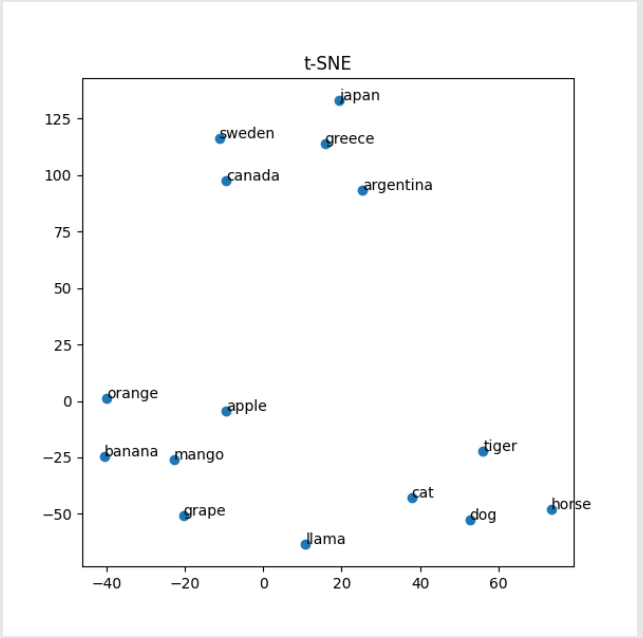
Comparing PCA, t-SNE, and UMAP

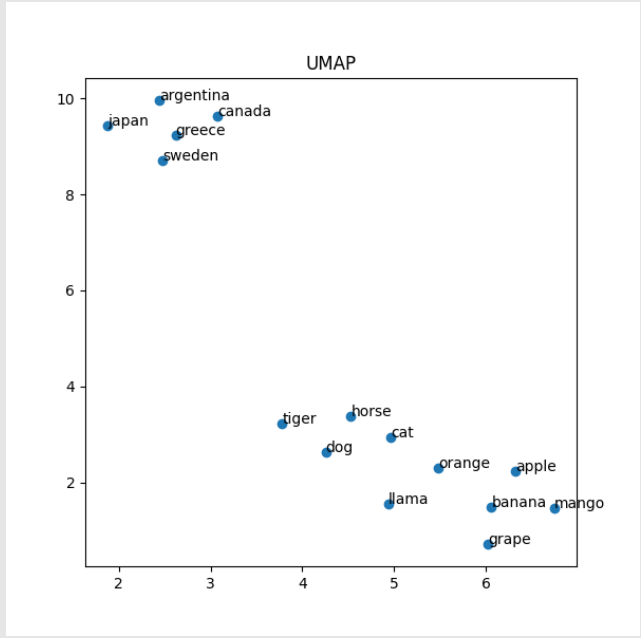
Method	Preserves	Pros	Cons
PCA	Global variance	Fast, simple, interpretable	Misses non-linear structure
t-SNE	Local neighborhoods	Great for visual clusters	Slow, misleading global distances
UMAP	Local + global structure	Fast and scalable	More parameters to tune

Simple Implementation

```python
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from umap import UMAP
from gensim.models import KeyedVectors
import numpy as np
import gensim.downloader as api

# Load pretrained Word2Vec Google News vectors
model = api.load("glove-wiki-gigaword-50")

# Picking a subset of words to demo
words = ["dog", "cat", "llama", "horse", "tiger",
         "apple", "banana", "grape", "mango", "orange",
         "greece", "argentina", "canada", "sweden", "japan"]
X = np.array([model[w] for w in words])

# PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# t-SNE
tsne = TSNE(n_components=2, random_state=42, perplexity=5)
X_tsne = tsne.fit_transform(X)

# UMAP
umap_model = UMAP(n_neighbors=5, min_dist=0.3, random_state=42)
X_umap = umap_model.fit_transform(X)

# Build plots
def plot_embedding(X, title):
    plt.figure(figsize=(6, 6))
    plt.scatter(X[:, 0], X[:, 1])
    for i, word in enumerate(words):
        plt.annotate(word, (X[i, 0], X[i, 1]))
    plt.title(title)
    plt.show()

plot_embedding(X_pca, "PCA")
plot_embedding(X_tsne, "t-SNE")
plot_embedding(X_umap, "UMAP")
```







Summary: Word Embeddings

- **Word2Vec** is a **predictive** word embedding approach, whereas **GloVe** is a hybrid predictive and **count-based** word embedding approach that learns an optimized, lower-dimensional version of a co-occurrence matrix
- **Word embeddings** can be evaluated through their incorporation in other language tasks, and they can be used to model syntactic and semantic properties of language over time
- A popular metric used to compute the similarity between word embeddings is **cosine similarity**
- We can visualize word embeddings using **PCA**, **t-SNE**, and **UMAP**