type-based 每个 word 一个 vector

token-based context based

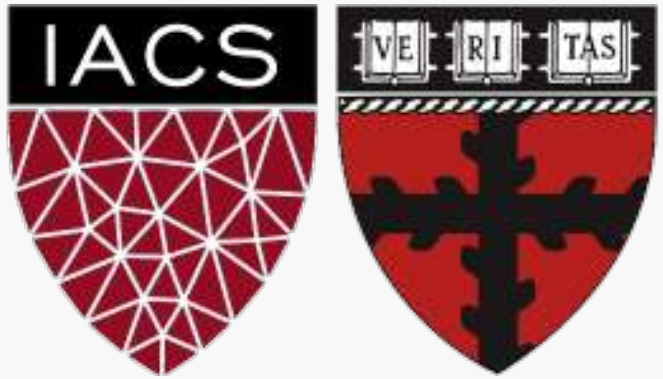
同样的 word 不同的出现位置 embedding 不一样

不同 Embedding 对比 ⇒ 反映 similarity

Word Embedding
A-sec 3

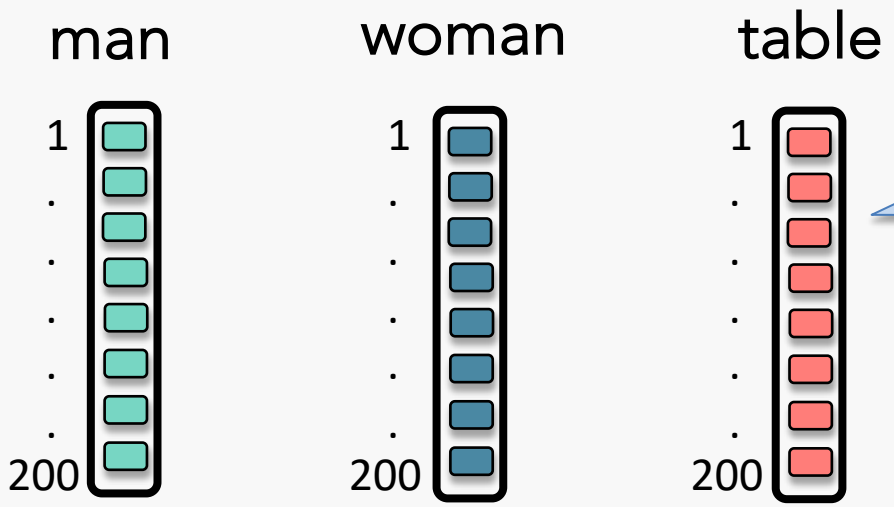
CS109B Data Science 2

Pavlos Protopapas, Mark Glickman, and Chris Tanner



RECAP: Word Embeddings

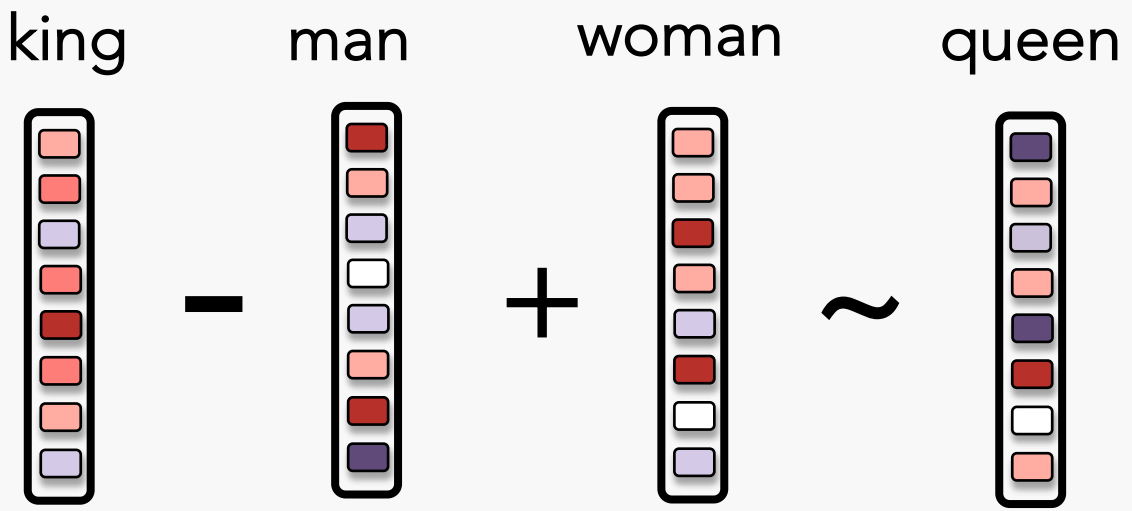
Each word is represented by a word embedding (e.g., vector of length 200)



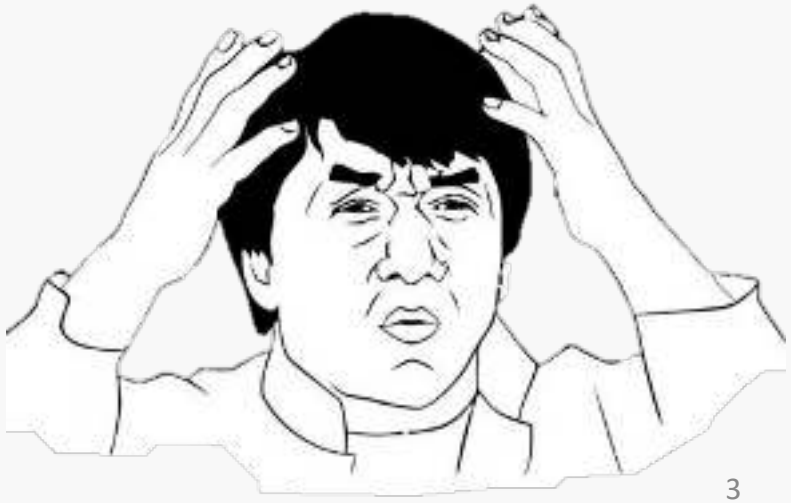
- Each rectangle is a *floating-point* scalar
- Words that are more *semantically similar* to one another will have **embeddings** that are also proportionally similar
- We can *use pre-existing* word embeddings that have been trained on gigantic corpora

Recap: Word Embeddings

These word embeddings are so rich that you get nice properties:



HOW?!?

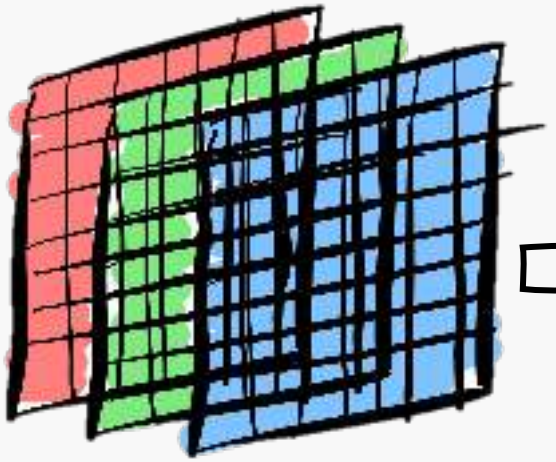


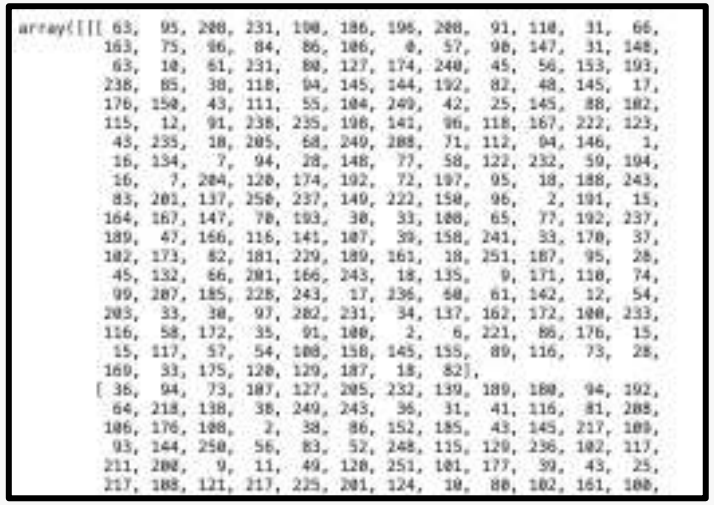
Computer Vision vs Language models

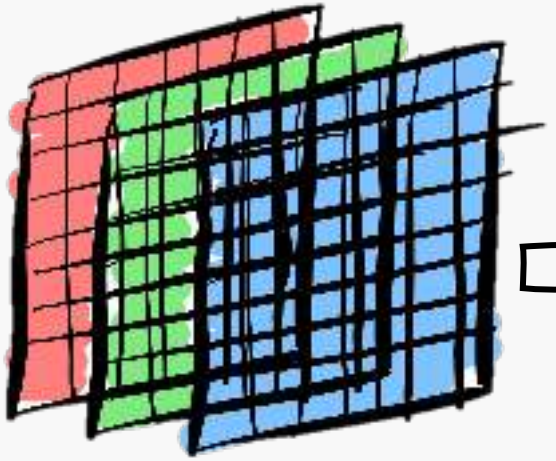
CAT

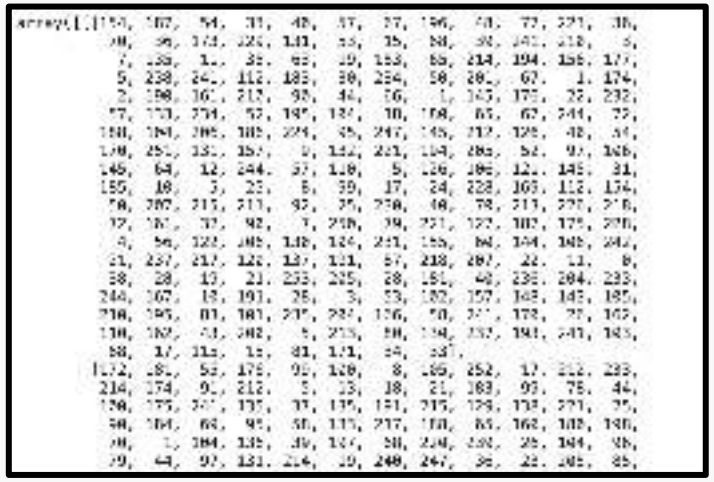
DOG

Computer Vision vs Language models





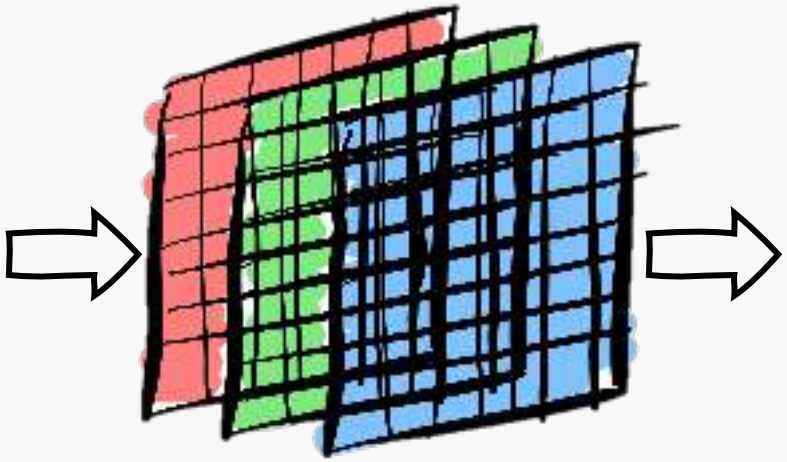




Computer Vision vs Language models

IMAGE OF A CAT

RGB CHANNELS



3-D TENSOR

```
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         217, 108, 121, 217, 225, 201, 124,  10,  88, 102, 161, 100,
```
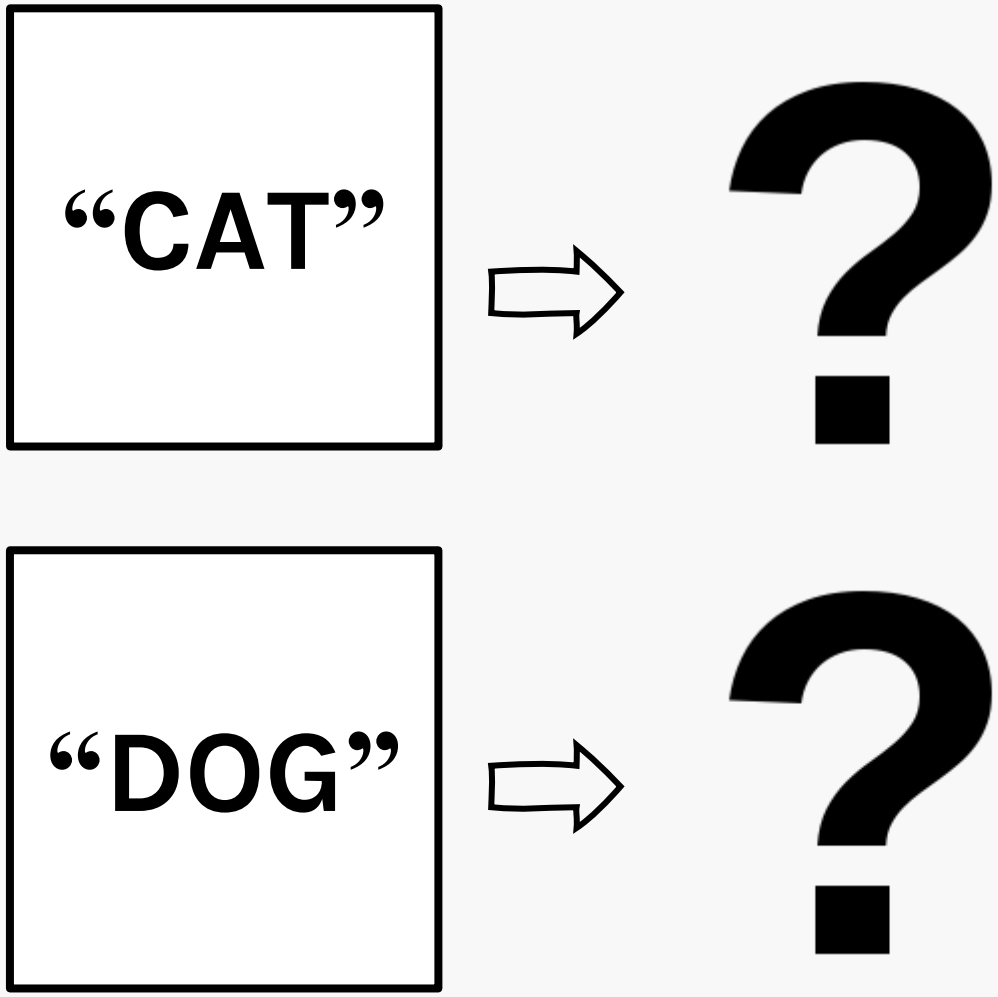
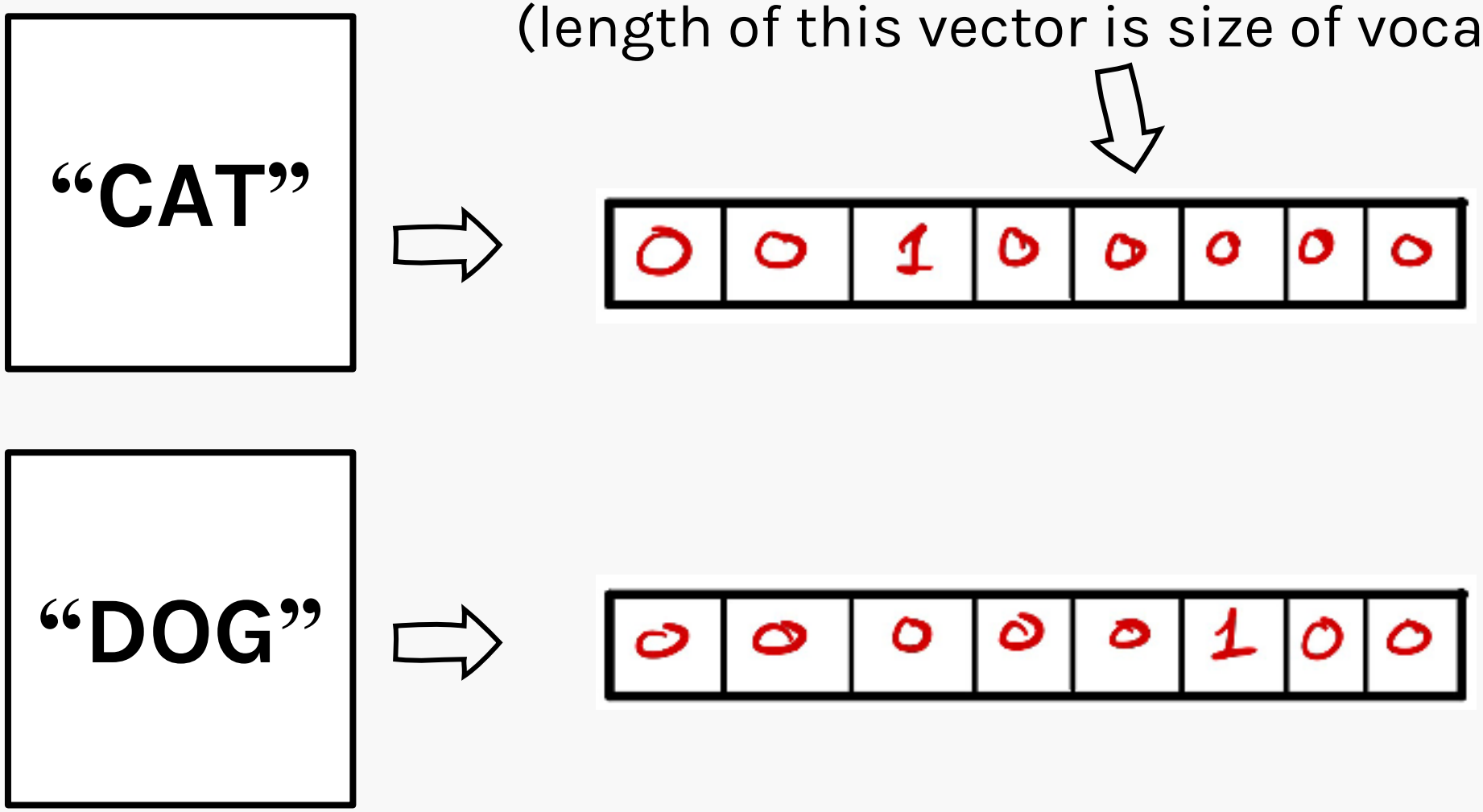

Computer Vision vs Language models



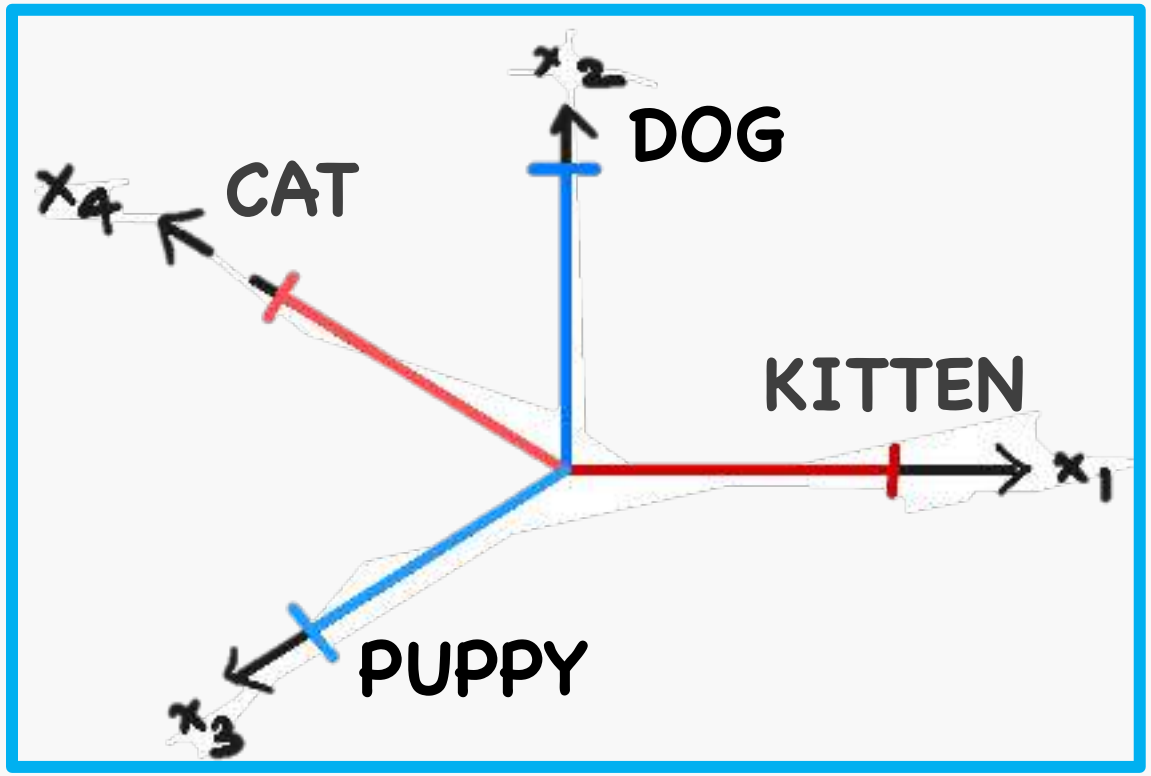
Words to numbers – One Hot Encoding

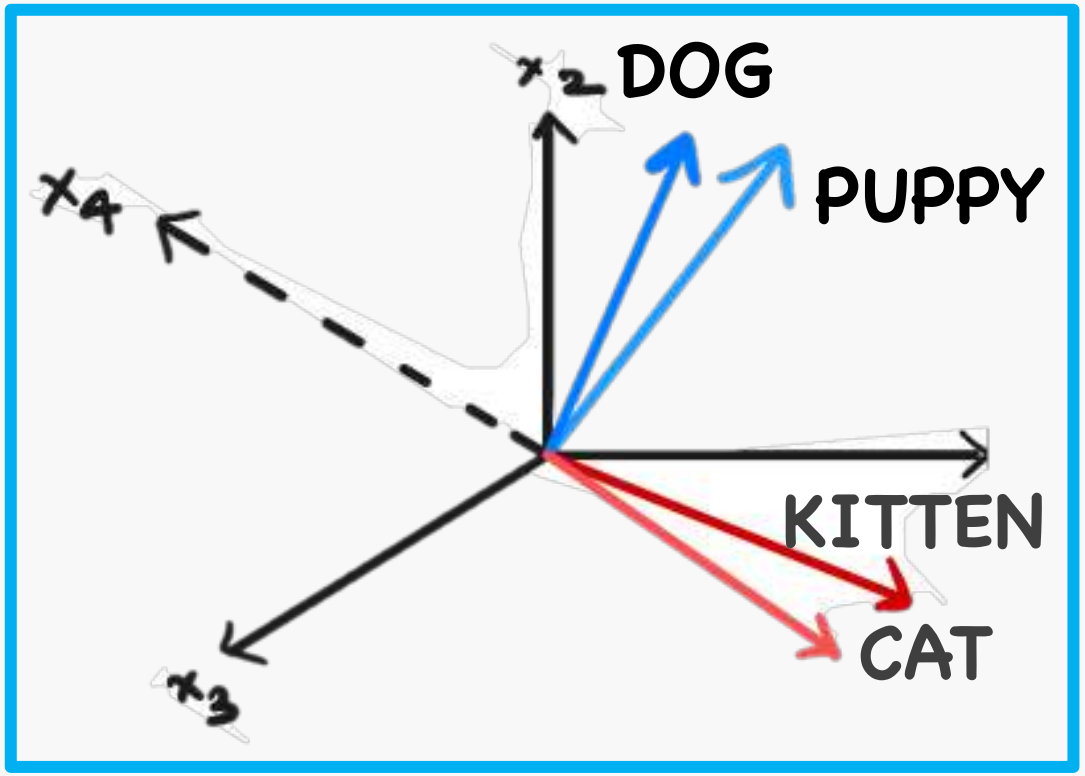
One-hot encoding of the word “cat”
(length of this vector is size of vocabulary)



One Hot Encoding Issues

- The vocabulary V of a corpus (large swath of text) can have 10,000 words.
- One-hot encoding of such a corpus is huge.
- Moreover, similarities between words cannot be established.





Pavlos game #4275

WHO IS MOST SIMILAR TO PAVLOS?

OPTION A

OPTION B

OPTION C

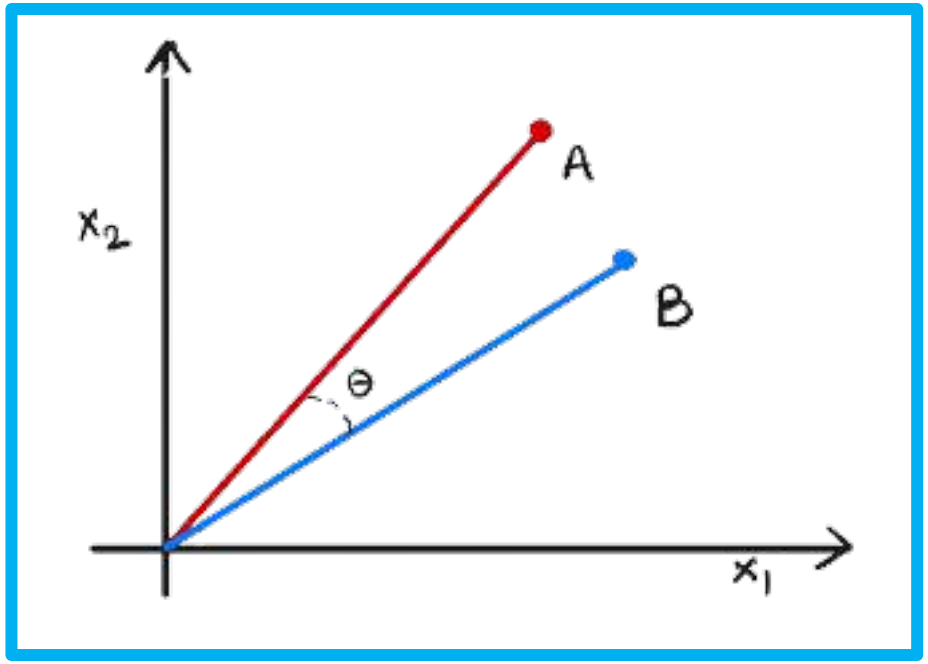
BIG 5

PERSONALITY TEST RESULTS

EXTROVERSION	97	70	88	67
EMOTIONAL STABILITY	98	74	13	87
AGREEABLENESS	73	62	51	56
CONSCIENTIOUSNESS	88	46	22	89
IMAGINATION	76	68	93	80

USING PERSONALITY DATA TO FIND SIMILARITY

What is "Cosine Similarity"?



(distance between two vectors)

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Where A_i & B_i are components of vector A & B respectively

WHO IS MOST SIMILAR TO PAVLOS?

COSINE SIMILARITY [ ] = 0.987

COSINE SIMILARITY [ ] = 0.912

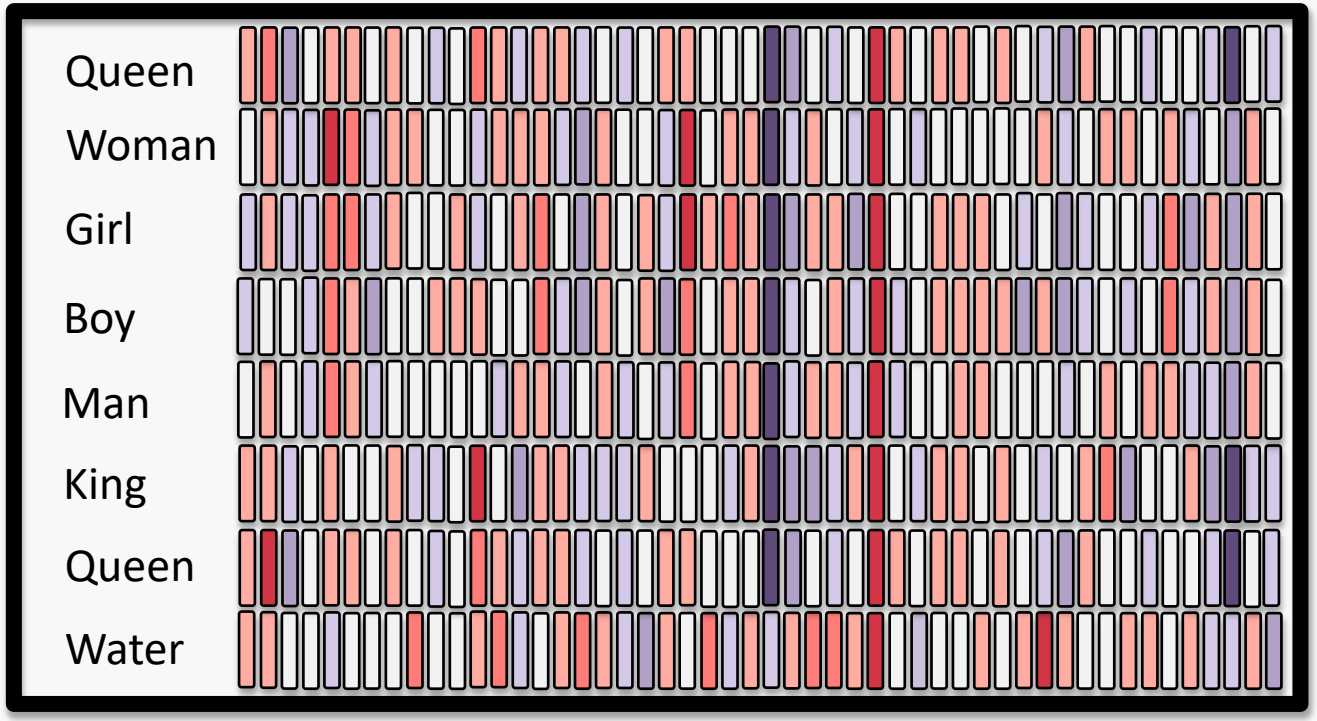
COSINE SIMILARITY [ ] = 0.826

Word Embeddings

- We use the same idea to map words in a vocabulary to a n-dimensional vector space.
- For example, if we choose a 50-dimensional vector space, each word will be represented by 50 numbers.
- Such a vector is called an **Embedding**.
- Two words will be "**similar**" if their vector representations are *close* to each other.
- An **Embedding Matrix** is simply a collection of embedding values for all words in the vocabulary.

Obligatory example

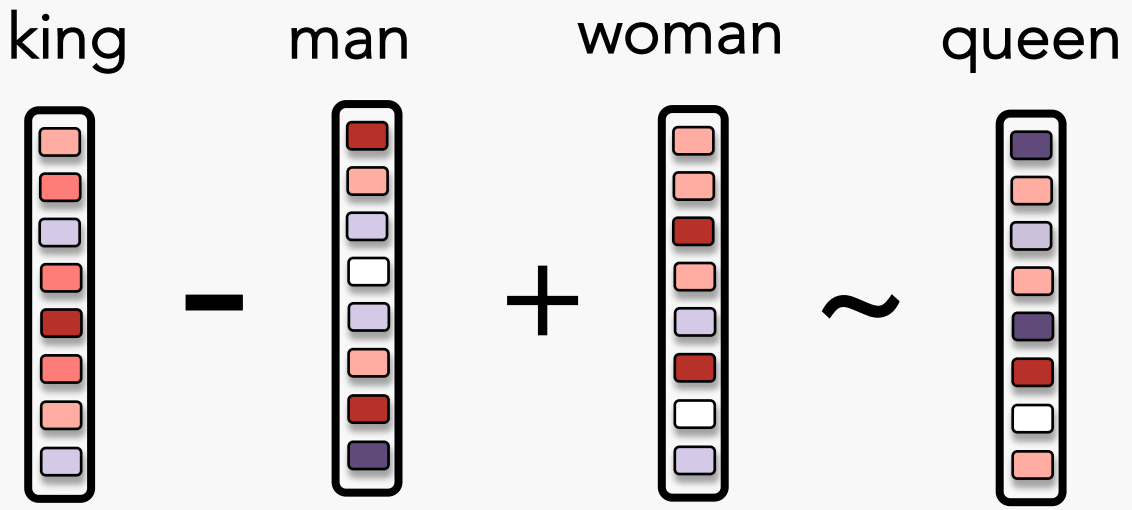
Embedding Matrix



Vector Representations for a few words

(Color gradient indicates values from embedding)

Since these **words** are now mapped to **numbers** in R^n, we can operate on them



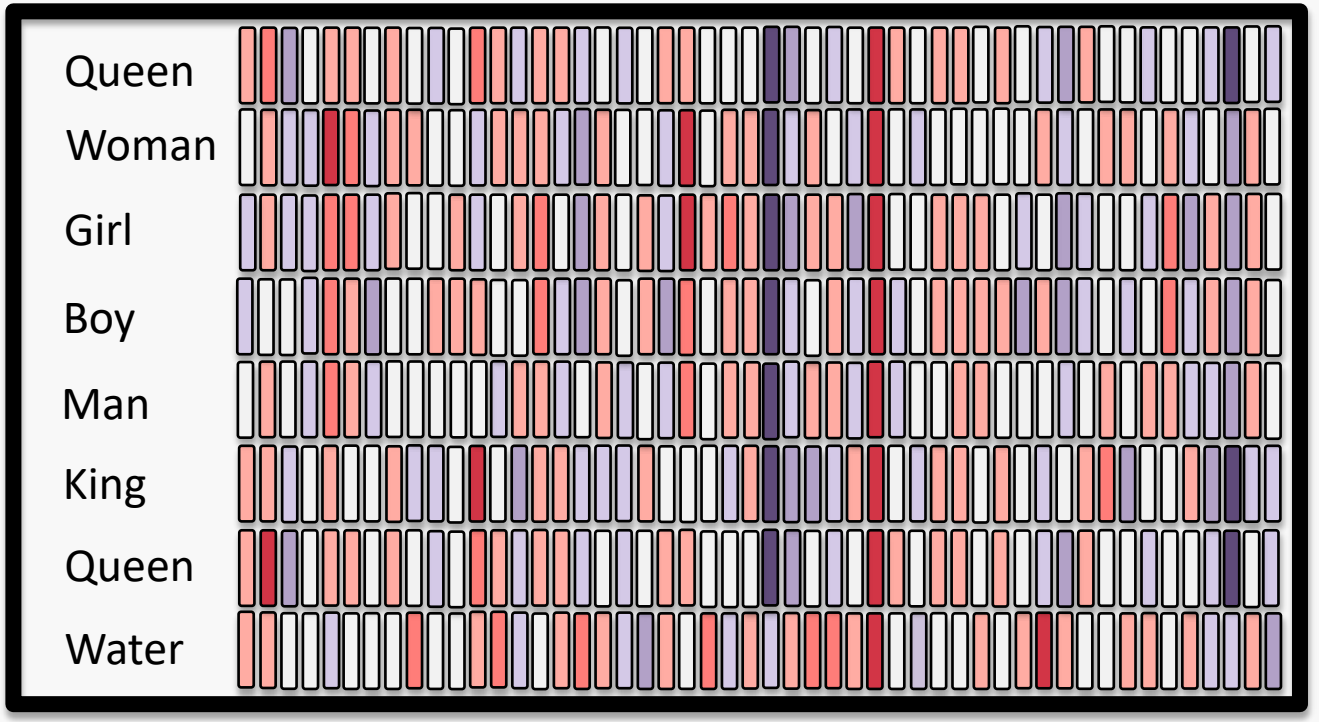
What we want

Embeddings Wishlist?

- We want the words of our vocabulary to be represented by a low-dimensional vector space.
- We also want these vector representations to have some semantic meaning, i.e vector representations of similar words must be close to each other.

Words to Vectors

So how do we get such a rich word "embedding?"



💡 **IDEA:** We could use a language model!

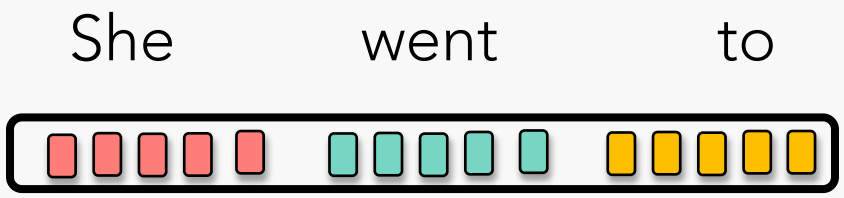
RECAP: Language Modelling: **neural networks**

Language modeling is about predicting the next word using the previous words

$$P(x_{t+1}|x_t, x_{t-1}, \dots, x_1)$$

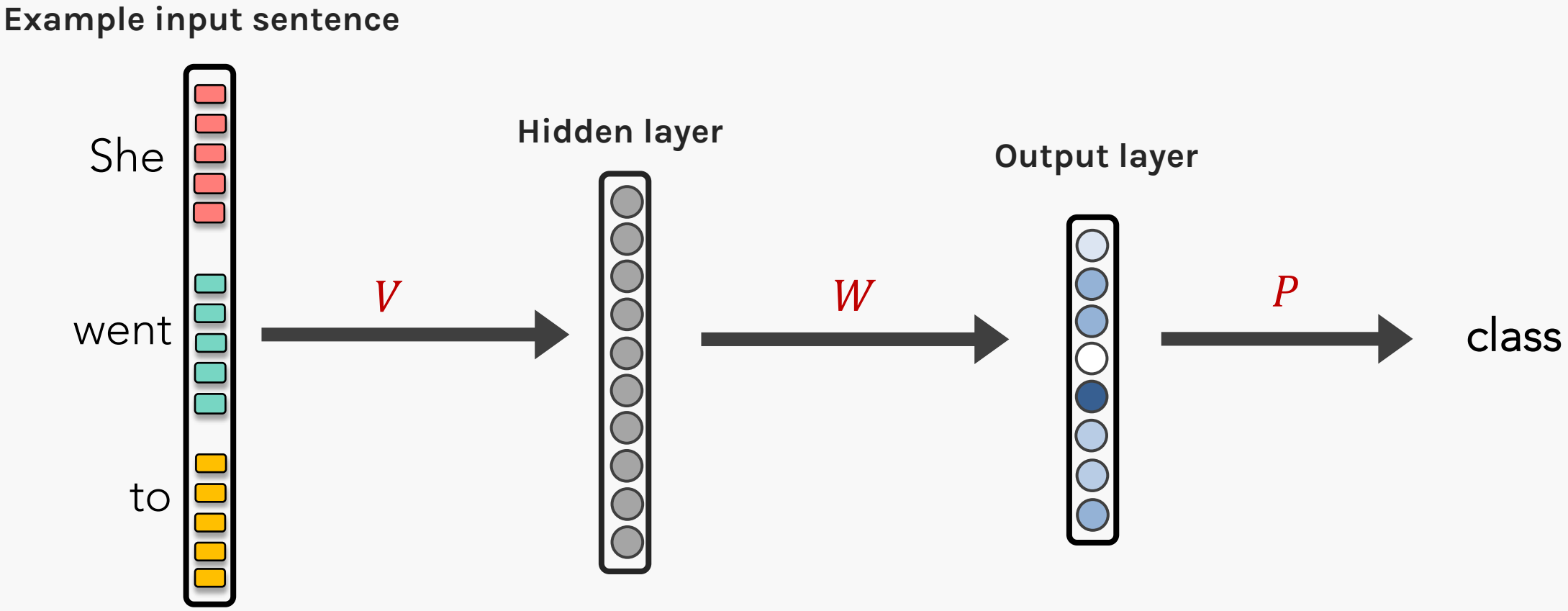
next word — previous words

Example input sentence



RECAP: Language Modelling: **Feed-forward Neural Net**

General Idea: using *windows* of words, predict the next word



Word Embeddings Training

- Text is a semantic sequence of words i.e., words used in a sentence are not random.
- We assume that If we build a neural network for language models and train them sufficiently well, we could get an embedding of words which can have a semantic relationship.
- We expect that two words that are similar will be mapped closely in the embedding space.

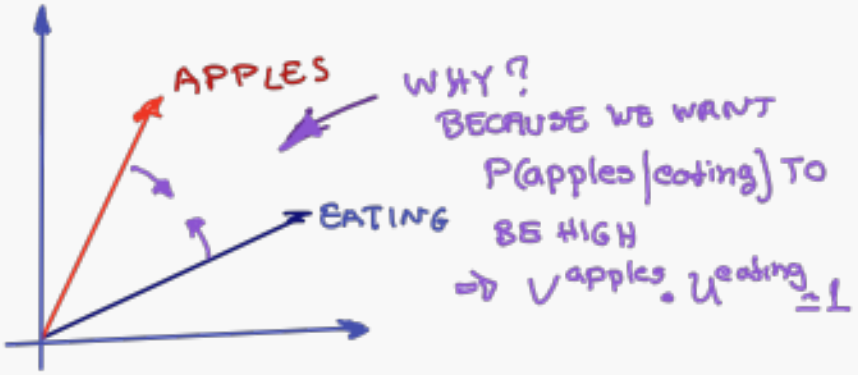
Example:

SENTENCE #1: Pavlos ate an apple before the lecture.

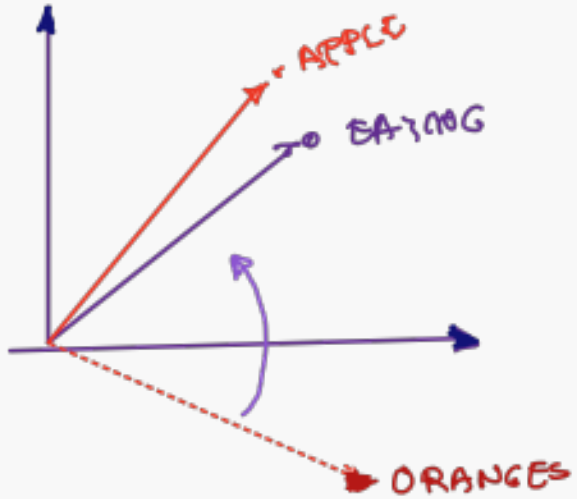
SENTENCE #2: Shivas ate an orange before the session.

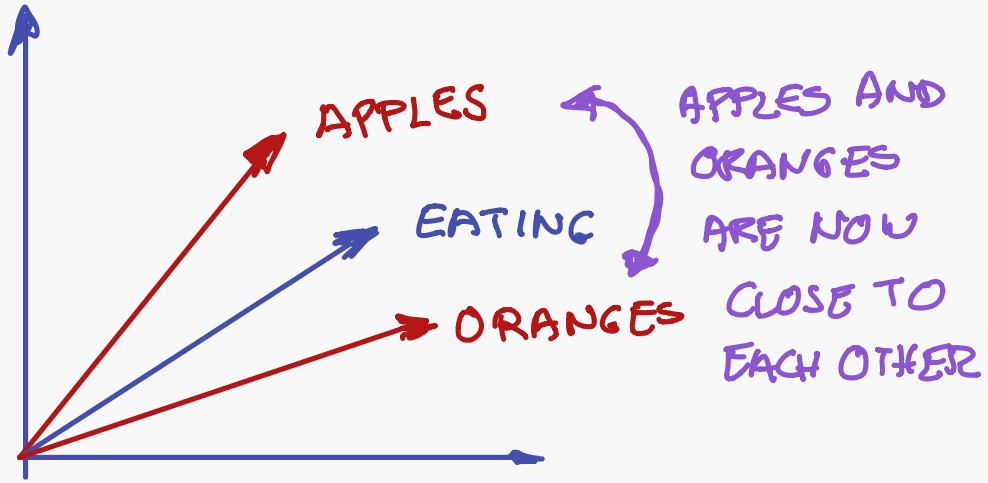
Both apple & orange are surrounded by similar words.

I like eating apples before dinner. I also like eating oranges after dinner.



I like eating apples before dinner. I also like eating oranges after dinner.

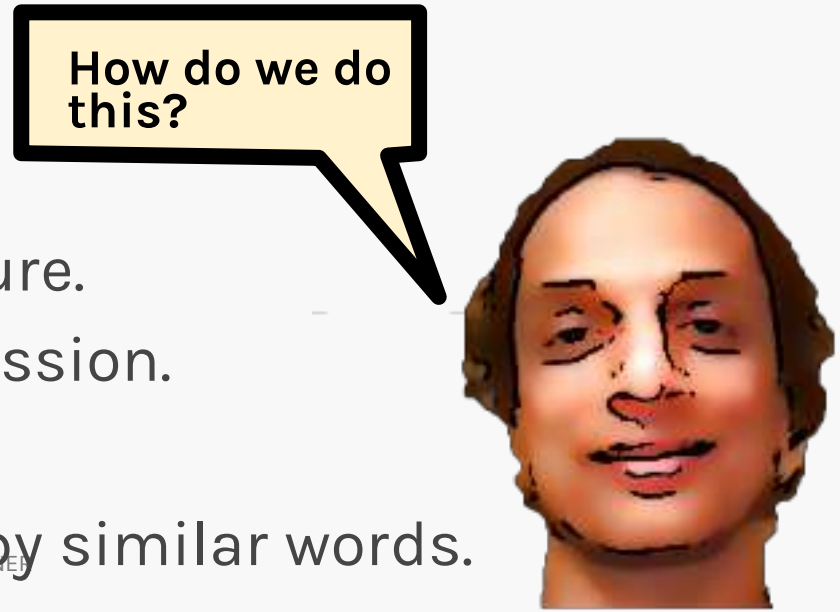




apples and oranges are forced to be close to each other

Word Embeddings Training

- Text is a semantic sequence of words i.e., words used in a sentence are not random.
- We assume that If we build a neural network for language models and train them sufficiently well, we could get an embedding of words which can have a semantic relationship.
- We expect that two words that are similar will be mapped closely in the embedding space.



Example:

SENTENCE #1: Pavlos ate an apple before the lecture.

SENTENCE #2: Shivas ate an orange before the session.

Both apple & orange are surrounded by similar words.

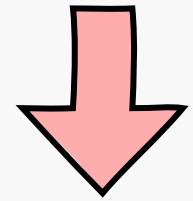
Word Embeddings Training

Training Set

Model/Neural Network

Loss Function

Word Embeddings Training



Training Set

Model/Neural Network

Loss Function

Training set

Training Set

- To build a language model training set, we need to select a sequence of some words as input and use the next immediate word as the output label.
- We can use a sliding window to create several such training examples.
- There are other approaches to building a language model training set, but more on that later.

Example sentence: Guess the next word

The dog was chased by a ___

How do we set up a training set?

The dog was chased by a cat as

Sliding window across running text

Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…

Dataset

input 1	input 2	output
was	chased	by

How do we set up a training set?

The dog was chased by a cat as

Sliding window across running text

Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…

Dataset

input 1	input 2	output
was	chased	by
chased	by	a

Continuous Bags of Words (CBOW)

The dog was chased by a cat as

Sliding window across running text

Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…
Shivas	was	chased	by	a	cat	as	…

Dataset

input 1	input 2	output
was	hit	by
hit	by	a
by	a	cat

NOTE: This approach of building training samples is called **Continuous Bags of Words (CBOW)**

Example sentence: Guess the next word

The dog was chased by a ___

Example sentence: Guess the next word

The dog was chased by a ____

If we go from left to right,

the most likely word is **CAT**

Example sentence: Guess the next word

The dog was chased by a ___ cat

However, if we see the complete sentence, the most likely word now is **WHITE or BROWN or BLACK**

Example sentence: Guess the next word

Why not look both ways?

The dog was chased by a ___ cat

This leads to the **Skip-Gram** architecture

SKIP-GRAM: Predict Surrounding Words

Choose a window size (here 4) and construct a dataset by sliding a window across.

The dog was chased by a white cat as it was

The	dog	was	chased	by	a	white	cat	as	it	…

input word	target word
by	was
by	chased
by	a
by	white

SKIP-GRAM: Predict Surrounding Words

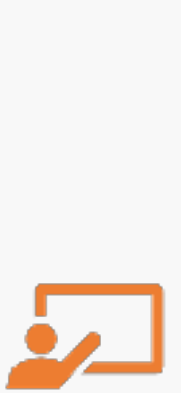
Choose a window size (here 4) and construct a dataset by sliding a window across.

The dog was chased by a white cat as it was

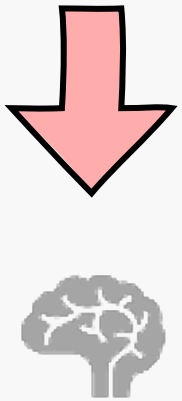
The	dog	was	chased	by	a	white	cat	as	it	…

input word	target word
by	was
by	chased
by	a
by	white
a	chased
a	by
a	white
a	cat

Word Embeddings Model

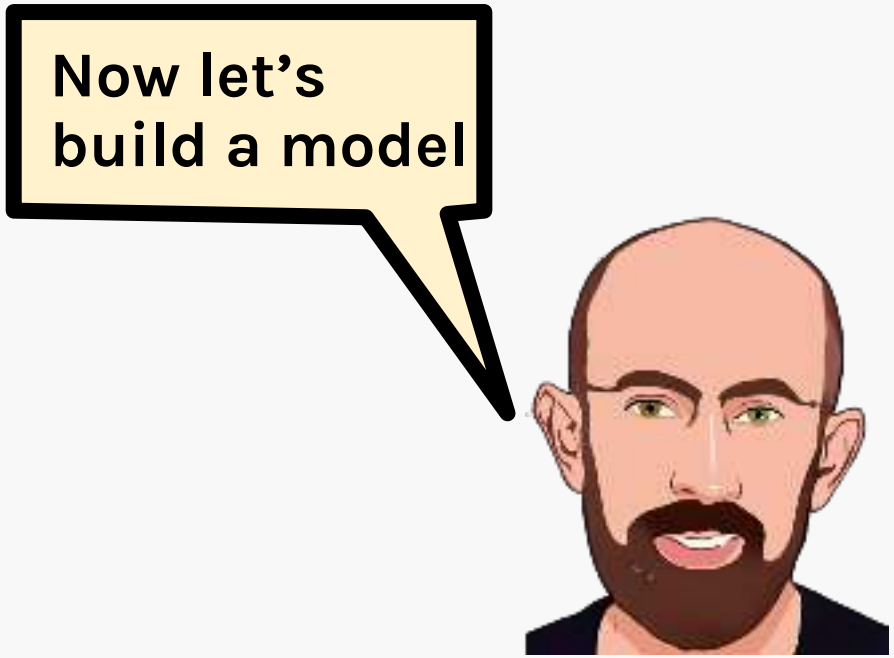


Training Set



Model/Neural Network

Loss Function



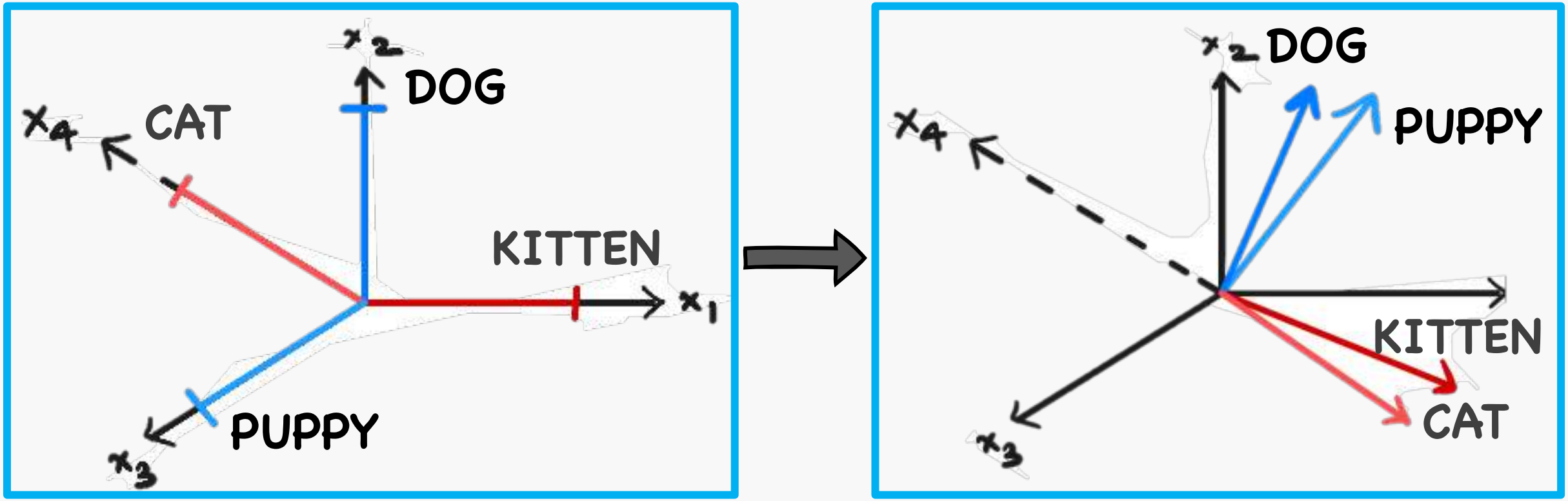
Model

Model/Neural Network

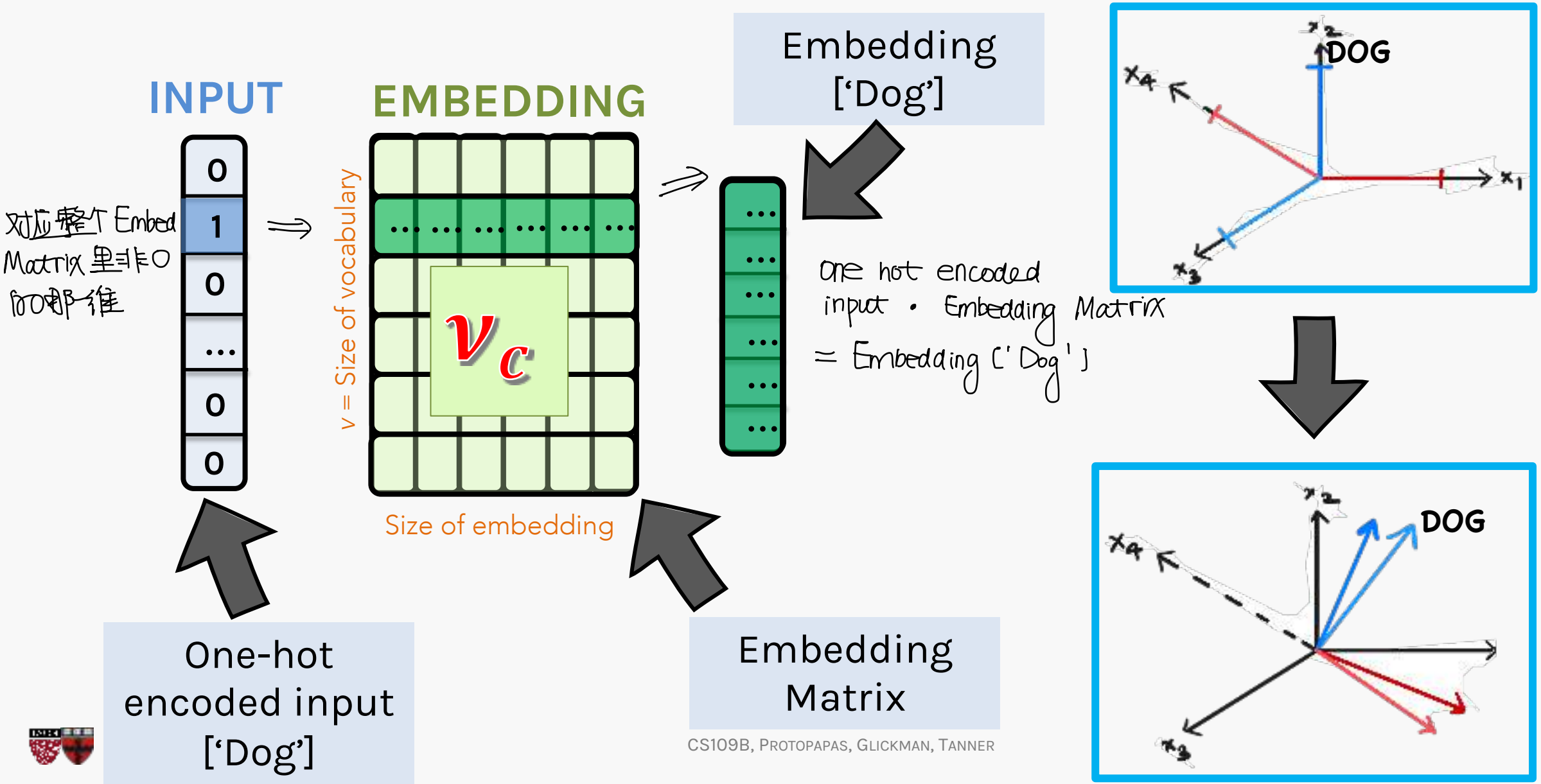
- To build a language model we need a network that takes a one-hot encoded input, connected to a low dimensional hidden state of size N, and outputs a vector with the same size as the input.
- We can then map the output (logits) to probabilities by using the softmax function.
- In principle, the hidden state will be the embedding of the word.

Going from One-Hot encoded to Embedding

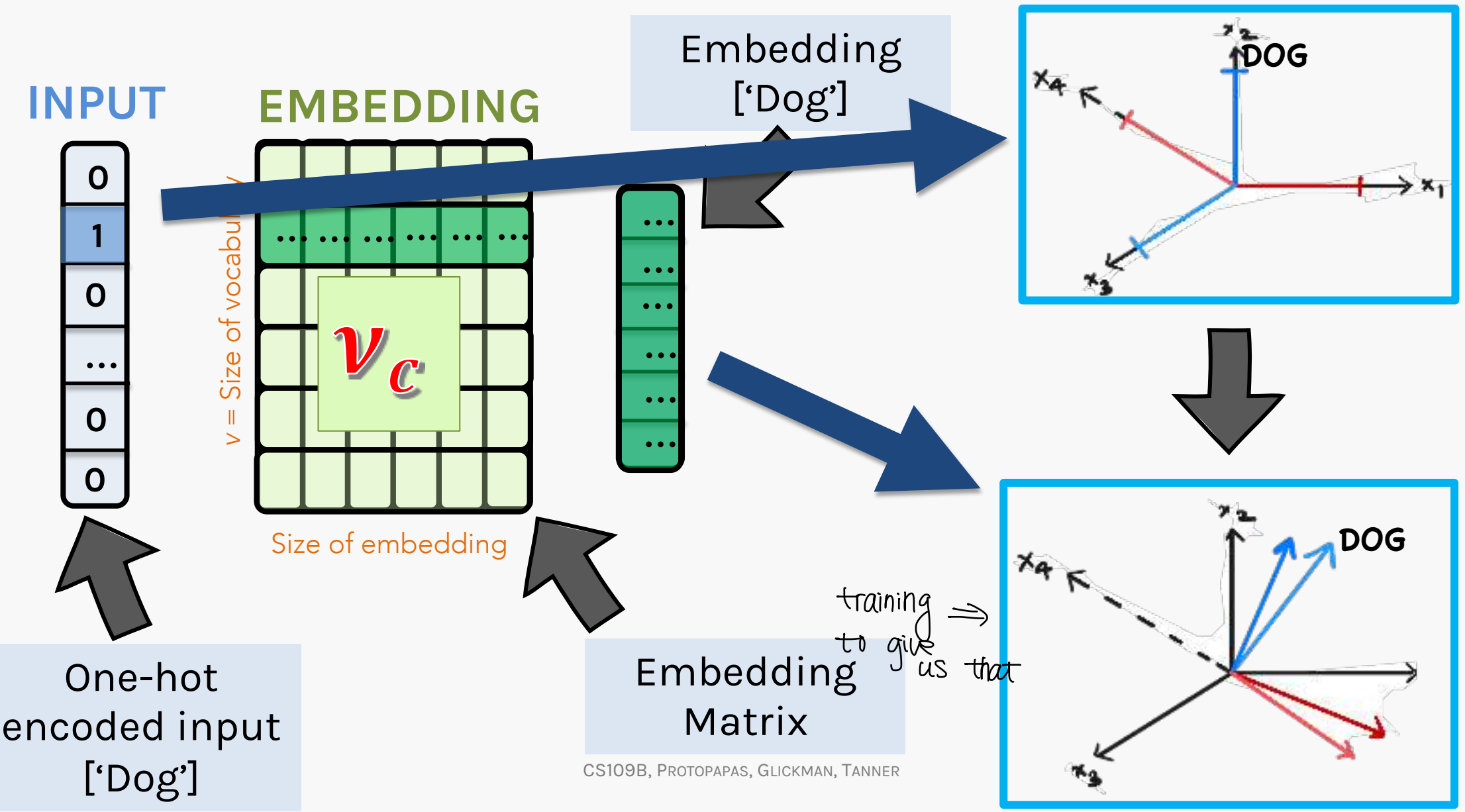
How do we go from one-hot encoding to embedding space?

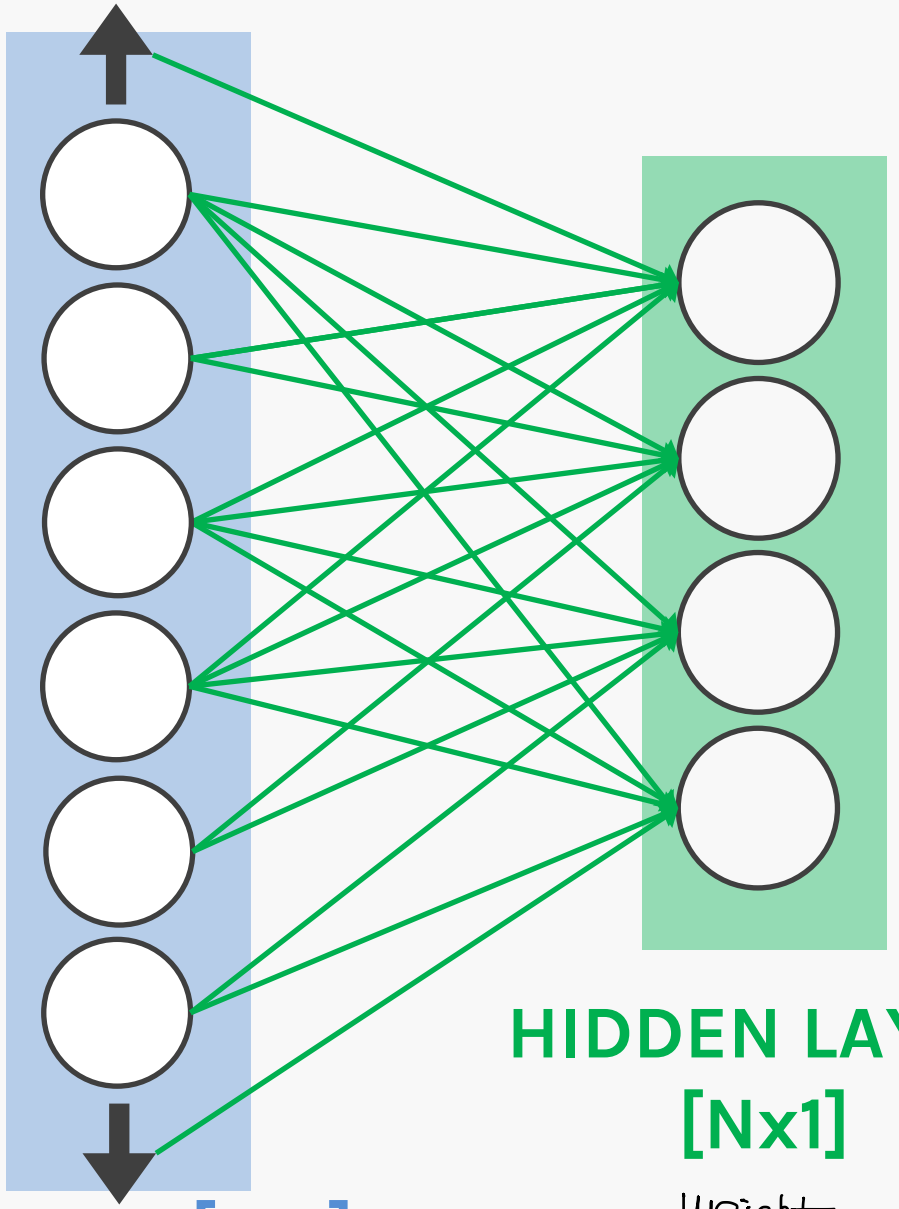


Going from One-Hot encoded to Embedding



Going from One-Hot encoded to Embedding



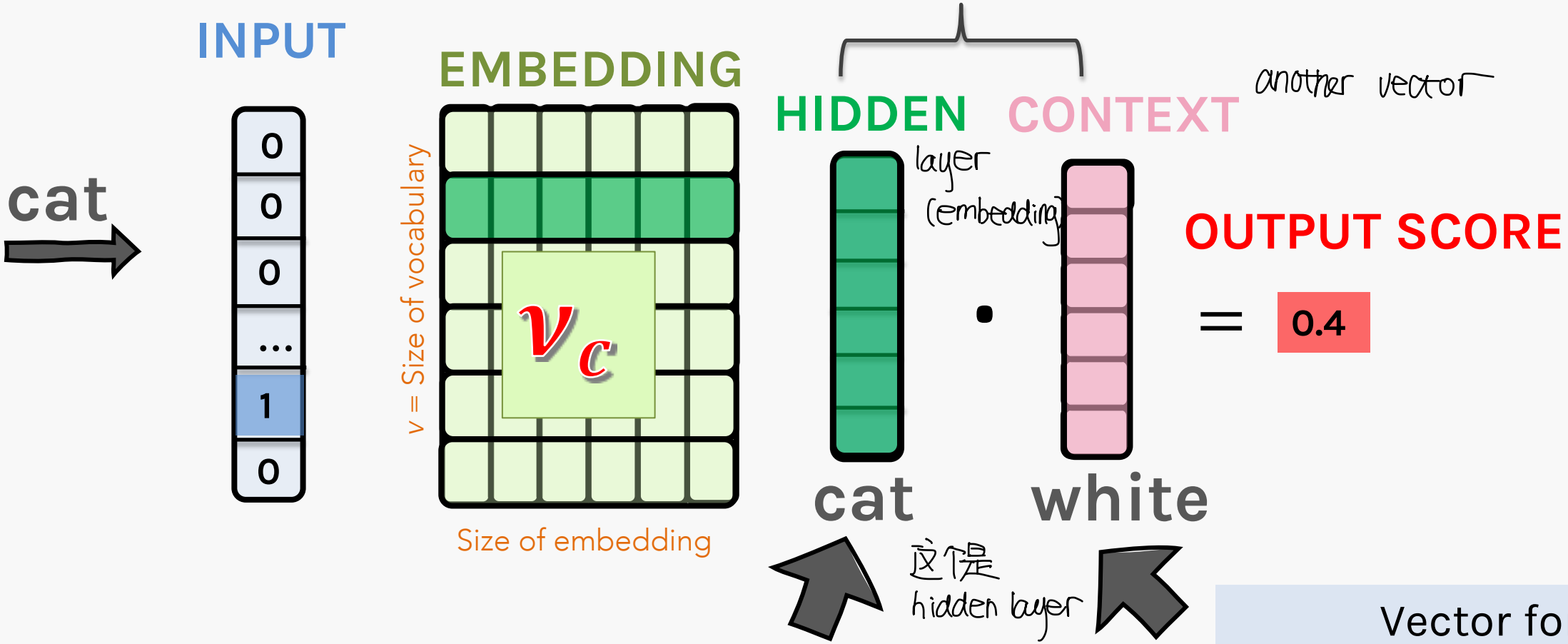


WISHLIST

We want to go from hidden state of center word, w_c, to probabilities $P(w_o|\ w_c)$ for each word, w_o, in the vocabulary

Skipgram Language model

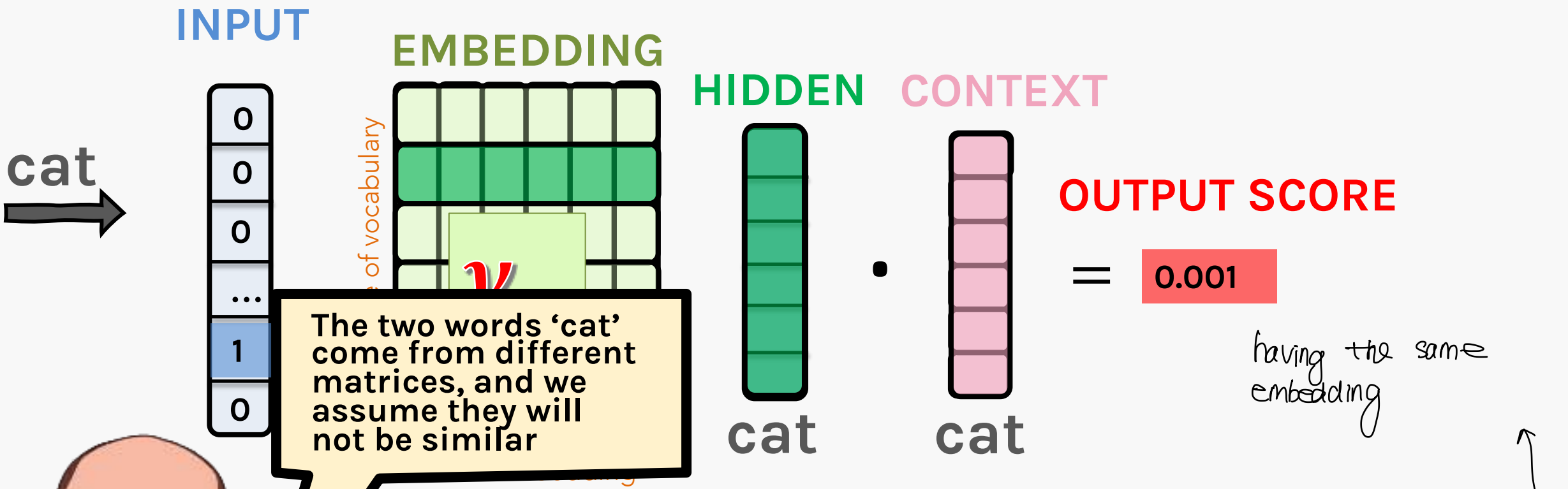
Cosine similarity
describes how close the two vectors are to each other



Vector for ['CAT'] from embedding matrix

Vector for ['WHITE'] from a 'different' context matrix

Skipgram Language model: Why two embeddings?

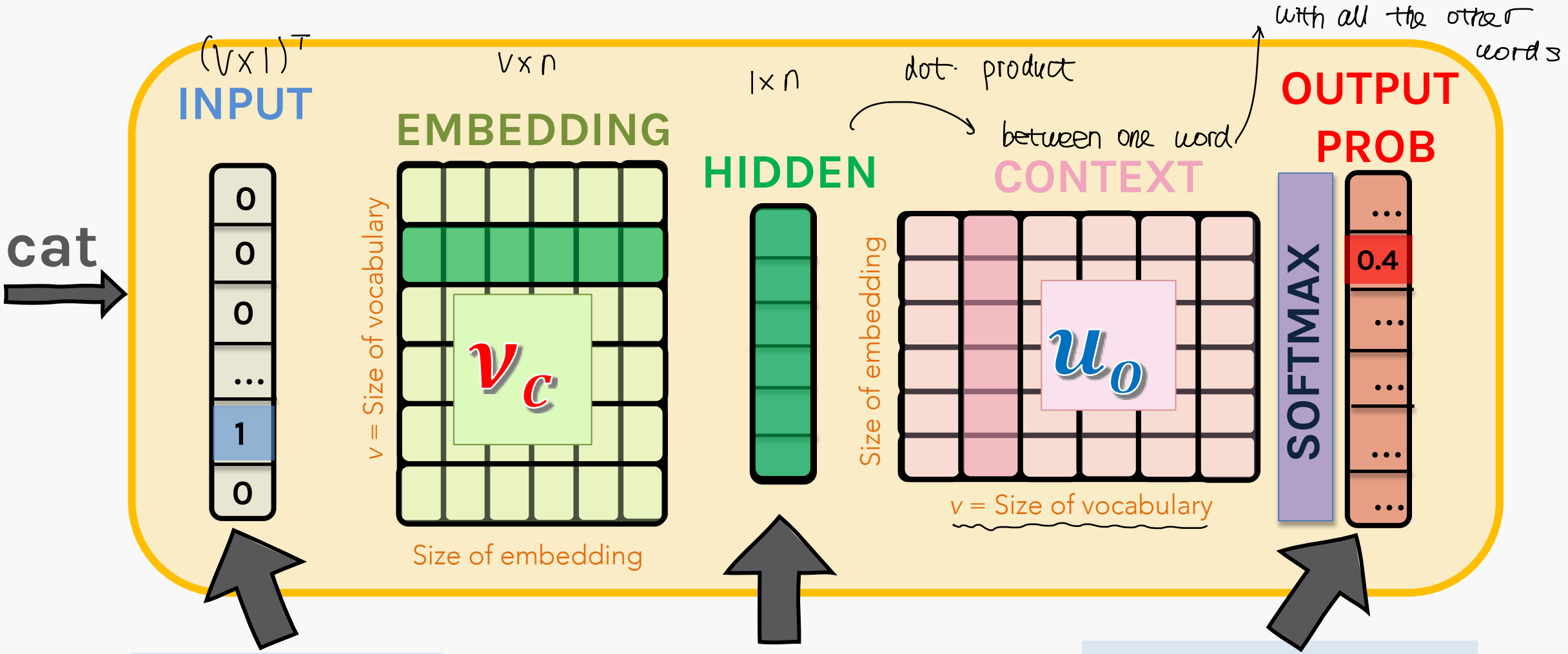


having the same embedding

two same words repeating in the context

same embedding ⇒ score 1
not want that
⇒ create a new embedding to make sure the same two words not

Skipgram Language model

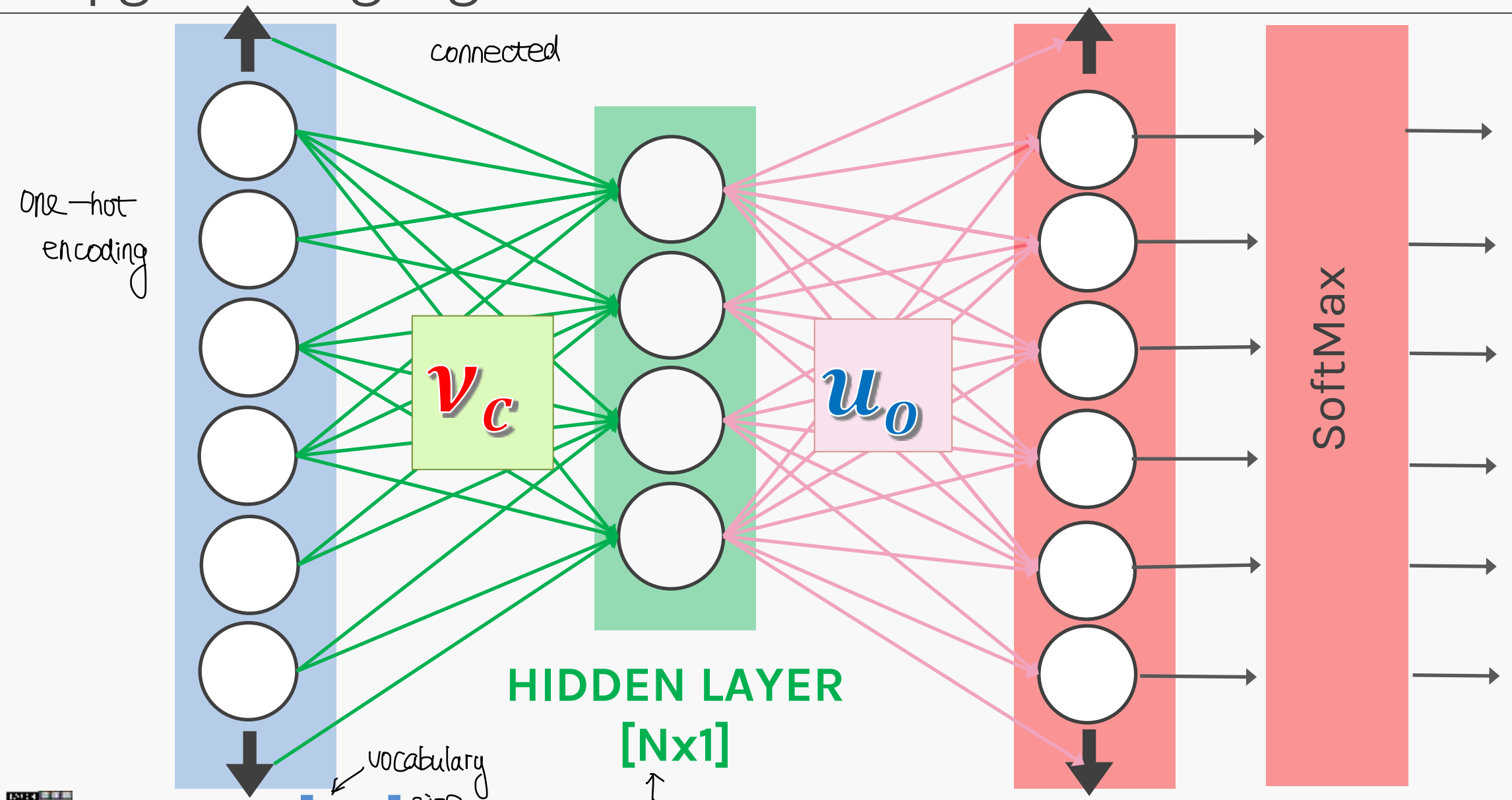


One-hot encoded input [Vx1]

Hidden layer [Nx1]

Output layer $p(w_{oi}|w_c)$ [VX1]

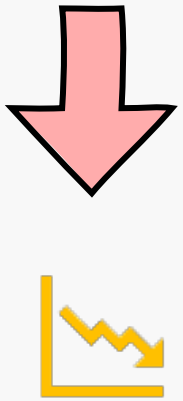
Skipgram language model – Neural net edition



Loss Function

Training Set

Model/Neural Network



Loss Function

Training set

Loss Function

- Once we have the output probabilities, we can select the context words for each input, and multiply the probabilities to construct the likelihood
- We then maximize this probability (likelihood)
- The loss of choice is the Negative Log Likelihood, which must be minimized – this is equivalent to maximize the likelihood of the context words given central words

SKIP-GRAM: Details

the dog was chased by a white dog

P("the" | "was")

P("dog" | "was")

We assume that Naive Bayes style, the joint probability of all **context** words (w_o) in a window conditioned on the central word (w_c), is the product of the individual conditional probabilities:

all the outside word

$$P(\{w_o\}|w_c) = \prod_{i \in window} \mathbb{P}(w_o^i|w_c)$$

$\{w_o\}$ = words in the window of the central word: context words

w_c = central word

product of the probabilities of each word in the window, given the central word

Loss function for gradient descent

Then, assuming a text sequence of length T and window size m, the likelihood function is:

$$\prod_{t=1}^{T} \prod_{-m \le j \le m, j \ne 0} \mathbb{P}\left(w^{(t+j)} \middle| w^{t}\right)$$

moving window

was . chase . a . white

by a

input word	target word
by	was
by	chased
by	a
by	white
a	chased
a	by
a	white
a	cat

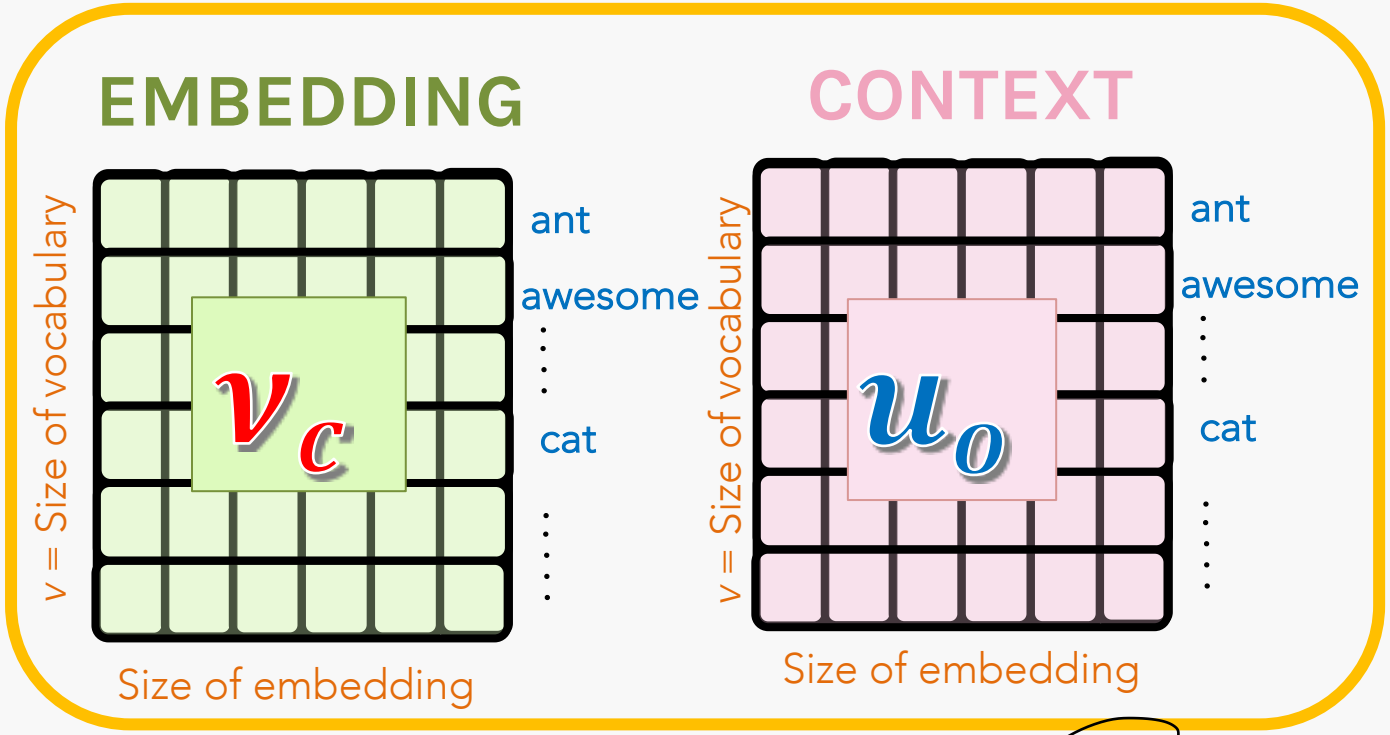
We want to maximize this likelihood hence we will minimize the Negative Log likelihood and use it as our loss function

$$\mathcal{L} = -\sum_{t=1}^{T} \sum_{-m \le j \le m, j \ne 0} \log \mathbb{P}\left(w^{(t+j)} \mid w^{(t)}\right)$$

summation

Alternatively…

Look-up table approach



Now assume that each word is represented as 2 embeddings, an **input** embedding, v_c, (c is for central) when we talk about the central word and a context embedding (u_o) when we talk about the surrounding window (o is for output).

this is the probability

cosine similarity

$$\mathbb{P}(w_o \mid w_c) = \frac{\exp(u_o^\top v_c)}{\sum_{i \in \mathcal{V}} \exp(u_i^\top v_c)},$$

turn into probability

The probability of an output word, given a central word, is assumed to be given by a softmax of the dot product of the embeddings.

Loss function for gradient descent

$$\mathcal{L} = -\sum_{t=1}^{T} \sum_{-m \leq j \leq m, j \neq 0} \log \mathbb{P}\left(w^{(t+j)} \mid w^{(t)}\right)$$

$$\mathcal{L} = -\sum_{t=1}^{T} \sum_{-m \leq j \leq m, j \neq 0} \log \frac{\exp(u_o^\intercal v_c)}{\sum_{i \in V} \exp(u_i^\intercal v_c)}$$

Sum over all the central words in the training

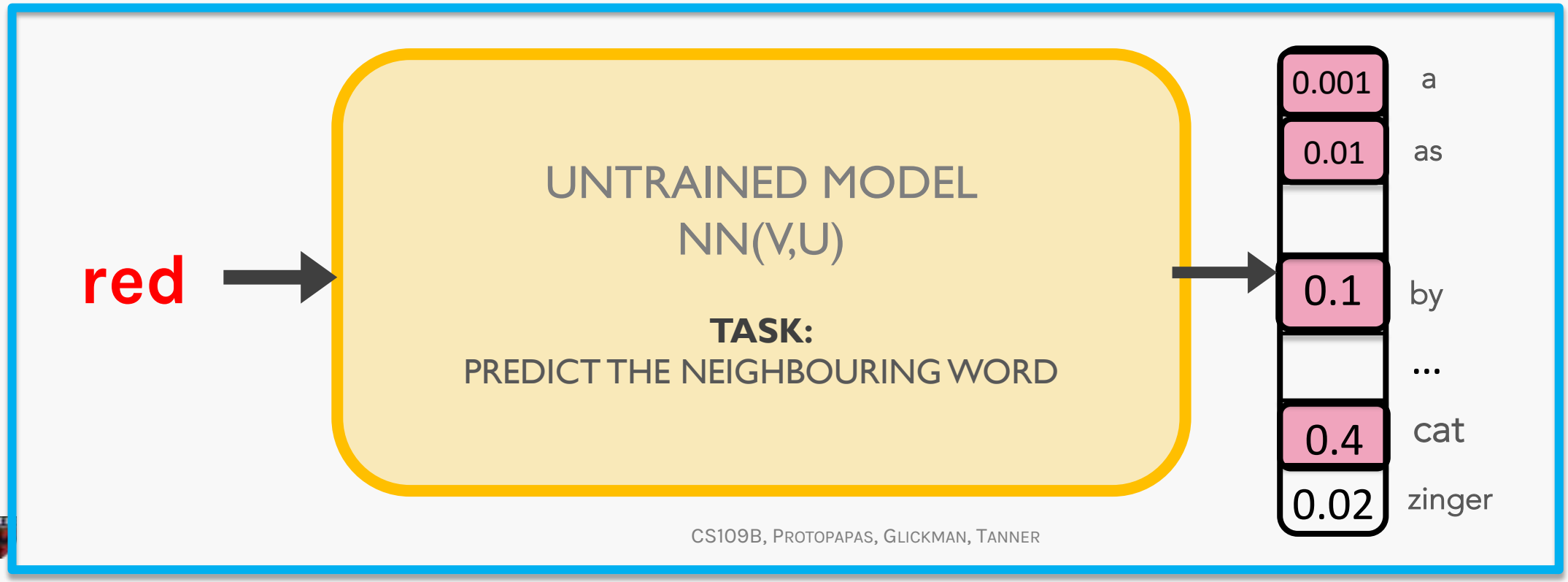
Sum over all the words in the window

Softmax over the dot product with every possible word in the vocabulary

Putting it all together…

1. Look up embeddings
2. Calculate predictions
3. Project to outward vocabulary

With random initial weights , we make a prediction for surrounding words, and calculate the NLL for the prediction. We then backpropagate the NLL's gradients to find new weights and repeat



Putting it all together…

1. Look up embeddings
2. Calculate predictions
3. Project to outward vocabulary

What weights are you talking about?

embedding

V and U

With random initial weights , we make a prediction for surrounding words, and calculate the NLL for the prediction. We then backpropagate the NLL's gradients to find new weights and repeat

DONE!?

Problems with implementation

- In the forward mode, the calculation of softmax requires a sum over the entire vocabulary

$$\mathbb{P}(w_o \mid w_c) = \frac{\exp(\boldsymbol{u}_o^\top \boldsymbol{v}_c)}{\sum_{i \in \mathcal{V}} \exp(\boldsymbol{u}_i^\top \boldsymbol{v}_c)},$$

Problems with implementation

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Problems with implementation

- In the backward mode, the gradients need this sum too. For example:

$$\frac{\partial \log P(w_o \mid w_c)}{\partial \boldsymbol{v}_c} = \boldsymbol{u}_o - \sum_{j \in \mathcal{V}} P(w_j \mid w_c) \boldsymbol{u}_j.$$

For large vocabularies, this is very expensive!

Problems with implementation

every word . need to sum up all the words
different words ⇒ differently can't be reused

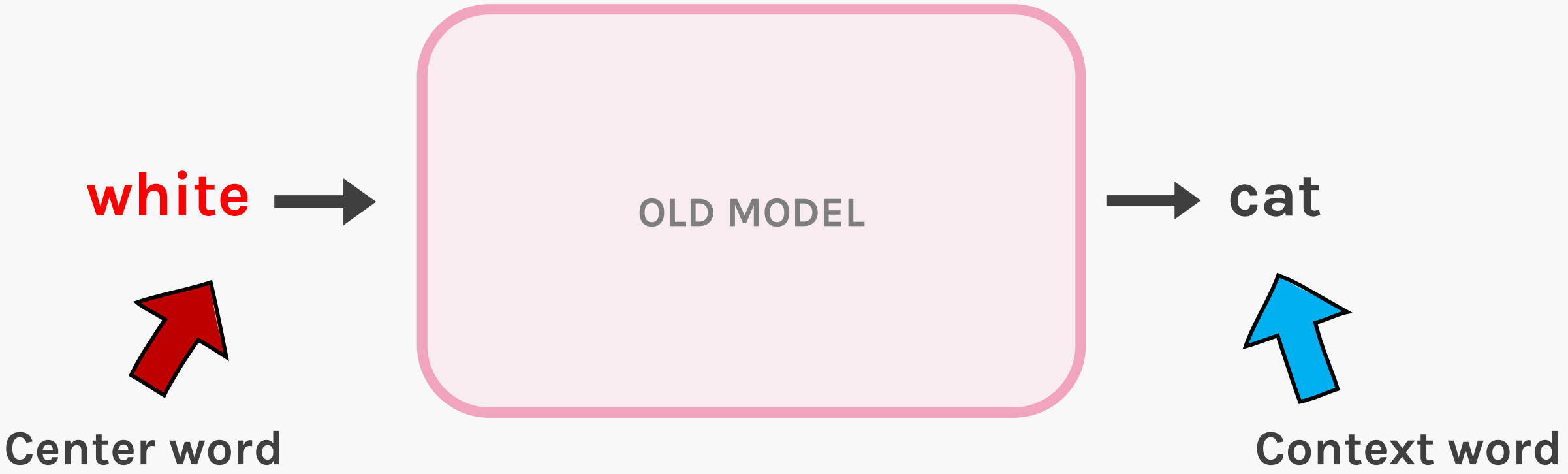
- In the backward mode, the gradients need this sum too. For example:

$$\frac{\partial \log P(w_o \mid w_c)}{\partial \boldsymbol{v}_c} = \boldsymbol{u}_o - \sum_{j \in \mathcal{V}} P(w_j \mid w_c) \boldsymbol{u}_j.$$

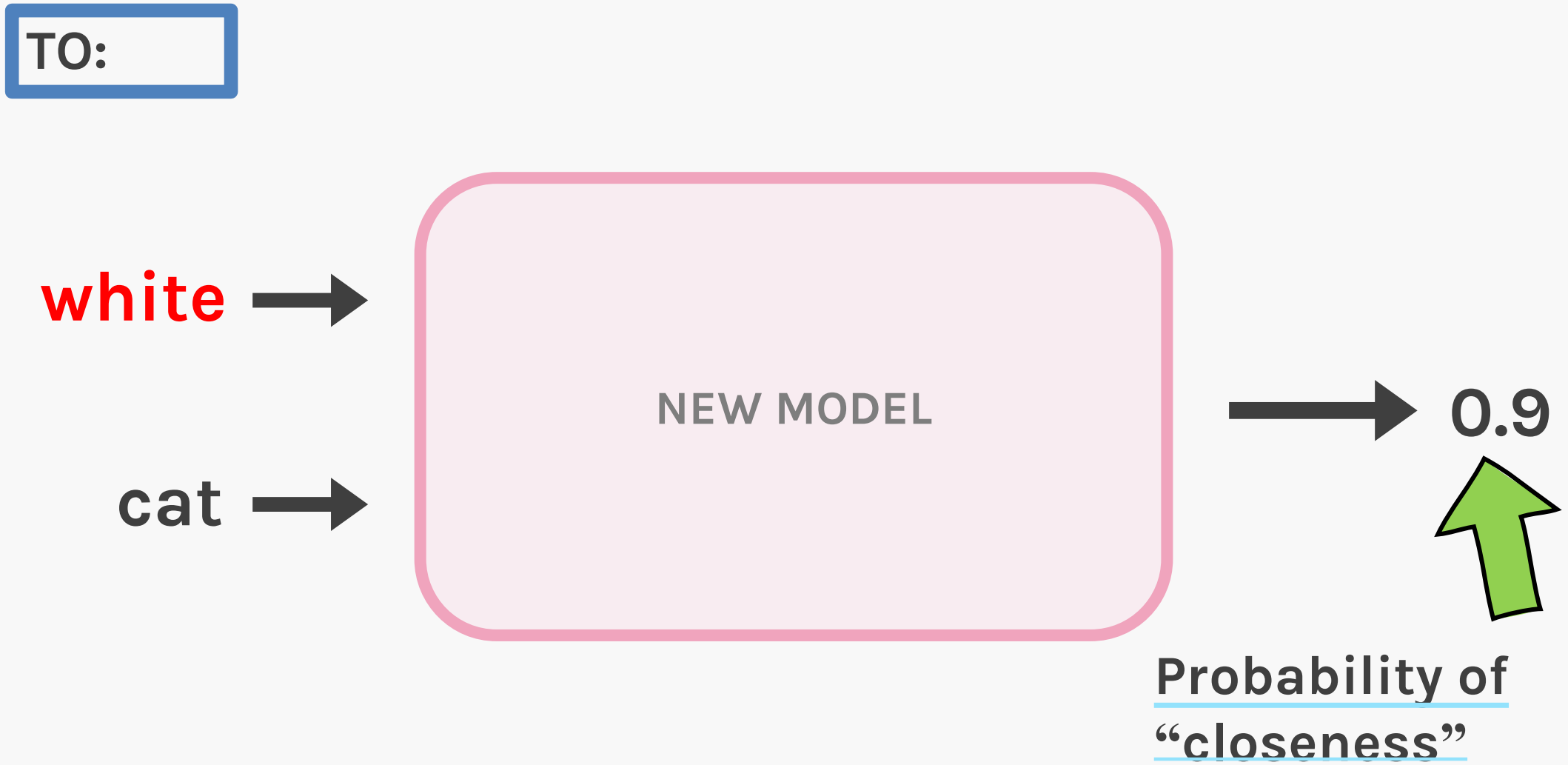
For large vocabularies, this is very expensive!

Changing Tasks

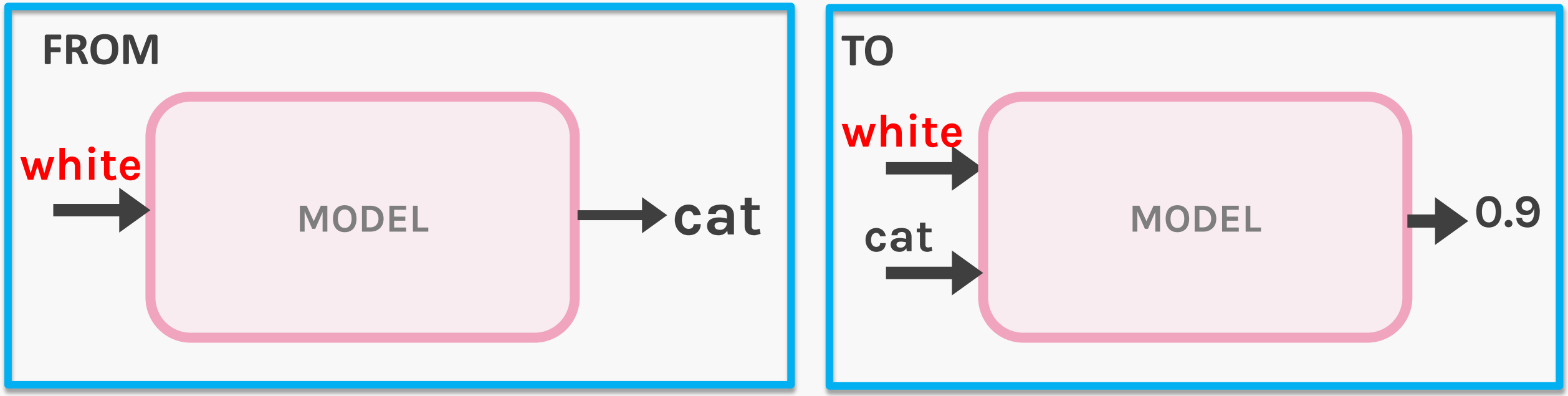
FROM:



Changing Tasks



Changing Tasks



Changing from predicting neighbors to "*are we neighbors?*" changes model from multi class classification to binary classification.

Changing Tasks (cont)

We now choose $P(D = 1|w_c, w_o) = \sigma(u_o^T v_c)$ and maximize the likelihood:

(nice and clean) take the center word. outside word only see those. so all of them is 1

$$\prod_{t=1}^{T} \prod_{-m \leq j \leq m, j \neq 0} P\left(D = 1 \mid w^{(t)}, w^{(t+j)}\right)$$

But the response variable in the dataset changes to all 1's, and a trivial classifier always returning 1 will give the best score.

Not good (this is equivalent to all embeddings being equal and infinite)!

Changing Tasks (cont)

We now choose $P(D = 1|w_c, w_o) = \sigma(u_o^T v_c)$ and maximize the likelihood:

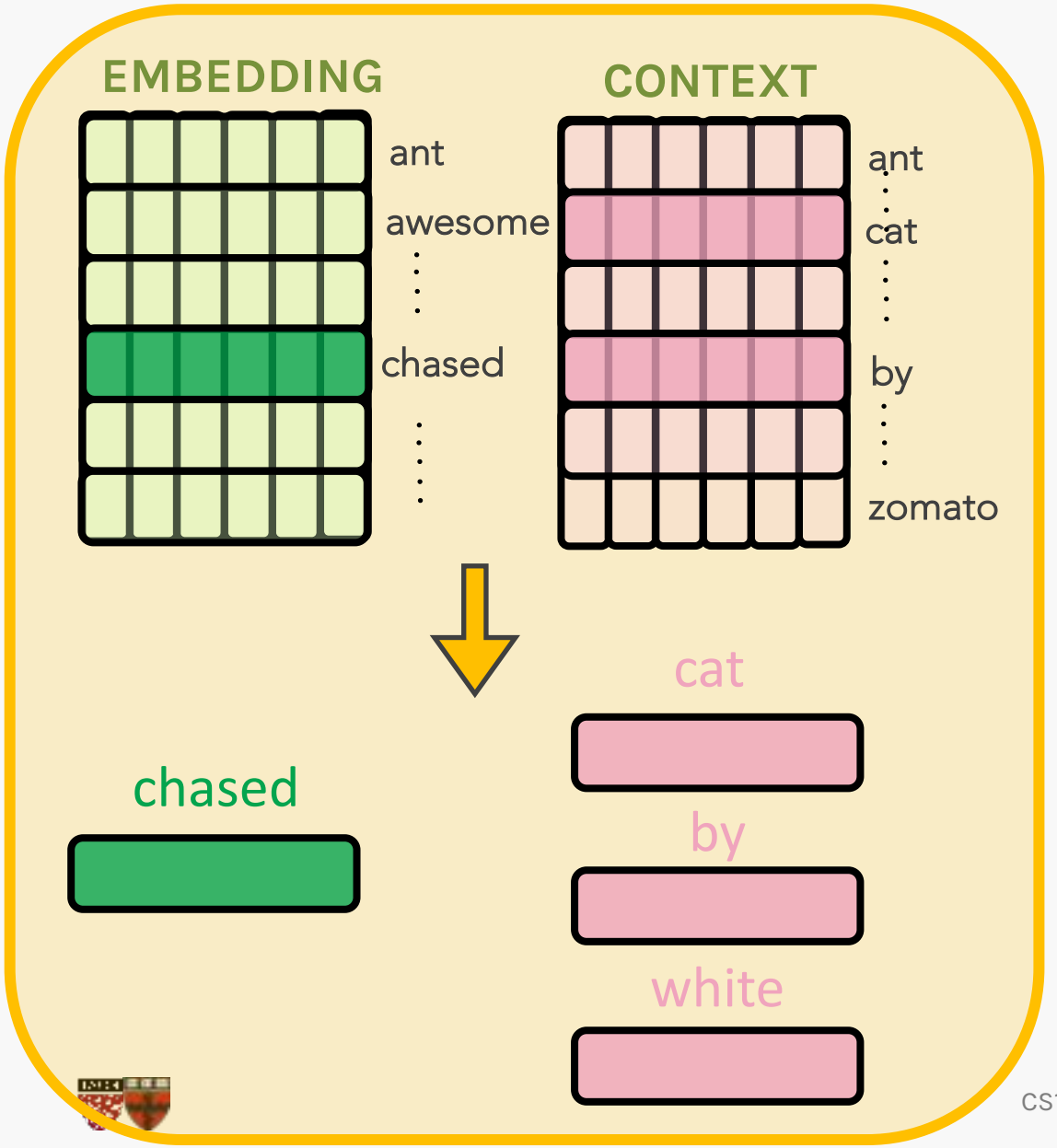
$$\prod_{t=1}^{T} \prod_{-m \leq j \leq m, j \neq 0} P\left(D = 1 \mid w^{(t)}, w^{(t+j)}\right)$$

But the response variable in the dataset changes to all 1's, and a trivial classifier always returning 1 will give the best score.

Infinite?

Not good (this is equivalent to all embeddings being equal and infinite)!

Training the model



- The positive sampling probabilities are simply sigmoids.
- We now compute the loss and repeat over training examples in our batch and backpropagate to obtain gradients and change the embeddings and weights some, for each batch, in each epoch.

Input word	Output word	Target	Input · Output	Sigmoid()
chased	cat	1	-1.11	0.25
chased	by	1	0.2	0.55
chased	white	1	0.74	0.68

Negative Sampling (change)

we need to introduce negative samples to our dataset – samples of words that are **not** neighbors. Our model needs to return 0 for those samples.

input word	target word
a	chased
a	by
a	white
a	cat
white	by
white	a
white	cat
white	as

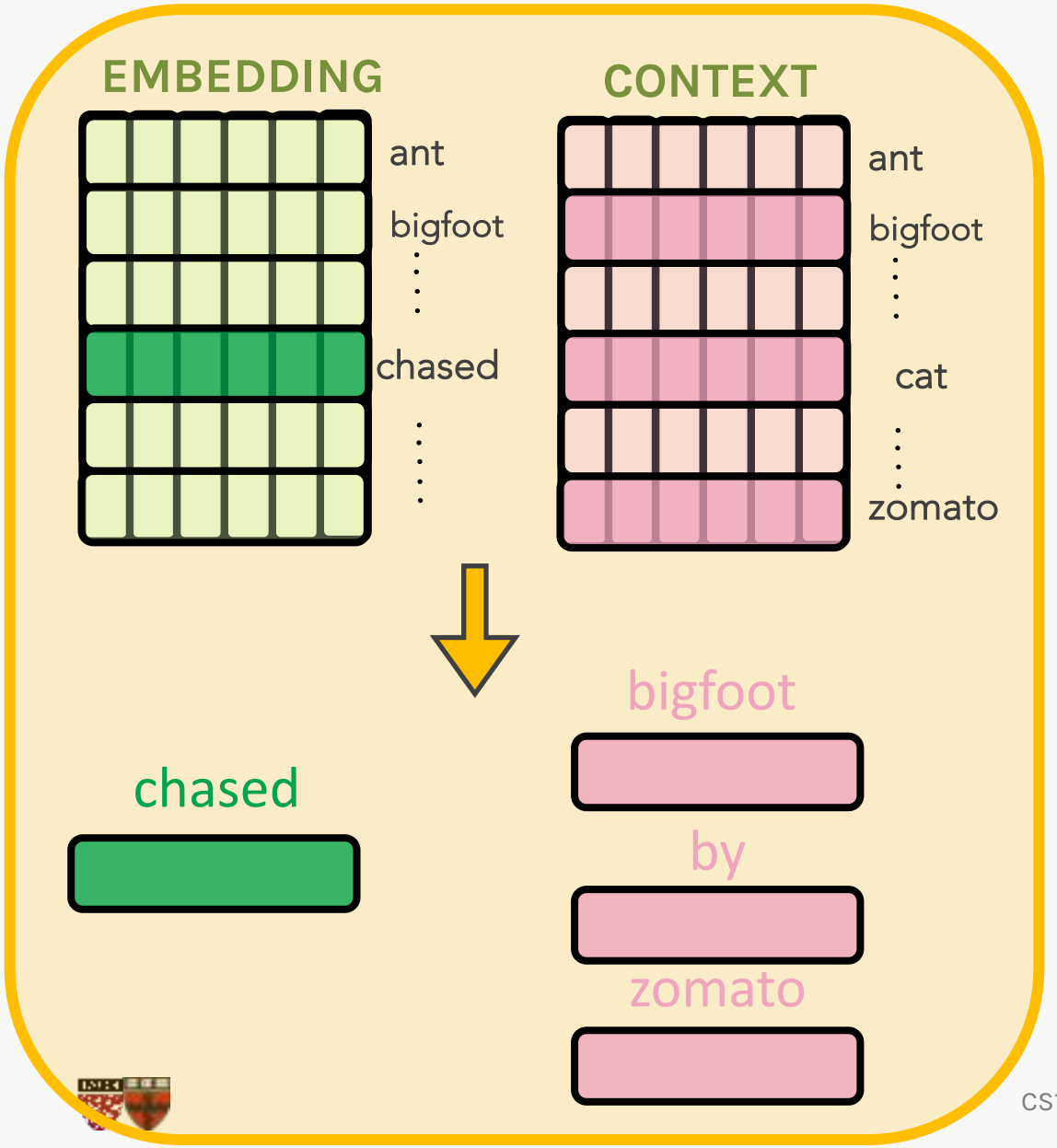
(Input to the model)

input word	Output word	target
a	chased	1
a	by	1
a	white	1
a	cat	1
white	by	1
white	a	1
white	cat	1
white	as	1

Pick randomly from our vocabulary (random sampling) and label them with **0**.

input word	Output word	target
a	chased	1
a	bigfoot	0
a	zomato	0
a	by	1
..	..	..
..	..	..
a	white	1

Training the model



- The negative sampling probabilities are now sigmoids subtracted from 1, whereas the positives are simply sigmoids.
- We now compute the loss, and repeat over training examples in our batch.
- And backpropagate to obtain gradients and change the embeddings and weights some, for each batch, in each epoch

Input word	Output word	Target	Input · Output	Sigmoid()
chased	bigfoot	0	-1.11	0.25
chased	by	1	0.2	0.55
chased	zomato	0	0.74	0.68

The result

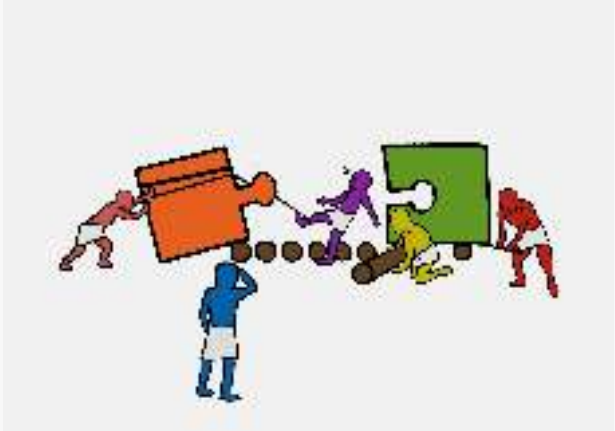
- We discard the Context matrix and **save the embedding matrix.**
- We can use the embedding matrix for our next task (perhaps a sentiment classifier).
- We could have trained embeddings along with that particular task to make the embeddings sentiment specific. There is always a tension between domain/task specific embeddings and generic ones.
- This tension is usually resolved in favor of using generic embeddings since task specific datasets seem to be smaller.
- We can still unfreeze pre-trained embedding layers to modify them for domain specific tasks via transfer learning.

Usage of word2vec

- The pre-trained word2vec and other embeddings (such as GloVe) are used everywhere in NLP today.
- The ideas have been used elsewhere as well. AirBnB and Anghami model sequences of listings and songs using word2vec like techniques.
- Alibaba and Facebook use word2vec and graph embeddings for recommendations and social network analysis.

hierarchical softmax 本质是把N分类问题变成 log(N)次二分类
用huffman tree 的编码

Exercise: 🆓

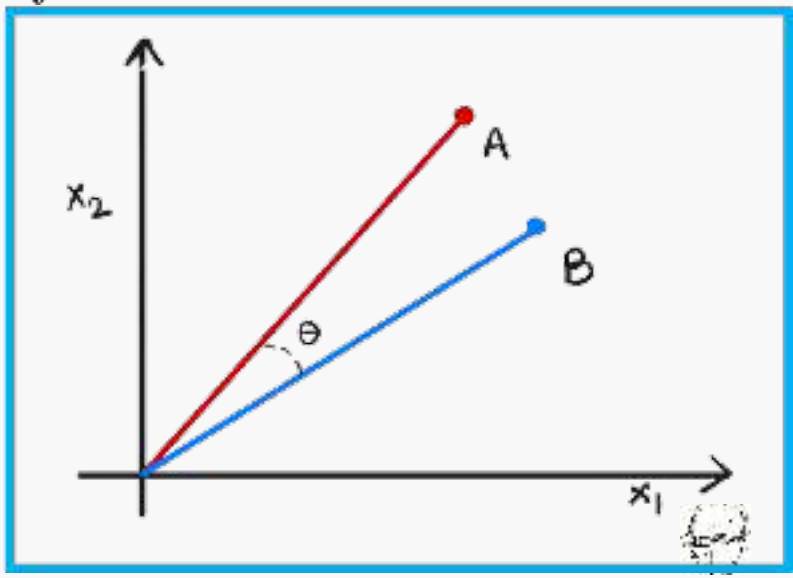


The goal of the exercise is to understand and implement the cosine similarity in context of embeddings.

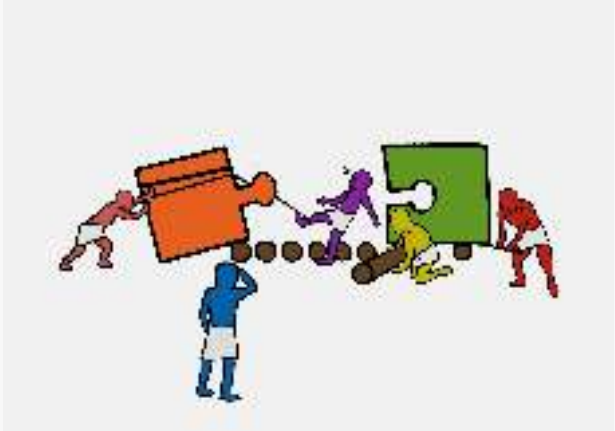
$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Use the embeddings to answer:

awesome - eagle + person = ?



Exercise: 🆓



The goal of this exercise is to understand the Word2Vec architecture with skipgram & negative sampling.

You will build and train a word2vec!