INF721

2024/2

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Deep Learning

L15: Word Embeddings

Logistics

Announcements

- PA4 is out and due on Wednesday (13/11), 11:59pm

Last Lecture

- Language Models
- Implementing RNNs
- Vanishing/Exploding Gradients
- LSTM and GRUs

Lecture Outline

- Problems with one-hot encoding
- Word Embeddings
  - Featurized Representation
  - Visualization
  - Properties
  - Applications
- Word2Vec and Negative Sampling
- GloVe

Problem with one-hot encoding

A problem of **one-hot encoding** is that it represents each word as an independent category

Man	**Woman**	**King**	**Queen**	**Apple**	**Orange**
(5391)	(9853)	(4914)	(7157)	(456)	(6257)

$$\underset{\mathbf{o}_{5391}}{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \dots \\ \mathbf{1} \\ \dots \\ 0 \\ 0 \end{bmatrix}} \quad \underset{\mathbf{o}_{5391}}{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \dots \\ \mathbf{1} \\ \dots \\ 0 \end{bmatrix}} \quad \underset{\mathbf{o}_{5391}}{\begin{bmatrix} 0 \\ 0 \\ 0 \\ \dots \\ \mathbf{1} \\ \dots \\ 0 \\ 0 \\ 0 \end{bmatrix}} \quad \underset{\mathbf{o}_{5391}}{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \dots \\ \mathbf{1} \\ \dots \\ 0 \end{bmatrix}} \quad \underset{\mathbf{o}_{5391}}{\begin{bmatrix} 0 \\ \dots \\ \mathbf{1} \\ \dots \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}} \quad \underset{\mathbf{o}_{5391}}{\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \dots \\ \mathbf{1} \\ \dots \\ 0 \end{bmatrix}}$$

It doesn't let a model easily generalize across words!

- For example, consider a language model that gives high probability to the sentence:

  *"I want a glass of **orange** juice"*

  Now, consider sampling from this model with context:

  *"I want a glass of **apple** _____ "*

  To the model, the relationship between **apple** and **orange** is the same as **apple** and **man**, or queen.

  This is because the distance between any two words is the same!

Vocabulary $V = [a, aaron, \dots, zebra, zulu], \quad |V| = 10{,}000$

Word Embedding: Featurized Representation

Ideally, we would like to have featurized representation for words, where words with similar meaning to have a similar representation:

apple and **orange** are close in the embedding space

	Man (5391)	**Woman** (9853)	**King** (4914)	**Queen** (7157)	**Apple** (456)	**Orange** (6257)
Gender	-1	1	-0.95	0.97	0.00	0.01
Royal	0.01	0.02	0.93	0.95	-0.01	0.00
Age	0.03	0.02	0.7	0.69	0.03	-0.02
Food	0.04	0.01	0.02	0.01	0.95	0.97
...						
	$\mathbf{e}_{5391}$	$\mathbf{e}_{9853}$	$\mathbf{e}_{4914}$	$\mathbf{e}_{7157}$	$\mathbf{e}_{456}$	$\mathbf{e}_{6257}$

Word embeddings are learned featurized representations:

- We can define the number of features d to be learned (e.g., 300), but **not** what they represent (e.g., gender)
- Words with similar meaning to have a similar representation:
- They allow a model to generalize across words more easily:

  *"I want a glass of **orange** juice"*

  *"I want a glass of **apple** juice "*

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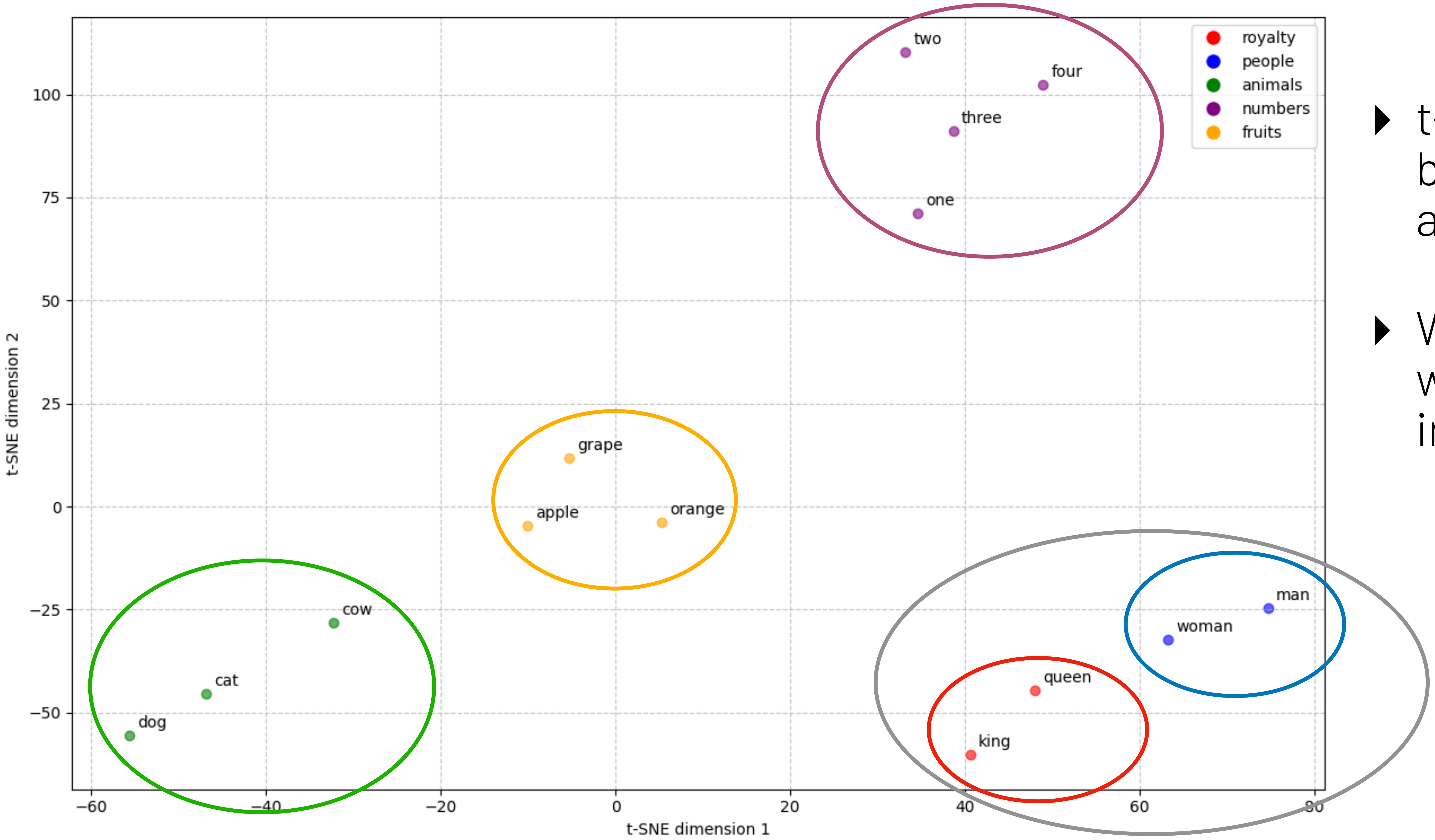
Visualizing Word Embeddings (with t-SNE)

We can visualize high dimentinoal word embeddings (e.g., 300 features) in 2D using the t-SNE algorithm:



- t-SNE learns a non-linear mapping between the original representation and a 2D space
- Word embeddings tend to group words with similar meaning together in the embedding space.

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van der Maaten and Hinton., 2008. Visualizing data using t-SNE

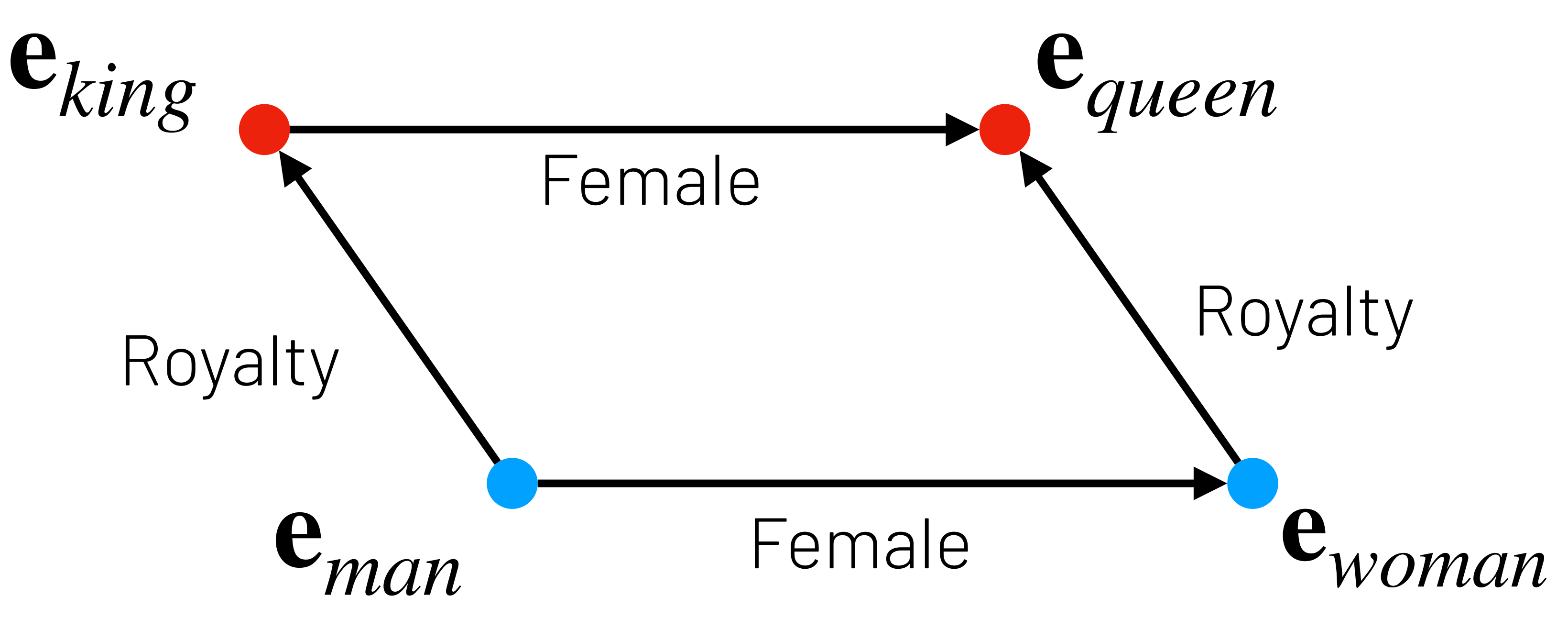
Properties of word embeddings

One interesting property of word embeddings is that they allow **word analogies** to be solved with vector arithmetic.

	Man (5391)	Woman (9853)	King (4914)	Queen (7157)	Apple (456)	Orange (6257)
Gender	-1	1	-0.95	0.97	0.00	0.01
Royal	0.01	0.02	0.93	0.95	-0.01	0.00
Age	0.03	0.02	0.7	0.69	0.03	-0.02
Food	0.04	0.01	0.02	0.01	0.95	0.97
…						
	$\mathbf{e}_{man}$	$\mathbf{e}_{woman}$	$\mathbf{e}_{king}$	$\mathbf{e}_{queen}$	$\mathbf{e}_{apple}$	$\mathbf{e}_{orange}$

Man is to Woman as King is to ______?

$$\mathbf{e}_{king} - \mathbf{e}_{queen} \approx \begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \end{bmatrix} \qquad \mathbf{e}_{man} - \mathbf{e}_{woman} \approx \begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$



$$\mathbf{e}_{man} - \mathbf{e}_{woman} \approx \mathbf{e}_{king} - \mathbf{e}_{w}$$

$$\mathbf{e}_{w} = argmax_{w} \underbrace{sim(\mathbf{e}_{w}, \mathbf{e}_{king} - \mathbf{e}_{man} + \mathbf{e}_{woman})}_{\text{Similarity}}$$

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Mikolov et. al., 2013, Linguistic regularities in continuous space word representations

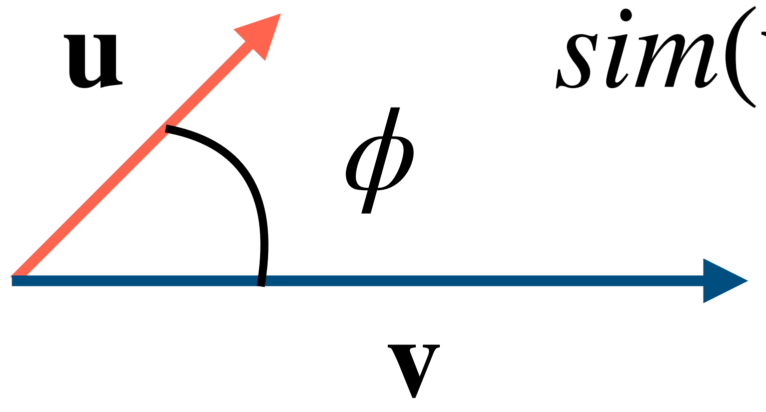
Similarity Between Vectors

Measuring similarity between vectors is very important in deep learning and one of the most populars functions to do that is the **cosine similarity**:

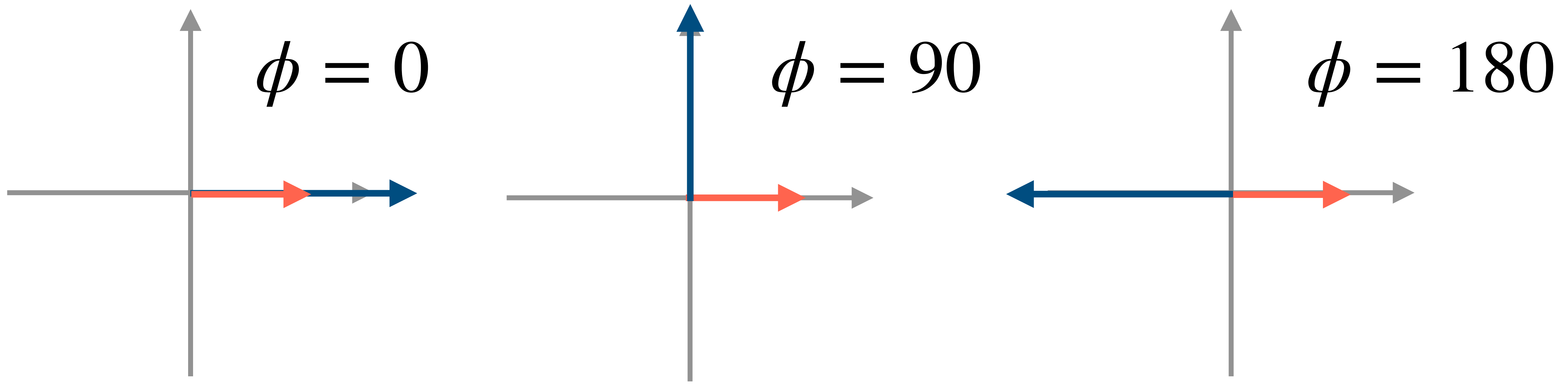
The **cosine similarity** between two vectors u and v is defined as:

$$sim(\mathbf{u}, \mathbf{v}) = \frac{\mathbf{u} \cdot \mathbf{v}}{||\mathbf{u}||_2 ||\mathbf{v}||_2}$$

This formula is equal to the cossine of the anble between u and v:



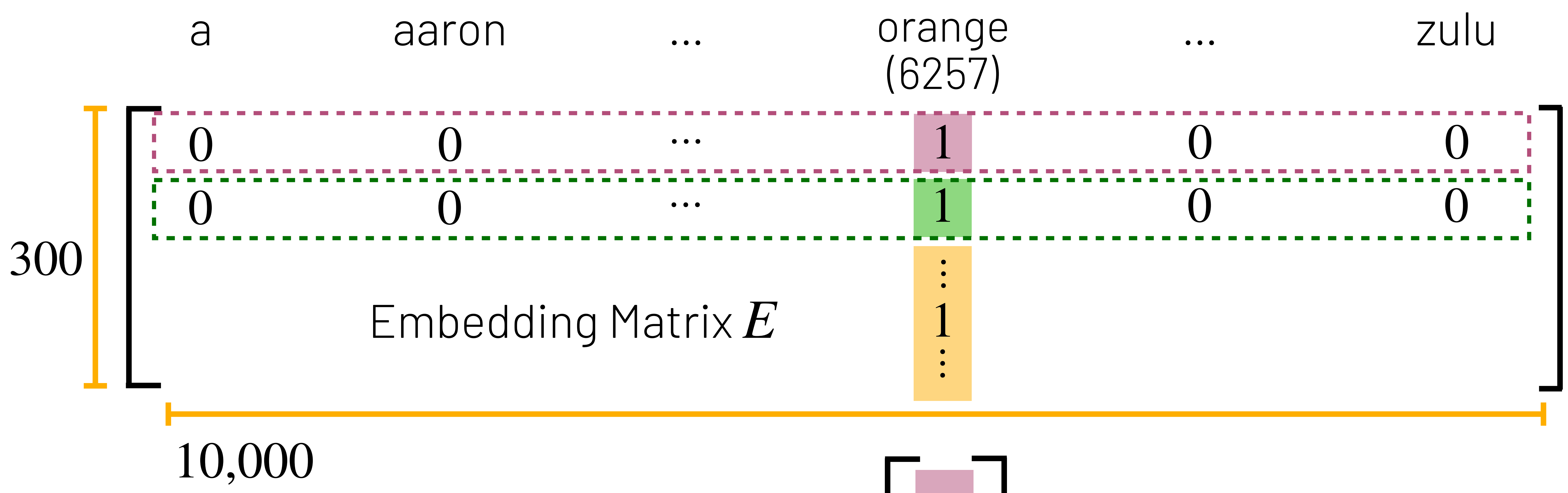
$$sim(\mathbf{u}, \mathbf{v}) = cos(\phi)$$

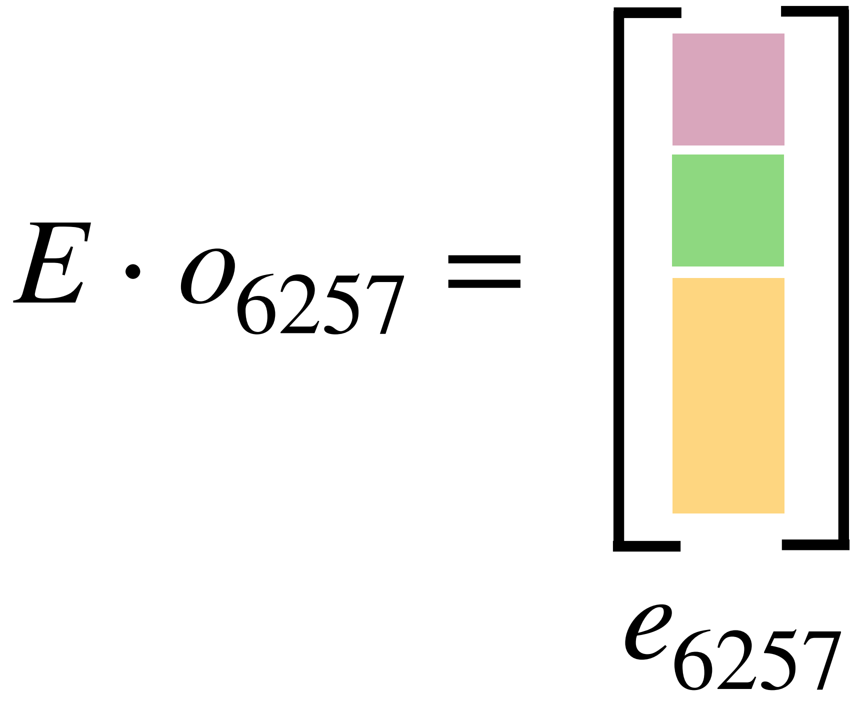


$sim(\mathbf{u}, \mathbf{v}) = 1$ $sim(\mathbf{u}, \mathbf{v}) = 0$ $sim(\mathbf{u}, \mathbf{v}) = -1$

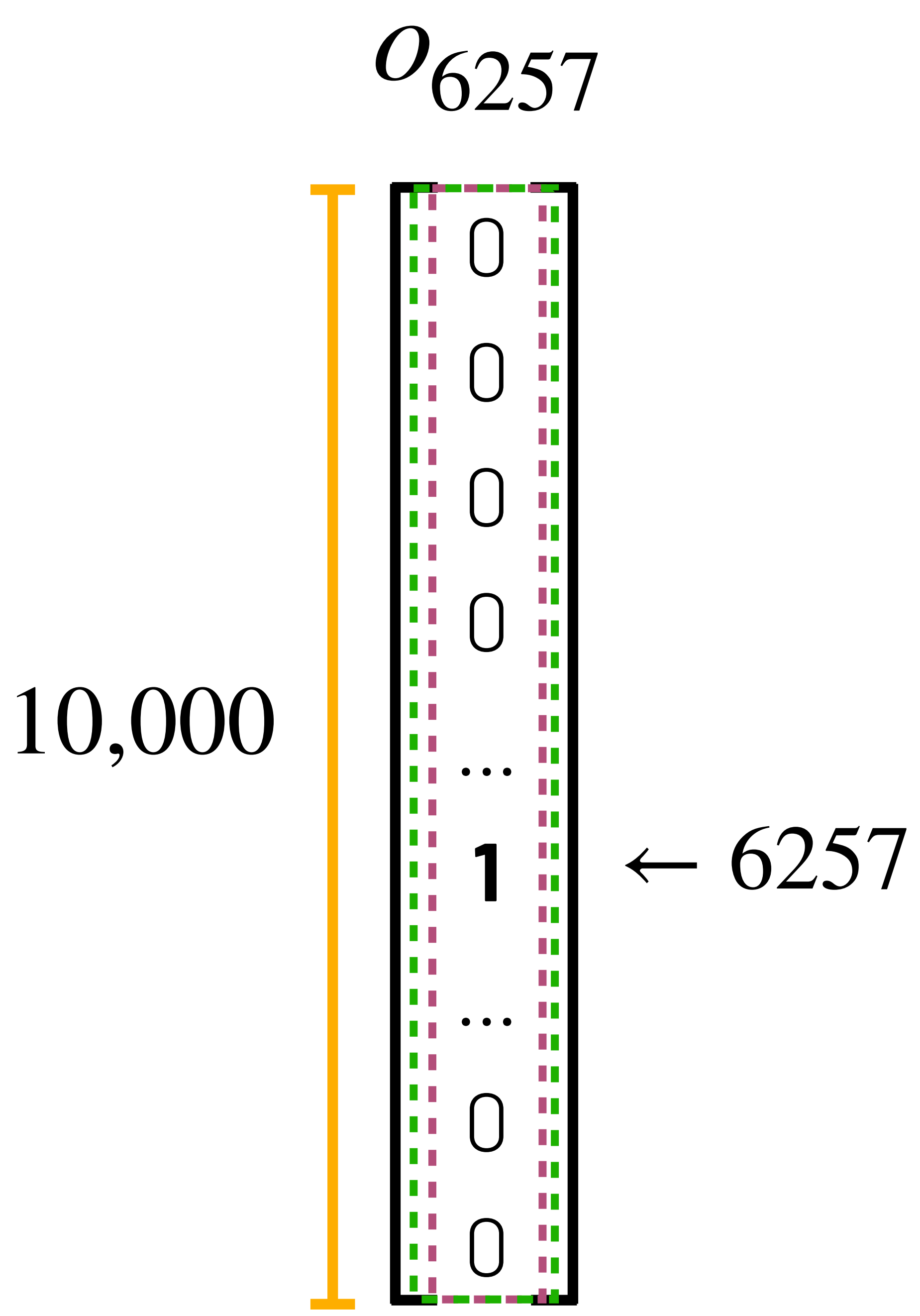
Embedding Matrix

Word embeddings with dimentionality d (e.g. 300) are learned by adding an extra weight matrix , called **embeddings matrix** E, to the model:





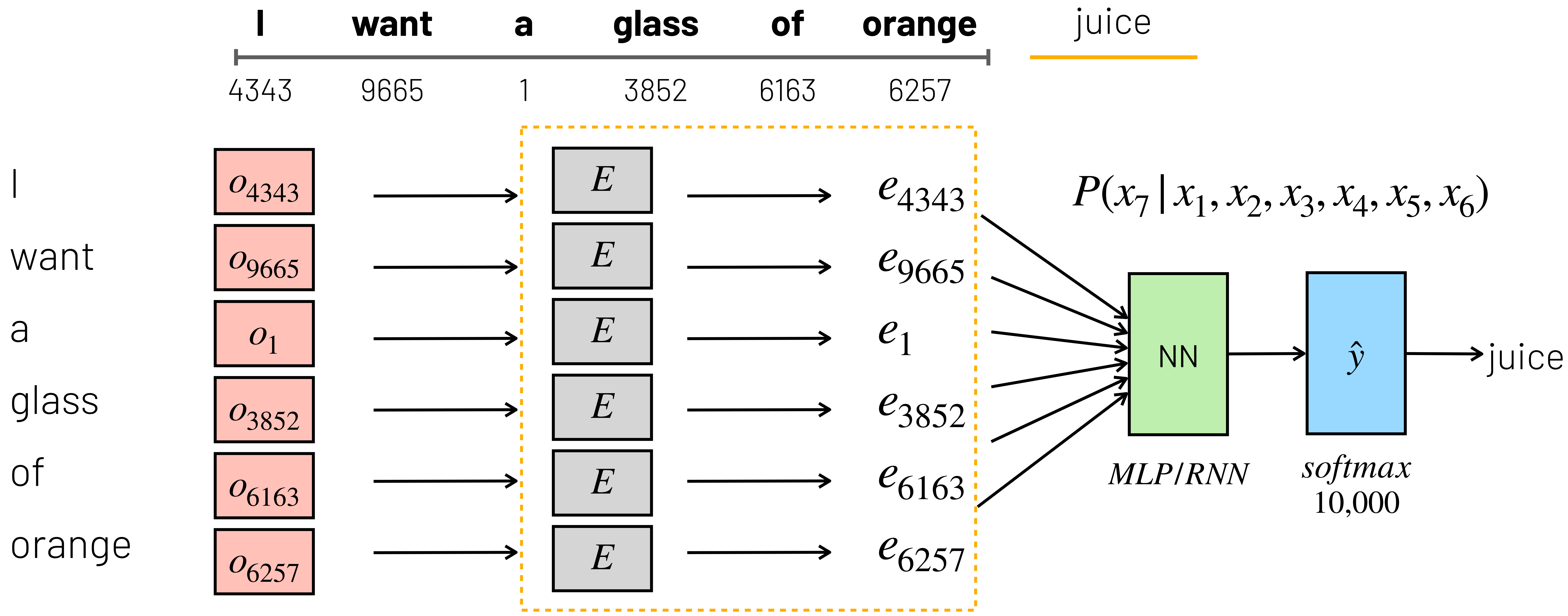
To compute the embedding e for a word, we multiply the embedding matrix on the left



Vocabulary $v = [a, aaron, \ldots, zebra, zulu], \quad |V| = 10{,}000$

Learning Word Embeddings

There are many ways to learn word embeddings, but a simple and popular one is to train a **language model** with an **embedding layer** before the model:



Bengio et. al., 2003, A neural probabilistic language model

Learning Word Embeddings

If your goal is not to learn a language model, but just the embeddings, you don't need to use the previous words as **context**. Here are other ideas that work well:

Context							**Target**					
Last words: (Language Model)	**I**	**want**	**a**	**glass**	**of**	**orange**	**juice**	**to**	**drink**	**with**	**my**	**cereal**
Surrounding words: (CBOW)	**I**	**want**	**a**	**glass**	**of**	**orange**	**juice**	**to**	**drink**	**with**	**my**	**cereal**
A nearby word: (Skip-gram)	**I**	**want**	**a**	**glass**	**of**	**orange**	**juice**	**to**	**drink**	**with**	**my**	**cereal**

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Word2Vec

Word2Vec is a model to learn word embeddings based on **CBOW** or **Skip-gram** contexts, where we produce examples by (1) randomly sampling a word and (2) selecting a neighboring context (e.g, ± 3)

CBOW: The goal is to predict the **target word** from the **surrounding context**!

I want a glass of orange juice to drink with my cereal

Context	Target
...	...
glass of orange _____ to drink with	juice
...	...

Skip-gram: The goal is to predict the **target word** from the **context word**!

I want a glass of orange juice to drink with my cereal

Context	Target
juice	glass
juice	of
juice	orange
juice	to
juice	drink
juice	with

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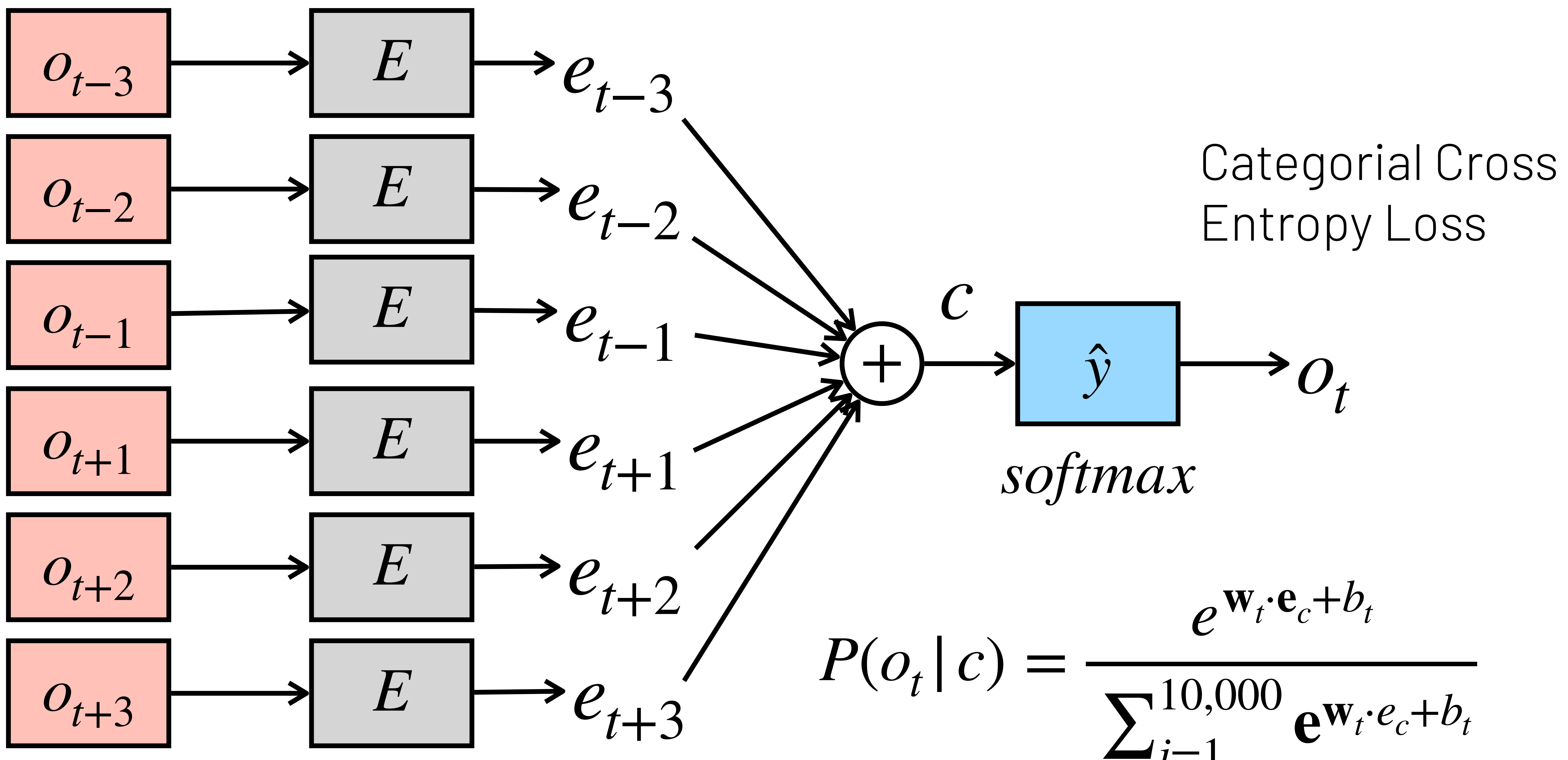
Mikolov et. al., 2013. Efficient estimation of word representations in vector space.

Word2Vec: CBOW

In **CBOW** model, the goal is to predict the **target word** from the **surrounding context.**

I want a glass of orange juice to drink with my cereal

Context	Target
...	...
glass of orange _____ to drink with	juice
...	...



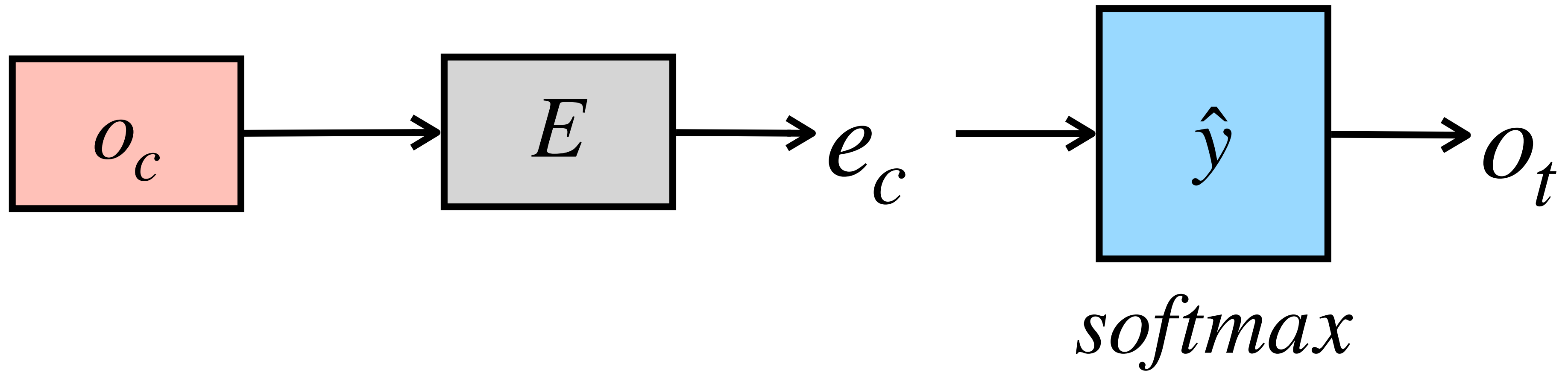
$$P(o_t | c) = \frac{e^{\mathbf{w}_t \cdot \mathbf{e}_c + b_t}}{\sum_{j=1}^{10,000} \mathbf{e}^{\mathbf{w}_t \cdot e_c + b_t}}$$

Word2Vec: Skip-Gram

In the **Skip-gram** model, the goal is to predict the **target word** from each **context word**!

I want a glass of orange juice to drink with my cereal

Context	Target
juice	glass
juice	of
juice	orange
juice	to
juice	drink
juice	with



Categorial Cross Entropy Loss

$$P(o_t | c) = \frac{e^{\mathbf{w}_t \cdot \mathbf{e}_c + b_t}}{\sum_{j=1}^{10,000} \mathbf{e}^{\mathbf{w}_t \cdot e_c + b_t}}$$

Negative Sampling

$$P(t \mid c) = \frac{e^{\mathbf{w}_t \cdot \mathbf{e}_c + b_t}}{\sum_{j=1}^{10,000} \mathbf{e}^{\mathbf{w}_t \cdot e_c + b_t}}$$

Since the vocabulary size is typically large (e.g., 10,000), computing a probability with the softmax layer is expensive!

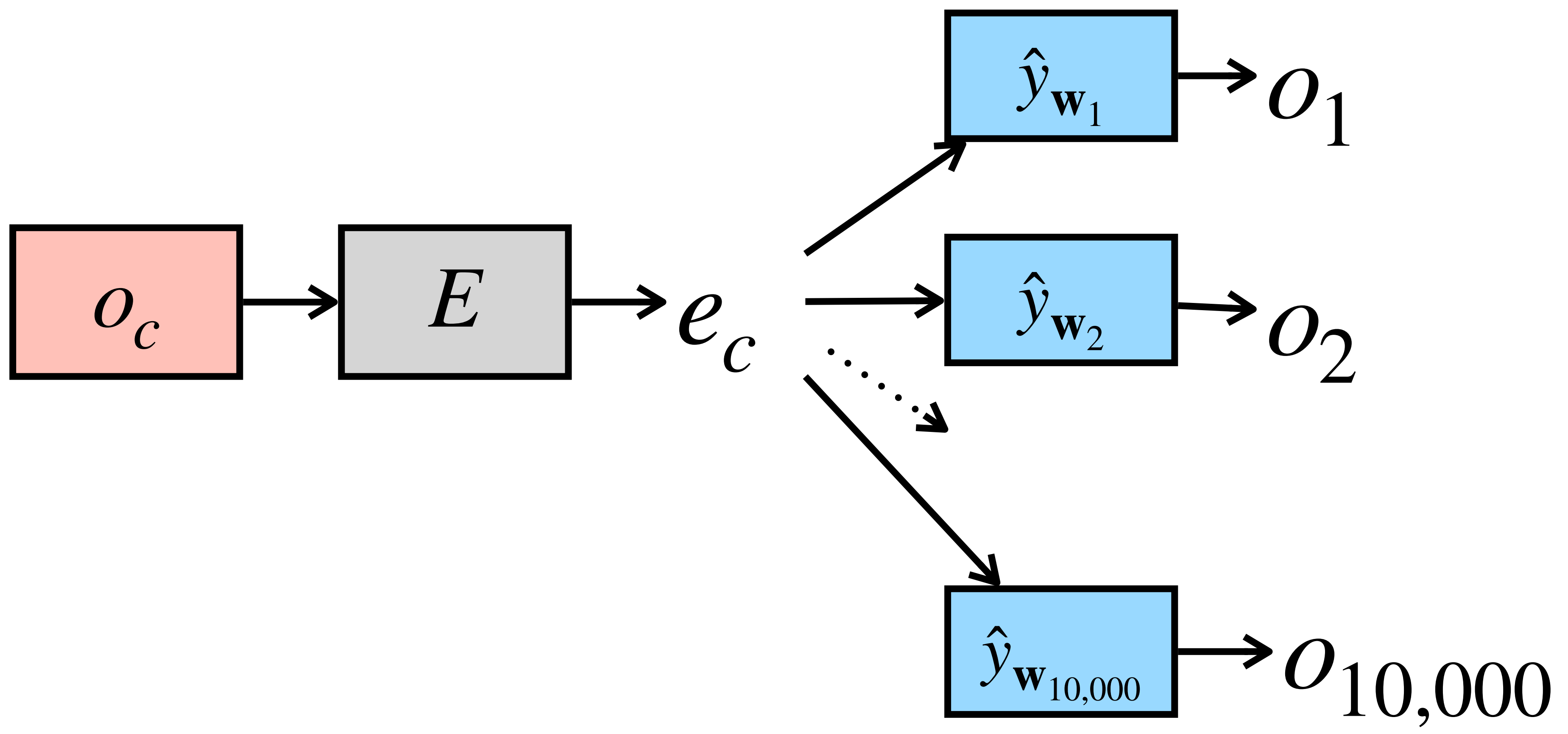
(we have to sum 10,000 terms)

Negative sampling changes the classification text to a binary classification problem by generating a dataset with positive and negative examples:

Context	Word	Target?
orange	juice	1
orange	king	0
orange	book	0
orange	the	0
orange	of	0

Sample with skip-gram

Sample k random words from the dictionary



Logistic Regression

$$P(y = 1 \mid c, t) = \sigma(\mathbf{w}_t \cdot \mathbf{e}_c + b)$$

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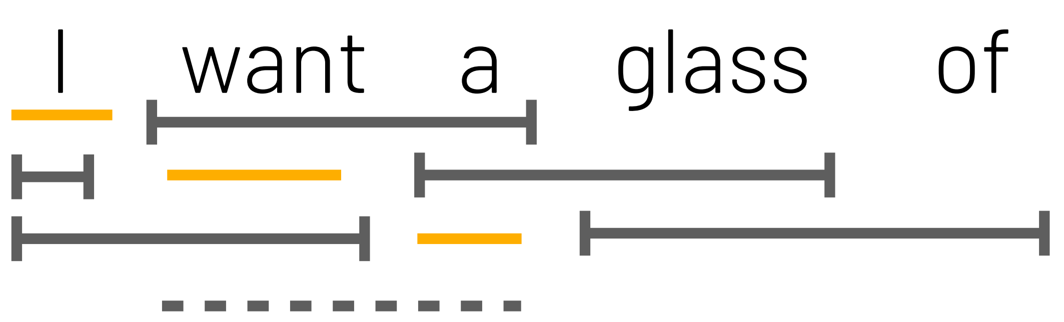
Mikolov et. al., 2013. Distributed representation of words and phrases and their compositionality

GloVe (Global Vectors for Word Representation)

In Word2Vec, the global information is not preserved. To address that, GloVe predicts the number of times a target word t appears in the context of the context word c

1. Build a word co-occurence matrix X



2. Assign a weight vector per context $\mathbf{w}_i$ and target word $\tilde{\mathbf{w}}_j$

3. Predict log co-occurance from $\mathbf{w}_i$ and $\tilde{\mathbf{w}}_j$ using weighted MSE

		$\tilde{\mathbf{w}}_1$ I	$\tilde{\mathbf{w}}_2$ want	$\tilde{\mathbf{w}}_3$ a	$\tilde{\mathbf{w}}_4$ glass	$\tilde{\mathbf{w}}_5$ of	$\tilde{\mathbf{w}}_6$ orange	$\tilde{\mathbf{w}}_7$ juice
$\mathbf{w}_1$	I	0	1.0	0.5	0	0	0	0
$\mathbf{w}_2$	want	1.0	0	1.0	0.5	0	0	0
$\mathbf{w}_3$	a	0.5	1.0	0	1.0	0.5	0	0
$\mathbf{w}_4$	glass	0	0.5	1.0	0	1.0	0.5	0
$\mathbf{w}_5$	of	0	0	0.5	1.0	0	1.0	0.5
$\mathbf{w}_6$	orange	0	0	0	0.5	1.0	0	1.0
$\mathbf{w}_7$	juice	0	0	0	0	0.5	1.0	0

$$X_{ij} = \sum_{j}^{C} \frac{1}{dist(i,j)}$$

where C is context window size (e.g, 2)

$$L = \sum_{i=1}^{10{,}000} \sum_{j=1}^{10{,}000} f(X_{ij}) \, (\underbrace{\mathbf{w}_i \tilde{\mathbf{w}}_j + b_i + b_j}_{\text{Prediction}} - \underbrace{log(X_{ij})}_{\text{Target}})^2$$

Using log helps compress the range of values

weighting function that helps balance the importance of different co-occurrences

4. Embedding:

$$e_i = \frac{w_i + \tilde{w}_i}{2}$$

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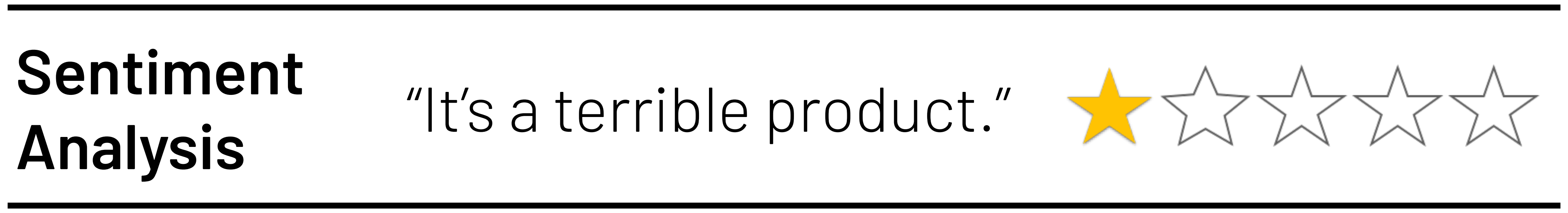
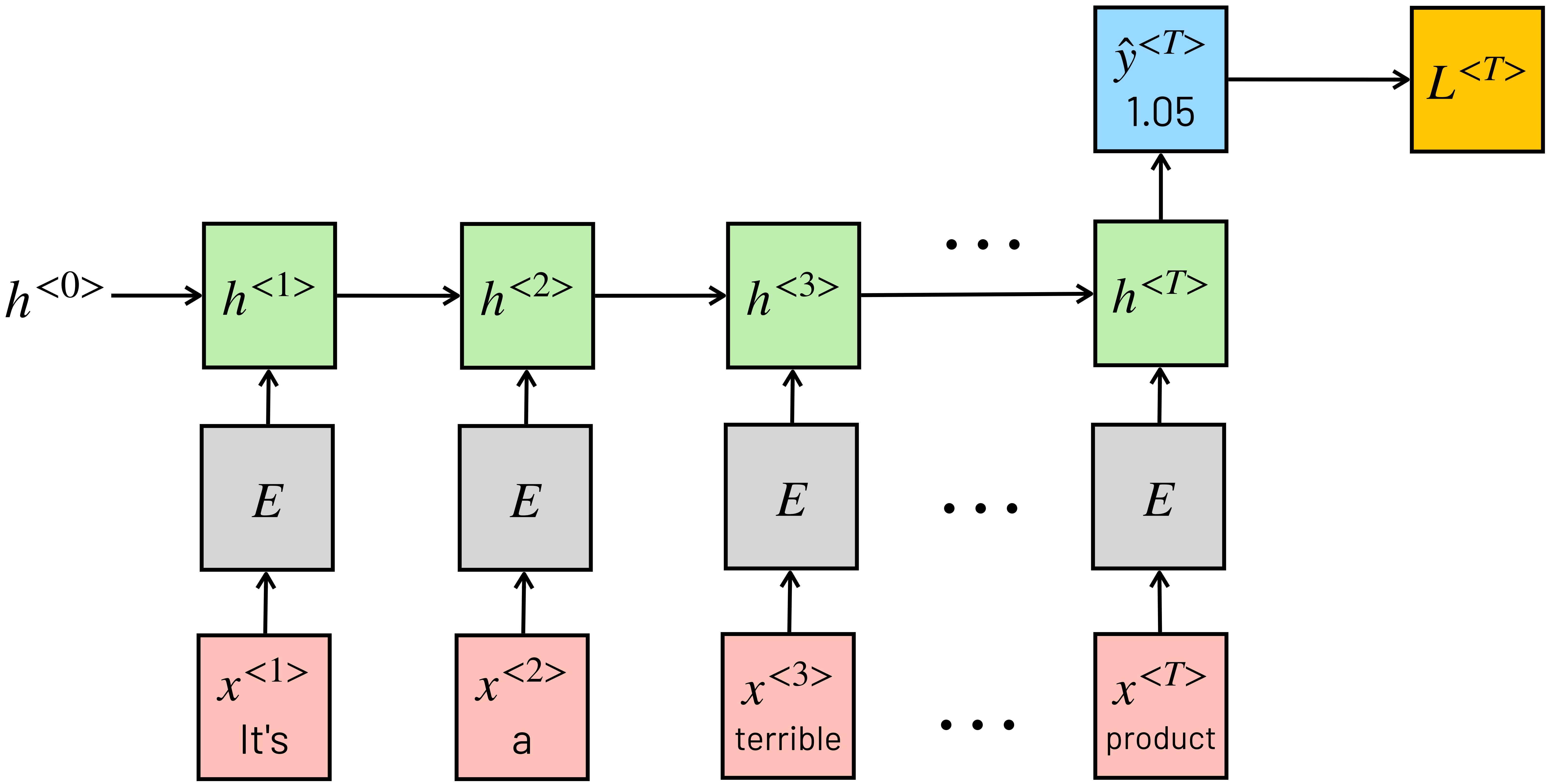
Pennington et. al., 2014. GloVe: Global vectors for word representation

Using Word Embeddings



When working with Natural Language Processing problems, you can learn word embeddings by just adding an embedding layer to your network:



Using Word Embeddings

Sentiment Analysis "It's a terrible product." ★☆☆☆☆

In PyTorch, you can use the Embedding layer to add an Embedding Matrix E to your model:

```
class RNNSentiment(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, output_dim, padding_idx=None):
        super().__init__()

        # Embedding layer
        self.embedding = nn.Embedding(
            num_embeddings=vocab_size, embedding_dim=embedding_dim, padding_idx=padding_idx
        )

        # RNN layer
        self.rnn = nn.RNN(input_size=embedding_dim, hidden_size=hidden_dim, num_layers=1,
            batch_first=True
        )

        # Output layer
        self.fc = nn.Linear(hidden_dim, output_dim)
```

Next Lecture

L15: Attention Mechanisms

Machine Translation, Decoding Strategies, Attention Mechanisms in RNNs