Natural Language Processing (NLP)

Neural Network Embeddings

Equipping You with Research Depth and Industry Skills

By:

Dr. Zohair Ahmed

Why do we need word representations?

I saw a cat.

Text (your input)

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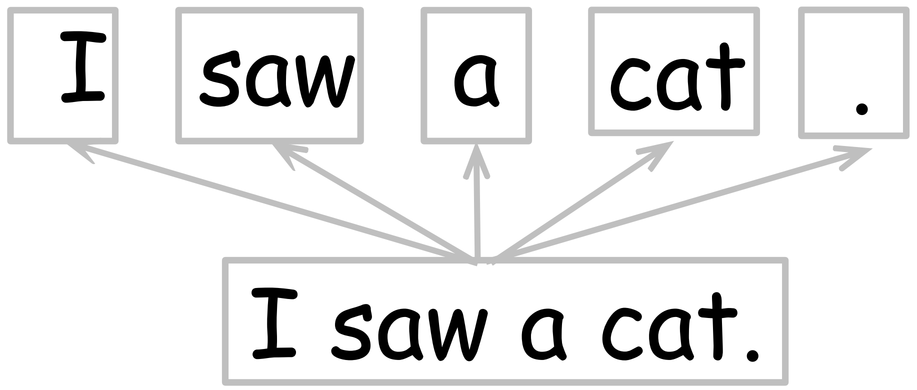

Sequence of tokens

Text (your input)

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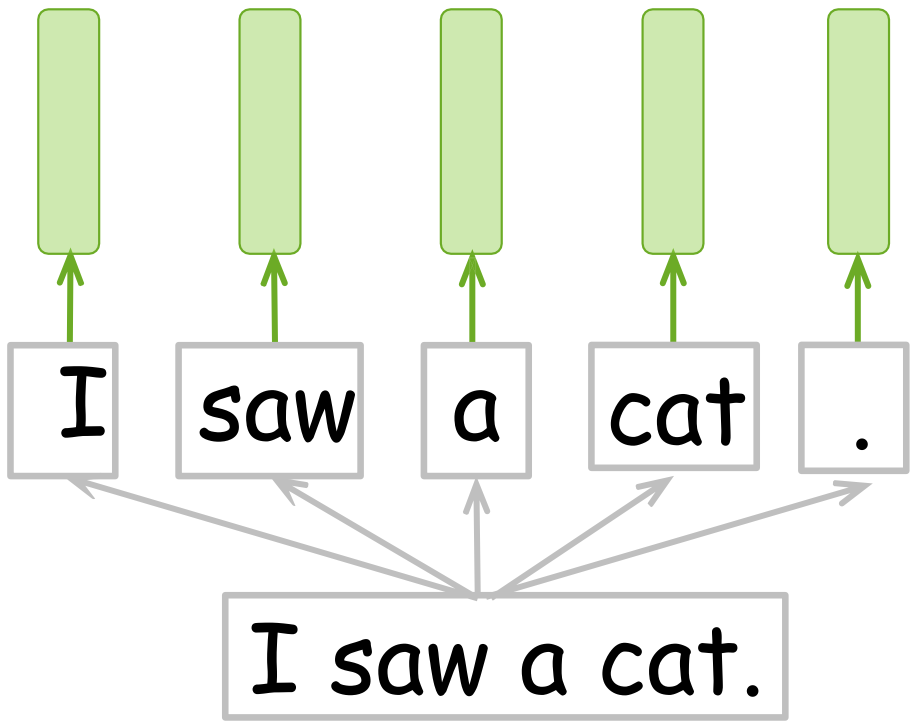

Word representation - vector
(input for your model/algorithm)

Sequence of tokens

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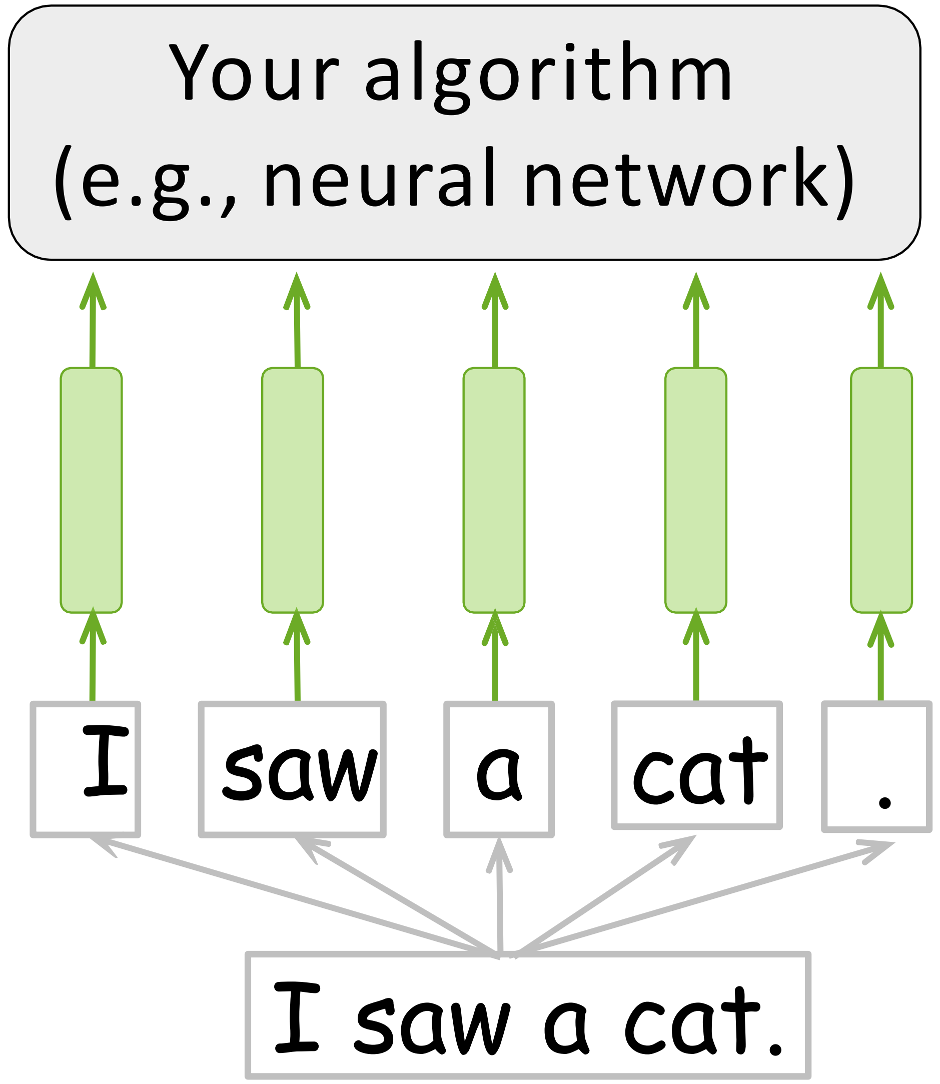


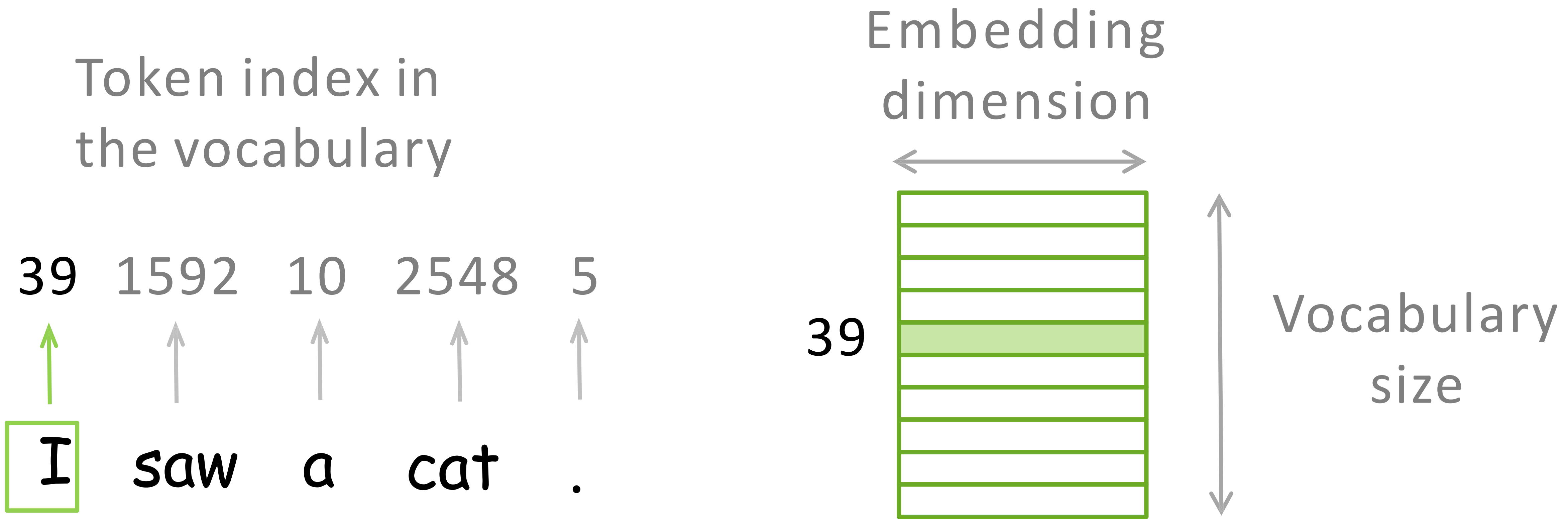
Any algorithm for solving a task

Word representation - vector
(input for your model/algorithm)

Sequence of tokens

Text (your input)

How it works: Look-up Table



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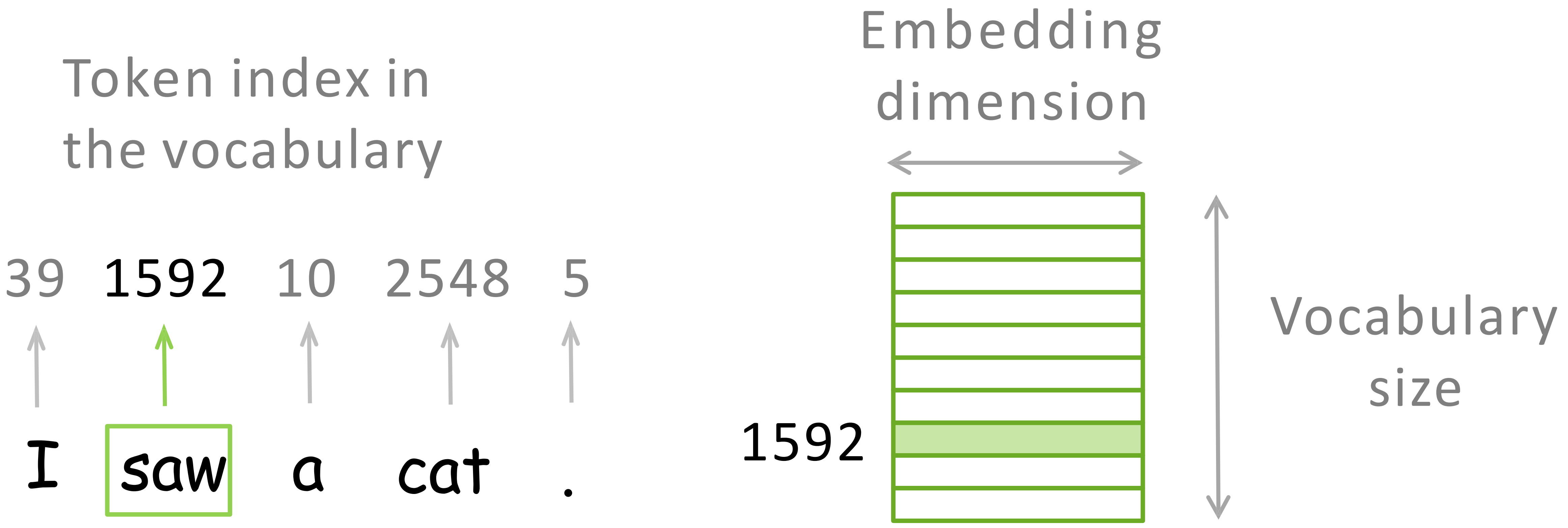

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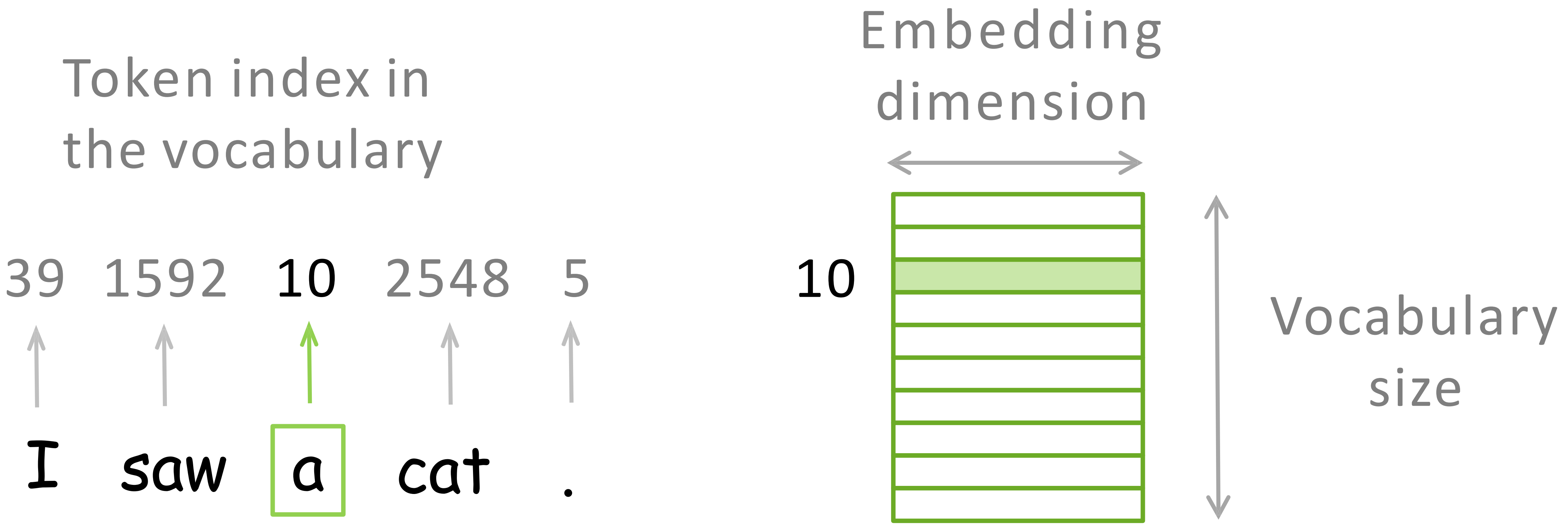

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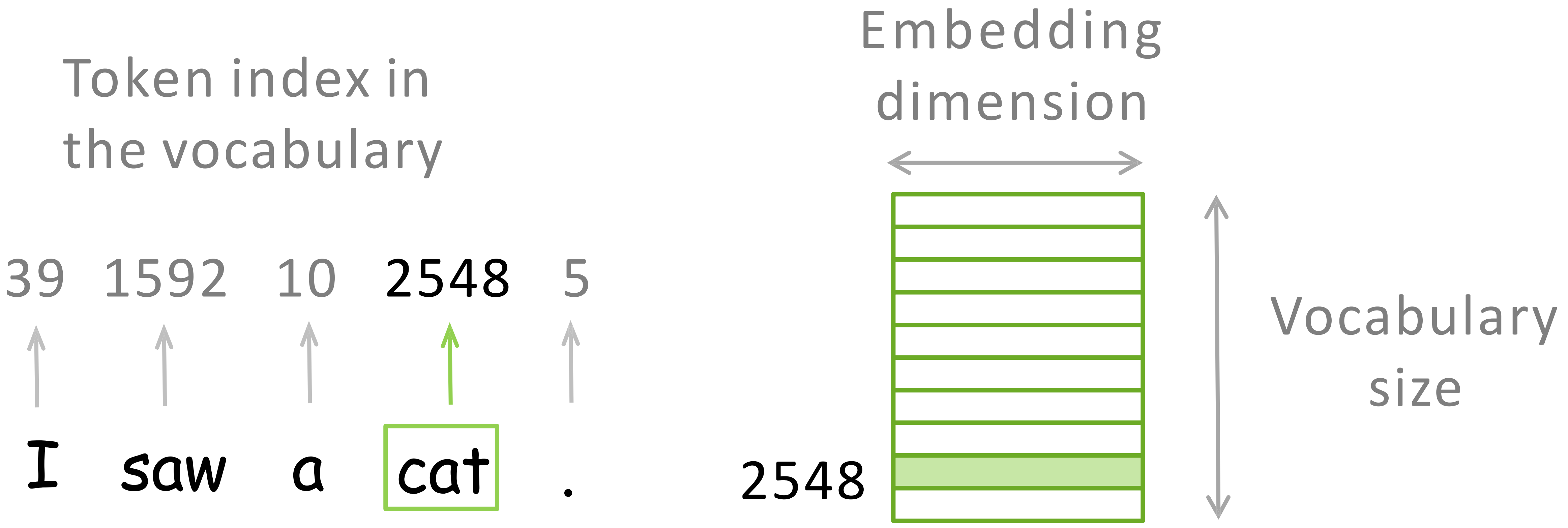

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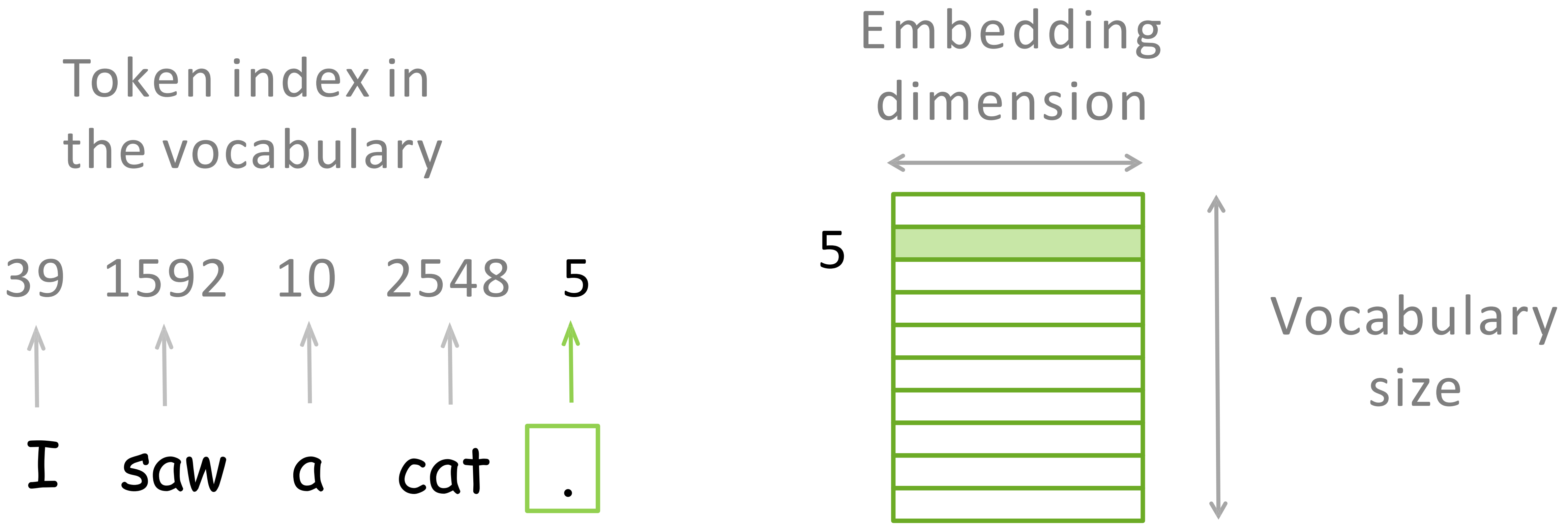

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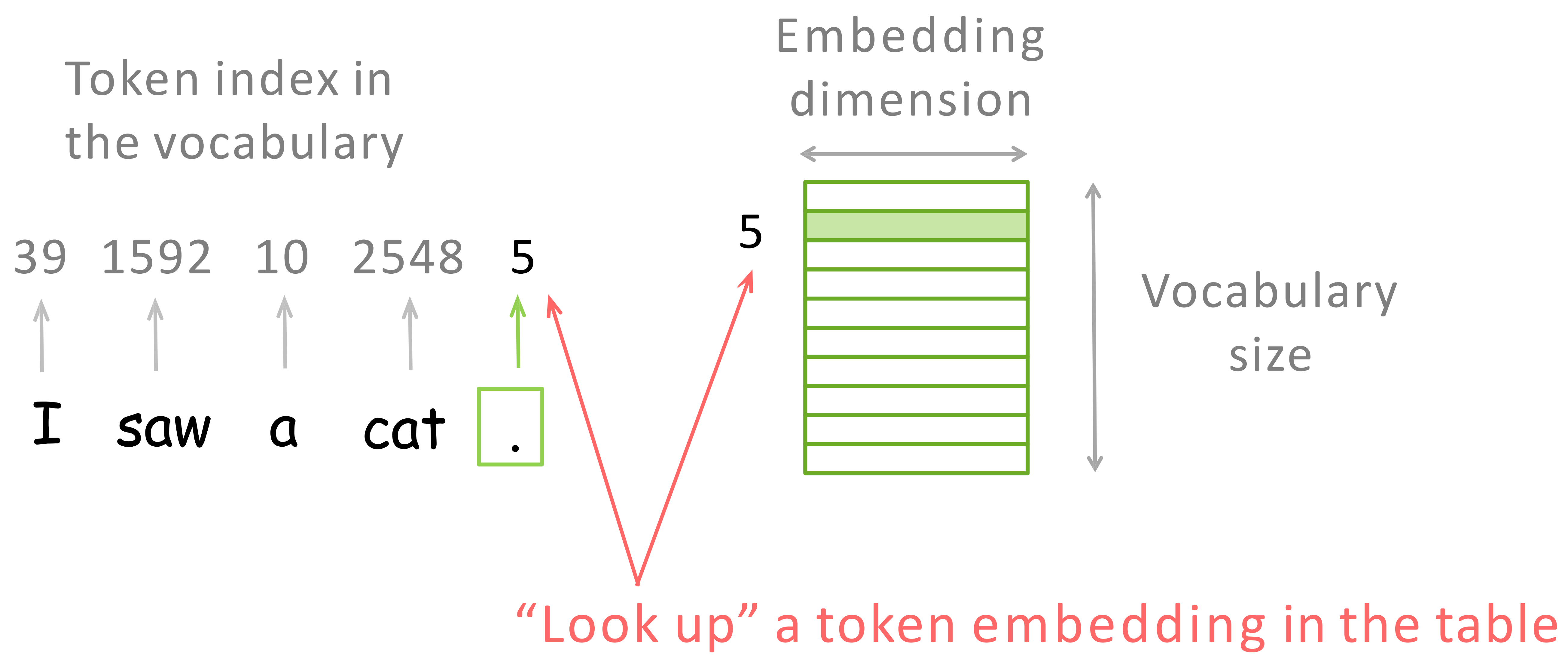
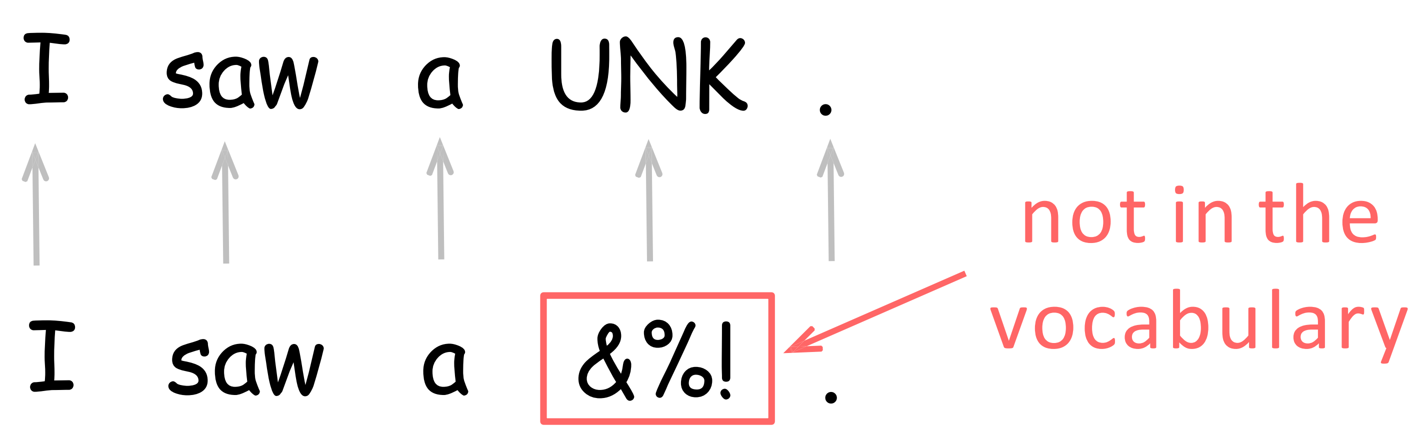


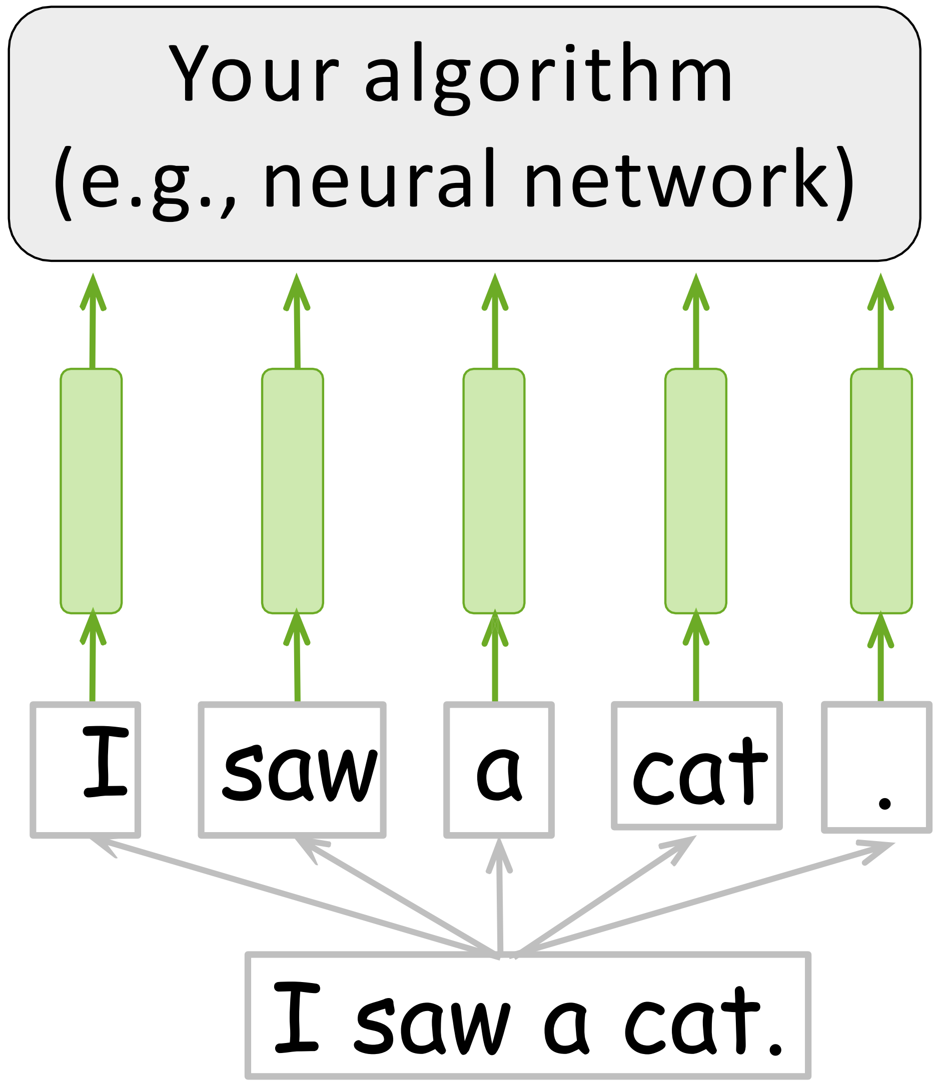
Note UNKs: Out-of-Vocabulary Tokens



Vocabulary is chosen in advance

Therefore, some tokens may be “unknown” – you can use a special token for them

How can we gat word representations?



<u>In the following</u>:

How can we get these representations?

One-hot Vectors

One-Hot Vectors: Represent Words as Discrete Symbols

One is 1, the rest are 0

dog	0…0…010….0…0
cat	0…010…0….0…0
table	0…0…0….0010…

Embedding dimension = vocabulary size

One-Hot Vectors: Represent Words as Discrete Symbols

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Any problems?

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Problems:

- Vector size is too large
- Vectors know nothing about meaning

  e.g., cat is as close to dog as it is to table!

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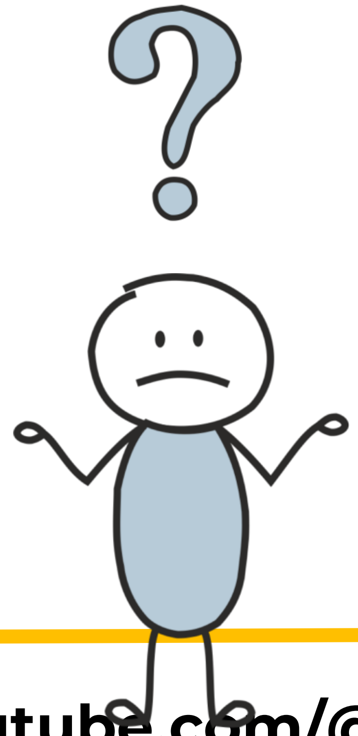
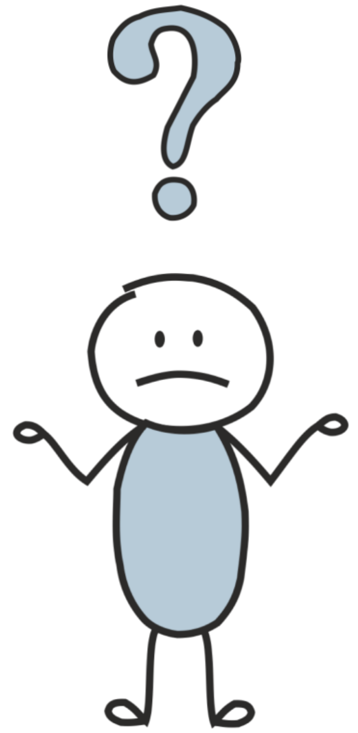


What is meaning?

What is meaning?

Do you know what the word tezgüino means ?

(We hope you do not)



What is meaning?

Now look how this word is used in different contexts:

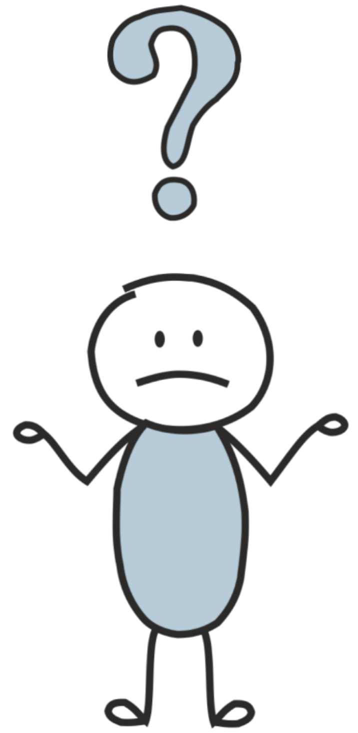
A bottle of tezgüino is on the table.

Everyone likes tezgüino.

Tezgüino makes you drunk.

We make tezgüino out of corn.

Can you understand what tezgüino means ?



What is meaning?

Now look how this word is used in different contexts:

A bottle of tezgüino is on the table.

Everyone likes tezgüino.

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We make tezgüino out of corn.

Tezgüino is a kind of alcoholic beverage made from corn.

With context, you can understand the meaning!

What is meaning?

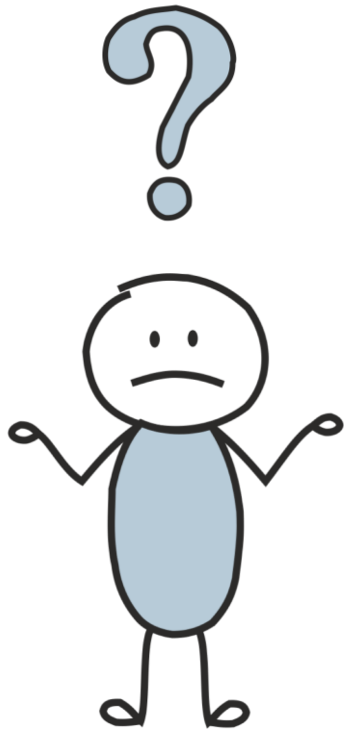
(1) A bottle of ______ is on the table.

(2) Everyone likes ______ .

(3) ______ makes you drunk.

(4) We make ______ out of corn.

What other words fit into these contexts ?



What is meaning?

(1) A bottle of ______ is on the table.

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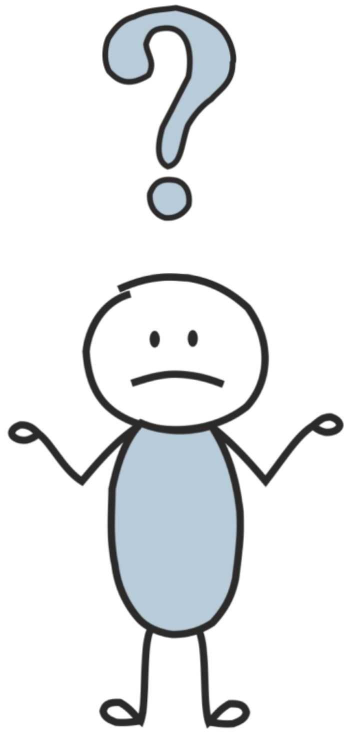
What other words fit into these contexts ?

	(1)	(2)	(3)	(4)	…
tezgüino	1	1	1	1	
loud	0	0	0	0	
motor oil	1	0	0	1	
tortillas	0	1	0	1	
wine	1	1	1	0	

← contexts

← rows show contextual properties: 1 if a word can appear in the context, 0 if not



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rows are similar

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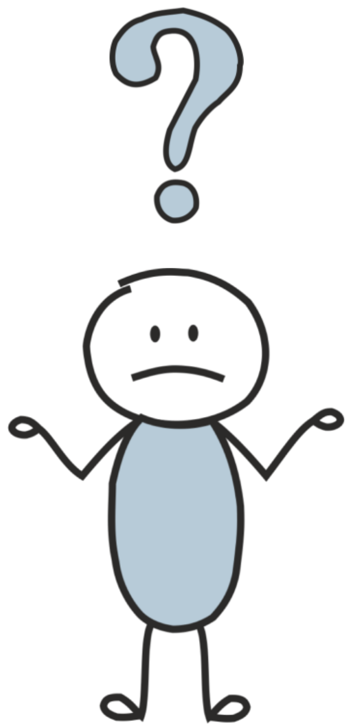

<u>rows</u> are similar → <u>meanings</u> of the words are similar

Is this true?

What is meaning?

(1) A bottle of _______ is on the table.

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This is the distributional hypothesis

rows are similar → meanings of the words are similar

Distributional Hypothesis

> Words which frequently appear in similar contexts have similar meaning.

(Harris 1954, Firth 1957)

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This can be used in practice to build word vectors!

Distributional Hypothesis

> Words which frequently appear in similar contexts have similar meaning.

(Harris 1954, Firth 1957)

<u>Main idea:</u>

> We have to put information about contexts into word vectors.

What comes next: different ways to do this

Count-Based Methods

Count-Based Methods Idea

Let’s remember our main idea:

We have to put information about contexts into word vectors.

Count-Based Methods: Idea

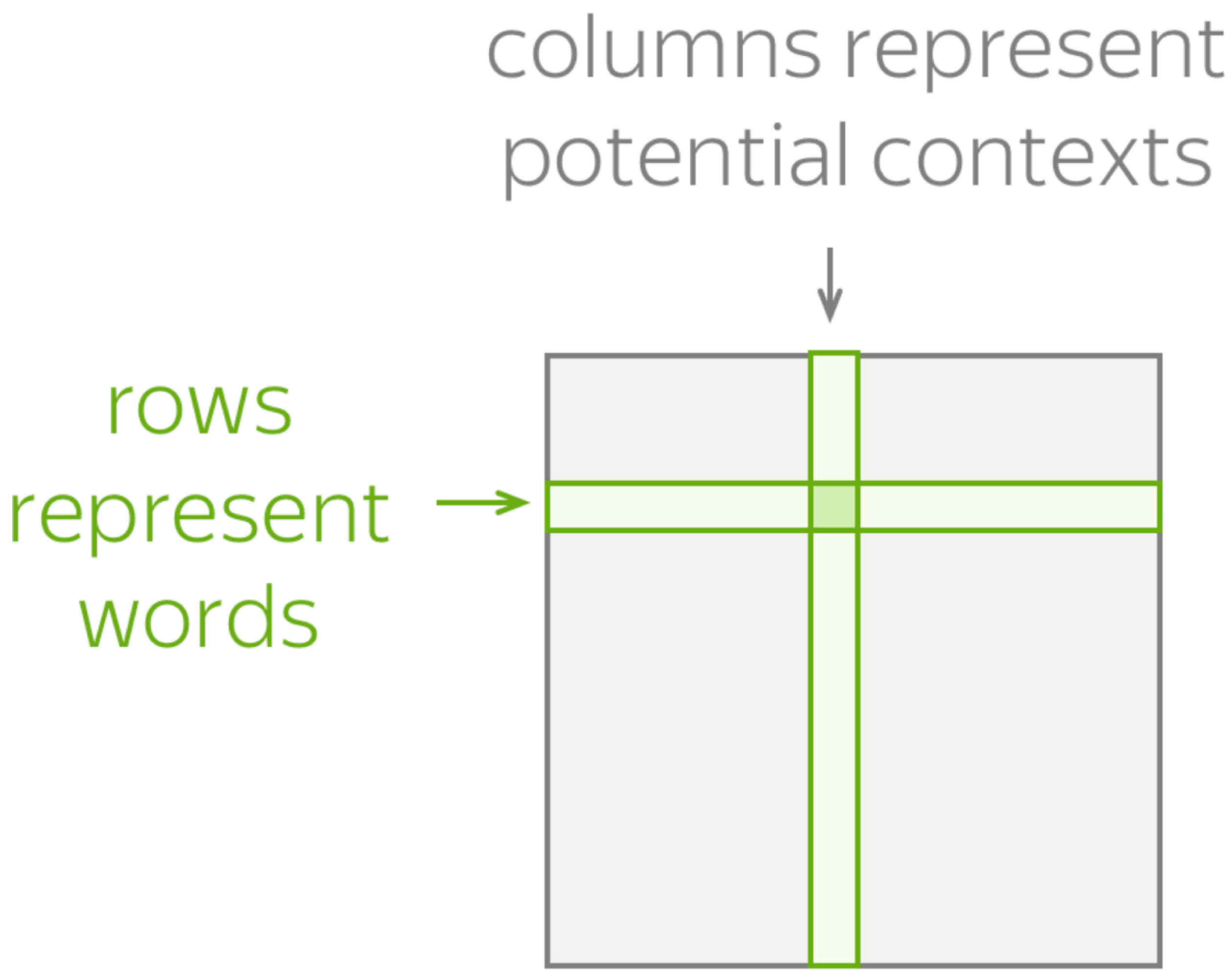
Let's remember our main idea:

We have to put information about contexts into word vectors.

Count-based methods take this idea quite literally :)

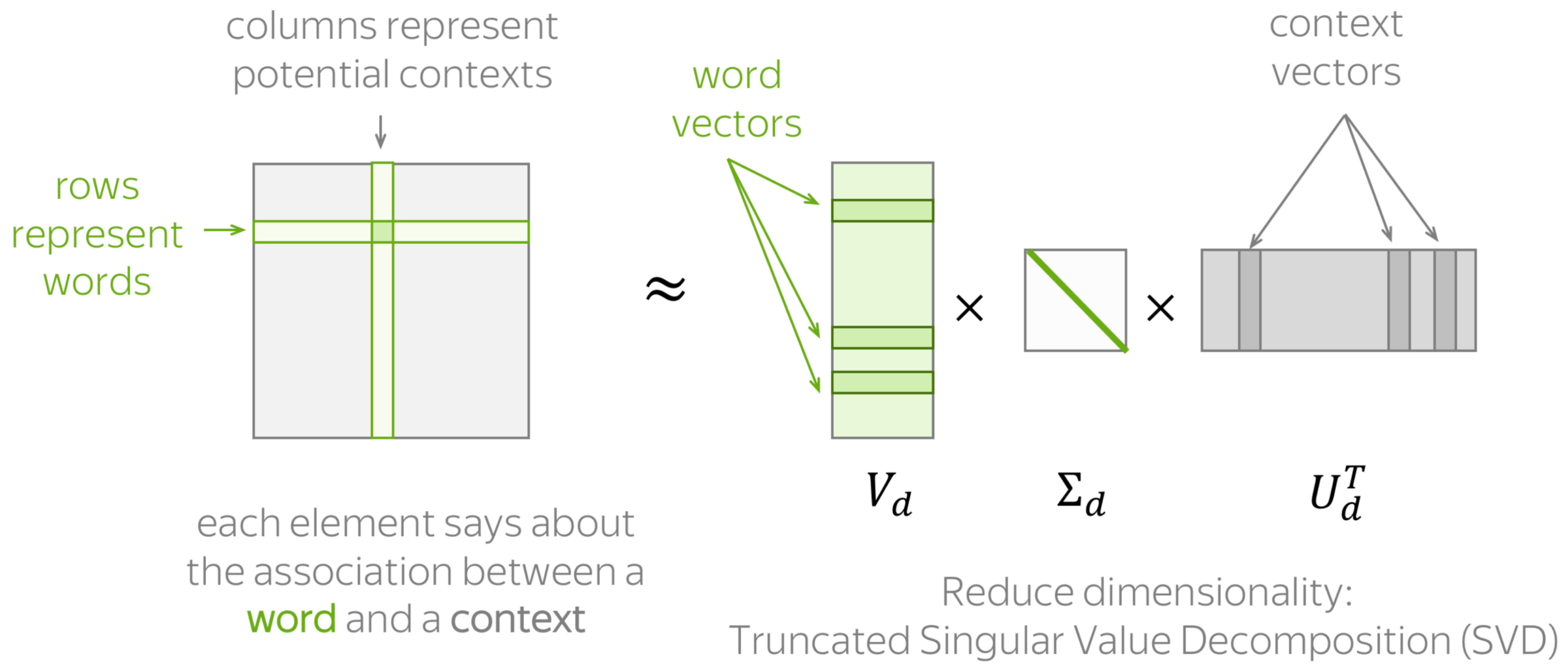
How: Put this information manually based on global corpus statistics.

Count-Based Methods: The General Pipeline



each element says about the association between a word and a context

Count-Based Methods: The General Pipeline



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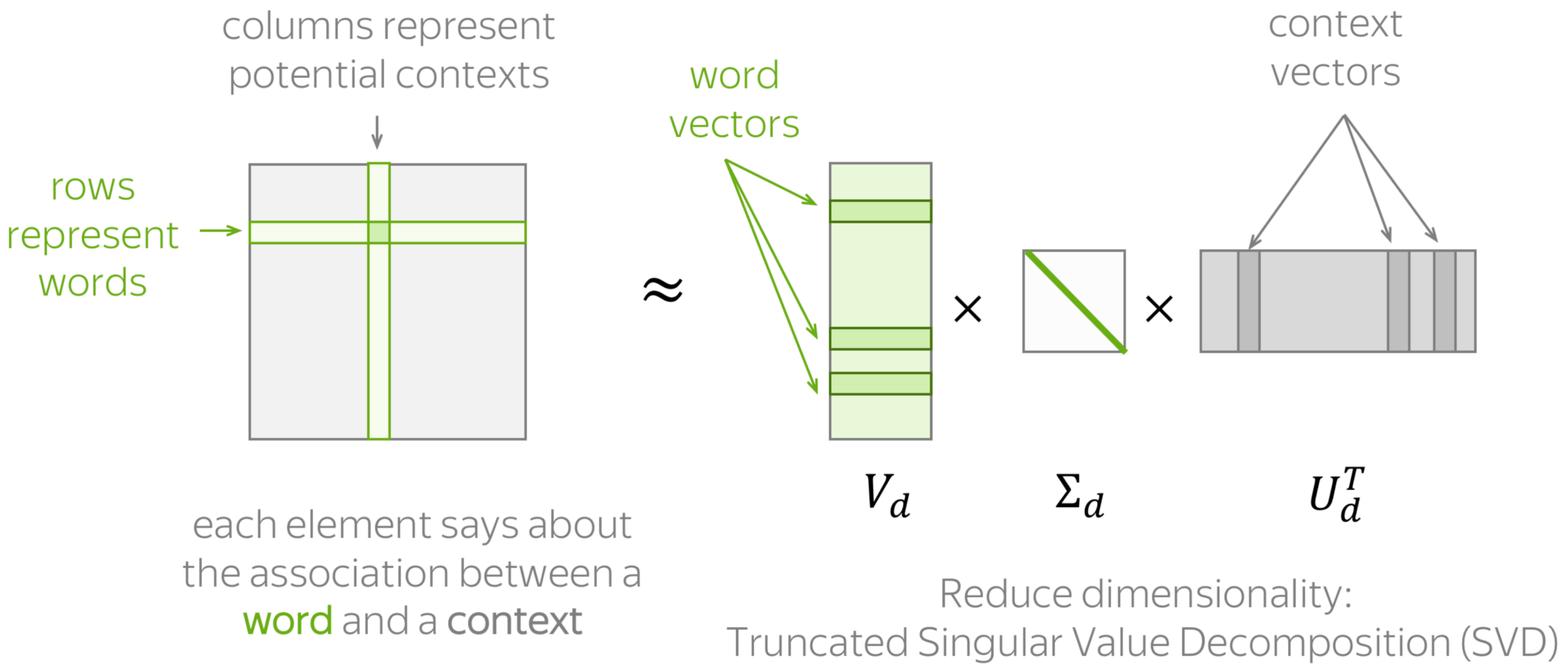


Need to define:

- what is context
- how to compute matrix elements

Simple: Co-Occurrence Counts

2-sized window for cat

… I saw a cute grey cat playing in the garden …

contexts for cat

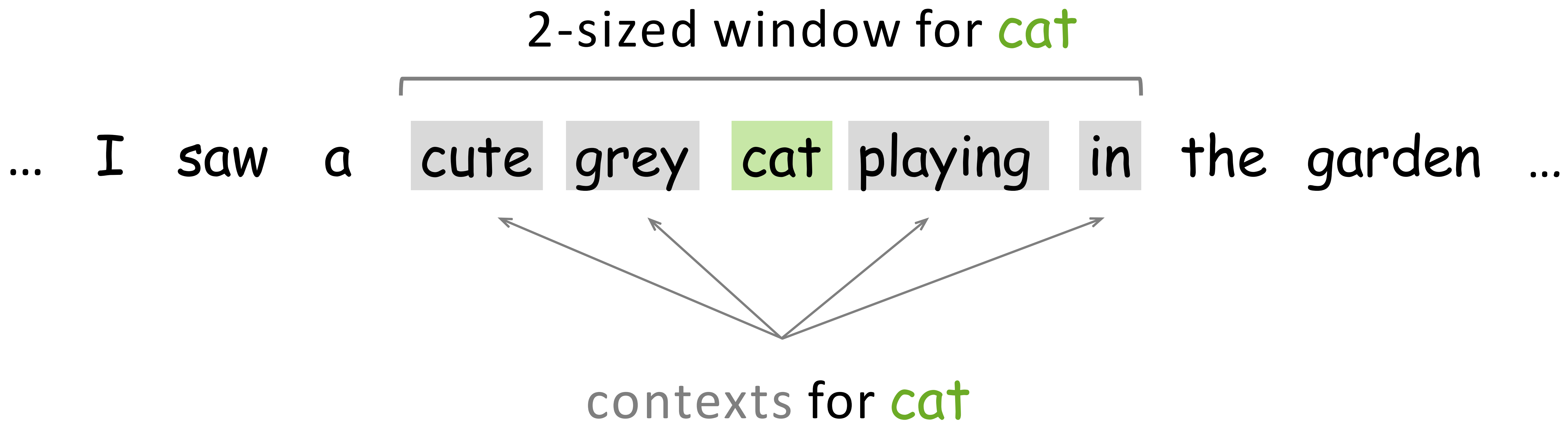
Context:

- surrounding words
  in a L-sized window

Matrix element:

- N(w, c) – number of times
  word w appears in context c

Point Wise Mutual Information (PMI)



Context:

- surrounding words in a L-sized window

$$PMI(w, c) = \log \frac{P(w, c)}{P(w) \cdot P(c)}$$

$P(w,c)$ = probability that w and c occur together (co-occurrence).

$P(w) \cdot P(c)$ = probability that they would occur together if they were independent.

Ratio > 1 (positive PMI) → words occur together more often than chance.

Ratio < 1 (negative PMI) → words occur together less often than chance.

Point wise Mutual Information (PMI)

- "The king rules the kingdom. The queen rules the empire."
- **Step 1: Word probabilities**
  - P(king) = 1/10 = 0.1
  - P(queen) = 1/10 = 0.1
  - P(rules) = 2/10 = 0.2
  - P(the) = 3/10 = 0.3
- Step 2: Co-occurrence (window size = 1)
  - Pair (king, rules) appears 1 time → P(king, rules) = 1/10 = 0.1
  - Pair (king, empire) appears 0 times → P = 0
  - Pair (queen, rules) appears 1 time → P(queen, rules) = 1/10 = 0.1

Point wise Mutual Information (PMI)

- **Step 3: Compute PMI**
- Formula: PMI(w, c) = log(P(w,c) / (P(w) * P(c)))
- PMI(king, rules) = log(0.1 / (0.1 * 0.2))
  - = log(0.1 / 0.02)
  - = log(5) ≈ 1.61 → positive (they co-occur more than chance)
- PMI(king, empire) = log(0 / (0.1 * 0.1))
- = log(0) = negative infinity → strong negative
- **Step 4: Apply PPMI**
- PPMI(king, rules) = 1.61
- PPMI(king, empire) = 0 (we clip negative values to zero)

Point wise Mutual Information (PMI)

- **Interpretation:**
- "king" and "rules" have a high positive PPMI → they are related.
- "king" and "empire" have zero PPMI → no useful relationship.

Word2Vec (Prediction-Based Method)

Word2Vec: Idea

Let's remember our main idea:

We have to put information about contexts into word vectors.

Word2Vec: Idea

Let's remember our main idea:

We have to put information about contexts into word vectors.

Word2Vec uses this idea differently from count-based methods:

How: Learn word vectors by teaching them to predict contexts.

Word2Vec: Idea

How: Learn word vectors by teaching them to predict contexts.

- Learned parameters: word vectors
- Goal: make each vector “know” about the contexts of its word
- How: train vectors to predict possible contexts from words (or, alternatively, words from contexts)

Word2Vec: High-Level pipeline

- take a huge text corpus

… I saw a cute grey cat playing in the garden …

Word2Vec: High-Level pipeline

- take a huge text corpus
- go over the text with a sliding window, moving one word at a time.

…	I	saw	a	cute	grey	cat	playing	in	the	garden	…
	w_{t-2}	w_{t-1}	w_t	w_{t+1}	w_{t+2}						

Word2Vec: High-Level pipeline

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context words | central word | context words

Word2Vec: High-Level pipeline

- take a huge text corpus
- go over the text with a sliding window, moving one word at a time.
- for the central word, compute probabilities of context words;
- adjust the vectors to increase these probabilities.

$P(w_{t-2}|w_t)$ $P(w_{t-1}|w_t)$ $P(w_{t+1}|w_t)$ $P(w_{t+2}|w_t)$

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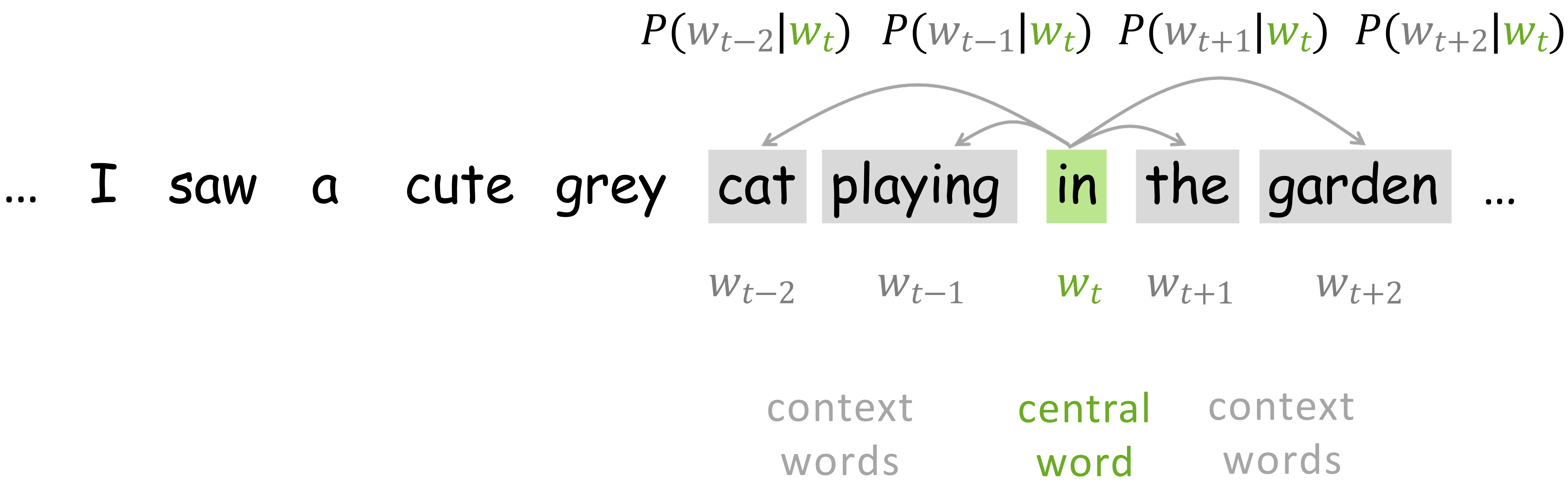


How Does Word2Vec Work?

- Train NN on a **fake problem**: predict missing word
- Example:
  - "The emperor ordered his ___."
- Correct word could be *king* or *minister*
- Goal: **not prediction**, but to **learn embeddings** (side effect)

Context Is Key

- Meaning of a word depends on **context**
- Example:
  - “Eating ___ is healthy.” → [apple, walnut] ✅
  - Not [pizza, truck] ❌
- Context words = training input

Objective Function: Negative Log-Likelihood

- **Word2Vec tries to find the parameters that maximize the data likelihood:**
- **wt** → → the current (center) word at position t.
- **wt+j** → a context word around wt.
- **m** → the size of the context window.
- **T** → total number of words in the corpus.
- P(wt+j|wt,θ) → the probability of seeing context word wt+j given center word wt, with parameters θ (neural network weights).
- So:

  The likelihood is the product of probabilities of predicting the context words for every center word in the training corpus.

$$\text{Likelihood} = L(\theta) = \prod_{t=1}^{T} \prod_{\substack{-m \le j \le m, \\ j \ne 0}} P(w_{t+j} | w_t, \theta)$$

Objective Function: Intuition (Why It Works)

- Training Word2Vec = making the model assign **high probability** to actual context words.
- If the model predicts wrong context words, probability is low → log-likelihood decreases → NLL increases.
- So by minimizing NLL, the model **learns embeddings that bring context words closer in vector space**.

Objective Function: Intuition (Why It Works)

- **Simple Analogy**
- Imagine the sentence: **"The king ruled the empire."**
- Center word = *king*
- Context words (window=2): *the*, *ruled*
- If the model says: P(ruled|king)=0.7 and P(the|king)=0.6
- High probabilities → good embeddings.

  If probabilities were low (e.g. 0.05), NLL would be large, pushing the model to adjust embeddings.

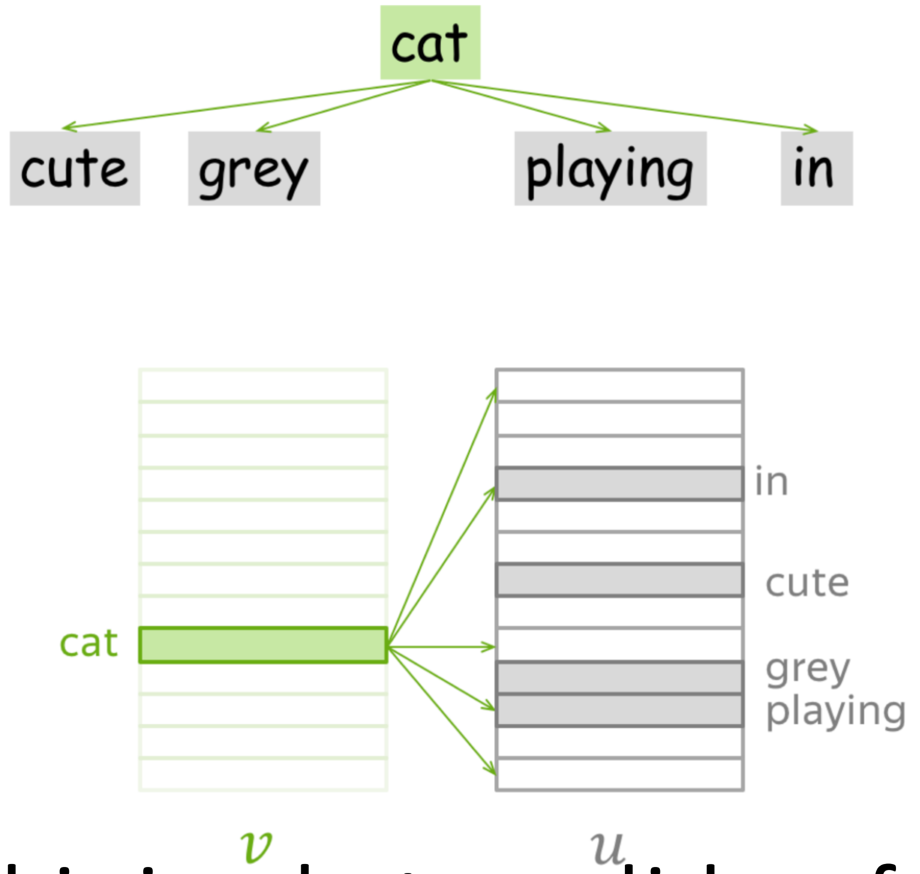
Objective Function: Intuition (Why It Works)

- Likelihood = probability of seeing all context words given their center words.
- Log-likelihood = makes computation manageable.
- Negative log-likelihood = the loss function we minimize, so embeddings improve.

Word2Vec Variants: Skip-Gram and CBOW

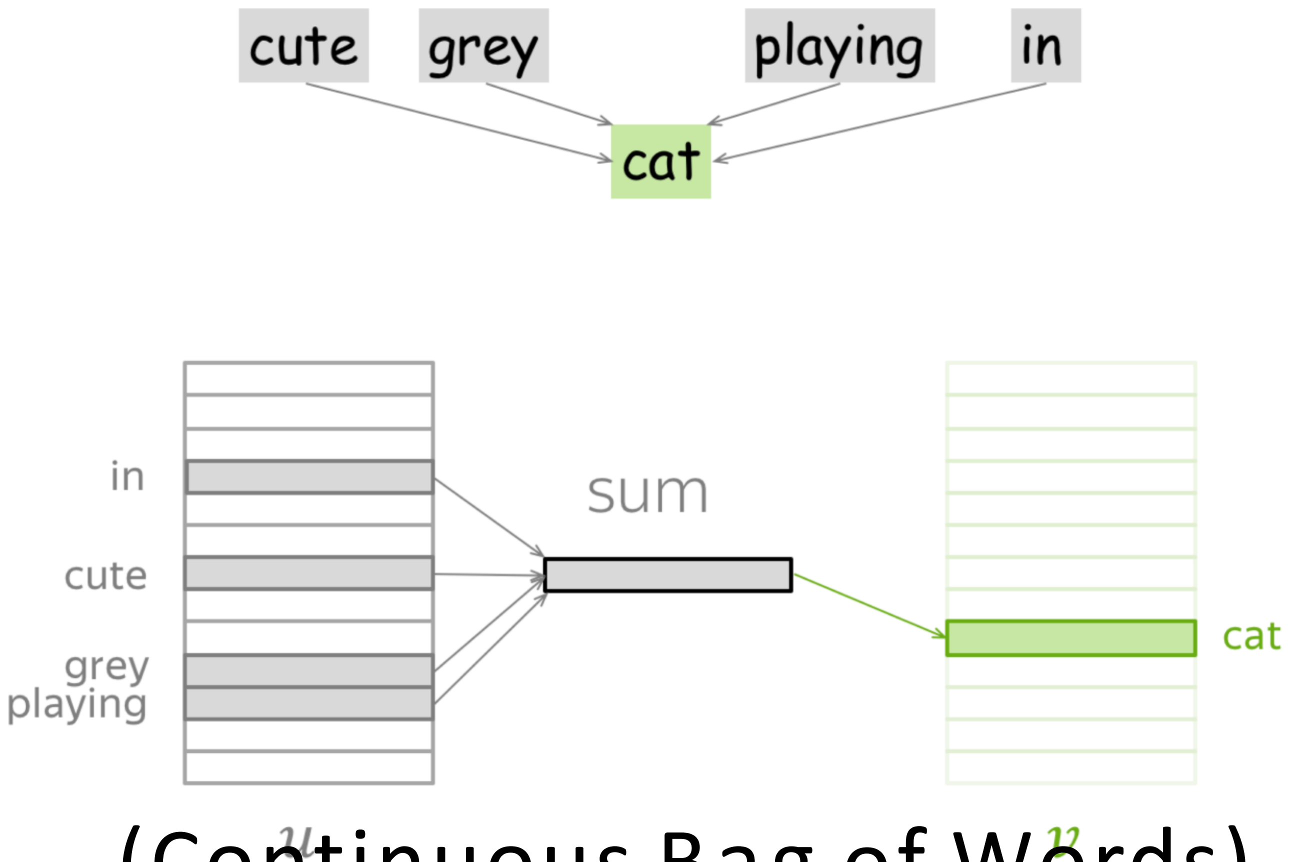
… I saw a cute grey cat playing in the garden …

Skip-Gram: from central predict context
(one at a time)



(this is what we did so far)

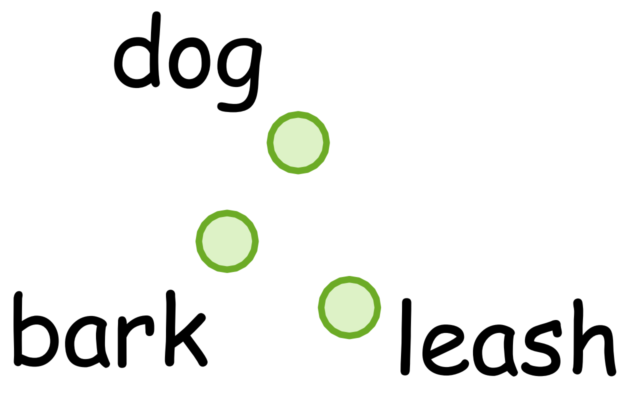
CBOW: from sum of context predict central



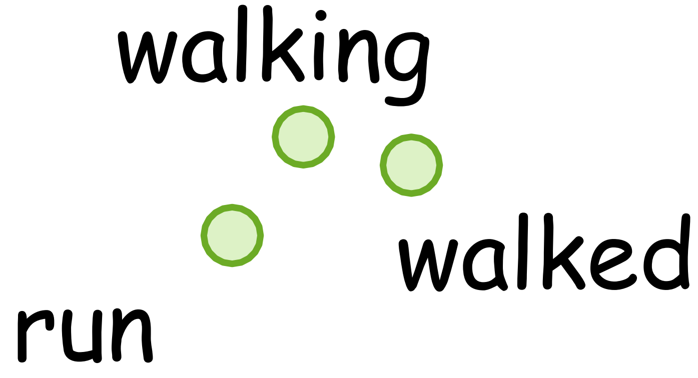
(Continuous Bag of Words)

The Effect of Context Window Size

- Larger windows – more topical similarities

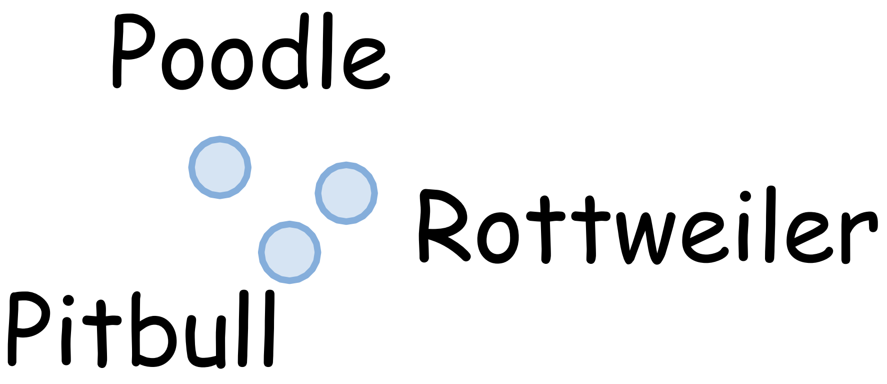


(grouped together)



(grouped together)

- Smaller windows – more functional and syntactic similarities



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