الجامعة السورية الخاصة
SYRIAN PRIVATE UNIVERSITY

الذكاء الصنعي العملي	كلية الهندسة	المحاضرة الثانية

Introduction to Generative AI & LLMs
Embedding Concept 2 / intro to Transformers

د. رياض سنبل

Word Embedding

- An embedding maps each word to a point in a much smaller m-dim space (e.g. 300 values)
- Two approaches:
  - **Learn the embedding jointly with your main task:**
    - An embedding layer with m hidden nodes to map word IDs to an m-dim vector.
    - Add your hidden layer and output layer, learn weights end-to-end with SGD.
  - **Use pre-trained embedding:**
    - Usually trained on another, much bigger dataset.
    - Freeze embedding weights to produce simple word embedding.

Training Embedding Layer

- Input layer use fixed length document (e.g. 100 nodes for 100 word IDs).
  - Pad with 0's is doc is shorter.
- Add an embedding layer to learn embeddings:
  - (1) Represent every word as an n-dim one hot encoding BOW.
  - (2) Learn an m-dim embedding using m-hidden nodes.
    - Learn weight matrix W(n*m) to map one hot encoded word to embedding.
  - (3) Use Linear activation function => $X_{embed} = W. X_{orig}$
- Add a layer to map word embedding to desired output.
- Learn all weights from labeled data.

Pre-trained embeddings

- More data => better embeddings BUT also **more labels**!
- **Solution**: self-supervised learning
  - Given a word, predict the surrounding words.
- Most common approaches:
  - **Word2vec:** learn neural embedding for word based on surrounding words.
  - **GloVe (Global Vector):** Count co-occurences of words in matrix.
  - **FastText:** learns embedding for character n-gram
  - Language models: learn context-dependenct embedding.
    - **BERT**, **ELMO**, **GPT3**

Skip-grams

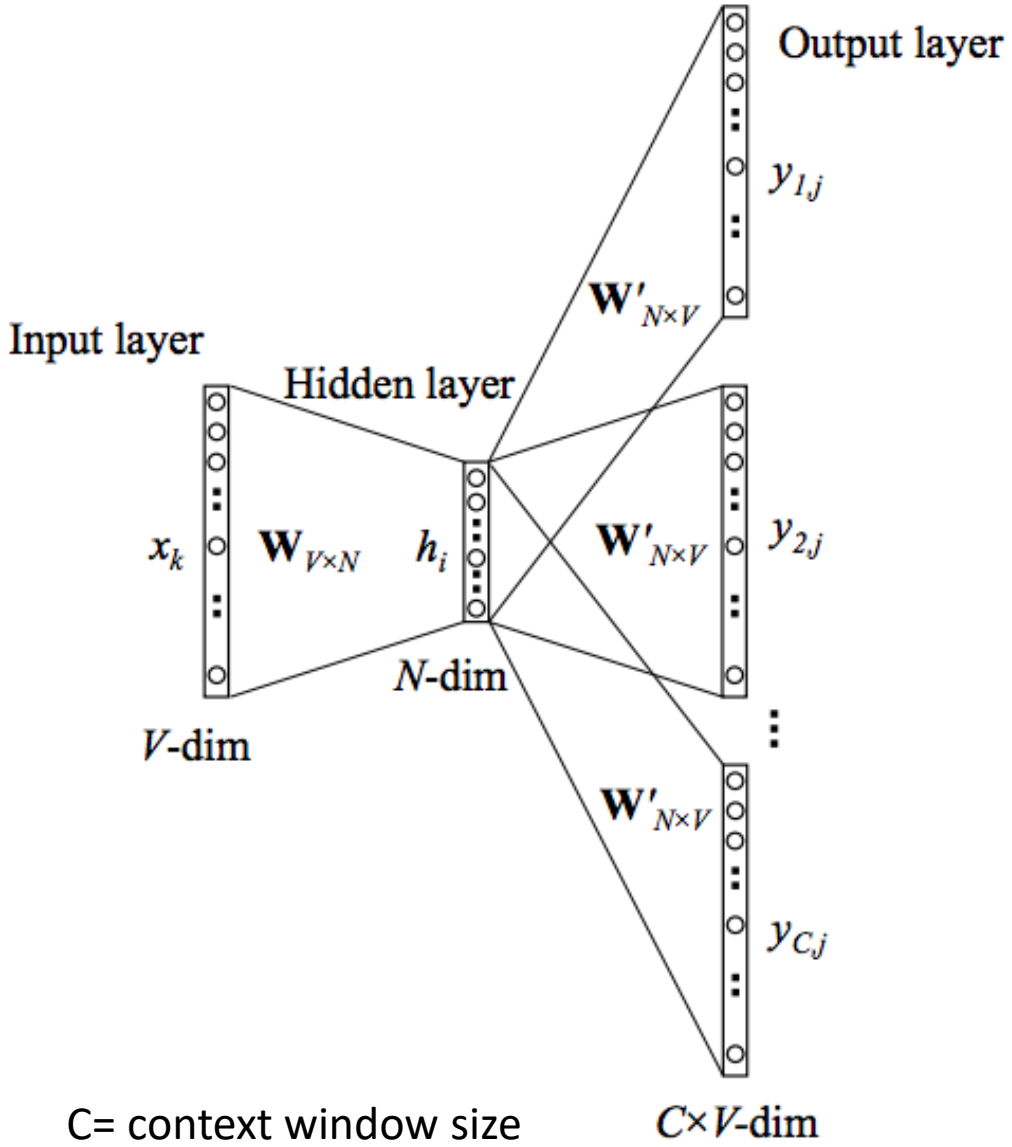
- We can also analyze the meaning of a particular word by looking at the contexts in which it occurs.
- The context is the set of words that occur near the word, i.e. at displacements of …,-3,-2,-1,+1,+2,+3,… in each sentence where the word occurs.
- A skip-gram is a set of non-consecutive words (with specified offset), that occur in some sentence.
- We can construct a BoSG (bag of skip-gram) representation for each word from the skip-gram table.
  - Example?

word2Vec: Local contexts

- Instead of entire documents, ***Word2Vec*** uses words ***k*** positions away from each center word.
  - These words are called **context words**.
- Example for ***k=3***:
  - "It was a bright cold day in April, and the clocks were striking".
  - Center word: red (also called focus word).
  - Context words: blue (also called target words).
- Word2Vec considers all words as center words, and all their context words.

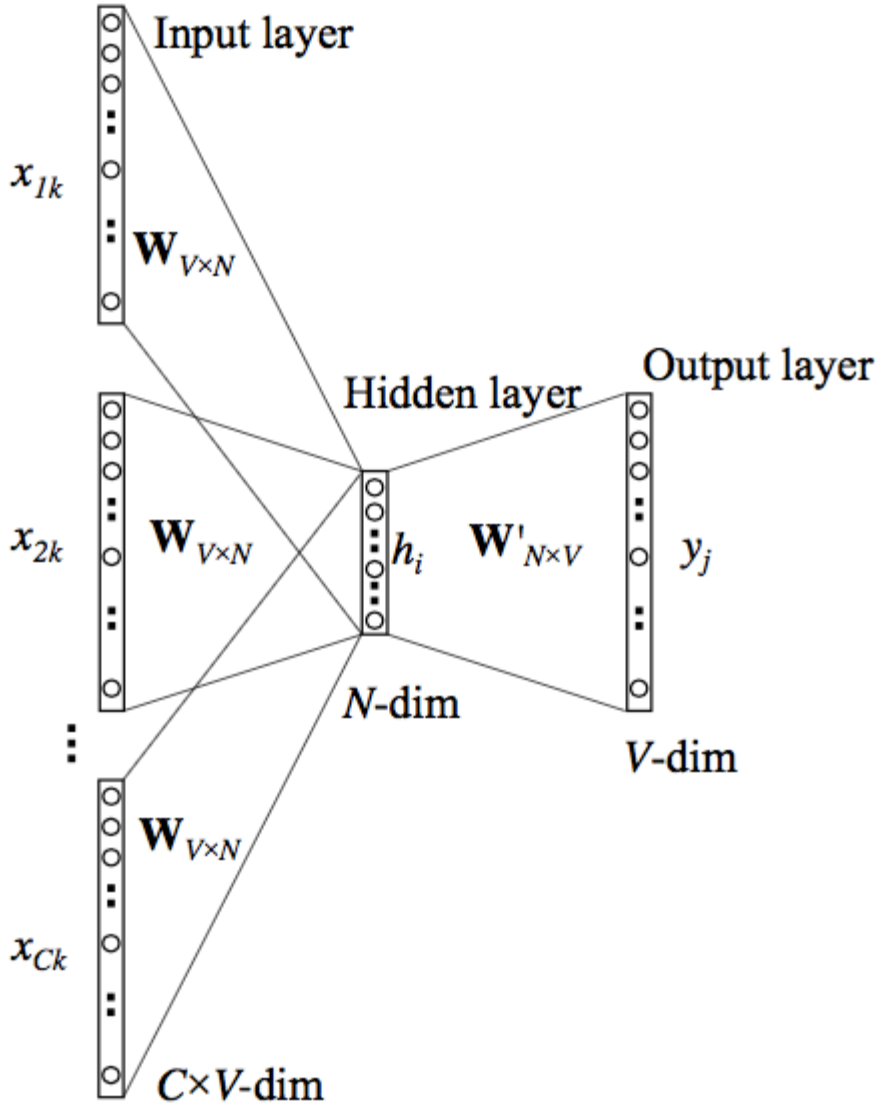
The skip-gram model

- Vocabulary size: V
- Input layer: center word in 1-hot form.
- k-th row of W_{VxN} is **center** vector of k-th word.
- k-th column of W'_{NXV} is **context** vector of the k-th word in V.
- **Note, each word has 2 vectors, both randomly initialized.**
- The output column y_{ij}, i=1..C, has 3 steps
  1) Use the context word 1-hot vector to choose its column in W'_{NxV}
  2) dot product with h_i the center word
  3) compute the softmax

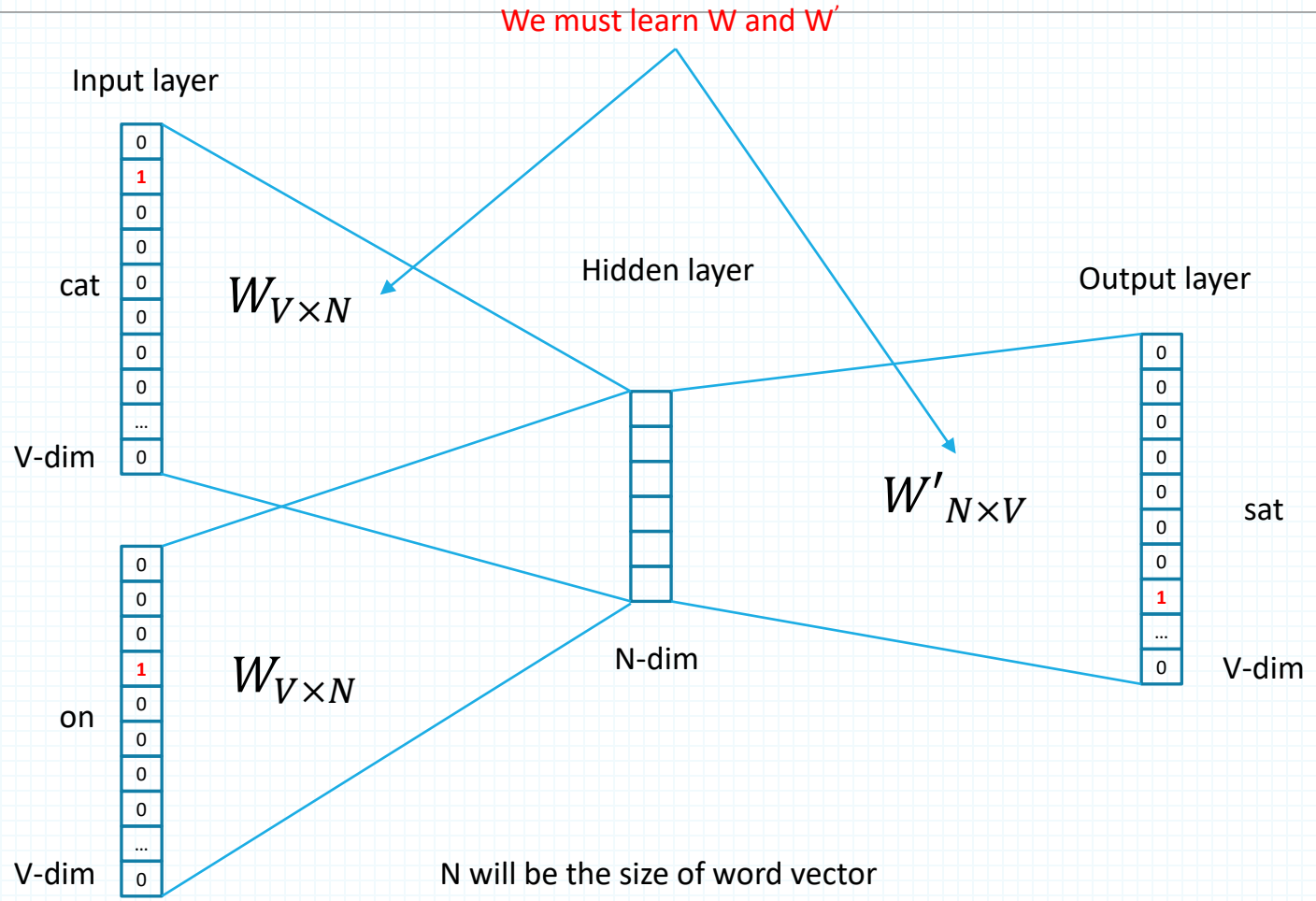


CBOW

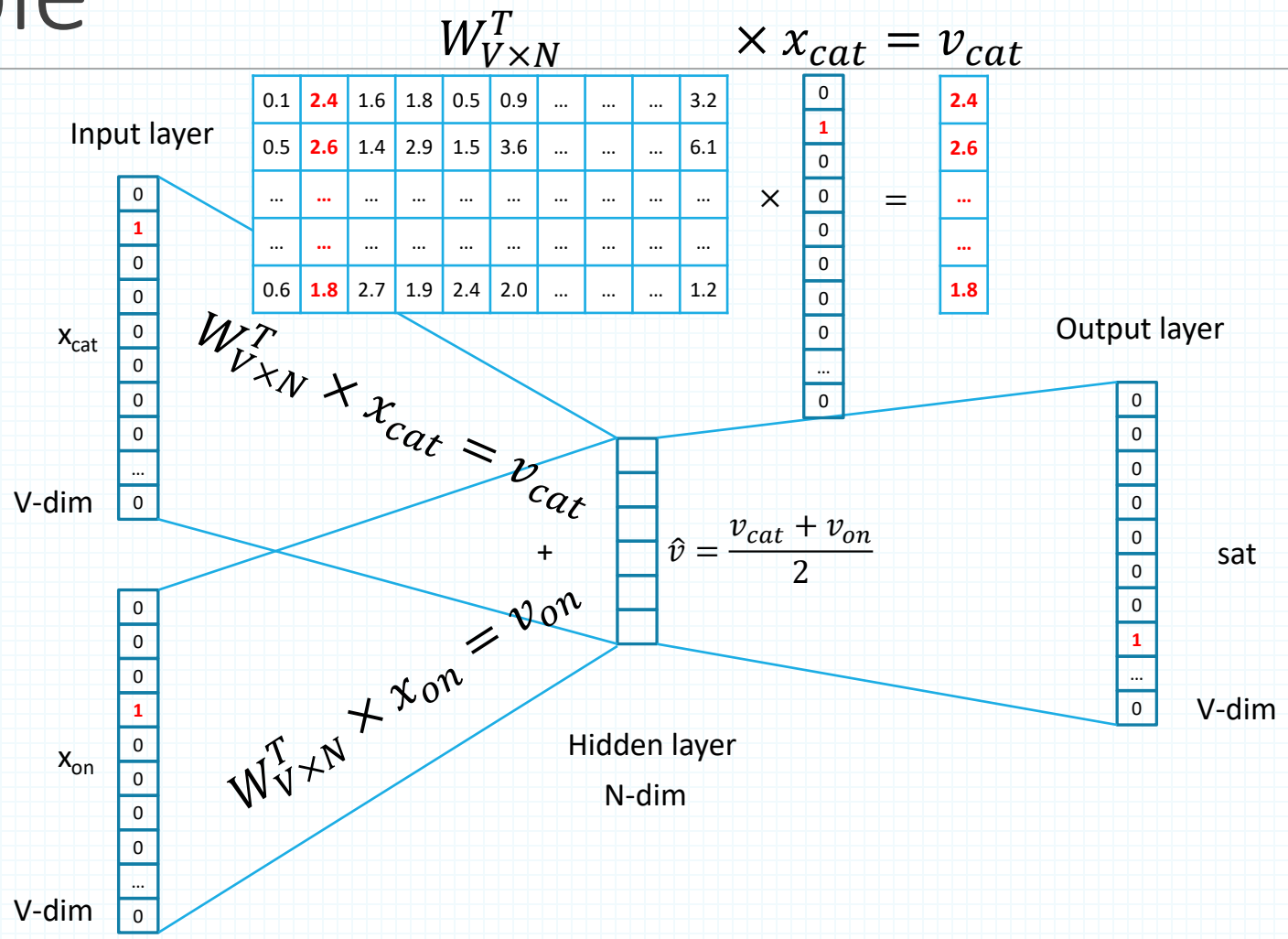
- What about we predict center word, given context word, opposite to the skip-gram model?
- Yes, this is called **Continuous Bag Of Words model** in the original Word2Vec paper.



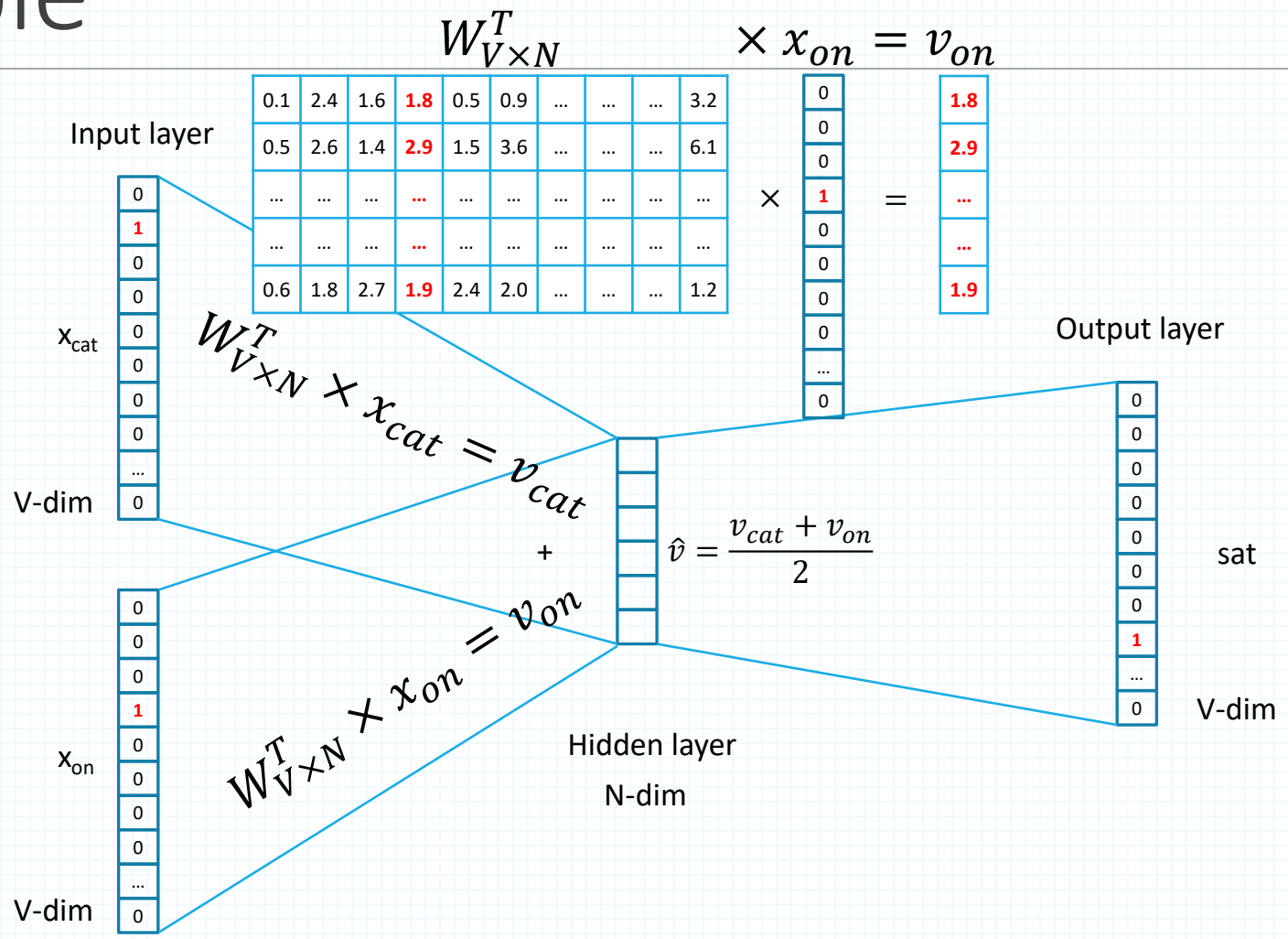
Example


We must learn W and W'
Input layer
cat
V-dim
on
V-dim
$W_{V\times N}$
$W_{V\times N}$
Hidden layer
N-dim
$W'_{N\times V}$
Output layer
sat
V-dim
N will be the size of word vector

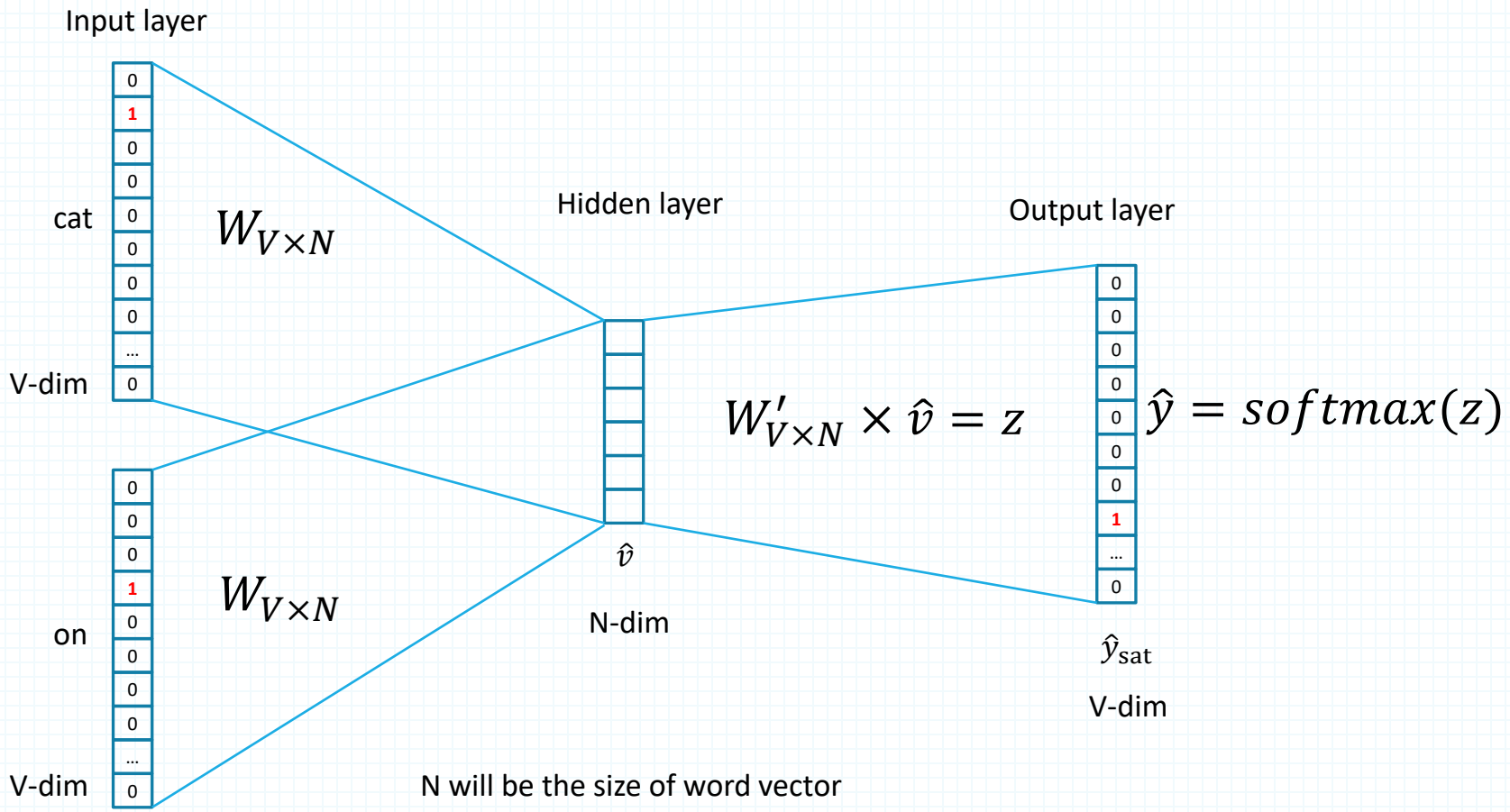
Example


$W^T_{V\times N}$
$\times x_{cat} = v_{cat}$
Input layer
x_{cat}
V-dim
$W^T_{V\times N} \times x_{cat} = v_{cat}$
+
$W^T_{V\times N} \times x_{on} = v_{on}$
x_{on}
V-dim
$\hat{v} = \frac{v_{cat} + v_{on}}{2}$
Hidden layer
N-dim
Output layer
sat
V-dim

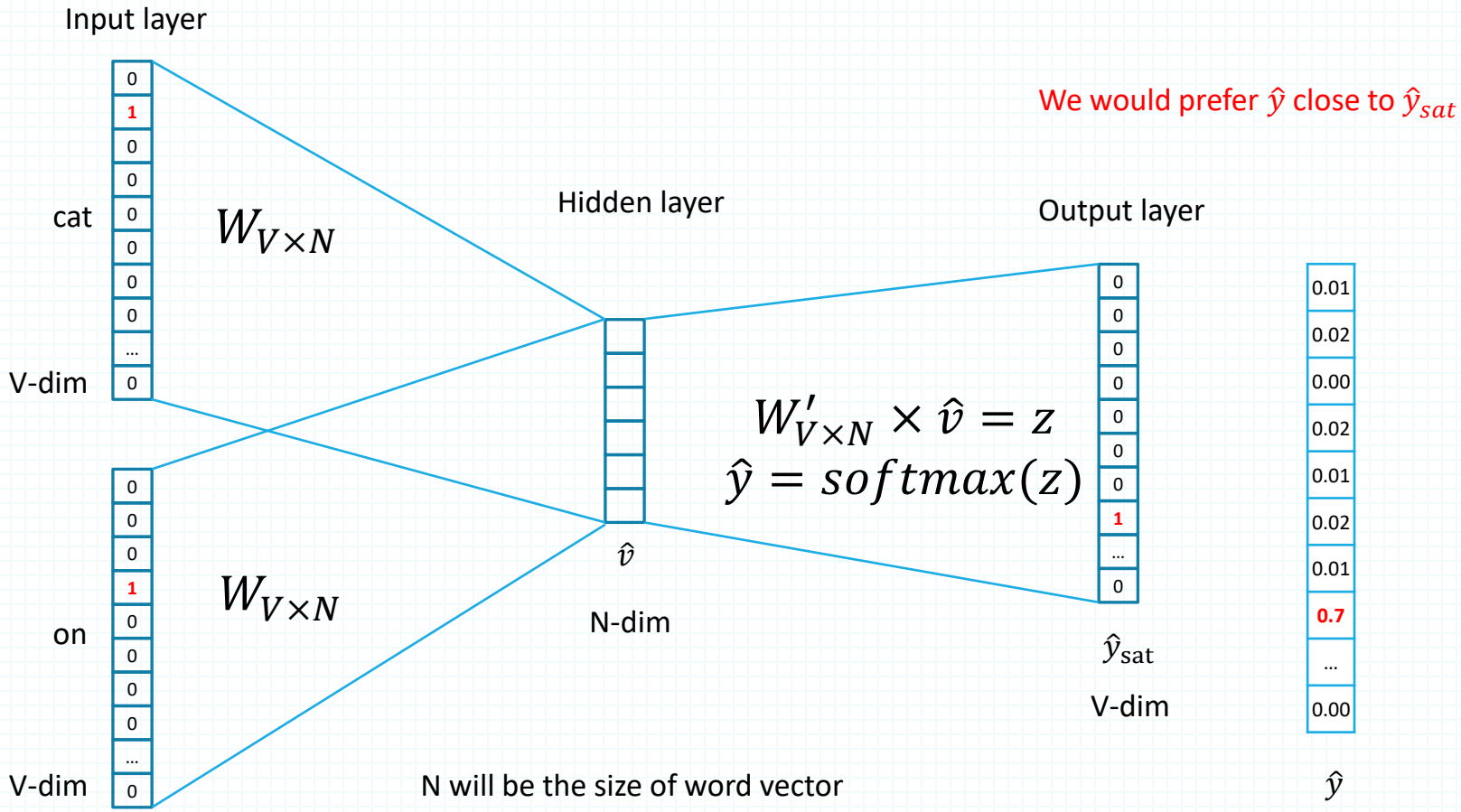
Example


$W^T_{V\times N}$
$\times x_{on} = v_{on}$
Input layer
x_{cat}
V-dim
x_{on}
V-dim
$W^T_{V\times N} \times x_{cat} = v_{cat}$
+
$W^T_{V\times N} \times x_{on} = v_{on}$
$\hat{v} = \frac{v_{cat} + v_{on}}{2}$
Hidden layer
N-dim
Output layer
sat
V-dim

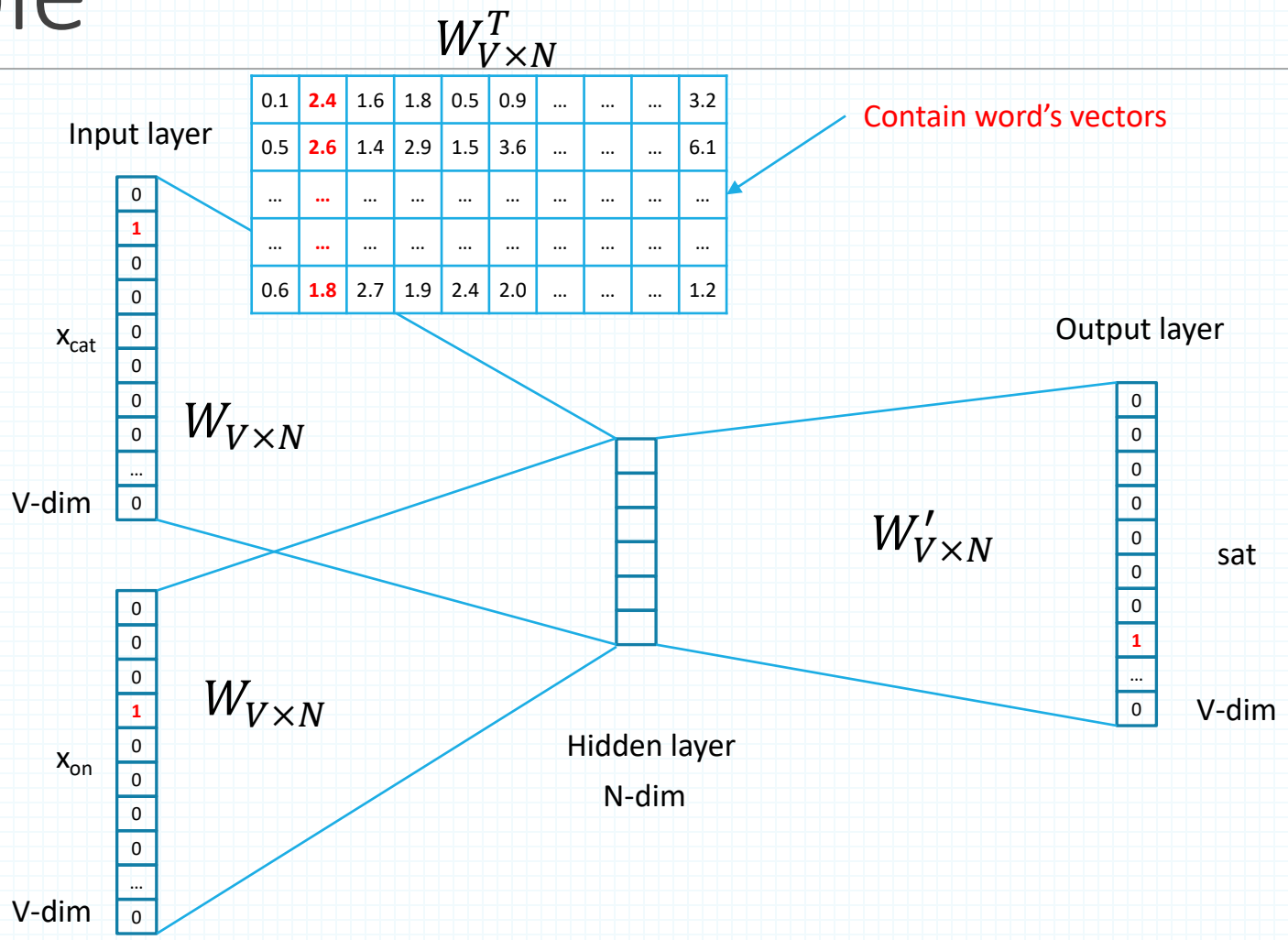
Example


Input layer
cat
V-dim
on
V-dim
$W_{V\times N}$
$W_{V\times N}$
Hidden layer
$\hat{v}$
N-dim
$W'_{V\times N} \times \hat{v} = z$
Output layer
$\hat{y} = softmax(z)$
$\hat{y}_{sat}$
V-dim
N will be the size of word vector

Example


Input layer
cat
V-dim
on
V-dim
$W_{V\times N}$
$W_{V\times N}$
Hidden layer
$\hat{v}$
N-dim
$W'_{V\times N} \times \hat{v} = z$
$\hat{y} = softmax(z)$
Output layer
$\hat{y}_{sat}$
V-dim
We would prefer $\hat{y}$ close to $\hat{y}_{sat}$
$\hat{y}$
N will be the size of word vector

Example



We can consider either W or W' as the word's representation. Or even take the average.

Using Pretrained Model

Do I need to Train Word2Vec?

- Answer: NO!
- You can download pre-trained Word2Vec models trained on massive corpora of data.
- Common example: Google News Vectors, 300 dimensional vecto for 3 million words, trained on Google News articles.
- File containing vectors (1.5 GB) can be downloaded for free and easily loaded into gensim.

```
from gensim.models import Word2Vec
import gensim.downloader as api
v2w_model = v2w_model = api.load('word2vec-google-news-300')
sample_word2vec_embedding=v2w_model['computer'];
```

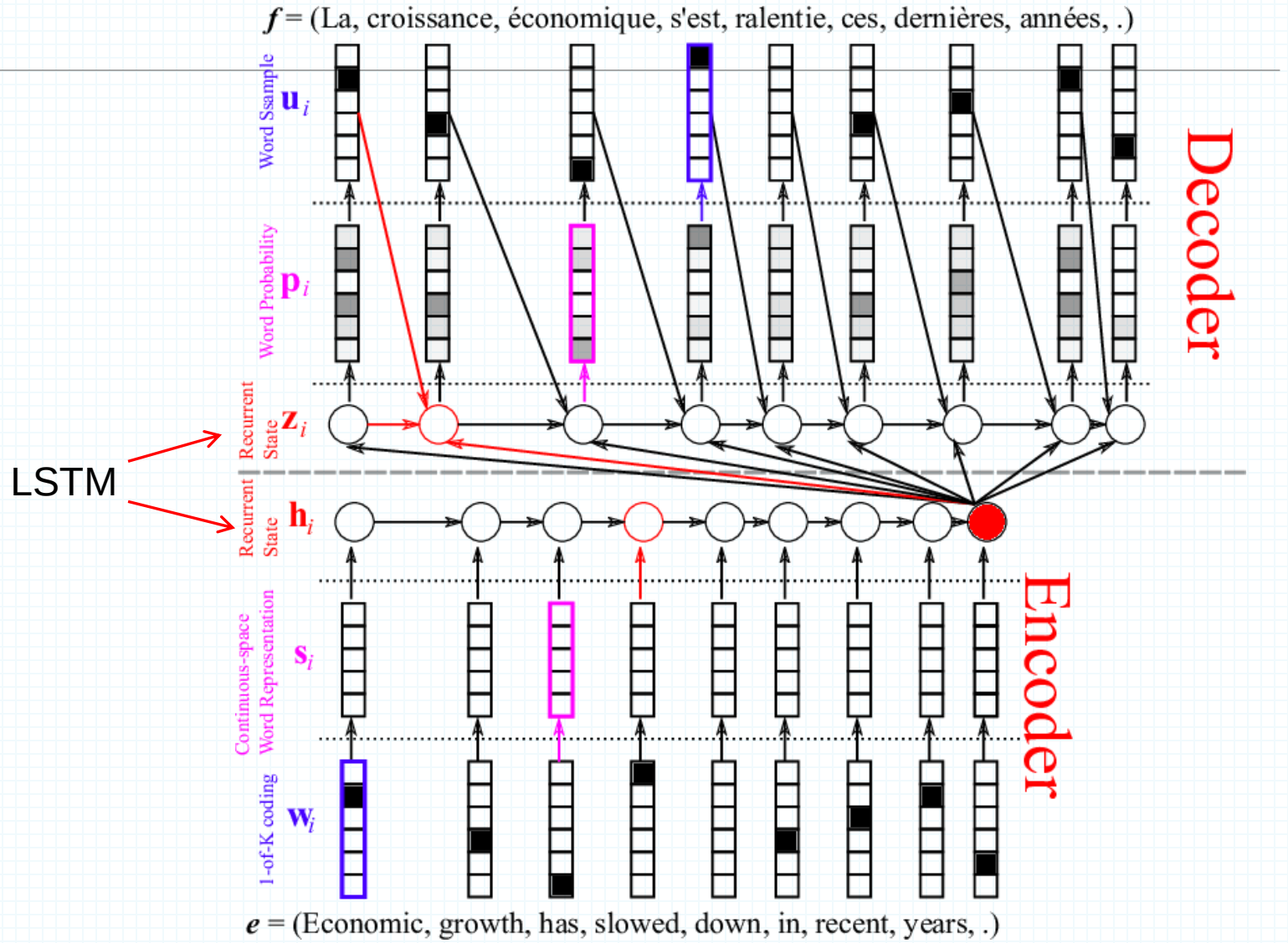
FastText

- Limitations of Word2Vec:
  - OOV problem.
  - Words like “meet” and “meeting” are learned independently (no param sharing)
- FastText use character n-gram (word hashing)
  - Basic model can be similar to word2vec model.
  - Words are represented by all char n-grams of length 3 to 6.
  - Represent words based on its n-gram embeddings.

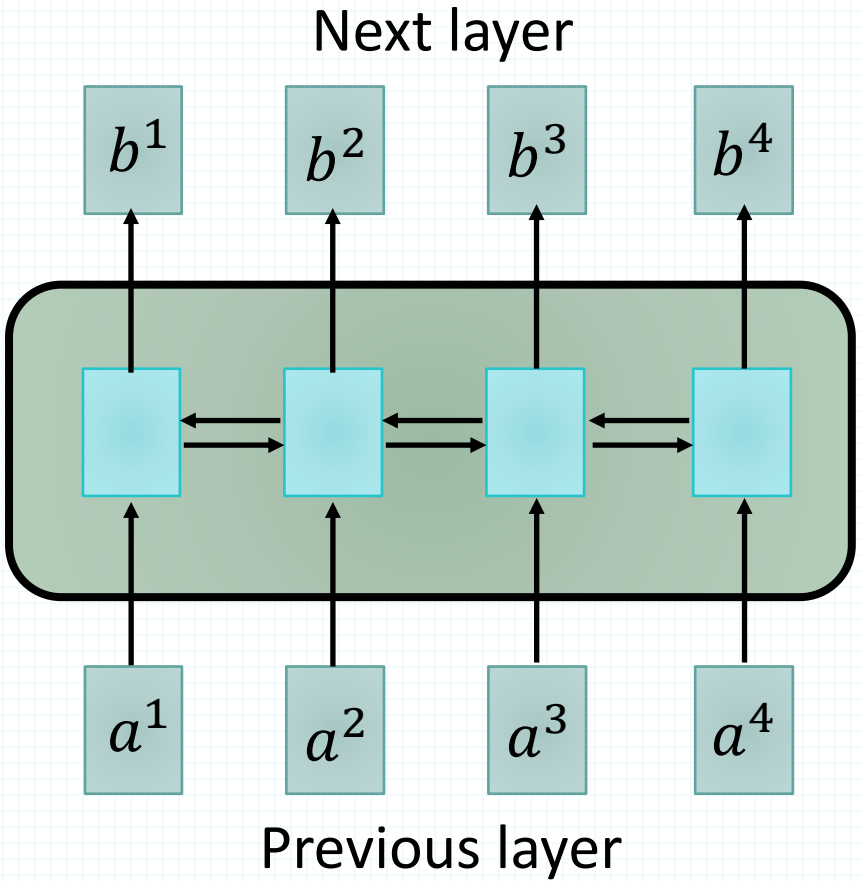
- short n-grams (n = 4) are good to capture syntactic information
- longer n-grams (n = 6) are good to capture semantic information

Transformer In *General*

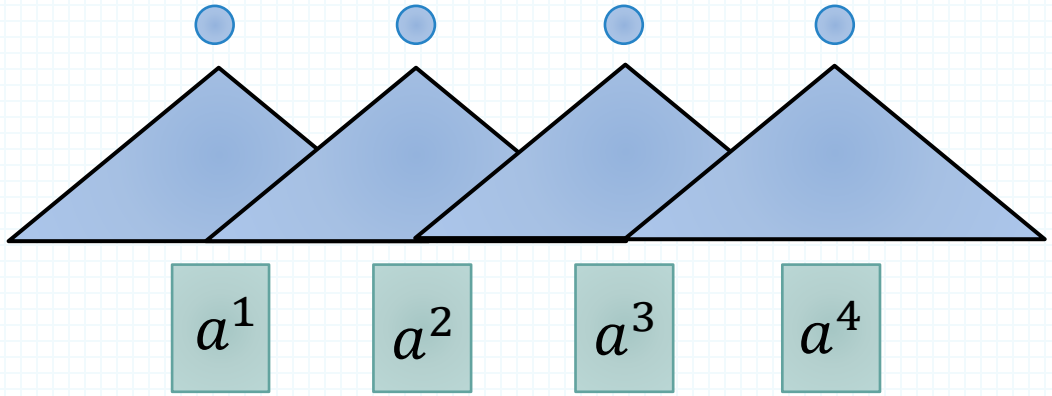
Encoder-Decoder



Sequence



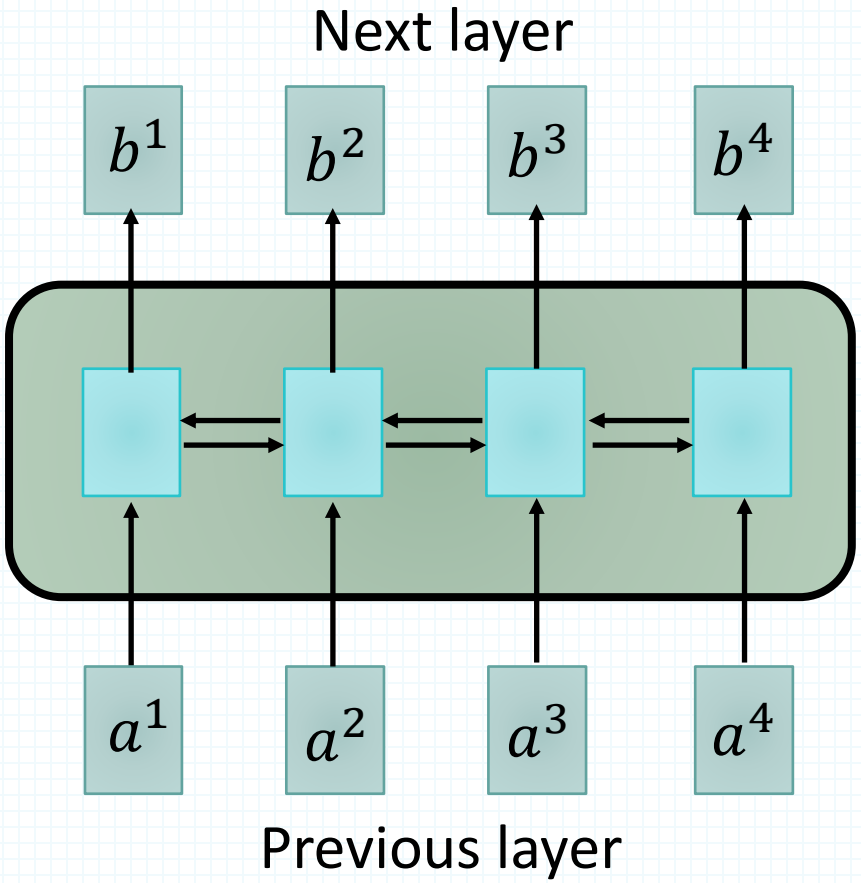
Hard to parallel !



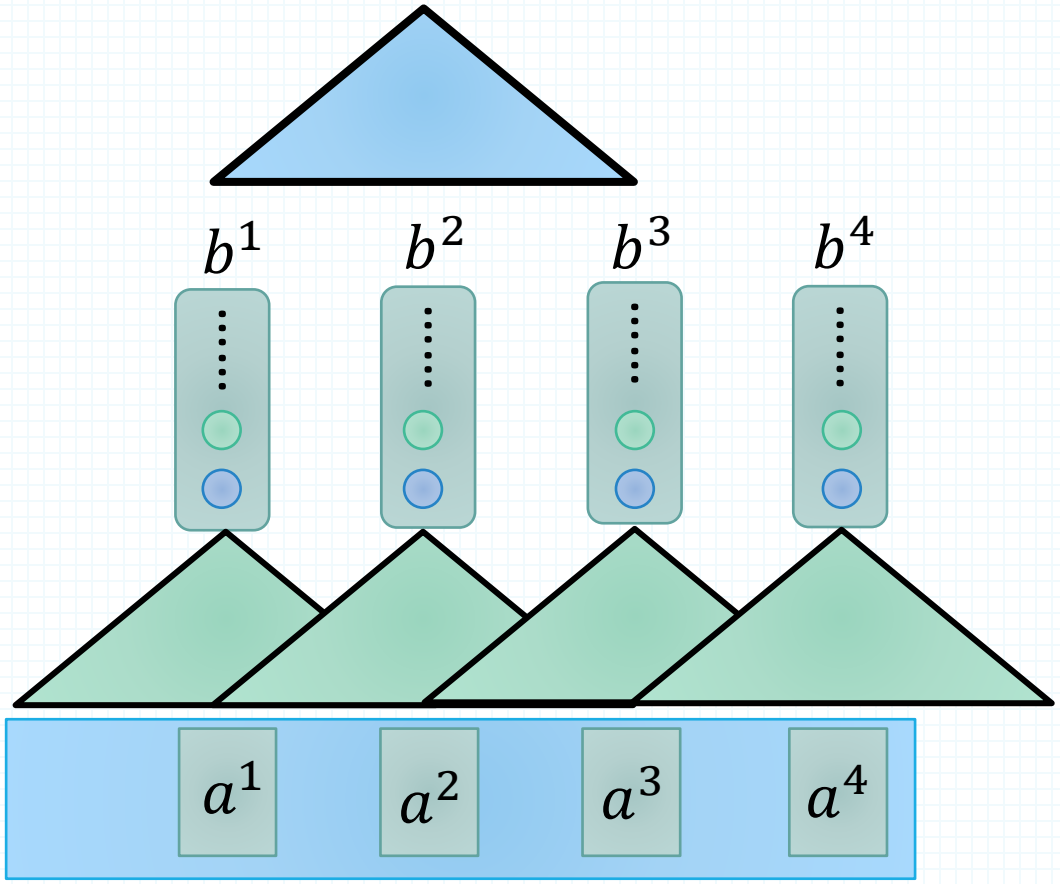
Using CNN to replace RNN

Sequence

Filters in higher layer can consider longer sequence



Hard to parallel

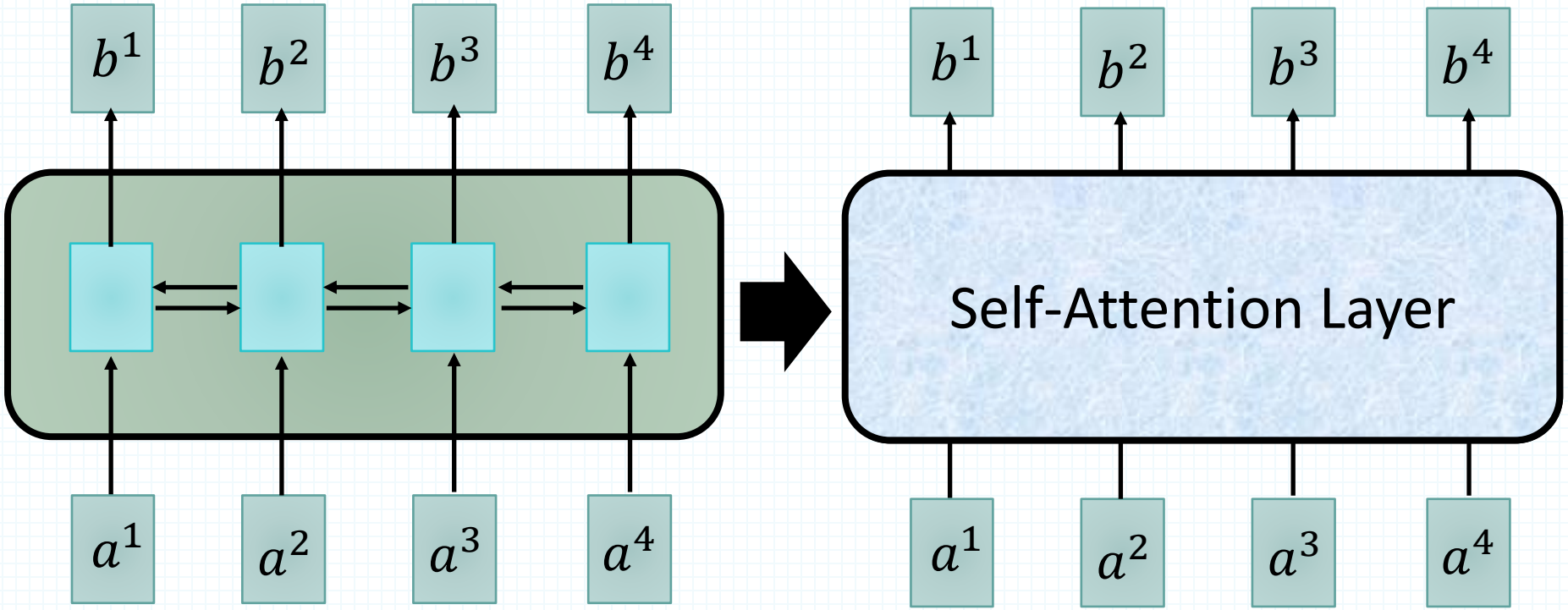


Using CNN to replace RNN (CNN can parallel)

Self-Attention

b^i is obtained based on the whole input sequence.

b^1, b^2, b^3, b^4 can be parallelly computed.



You can try to replace any thing that has been done by RNN with self-attention.

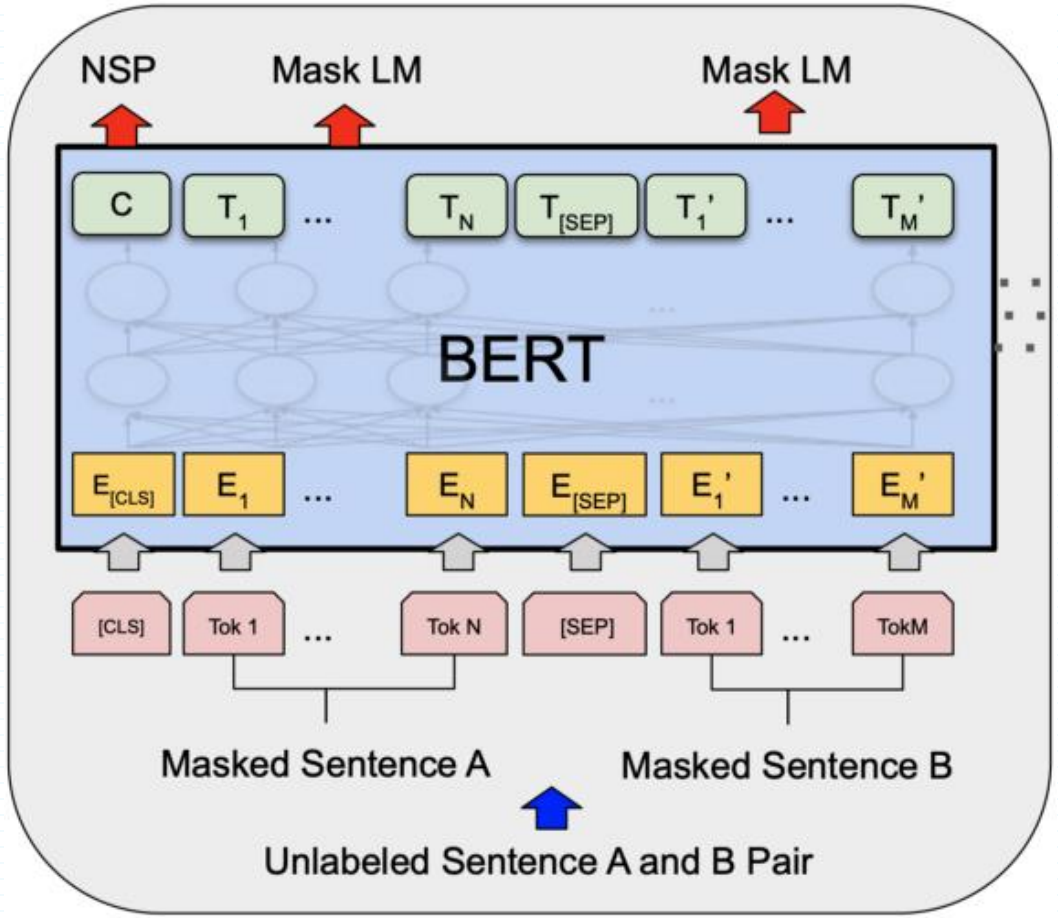
BERT

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

2018

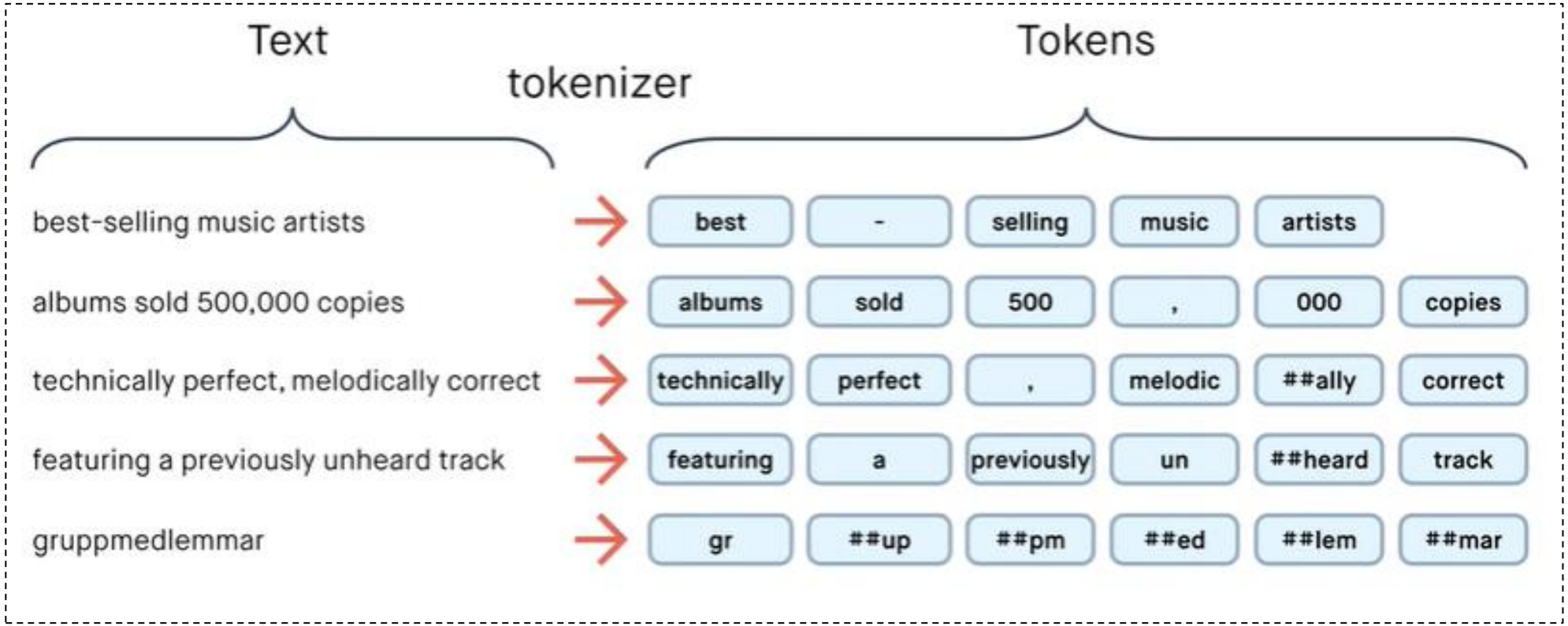
Jacob Devlin **Ming-Wei Chang** **Kenton Lee** **Kristina Toutanova**
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

Next Sentence Prediction

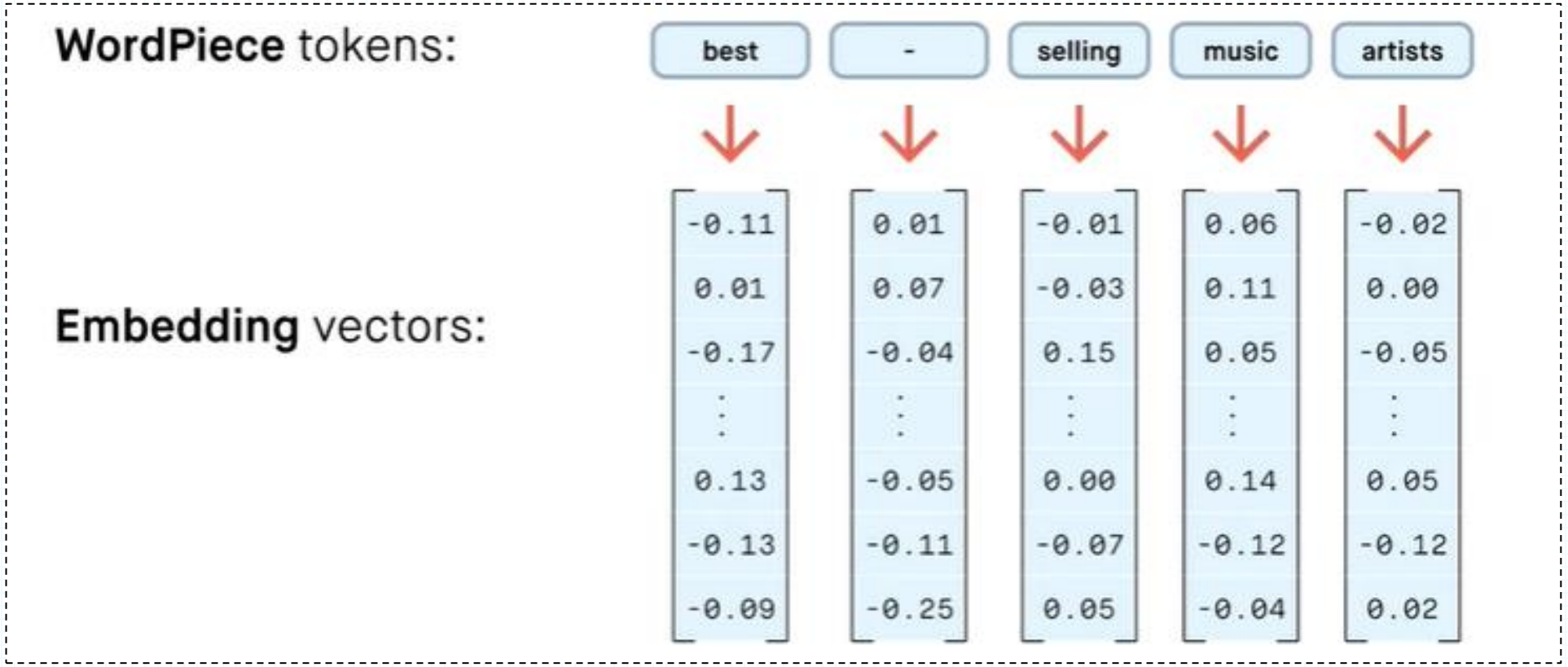


Pre-training

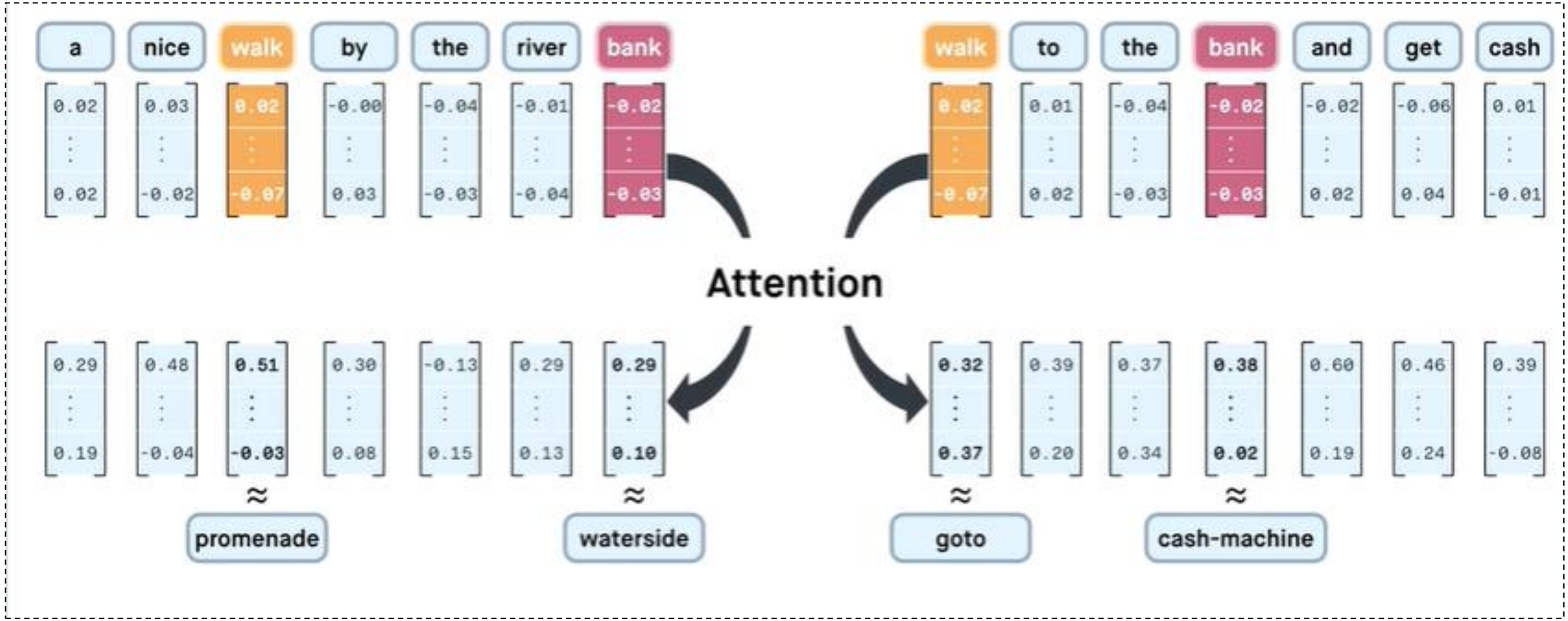
Tokenization



Initial Embedding



Contextual Embedding



How?

In the next Lectures