Machine Learning to Language Model

Topic 02 - Word Embedding

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https://jaihuayen.github.io/homeweb/

Contents

Review Bi-Gram Model

Bi-Gram Model

A Very Simple Language Model

- **Intuition:** We only predict the next word based on the previous word.
- Model the predicted probability of a certain word based on a given word.

$$P(c_i \mid c_{i-1})$$

c_i is the word in the i position.

- Here we give an example of a sentence:

$\boxed{\text{<s>}}$ AI could finally be introduced into practice in general tasks $\boxed{\text{<e>}}$

Start Token

End Token

Bi-Gram Model

A Very Simple Language Model

<s> AI could finally be introduced into practice in general tasks <e>

$$c_{i-1} \qquad\qquad c_i$$

<s> AI

Bi-Gram Model

A Very Simple Language Model

<s> $\boxed{\text{AI could}}$ finally be introduced into practice in general tasks <e>

c_{i-1} c_i

AI could

Bi-Gram Model

A Very Simple Language Model

<s> AI could finally be introduced into practice in general $\boxed{\text{tasks <e>}}$

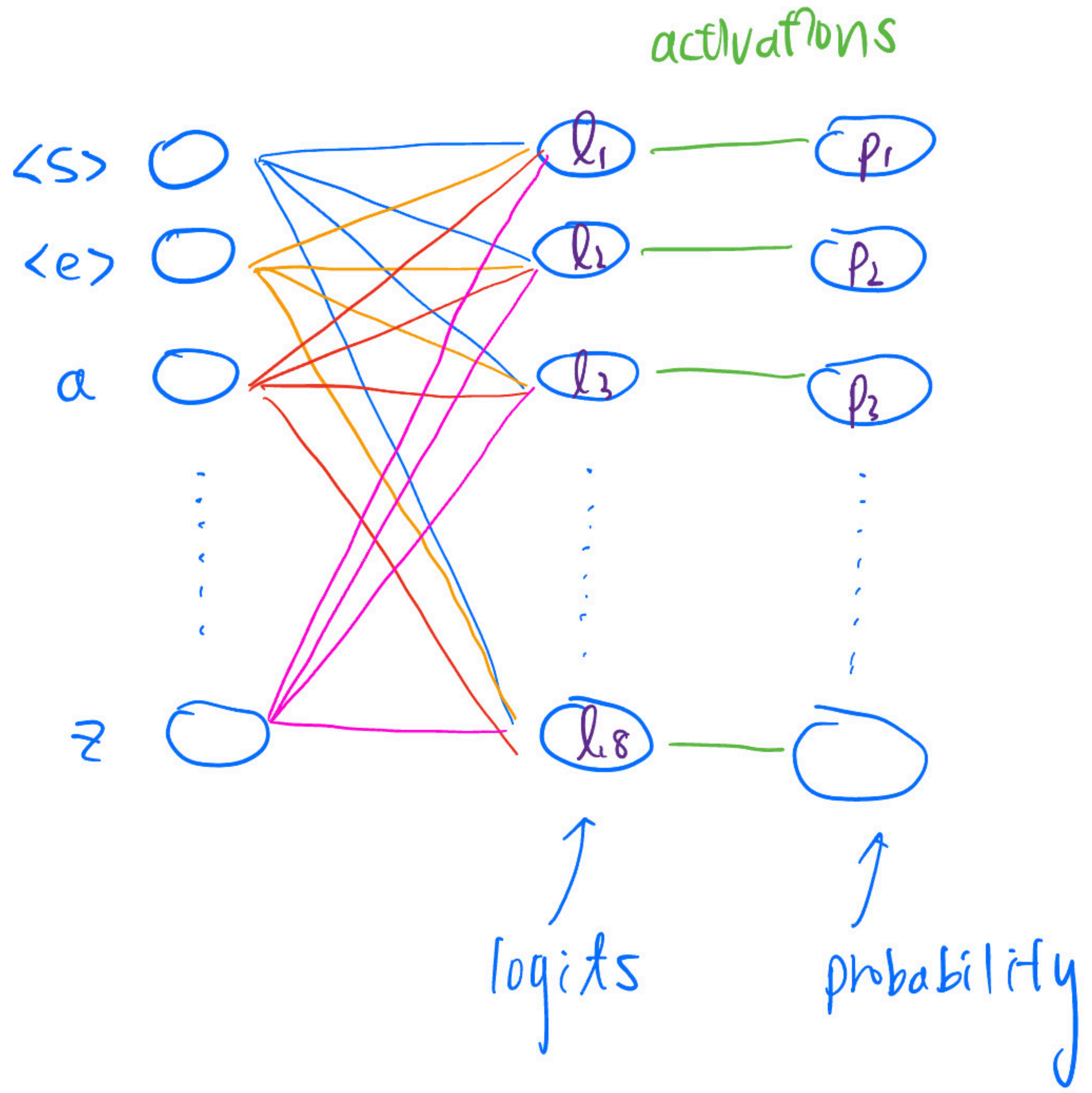
c_{i-1} c_i

tasks <e>

Bi-Gram Model

A Very Simple Language Model

- What if the features cannot be extracted only by one layer of neural network?

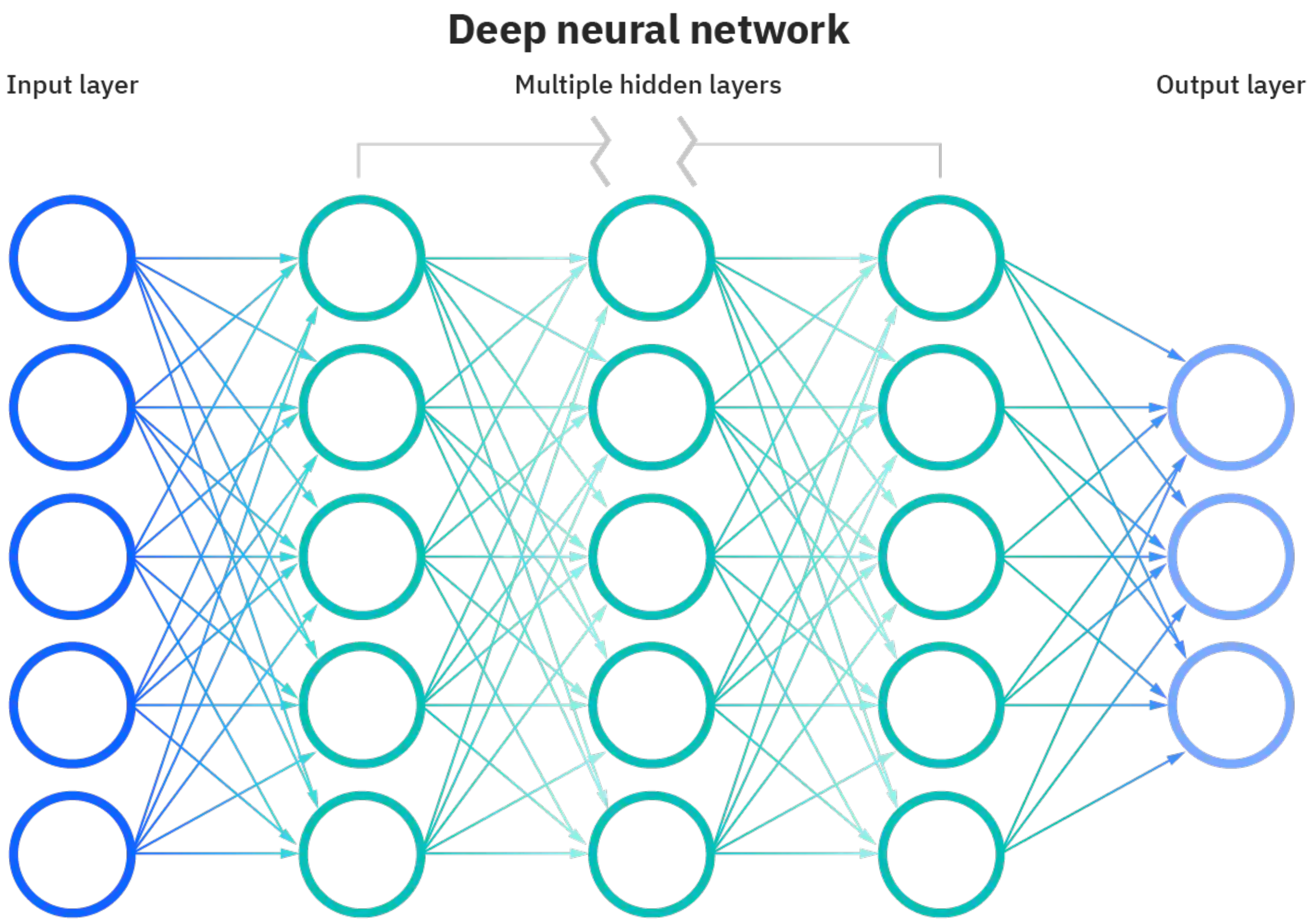


$$p_i = \frac{e^{l_i}}{\sum_{i=1}^{28} e^{l_i}}$$

Deep Neural Network

What Deeper?

- Deep Neural Networks (DNN) extract text semantics meanings on a deeper level.



https://www.ibm.com/cloud/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks

Word Embedding

Word Embedding

Word Representation

- From all the experiments above, we all use one-hot encodings.

$$v_{dog} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \qquad v_{cat} = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

Word Embedding

Word Representation

- However, we cannot extract the meaning between those two words.

$$v_{dog} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \qquad v_{cat} = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

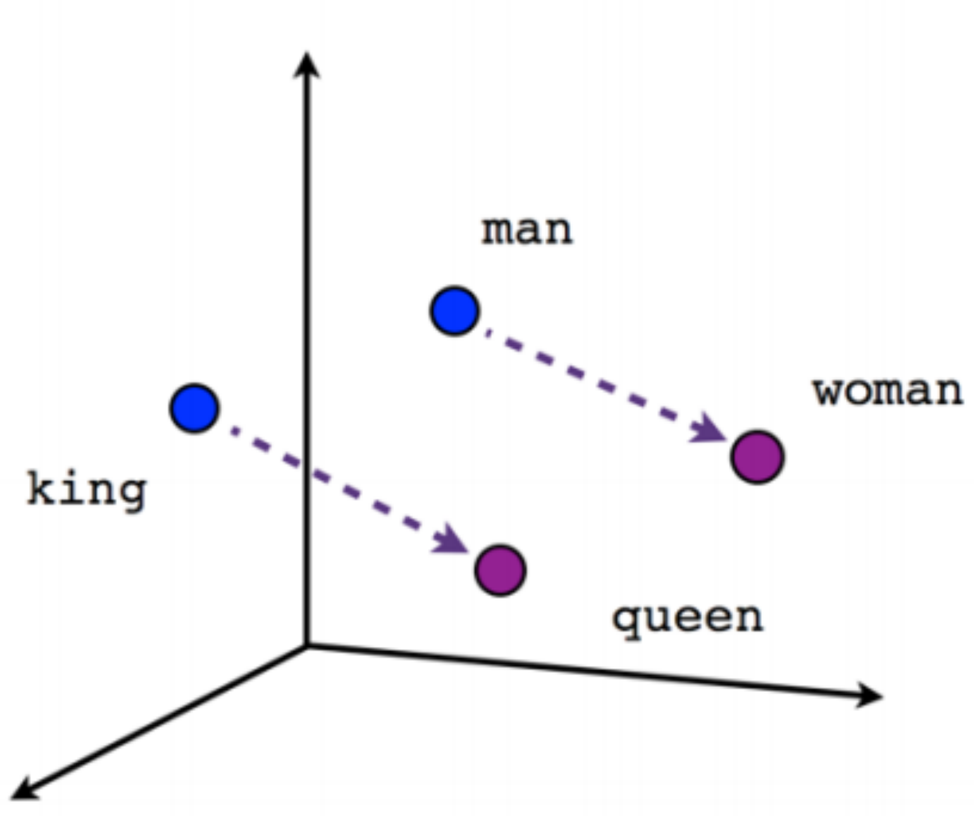
$$\cos(\theta) = \frac{v_{dog}^T v_{cat}}{\|v_{dog}\| \|v_{cat}\|} = 0$$

$$\cos(\theta) = \frac{v_{dog}^T v_{table}}{\|v_{dog}\| \|v_{table}\|} = 0$$

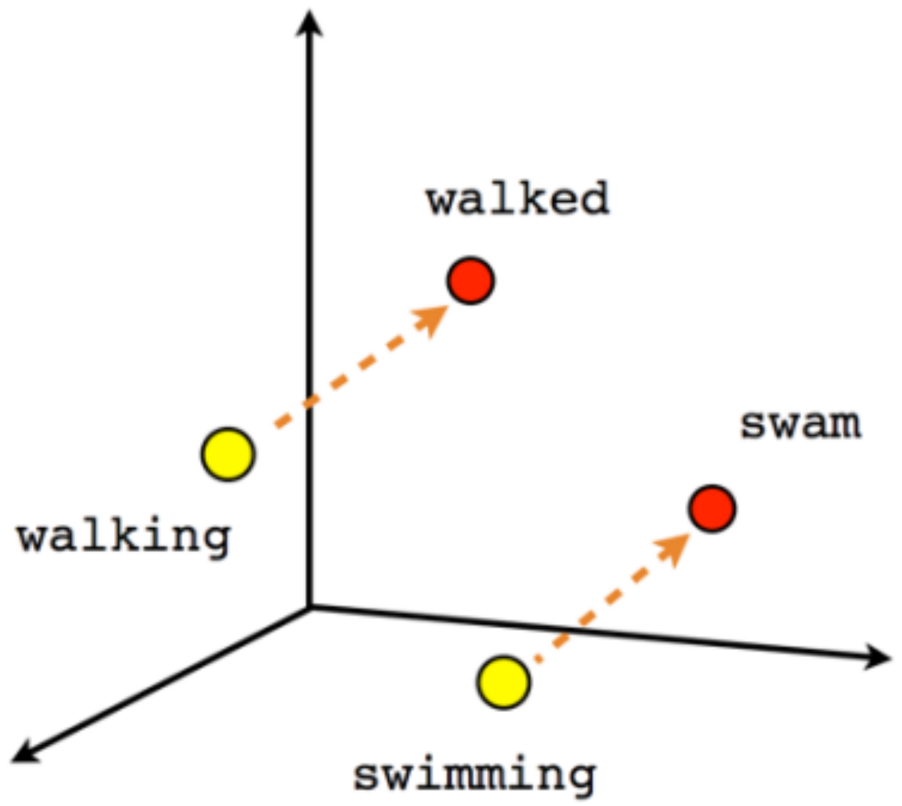
Word Embedding

Word Representation

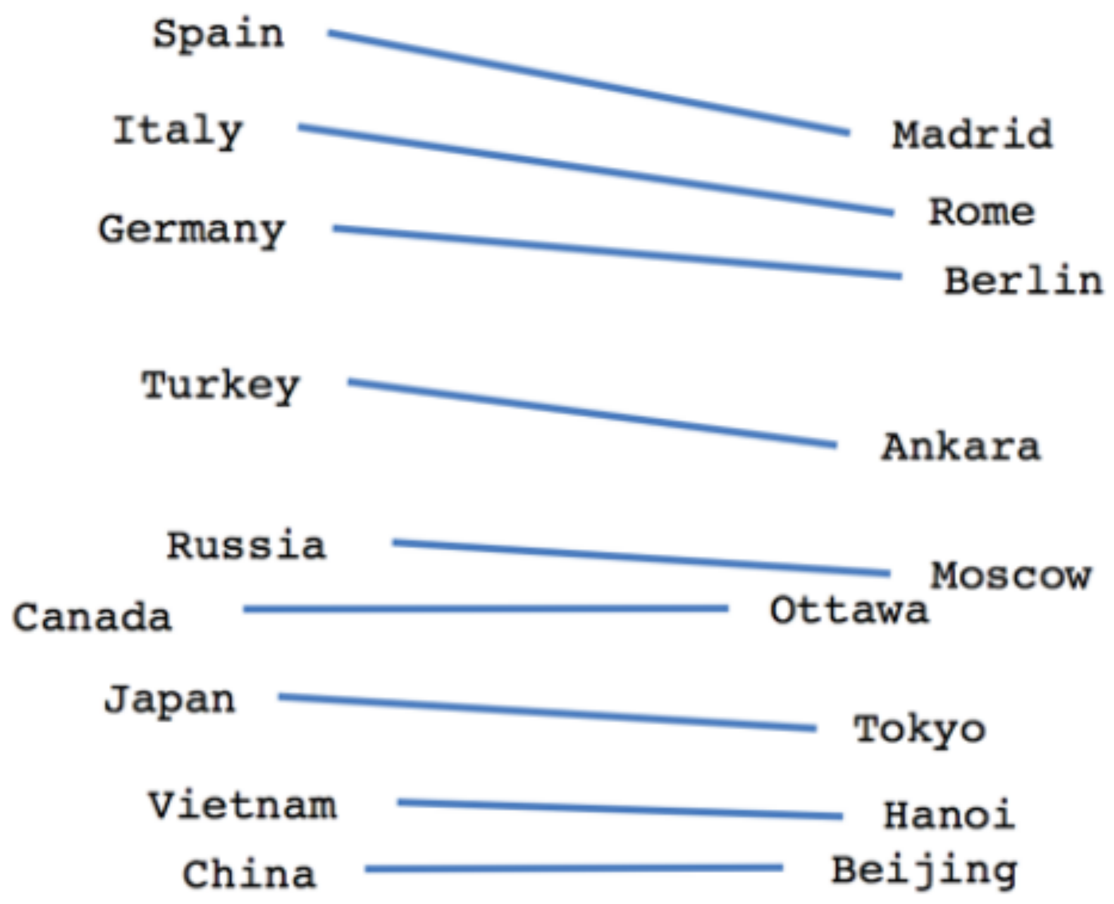
- Word embedding uses a vector representation which could indicate the semantic relationship between words.



Male-Female



Verb tense



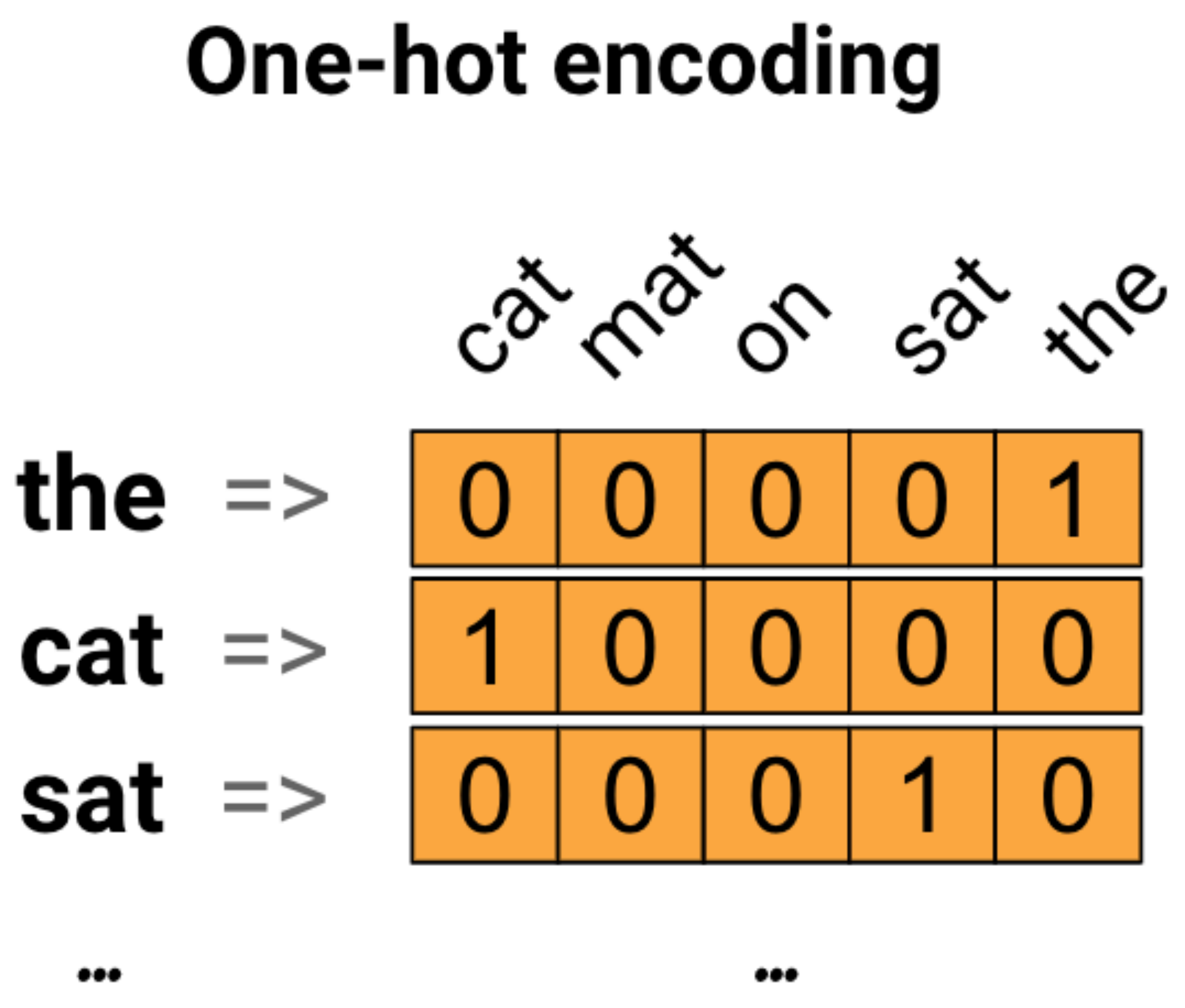
Country-Capital

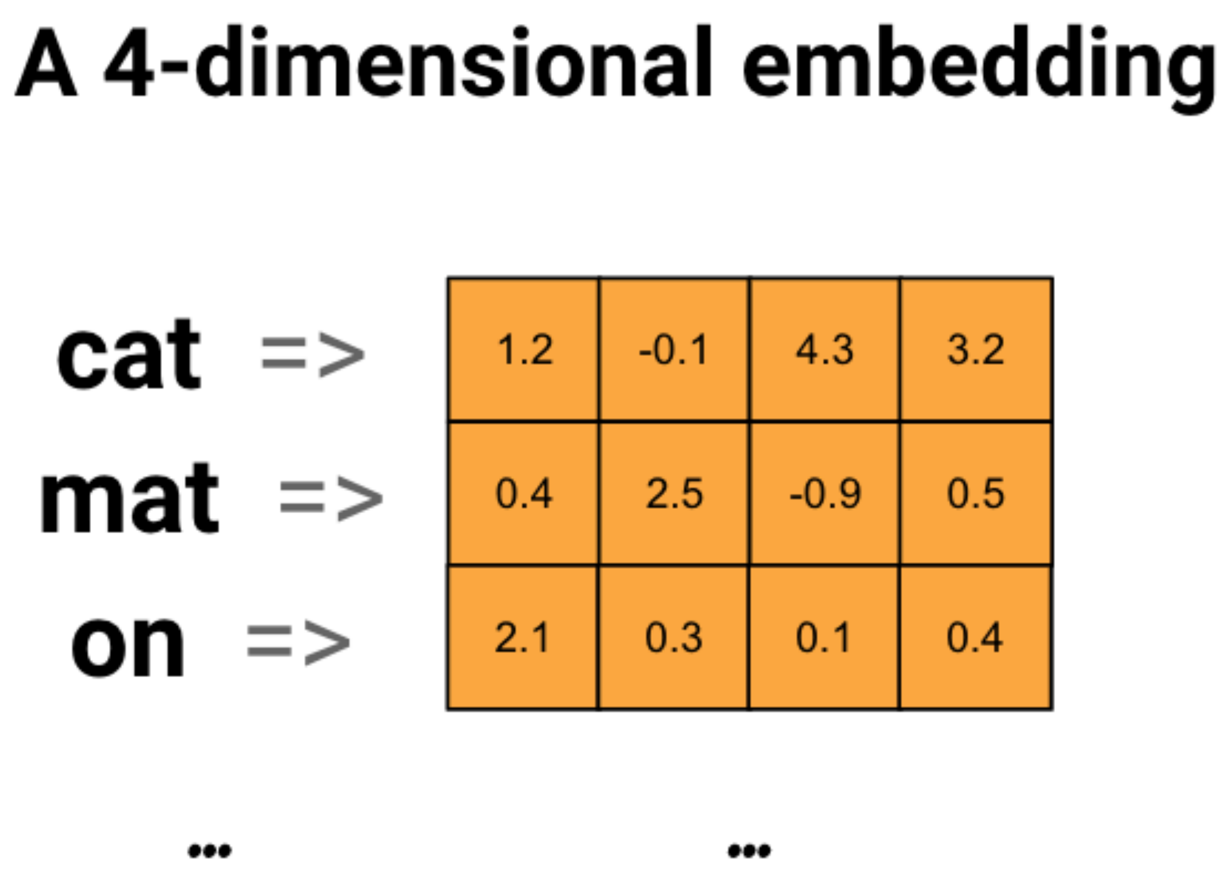
https://leemeng.tw/find-word-semantic-by-using-word2vec-in-tensorflow.html

Word Embedding

Advantages using word embeddings

- Find the semantic relationship between words.
- Map a high-dimensional one-hot encoding vector to a lower-dimensional word embedding vector



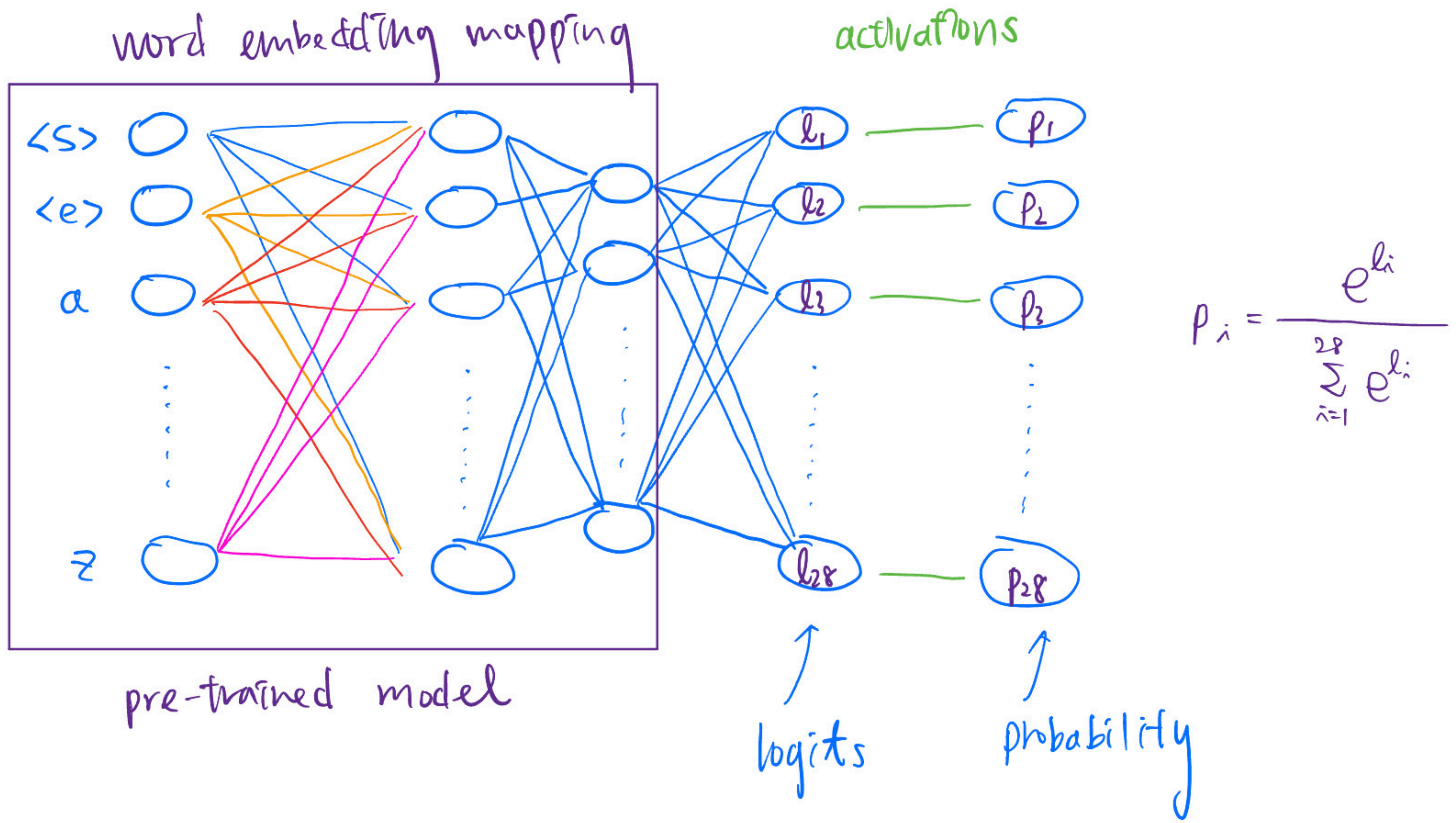


https://www.tensorflow.org/text/guide/word_embeddings

How to Train Word Embedding?

Deep Neural Network

Word embedding layer is in the hidden layer of DNN



Let’s do this in Colab!

Questions

- What if we have a massive dataset that cannot fit in memory?
- How can we compute gradient with more than one hidden layer?

Further Reading

A Neural Probabilistic Language Model

Journal of Machine Learning Research 3 (2003) 1137–1155 Submitted 4/02; Published 2/03

A Neural Probabilistic Language Model

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Editors: Jaz Kandola, Thomas Hofmann, Tomaso Poggio and John Shawe-Taylor

Abstract

A goal of statistical language modeling is to learn the joint probability function of sequences of words in a language. This is intrinsically difficult because of the **curse of dimensionality**: a word sequence on which the model will be tested is likely to be different from all the word sequences seen during training. Traditional but very successful approaches based on n-grams obtain generalization

Further Reading

Efficient Estimation of Word Representations in Vector Space (Word2Vec)

Efficient Estimation of Word Representations in Vector Space

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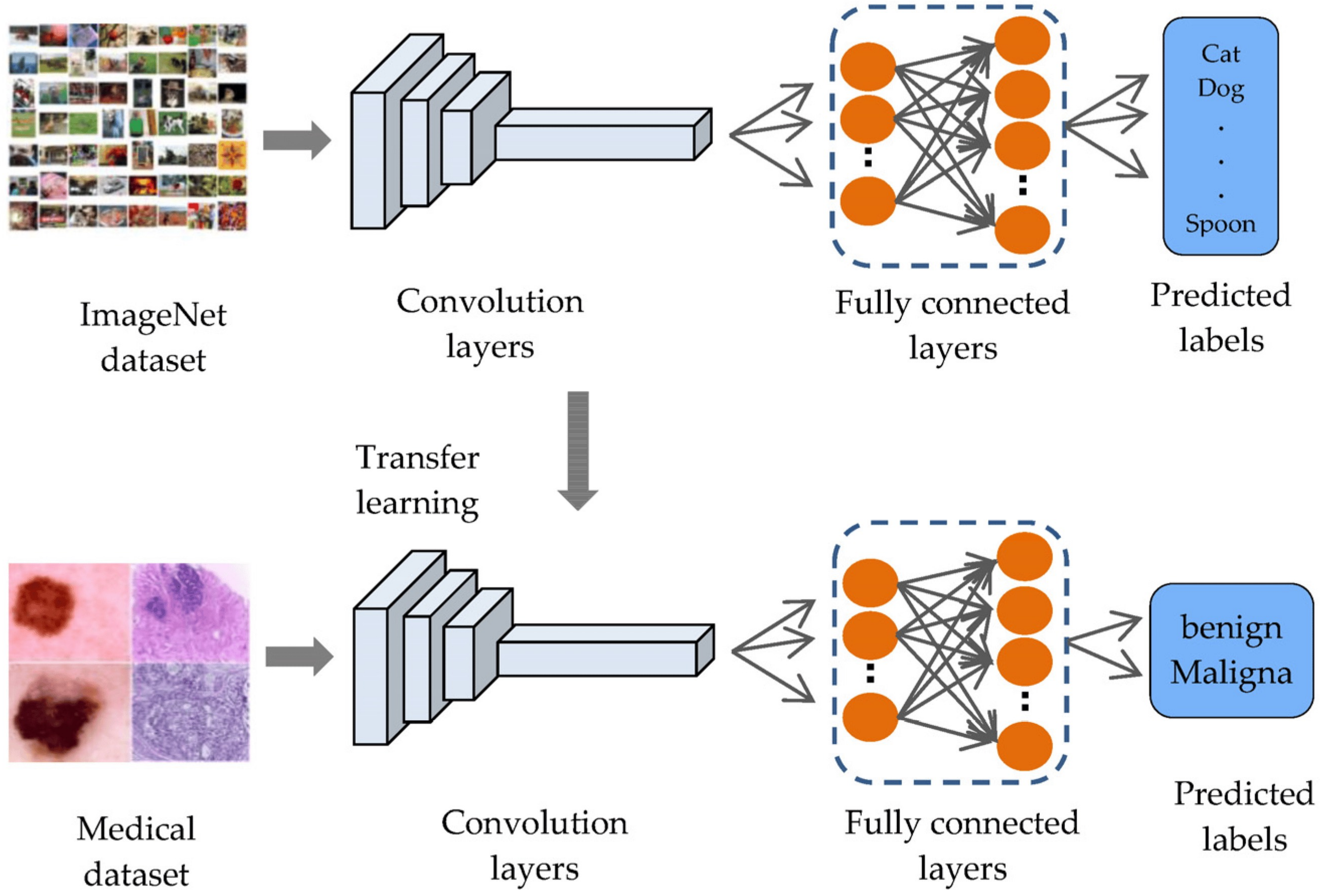
Abstract

We propose two novel model architectures for computing continuous vector representations of words from very large data sets. The quality of these representations

Transfer Learning

Transfer Learning

Use Pre-trained Model in other tasks

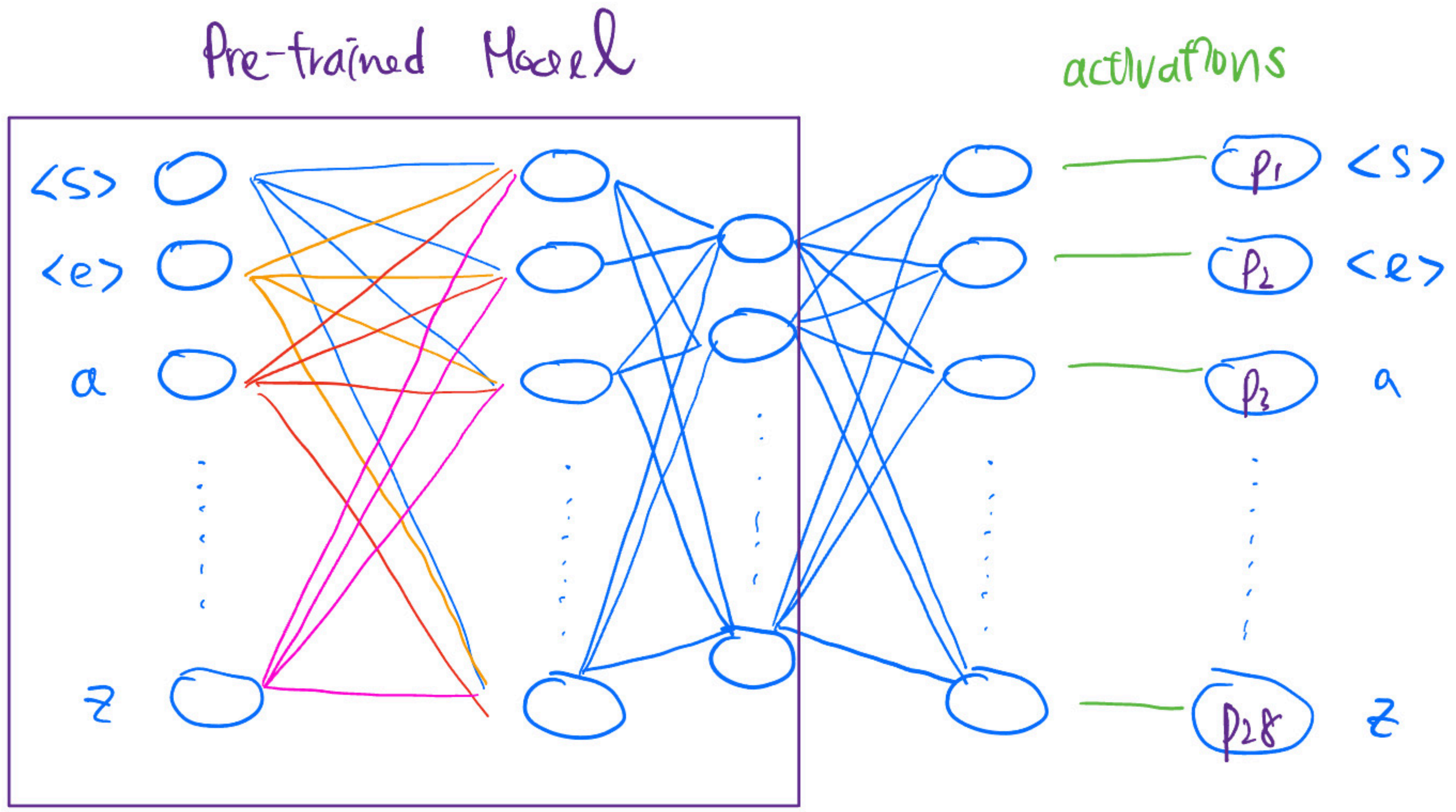


https://www.mdpi.com/1424-8220/23/2/570

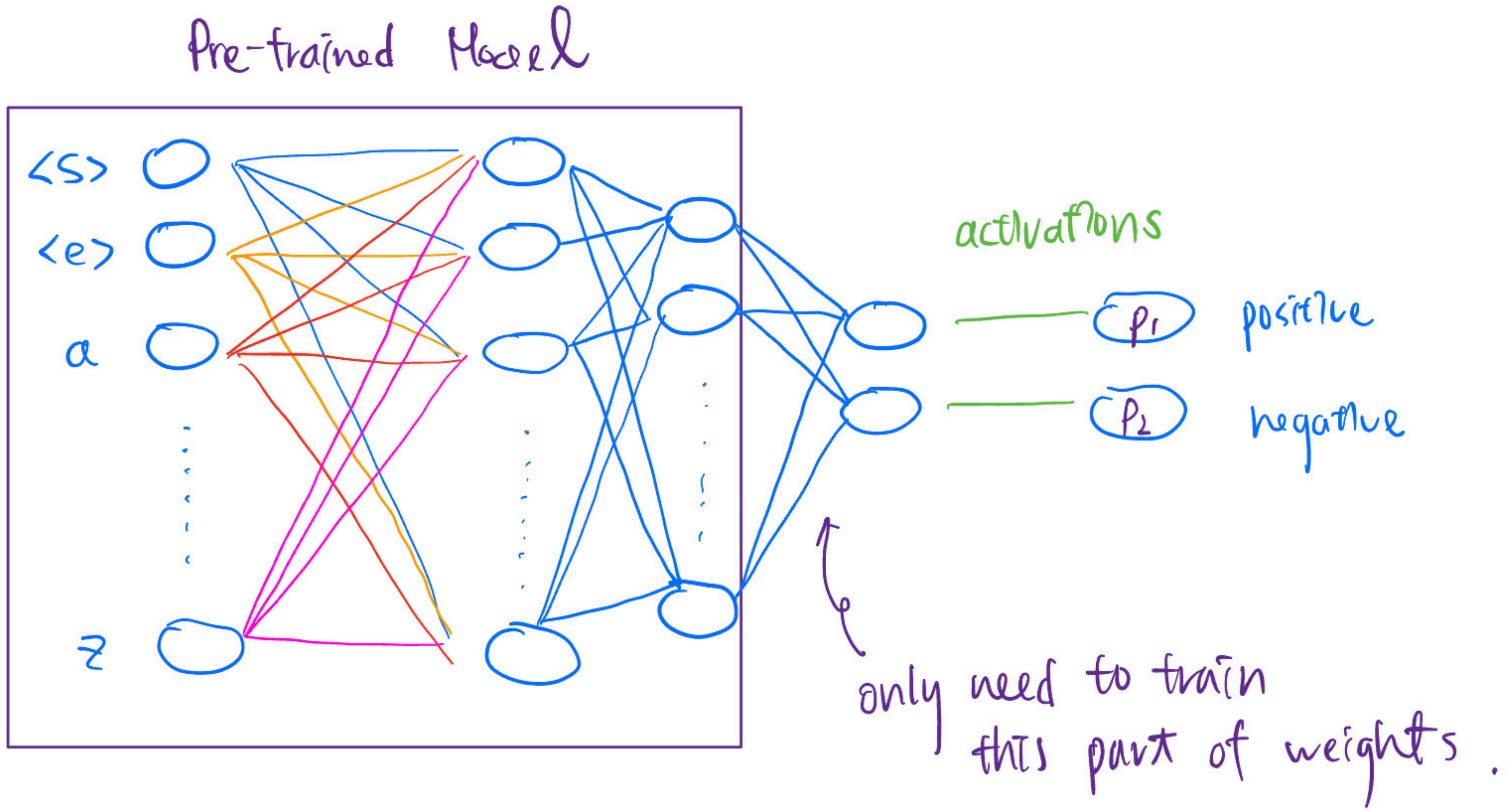
Transfer Learning

Use Pre-trained Model in other tasks

Original Task



New Classification Task



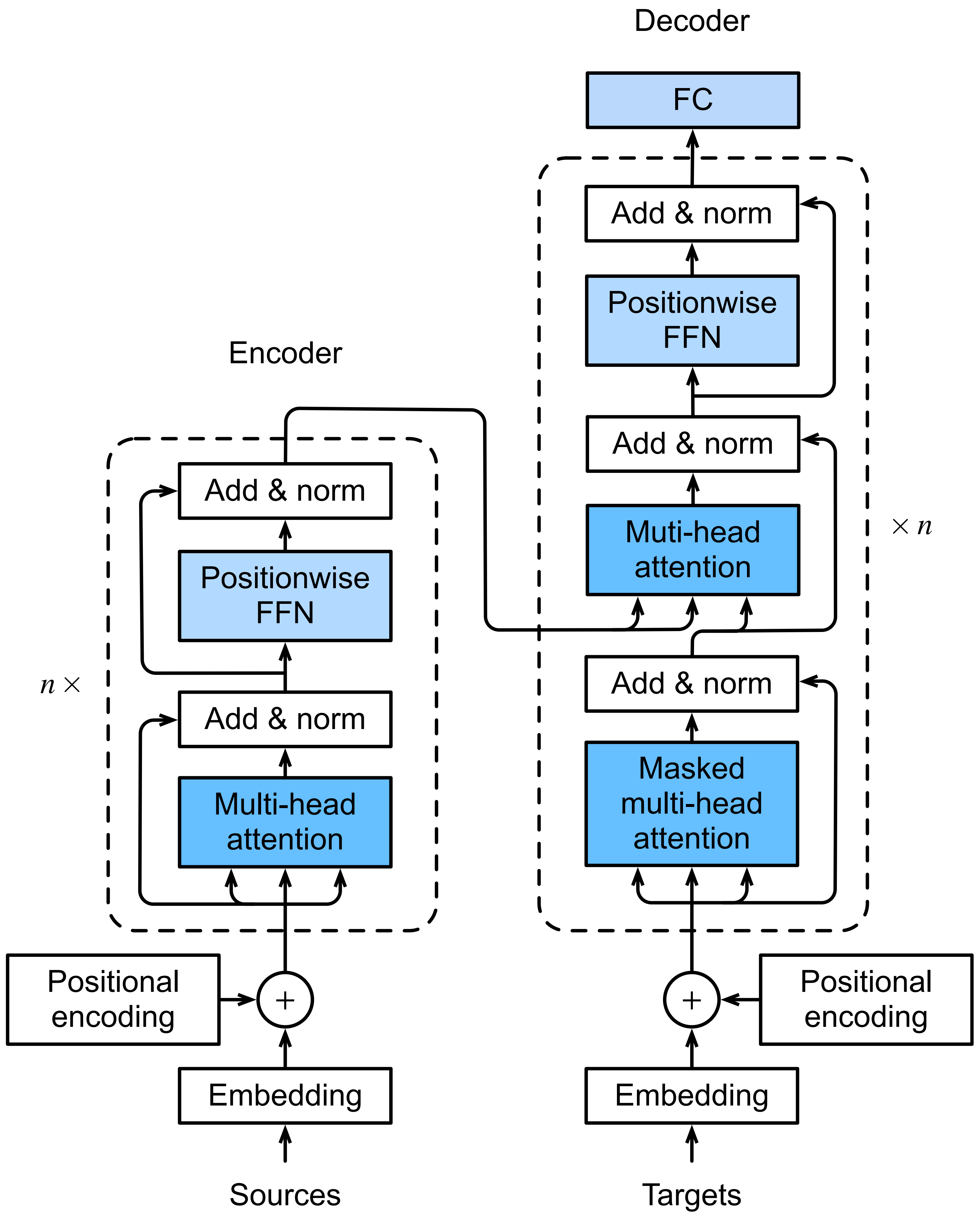
Wrap Up

What We Have Gone Through

- Deep Neural Network
- Word Embedding
- Transfer Learning

What's Next

- Transformer - Self Attention



Q & A