

Hi BERT !



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Bidirectional Encoder Representations from Transformers

- **Representations**
 - Traditional word embedding
 - Contextualized embedding
 - ELMo
- **Transformers**
 - Bert
 - Seq2Seq
 - Self Attention Mechanism
- **Applications - Transfer Learning**

Make computer understand the meaning of the words

Representations

Representations

1 of N encoding

Informatics = [1, 0, 0, 0]

Computer Science = [0, 1, 0, 0]

Python = [0, 0, 1, 0]

Hogwarts = [0, 0, 0, 1]

- Sparse
- High Dimension
- Can't express word relationship

Representations

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- Sparse
- High Dimension
- Can express word relationship

Word Embedding

Informatics = [0.5, 0.4, 0, 1, 0.9]

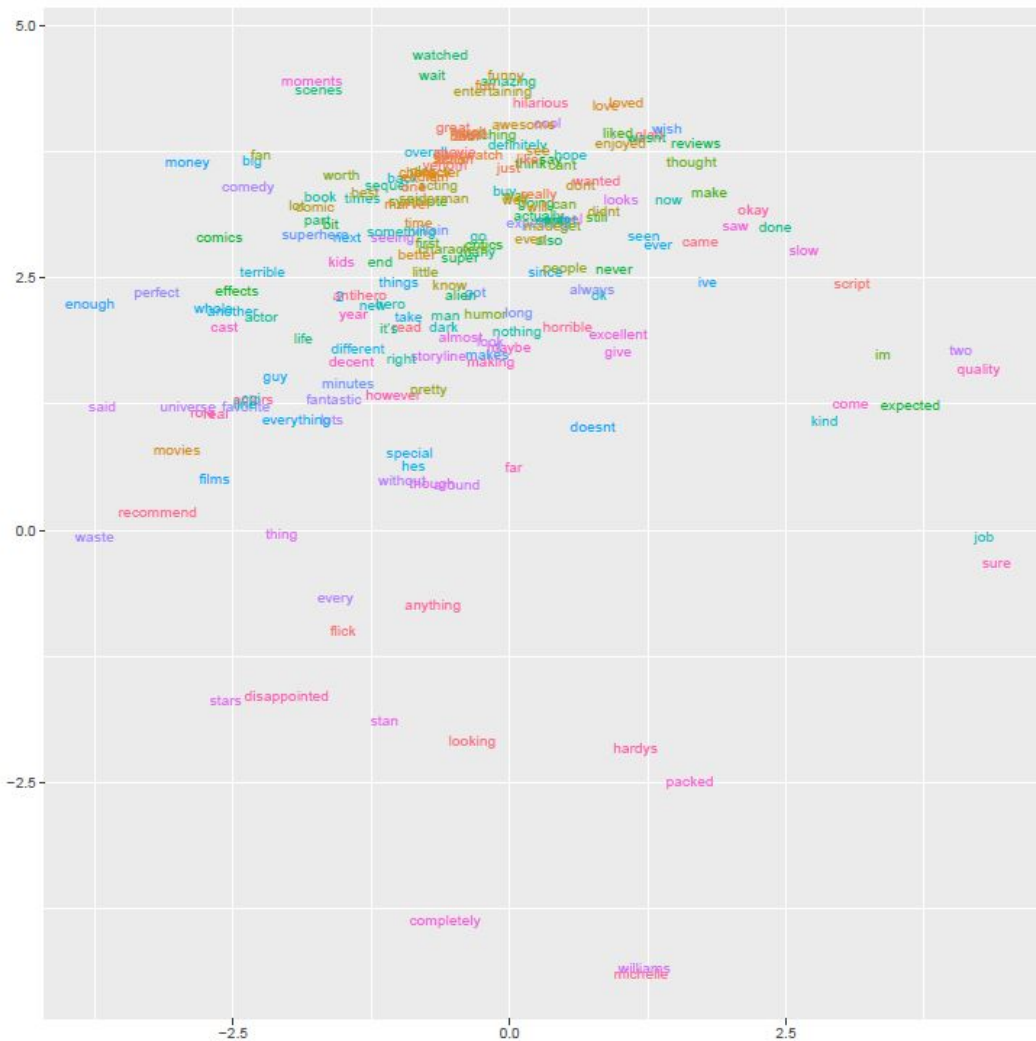
Computer Science = [0.5, 1, 0, 0.9, 0.8]

Python = [0.3, 0.99, 0, 0.1, 0.8]

Hogwarts = [0, 0, 1, 0, 0]

- Dense
- Lower-dimension
- Learn from data

Representations



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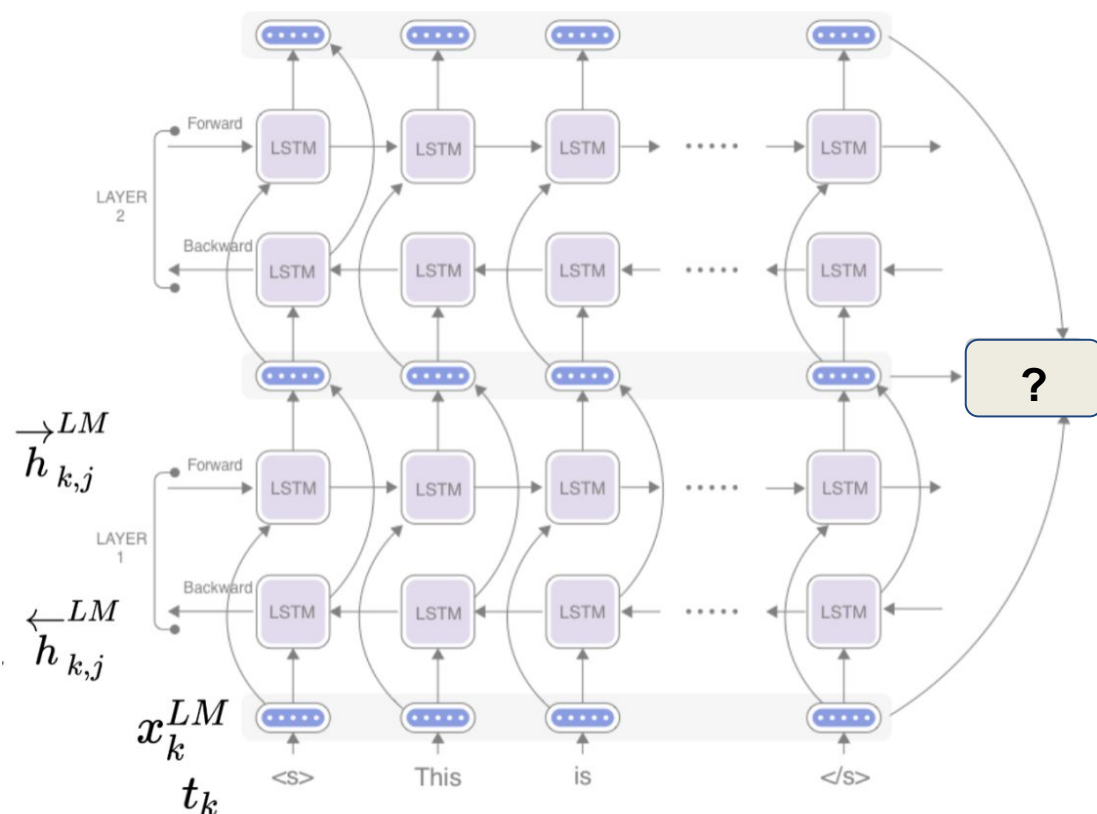
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polysemy?

Representations

Contextualized Word Embedding

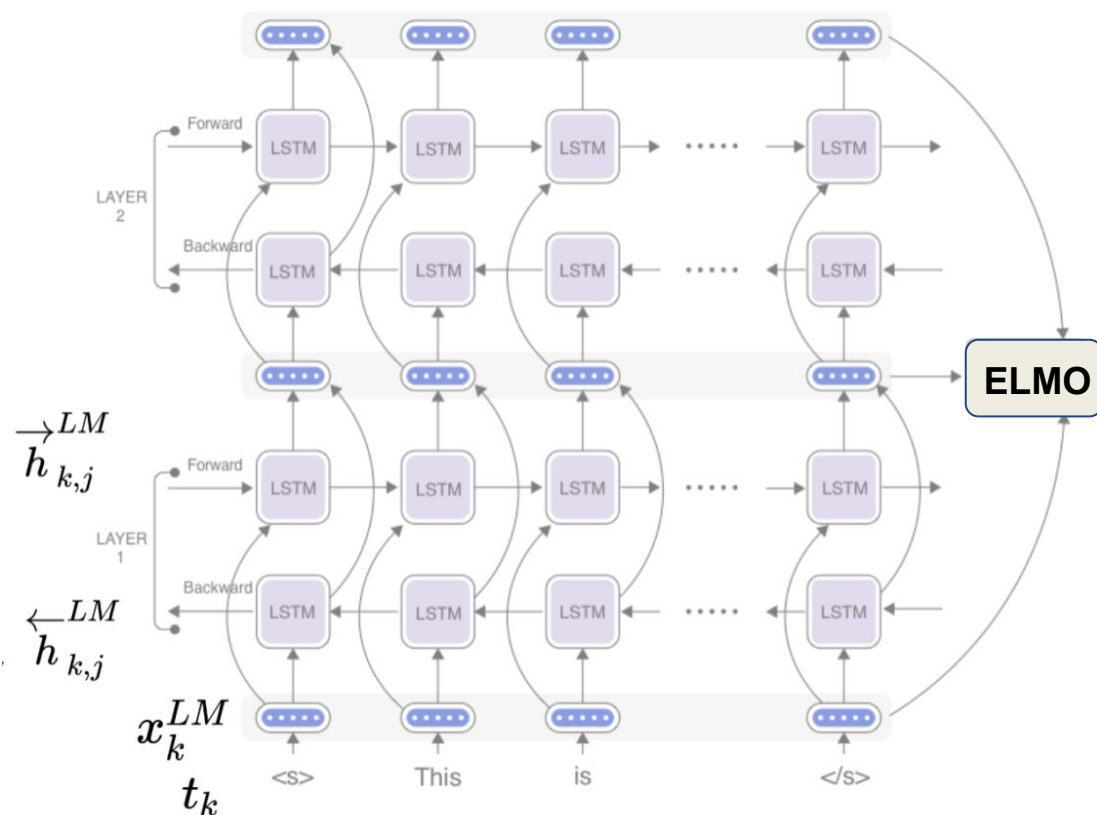
- Each word token has it's own embedding



Representations

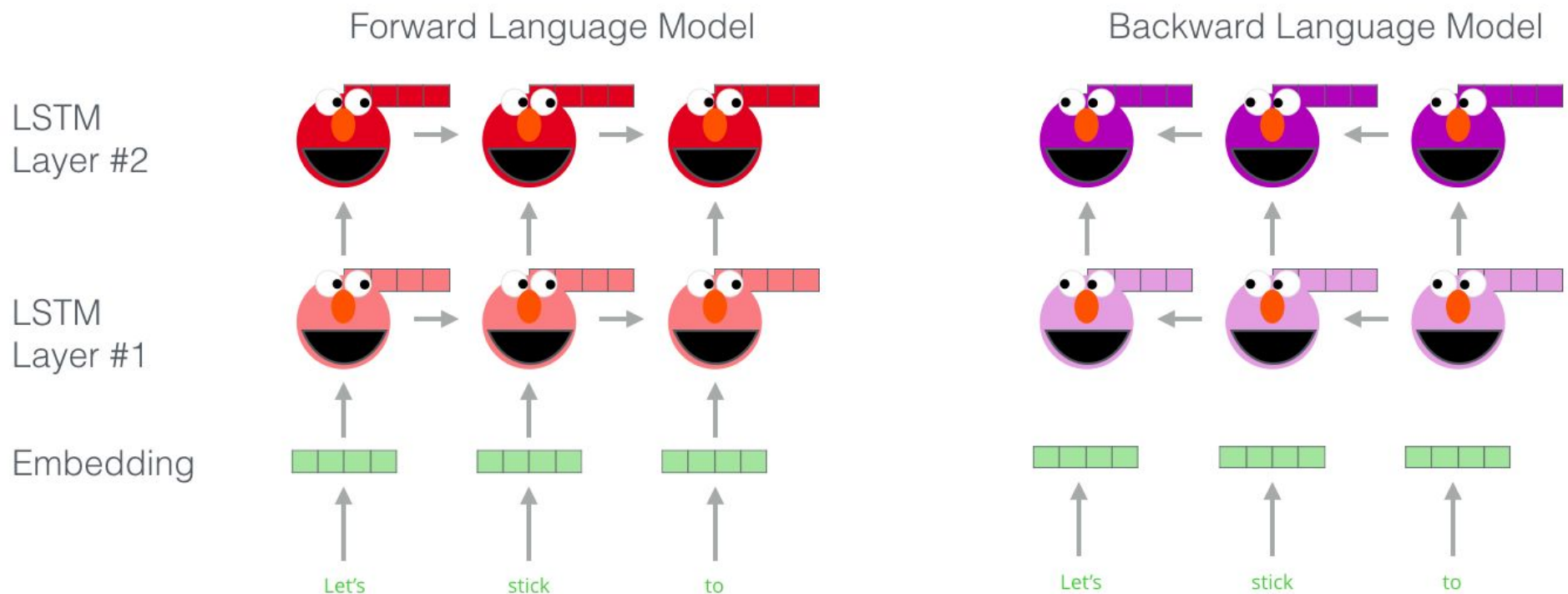
Contextualized Word Embedding

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Representations & Bidirections

Embedding from Language Model(ELMo)



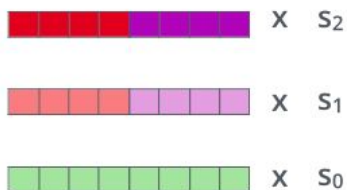
Representations & Bidirections

Embedding from Language Model(ELMo)

1- Concatenate hidden layers



2- Multiply each vector by a weight based on the task

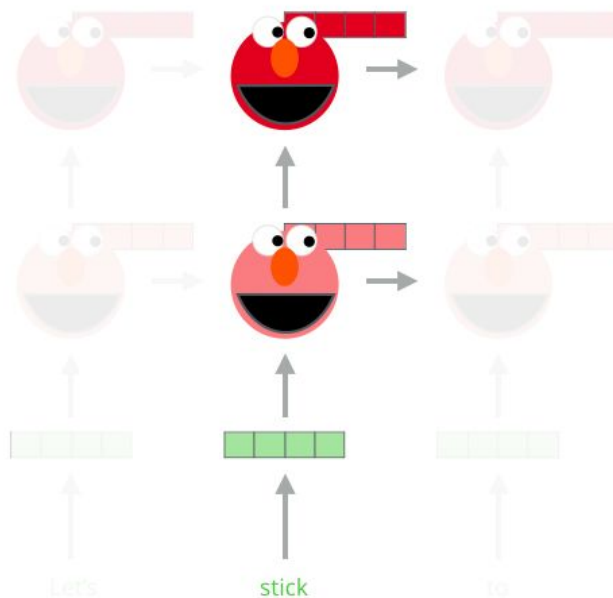


3- Sum the (now weighted) vectors

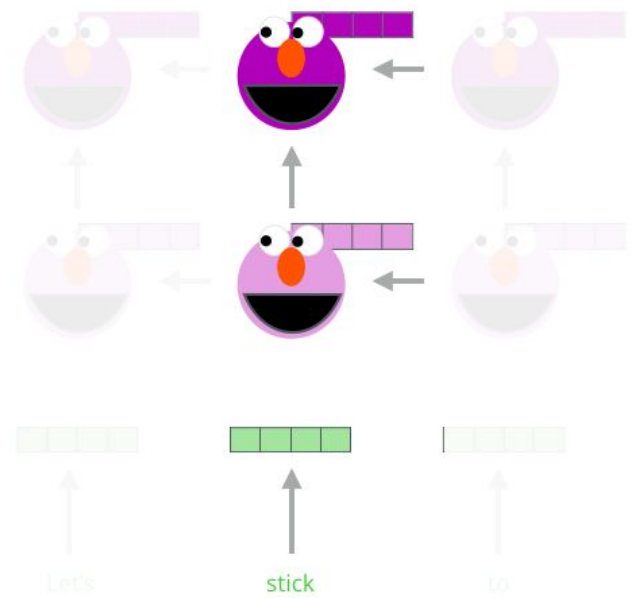


ELMo embedding of "stick" for this task in this context

Forward Language Model



Backward Language Model

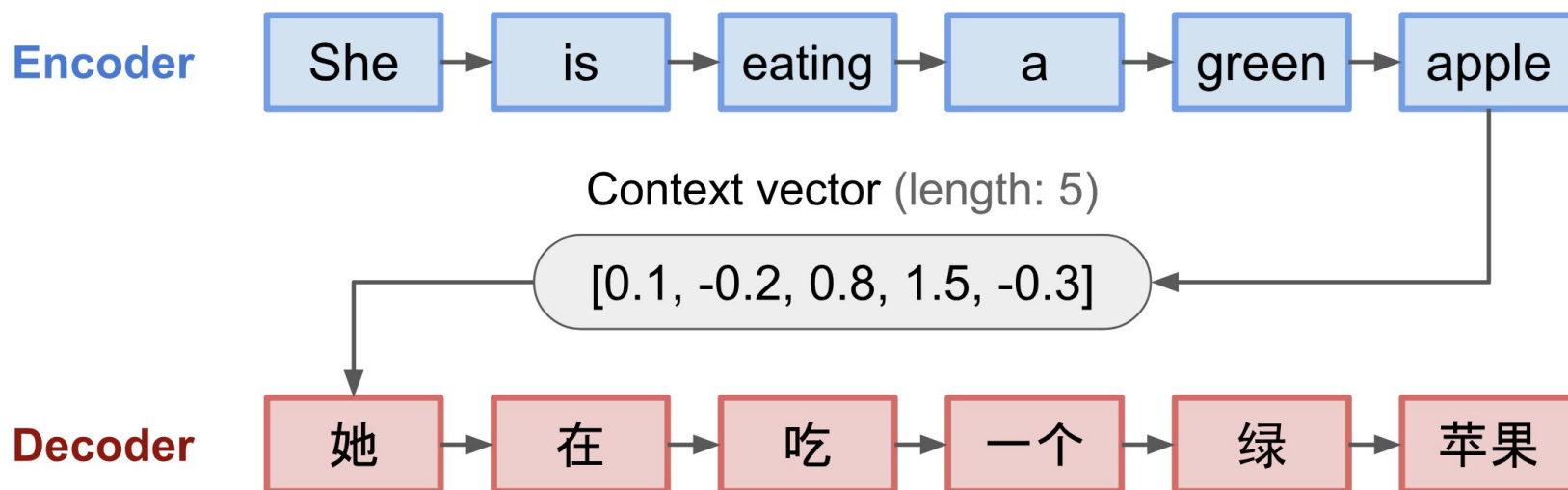


A step from BERT

Transformer

Seq2Seq Model

- An **encoder** processes the input sequence and compresses the information into a context vector of a *fixed length*. This representation is expected to be a good summary of the meaning of the *whole* source sequence.
- A **decoder** is initialized with the context vector to emit the transformed output. The early work only used the last state of the encoder network as the decoder initial state.

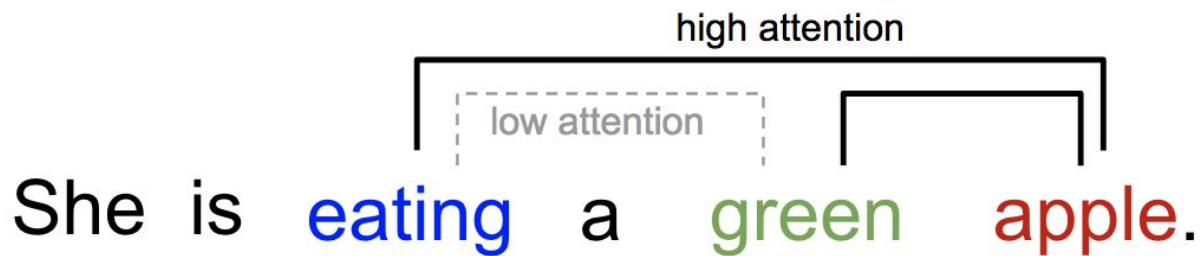


Transformers

Attention Mechanism

Attention
is all you
need

Attention is, to some extent, motivated by how we pay visual attention to different regions of an image or correlate words in one sentence



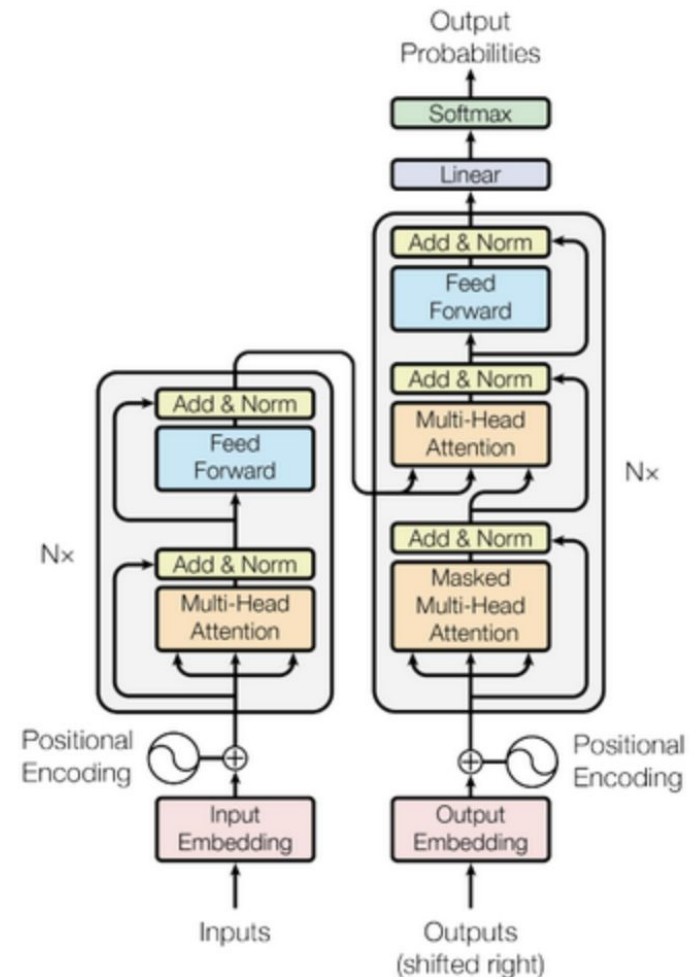
Transformers

Key The word to be matched

Query Match other words

Value attention weight
Information need to be matched

$$\text{softmax}\left(\frac{\begin{matrix} \text{Q} \\ \text{3x3 grid} \end{matrix} \times \begin{matrix} \text{K}^T \\ \text{3x3 grid} \end{matrix}}{\sqrt{d_k}}\right) \begin{matrix} \text{V} \\ \text{3x3 grid} \end{matrix}$$
$$= \begin{matrix} \text{Z} \\ \text{3x3 grid} \end{matrix}$$



BERT

1. Masked language model

Where some words are hidden (15% of words are masked) and the model is trained to predict the missing words

2. Next sentence prediction

Where the model is trained to identify whether sentence B follows (is related to) sentence A



Why Bert is so popular

Applications

Applications

Downstream tasks

- Machine Translation
- Sentiment Analysis
- Text summarization
- Recommended system
- Inference
-

XL-BERT, RoBERTa
ALBERT, ERNIE,
DistillBERT,
Multilingual-BERT
.....



Applications

Medical related BERT?

- Readmission prediction- **ClinicalBERT**
- Patient matching - **DeepEnroll**
- Pretrain on Medical paper- **BlueBERT/BioBERT**
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Conclusions and discussions