

# BIDIRECTIONAL ENCODER REPRESENTATIONS FROM TRANSFORMERS

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MT2A - S  
CR1A - C1  
MT1A - X1  
MT2A - X2  
CR1A - B1  
CP1A - B0  
CP1A - B1  
TY1A - TY  
CR1A - SI  
LP1A - L0  
MT2A - G0

# BERT





# Word Embedding

0



[ 1 , 0 , 0 , 0 ]

1



[ 0 , 1 , 0 , 0 ]

2



[ 0 , 0 , 1 , 0 ]

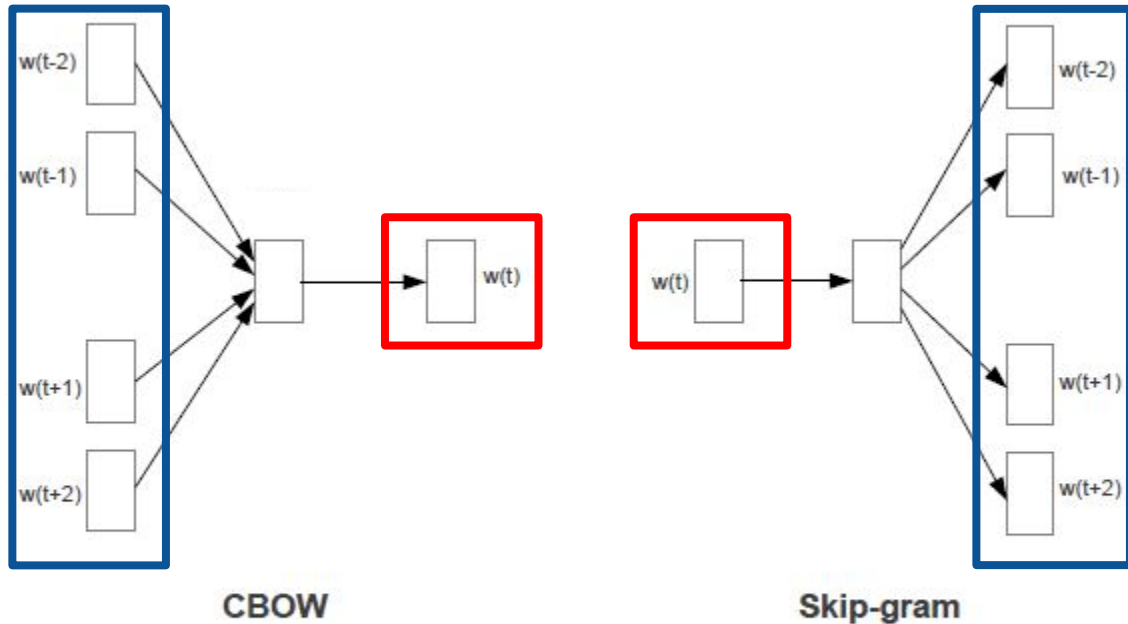
3



[ 0 , 0 , 0 , 1 ]



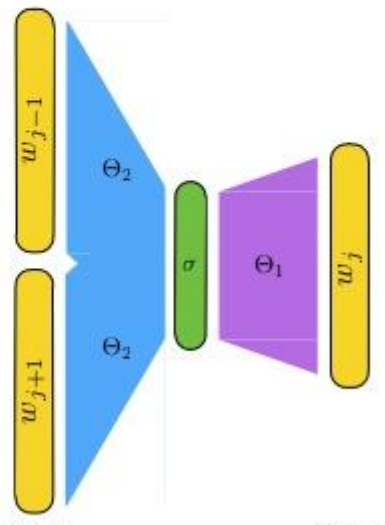
“The fat **cat** sat on the mat.”





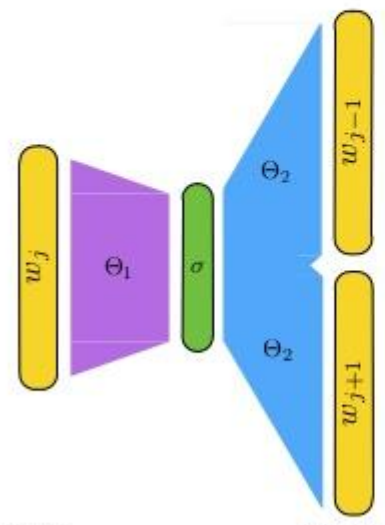
# CBOW

$$\max p(w|C)$$

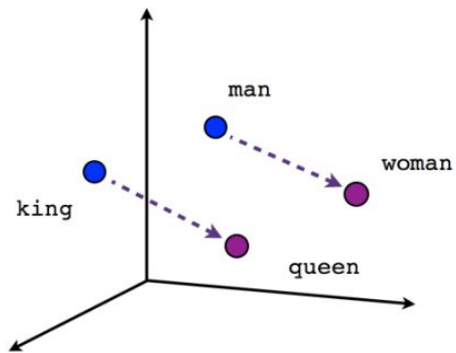


# Skip-gram

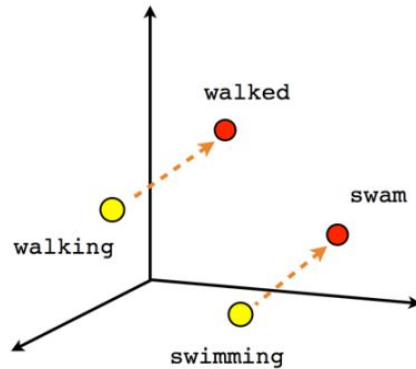
$$\max p(C|w)$$



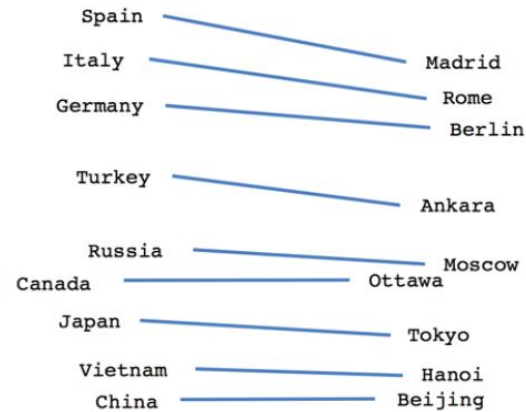




Male-Female



Verb tense

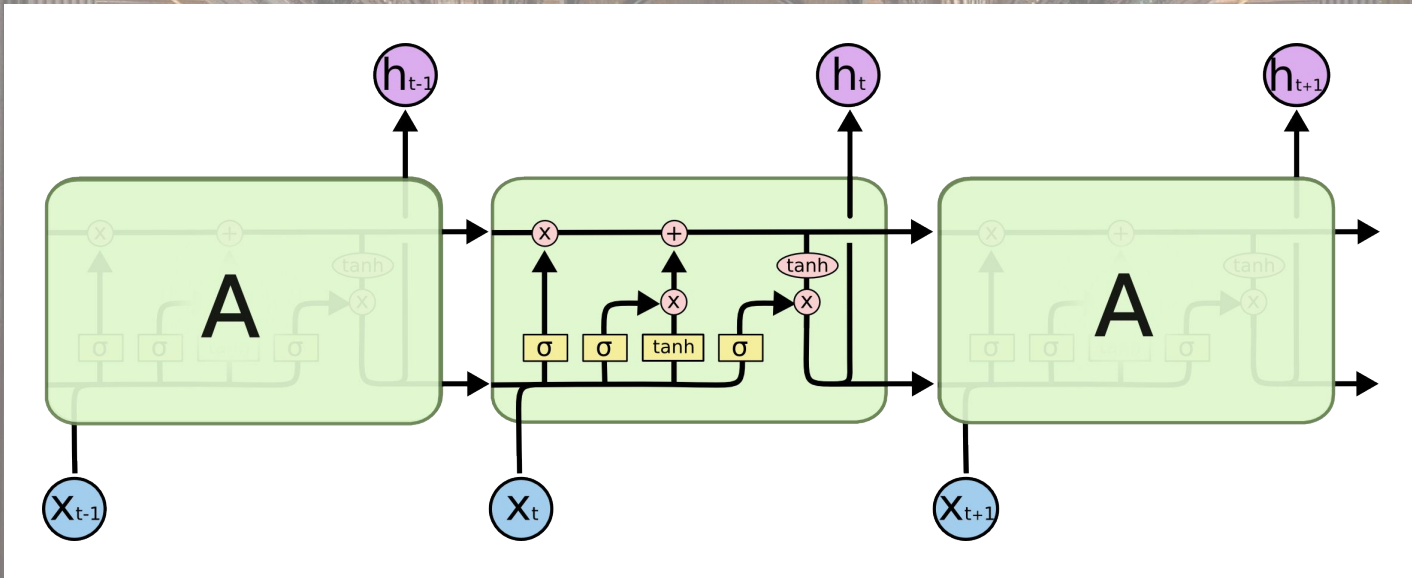


Country-Capital



# Long Short-Term Memory



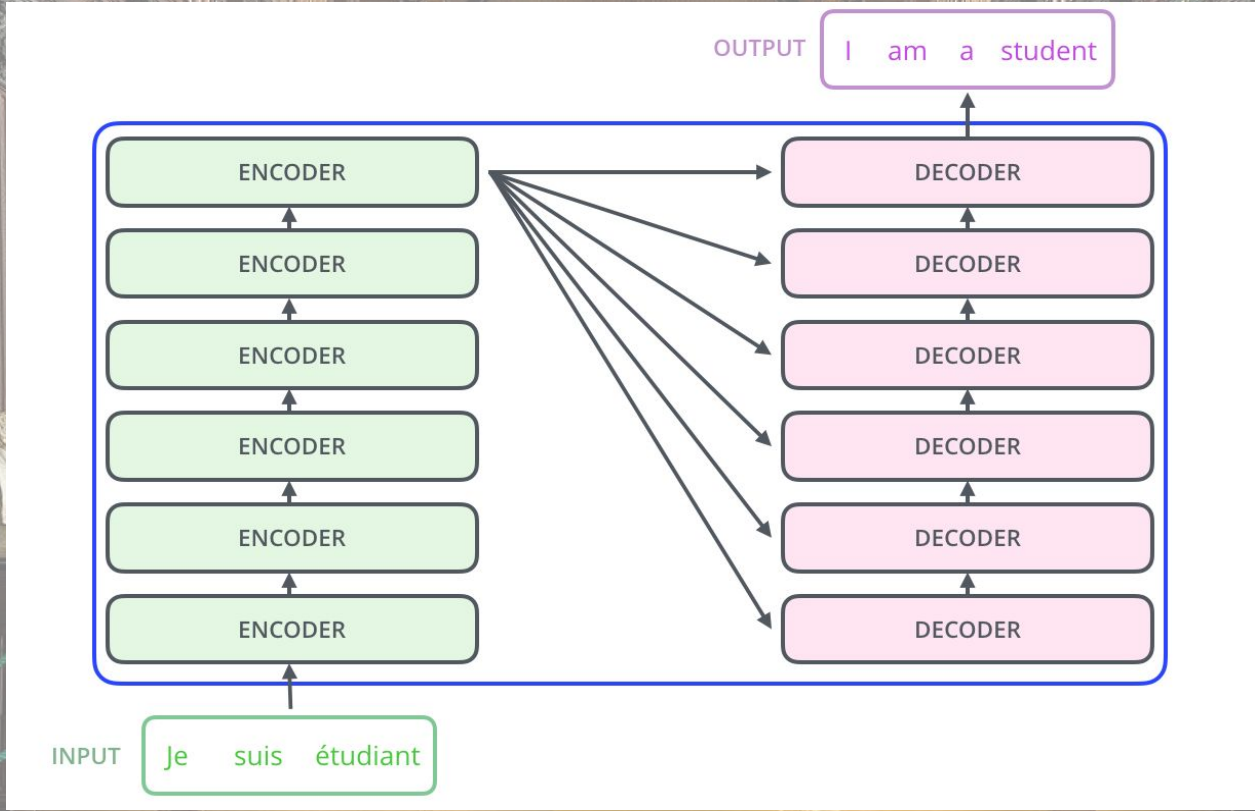


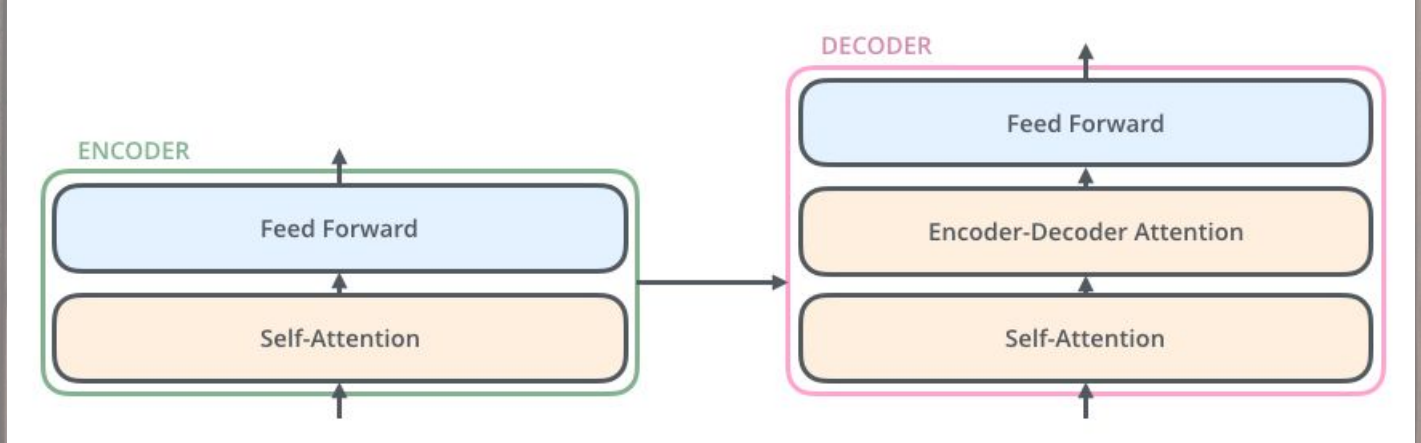


# Transformer

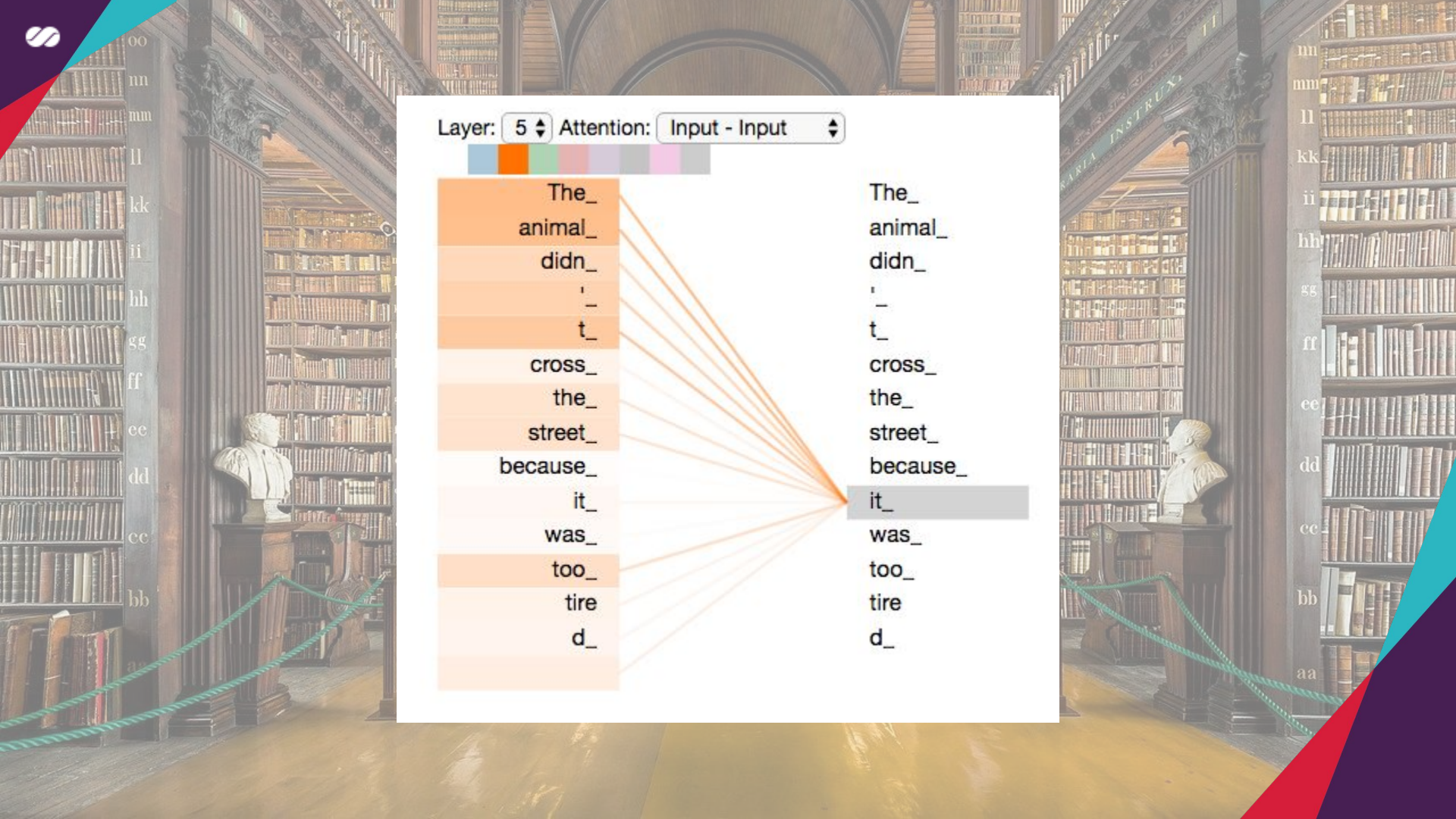




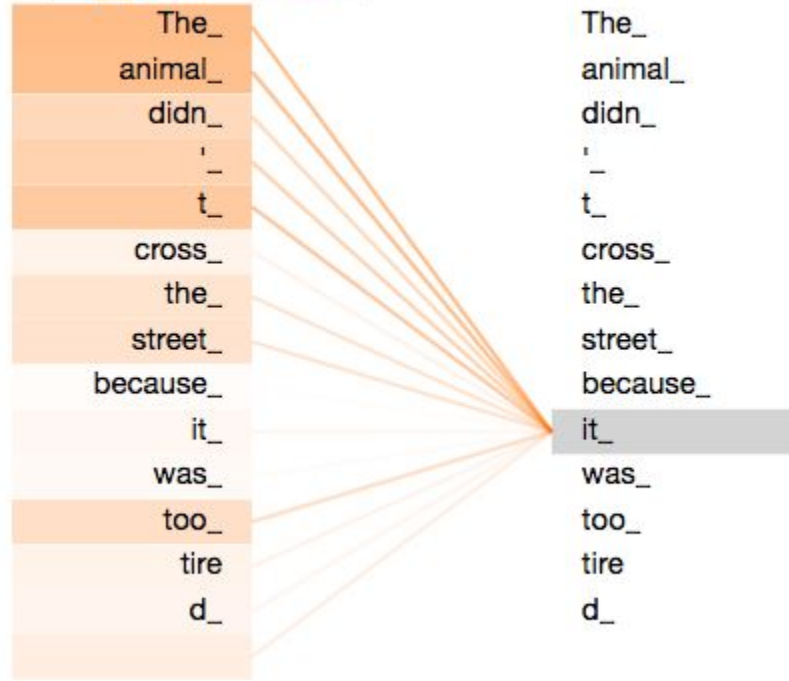








Layer: 5 Attention: Input - Input







# Semi-supervised Sequence Learning



## 1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

### Semi-supervised Learning Step

**Model:**



**Dataset:**



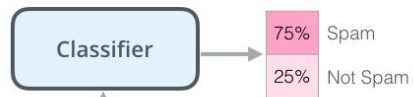
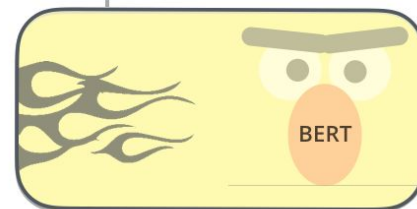
**Objective:**

Predict the masked word  
(language modeling)

## 2 - Supervised training on a specific task with a labeled dataset.

### Supervised Learning Step

**Model:**  
(pre-trained in step #1)



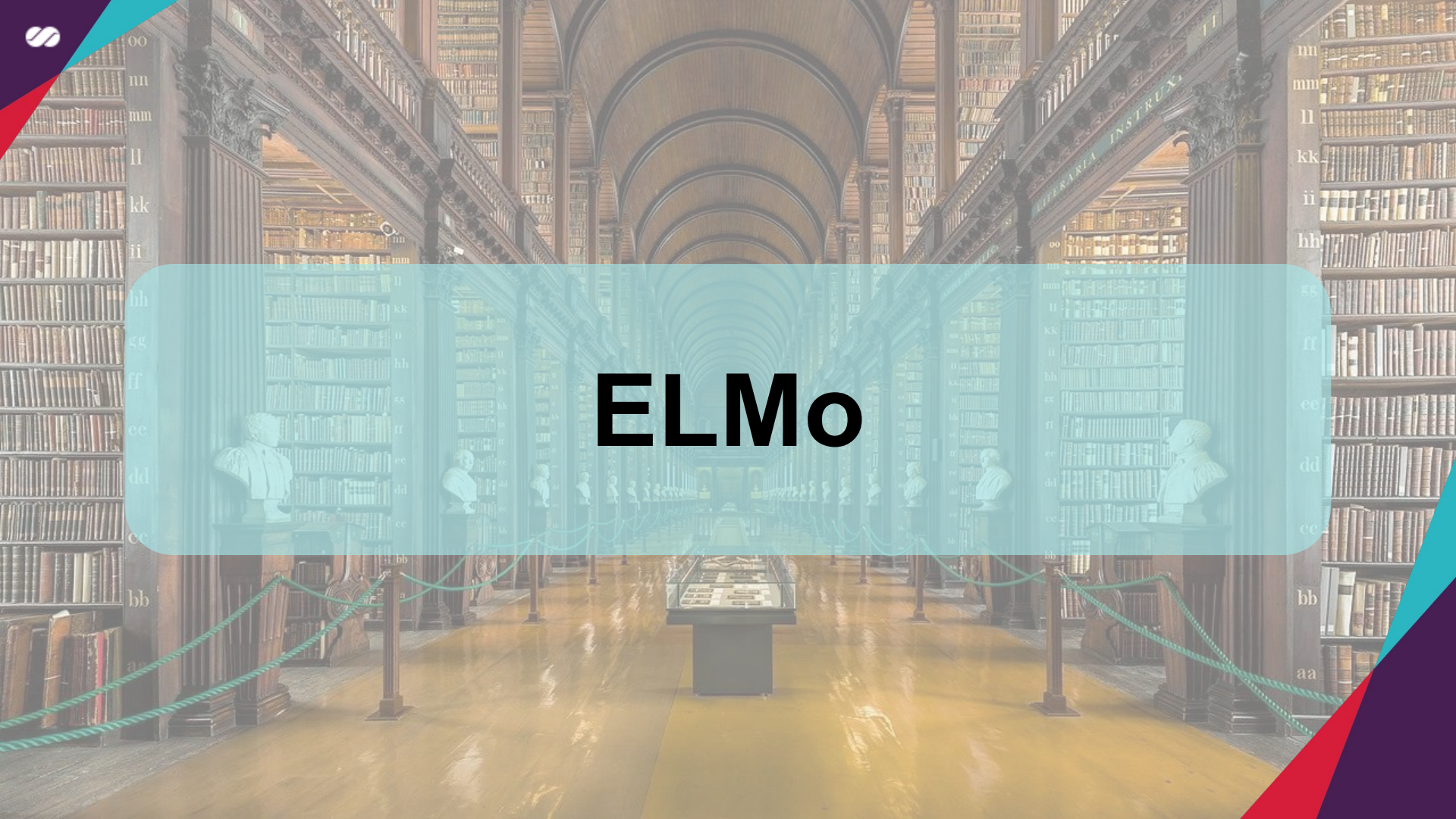
**Dataset:**

Email message	Class
Buy these pills	Spam
Win cash prizes	Spam
Dear Mr. Atreides, please find attached...	Not Spam

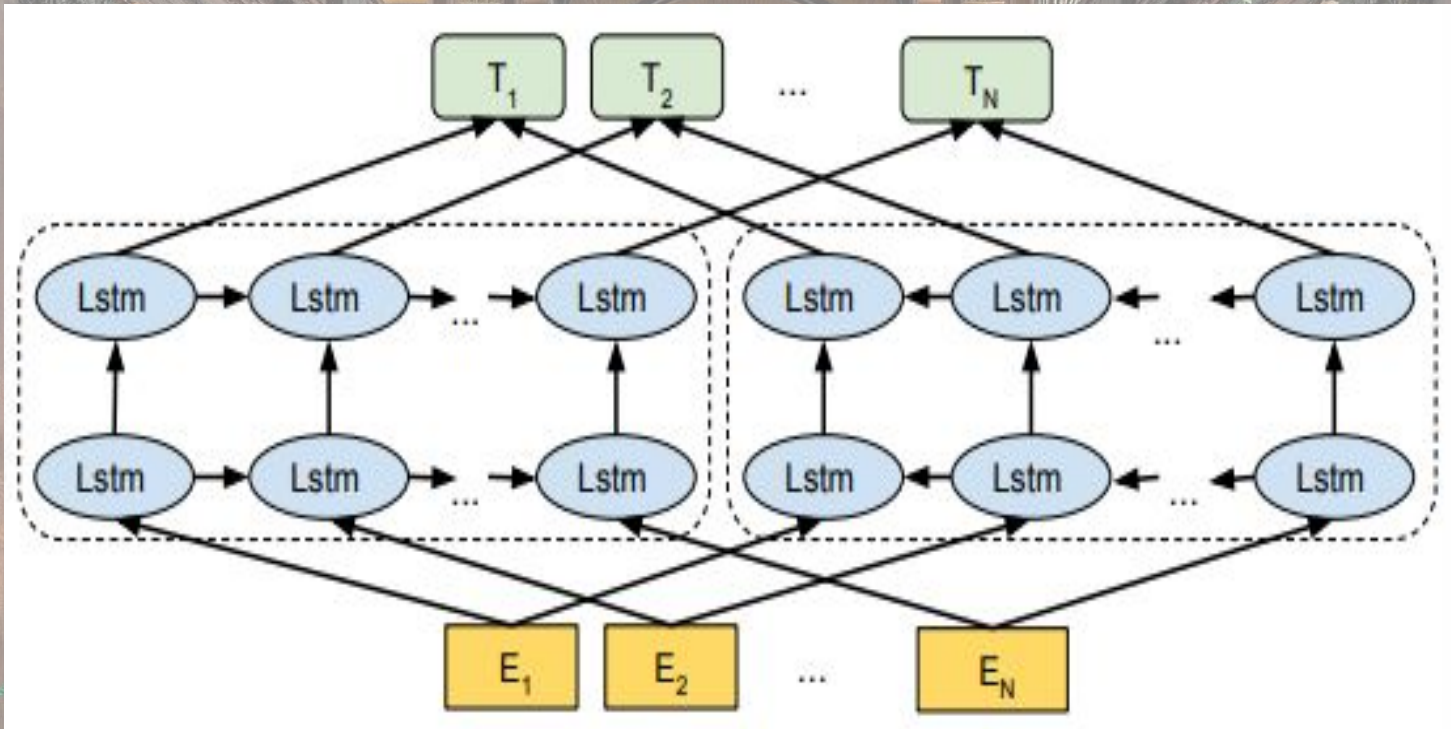




# ELMo







oo  
nn  
mm  
ll  
kk  
ii  
hh  
gg  
ff  
ee  
dd  
cc  
bb  
aa





# ULMFiT







oo  
nn  
mm  
ll  
kk  
ii  
hh  
gg  
ff  
ee  
dd  
cc  
bb

mm  
mm  
ll  
kk  
ii  
hh  
gg  
ff  
ee  
dd  
cc  
bb  
aa

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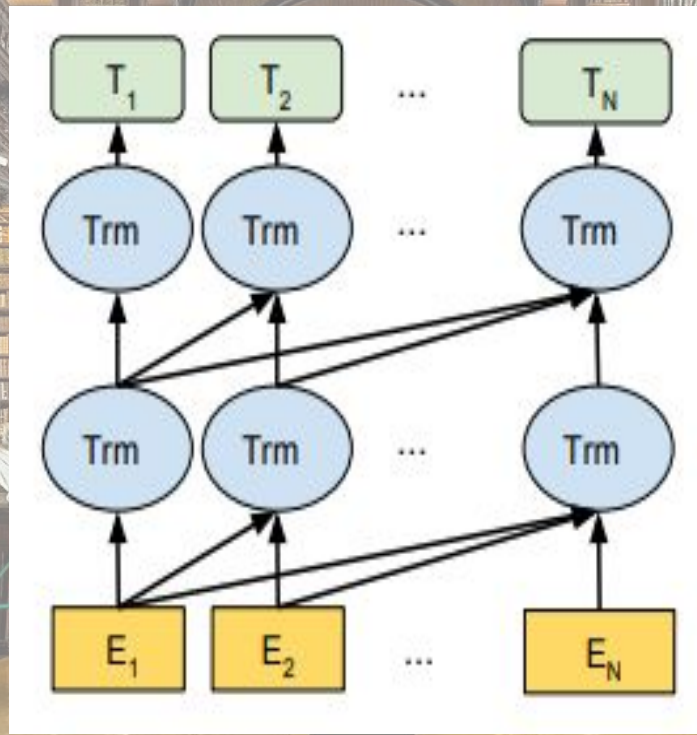
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# OpenAI Transformer





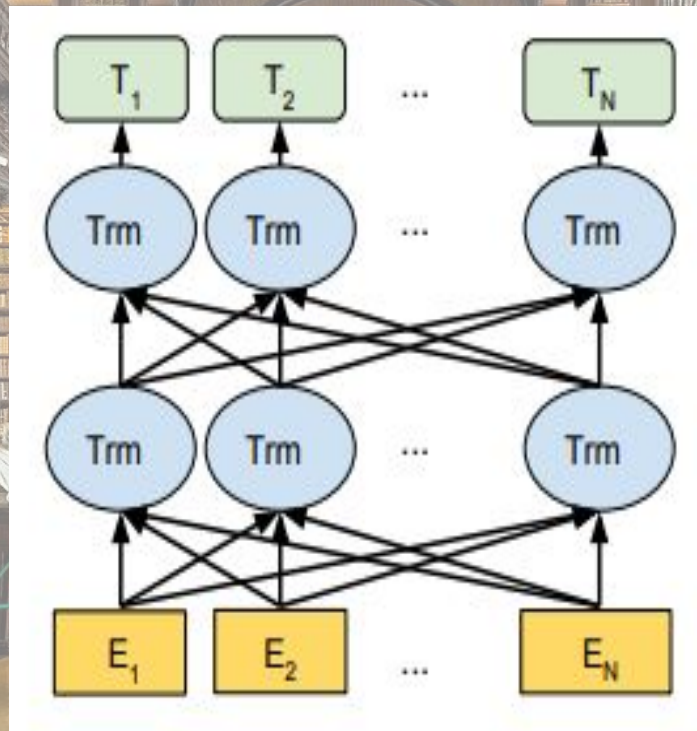




# BERT









**Input** = [CLS] the man went to [MASK] store [SEP]

he bought a gallon [MASK] milk [SEP]

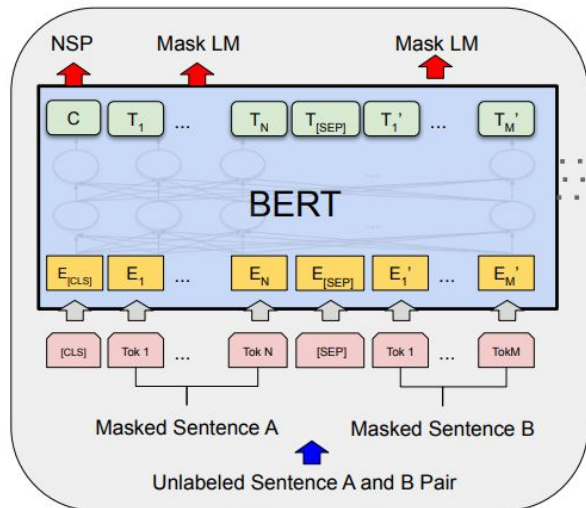
**Label** = IsNext

**Input** = [CLS] the man [MASK] to the store [SEP]

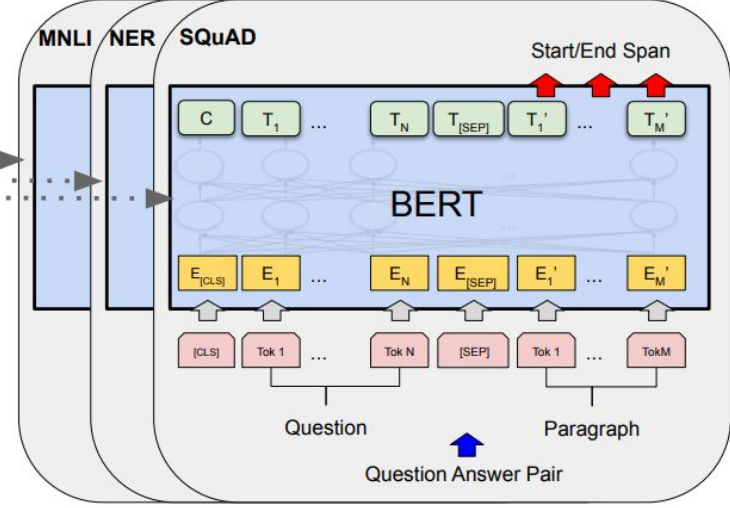
penguin [MASK] are flight ##less birds [SEP]

**Label** = NotNext

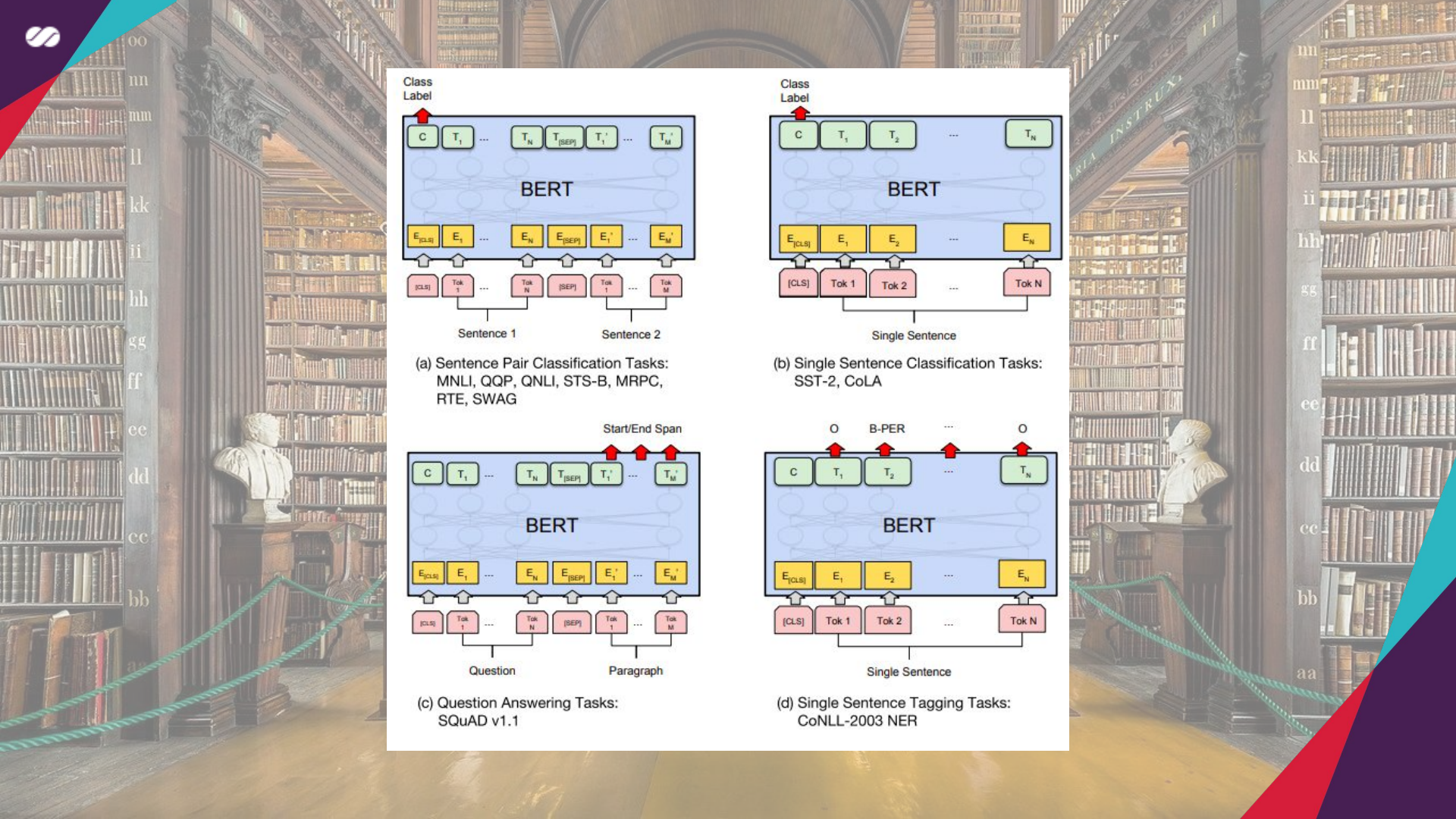
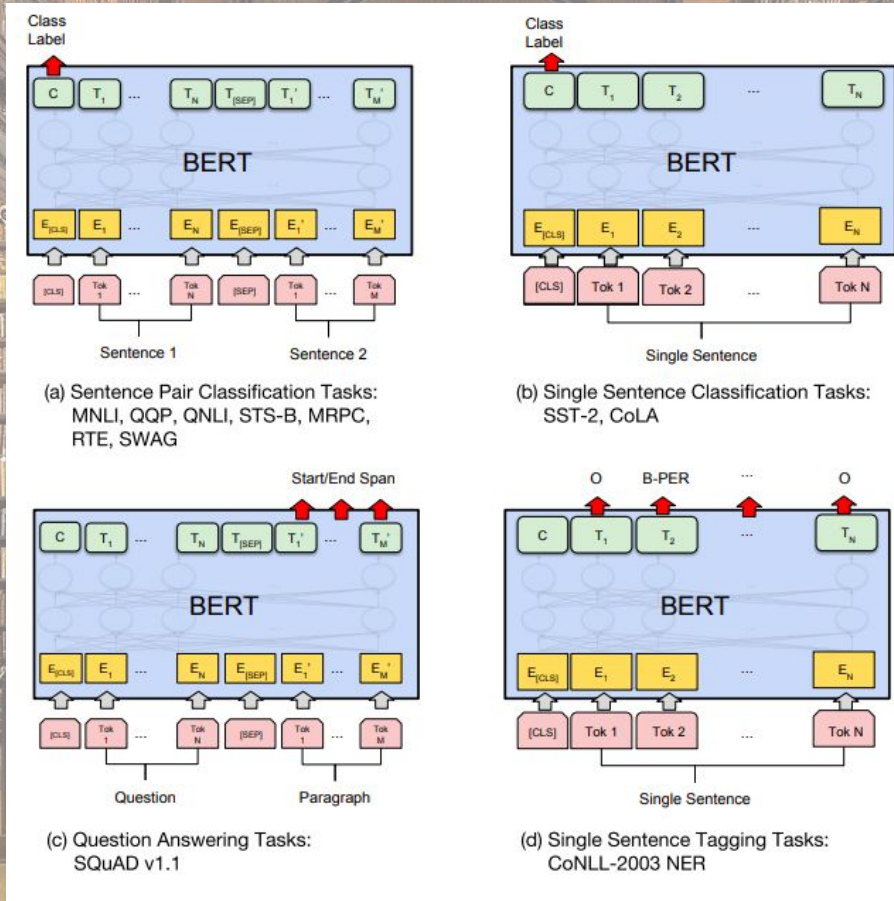




Pre-training



Fine-tuning

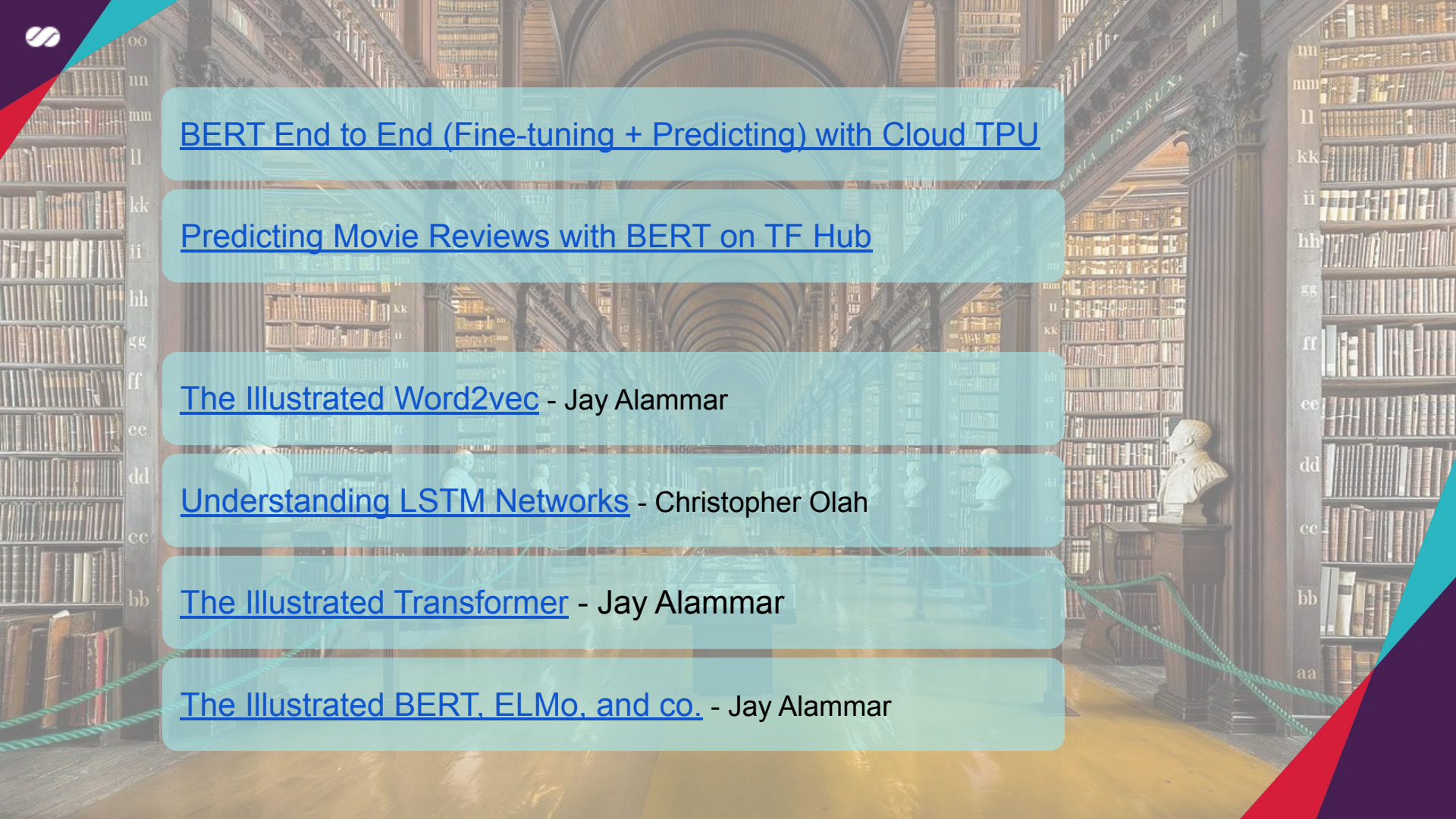




System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	Average
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
BERT <sub>BASE</sub>	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
BERT <sub>LARGE</sub>	<b>86.7/85.9</b>	<b>72.1</b>	<b>92.7</b>	<b>94.9</b>	<b>60.5</b>	<b>86.5</b>	<b>89.3</b>	<b>70.1</b>	<b>82.1</b>

Table 1: GLUE Test results, scored by the evaluation server (<https://gluebenchmark.com/leaderboard>). The number below each task denotes the number of training examples. The “Average” column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.<sup>8</sup> BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.





[BERT End to End \(Fine-tuning + Predicting\) with Cloud TPU](#)

[Predicting Movie Reviews with BERT on TF Hub](#)

[The Illustrated Word2vec](#) - Jay Alammar

[Understanding LSTM Networks](#) - Christopher Olah

[The Illustrated Transformer](#) - Jay Alammar

[The Illustrated BERT, ELMo, and co.](#) - Jay Alammar





## Pedro Leis

Moved by curiosity, I'm an entrepreneurial scientist who seeks to improve people's lives through Artificial Intelligence solutions.

Main researches and interests: Fairness in Machine Learning, Few-shot Learning, Transformer (Attention), Generative Adversarial Network, Reinforcement Learning and Memory-Augmented Neural Network.



<https://forms.gle/eWuLqj3yoQNq15SC8>



<PEOPLE>  
<COMMUNITIES>  
<KNOWLEDGE>

All together\_

