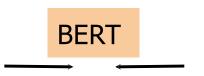
Question Answering



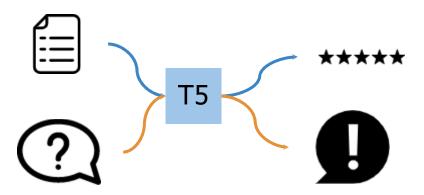
Question Answering





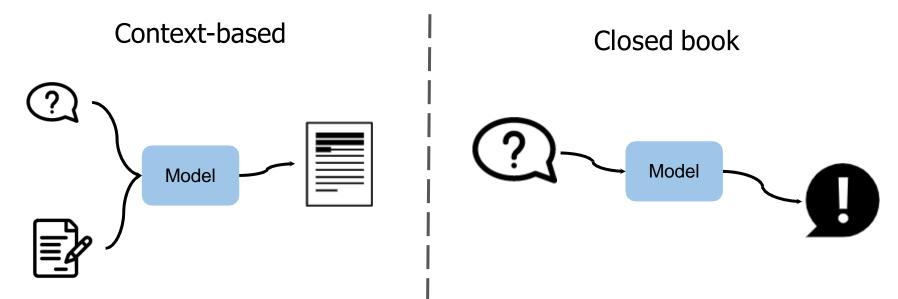
Transfer learning





Question Answering





Not just the model

Data

Training

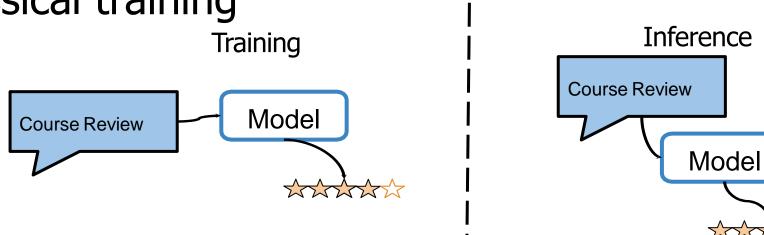
Model

Training } Transfer Learning!

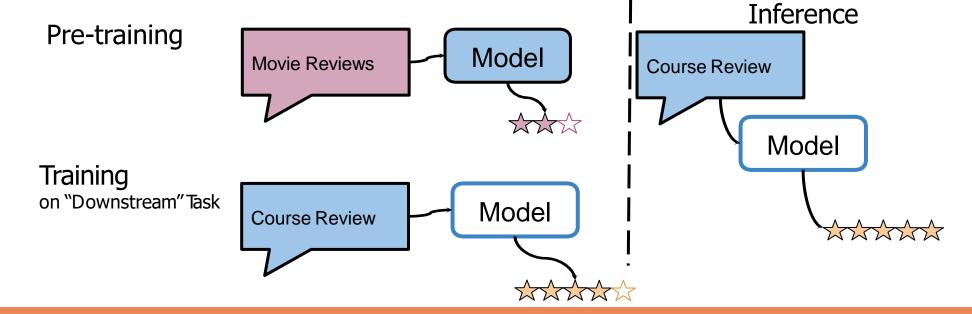
Model

Classical training



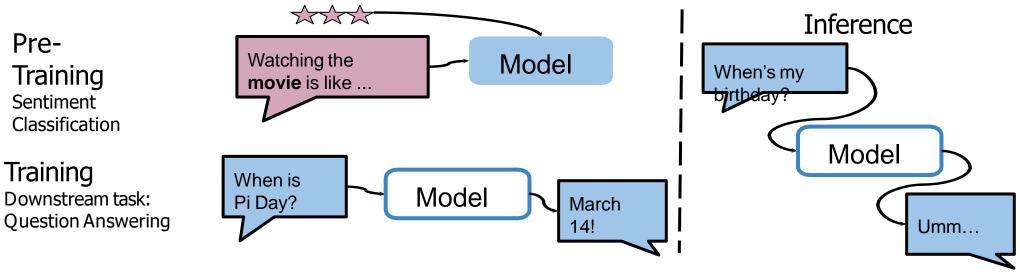


Transfer learning



Transfer Learning: Different Tasks





• BERT: Bi-directional Context

Uni-directional

Learning from deeplearning.ai is like watching the sunset with my best friend!

context

Bi-directiona

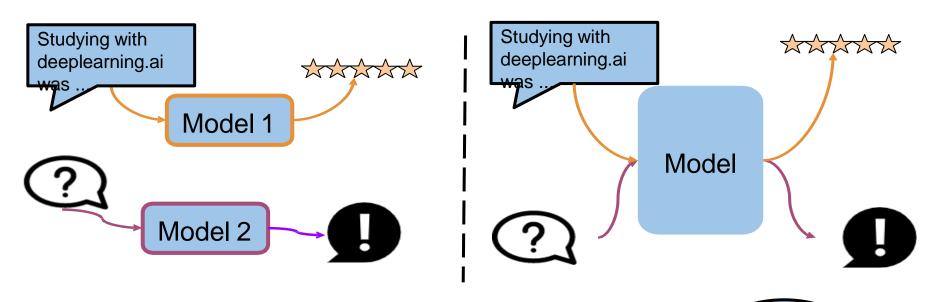
Learning from deeplearning.ai is like watching the sunset with my best friend!

context

context

T5: Single task vs. Multi task





• T5: more data, better performance

English wikipedia ~13 GB

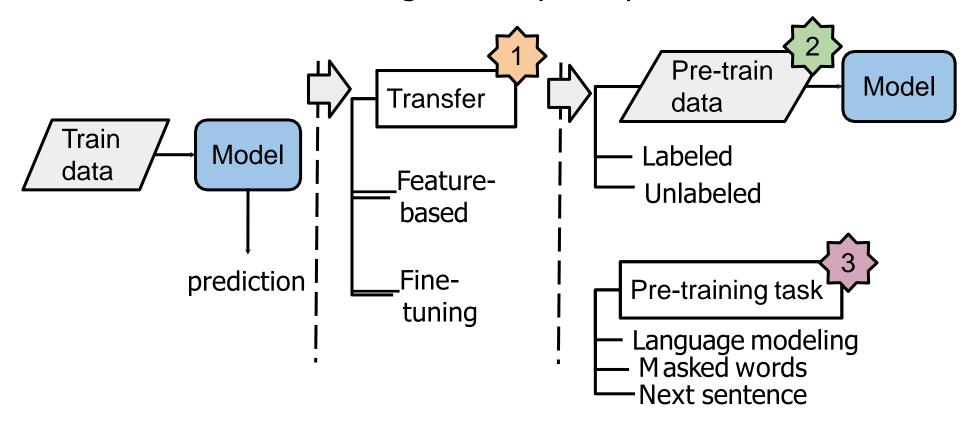
Desirable Goals of

Colossal Clean
Crawled
Corpus
~800 GB

Transfer learning



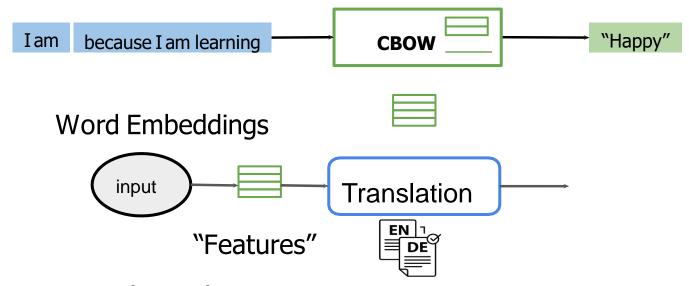
Desirable Goals: Reduce training time Improve predictions; Small datasets



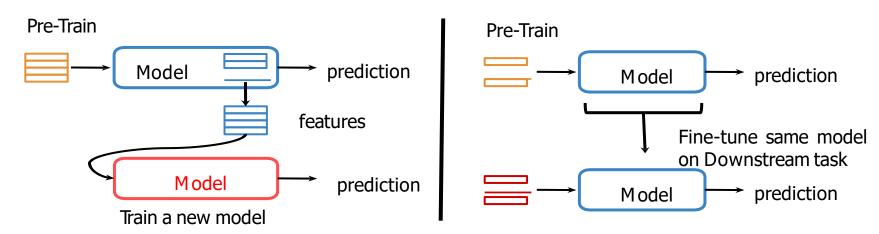
General purpose learning



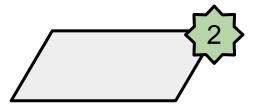




Feature-based vs. Fine-Tuning

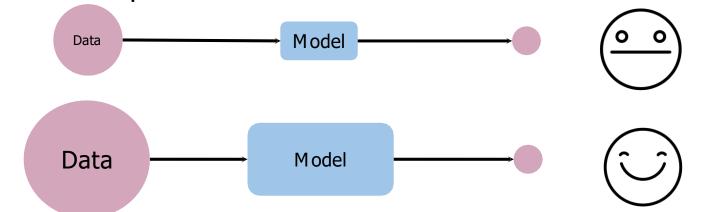


Pre-train data





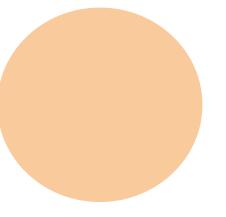
Data and performance



 Labeled vs Unlabeled Data Labeled text data

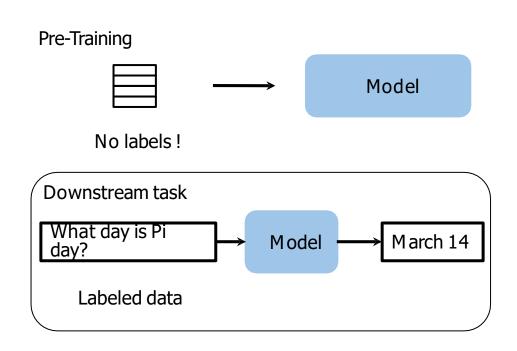


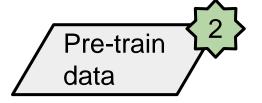




Transfer learning with unlabeled data



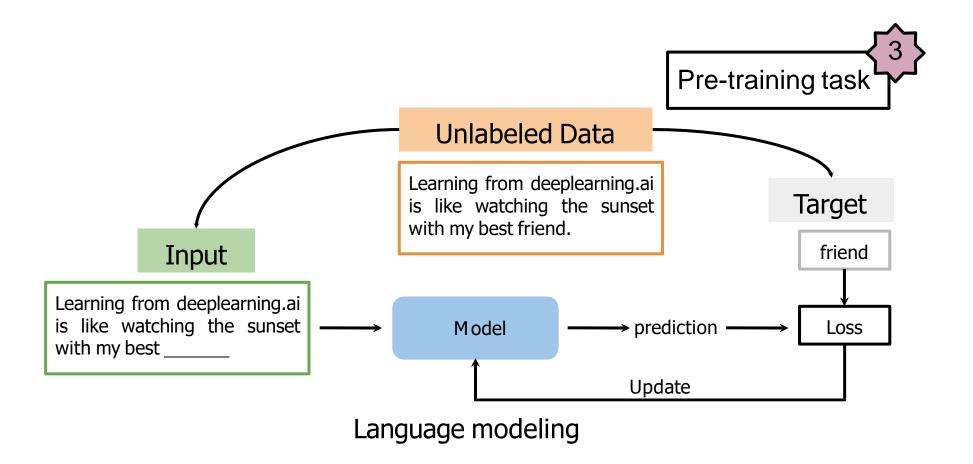




Which tasks work with **unlabeled** data?

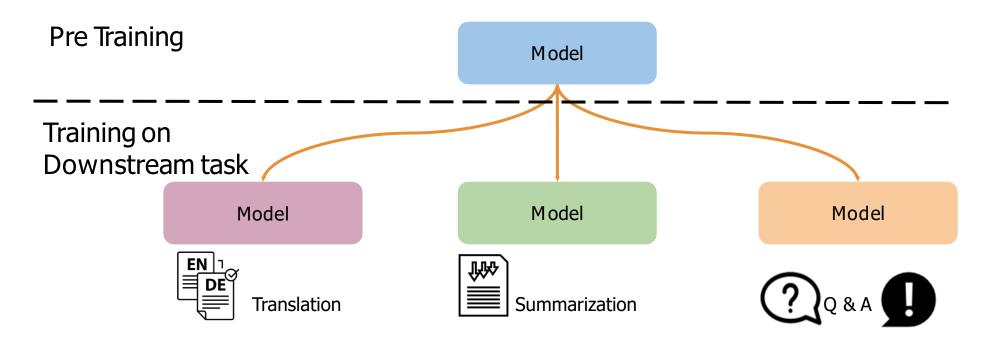
Self-supervised tasks





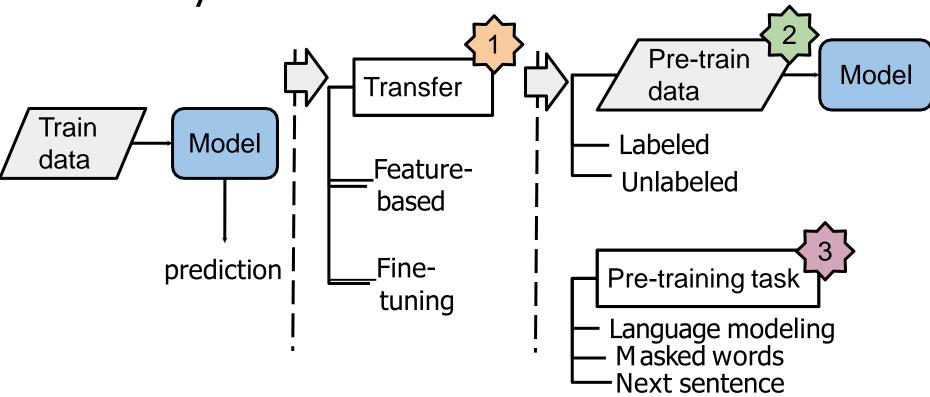
Fine-tune a model for each downstream task





Summary





ELMo, GPT, BERT, T5 - Outline





... right ...

Context

... they were on the right ...

... they were on the right side of the street

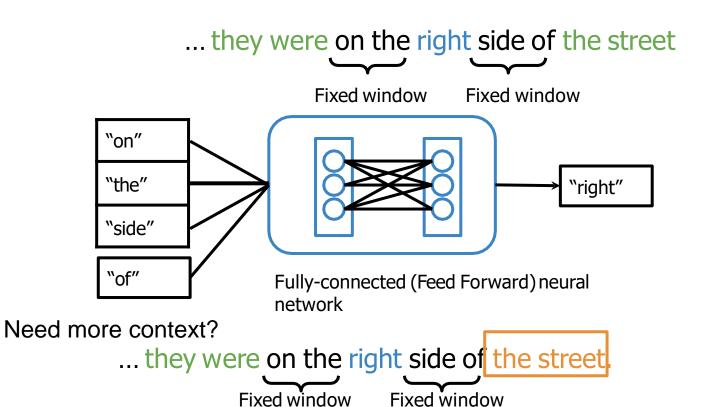
Continuous Bag of Words

"on"

"the"

"of"



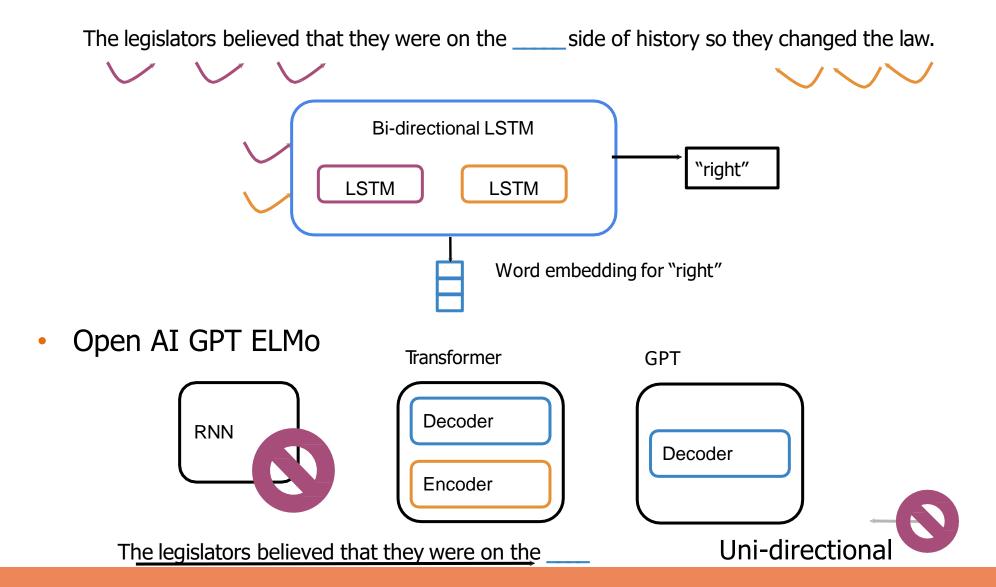


... they were on the right side of history.

The legislators believed that they were on the right side of history, so they changed the law.

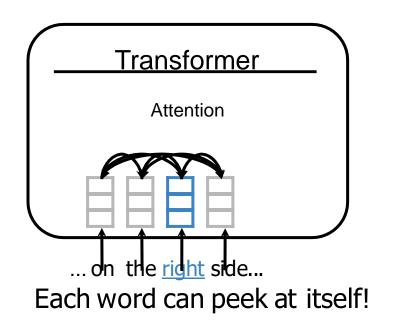
ELMo: Full context using RNN

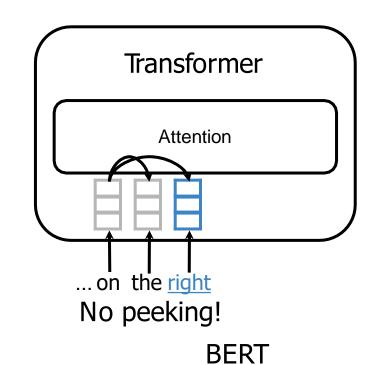




GPT: Uni-directional







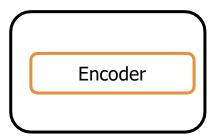
BERT Transformer

Decoder

Encoder



GPT

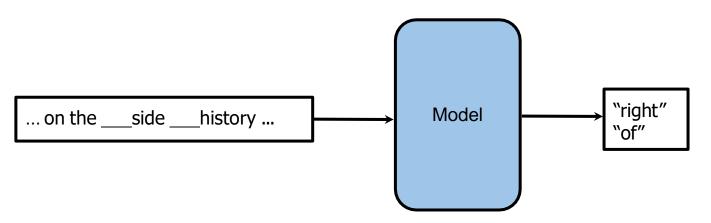


The legislators believed that they were on the Bi-directional

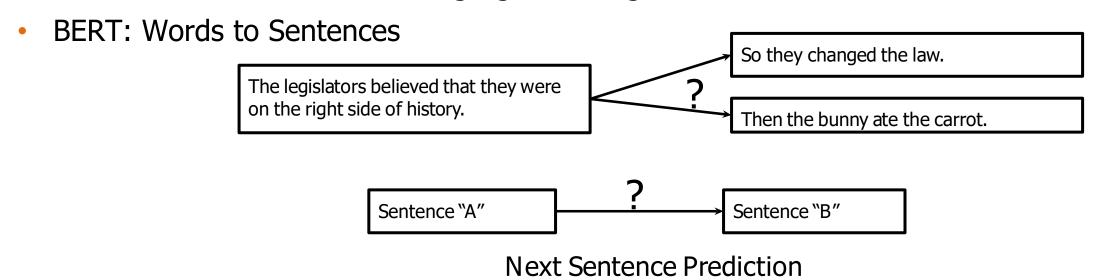
_side of history, so they changed the law.

Transformer + Bi-directional Context





Multi-Mask Language Modeling



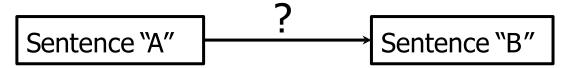
BERT Pre-training Tasks



Multi-Mask Language Modeling



Next Sentence Prediction

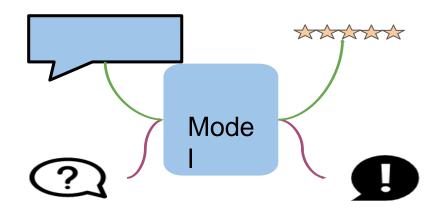


T5: Encoder vs. Encoder-Decoder





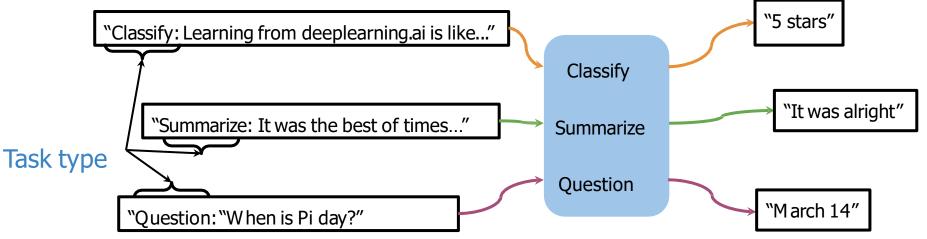
- T5: Multi-task
 - Studying with deeplearning.aiwas ...



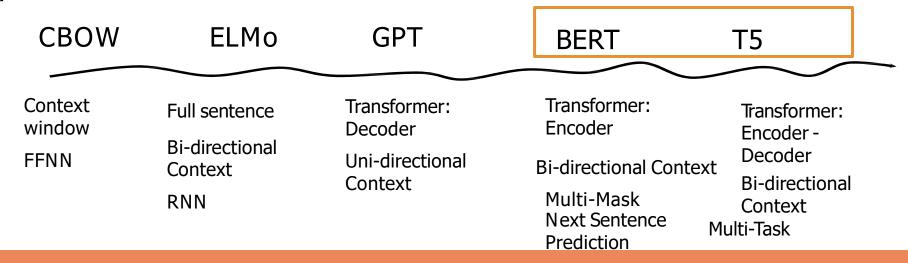
How

T5: Text-to-Text





Summary

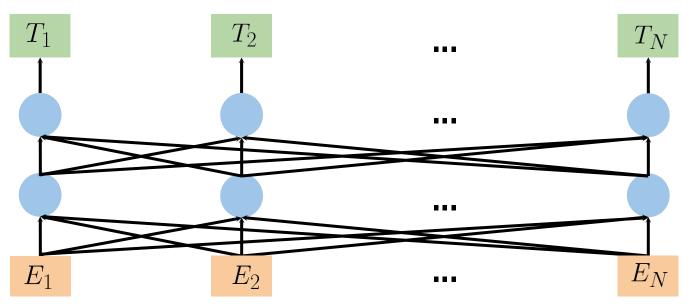


Bidirectional Encoder Representations from Transformers (BERT)



- BERT architecture
- BERT pre-training works

Makes use of transfer learning/pre-training:



BERT



- A multi layer bidirectional transformer
- Positional embeddings
- BERT_base:
 - 12 layers (12 transformer blocks); 12 attentions heads; 110 million parameters
- BERT pre-training

After school Lukasz does his ______ in the library.

Masked language modeling (MLM)

After school Lukasz does his homework in the library.

After school _____ his homework in the _____

BERT Objective

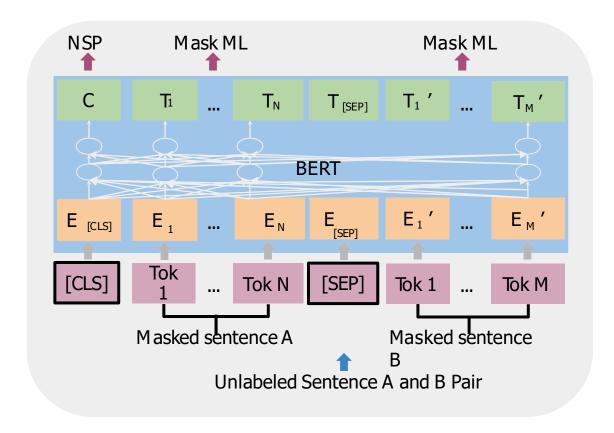


- Understand how BERT inputs are fed into the model
- Visualize the output
- Learn about the BERT objective
- Formalizing the input

Input	[CLS]	my	dog	is	cute	[SEP]	he	likes	play	##ing	[SEP]
Token Embeddings	E [CLS]	E my	E dog	E is	E cute	E [SEP]	E he	E likes	E play	E ##ing	E [SEP]
Segment Embeddings	E A	E A	E _A	E A	E A	E A	E _B				
Position Embeddings	E ₀	E ₁	E ₂	E 3		E 5	E ₆	E 7			

Visualizing the output





 [CLS]: a special classification symbol added in front of every input

[SEP]: a special separator token

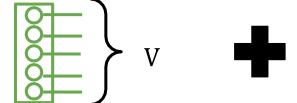
BERT Objective

EPT Education

FPT UNIVERSITY

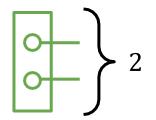
Objective 1: Multi-Mask LM

Loss: Cross Entropy Loss



Objective 2: Next Sentence Prediction

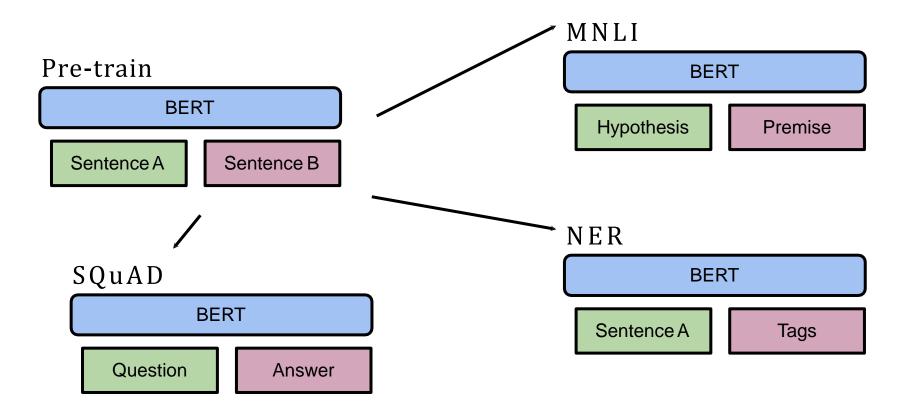
Loss: Binary Loss



- Summary
 - BERT objective
 - Model inputs/outputs

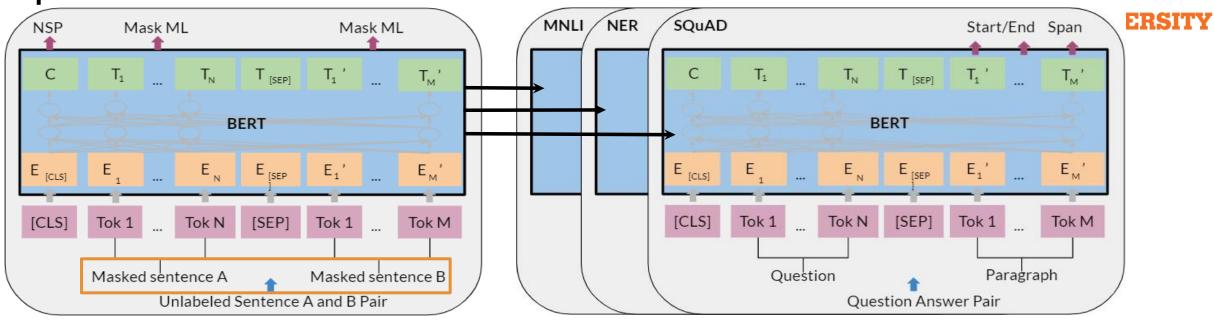
Fine-tuning BERT: Outline



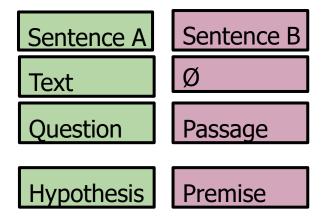


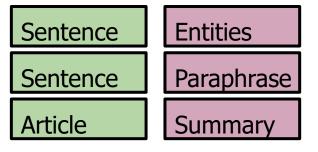
Inputs





Summary

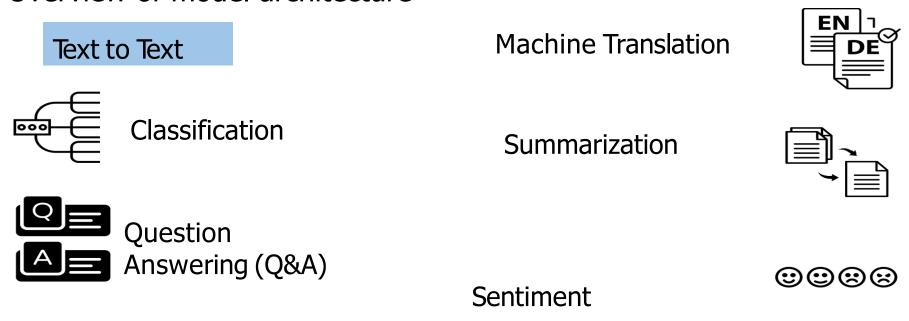




Transformer - T5 Model

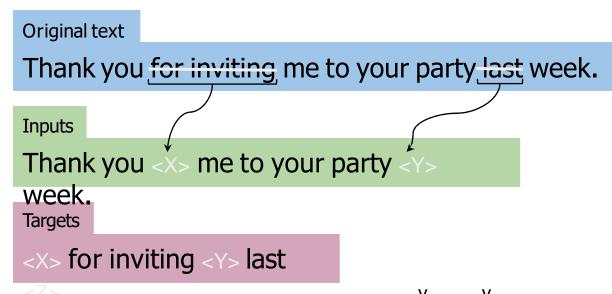


- Understand how T5 works
- Recognize the different types of attention used
- Overview of model architecture

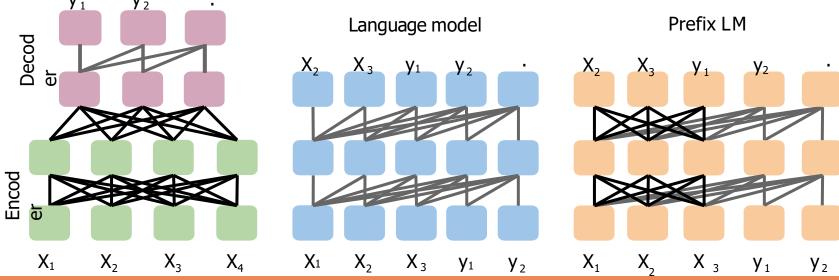


Transformer - T5 Model





Model Architecture

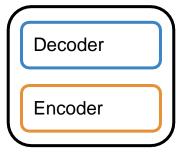


Model Architecture

- Encoder/decoder
- 12 transformer blocks each
- 220 million parameters

© Exploring the Limits of Transfer learning with a unified text to Text Transformer. Raffel et. al. 2020

- Summary
 - Prefix LM attention
 - Model architecture
 - Pre-training T5 (MLM)



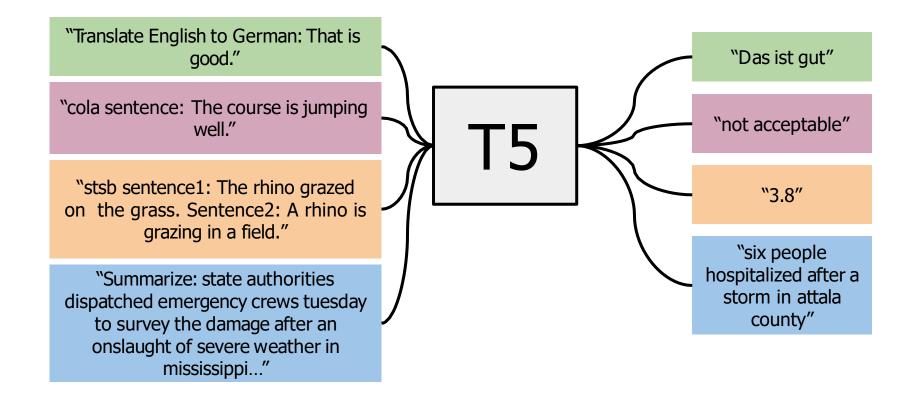






Multi-task training strategy





Input and Output Format

FPT UNIVERSITY

Machine translation:

- translate English to German: That is good.
- Predict entailment, contradiction, or neutral
 - mnli premise: I hate pigeons hypothesis: My feelings towards pigeons are filled with animosity. target: entailment
- Winograd schema
 - The city councilmen refused the demonstrators a permit because *they* feared violence

Multi-task Training Strategy



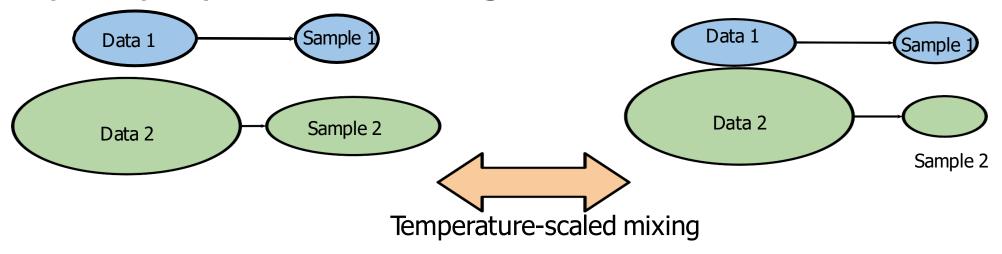
Fine-tuning method	GLUE	CNNDM	SQuAD	SGLUE	EnDe	EnFr	EnRo
* All parameters	83.28	19.24	80.88	71.36	26.98	39.82	27.65
Adapter layers, $d=32$	80.52	15.08	79.32	60.40	13.84	17.88	15.54
Adapter layers, $d=128$	81.51	16.62	79.47	63.03	19.83	27.50	22.63
Adapter layers, $d=512$	81.54	17.78	79.18	64.30	23.45	33.98	25.81
Adapter layers, $d=2048$	81.51	16.62	79.47	63.03	19.83	27.50	22.63
Gradual unfreezing	82.50	18.95	79.17	70.79	26.71	39.02	26.93

How much data from each task to train on?

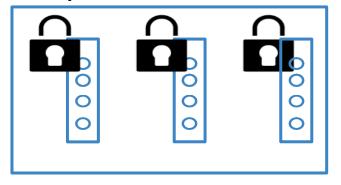
Data Training Strategies Examples-proportional mixing



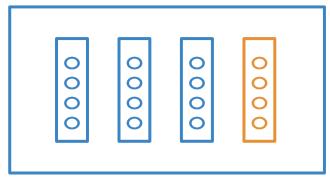
Equal mixing



Gradual unfreezing vs. Adapter layers



Gradual unfreezing

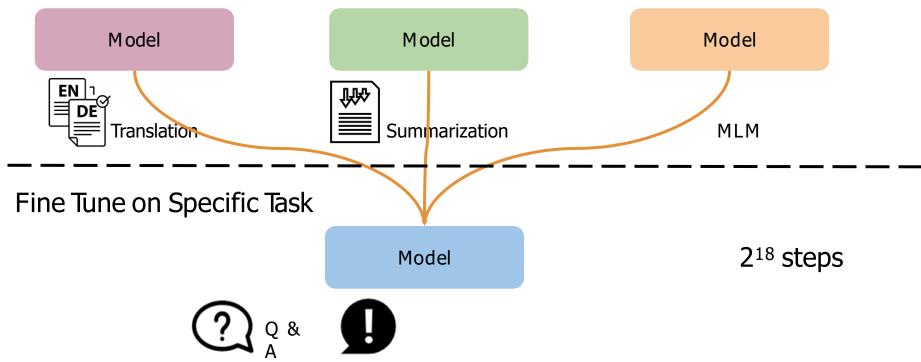


Adapter layers

Fine-tuning



Pre Training



GLUE Benchmark



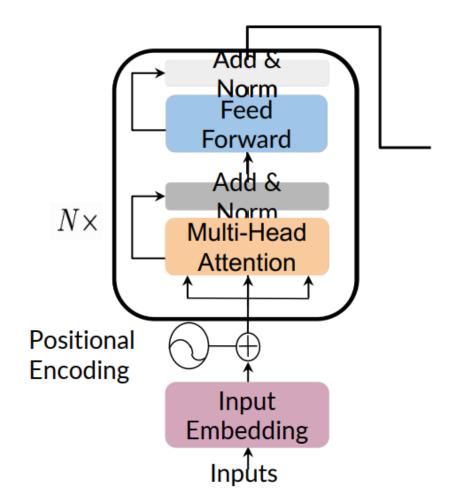
- General Language Understanding Evaluation
 - A collection used to train, evaluate, analyze natural language
 - understanding systems
 - Datasets with different genres, and of different sizes and difficulties
 - Leaderboard
- Tasks Evaluated on
 - Sentence grammatical or not?
 - Sentiment; Paraphrase; Similarity
 - Questions duplicates; Answerable; Contradiction
 - Entailment; Winograd (co-ref)
- General Language Understanding Evaluation
 - Drive research; Model agnostic; Makes use of transfer learning

Question Answering - Transformer encoder



Feedforward:





```
LayerNorm,
dense,
activation,
dropout_middle,
dense,
dropout final
```

```
Residual(
    LayerNorm,
    attention,
    dropout_,
Residual(
    feed_forward,
```

Data examples



Question: What percentage of the French population today is non - European?

Context: Since the end of the Second World War , France has become an ethnically diverse country . Today , approximately five percent of the French population is non - European and non - white . This does not approach the number of non - white citizens in the United States (roughly 28 – 37 %, depending on how Latinos are classified; see Demographics of the United States). Nevertheless, it amounts to at least three million people, and has forced the issues of ethnic diversity onto the French policy agenda. France has developed an approach to dealing with ethnic problems that stands in contrast to that of many advanced, industrialized countries. Unlike the United States, Britain, or even the Netherlands, France maintains a "color - blind" model of public policy. This means that it targets virtually no policies directly at racial or ethnic groups. Instead, it uses geographic or class criteria to address issues of social inequalities. It has, however, developed an extensive anti-racist policy repertoire since the early 1970s. Until recently, French policies focused primarily on issues of hate speech—going much further than their American counterparts—and relatively less on issues of discrimination in jobs, housing, and in provision of goods and services.

Target: Approximately five percent

Implementing Q&A with T5



- Load a pre-trained model
- Process data to get the required inputs and outputs: "question: Q context: C" as input and "A" as target
- Fine tune your model on the new task and input
- Predict using your own model

