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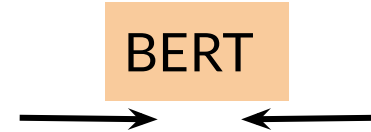


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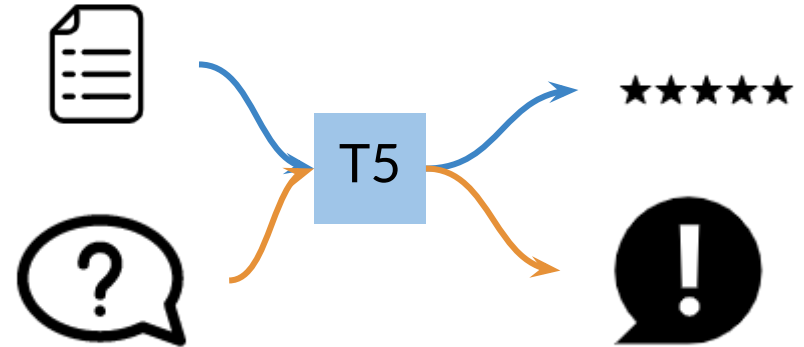
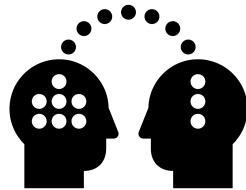
Week 3 Overview

Week 3

Question
Answering

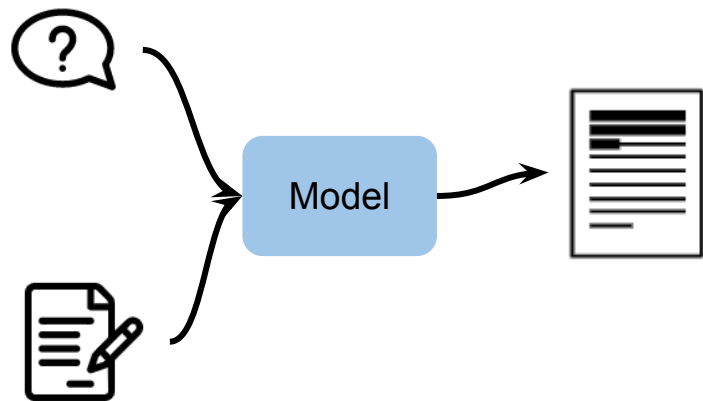


Transfer
learning

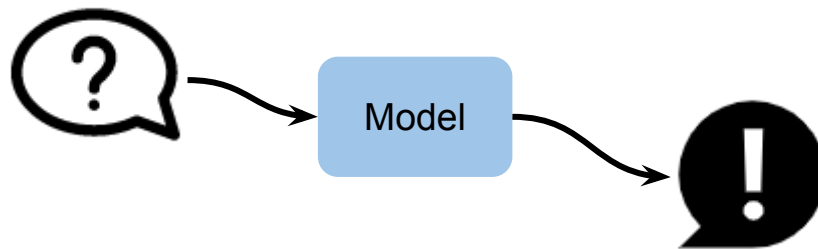


Question Answering

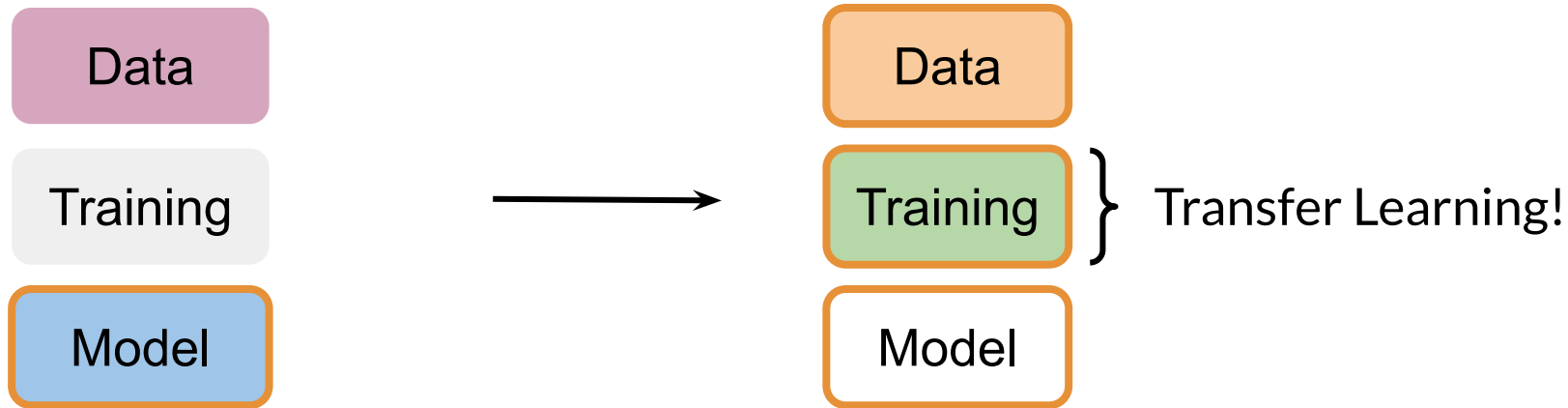
Context-based



Closed book

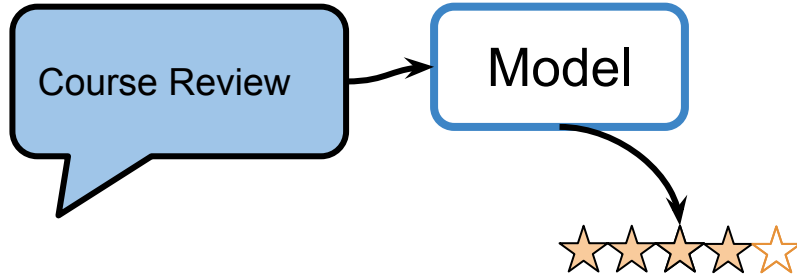


Not just the model

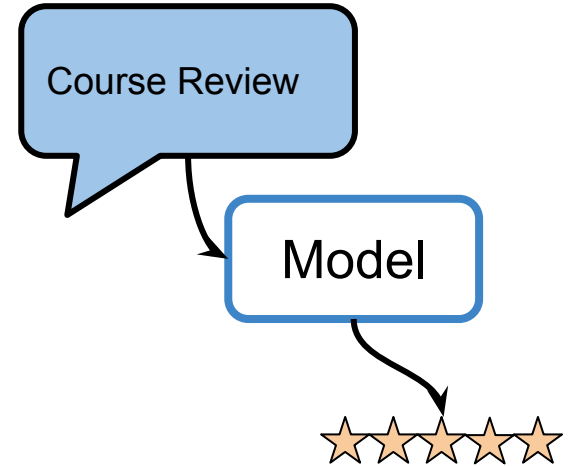


Classical training

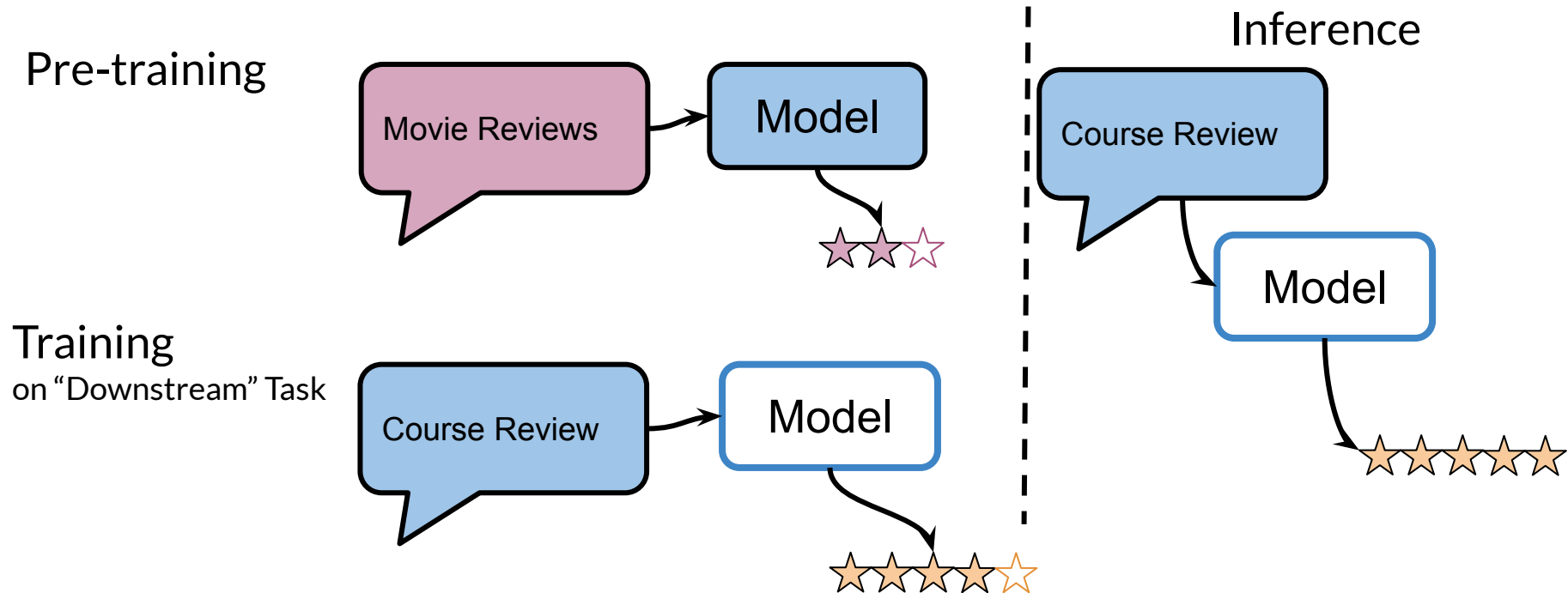
Training



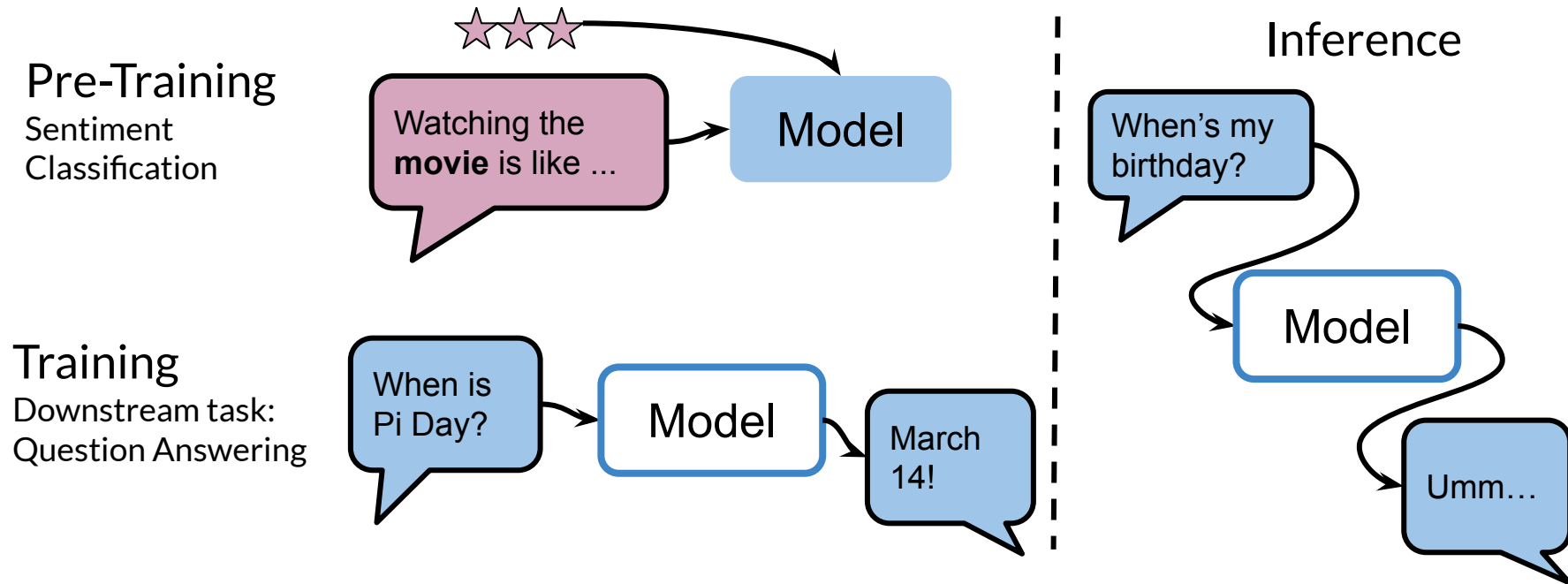
Inference



Transfer learning

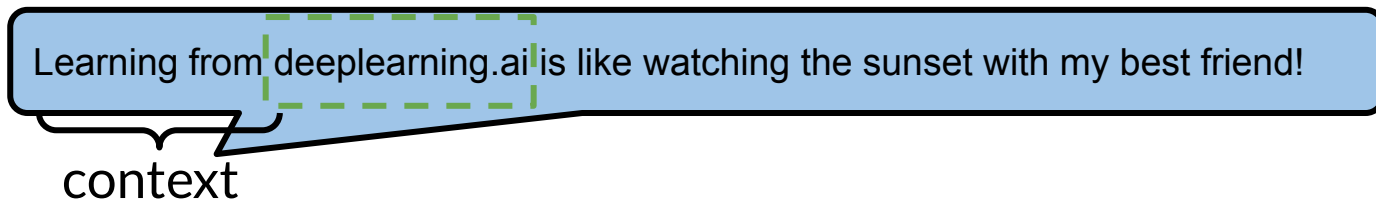


Transfer Learning: Different Tasks

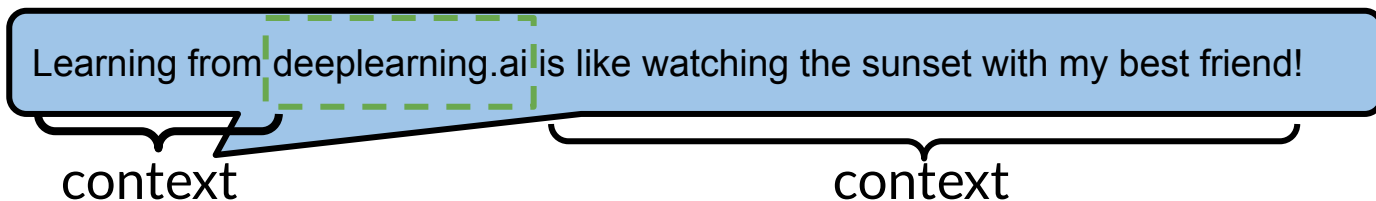


BERT: Bi-directional Context

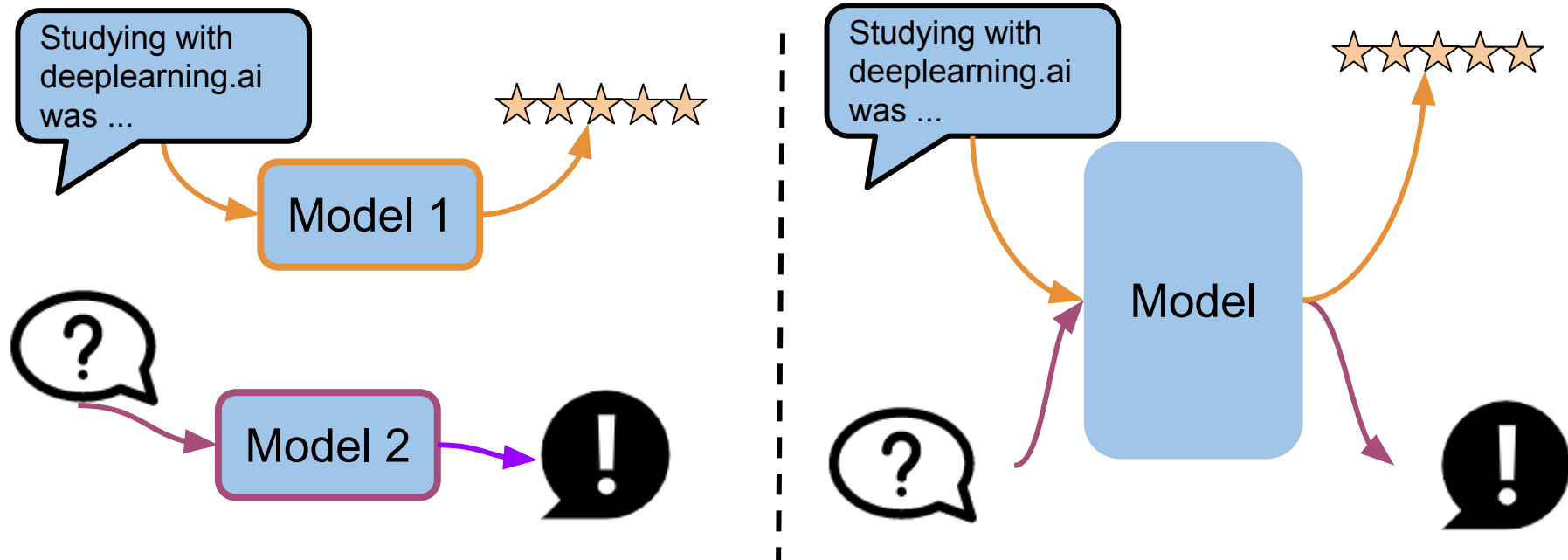
Uni-directional



Bi-directional



T5: Single task vs. Multi task



T5: more data, better performance

English wikipedia
~13 GB



C4
Colossal Clean Crawled
Corpus
~800 GB





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Transfer Learning in NLP

Desirable Goals



- Reduce training time



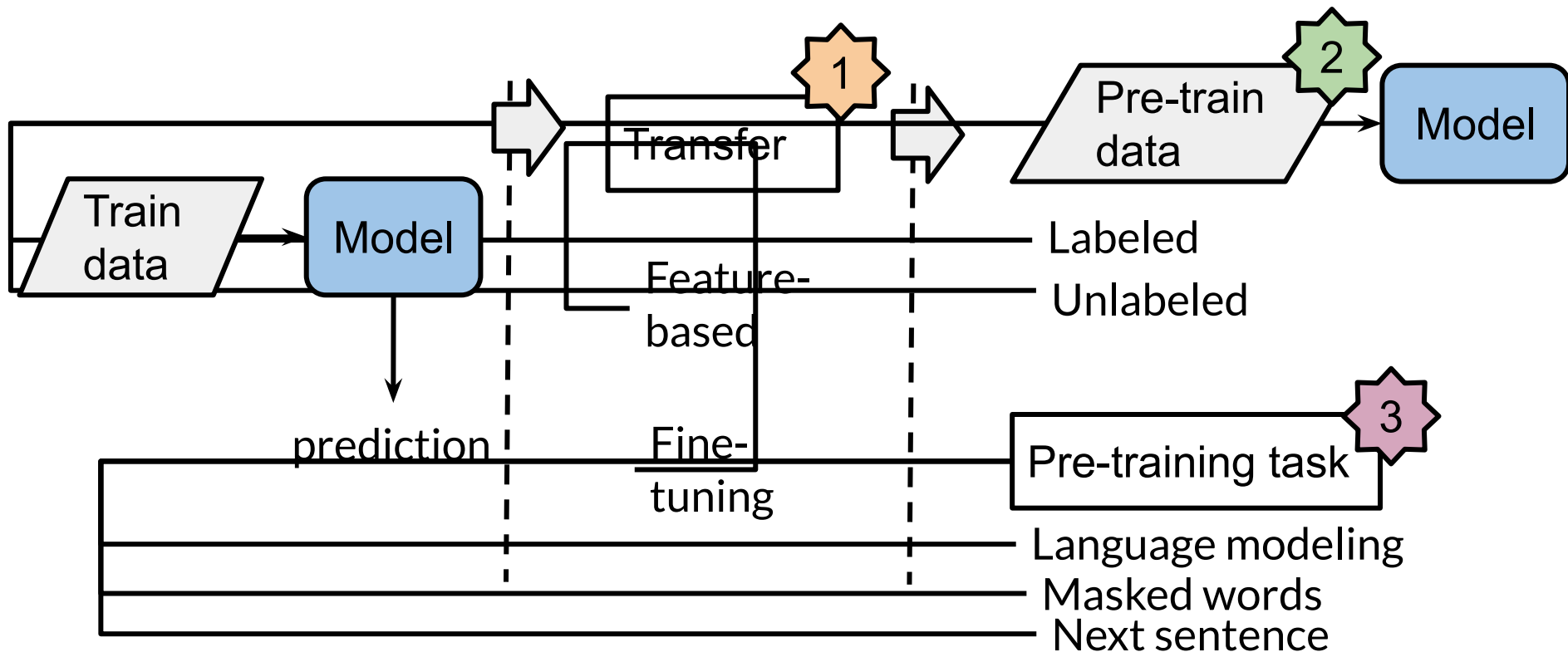
- Improve predictions



- Small datasets

Transfer Learning!

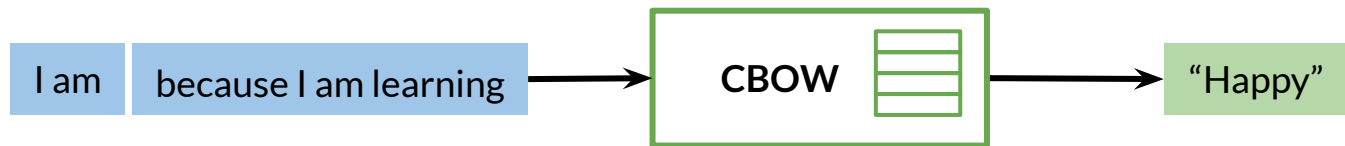
Transfer learning options



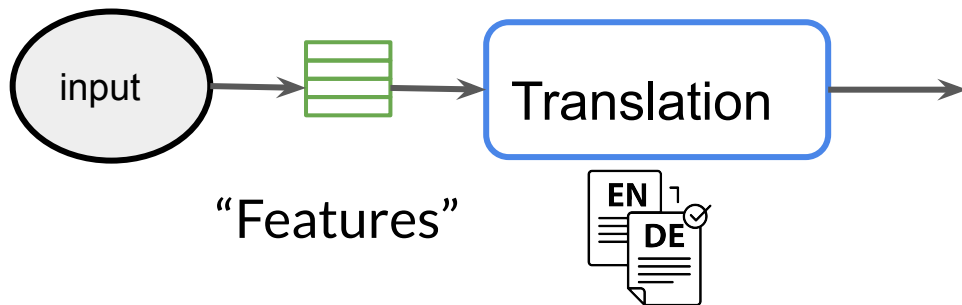
General purpose learning

Transfer

1

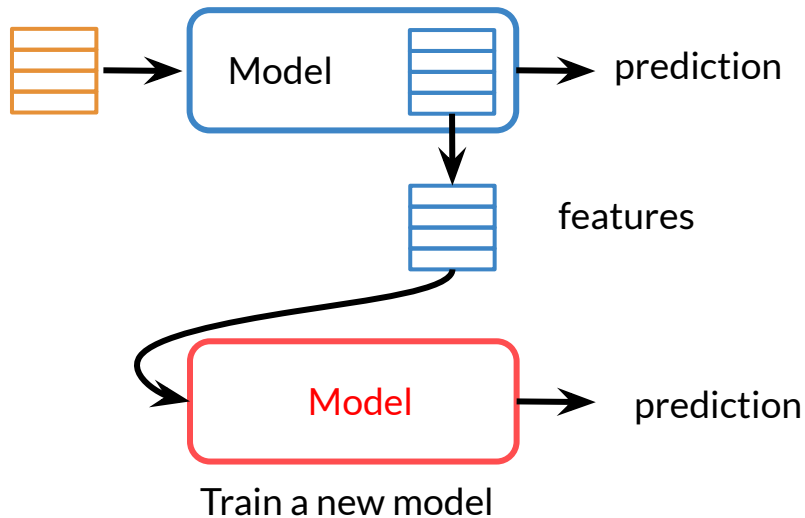


Word Embeddings

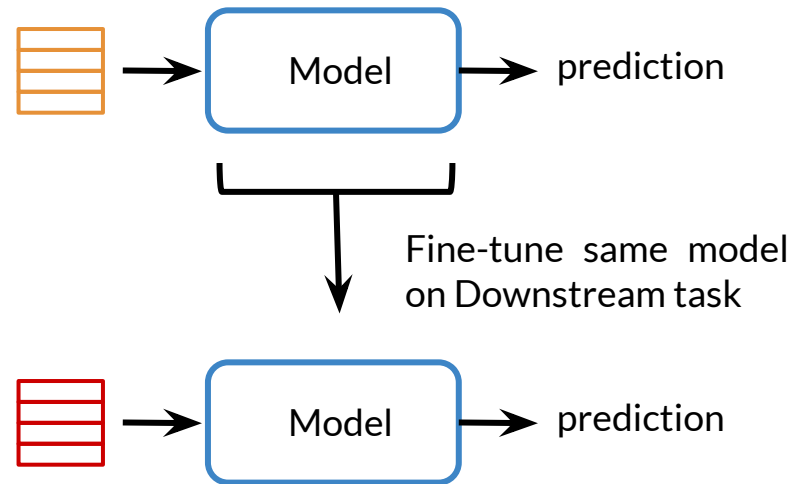


Feature-based vs. Fine-Tuning

Pre-Train

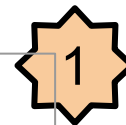


Pre-Train

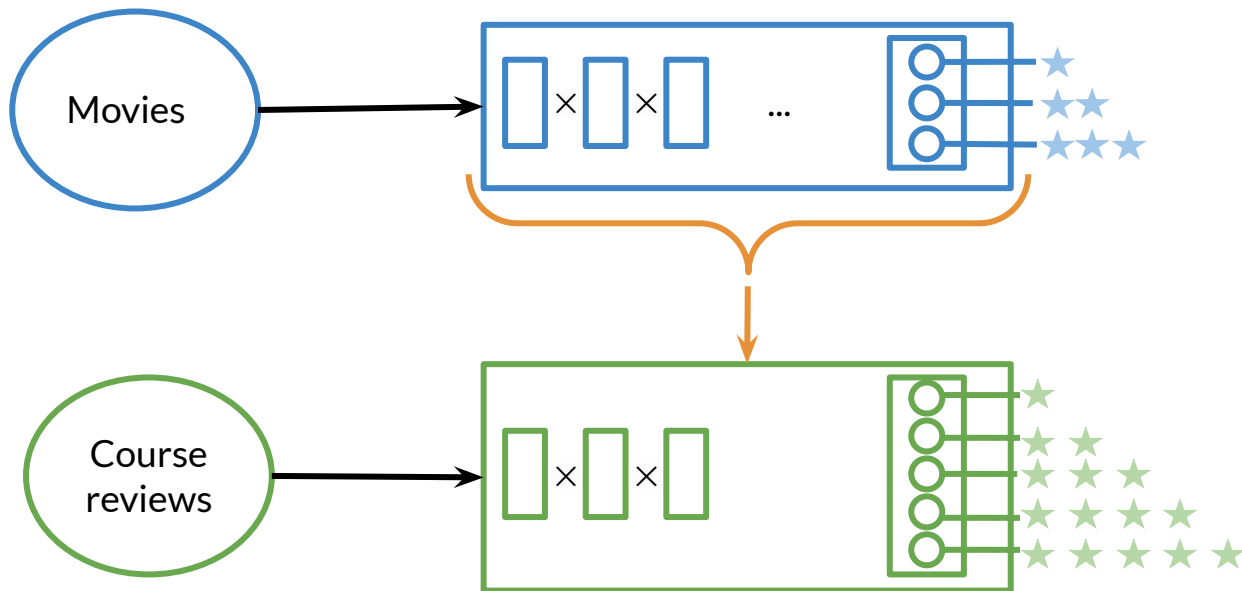


Fine-tune: adding a layer

Transfer



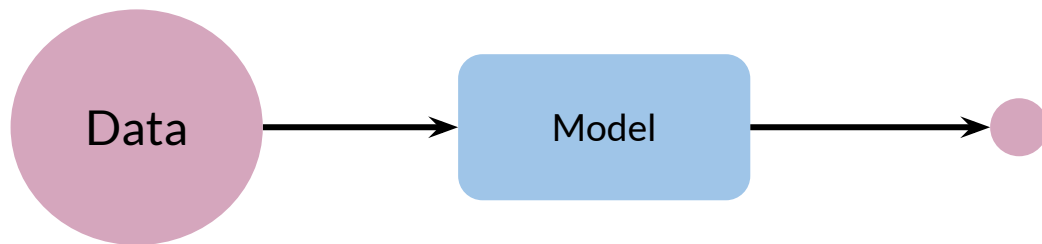
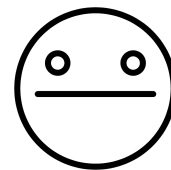
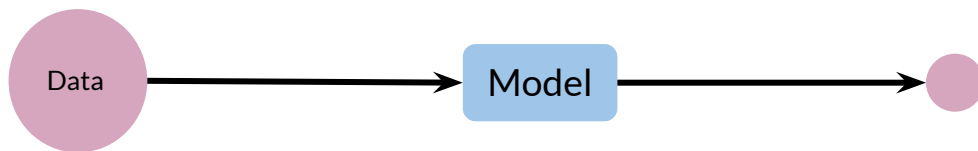
Pre-Training



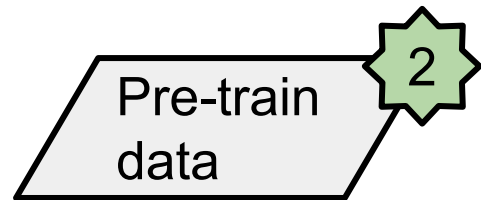
Data and performance

Pre-train
data

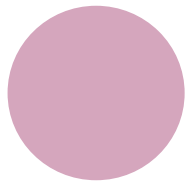
2



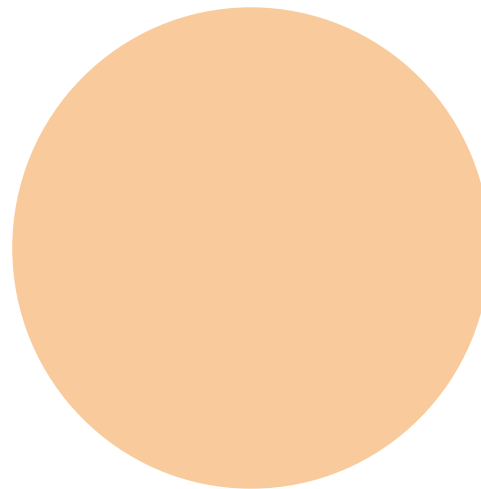
Labeled vs Unlabeled Data



Labeled text data



Unlabeled text data



Transfer learning with unlabeled data

Pre-train
data

2

Pre-Training



Model

No labels !

Downstream task

What day is Pi day?

Model

March 14

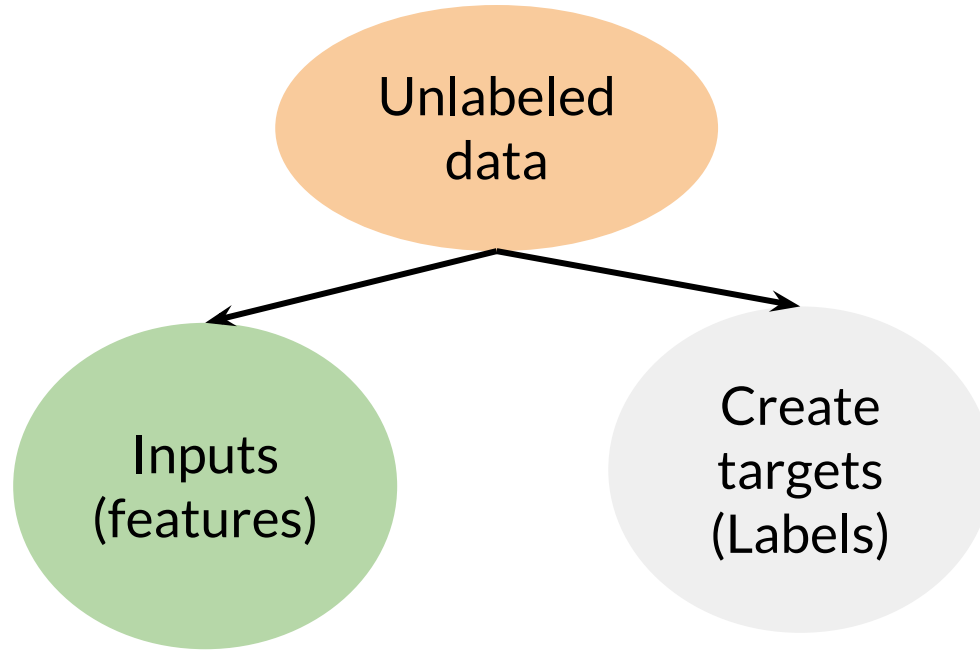
Labeled data

Which tasks work with
unlabeled data?

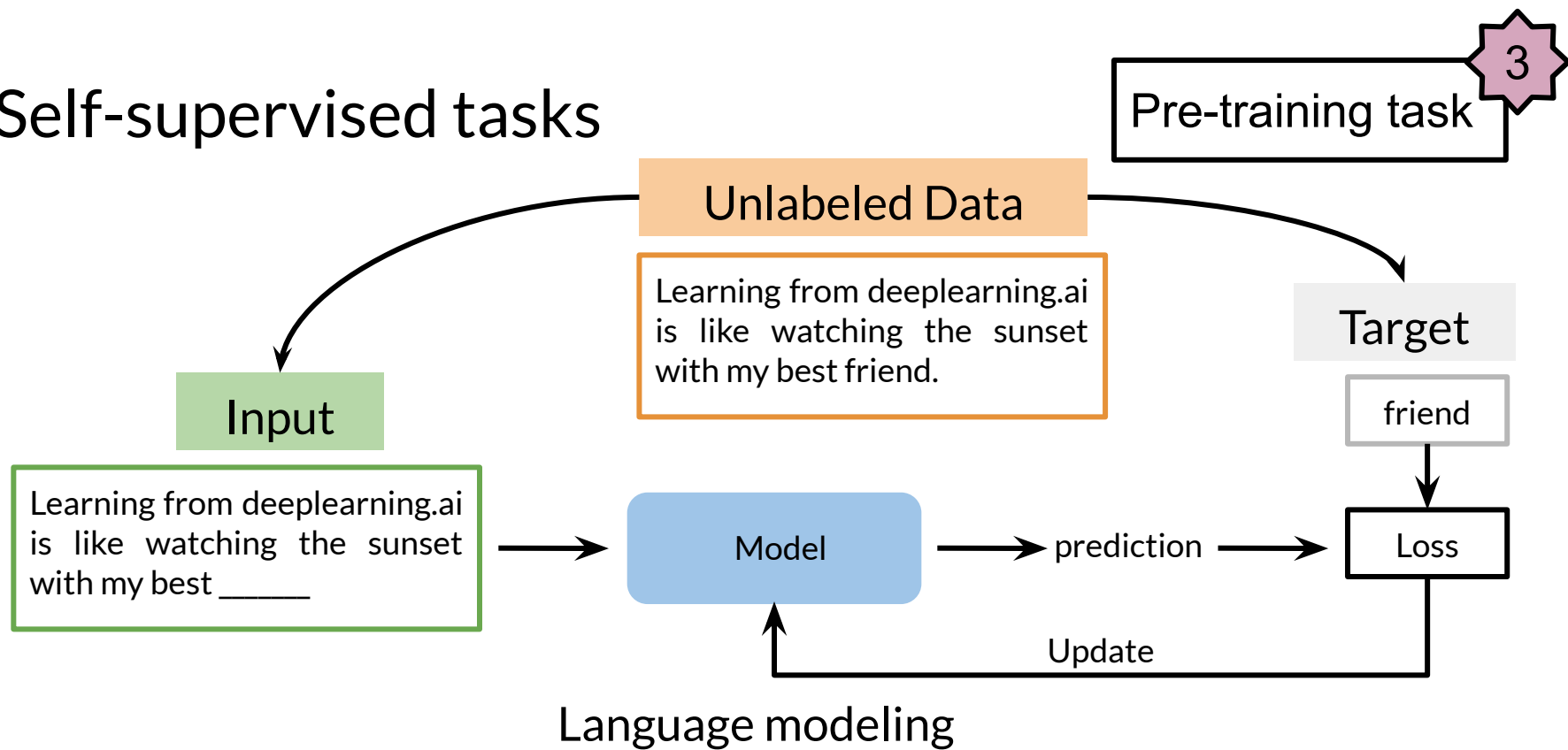
Self-supervised task

Pre-training task

3

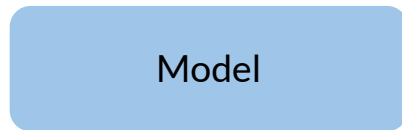


Self-supervised tasks

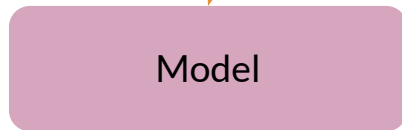


Fine-tune a model for each downstream task

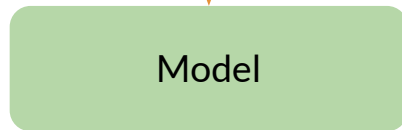
Pre Training



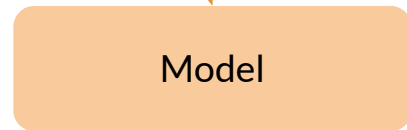
Training on
Downstream task



Translation

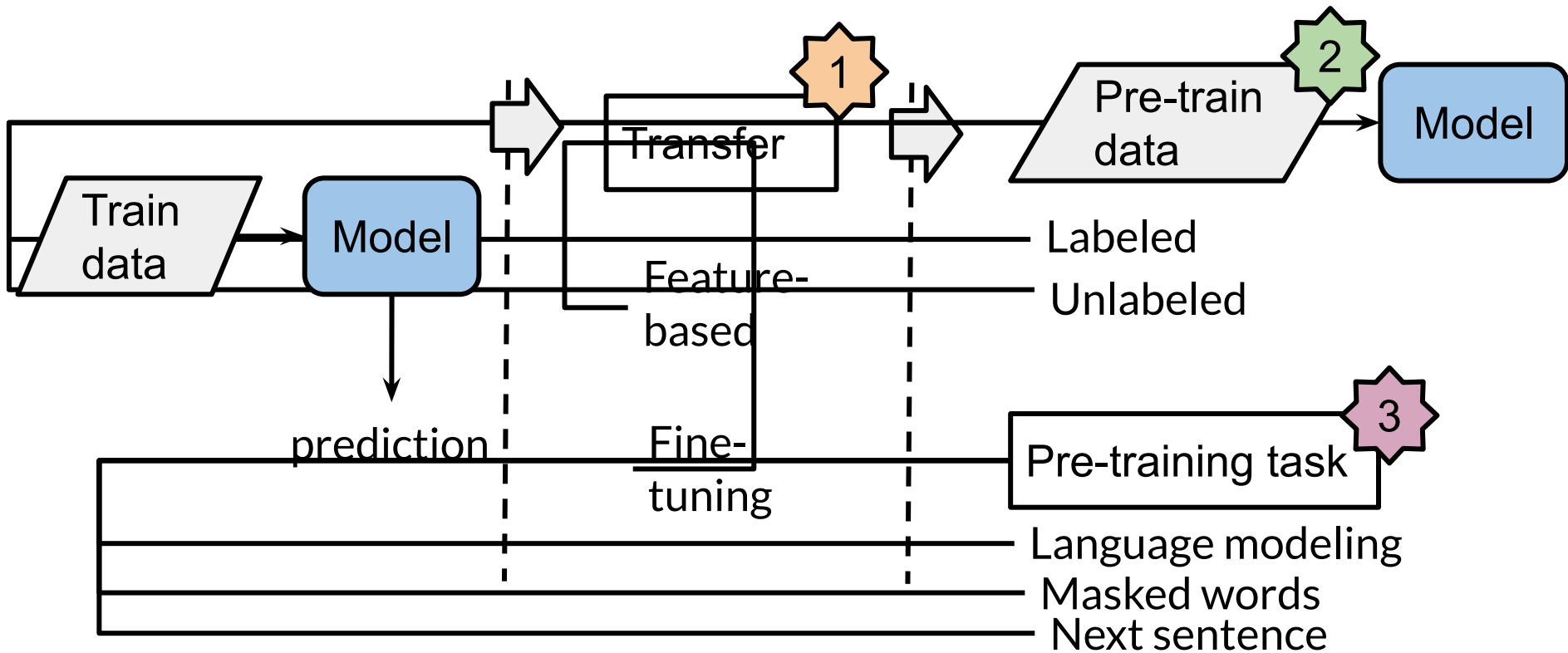


Summarization



Q & A

Summary





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ELMo, GPT, BERT, T5

Outline

CBOW

ELMo

GPT


BERT

T5



Context

... right ...

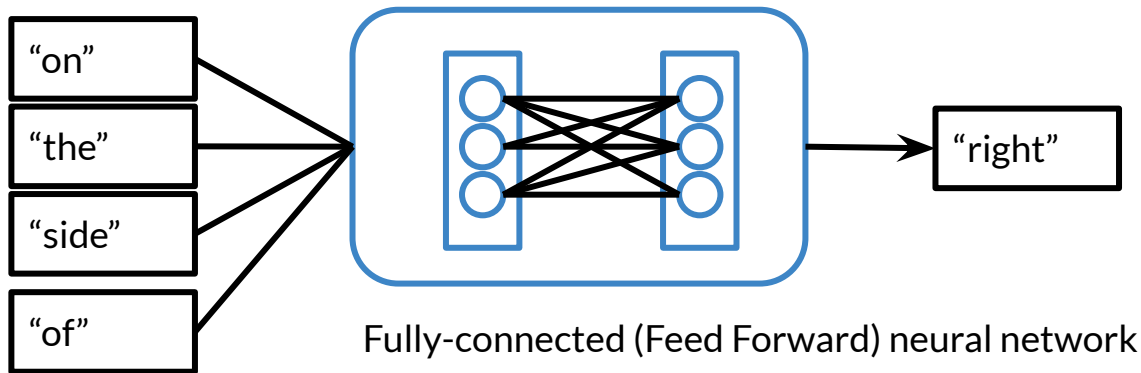
... they were on the right ...


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


Continuous Bag of Words

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

Fixed window Fixed window



Need more context?

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

Fixed window Fixed window

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

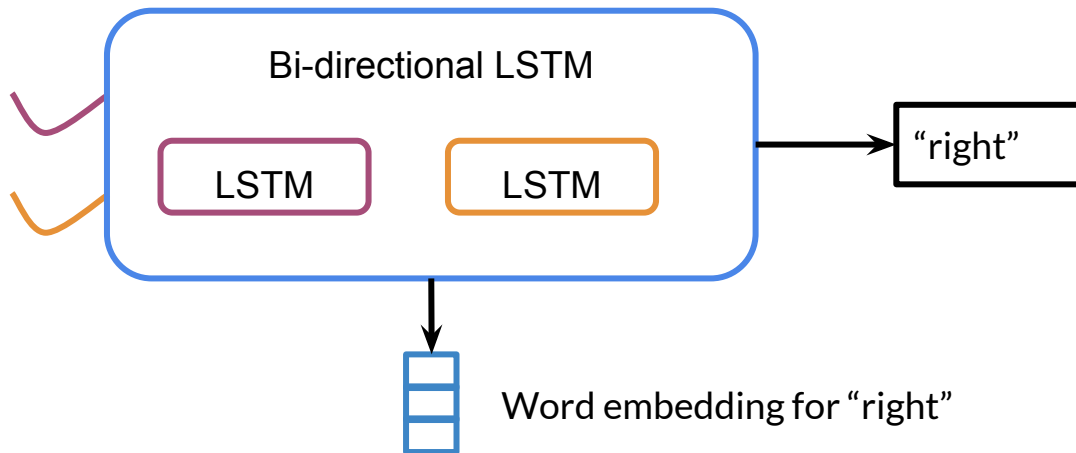
Use all context words

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



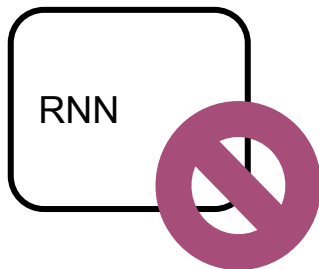
ELMo: Full context using RNN

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

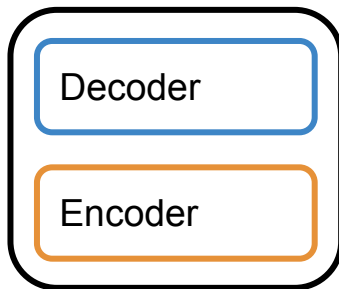


Open AI GPT

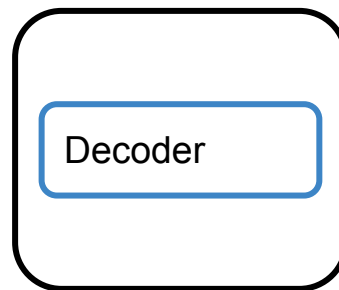
ELMo



Transformer



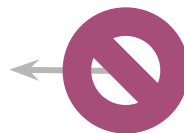
GPT



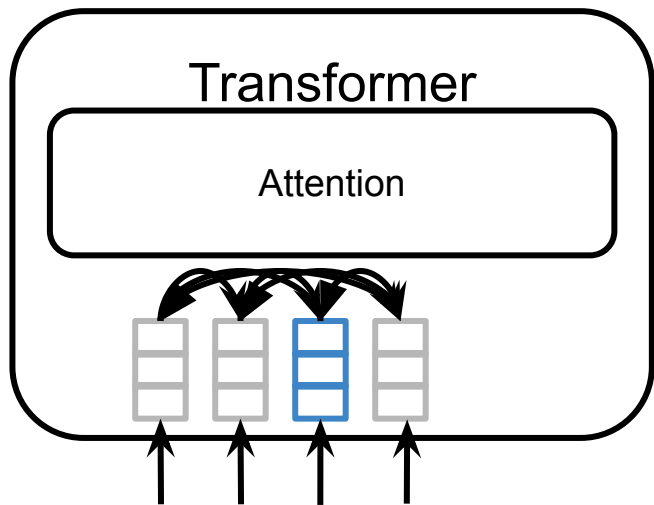
The legislators believed that they were on the ____



Uni-directional



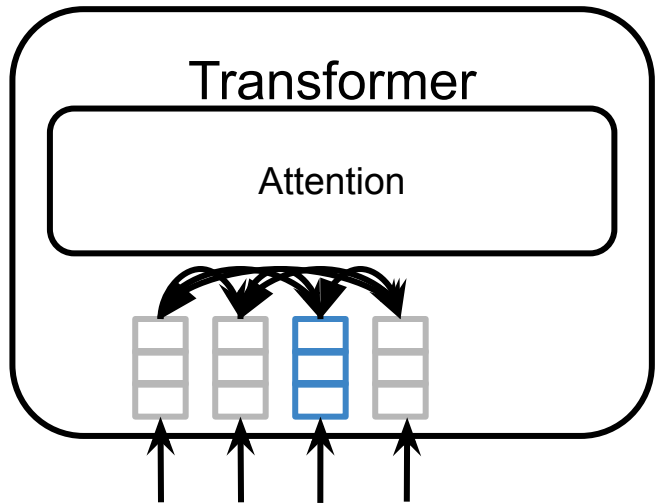
Why not bi-directional?



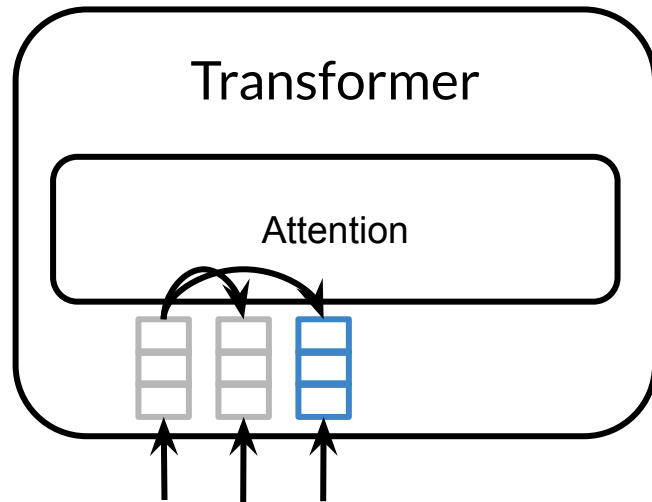
...on the right side...

Each word can peek at itself!

GPT: Uni-directional



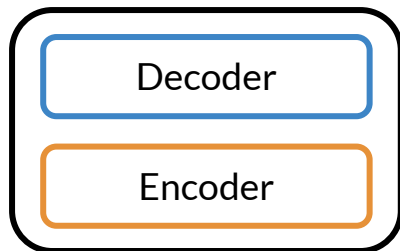
...on the right side...
Each word can peek at itself!



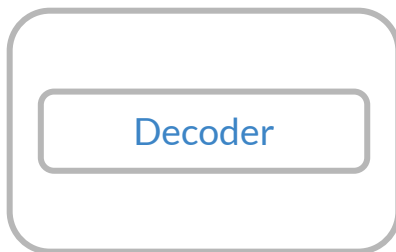
...on the right
No peeking!

BERT

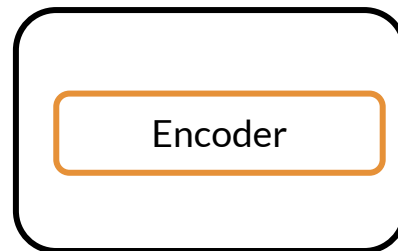
Transformer



GPT



BERT

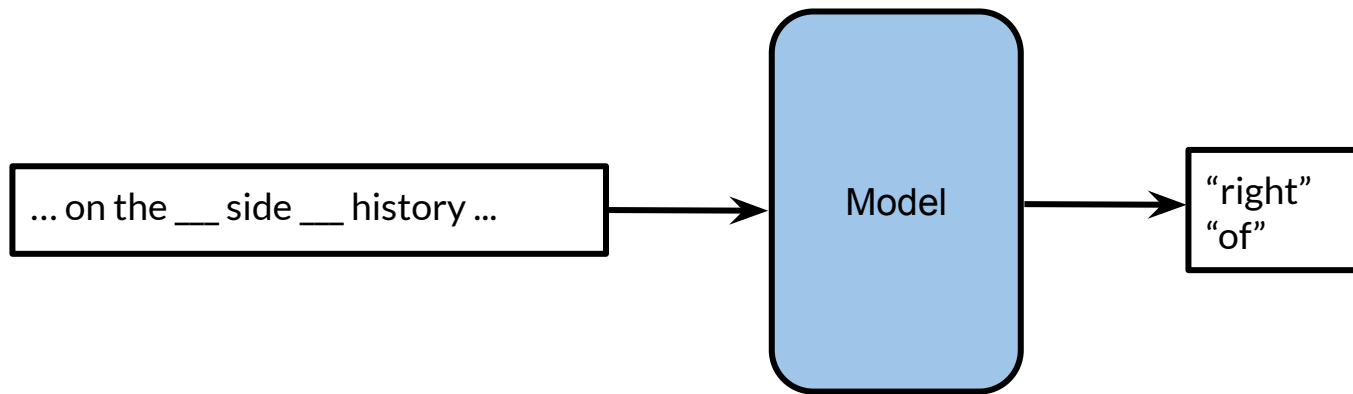


The legislators believed that they were on the ____ side of history, so they changed the law.



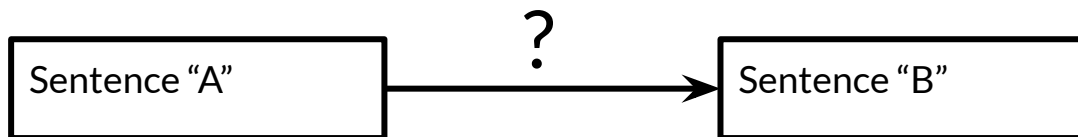
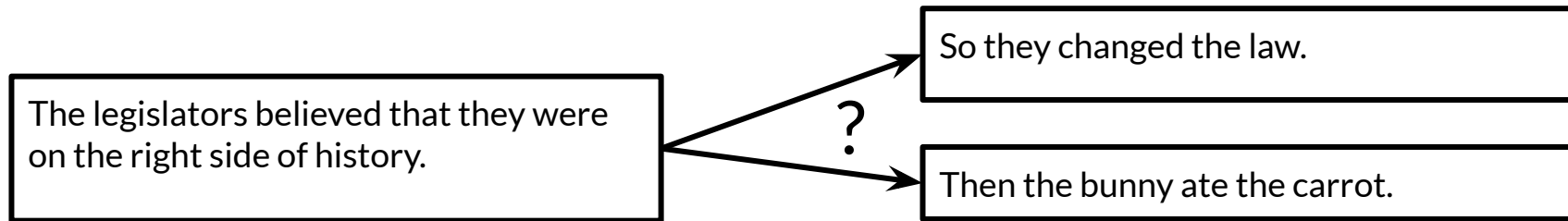
Bi-directional

Transformer + Bi-directional Context



Multi-Mask Language Modeling

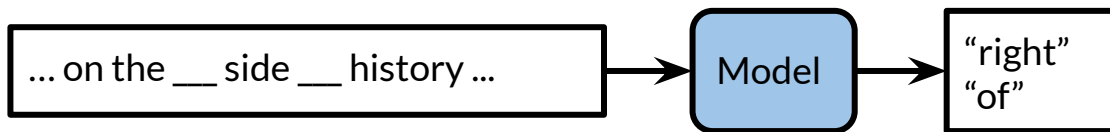
BERT: Words to Sentences



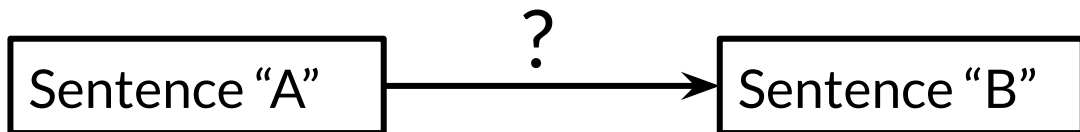
Next Sentence Prediction

BERT Pre-training Tasks

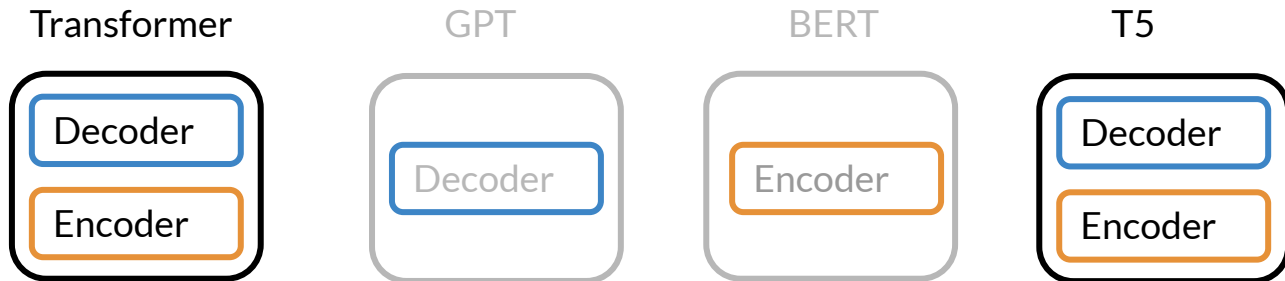
Multi-Mask Language Modeling



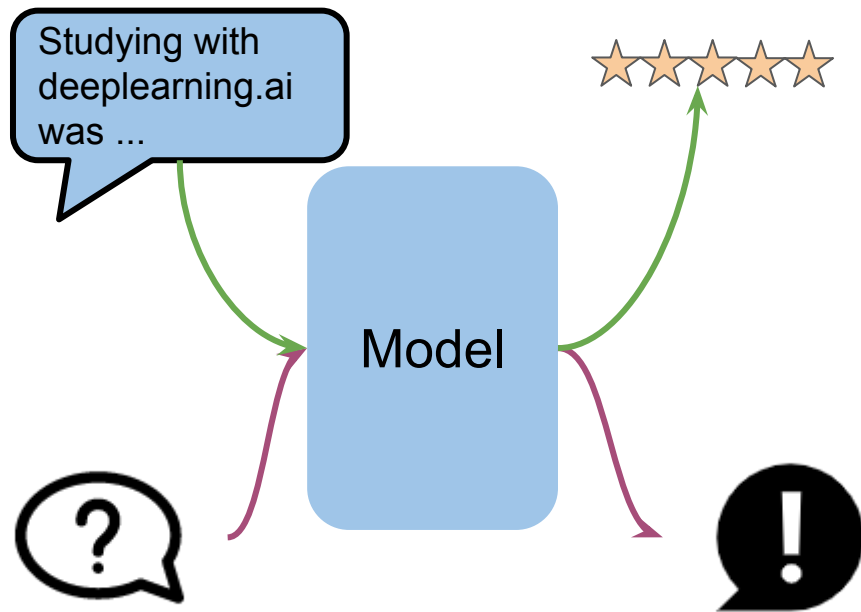
Next Sentence Prediction



T5: Encoder vs. Encoder-Decoder

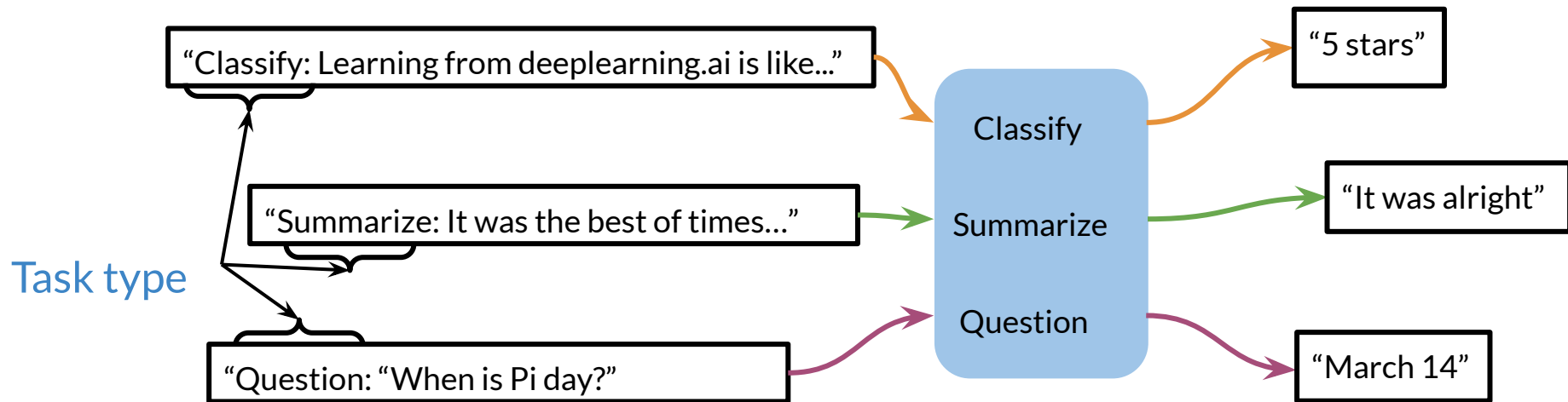


T5: Multi-task



How?

T5: Text-to-Text



Summary

More details next!

CBOW

ELMo

GPT

BERT

T5

Context
window

Full sentence

Transformer:
Decoder

Transformer:
Encoder

Transformer:
Encoder - Decoder

FFNN

Bi-directional
Context

Uni-directional
Context

Bi-directional
Context

Bi-directional
Context

RNN

Multi-Mask

Multi-Task

Next Sentence
Prediction



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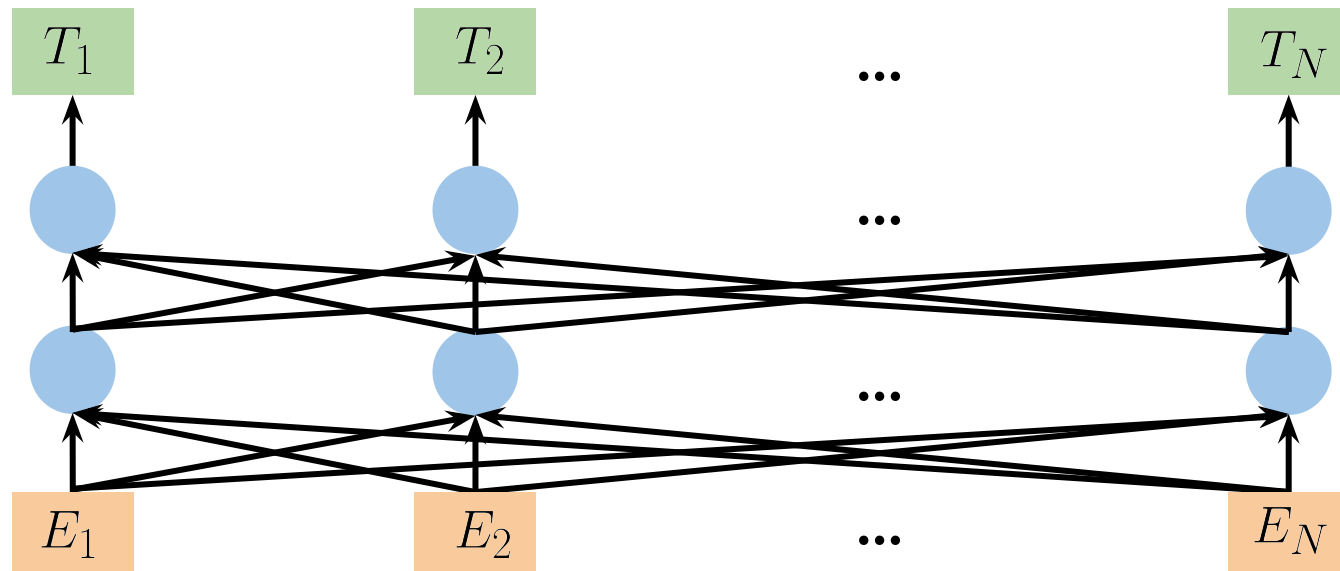
Bidirectional Encoder Representations from Transformers (BERT)

Outline

- Learn about the BERT architecture
- Understand how BERT pre-training works

BERT

- 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)

BERT pre-training

After school **Lukasz** **does** **his** homework in the **library**.

After school _____ his homework in the _____ .

Summary

- Choose 15% of the tokens at random: mask them 80% of the time, replace them with a random token 10% of the time, or keep as is 10% of the time.
- There could be multiple masked spans in a sentence
- Next sentence prediction is also used when pre-training.



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BERT

Objective

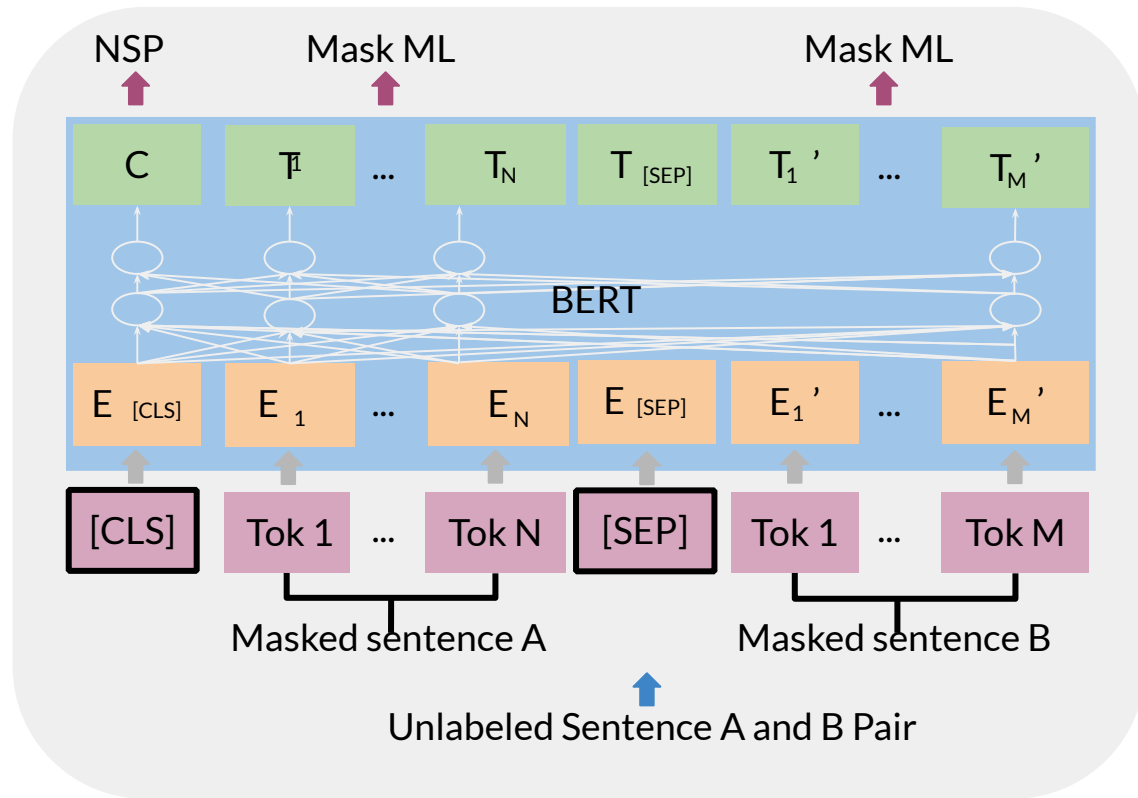
Outline

- 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	E _[CLS]	E _{my}	E _{dog}	E _{is}	E _{cute}	E _[SEP]	E _{he}	E _{likes}	E _{play}	E _{##ing}	E _[SEP]
Embeddings	+	+	+	+	+	+	+	+	+	+	+
Segment	E _A	E _A	E _A	E _A	E _A	E _A	E _B	E _B	E _B	E _B	E _B
Embeddings	+	+	+	+	+	+	+	+	+	+	+
Position	E ₀	E ₁	E ₂	E ₃	E ₄	E ₅	E ₆	E ₇	E ₈	E ₉	E ₁₀
Embeddings											

Visualizing the output

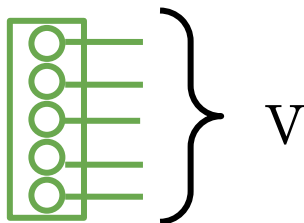


- **[CLS]**: a special classification symbol added in front of every input
- **[SEP]**: a special separator token

BERT Objective

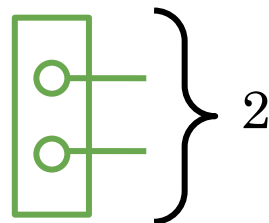
Objective 1:
Multi-Mask LM

Loss: Cross Entropy Loss



Objective 2:
Next Sentence Prediction

Loss: Binary Loss



Summary

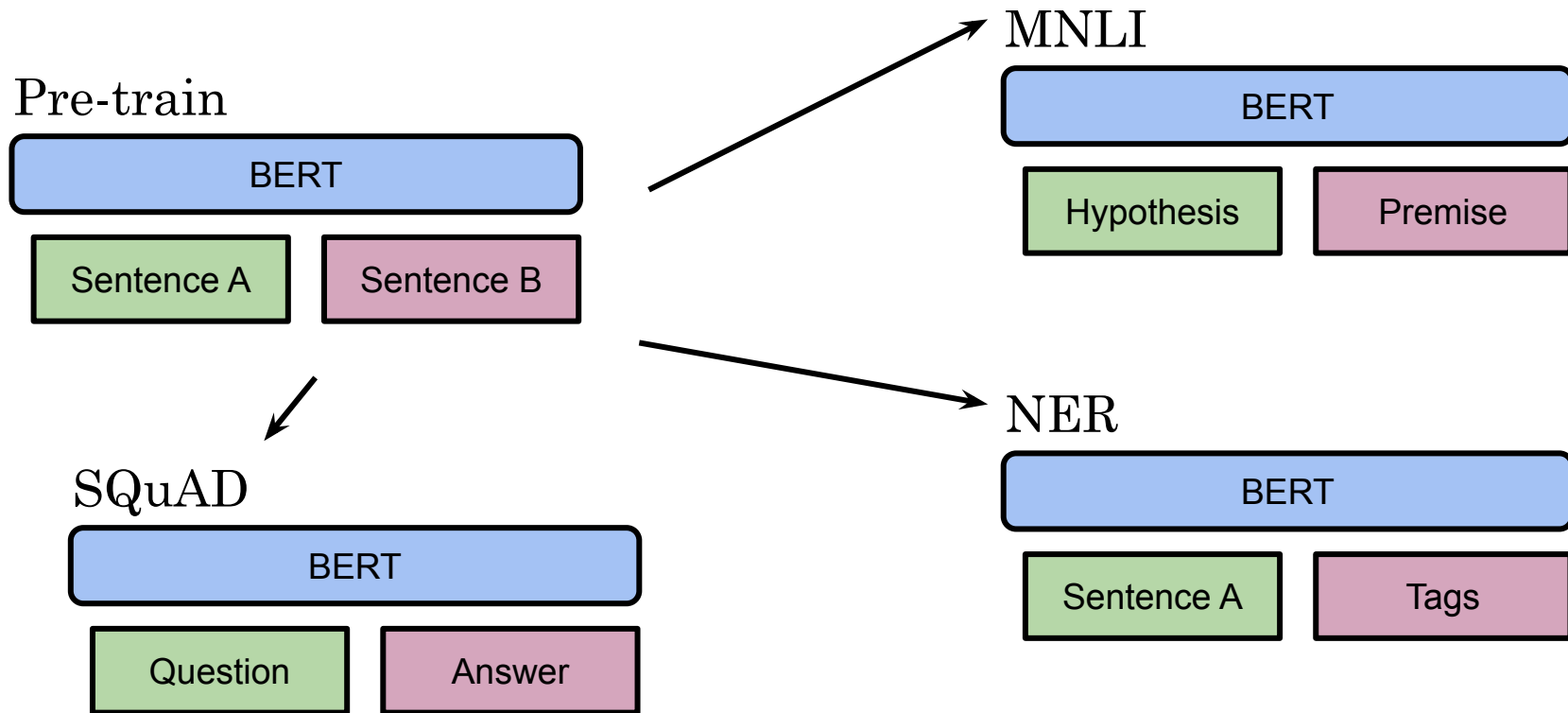
- BERT objective
- Model inputs/outputs



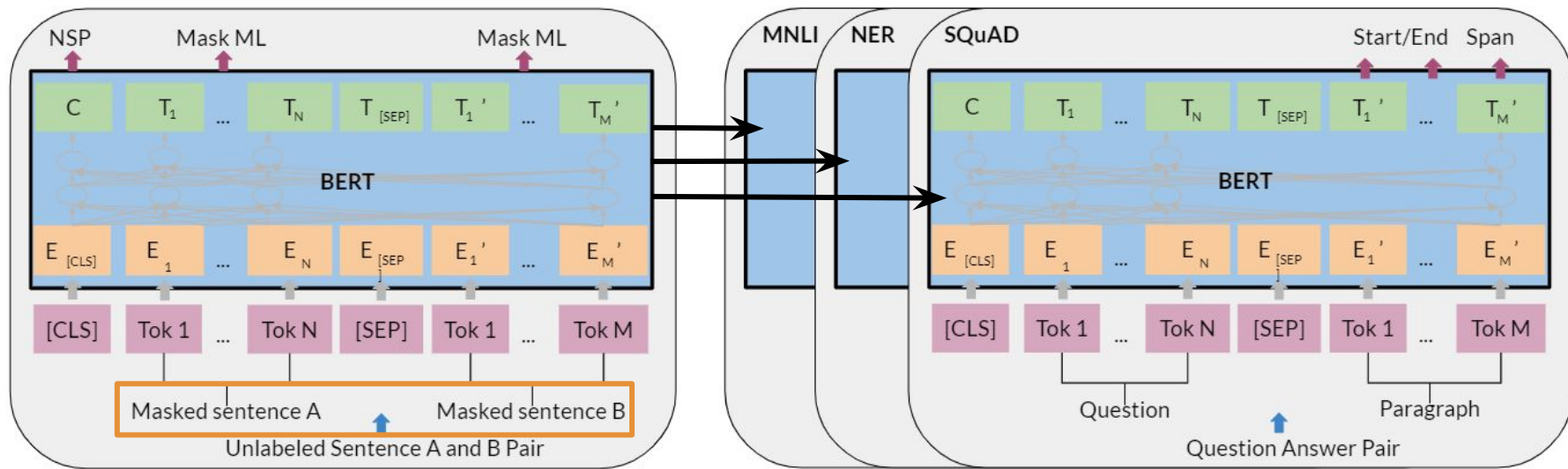
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Fine-tuning BERT

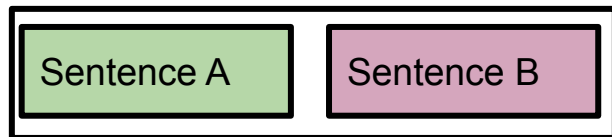
Fine-tuning BERT: Outline



Inputs



Summary



⋮



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Transformer

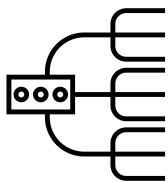
T5

Outline

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

Transformer - T5 Model

Text to Text



Classification

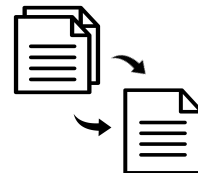


Question
Answering (Q&A)

Machine Translation



Summarization



Sentiment



Transformer - T5 Model

Original text

Thank you for inviting me to your party last week.

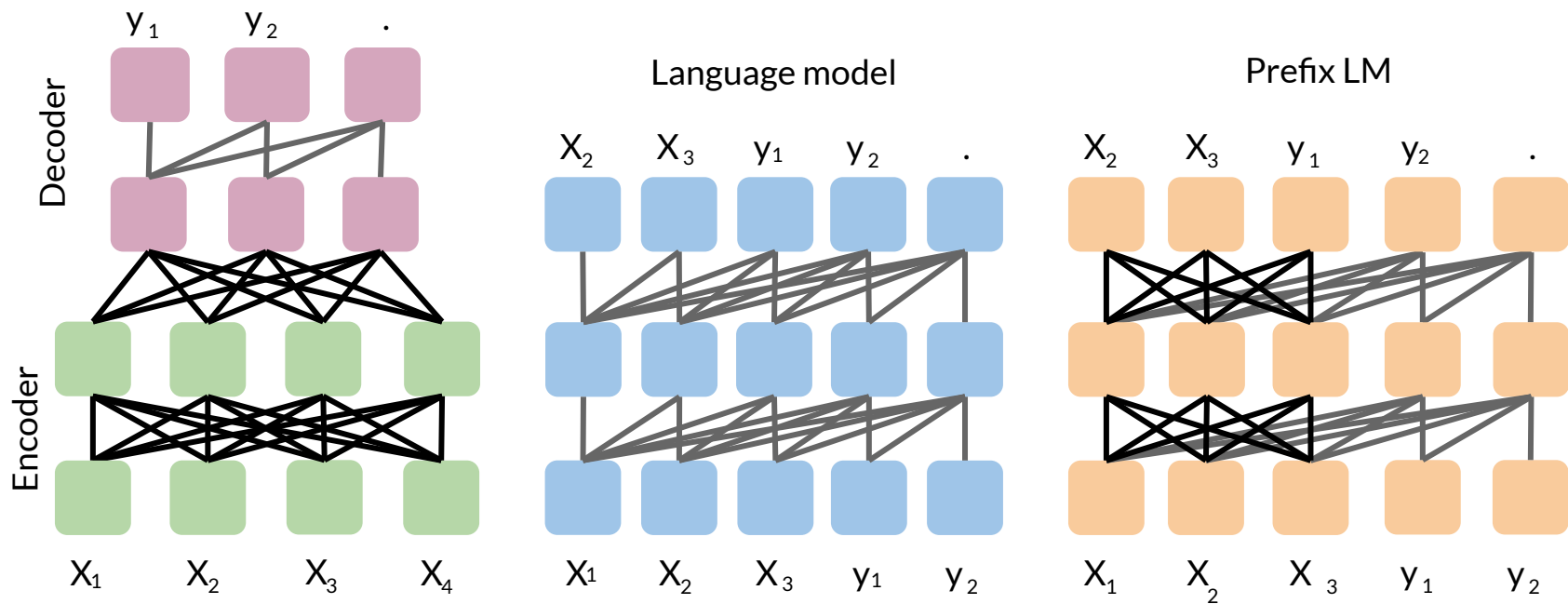
Inputs

Thank you <X> me to your party <Y> week.

Targets

<X> for inviting <Y> last <Z>

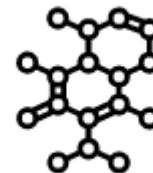
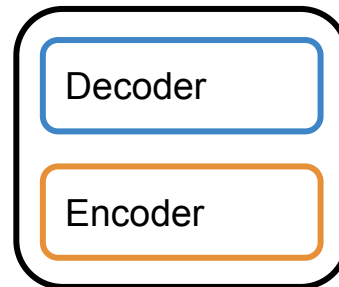
Model Architecture



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

Model Architecture

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



Summary

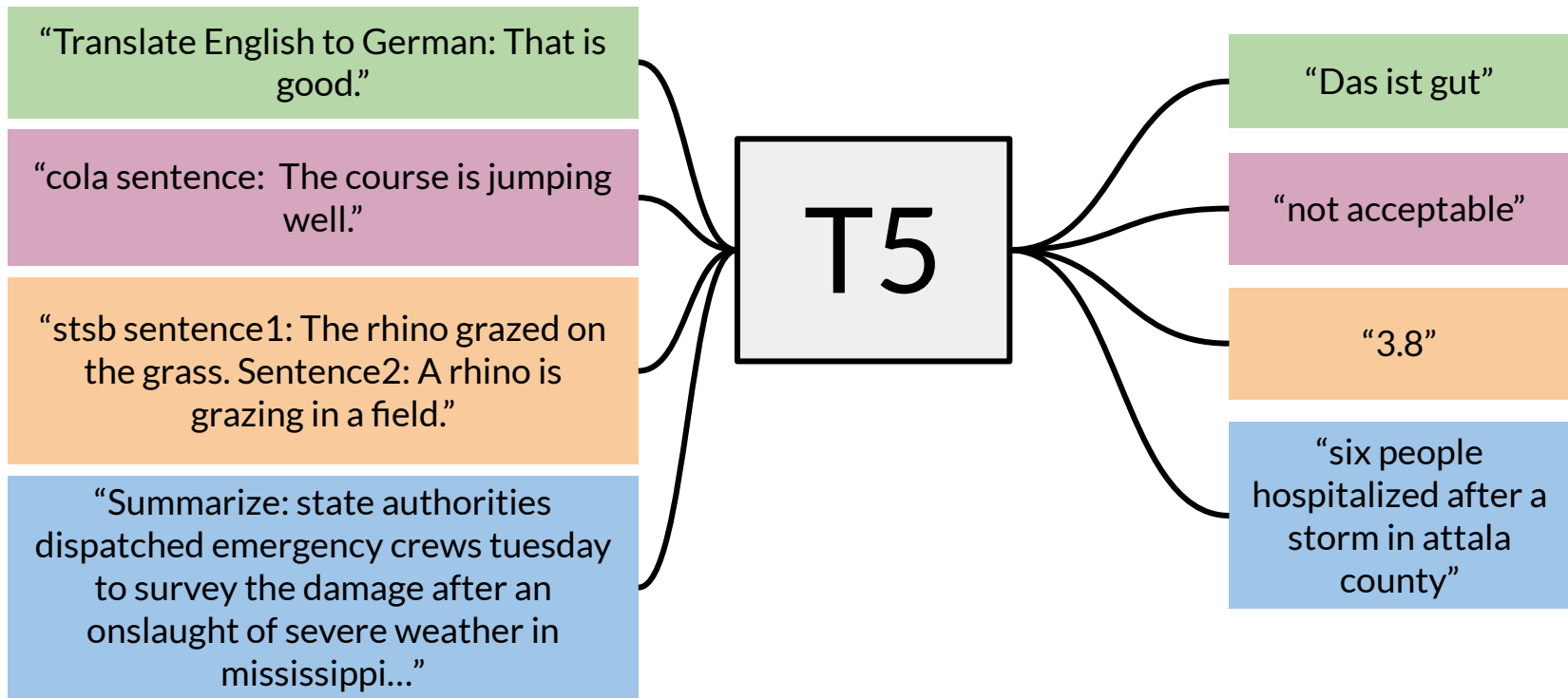
- Prefix LM attention
- Model architecture
- Pre-training T5 (MLM)



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Multi-task Training Strategy

Multi-task training strategy



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

Input and Output Format

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

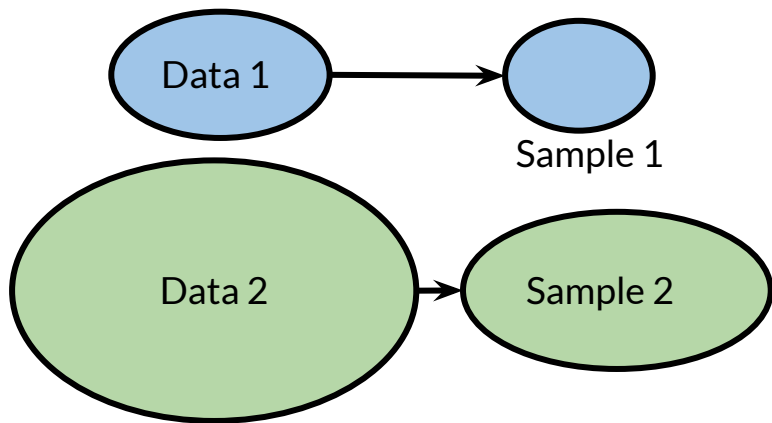
Multi-task Training Strategy

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

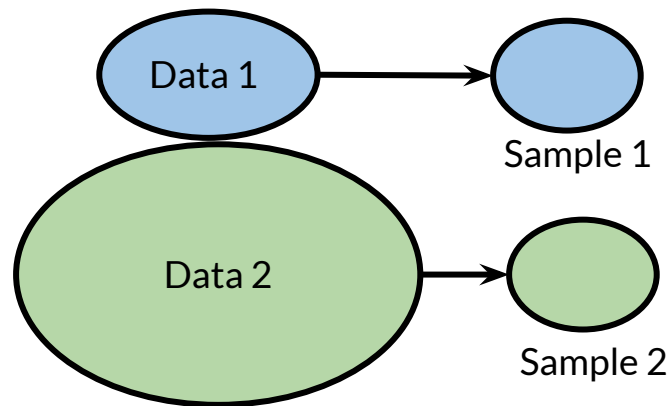
How much data from each task to train on?

Data Training Strategies

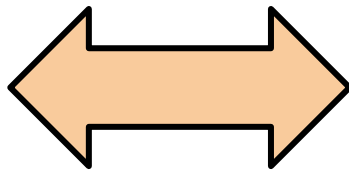
Examples-proportional mixing



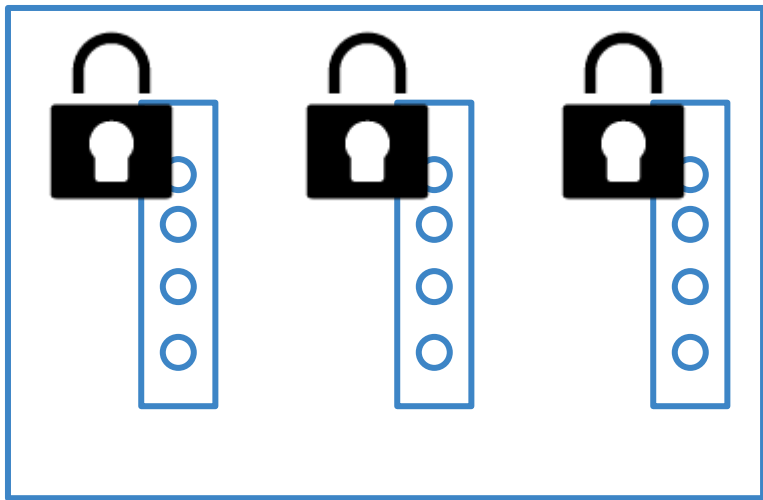
Equal mixing



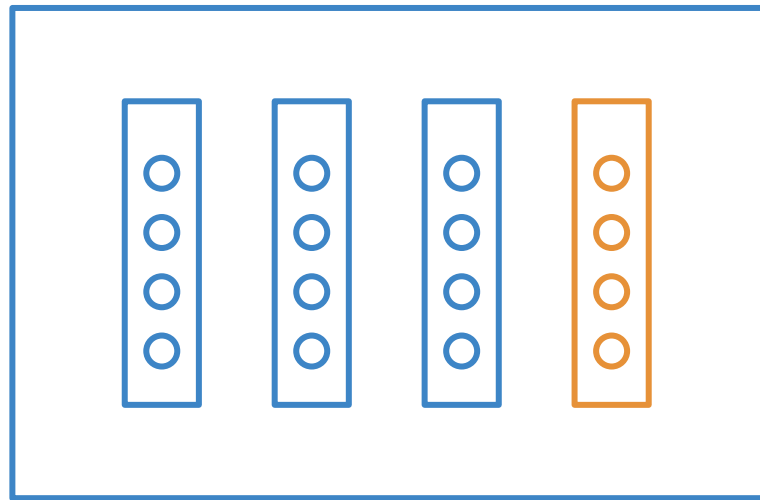
Temperature-scaled mixing



Gradual unfreezing vs. Adapter layers



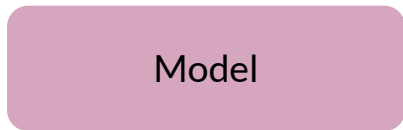
Gradual unfreezing



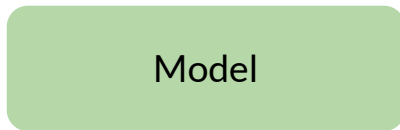
Adapter layers

Fine-tuning

Pre Training



Translation

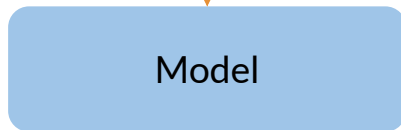


Summarization



MLM

Fine Tune on Specific Task



2^{18} steps





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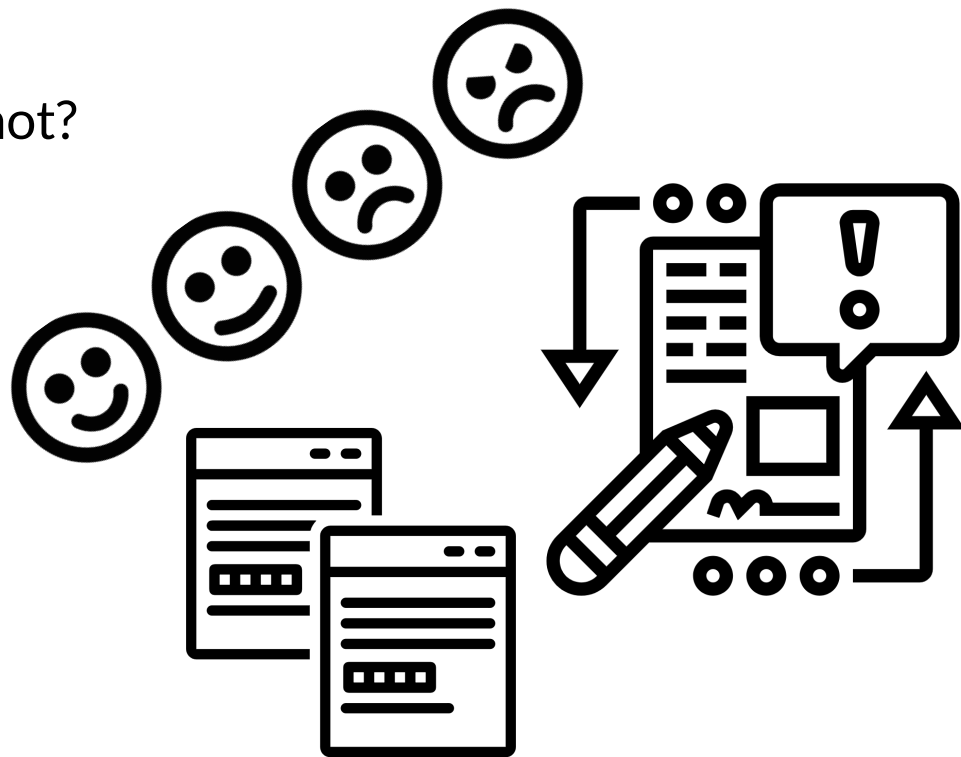
GLUE Benchmark

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

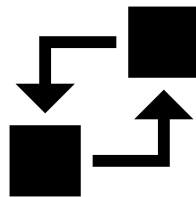
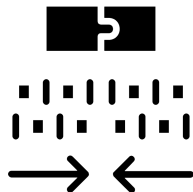
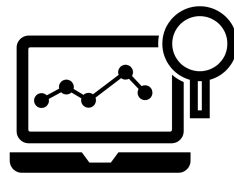
Tasks Evaluated on

- 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

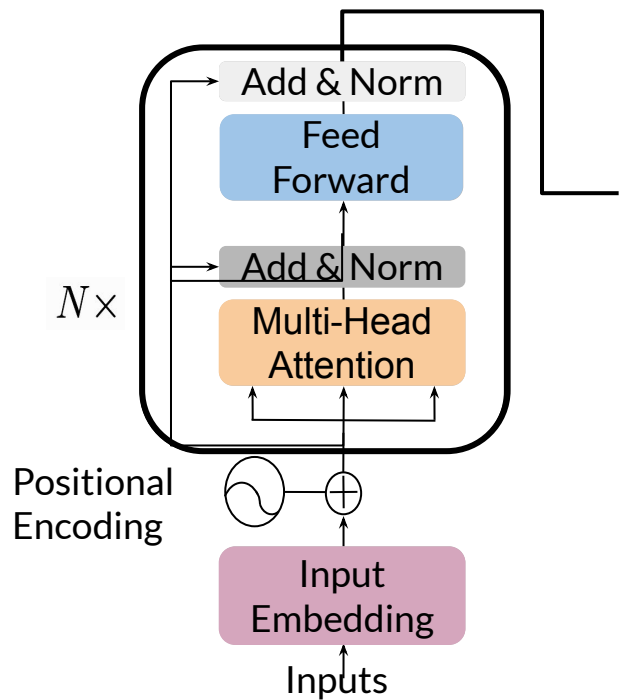




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Question Answering

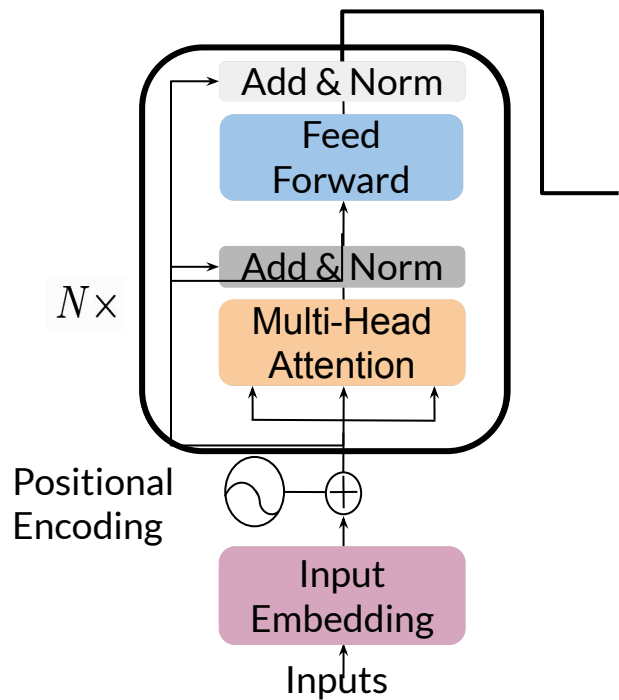
Transformer encoder



Feedforward:

```
[  
    LayerNorm,  
    dense,  
    activation,  
    dropout_middle,  
    dense,  
    dropout_final  
]
```

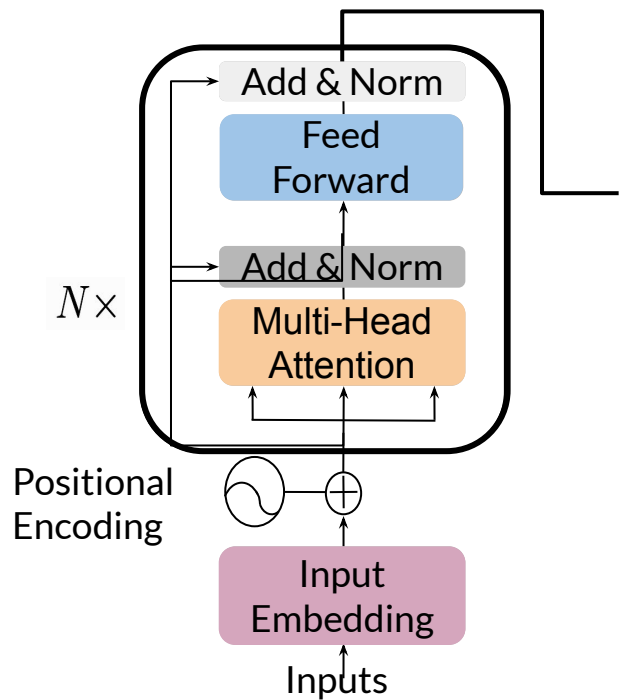
Transformer encoder



Encoder block:

```
[  
    Residual(  
        LayerNorm,  
        attention,  
        dropout_,  
    ),  
    Residual(  
        feed_forward,  
    ),  
]
```


Transformer encoder



Feedforward:

```
[  
    LayerNorm,  
    dense,  
    activation,  
    dropout_middle,  
    dense,  
    dropout_final  
]
```

Encoder block:

```
[  
    Residual(  
        LayerNorm,  
        attention,  
        dropout_  
    ),  
    Residual(  
        feed_forward,  
    )  
]
```

Data examples

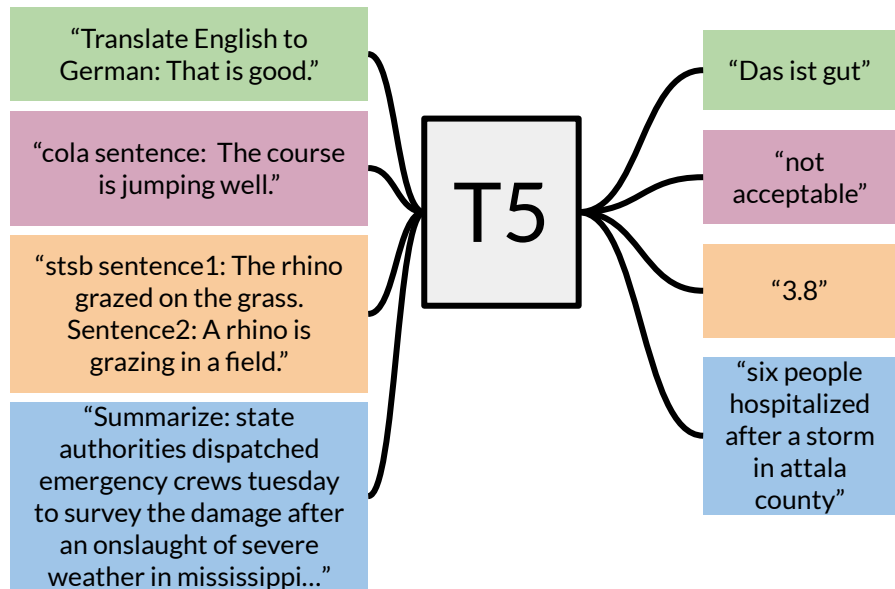
Question: What percentage of the French population today is non - European ?

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





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Hugging Face: Introduction

Outline

- What is Hugging Face?
- How you can use the Hugging Face ecosystem



Hugging Face

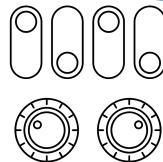
Transformers library

Use it with



Use it for

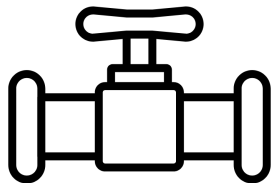
Applying state of the art
transformer models



Fine-tuning pretrained
transformer models

Hugging Face: Using Transformers

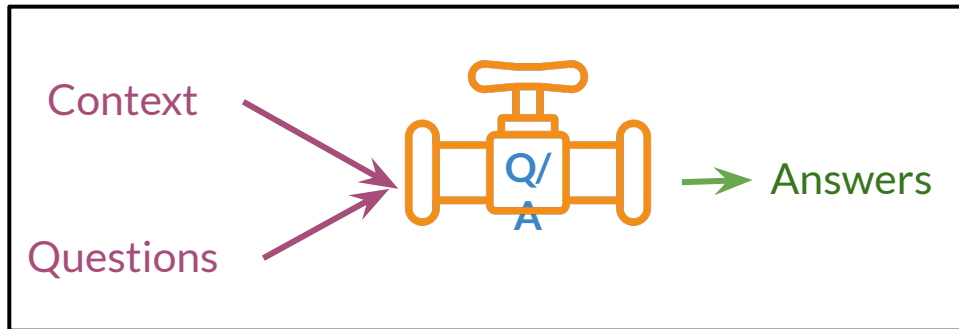
Pipelines



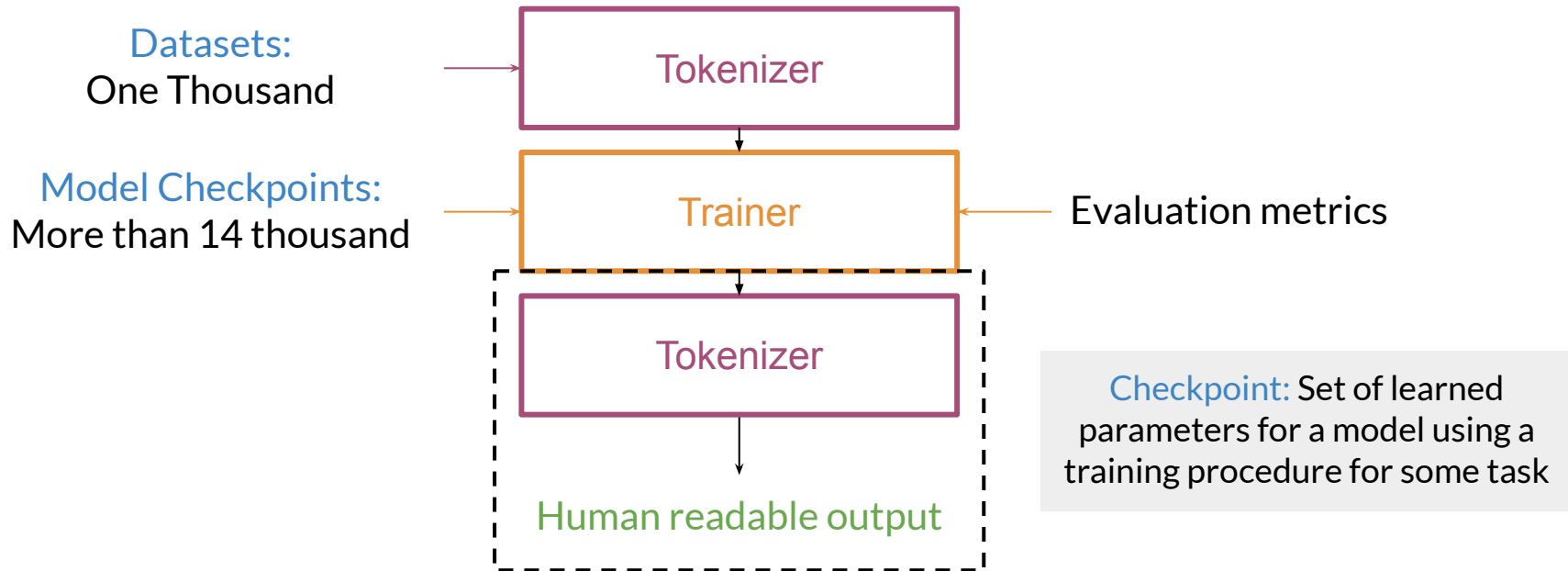
1. Pre-processing your inputs

2. Running the model

3. Post-processing the outputs



Hugging Face: Fine-Tuning Transformers



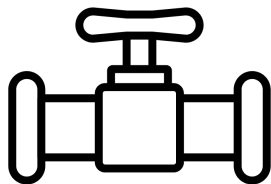


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Hugging Face: Using Transformers

Using Transformers

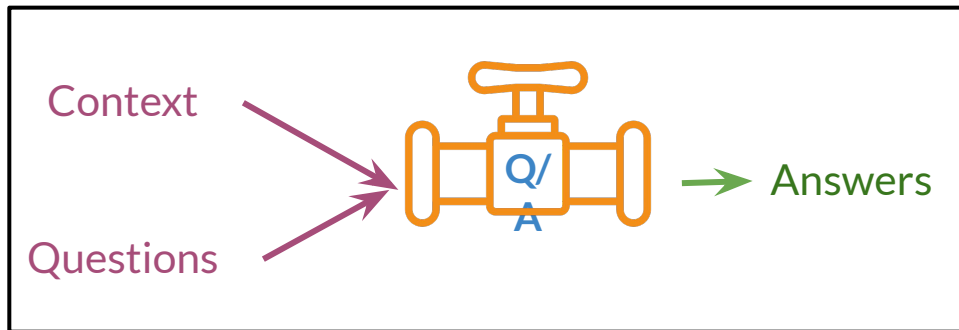
Pipelines



1. Pre-processing your inputs

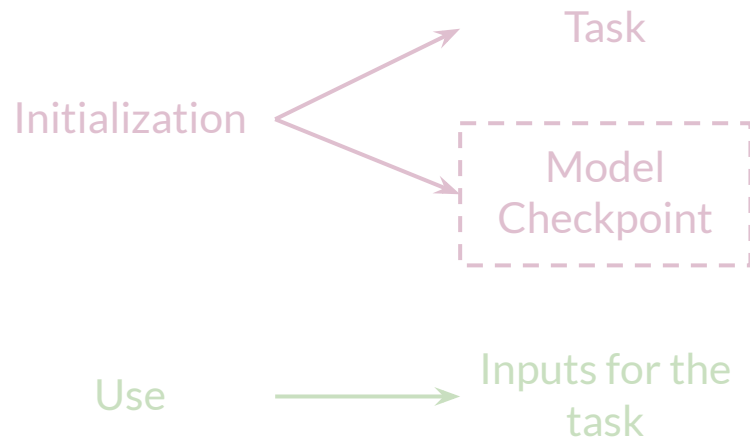
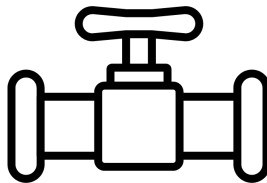
2. Running the model

3. Post-processing the outputs



Tasks

Pipelines



Sentiment Analysis

Sequence

Question Answering

Context and
questions

Fill-Mask

Sentence and
position

Checkpoints



Huge number of model checkpoints that you can use in your pipelines.

But **beware**, not every checkpoint would be suitable for your task.

Model Hub



Hub containing models that you can use in your [pipelines](#) according to the [task](#) you need:
<https://huggingface.co/models>

Model Card shows a description of your selected model and useful information such as code snippet examples.



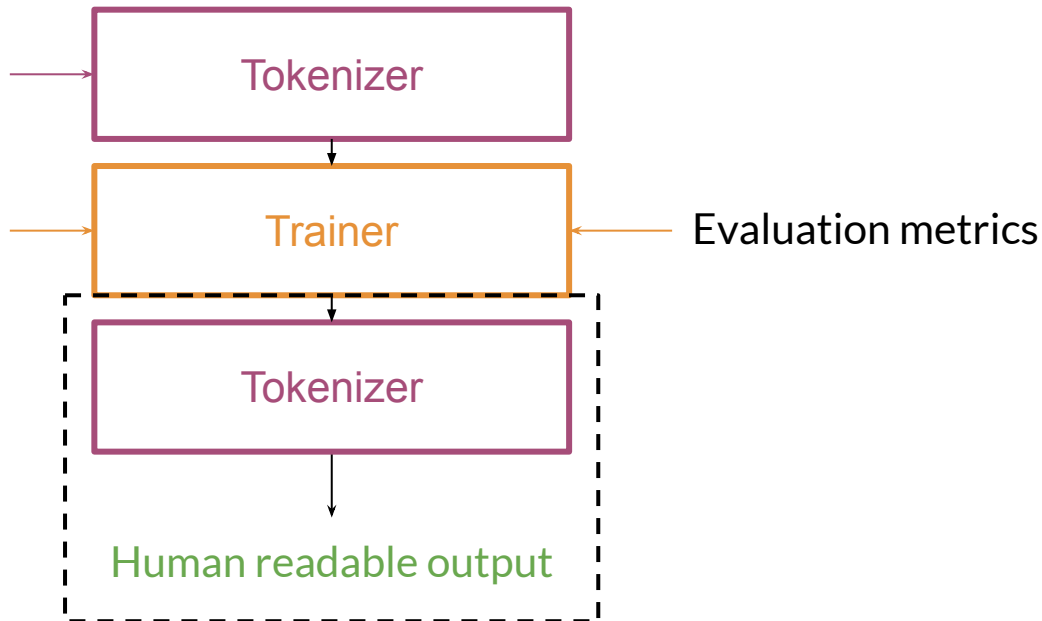
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Hugging Face: Fine-Tuning Transformers

Fine-Tuning Tools

Datasets:
One Thousand

Model Checkpoints:
More than 14 thousand



Model Checkpoints

Model Checkpoints:

More than 15 thousand
(and increasing)

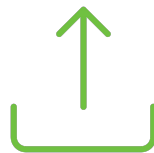
Upload the architecture
and weights with 1 line
of code!

Model	Dataset	Name in 🤖
DistilBERT	Stanford Question Answering Dataset (SQuAD)	distilbert-base-cased-distilled-squad
BERT	Wikipedia and Book Corpus	bert-base-cased
...

Datasets

Datasets:
One Thousand

Load them using **just one function**



Optimized to work with massive amounts of data!

Tokenizers

"What well-known
superheroes were introduced
between 1939 and 1941 by
Detective Comics?"



[101, 1327, 1218, 118, 1227,
18365, 1279, 1127, 2234,
1206, 3061, 1105, 3018,
1118, 9187, 7452, 136, 102]

Depending on the use case, you
might need to run additional steps.

Trainer and Evaluation Metrics

Trainer object let's you define the training procedure

- Number of epochs

- Warm-up steps

- Weight decay

- ...

Train using one line of code!

Pre-defined evaluation metrics, like BLEU and ROUGE

