Working with HF Transformers Library

CS XXX: Introduction to Large Language Models

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- pipeline object
- Raw text to prediction
- Tokenizer
- Model
- Postprocessing
- Finetuning
- Loading custom model into pipeline

The pipeline Object

• The pipeline object in Hugging Face is a high-level API designed to simplify working with popular machine learning tasks. It abstracts away much of the complexity involved in loading models, tokenizing inputs, and post-processing outputs. With just a few lines of code, you can use state-of-the-art models for a wide variety of tasks.

0 | from transformers import pipeline

The pipeline Object

 With just a few lines of code, you can use state-of-the-art models for a wide variety of tasks.

Sentiment Analysis

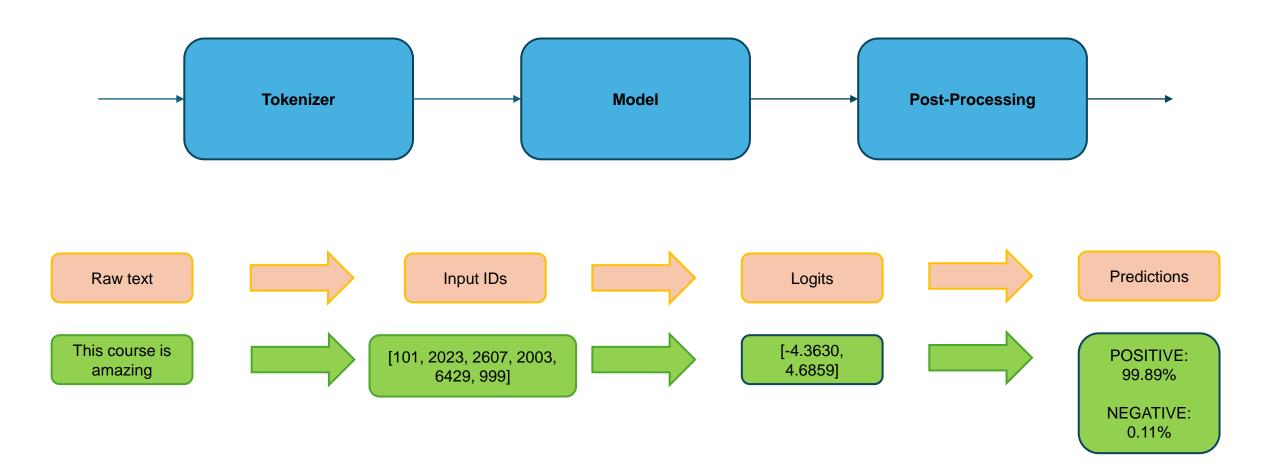
```
# Import the pipeline function from the transformers library
from transformers import pipeline

# Initialize a pipeline for sentiment analysis
classifier = pipeline("sentiment-analysis")

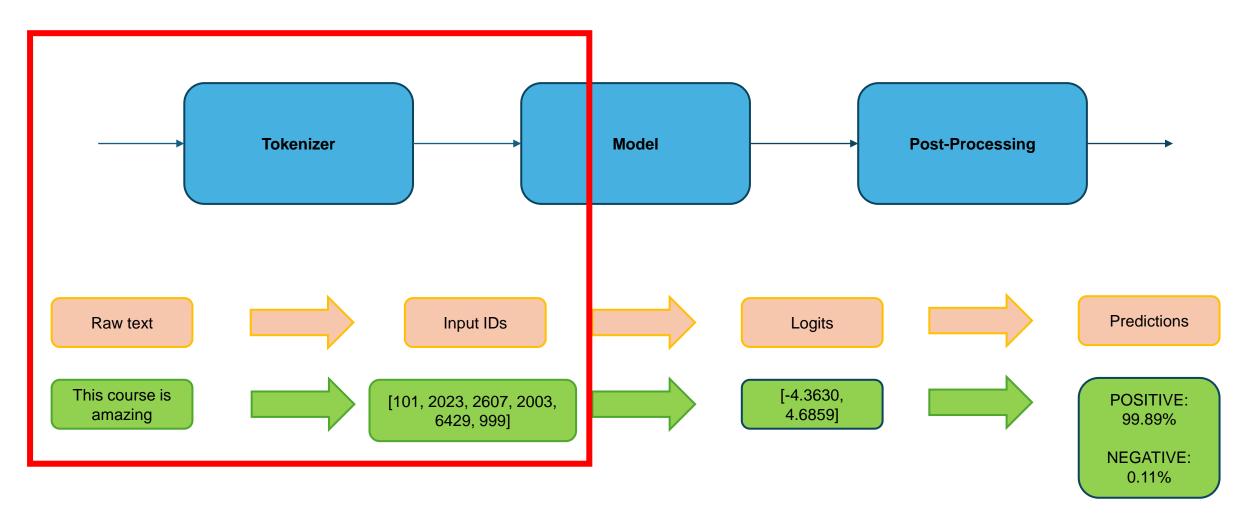
# Use the classifier to analyze the sentiment of a text
classifier("I love AI and want to know more about the current state of generative AI.")
```

```
No model was supplied, defaulted to distilbert-base-uncased-finetuned-sst-2-English [{'label': 'POSITIVE', 'score': 0.9966887831687927}]
```

Raw text to Predictions

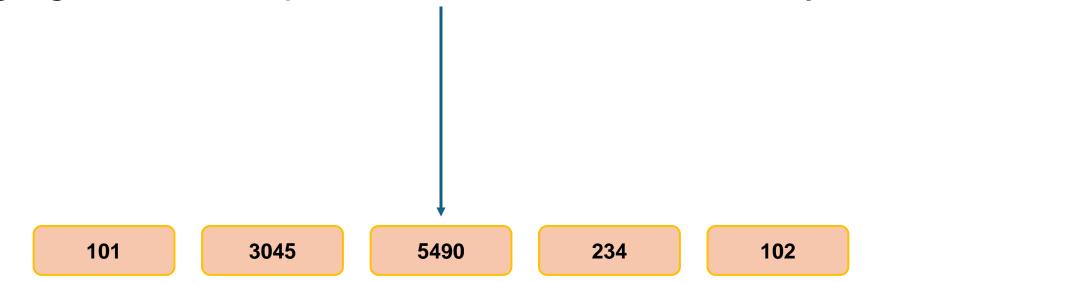


The tokenizer is used to transform raw text to numbers



• The tokenizer's objective is find a meaningful representation

"The HuggingFace headquarters are based in Brooklyn, New York"



- Three different ways to tokenize
 - Word Based: Splitting a raw text into words
 - Character Based: Splitting a raw text into characters
 - Sub-word Based: Splitting a raw text into subwords

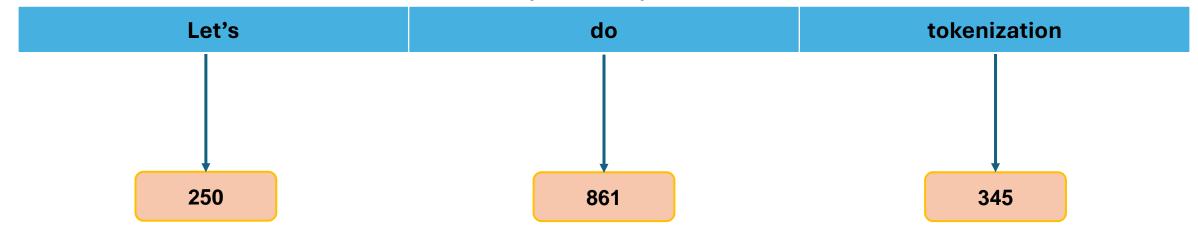
• Word Based: Splitting a raw text into words

Split on spaces

Let's do tokenization

- Word Based: Splitting a raw text into words
 - Each word has a specific ID

Split on spaces



- Word Based: Splitting a raw text into words
 - Very similar words have entirely different meanings

the	\rightarrow	1
of	\rightarrow	2
and	\rightarrow	3
to	\rightarrow	4
in	\rightarrow	5
was	\rightarrow	6
the	\rightarrow	7
is	\rightarrow	8
for	\rightarrow	9
as	\rightarrow	10
on	\rightarrow	11
with	\rightarrow	12
that	\rightarrow	13
dog	\rightarrow	14
dogs	\rightarrow	15

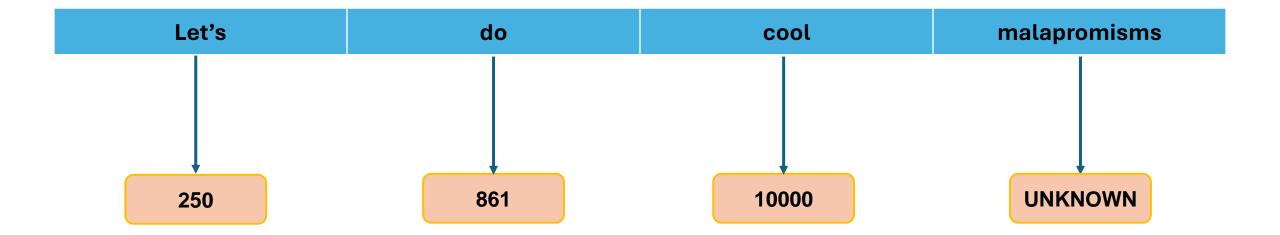
- Word Based: Splitting a raw text into words
 - The vocabulary can end up being very large

	the	\rightarrow	1
ords	of	\rightarrow	2
	and	\rightarrow	3
je	to	\rightarrow	4
	in	\rightarrow	5
	was	\rightarrow	6
	the	\rightarrow	7
	is	\rightarrow	8
	for	\rightarrow	9
	as	\rightarrow	10
	on	\rightarrow	11
	with	\rightarrow	12
	That	\rightarrow	13
	•••	\rightarrow	•••
Malap	ropism	\rightarrow	170,000

- Word Based: Splitting a raw text into words
 - The vocabulary can end up being very large
 - Large vocabularies result in heavy models
 - We can limit the amount of words we add to the vocabulary

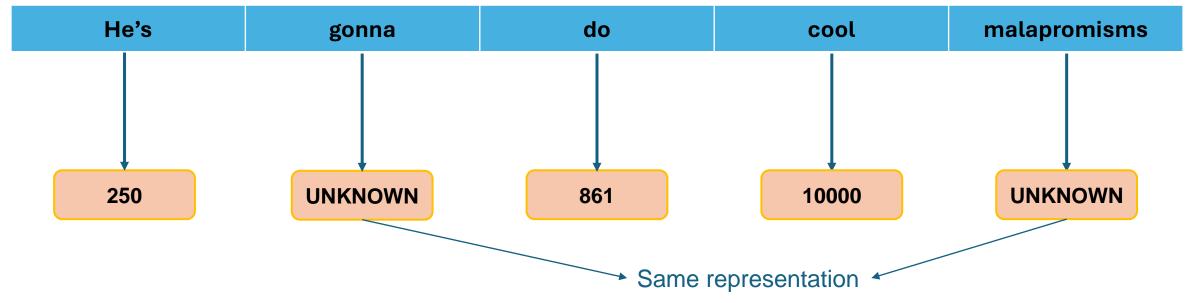
the	\rightarrow	1
of	\rightarrow	2
and	\rightarrow	3
to	\rightarrow	4
in	\rightarrow	5
was	\rightarrow	6
the	\rightarrow	7
is	\rightarrow	8
for	\rightarrow	9
as	\rightarrow	10
on	\rightarrow	11
with	\rightarrow	12
that	\rightarrow	13
•••	\rightarrow	•••
hug	\rightarrow	10,000

- Word Based: Splitting a raw text into words
 - Out of vocabulary words result in a loss of information



- Word Based: Splitting a raw text into words
 - Out of vocabulary words result in a loss of information





- Character Based: Splitting a raw text into characters
 - Out of vocabulary words result in a loss of information

Split on characters



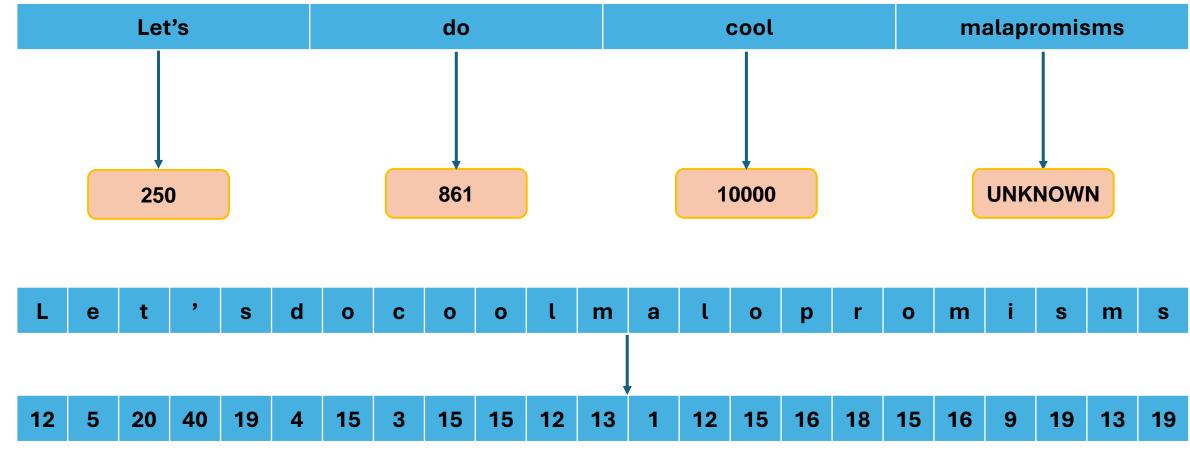
• Character Based: Splitting a raw text into characters

Vocabularies are slimmer

Character-based vocabulary

28 256

- Character Based: Splitting a raw text into characters
 - Fewer out-of-vocabulary words



- Sub-word Based: Splitting a raw text into subwords
 - Middle ground between word and character based algorithms

Word-based vocabulary

Very large vocabularies

Large quantity of out of vocabulary tokens

Loss of meaning across very similar words

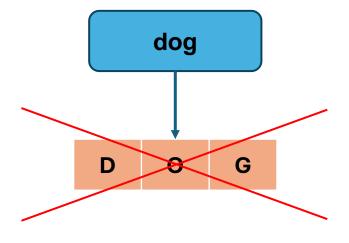
Char-based vocabulary

Very long sequences

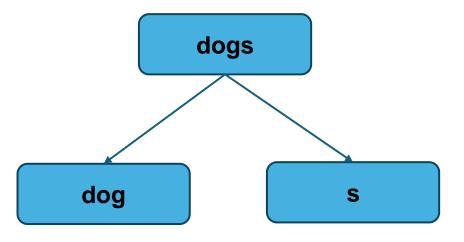
Less meaningful individual tokens

- Sub-word Based: Splitting a raw text into subwords
 - Middle ground between word and character based algorithms

Frequently used words should not be split into smaller subwords

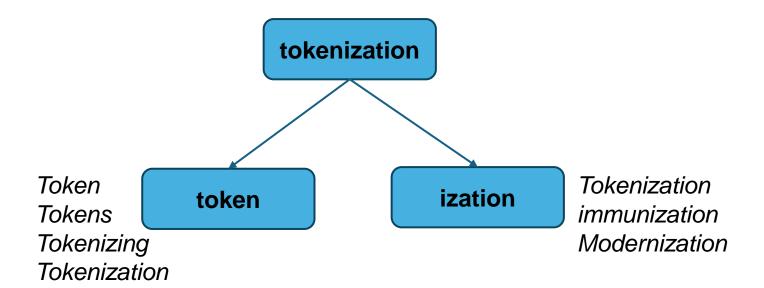


Rare words should be decomposed into meaningful subwords

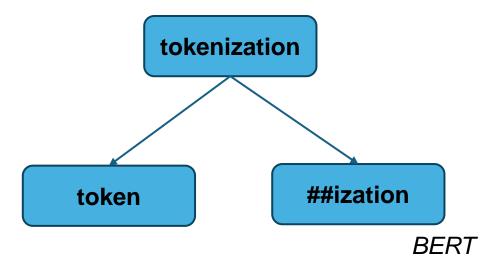


- Sub-word Based: Splitting a raw text into subwords
 - Subwords help identify similar syntactic or semantic situations in text

Rare words should be decomposed into meaningful subwords



- Sub-word Based: Splitting a raw text into subwords
 - Subword tokenization algorithms can identify start of word tokens

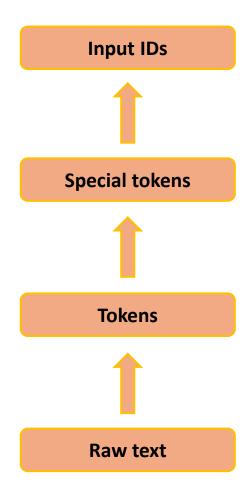


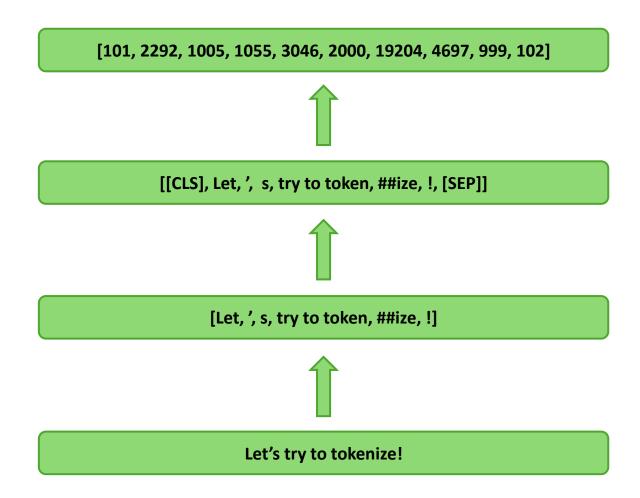
• ## is a marker to indicate that the subword is part of a word and not a standalone token.

- Sub-word Based: Splitting a raw text into subwords
 - Most models obtaining state-of-the-art results in English today use some kind of subword-tokenization algorithm

WordPieceUnigramByte-Pair EncodingBERT, DistilBERTXLNet, ALBERTGPT2, RoBERTa

Tokenization Pipeline





The first step of the pipeline is to split the text into tokens

```
from transformers import AutoTokenizer
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
tokens = tokenizer.tokenize("Let's try to tokenize!")
print(tokens)
```

```
['let', "'", 's', 'try', 'to', 'token', '##ize', '!']
```

Each token has a unique ID

```
from transformers import AutoTokenizer
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
tokens = tokenizer.tokenize("Let's try to tokenize!")
input_ids = tokenizer.convert_tokens_to_ids(tokens)
print(input_ids)
```

```
[2292, 1005, 1055, 3046, 2000, 19204, 4697, 999]
```

```
0 decoded_string = tokenizer.decode([2292, 1005, 1055, 3046, 2000, 19204, 4697, 999])
1 print(decoded_string)
```

```
['let', "'", 's', 'try', 'to', 'token', '##ize', '!']
```

The tokenizer adds special tokens the model expects

0 | from transformers import AutoTokenizer

```
1 tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
2 tokens = tokenizer.tokenize("Let's try to tokenize!")
3 input_ids = tokenizer.convert_tokens_to_ids(tokens)
4 print(input_ids)
6 final_inputs = tokenizer.prepare_for_model(input_ids)
7 print(final_inputs["input_ids"])

[2292, 1005, 1055, 3046, 2000, 19204, 4697, 999]
[101, 2292, 1005, 1055, 3046, 2000, 19204, 4697, 999, 102]

0 print(tokenizer.decode([101, 2292, 1005, 1055, 3046, 2000, 19204, 4697, 999, 102])
```

['[CLS]', 'let', "'", 's', 'try', 'to', 'token', '##ize', '!', '[SEP]']

 A tokenizer takes texts as inputs and outputs numbers the associated model can make sense of

```
0  from transformers import AutoTokenizer
1  tokenizer = AutoTokenizer.from_pretrained("bert-base-cased")
2  print(tokenizer("Using a Transformer network is simple"))

{'input_ids': [101, 7993, 170, 11303, 1200, 2443, 1110, 3014, 102],
  'token type ids': [0, 0, 0, 0, 0, 0, 0, 0],
```

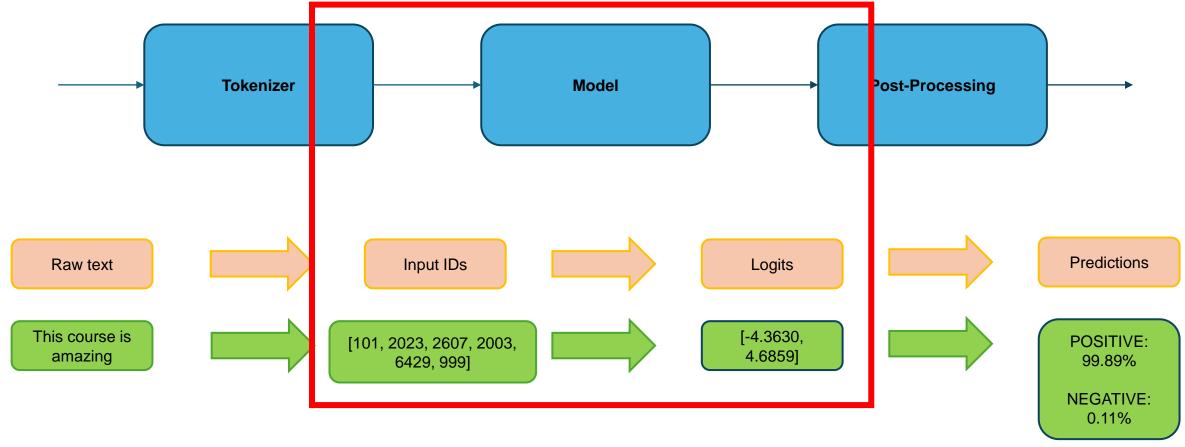
'attention mask': [1, 1, 1, 1, 1, 1, 1, 1]}

 A tokenizer takes texts as inputs and outputs numbers the associated model can make sense of

```
from transformers import AutoTokenizer
checkpoint = "distilbert-base-uncased-finetuned-sst-2-english"
tokenizer = AutoTokenizer.from_pretrained(checkpoint)
raw_inputs = [
    "I've been waiting for a HuggingFace course my whole life.",
    "I hate this so much!",
    "I hate this so much!",
    "I print(inputs)
```

Model

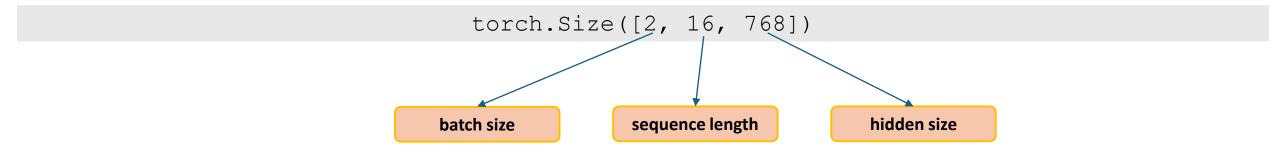
 The model takes the input IDs and processes them through its layers to generate logits. Logits are unnormalized scores representing the likelihood of different outcomes.



Model

 The AutoModel class loads a model without a task-specific pretrained head

```
from transformers import AutoModel
    checkpoint = "distilbert-base-uncased-finetuned-sst-2-english"
    model = AutoModel.from_pretrained(checkpoint)
    outputs = model(**inputs)
    print(outputs.last_hidden_state.shape)
```



Model

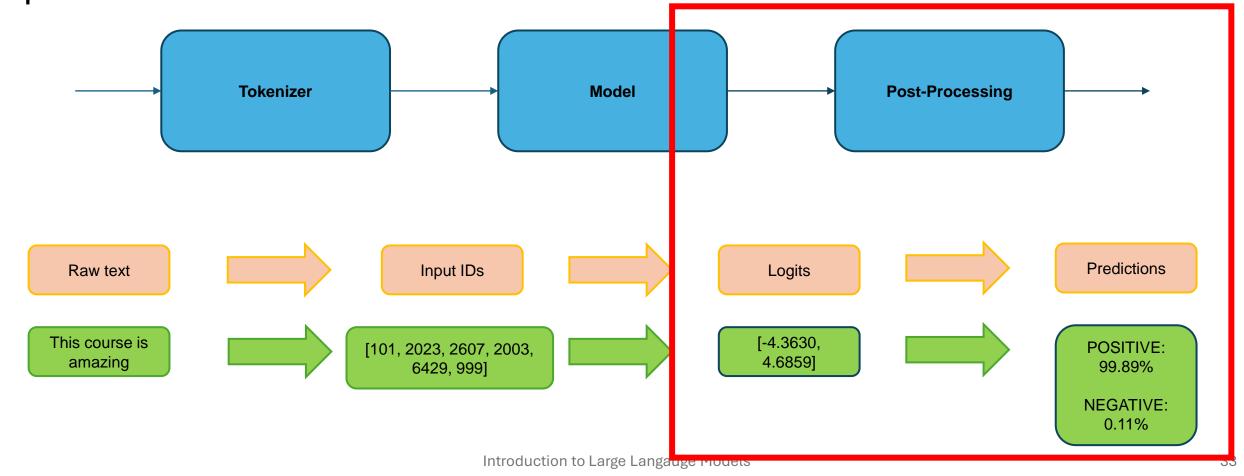
Each AutoModelFor X class loads a model suitable for a specific task

```
from transformers import AutoModelForSequenceClassification
checkpoint = "distilbert-base-uncased-finetuned-sst-2-english"
model = AutoModelForSequenceClassification.from_pretrained(checkpoint)
outputs = model(**inputs)
print(outputs.logits)
```

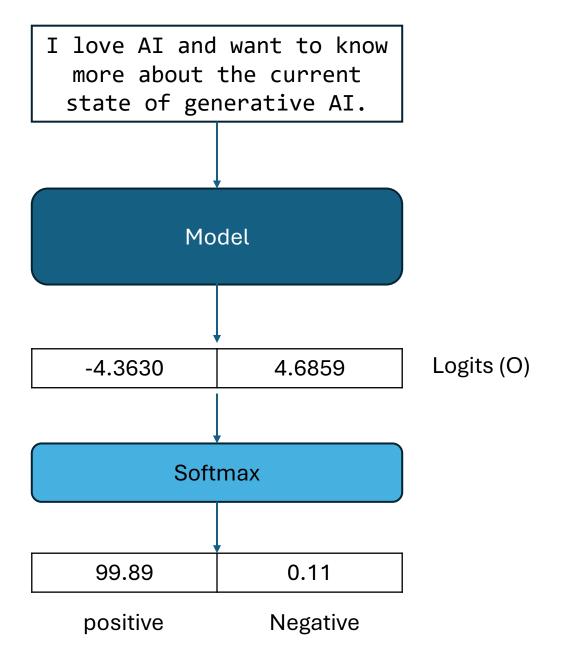
```
tensor([[-1.5607, 1.6123], [ 4.1692, -3.3464]], grad_fn=<AddmmBackward>)
```

Post-Processing

 The logits are transformed into meaningful predictions. This involves normalizing the logits using methods like softmax to produce probabilities



Post-Processing



1. Load model for finetuning

```
from transformers import AutoModelForSequenceClassification, AutoTokenizer
    # 1. Load the model and tokenizer
    model_name = "bert-base-uncased"
    model = AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=2) #
    Binary classification
    tokenizer = AutoTokenizer.from_pretrained(model_name)
```

2. Prepare Data

```
from datasets import load dataset
   # 2. Prepare the dataset
   # Example dataset: SST2 for sentiment classification
   dataset = load dataset("glue", "sst2")
 4
   # Tokenize the dataset
   def tokenize function(examples):
       return tokenizer(examples['sentence'], padding="max length", truncation=True)
 8
   tokenized_datasets = dataset.map(tokenize_function, batched=True)
10
   # Split into train, validation, and test datasets
   train dataset = tokenized datasets["train"]
   val dataset = tokenized datasets["validation"]
14 | test_dataset = tokenized_datasets["test"]
```

3. Define Training Arguments

```
0 | from transformers import TrainingArguments
  # 3. Define Training Arguments
   training args = TrainingArguments(
      output dir="./results",
                                    # output dir for model predictions & checkpoints
      evaluation_strategy="epoch",
                                    # Evaluate every epoch
      learning rate=2e-5,
                                   # Learning rate
6
      per_device_train_batch_size=16, # Batch size per GPU/CPU for training
      per_device_eval_batch_size=64,
                                   # Batch size for evaluation
8
                                   # Number of training epochs
      num train epochs=3,
      weight_decay=0.01,
                                    # Strength of weight decay
10
      logging_steps=10,
                           # Log every 10 steps
11
      load_best_model_at_end=True,  # Load the best model when finished training
12
      metric_for_best_model="accuracy",# Metric to use for best model
13
14
```

4. Train the model and save

```
from transformers import Trainer
  # Define Trainer
  trainer = Trainer(
      model=model,
                                      # The model to train
      args=training_args,
                                      # Training arguments
      # Evaluation dataset
6
      eval_dataset=val_dataset,
      tokenizer=tokenizer,
                                   # Tokenizer
8
9
  # 4. Train the model
  trainer.train()
12
  # Save the fine-tuned model
  trainer.save_model("./fine_tuned_bert")
  tokenizer.save_pretrained("./fine_tuned_bert")
```

5. Test the model

```
0 # 5. Testing the model on the test set
1 test_results = trainer.evaluate(eval_dataset=test_dataset)
2 print("Test Results:", test_results)
```

Loading custom model or tokenizer into pipeline

 If you have a custom model or tokenizer, you can load it into pipeline for inference as follows

```
from transformers import pipeline, AutoModelForSequenceClassification, AutoTokenizer
   # Load a custom model and tokenizer
   model_path = "./fine_tuned_bert" # This is where your model and tokenizer are saved
   model = AutoModelForSequenceClassification.from_pretrained(model_path)
   tokenizer = AutoTokenizer.from pretrained(model path)
   # Initialize the pipeline with the custom model and tokenizer
   classifier = pipeline("text-classification", model=model, tokenizer=tokenizer)
10
   # Use the pipeline
   text = "This is a fantastic example!"
   output = classifier(text)
   print(output)
```

References

• Hugging Face. The Hugging Face Natural Language Processing Course.