Center of Data Science
Universitas Islam Indonesia

Large Language Model for Text Analysis

Ahmad Fathan Hidayatullah

fathan@uii.ac.id

Pesantren Sains Data 1445 H

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Outline

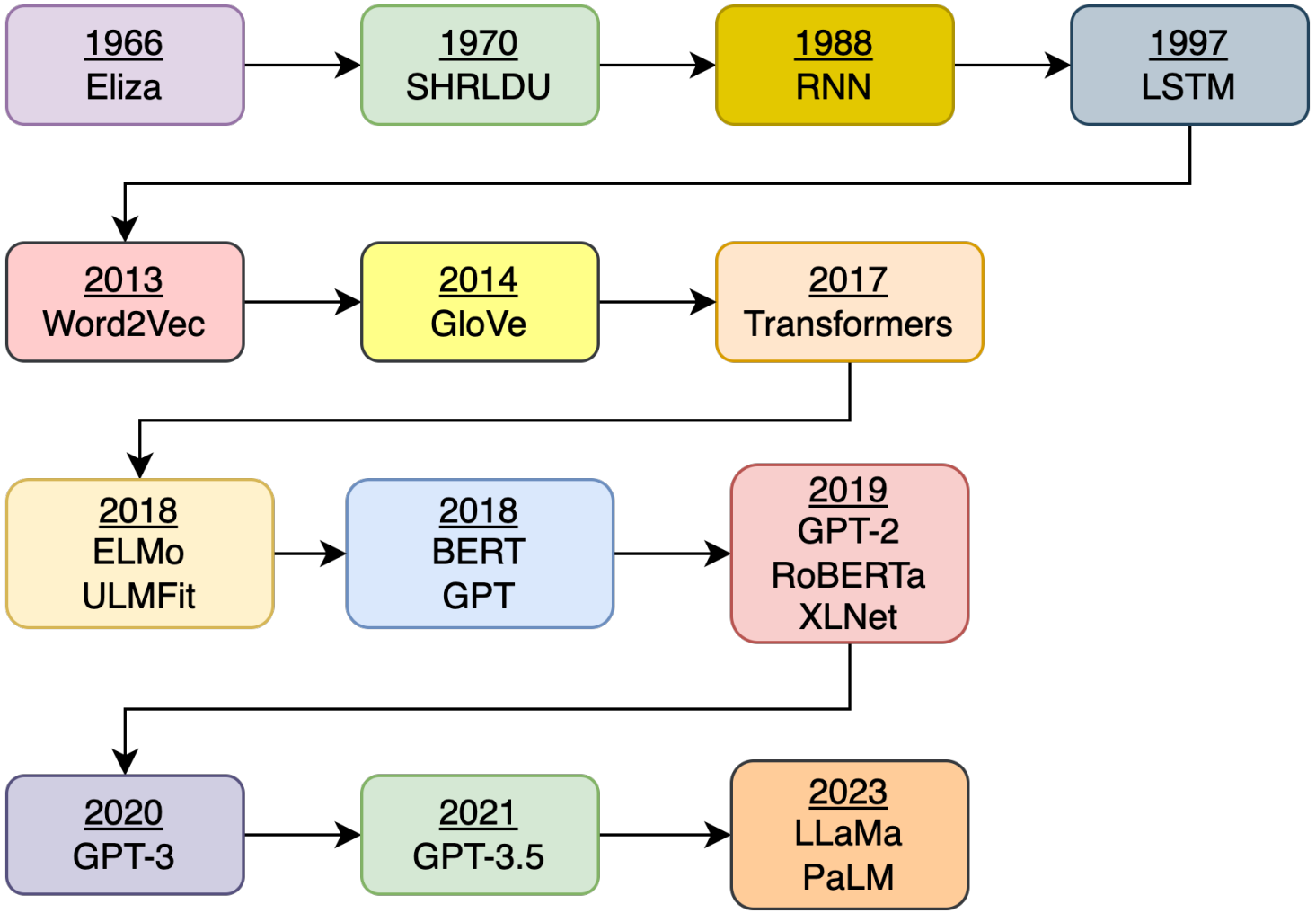
- Large Language Models
- Text Analysis
- Case Study

Large Language Models (LLMs)

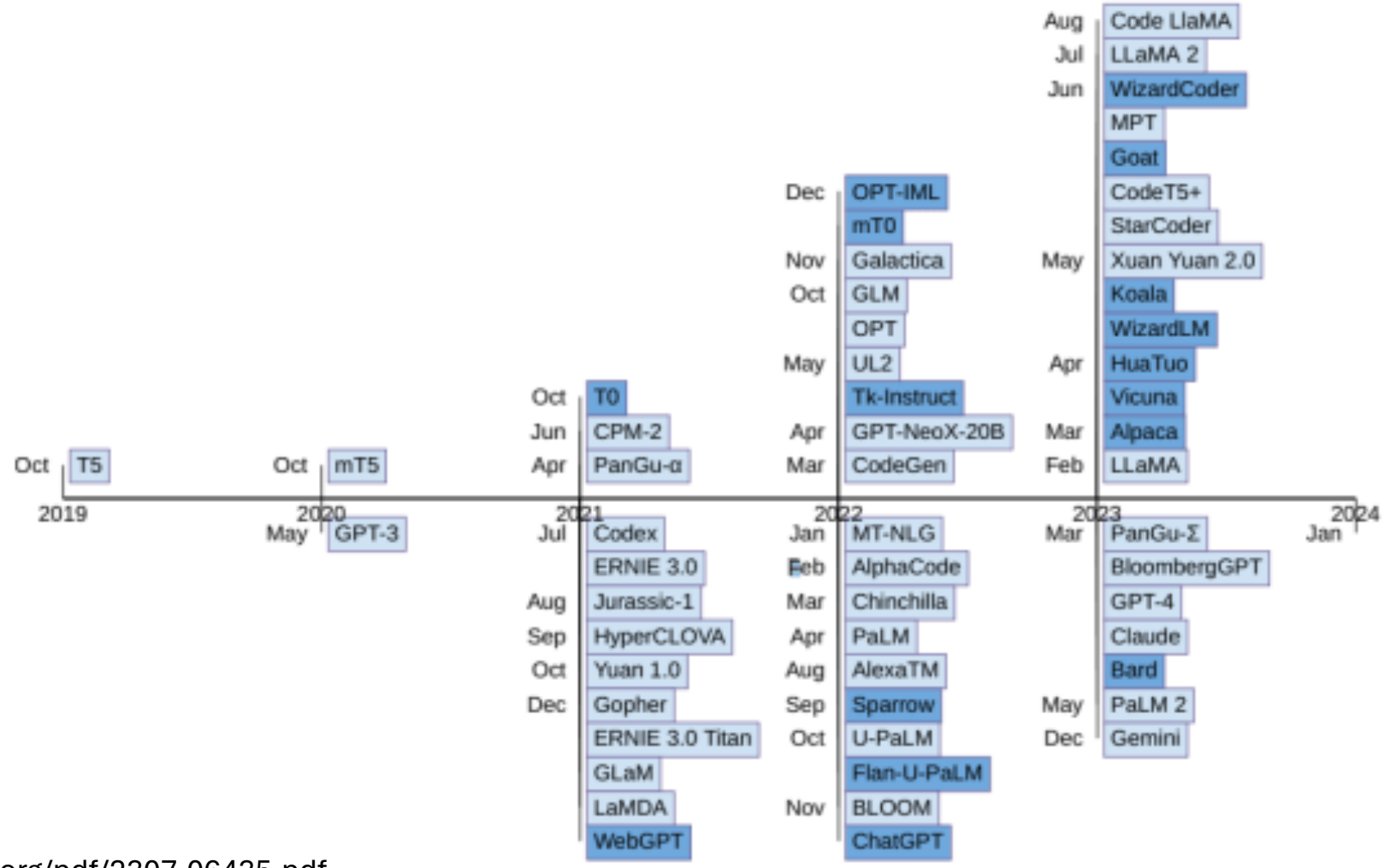
Large Language Models (LLMs)

- LLMs are **foundation models** pre-trained on **large** amounts of **unlabeled** and **self-supervised** text data, including books, articles, and conversations.
- LLMs utilize **Transformer-based neural networks** to **learn patterns** and connections within language, encompassing syntactic and semantic structures like grammar, word order, and word meanings.
- The **primary objective** of LLMs is to **replicate** human-like language understanding in machines, focusing specifically on text and text-like inputs.

A Brief History of LLMs



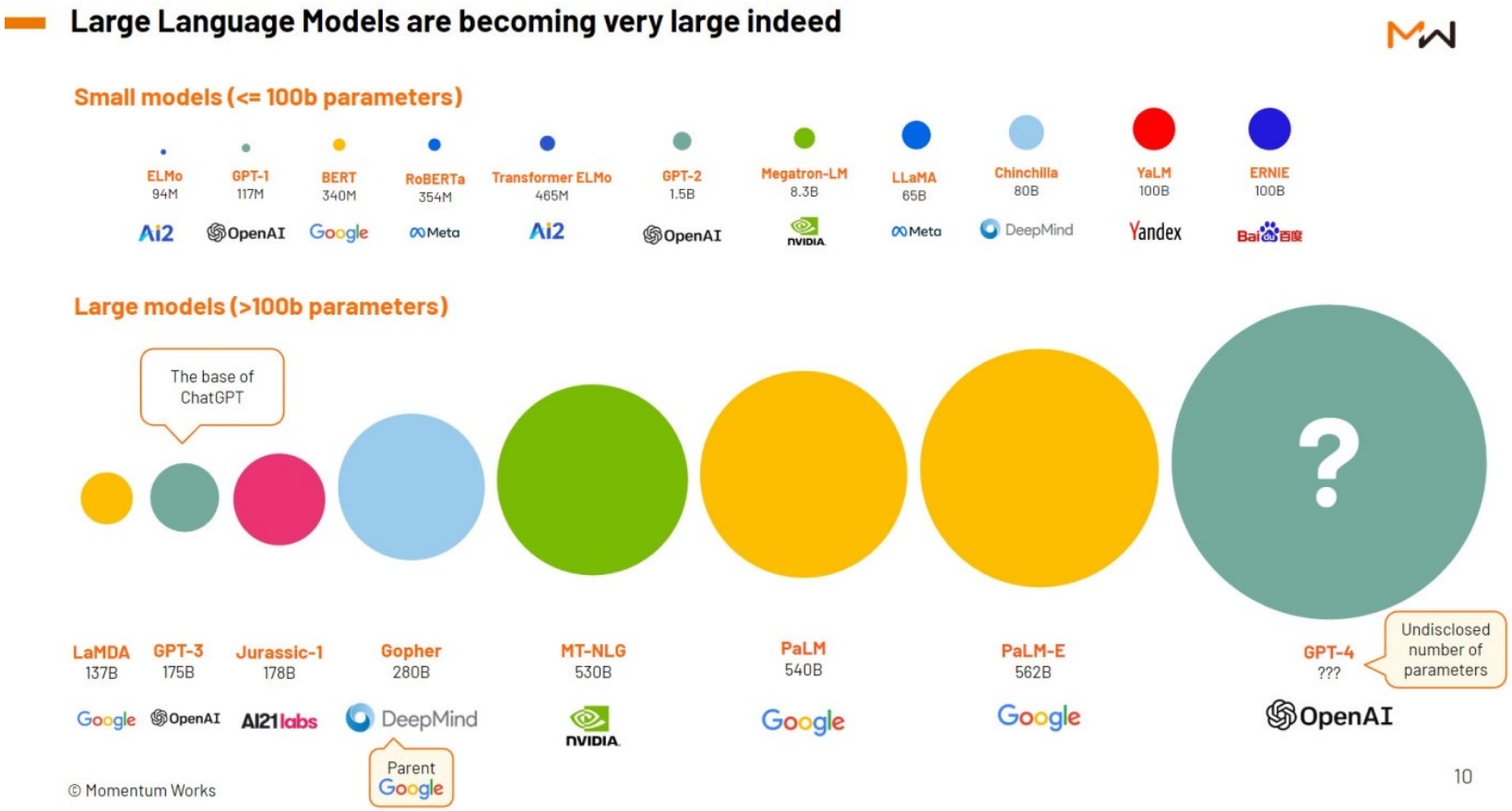
Chronological Display of LLM Releases



https://arxiv.org/pdf/2307.06435.pdf

Why are they called “Large”?

- LLMs are called "large" because they are pre-trained with a large number of **parameters** (100M+) **on large corpora** of text to process/understand and generate natural language text for a wide variety of NLP tasks.



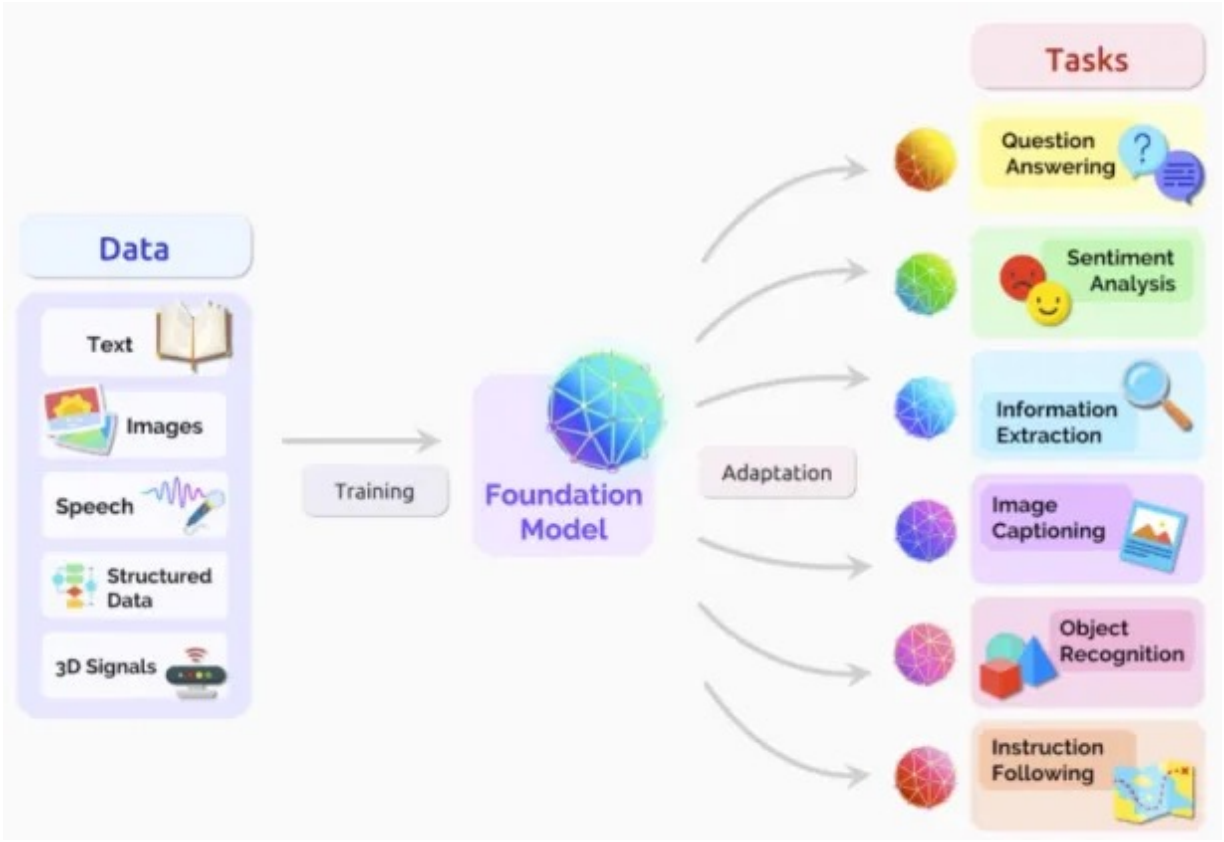
List of Large Language Models Compared to Different Parameters

Model	Disk Size (GB)	Memory Usage (GB)	Parameters (Millions)	Training Data Size (GB)
BERT-Large	1.3	3.3	340	20
GPT-2 117M	0.5	1.5	117	40
GPT-2 1.5B	6	16	1,500	40
GPT-3 175B	700	2,000	175,000	570
T5-11B	45	40	11,000	750
RoBERTa-Large	1.5	3.5	355	160
ELECTRA-Large	1.3	3.3	335	20

https://vitalflux.com/large-language-models-concepts-examples/#How_does_LLM_work_Key_Building_Blocks

LLMs are Task-agnostic Models

- LLMs can solve and perform any tasks, such as answering questions, translating documents, summarizing documents, completing sentences, etc.



Source: https://research.aimultiple.com/large-language-models/

LLMs vs Traditional Language Model

LLMs

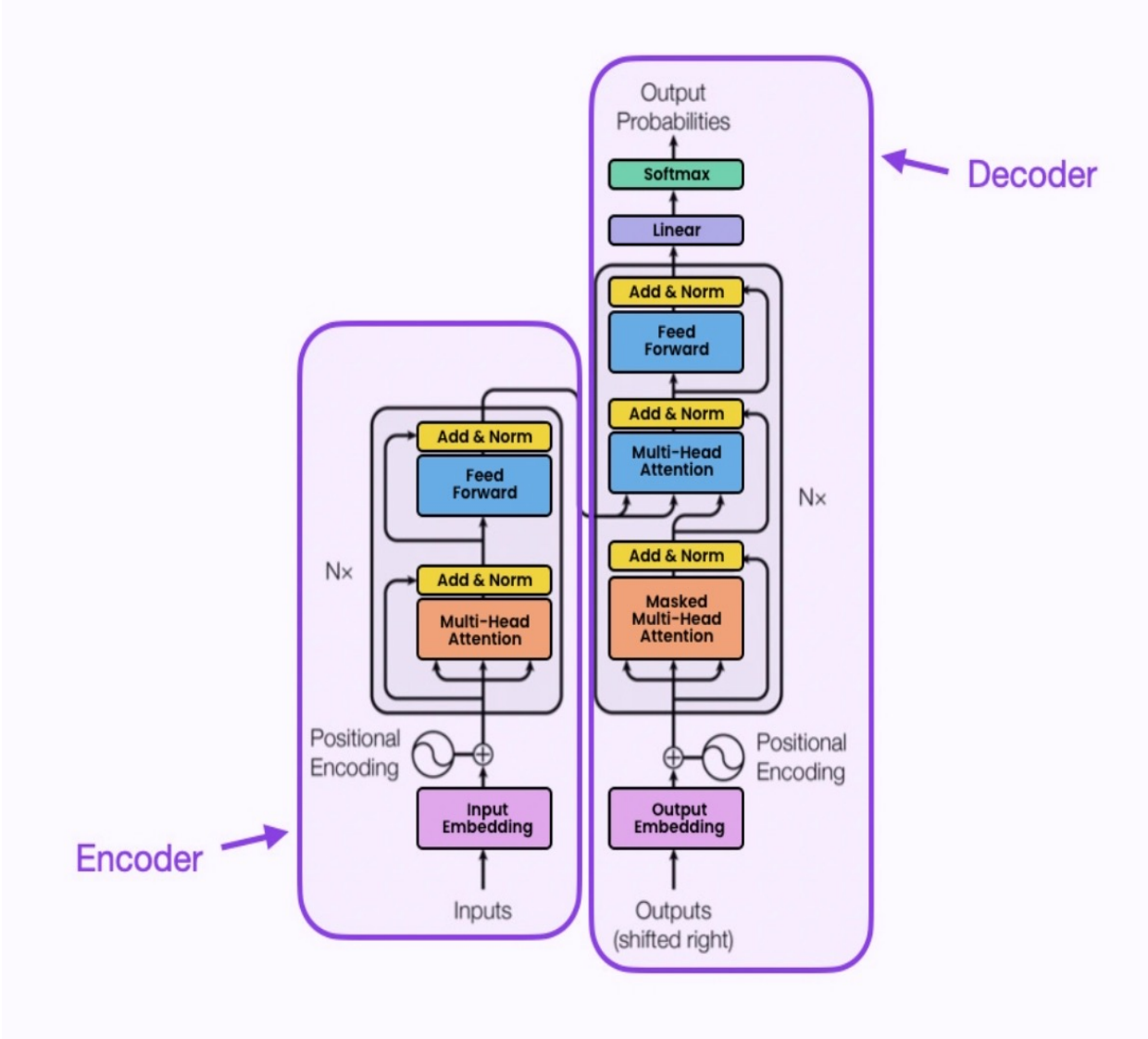
- Based on Transformer architecture and self-attention mechanism
- Learning from extensive text datasets through data-driven approaches
- LLMs consider broader context
- Capable of performing tasks with limited or no task-specific examples
- LLMs can be fine-tuned for a specific task or domain to improve performance
- Adaptable to different languages due to data-driven learning

Traditional Language Model

- Relied on statistical approaches, n-gram models, rules, and hand-crafted linguistic features
- Limited contextual understanding and struggled with complex language structures
- A traditional language model only considers smaller context windows
- It utilizes rule-based syntactic parsers for sentence structure analysis
- Heavily dependent on human experts for linguistic features creation
- Often tailored for specific task, lacking versatility across various contexts

Architecture of LLMs

- Input embeddings
- Positional encoding
- Encoder:
  - Self-attention mechanism
  - Feed-forward neural network
- Decoder layers
- Multi-head attention
- Layer normalization
- Output layers

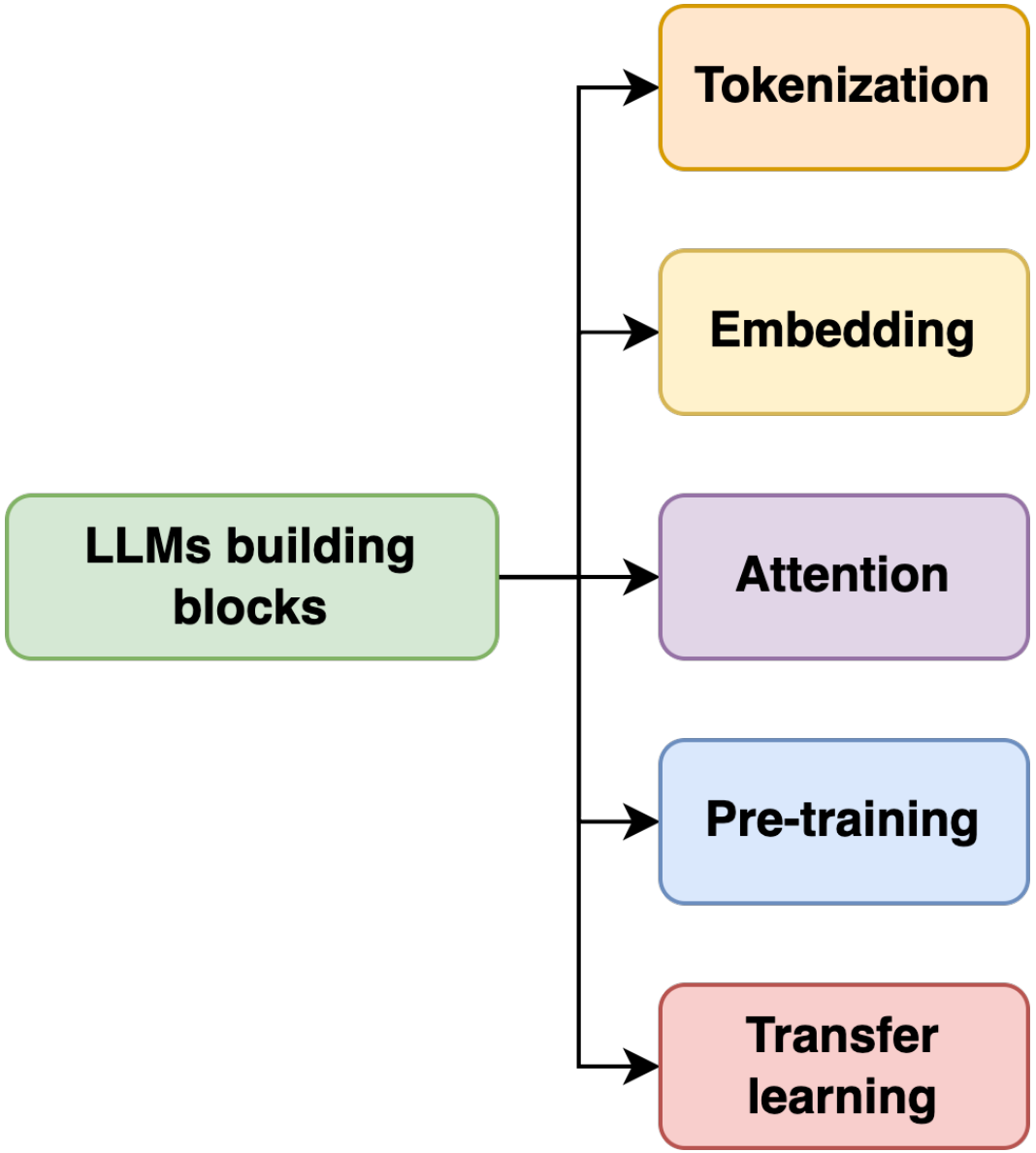


Architecture of LLMs

- The original Transformer architecture uses an encoder-decoder architecture, although variants with only an encoder or only a decoder also exist.

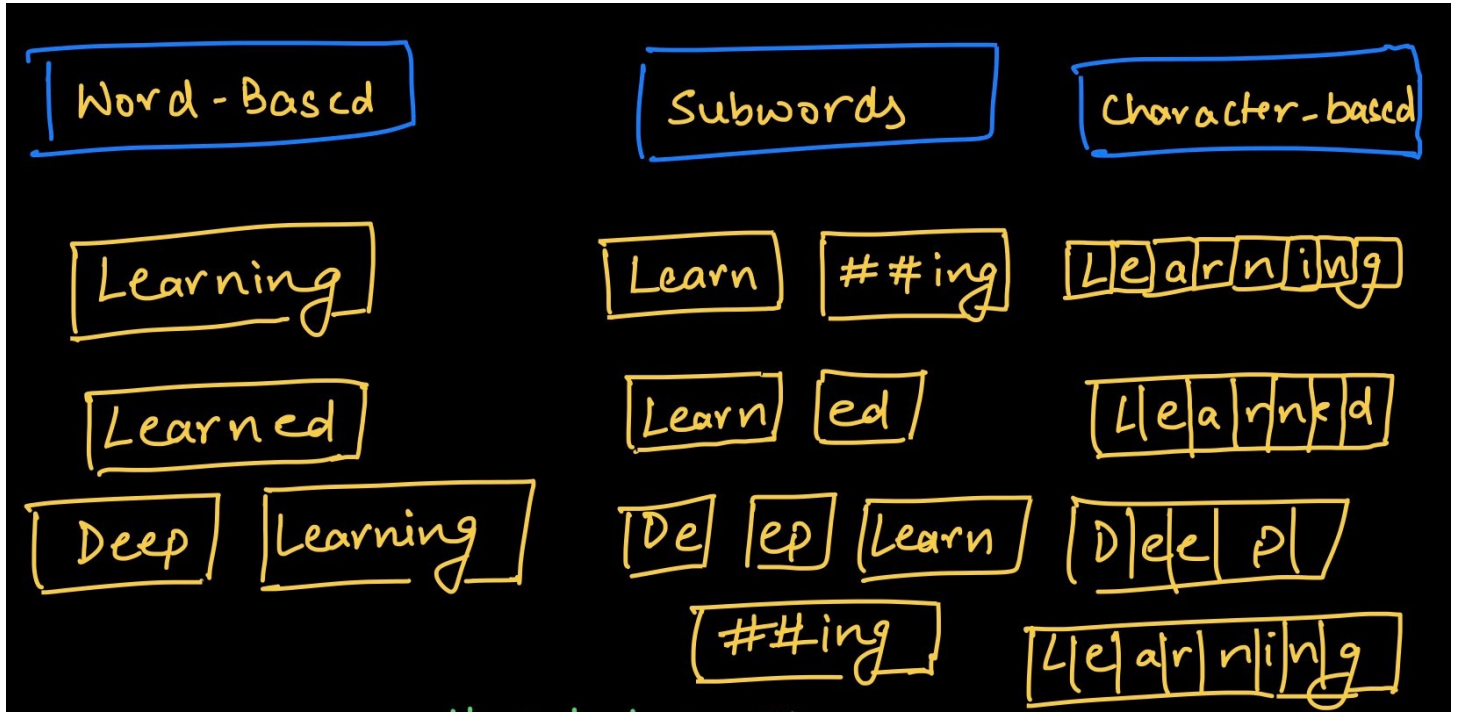
Architecture	Key Features	Notable LLMs	Use Cases
Encoder-only	• Captures bidirectional context • Suitable for NLU	BERT and other BERT-based architectures (RoBERTa, XLNet)	Text classification, question answering
Decoder-only	• Unidirectional language model • Autoregressive generation	GPT, PaLM	Text generation, text completion
Encoder-decoder	• Input text to target text • Any text-to-text task	T5, BART	Summarization, translation, question answering, document classification

https://www.kdnuggets.com/7-steps-to-mastering-large-language-models-llms


LLMs building blocks
Tokenization
Embedding
Attention
Pre-training
Transfer learning

Tokenization

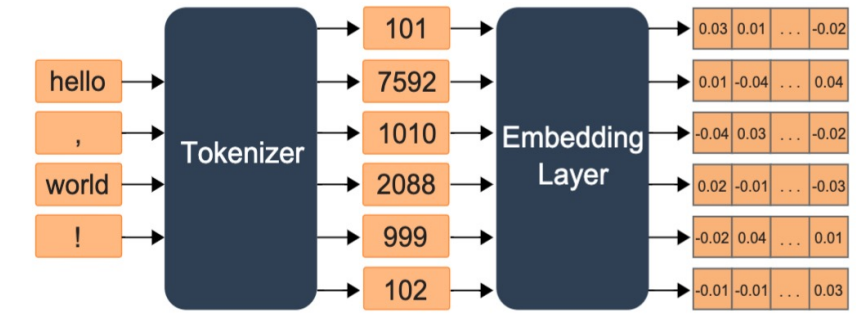
- Converting a sequence of text into tokens using subword algorithms like Byte Pair Encoding (BPE) or WordPiece.

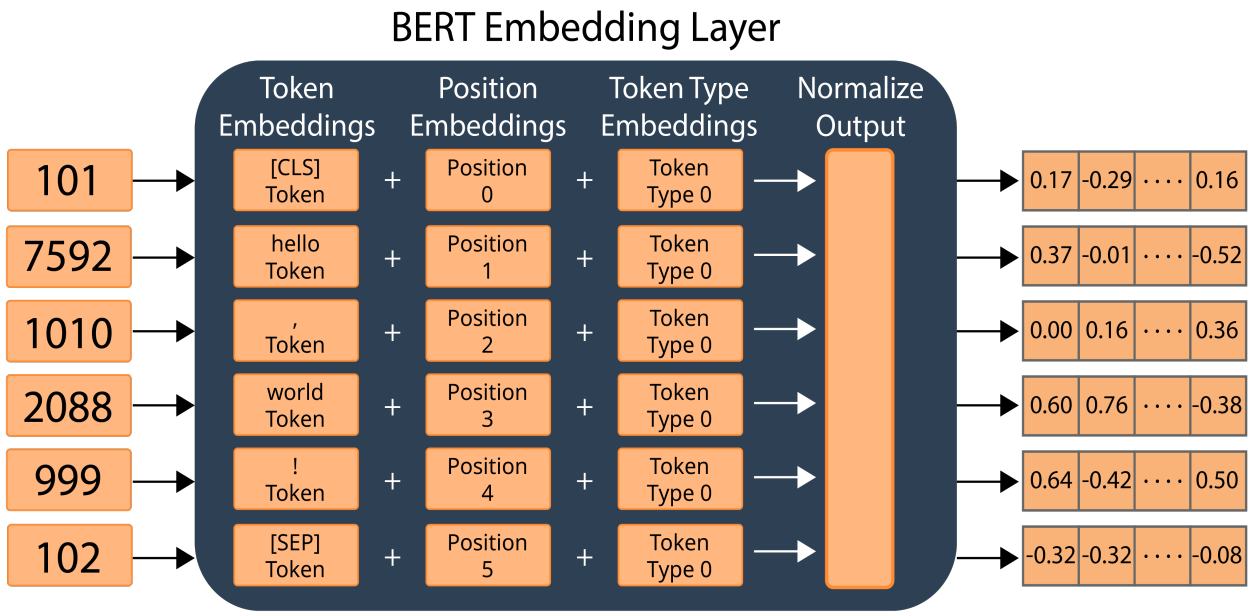


https://dswharshit.substack.com/p/the-evolution-of-tokenization-byte

Embedding

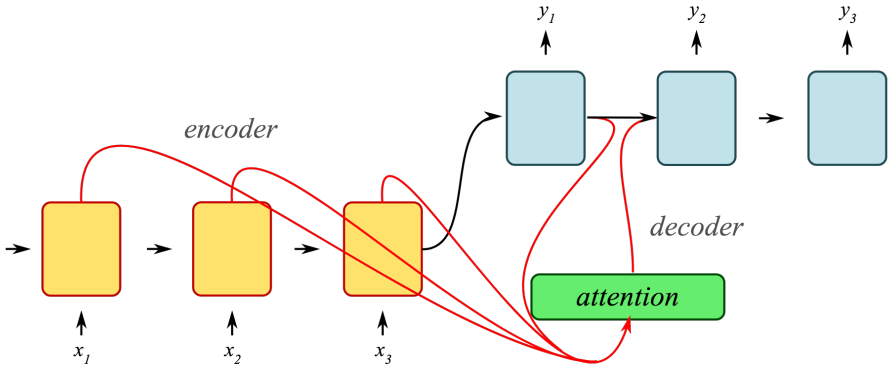
- Embeddings are vector representations that map words or tokens into a multidimensional space, capturing semantic meanings.

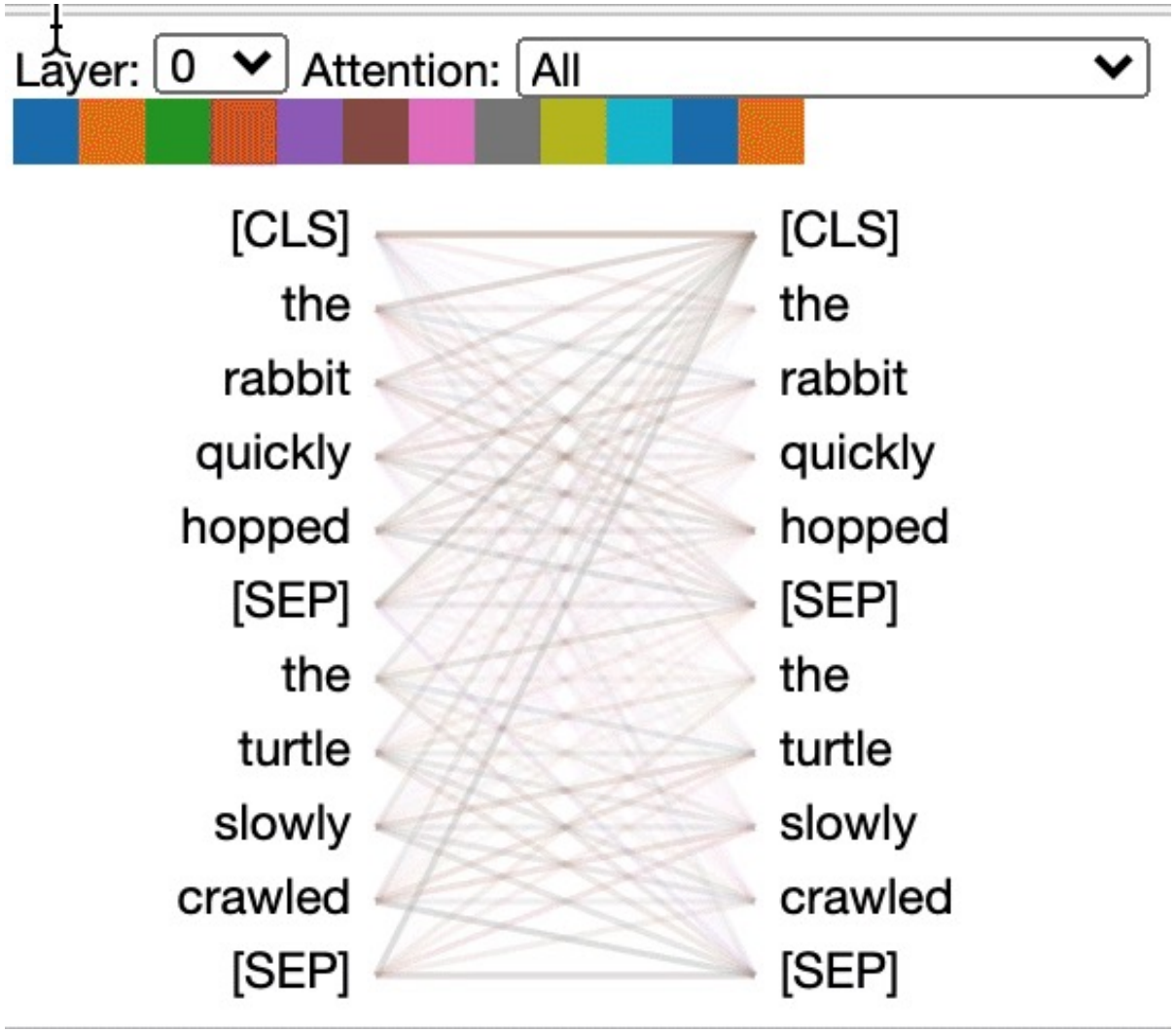




Attention

- The self-attention enables the model to weigh the significance of different elements within a given context.

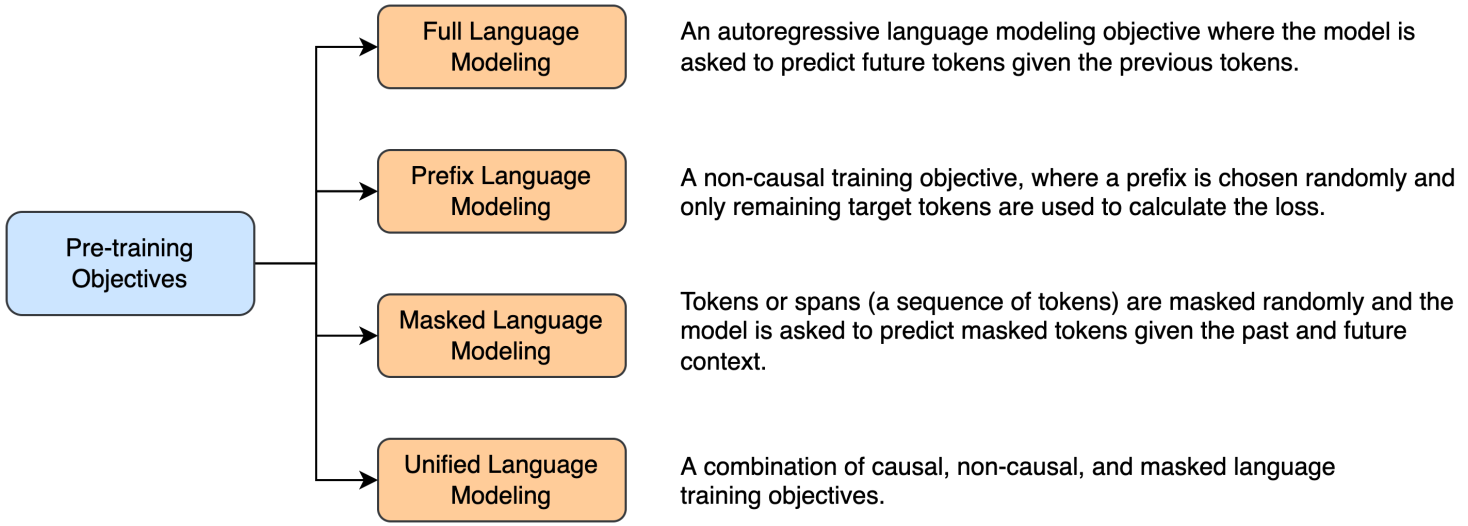


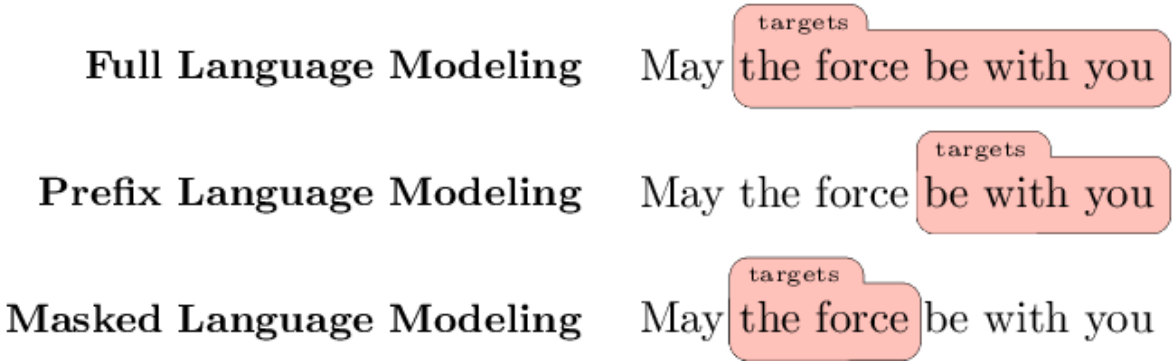


https://towardsdatascience.com/deconstructing-bert-part-2-visualizing-the-inner-workings-of-attention-60a16d86b5c1

Pre-training

- It is the initial training phase of an LLM on a large dataset to learn general language patterns before fine-tuning for specific tasks.

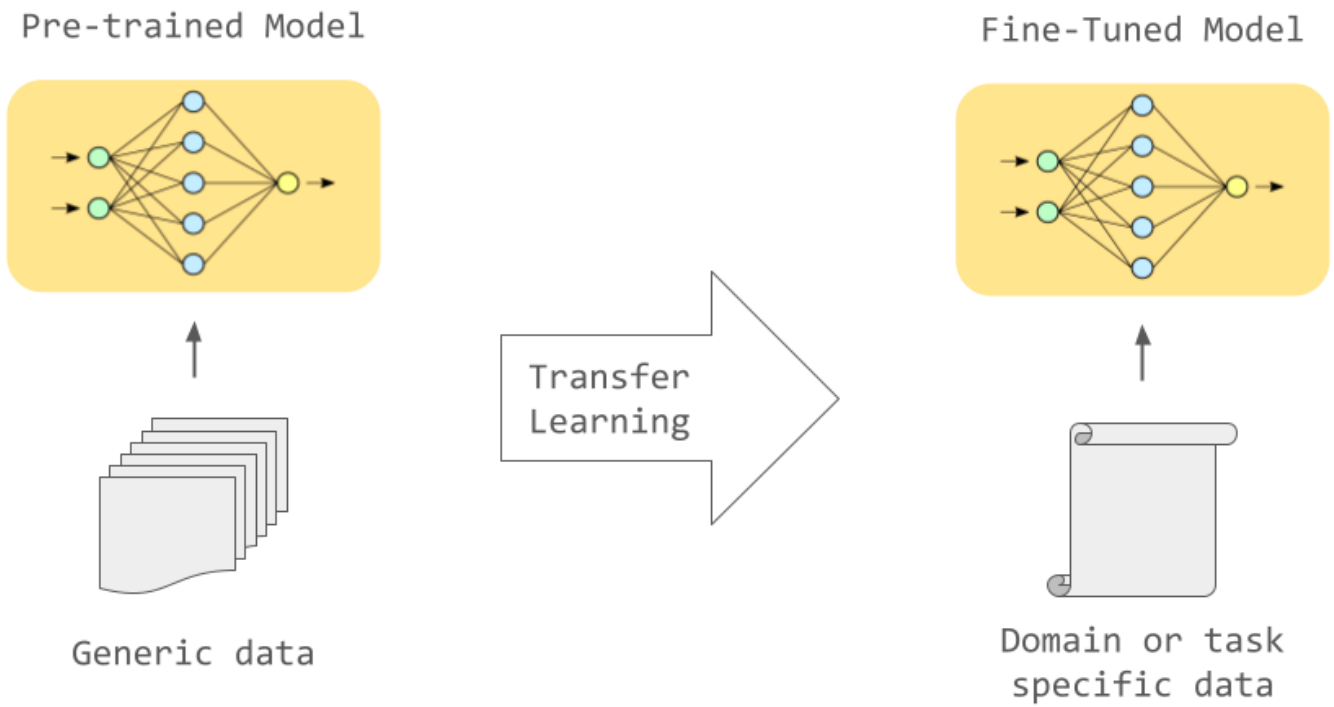




https://arxiv.org/pdf/2307.06435.pdf

Transfer Learning

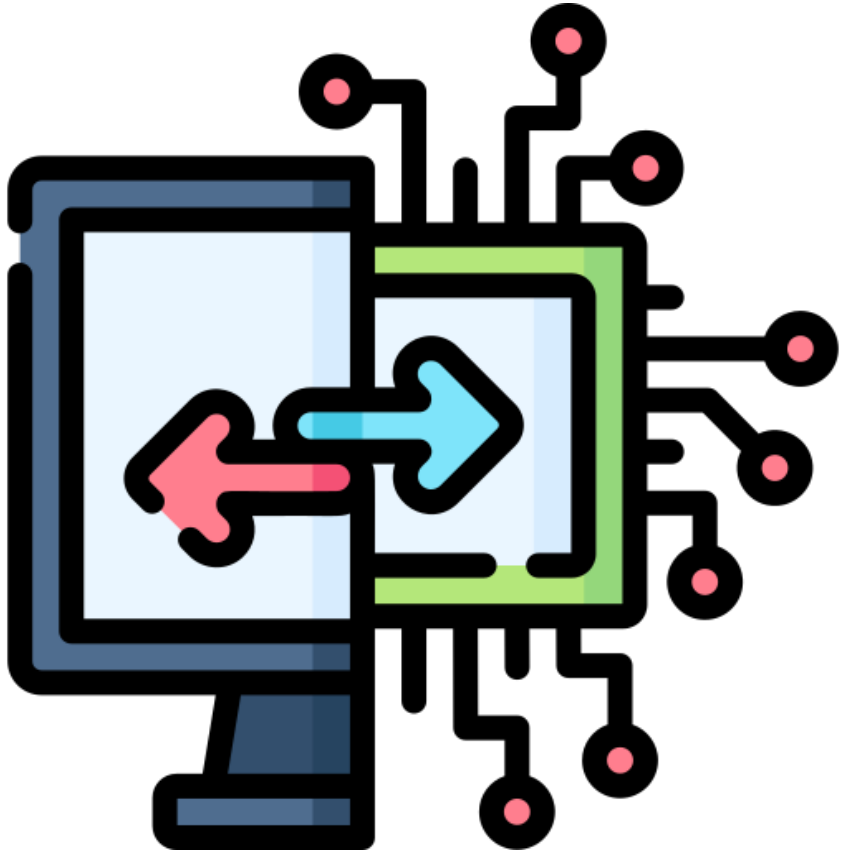
- Transfer learning involves applying the knowledge obtained during pre-training to the new task on a smaller specific dataset.



https://www.labellerr.com/blog/hands-on-with-fine-tuning-llm/

Transfer Learning Techniques

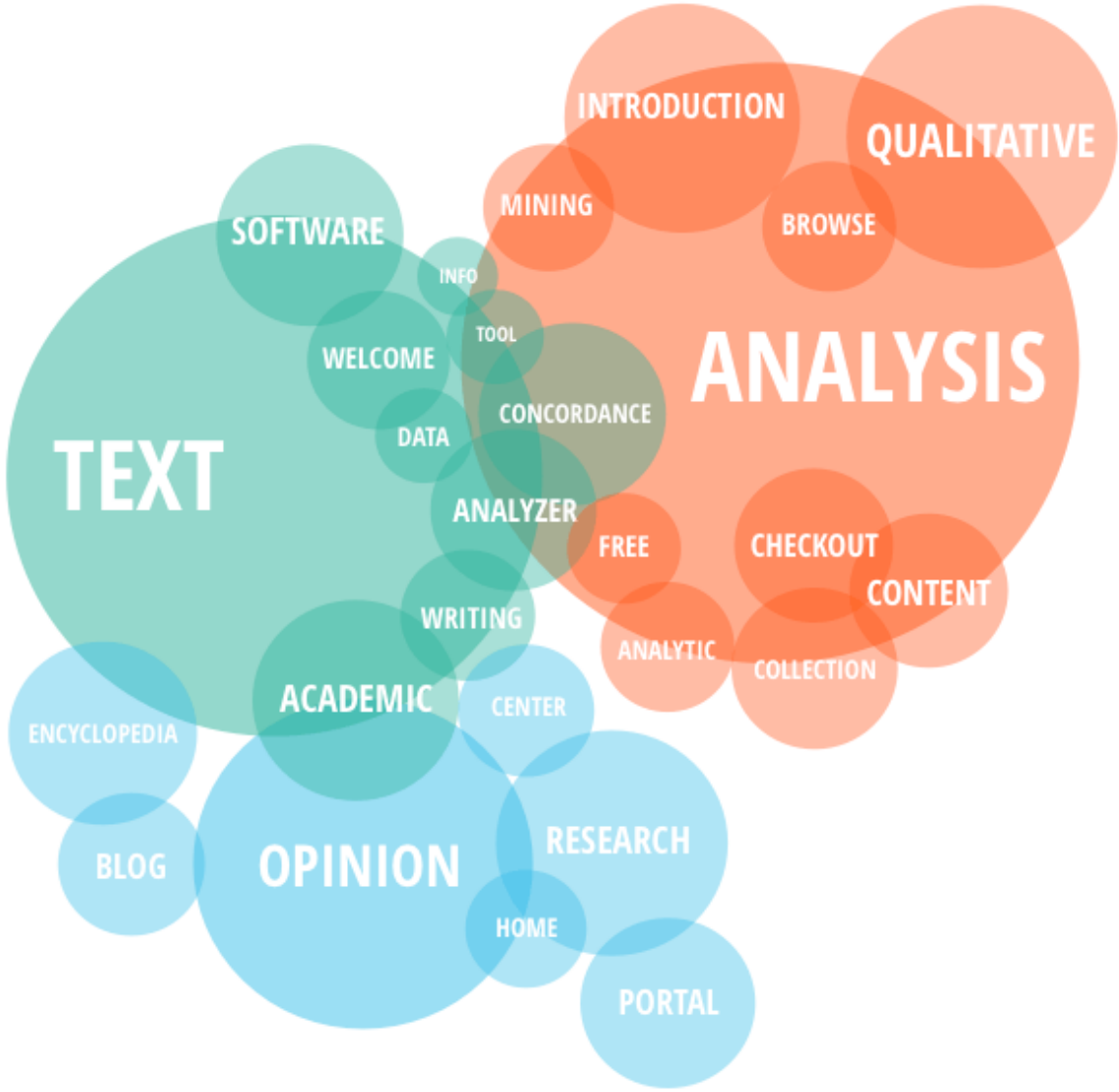
- **Fine-tuning**
  - A process of adapting the pre-trained model to a new task or domain.
- **Zero-shot**
  - A technique wherein a model can perform a task without any labeled examples or training data for that specific task.
- **One-Shot**
  - A technique involving the training of a model with only one example or a very small number of examples per class.
- **Few-shot**
  - A technique referring to the training of a model with a small number of examples per class, typically more than one but fewer than what is required for conventional supervised learning.



Text Analysis

Text Analysis

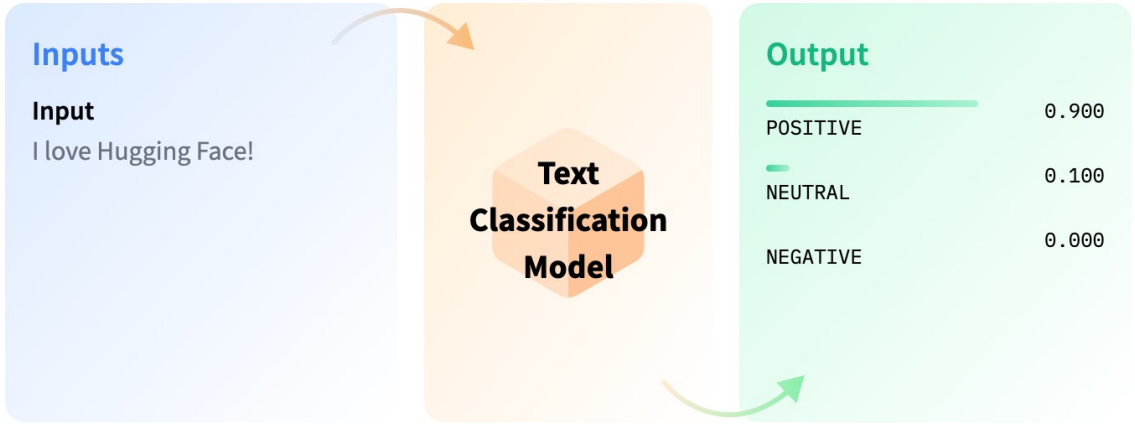
- Text analysis is the process of extracting meaningful insights, patterns, and information from textual data.
- It involves applying various techniques and methodologies to understand, interpret, and derive actionable insights from large volumes of text.



LLMs Use Cases for Text Analysis

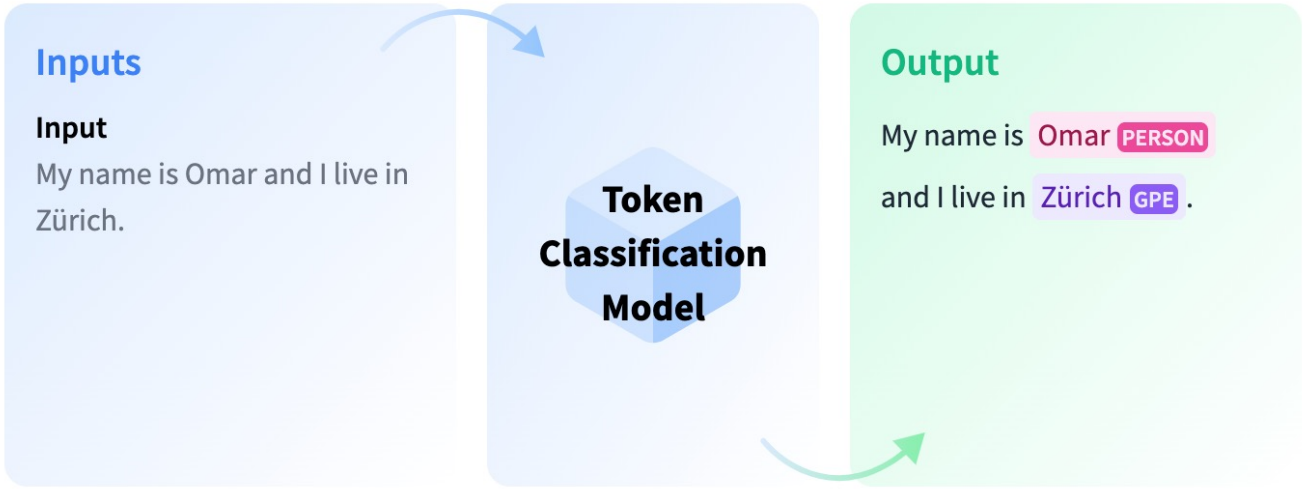
Text Classification

- Text classification is the task of assigning a label or class to a given text.
- Use cases:
  - sentiment analysis
  - spam detection
  - topic detection
  - language detection
  - offensive language identification



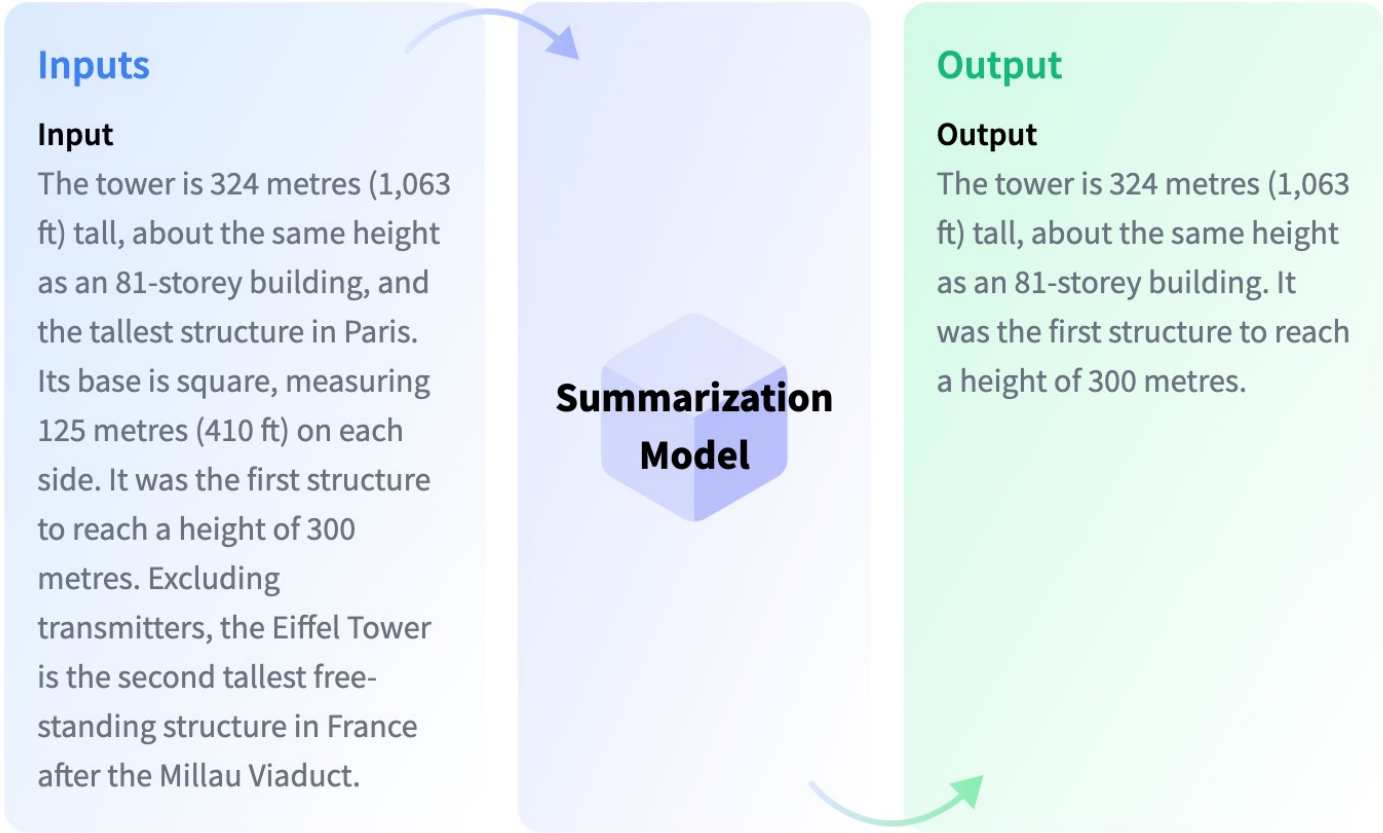
Token Classification

- Token classification is a natural language understanding task in which a label is assigned to some tokens in a text.
- Use cases:
  - Named Entity Recognition (NER)
  - Part-of-Speech (PoS) tagging
  - Word level language identification



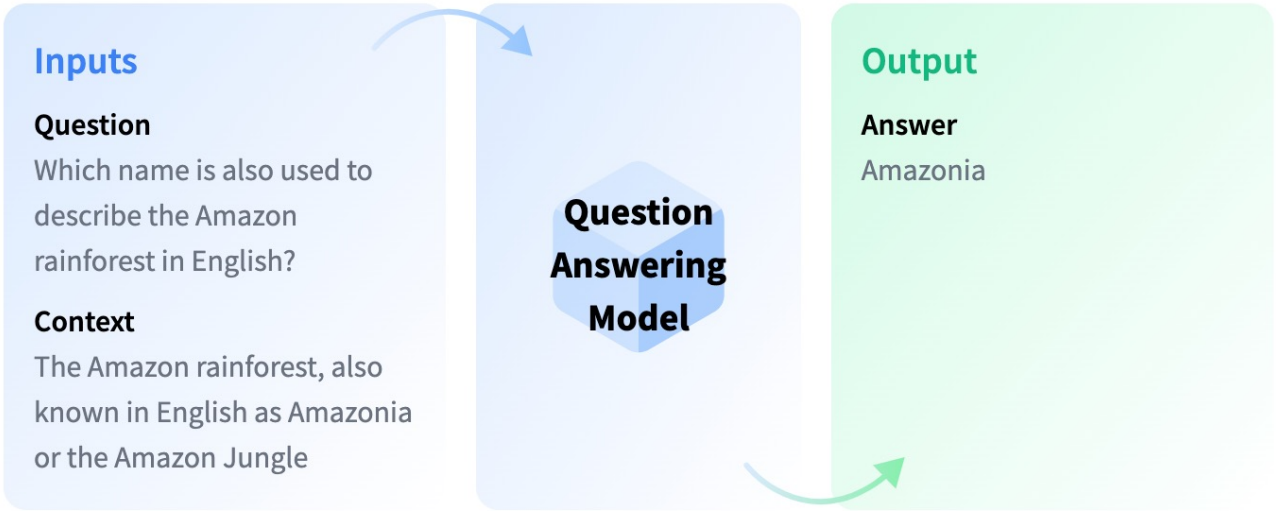
Text Summarization

- Summarization is the task of producing a shorter version of a document while preserving its important information.



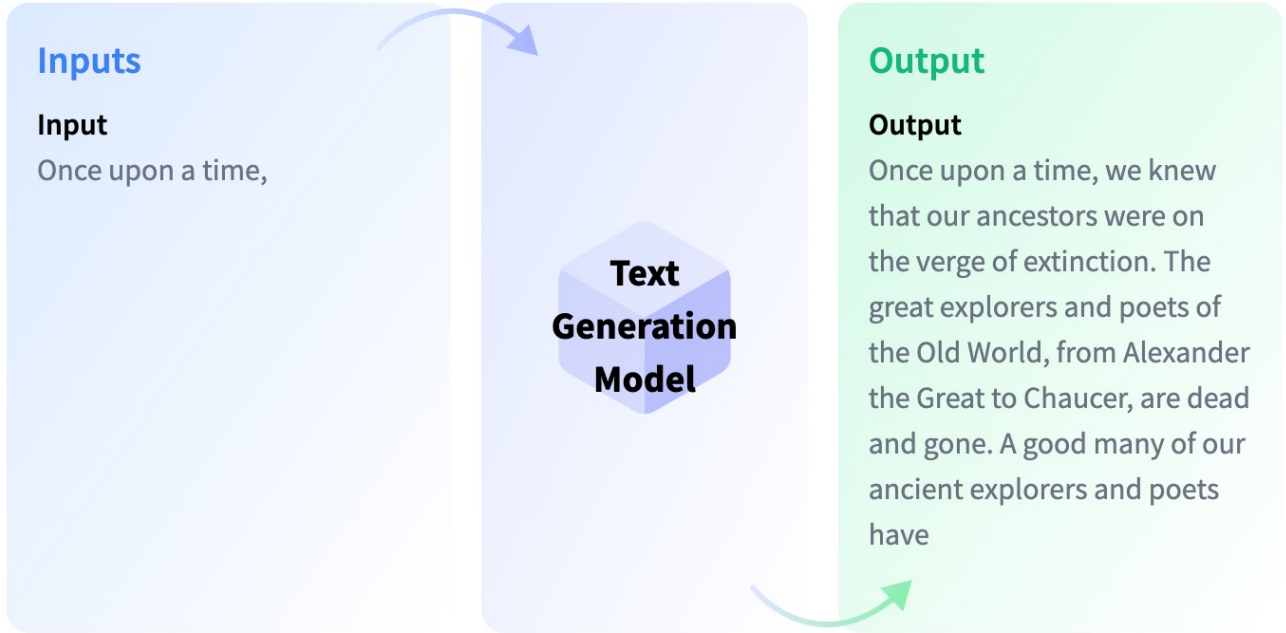
Question Answering

- Question Answering models can retrieve the answer to a question from a given text, which is useful for searching for an answer in a document.



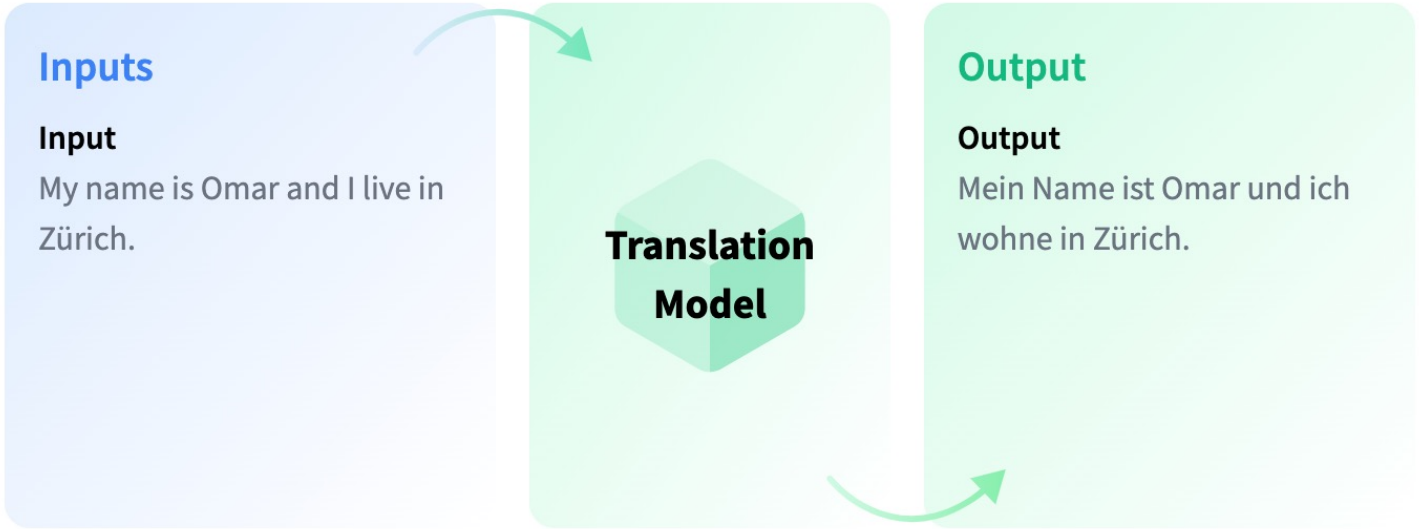
Text Generation

- Generating text is the task of generating new text given another text. These models can, for example, fill in incomplete text or paraphrase.



Translation

- Translation is the task of converting text from one language to another.



Case Study 1

Sentiment Analysis by Fine-tuning

Tools

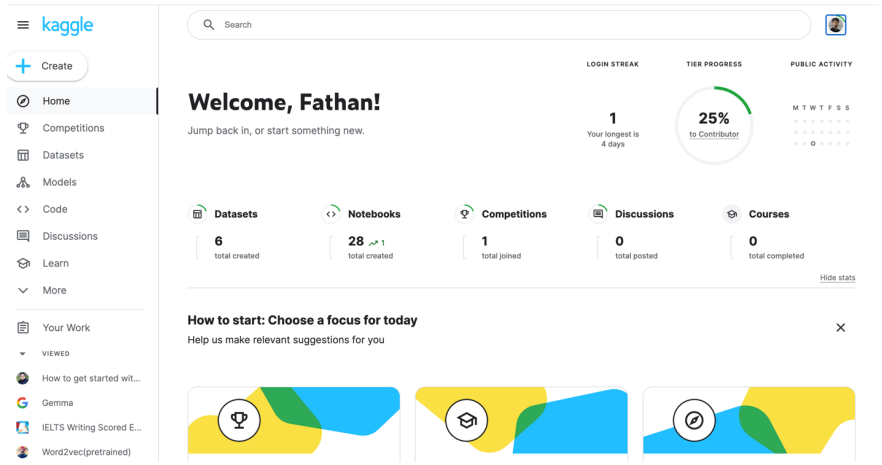
- Kaggle with GPU
- Hugging Face

kaggle + 

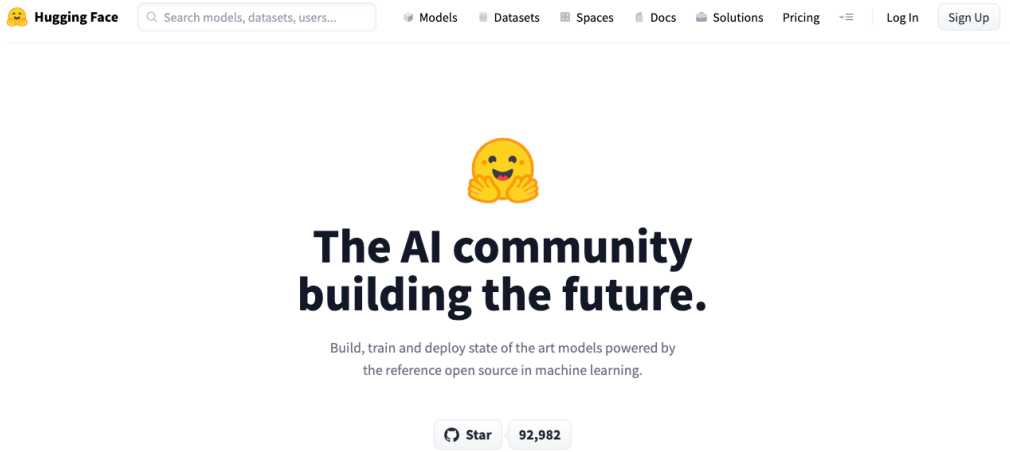
HUGGING FACE

Prerequisite

- Make sure that you already have a Kaggle and Hugging Face account!



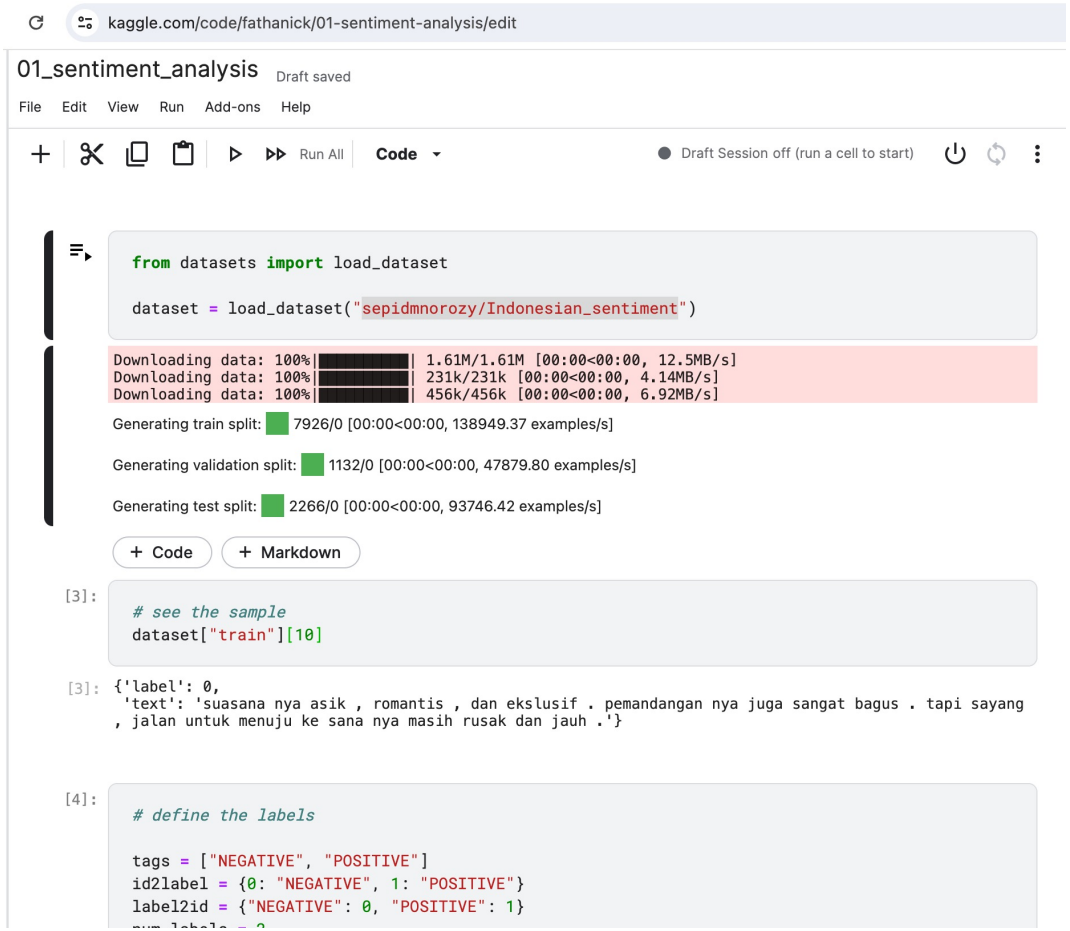
https://www.kaggle.com/



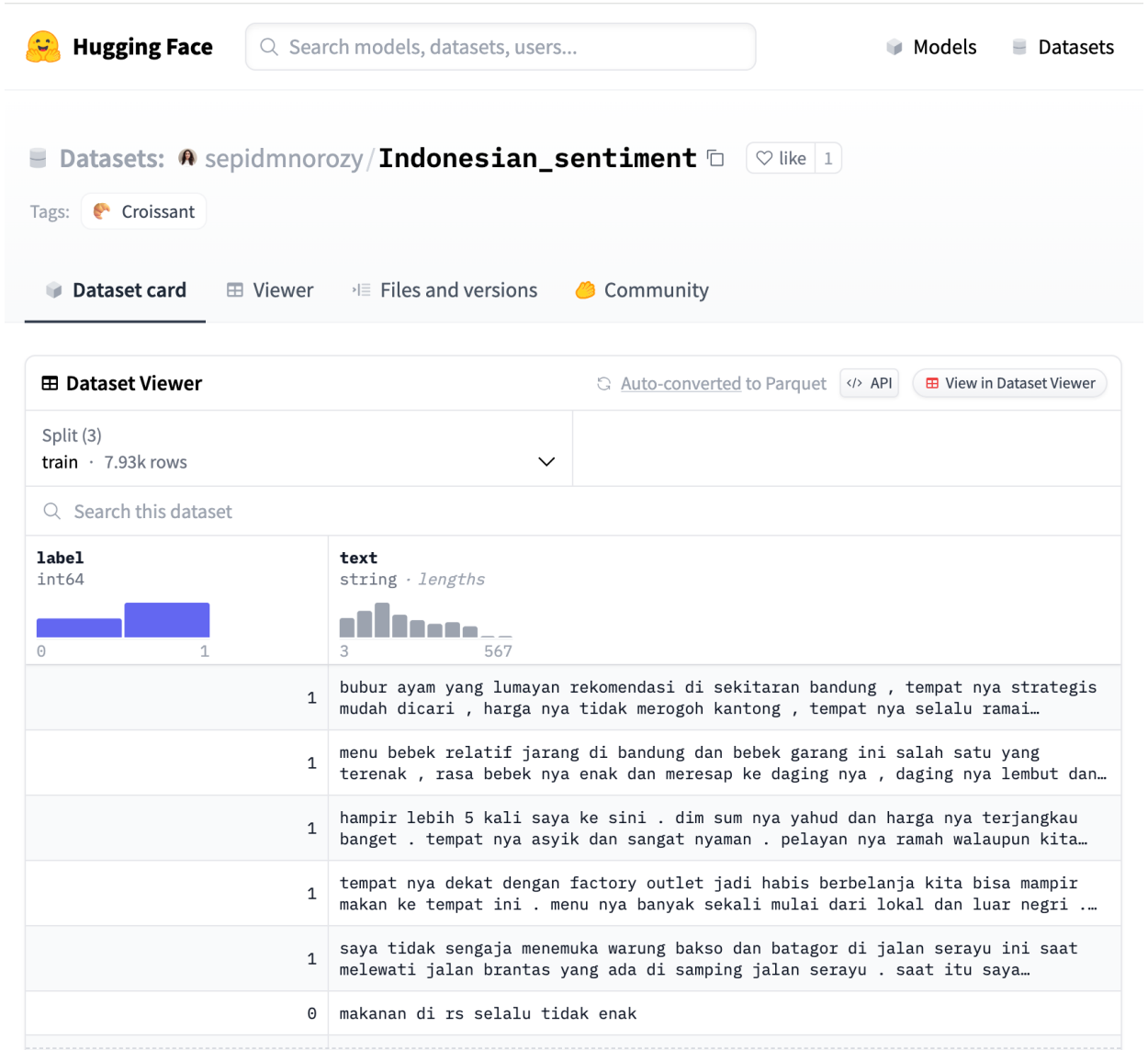
https://huggingface.co/

Get the code here...

- https://www.kaggle.com/code/fathanick/01-sentiment-analysis



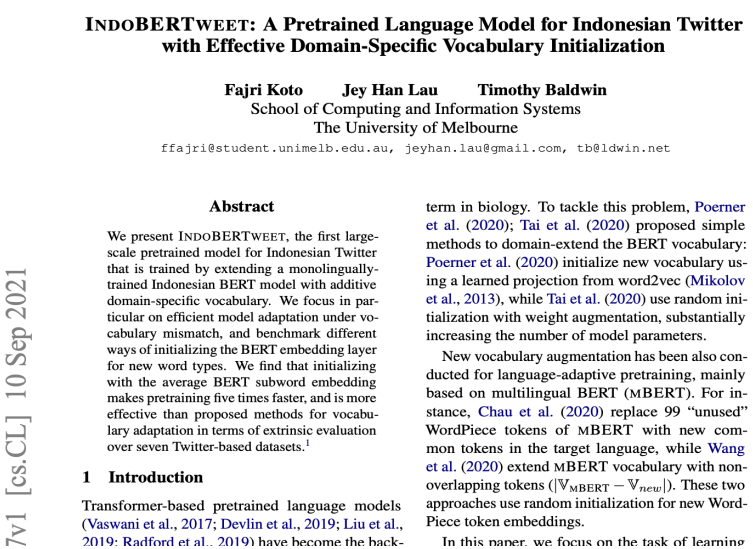
Dataset



https://huggingface.co/datasets/sepidmnorozy/Indonesian_sentiment

Fine-tuning with IndoBERTweet

- In this tutorial, we're going to fine-tune IndoBERTweet model sentiment data.
- IndoBERTweet is the first large-scale pretrained model for Indonesian Twitter that is trained by extending a monolingually trained Indonesian BERT model with additive domain-specific vocabulary.



INDOBERTWEET: A Pretrained Language Model for Indonesian Twitter with Effective Domain-Specific Vocabulary Initialization

Fajri Koto **Jey Han Lau** **Timothy Baldwin**
School of Computing and Information Systems
The University of Melbourne
ffajri@student.unimelb.edu.au, jeyhan.lau@gmail.com, tb@ldwin.net

Abstract

We present INDOBERTWEET, the first large-scale pretrained model for Indonesian Twitter that is trained by extending a monolingually-trained Indonesian BERT model with additive domain-specific vocabulary. We focus in particular on efficient model adaptation under vocabulary mismatch, and benchmark different ways of initializing the BERT embedding layer for new word types. We find that initializing with the average BERT subword embedding makes pretraining five times faster, and is more effective than proposed methods for vocabulary adaptation in terms of extrinsic evaluation over seven Twitter-based datasets.[1]

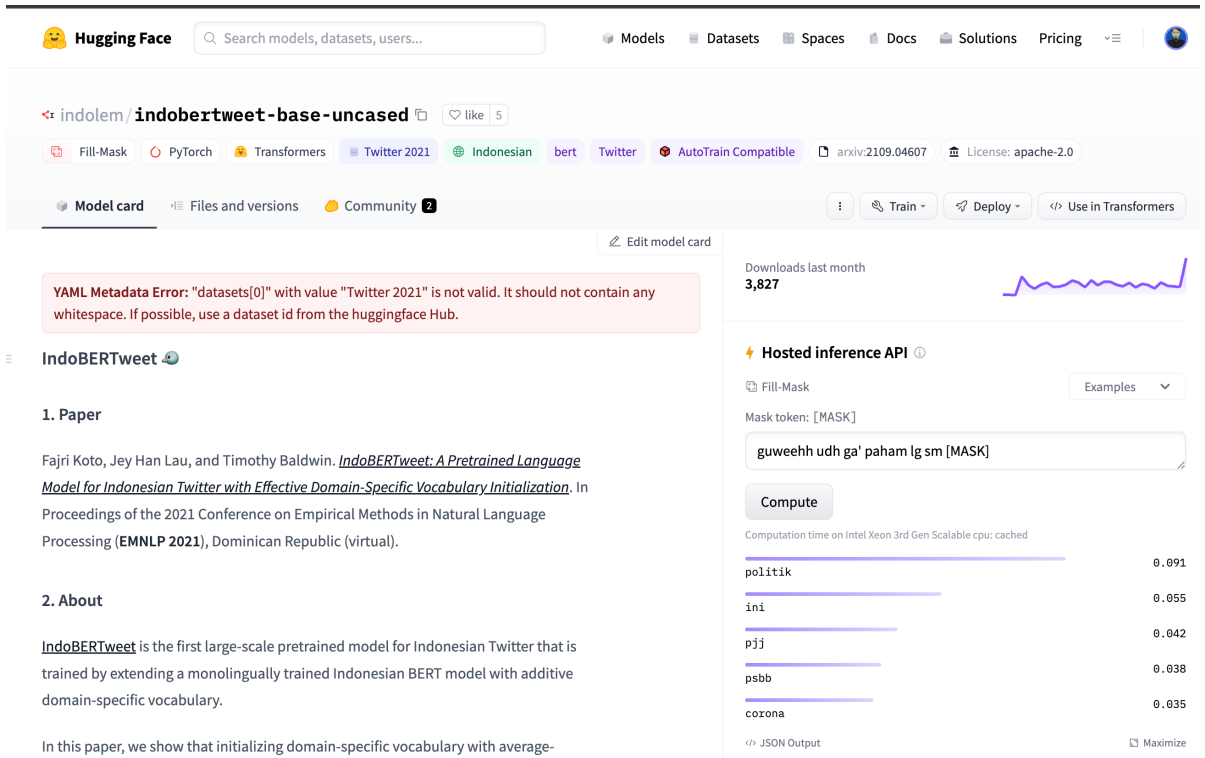
1 Introduction

Transformer-based pretrained language models (Vaswani et al., 2017; Devlin et al., 2019; Liu et al., 2019; Radford et al., 2019) have become the back-

term in biology. To tackle this problem, Poerner et al. (2020); Tai et al. (2020) proposed simple methods to domain-extend the BERT vocabulary: Poerner et al. (2020) initialize new vocabulary using a learned projection from word2vec (Mikolov et al., 2013), while Tai et al. (2020) use random initialization with weight augmentation, substantially increasing the number of model parameters.

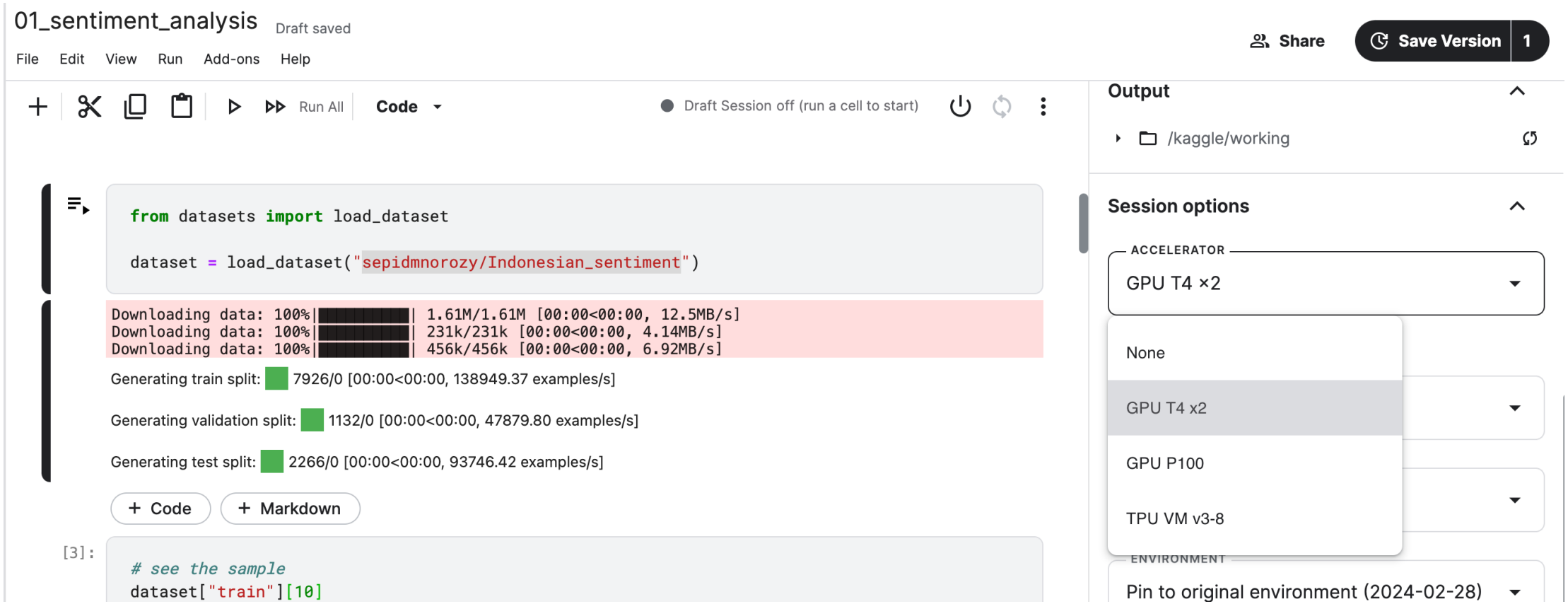
New vocabulary augmentation has been also conducted for language-adaptive pretraining, mainly based on multilingual BERT (MBERT). For instance, Chau et al. (2020) replace 99 "unused" WordPiece tokens of MBERT with new common tokens in the target language, while Wang et al. (2020) extend MBERT vocabulary with non-overlapping tokens ($|\mathbb{V}_{\text{MBERT}} - \mathbb{V}_{new}|$). These two approaches use random initialization for new WordPiece token embeddings.

In this paper, we focus on the task of learning



https://huggingface.co/indolem/indobertweet-base-uncased

GPU Activation

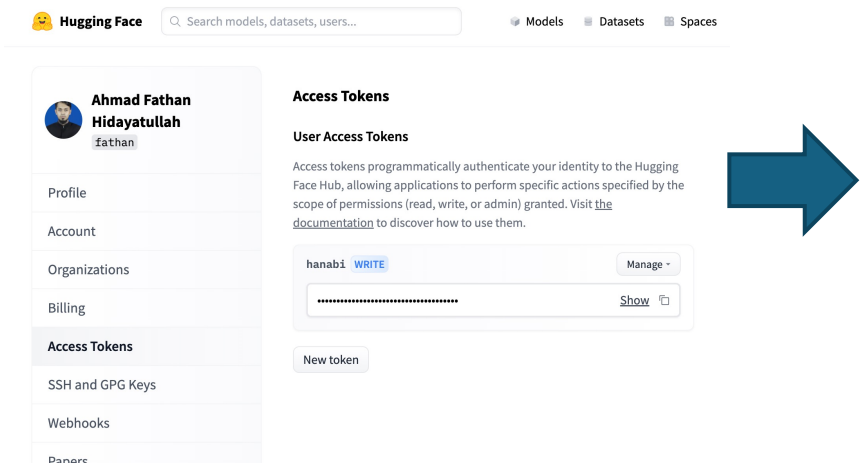


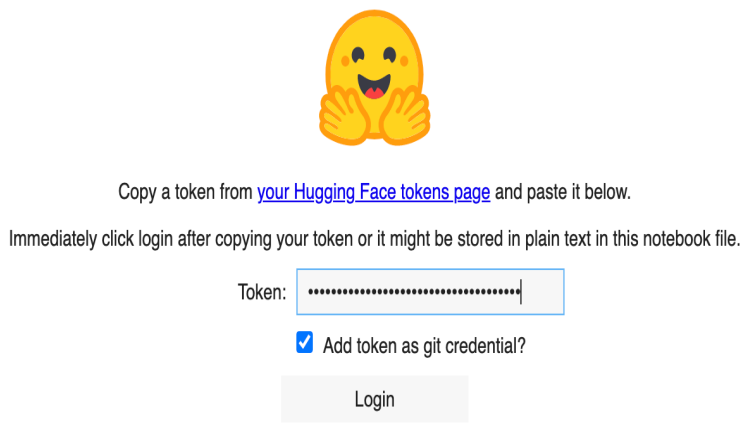
Install Packages

```
# Install required packages
!pip install transformers[torch]
!pip install -U datasets
!pip install huggingface_hub
!pip install accelerate -U
```

Connect to Hugging Face

- Get access token from your Hugging Face account
  - Go to: https://huggingface.co/settings/tokens





Load Dataset

```
from datasets import load_dataset

dataset = load_dataset("sepidmnorozy/Indonesian_sentiment")
```

```
Downloading data: 100%|██████████| 1.61M/1.61M [00:00<00:00, 12.5MB/s]
Downloading data: 100%|██████████| 231k/231k [00:00<00:00, 4.14MB/s]
Downloading data: 100%|██████████| 456k/456k [00:00<00:00, 6.92MB/s]
Generating train split: 7926/0 [00:00<00:00, 138949.37 examples/s]
Generating validation split: 1132/0 [00:00<00:00, 47879.80 examples/s]
Generating test split: 2266/0 [00:00<00:00, 93746.42 examples/s]
```

+ Code + Markdown

[3]:
```
# see the sample
dataset["train"][10]
```

[3]:
```
{'label': 0,
 'text': 'suasana nya asik , romantis , dan ekslusif . pemandangan nya juga sangat bagus . tapi sayang
, jalan untuk menuju ke sana nya masih rusak dan jauh .'}
```

[4]:
```
# define the labels

tags = ["NEGATIVE", "POSITIVE"]
id2label = {0: "NEGATIVE", 1: "POSITIVE"}
label2id = {"NEGATIVE": 0, "POSITIVE": 1}
num_labels = 2
```

Load Packages

```
from transformers import (
    AutoTokenizer,
    AutoModelForSequenceClassification,
    DataCollatorWithPadding,
    TrainingArguments,
    Trainer,
)
```

Initialize The Model

```
def model_init(model_name):
    global tokenizer
    global data_collator
    global tr_model

    model = AutoModelForSequenceClassification.from_pretrained(
        model_name,
        num_labels=num_labels,
        id2label=id2label,
        label2id=label2id
    )
    tokenizer = AutoTokenizer.from_pretrained(model_name, model_max_length=max_length)

    return model, tokenizer
```

Tokenization and Preprocessing

```
def tokenize_function(examples):
    # process the input sequence
    tokenized_input = tokenizer(examples["text"],
                                truncation=True,
                                padding="max_length",
                                max_length=max_length)

    return tokenized_input

def preprocessing():
    tokenized_train_data = dataset["train"].map(tokenize_function, batched=True)
    tokenized_val_data = dataset["validation"].map(tokenize_function, batched=True)
    tokenized_test_data = dataset["test"].map(tokenize_function, batched=True)

    return tokenized_train_data, tokenized_val_data, tokenized_test_data
```

Define Function for Evaluation

```python
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, classification_report
import numpy as np

def compute_metrics(p):
    pred, labels = p
    pred = np.argmax(pred, axis=1)

    true_labels = [tags[l] for l in labels]
    true_predictions = [tags[pr] for pr in pred]

    report = classification_report(true_labels, true_predictions, digits=4)
    acc = accuracy_score(y_true=true_labels, y_pred=true_predictions)
    rec = recall_score(y_true=true_labels, y_pred=true_predictions, average="macro")
    prec = precision_score(y_true=true_labels, y_pred=true_predictions, average="macro")
    f1 = f1_score(y_true=true_labels, y_pred=true_predictions, average="macro", zero_division=1.0)

    print("Classification Report:\n{}".format(report))
    return {"accuracy": acc, "precision": prec, "recall": rec, "f1": f1}
```

Function for Generating Confusion Matrix

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

def generate_confusion_matrix(true_labels, pred_labels, num_labels):
    cm = confusion_matrix(true_labels, pred_labels)
    labels = [id2label[i] for i in range(num_labels)]
    plt.figure(figsize=(8, 6))
    sns.set(font_scale=1.5)
    sns.heatmap(cm,
                annot=True,
                fmt="d",
                cmap="Blues",
                xticklabels=labels,
                yticklabels=labels)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.yticks(rotation=0)
    plt.show()
```

```python
def train_model(model_name, output_dir, learning_rate, num_epochs):

    model, tokenizer = model_init(model_name)
    train_tokenized, val_tokenized, test_tokenized = preprocessing()

    training_args = TrainingArguments(
        output_dir=output_dir,
        logging_strategy="epoch",
        evaluation_strategy="epoch",
        save_strategy="epoch",
        save_total_limit = 1,
        learning_rate=learning_rate,
        num_train_epochs=num_epochs,
        per_device_train_batch_size=32,
        per_device_eval_batch_size=32,
        load_best_model_at_end=True,
        push_to_hub=True, # to push to hub during the training
    )

    trainer = Trainer(
        model=model,
        args=training_args,
        train_dataset=train_tokenized,
        eval_dataset=val_tokenized,
        tokenizer=tokenizer,
        compute_metrics=compute_metrics,
    )

    trainer.train()
    trainer.save_model(output_dir)
    trainer.push_to_hub(commit_message="Training complete")

    # Get the evaluation results
    trainer.eval_dataset=test_tokenized
    evaluation_results = trainer.evaluate()
    print(evaluation_results)

    # make prediction on the test set
    predictions = trainer.predict(test_tokenized)
    pred_labels = np.argmax(predictions.predictions, axis=1)
    true_labels = test_tokenized["label"]

    # Generate confusion matrix
    generate_confusion_matrix(true_labels, pred_labels, num_labels)

    # Show log history
    log_history = pd.DataFrame(trainer.state.log_history)
    log_history = log_history.fillna(0)
    log_history = log_history.groupby(["epoch"]).sum()

    log_history[["loss", "eval_loss"]].plot()
    plt.show()
```

Train The Model

```python
train_model(
    model_name="indolem/indobertweet-base-uncased",
    output_dir="indo_sentiment_indobertweet",
    learning_rate=0.0001,
    num_epochs=3
)
```

Results

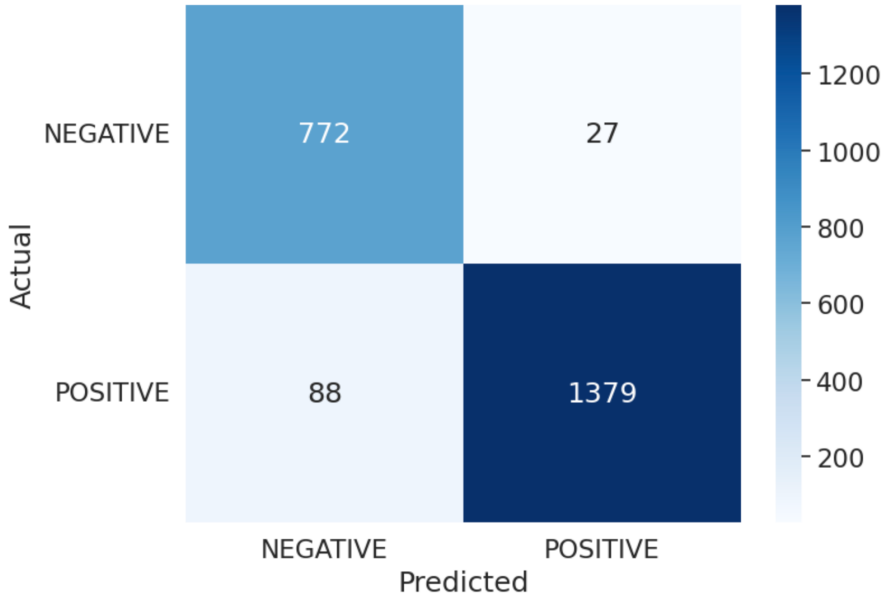
[372/372 04:55, Epoch 3/3]

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1
1	0.183500	0.103949	0.960247	0.953081	0.962508	0.957393
2	0.063900	0.109426	0.963781	0.958891	0.963151	0.960946
3	0.017600	0.136030	0.965548	0.963370	0.961879	0.962616

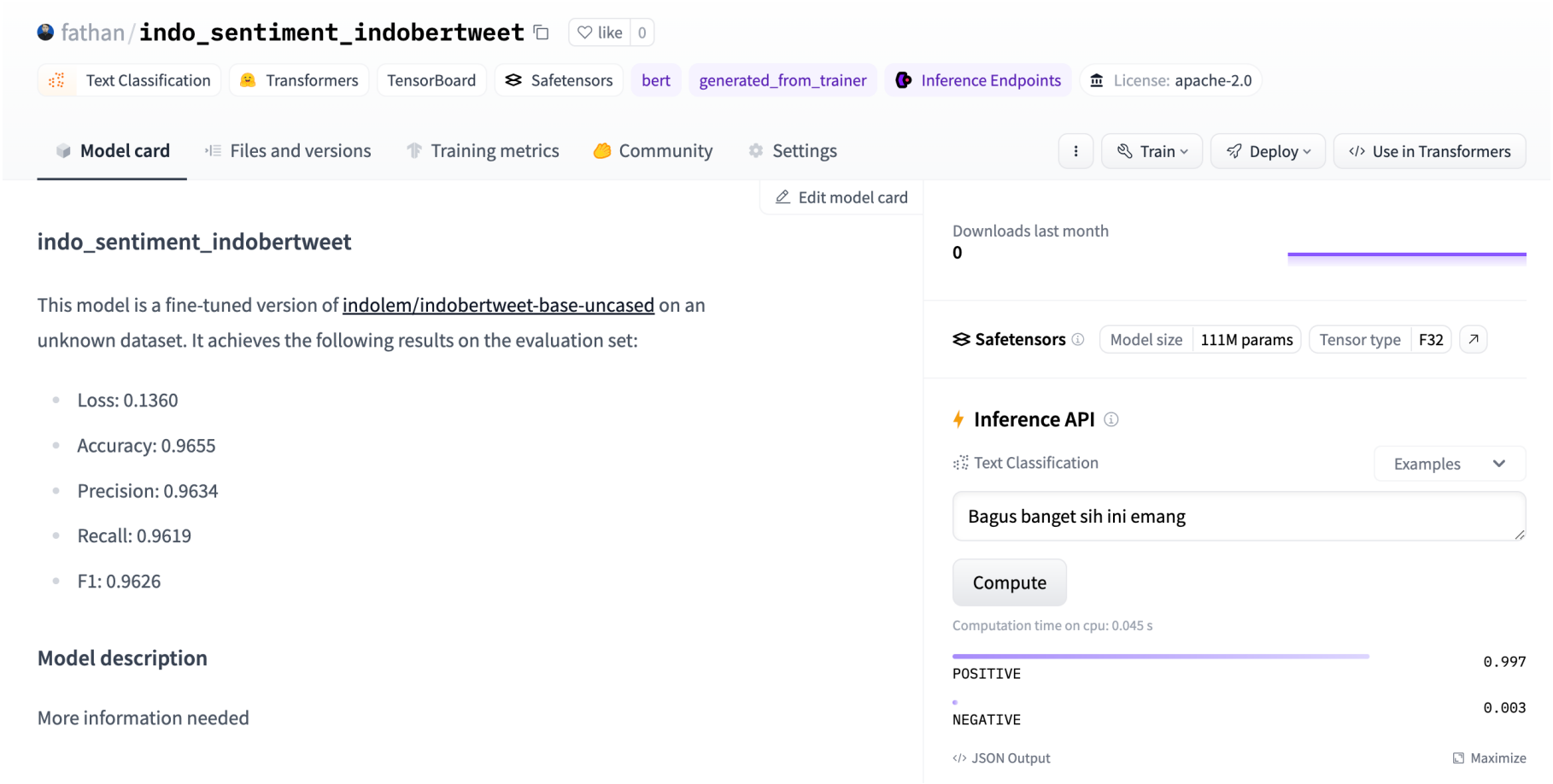
```
Classification Report:
              precision    recall  f1-score   support

    NEGATIVE     0.8977    0.9662    0.9307       799
    POSITIVE     0.9808    0.9400    0.9600      1467

    accuracy                         0.9492      2266
   macro avg     0.9392    0.9531    0.9453      2266
weighted avg     0.9515    0.9492    0.9496      2266
```



Hugging Face

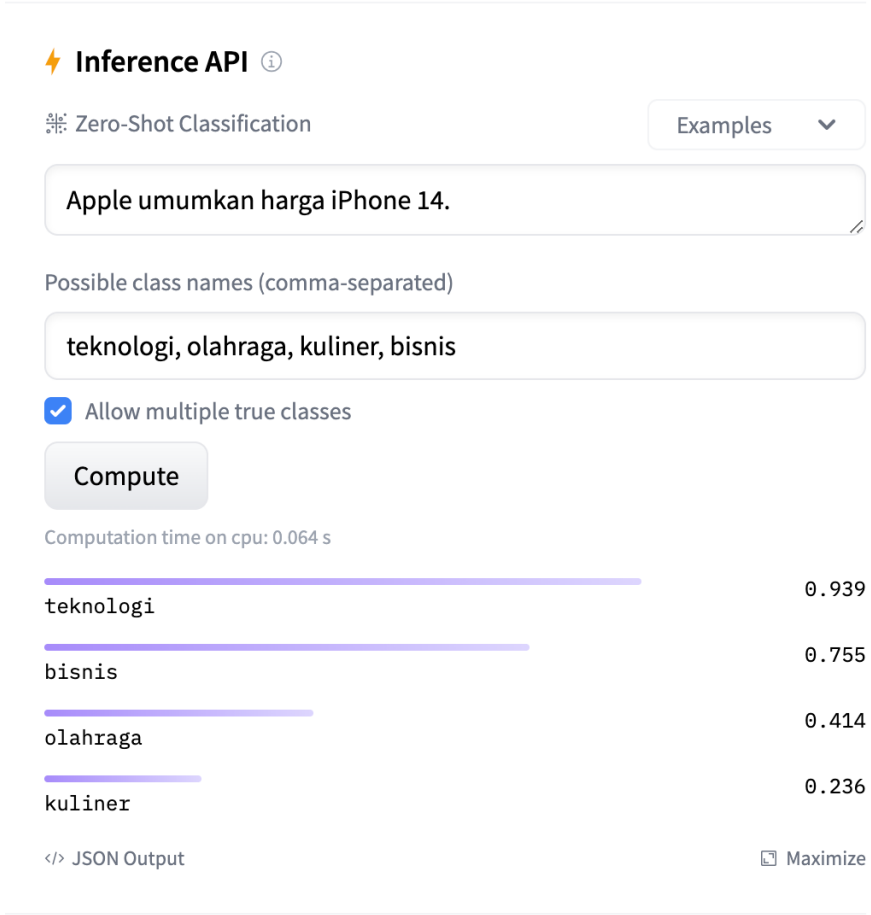


Case Study 2

Zero-shot classification: Topic Detection

Zero-shot Classification

- These models classify text into any categories we want by inputting them as labels.



https://huggingface.co/ilos-vigil/bigbird-small-indonesian-nli

Define The Model

```
from transformers import pipeline
```

```
# define the pipeline
classifier = pipeline("zero-shot-classification", model="facebook/bart-large-mnli")
```

Prediction

```
# sample 1
candidate_labels_sentiment = ["positive", "negative"]

text1 = "I hate this movie and I don't recommend people to watch this."
classifier(sequences=text1,
           candidate_labels=candidate_labels_sentiment,
           multi_label=True)
```

+ Code + Markdown

```
# sample 2
text2 = "I really love this movie!"
classifier(sequences=text2,
           candidate_labels=candidate_labels_sentiment,
           multi_label=True)
```

```
# sample 3
candidate_labels_news = ["world", "sports", "business", "sci/tech"]

text3 = "Liverpool were not given a penalty by VAR in the final minute of their pulsating 1-1 draw against Manchester City on Super Sunday."
classifier(sequences=text3,
           candidate_labels=candidate_labels_news,
           multi_label=True)
```

```
# sample 4
text4 = "Microsoft has expanded the availability of its AI-powered cybersecurity assistant, Copilot for Security, using the power of generative AI (Gen AI)"
classifier(sequences=text4,
           candidate_labels=candidate_labels_news,
           multi_label=True)
```


thank you