All about Transformers

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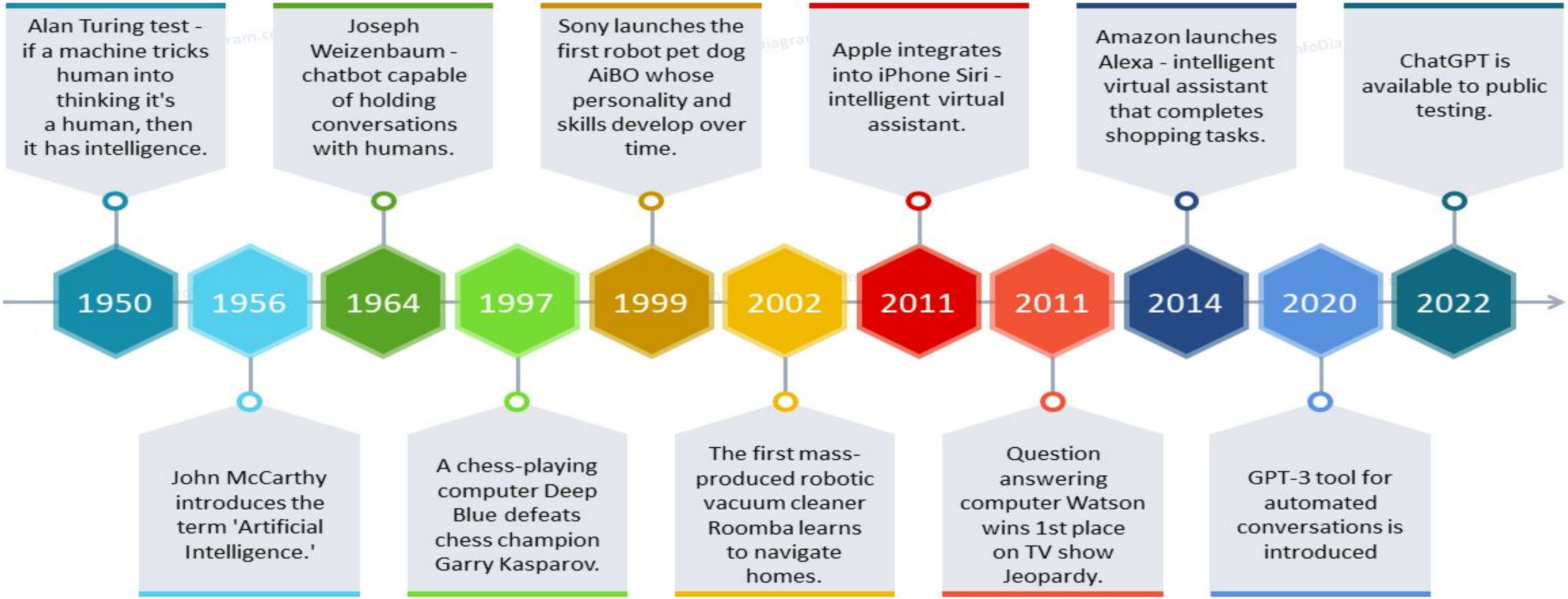
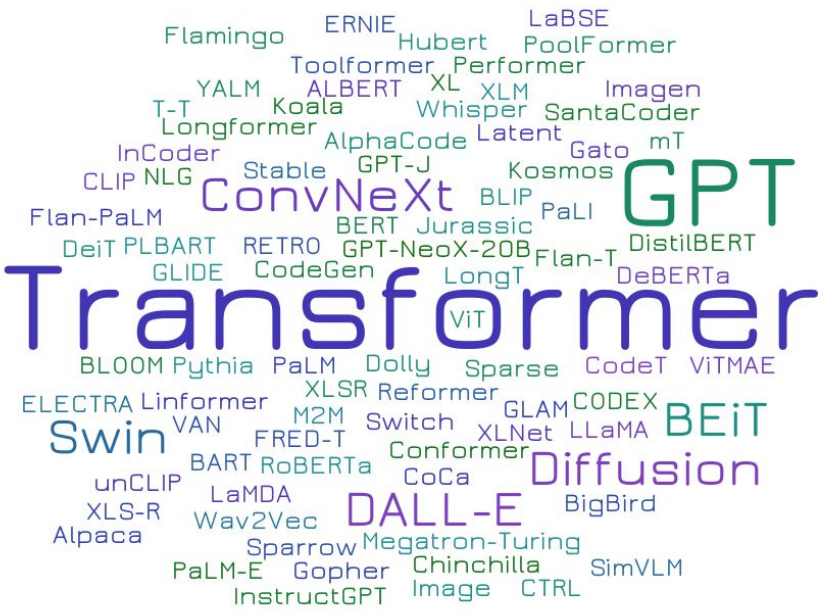
AI’s History Timeline



AI’s History Timeline [1]

Attention is All you need!

- Imports an attention mechanism to draw global dependencies between input and output sequences.[3]



Popular Transformer Models [2][3]

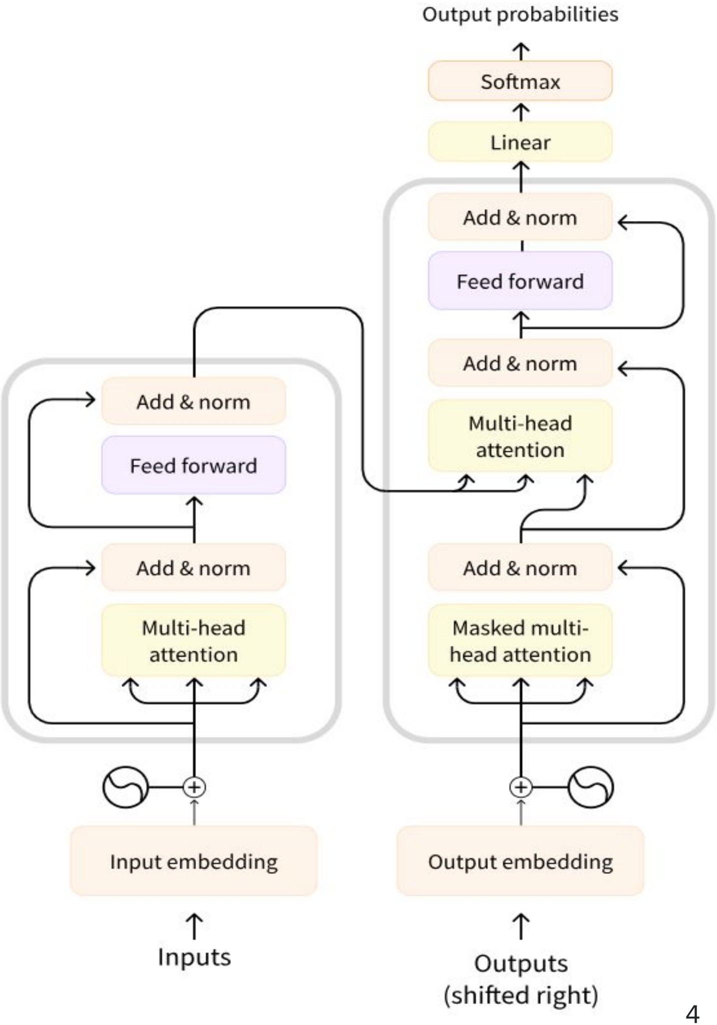
Structure and Architecture

A Transformer model is composed of two blocks:

- Encoder (left)
- Decoder (right)

Each of parts can be used independently, depending on the task:

- Encoder-only models
- Decoder-only models
- Encoder-decoder models or sequence-to-sequence models. [4]

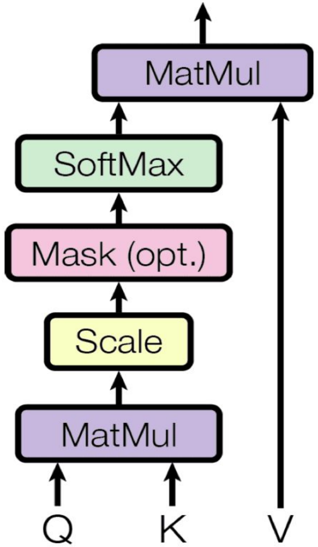


Transformer Architecture [4]

Attention Mechanism

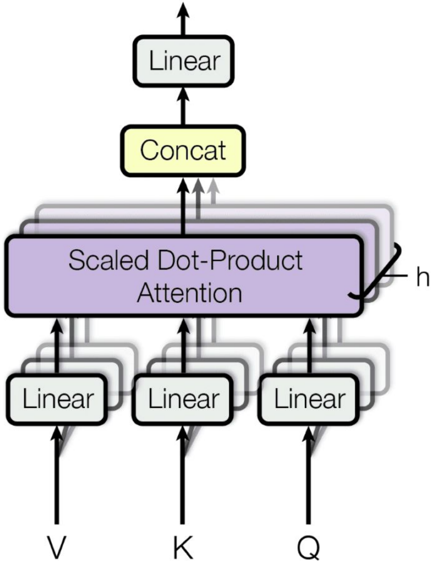
''The attention function can be considered as a mapping between a query and a set of key-value pairs to an output.''

- Scaled Dot-Product Attention [5]



$$attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d_K}}\right)V$$

- Multi-Head Attention [5]

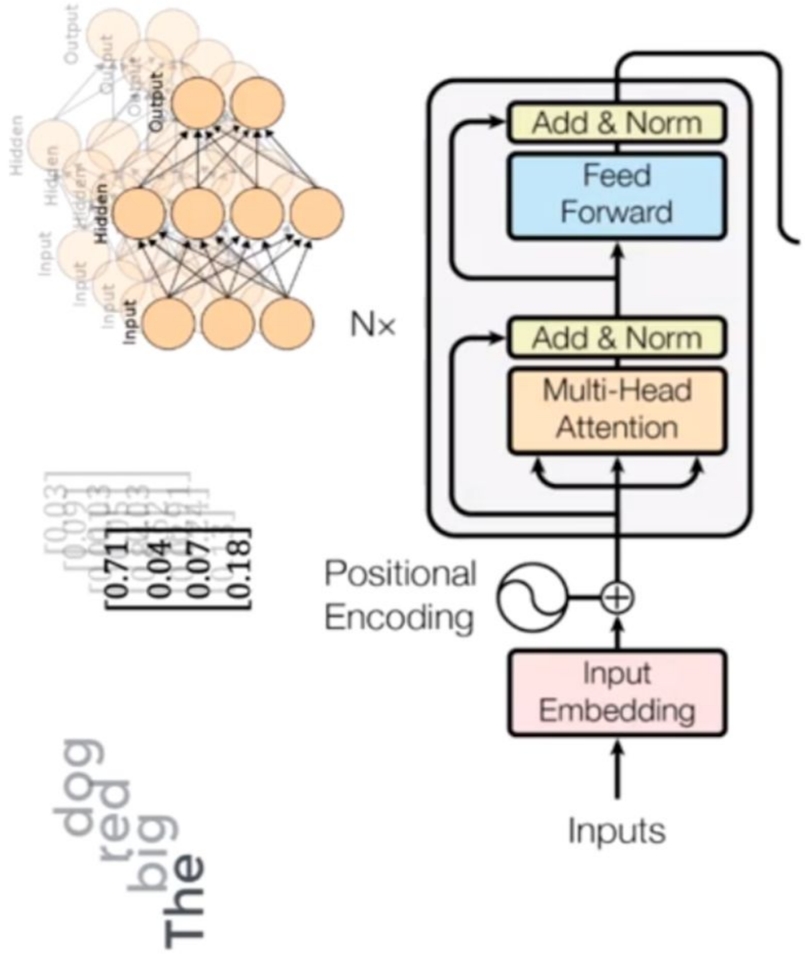


$$multihead(Q,K,V) = concat(head_1,\ldots,head_h)\,W^O$$

$$head_i = attention\left(QW_i^Q, KW_i^K, VW_i^V\right)$$

Encoder Block

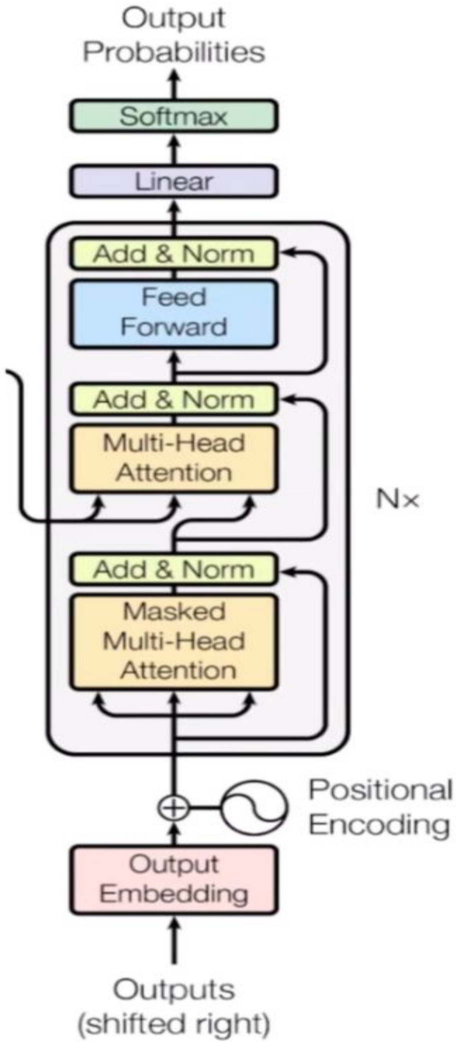
- Words as input to create numerical vectors (Embeddings).
- Positional Encoding for words with multiple meanings (depending of their position).
- Attention layer to create attention vectors (about the relations between the words).
- Feed-forward Neural Network (convert into an acceptable form for the next layer). [6]



Encoder Block [6]

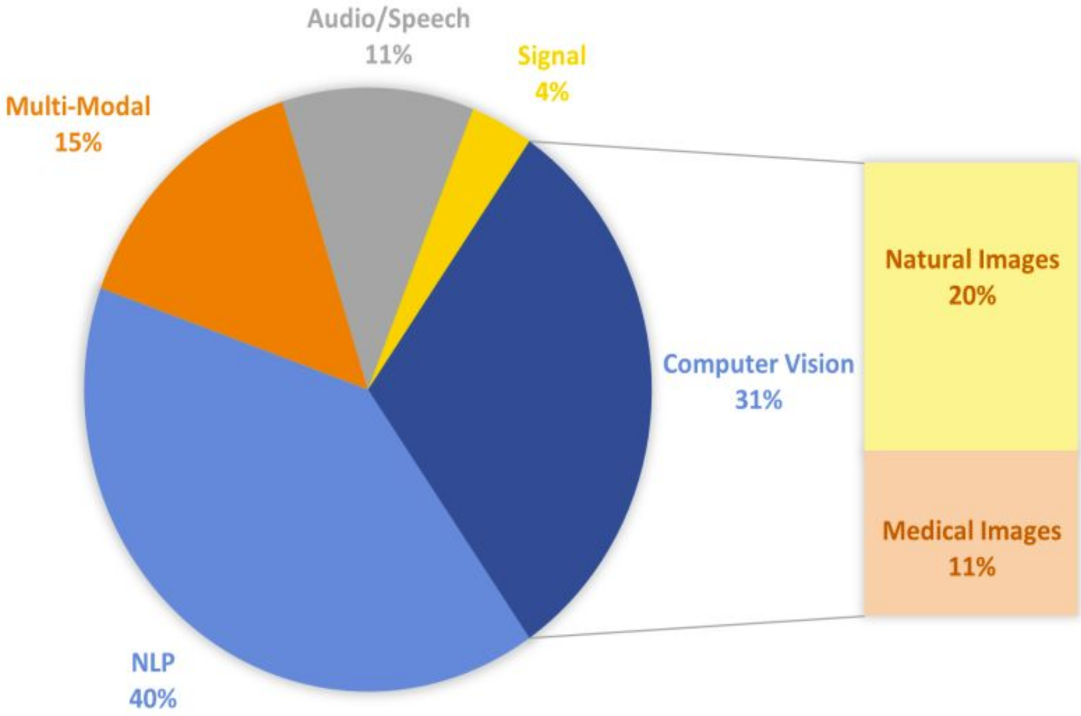
Decoder Block

- Give outputs as decoder's input in order to learn.
- Create vectors from words in Embedding and Positional Encoding Part similar to the Encoder.
- Create attention vectors for every word to represent relations of every word in the sentence.
- Attention vector that combines vectors from both encoder and decoder blocks.
- Use a feed-forward layer to form it for a Linear layer where it expands the dimensions of the output.
- Softmax layer that transforms the input into a probability distribution. [6]



Decoder Block [6]

Application-Based Classification of Transformers

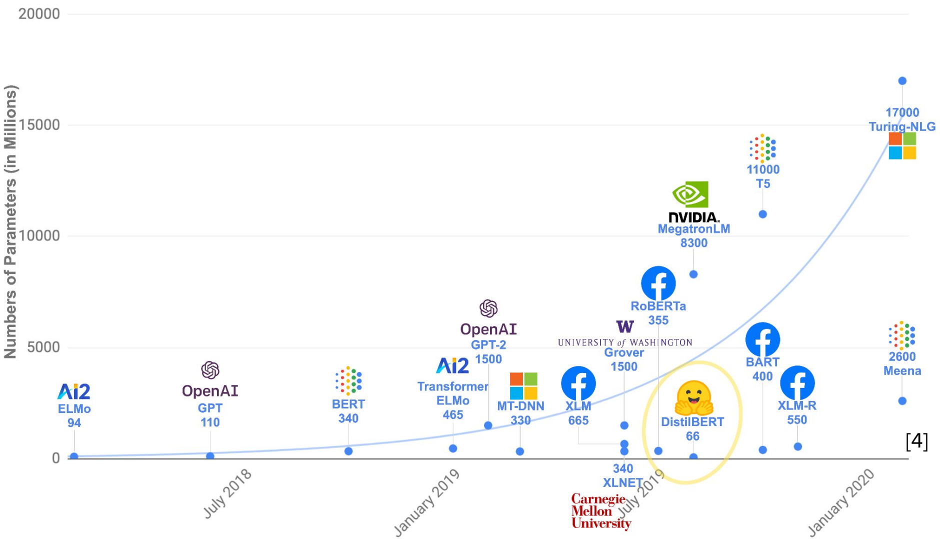


Applications of Transformers [7]

- Natural Language Processing (NLP)
  - Language Translation
  - Questioning Answering
  - Text Summarization & Generation
  - Natural Language Reasoning
- Computer Vision
  - Natural & Medical Image Processing
  - Image Generation & Segmentation
  - Image Classification
  - Object Detection
- Multi-Modal
- Audio/Speech
- Signal [7]

Popular Transformer Models

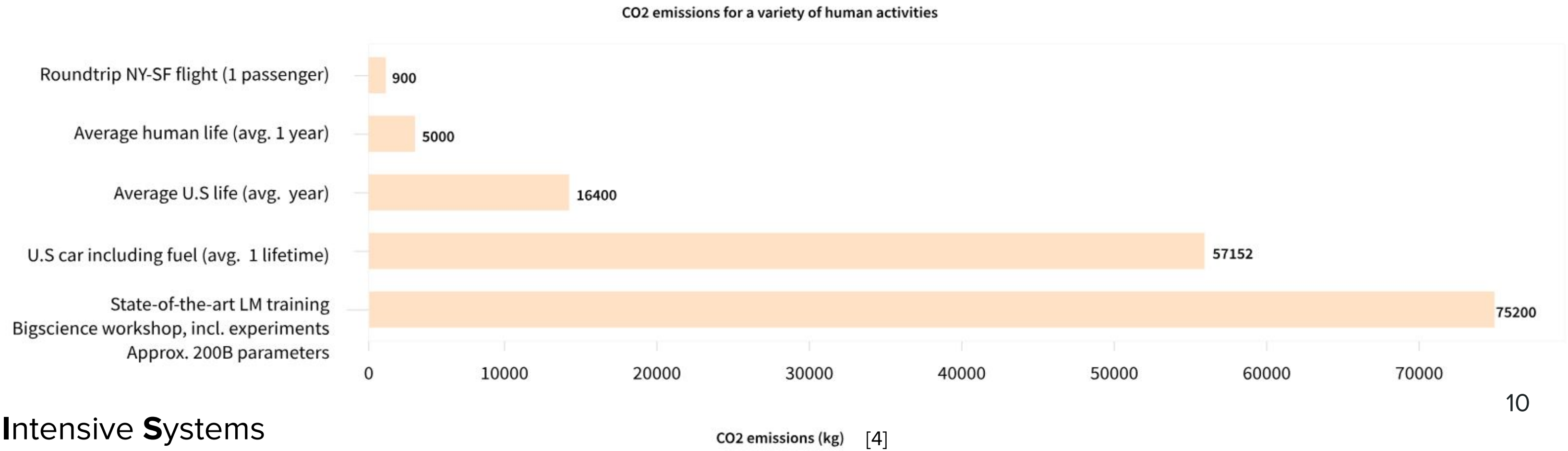
Transformer	**BERT** [8],[9],[10]	**GPT-3** [8],[10],[11]	**T-5** [8],[10],[12]
Main Uses	Questioning Answering, Text Classification, Text Generation, Sentiment Analysis	Natural Language Processing (NLP), Natural Language Generalization(NLG)	Language Translation, Question Answering
Popular Applications	Google Search (since 2020)	Chat-GPT, Dall-E	
Parameters	110 M(based) 340 M(large)	175 B	60 M to 11B
Training Time	1-130 min (fine-tuning on a GPU) 4 days on 4 Cloud TPUs (base) 4 days on 16 Cloud TPUs (large)	355 years on a single GPU (theoretically)	few days on Cloud TPUs



[4]

Challenges and Limitations

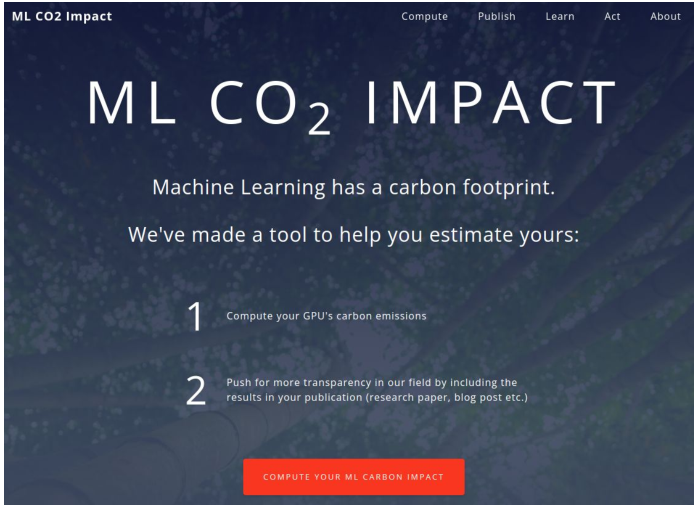
- Computational resources and memory to run and train.
- Large cost of deployment and scaling(especially on LLM's)
- Overfitting, generalization and robustness issues (noisy or incomplete data).
- Lack interpretability and explainability.
- Carbon footprint of transformer models. [13]



[4]

Possible solutions to consider

- Using pretrained models when they are available
- Fine-tuning vs Training from scratch
- Starting with small experiments and debugging
- Doing a review to choose hyperparameter ranges
- Random search vs Grid Search [4], [14]



Tool for estimate carbon footprint of your ML model. [14]

Fine-tune a pre-trained Transformer

- Load the model and the tokenizer
- Prepare Datasets (Train, Validate, Test)
- Compute metrics
- Combine everything in a trainer
- Start Training [10], [15]

```
[ ] from transformers import AutoTokenizer, AutoModelForSequenceClassification, DataCollatorWithPadding
    from torch.utils.data import DataLoader

    BASE_MODEL = "camembert-base"
    LEARNING_RATE = 2e-5
    MAX_LENGTH = 256
    BATCH_SIZE = 16
    EPOCHS = 20

    tokenizer = AutoTokenizer.from_pretrained(BASE_MODEL)
    model = AutoModelForSequenceClassification.from_pretrained(BASE_MODEL, id2label=id2label, label2id=label2id)
```

```
[ ] import numpy as np
    from datasets import load_metric

    metric = load_metric("accuracy")

    def compute_metrics(eval_pred):
        logits, labels = eval_pred
        predictions = np.argmax(logits, axis=-1)
        return metric.compute(predictions=predictions, references=labels)
```

```
[ ] from transformers import Trainer

    trainer = Trainer(
        model=model,
        args=training_args,
        train_dataset=ds["train"],
        eval_dataset=ds["validation"],
        compute_metrics=compute_metrics
    )

    trainer.train()
```

References

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