Foundation models definition

> Models trained on broad data (generally using self-supervision at scale) that can be adapted to a wide range of downstream tasks[^1]

Training

Using:

1. Self-supervises learning
2. Scale

Unifying tasks

- Question answering
- Sentiment classification
- Translation
- Coreference resolution
- Parsing

Potential Harms

- Generate offensive content
- Generate untruthful content
- Enable disinformation/malicious

Use of foundation models

- Linear probing

  >  Simple and efficient, model must be very good

- (Full)Fine-tuning

  >  Best method when we have lots of data, lots of memory

- Prefix-Tuning/Prompt-Tuning (consume less memory than Fine-tuning)

  >  Good for mid-sized datasets, memory-efficient

- Zero-shot Prompting

  >  Open ended task (no dataset collection), need to engineer prompts, accuracy can be low

- In-context Learning

>  Open ended task (minimal dataset collection), accuracy can be lower than tuning methods

- Chain-of-Thought

Fine-tuning methods

Why? fine-tuning can decreasing cost of use

1. Finetune LLM Behave in certain way
2. Knowledge base Embedding Gain domain knowledge

Transformers

1. Training model 1 GPT-LLM-Trainer, through Google Colab

- Prepare data: Dataset Generation: Using GPT-4, gpt-llm-trainer will generate a variety of prompts and responses based on the provied use-case
- System Message Generation: gpt-llm-trainer will generate an effective system prompt for your model
- Fine-tuning: After your dataset has been generated, the system will automatically split it into training and validation sets, fine-tune a model for you, and get it ready for inference

> tut

Terms	Definition
temperature	Entropy (?) high = creative, Low = precise
number_of_examples	min ~100, the more the better for higher-quality model

2. Training model 2 autotrain, through Google Colab

- use-4bit (int4)

> tut

```
autotrain llm --train --project_name 'llama2-openassistant'
--model TinyPixel/Llama-2-7B-bf16-shared #using sharded model helps when
you're low on VRAM. It will not load the model all at once
--data_path timdettmers/openassistant-guanaco #huggingface git repo id or
local path all work with this. each model requires certain dataset format
--text_column text # name of the column
--use_peft #fine-tuning method. In this case, it's PEFT: Parameter-
Efficient Fine-tuning methods (by huggingface)
--use_int4 #precision. In this case, it's 4bit precision
--learning_rate 2e-4 #the speed of conversion during training process.
Lower value takes longer, but converge better
--train_batch_size 2 # raise this value for smaller dataset. for instance,
4. This depends on number of GPUs and amount of VRam
--num_train_epochs 3 # higher value for better quality
--trainer sft # trainer method. In this case, it's supervised fine-
```

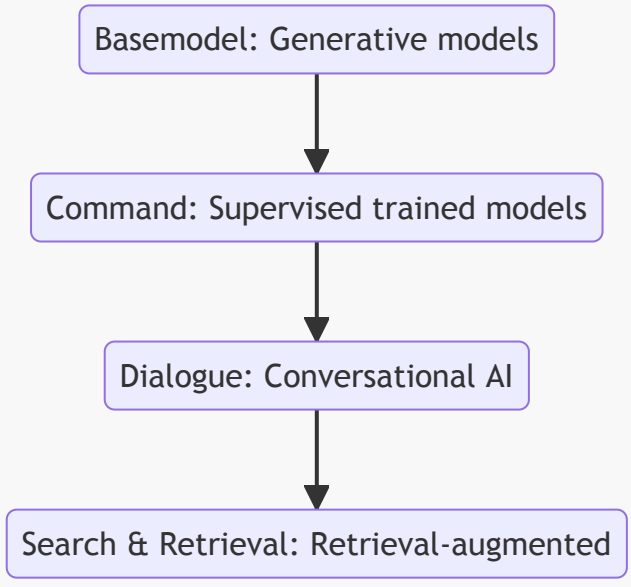
```
tunning. Works with input-output data format
--model_max_length 2048 # related to context-window (2k, 4k tokens...).
llama2 models have 4096tokens context-windows. value of 2048 here will
speed up training process
--pus_to_hub #push to huggingface hub
--repo_id Promptengineering/llama2-openassistant #if push to hub enabled,
repo id needs to be filled
--block_size 2048 > training.log &
```

- after tokenizing process done, config.json will be created. The model is then be loaded using Transformer library
- source of explaination explain

Terms	Definition
auto-train	huggingface/autotrain-advanced library

3. Training model 3 tut

Large Language Model Technology stack



Foundation models

1. BERT
2. RoBERTa
3. GPT-2
4. T5
5. Turing NLG
6. GPT-3

Organization	Models
OpenAI	GPT-3, Codex, DALL-E, CLIP
Meta	OPT
AI21labs	Jurassic
HuggingFace + BigSciece	BLOOM
Nvidia + Microsoft	MT-NLG
Stability.ai	Stable diffusion
BAAI	Wu Dao 2.0
EleutherAI	GPT-NeoX
DeepMind	Gopher, Chinchilla
Huawei	PanGu-Alpha
Naver	HyperCL, OVA
Google	PaLM, MUM

[^1]: "Introducing the Center for Research on Foundation Models (CRFM)" Stanford HAI. Retrieved 11 June 2022.