

Demystifying Generative Al

FOCUSING ON NLP MAY 16, 2023





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Traditional Approach

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Types of Fine-tuning

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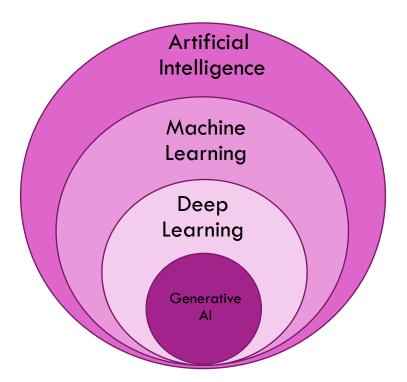
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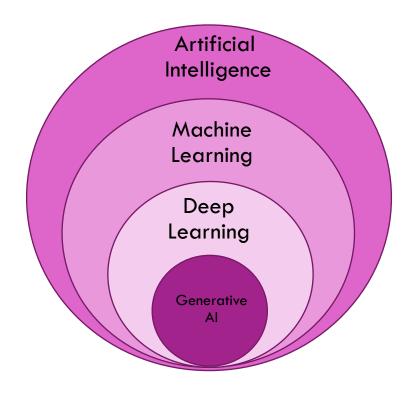
What is Generative AI?



- •Al: Build intelligent agents that can act like humans autonomously.
- •ML: A machine learns the patterns in the data by training a model.
 - •Supervised learning Use labeled data, train models, predict on unseen data.
 - •Classification/Regression
 - •Unsupervised learning Use unlabeled data to identify groups or clusters.
 - •Semi supervised learning uses little labeled data and more unlabeled data to train models.
 - •Reinforcement Learning An agent performs actions based on the environment and learns through trial and error (either rewarded or punished).



What is Generative AI?



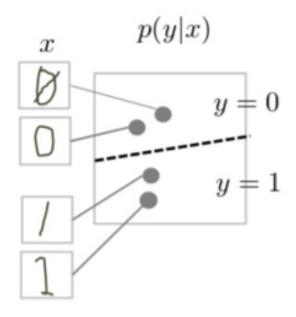
- •DL: A neural network with interconnected nodes and layers is trained to learn complex patterns in the data.
 - Uses supervised, Unsupervised and Semi supervised methods of learning.
- •Generative Al: It is a type of Al that can create new content, such as text, images, audio, and video.
 - Learns from existing data and then uses that knowledge to generate new and unique outputs.



Types of Models

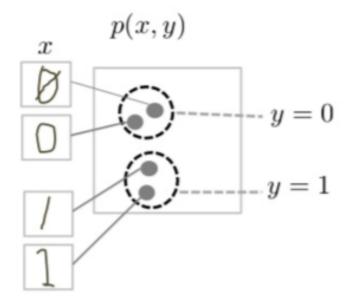
Discriminative Models:

- Discriminates between different classes.
- Approximates the decision boundary or the distribution function, given the data points it predicts the labels.



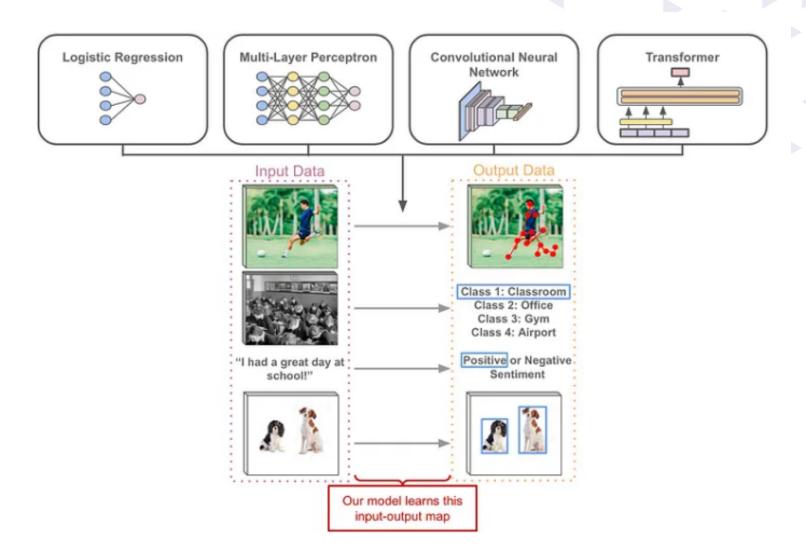
Generative Models:

- Generates new data points.
- Assumes the data distribution and produces convincing data points the are close to its real counterparts in the space.





Traditional Approach





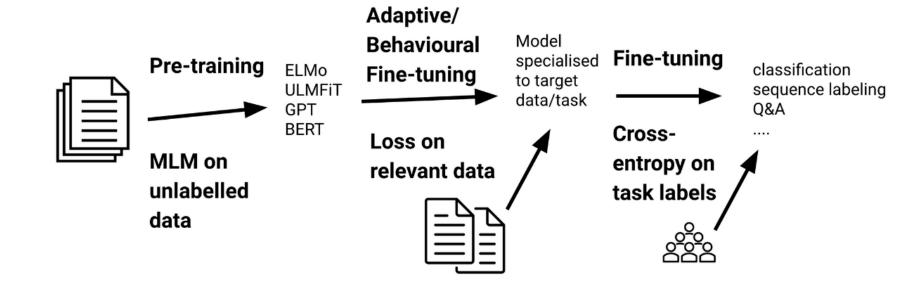
Transfer Learning

Step 1: Pre-training

- Use large amounts of generic data and train on a specific objective function.
- Unlabeled data is used to train on the language modelling objective like MLM.

Step 2: Fine-tuning

- Fine-tuning is done using task-specific objective function.
- Labelled data is used to fine-tune model on the downstream tasks.





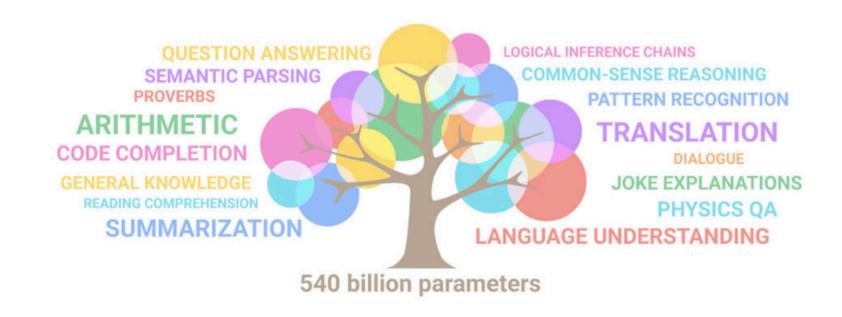
Types of Fine Tuning

Category	Methods	Motivation
Adaptive Fine-tuning	Domain/task/ language adaptive fine-tuning	Specialise to target domain
Behavioural Fine-tuning	Intermediate-task training, self-supervised, frame as MLM	Specialise to target task
Parameter-efficient Fine-tuning	Adapters, sparse parameter permutations, pruning	Reduce space of fine-tuned models
Text-to-text Fine-tuning	Frame as text-to-text, prompt engineering, controllable NLG	Effectively use large autoregressive pre-trained LMs
Mitigating Fine-tuning Instabilities	Stop runs early, use a small lr, regularisation, avoid random init	Reduce variance of fine-tuning runs



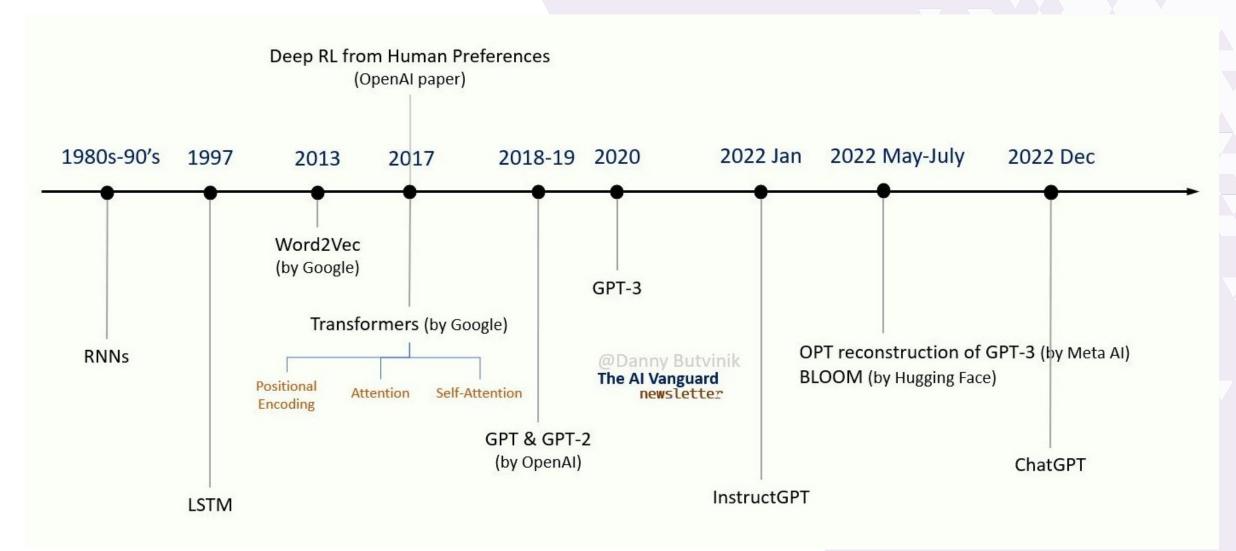
Foundation Models

A foundation model is a large Al model pre-trained on a vast quantity of unlabelled data that
was "designed to be adapted" (or fine-tuned) to a wide range of downstream tasks, such as
sentiment analysis, image captioning, and object recognition.



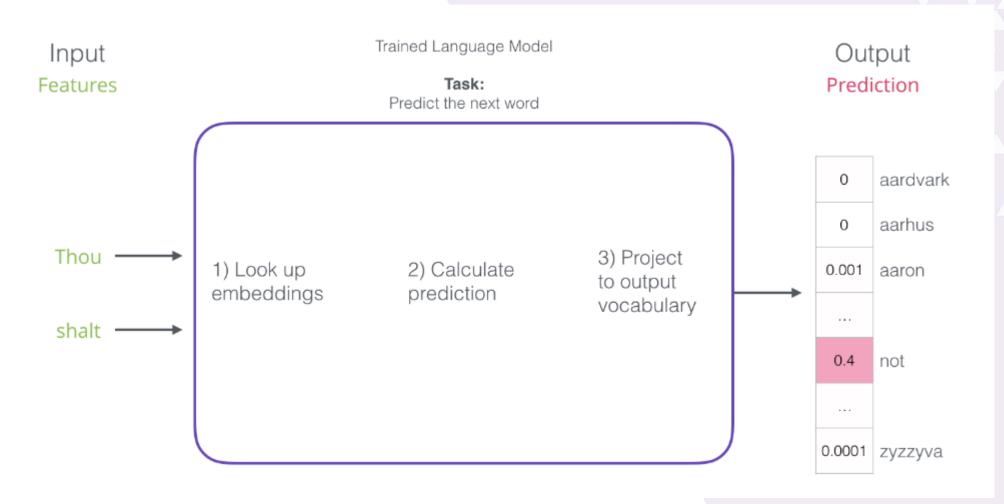


NLP Timeline



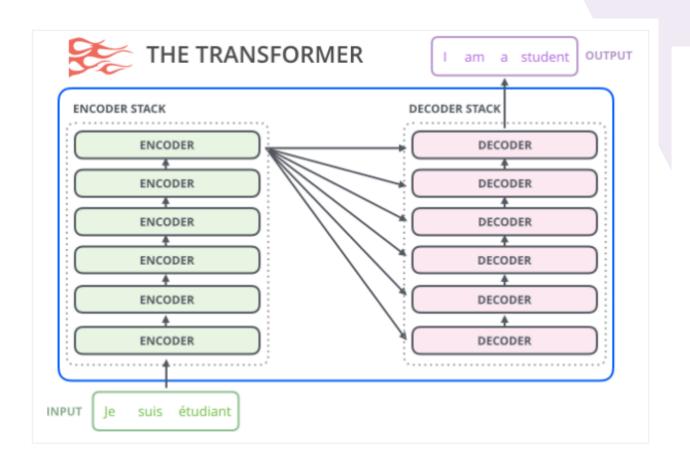


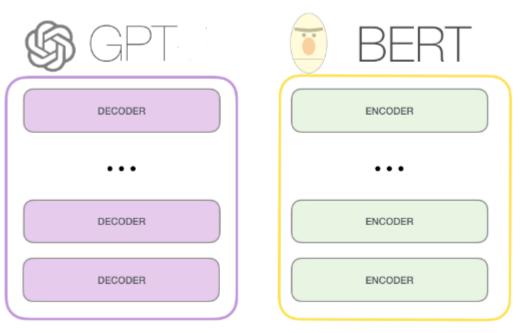
Concepts: Language Modelling





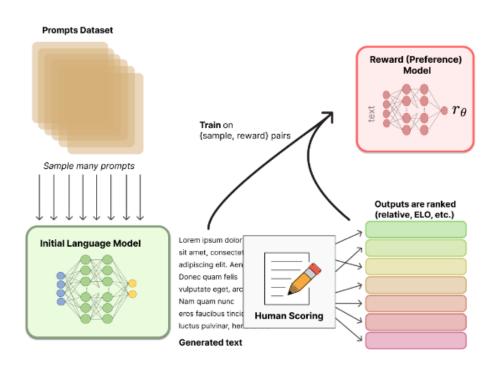
Concepts: Encoder / Decoder



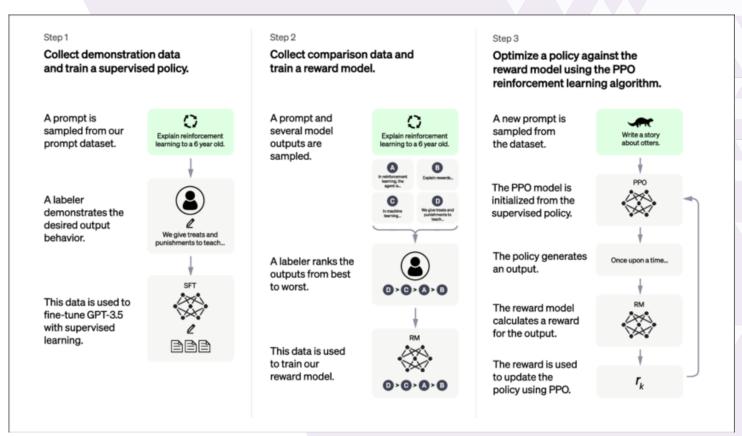




Concepts: RLHF



https://huggingface.co/blog/rlhf



The ChatGPT training process. The figure is from OpenAl (2022a).



Concepts: Prompt

A prompt is a short piece of text that is given to the large language model as input, and it can be used to control the output of the model in many ways.

A prompt contains any of the following elements:

Instruction - a specific task or instruction you want the model to perform

Context - external information or additional context that can steer the model to better responses

Input Data - the input or question that we are interested to find a response for

Output Indicator - the type or format of the output.



Concepts: Prompt Engineering

Zero-shot Prompting

Few-shot Prompting

Prompt:

Classify the text into neutral, negative or positive.

Text: I think the vacation is okay.

Sentiment:

Output:

Neutral

Prompt:

A "whatpu" is a small, furry animal native to Tanzania. An example of a sentence that uses the word whatpu is:

We were traveling in Africa and we saw these very cute whatpus.

To do a "farduddle" means to jump up and down really fast. An example of a sentence that uses the word farduddle is:

Output:

When we won the game, we all started to farduddle in celebration.



Concepts: Prompt Engineering

Chain-of-Thought Prompting

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27.

Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

(a) Few-shot

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A:

(Output) The answer is 8. X

(c) Zero-shot

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A: The answer (arabic numerals) is

(Output) 8 X

(b) Few-shot-CoT

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A:

(Output) The juggler can juggle 16 balls. Half of the balls are golf balls. So there are 16 / 2 = 8 golf balls. Half of the golf balls are blue. So there are 8 / 2 = 4 blue golf balls. The answer is 4.

(d) Zero-shot-CoT (Ours)

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?

A: Let's think step by step.

(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls.



Limitations of Generative Al

- Hallucinations are words or phrases that are generated by the model that are often nonsensical or grammatically and factually incorrect.
 - The model is not trained on enough data. Misleading information.
 - The model is trained on noisy or dirty data. Garbage in => Garbage out!
 - The model is not given enough context. Misleading information.
 - The model is not given enough constraints. Anyone can use it.
- Ethical concerns what if the models are biased and are used for unintended purpose.
- Cost and Time Costly and takes longer to build your own LLMs.
- Explainability is difficult.



Thank You:)

Questions?





At AnitaB.org, we envision a future where the people who imagine and build technology mirror the people and societies for whom they build it. We connect, inspire, and guide women and non-binary people in computing, and organizations that view technology innovation as a strategic imperative.

