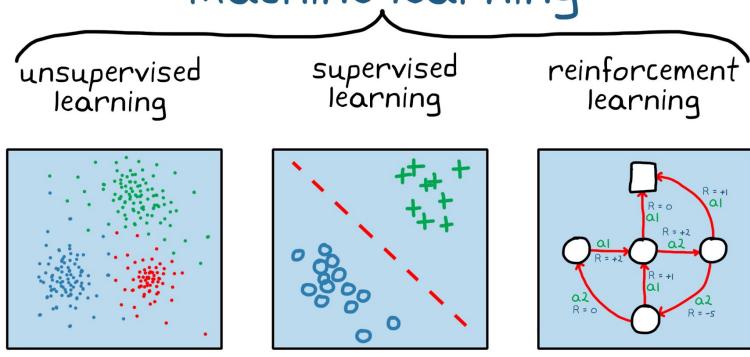
LLMs: Large Language Models

Supervised vs Unsupervised learning

machine learning



Supervised vs Unsupervised learning

Supervised learning:

- Known labels
- Examples:

credit, fraud, image labels



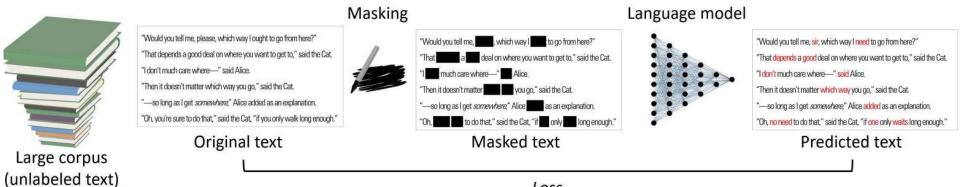
- Labels are expensive

Unsupervised learning:

- No labels
- Examples:
 - customer segmentation
 - cell type classification
- Messy

Self-supervised learning

Pretraining



Loss

Self-supervised learning: learning a representation of language one word at a time

$p(w_1,w_2,w_3,\ldots,w_N) = \\ p(w_1)\; p(w_2|w_1)\; p(w_3|w_1,w_2)\times\ldots\times p(w_N|w_1,w_2,\ldots w_{N-1})$ Sentence: "the cat sat on the mat"

$$P(\text{the cat sat on the mat}) = P(\text{the}) * P(\text{cat}|\text{the}) * P(\text{sat}|\text{the cat})$$
 $*P(\text{on}|\text{the cat sat}) * P(\text{the}|\text{the cat sat on})$
 $*P(\text{mat}|\text{the cat sat on the})$
Implicit order

Source: COS 484

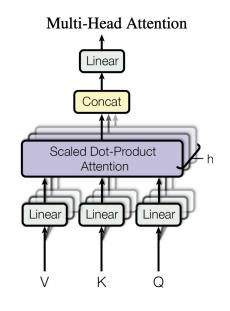
GPT-3 still acts in this way but the model is implemented as a very large neural network of 175-billion parameters!

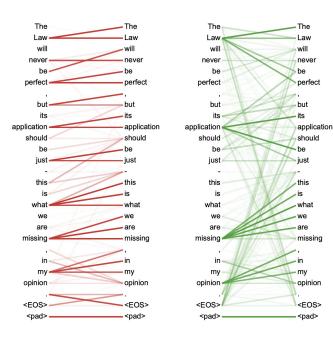
Architecture: Transformers & Attention

Transformer block: stacked attention blocks

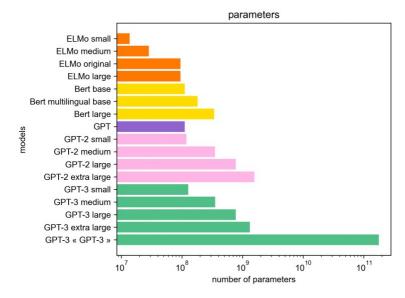
Probabilities Softmax Linear Add & Norm Feed Forward Add & Norm Add & Norm Forward N× Add & Norm N× Add & Norm Multi-Head Attention Attention Positional Positional Encoding Encoding Input Output Embeddina Embeddina Inputs (shifted right)

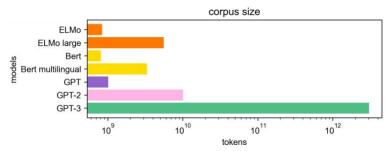
Attention: how important is each word for the others

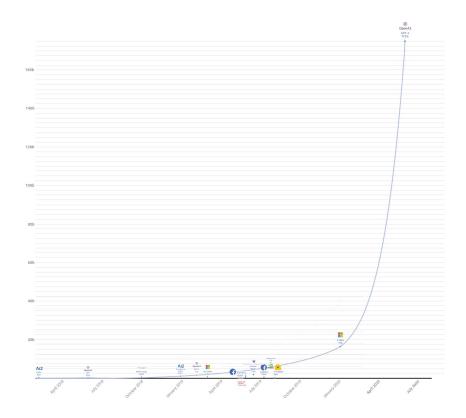




Scale matters



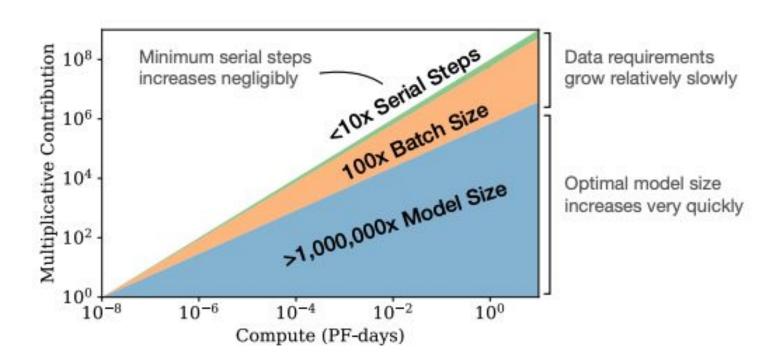




https://hellofuture.orange.com/en/the-gpt-3-language-model-revolution-or-evolution/

https://bmk.sh/2020/05/29/GPT-3-A-Brief-Summary/

Scale matters: model size matters most



Problem: size matters for inference

- model parameters and intermediate states are needed in memory at inference time
- Inference cost from the attention mechanism scales quadratically with input sequence length
- Example: ESM2 3B parameter model will fit on a single GPU (largest available on AWS), the ESM2 15B parameter model will not
- Slows down inference time by an order of magnitude, from ~20 peptides per sec to ~2 per second

Memorization: large models leave room for memorization of training data

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memorized the code,	while the larger models try to	generate some GUIDs.	
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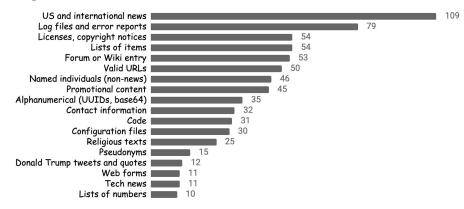
Memorization: large models leave room for memorization of training data

Memorization increases with:

- (1) the capacity of a model,
- (2) the number of times an example has been duplicated,
- (3) the number of tokens of context used to prompt the model.

Carlini et al 2023

Categorization of memorized data



https://bair.berkeley.edu/blog/2020/12/20/lmmem/

Memorization: large models leave room for memorization of training data

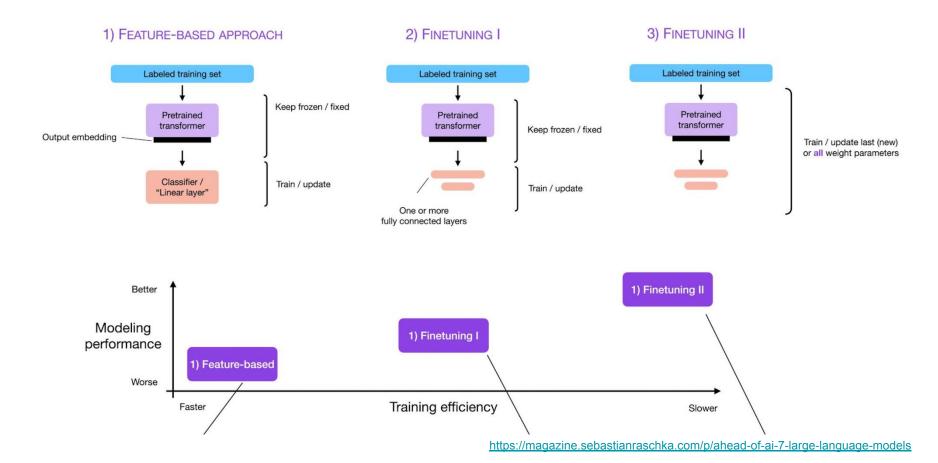
Below, we prompt GPT-3 with the beginning of chapter 3 of *Harry Potter and the Philosopher's Stone*. **The model correctly reproduces about one full page of the book** (about 240 words) before making its first mistake.

The escape of the Brazilian boa constrictor earned Harry his longest-ever punishment. By the time he was allowed out of his cupboard again, the summer holidays had started and Dudley had already broken his new video camera, crashed his remote-control aeroplane, and, first time out on his racing bike, knocked down old Mrs Figg as she crossed Privet Drive on her crutches.

Harry was glad school was over, but there was no escaping Dudley's gang, who visited the house every single day. Piers, Dennis, Malcolm, and Gordon were all big and stupid, but as Dudley was the biggest and stupidest of the lot, he was the leader. The rest of them were all quite happy to join in Dudley's favourite sport: Harry Hunting.

This was why Harry spent as much time as possible out of the house, wandering around and thinking about the end of the holidays, where he could see a tiny ray of hope. When September came he would be going off to secondary school and, for the first time in his life, he wouldn't be with Dudley. Dudley had been accepted at Uncle Vernon's old private school, Smeltings. Piers Polkiss was going there too. Harry, on the other hand, was going to Stonewall High, the local public school. Dudley thought this was very funny.

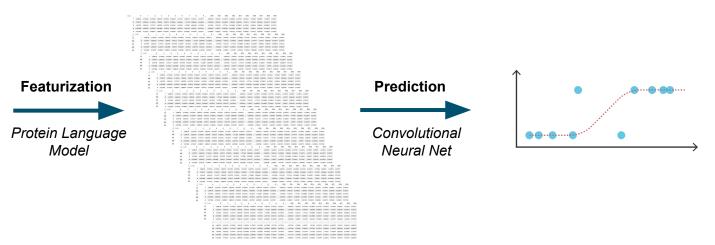
Fine-tuning LLM's: how to apply LLM's in practice

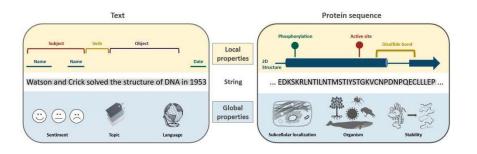


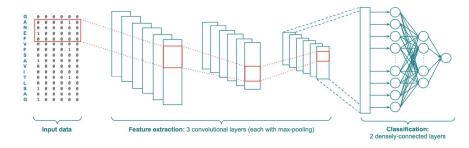
Fine tuning example: building protein fitness model with limited data

DEDEFELQPQEPNSFFDGIGADATHMDGDQIVVEIQEAVF ADVSENVIIPEQULDSDVTEEVSLPHCTVPDDVLASDITSN VSEEVLVADCAPEAVIDASGISVDQQDNDKASCEDYLMIS GEDDLGGTVDIVESEPENDHGVELLDQNSSIRVPREKMVY QIDEDEMKTFVPIAWAAYGNNSDGIENRNGTASALLHIDK GKKFKSRGFLKRHMKNHPEHLAKKKYHCTDCDYTTNKKIS KEMPFKCDICLLTFSDTKEVQQHTLVHQESKTHQCLHCDH GKKMHQCRHCDFKIADPFVLSRHILSVHTKDLPFRCKRCR NIVDSDITVHNFVPDDPDSVVIQDVVEDVVIEEDVQCSDIED DAGKIEHDGSTGVTIDAESEMDPCKVDSTCPEVIKVYIFKID

VNDSQQEDEDLNVAEIADEVYMEVIVGEEDAAVAAAAAN NHLESHKLTSKAEKAIECDECGKHFSHAGALFTHKMYHKE HPSELRKHMRIHTGEKPYQCQYCEYRSADSSNLKTHIKT IAKESKRDVPSETEPGIHQEVKSETSREMGEFFKDLEAPM PIKSKYSVGNDELEHREPKRGKLSLSDKFRKEYYALGSLR NFEDMKAISRHTQELLEIEEPLFKRSISLPYRDIIGLYLEPM DSKLPAEIYQEPQPETEEEDFKEGEPDSAKNVQLKPGGTS THKESDLEPPEBAKPNVTEDVFLESAMETDPDPVPTETM EESIGTHYEFLQPLQKLLNVSEECSYSDPSESQTELSEFV ISQLGFPQYKECFITNFISGRKLIHVNCSNLPQMGITNFELI





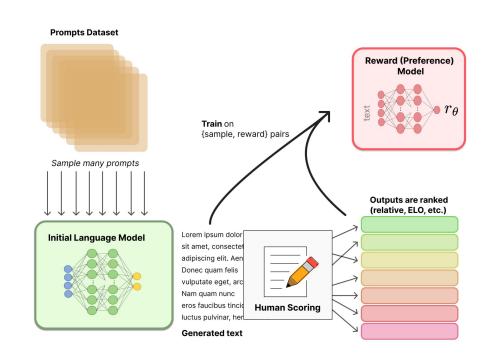


Fine-tuning LLM's for Human use (e.g ChatGPT)

RLHF: Reinforcement learning from human feedback

Iteratively update the tuned model based on interaction with the model

Expensive!



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