Compression for AGI

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Takeaways

- Generative models are *Lossless* compressors
  - "ChatGPT Is a Blurry JPEG of the Web"? No!
- LLMs are *State-of-the-Art* text compressors
  - comparing to deflate(gzip), Zstd, etc.
- Re-think about the training objective of foundation models

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Revisit the Training Process of LLMs

Transformer: A Black Box

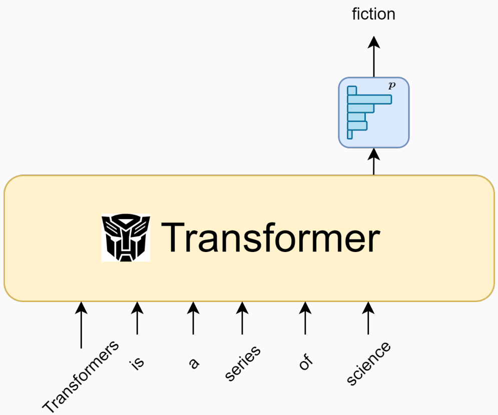

Figure 1: Transformer: A Black Box – step 1

Transformer: A Black Box

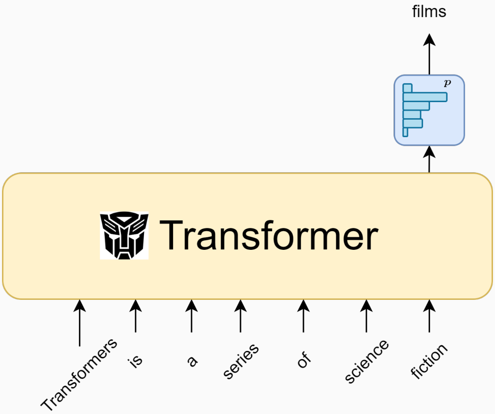

Figure 2: Transformer: A Black Box – step 2

Transformer: A Black Box

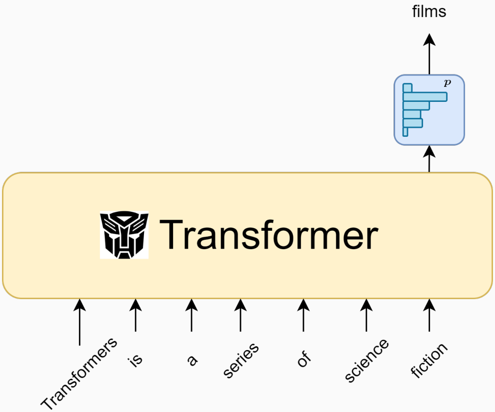

Figure 3: Transformer: A Black Box – step 2

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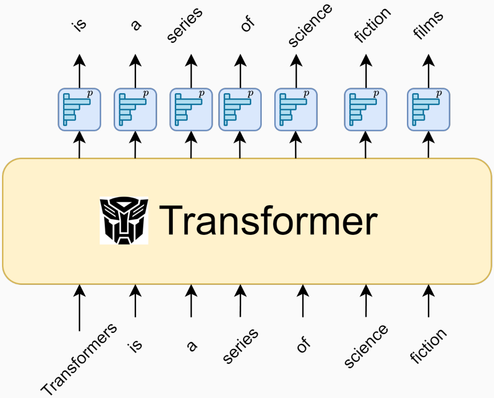

Figure 4: Transformer: A Black Box – training

Transformer: A Black Box

- We have a sequence: $X = [x_1, x_2, \ldots, x_n]$
- We put this sequence into LLM and get a sequence of probabilities:
  - $p_i = P(x_i | x_{<i})$
- We want p_i approaches 1, so we minimize the following loss during pre-training:
  - $L = \sum_{i=1}^{n} - \log P(x_i | x_{<i})$

Questions?

What are compressors

Compressor

- Compressors aims to find a better (smaller) way to express the same thing
-

Why are LLMs *Lossless* compressors

LLMs as compressors

- Naturally, you would assume an LLM is a *lossy* compressor
  - That turns trainig corpus to model parameters
  - For LLaMa, the training dataset is 5.6TB
  - And the 65 billion parameters takes about 130GB of storage
    - So 43x compression rate?
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  - And the 65 billion parameters takes about 130GB of storage
    - So 43x compression rate?
    - Lossy!
- Actually, LLaMa can compress the entire 5.6TB of training corpus to 397.3 GB losslessly
  - 14x compression
  - Best text compressor: 8.7x compression

LLMs as compressors

- To compress the *entire training corpus* $\mathcal{C}$ *losslessly*, we only need *the CODE to train the models* and $\sum_{i \in \mathcal{C}} -\log P(x_i | x_{<i})$ bits of imformation.
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- But, HOW?

LLMs as compressors – How

- Imagine Alice is trying to send some text to Bob through a telephone wire
- Sending the raw text is very expensive
  - too large
- So Alice need to find a way to compress the data losslessly
- Alice needs to encode the data to “something”
- Bob needs to decode the “something” back to data
- So we need an “encoding” algorithm and a “decoding” algorithm

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- ... and update the model to minimize the loss, and repeat these steps for every data

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- So he will have the *exact same distribution* p for the first token
  - He then can decode the token with p and z_1 with arithmetic decoding, get x_1
- And he will run the training loop to update the model with x_1
- Note that the model parameters isn't transmitted through the phone wire

LLMs as compressors – Conclusion

- By sharing the same code, Bob can initialize the same model as Alice's
- With arithmetic encoding and decoding, bob can decode the token with the same probability distribution produced by the model and the encode transmitted from Alice
- And by training at the same time, the model is always synced between Alice and Bob

LLMs as compressors – Conclusion

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- With arithmetic encoding, we can use fewer bits to encode something have a higher probability in a distribution.
  - If the distribution is uniform, $-\log_2 p_{x_i} = -\log_2 \frac{1}{|\mathcal{V}|}$, which is same as naive storage
  - And as the model is continually training, it can predict the next token with higher and higher probability.
- Bob can re-construct the entire training corpus $\mathcal{C}$ with $\sum_{i \in \mathcal{C}} -\log P(x_i | x_{<i})$ bits of information
  - Which is exactly the same with the sum of training loss on all tokens!

Questions?

Rethink the goal for foundation models

Classic Chinese Room thought experiment

- If a computer program translates English and Chinese using an oracle comprising all possible combinations of Chinese and English combinations.
    - Does it have understanding of translation?

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- What if it do it by a set of rules?
  - Tt have *some* understanding of translation.
- If we can make the rule set smaller, it will generalise better.

Lossy V.S. Lossless

- "Lossy" compression means the model "remembers" everything in the training dataset
  - BAD generalization
- "Lossless" compression means the model can better predict unseen data samples
  - Better compression means GOOD generalization
    - Because *EVERY* example is unseen

Target for Foundation Models

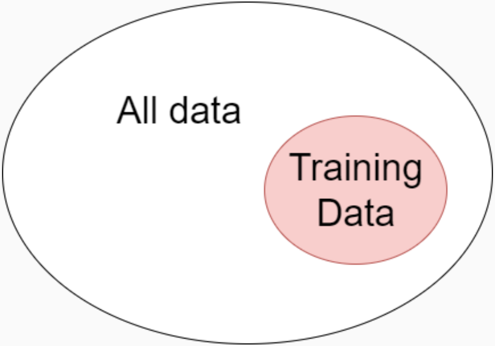

Figure 5: All data V.S. Training Data

- For foundation models, what we want is good generalization ability
  - i.e. ability to generate or write *UNSEEN* samples.

A recipe for perception

- Collet all useful perceptual information
- Learn to compress it as best as possible with a powerful fundation model
    - Better architecture
    - Scale
    - Tool use
    - ...

Conclusion

- How LLM works
- How LLM works as a compressor
  - And how should we use LLM
  - LLM isn't a search engine
- How compressor generates intelligence

Questions?