How LLMs Work?

High level look at internal workings for the general audience

Mohahmmad "Kiyarash" Fazeli

May 15, 2025

• ChatGPT generates human-like text ...

- ChatGPT generates human-like text ...
- ... through predicting next word in a text, one word at a time

- ChatGPT generates human-like text ...
- ... through predicting next word in a text, one word at a time
- No explicit understanding pure mathematical prediction

- ChatGPT generates human-like text ...
- ... through predicting next word in a text, one word at a time
- No explicit understanding pure mathematical prediction
- Emergent capabilities

The Core Mechanism

• Primary objective: Produce "reasonable continuation" of text

The Core Mechanism

- Primary objective: Produce "reasonable continuation" of text
- Analogous to human conversation prediction

The Core Mechanism

- Primary objective: Produce "reasonable continuation" of text
- Analogous to human conversation prediction
- Built from >1 trillion word patterns

learn 4.5%
predict 3.5%
make 3.2%
understand 3.1%
do 2.9%

The best thing about AI is its ability to

Statistical likelihood derived from:

- Statistical likelihood derived from:
 - Billions of web pages

- Statistical likelihood derived from:
 - Billions of web pages
 - Digitized books

- Statistical likelihood derived from:
 - Billions of web pages
 - Digitized books
 - Online conversations

- Statistical likelihood derived from:
 - Billions of web pages
 - Digitized books
 - Online conversations
- Not rule-based pure probability

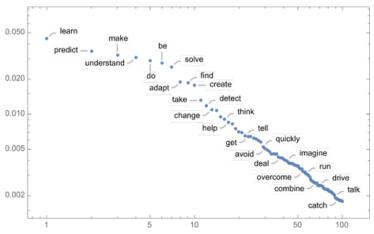
Example: Predicting the Next Word

• Input: "The best thing about AI is its ability to..."

The best thing about AI is its ability to

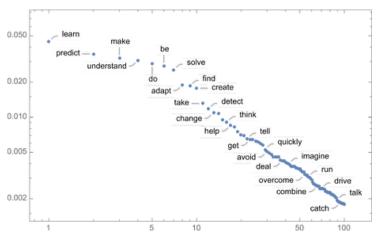
learn	4.5%
predict	3.5%
make	3.2%
understand	3.1%
do	2.9%

Probability Distribution in Action



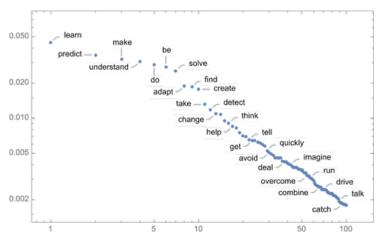
• High-probability choices: "learn", "adapt"

Probability Distribution in Action



- High-probability choices: "learn", "adapt"
- Creative possibilities: "dream", "collaborate"

Probability Distribution in Action



- High-probability choices: "learn", "adapt"
- Creative possibilities: "dream", "collaborate"
- Long-tail distribution pattern

• LLMs(Deepseek, Chatgpt and etcs)

- LLMs(Deepseek, Chatgpt and etcs)
- LLMs creates text through iterative prediction:

- LLMs(Deepseek, Chatgpt and etcs)
- LLMs creates text through iterative prediction:
- Fundamental operation: "What's the next word given previous text?"

- LLMs(Deepseek, Chatgpt and etcs)
- LLMs creates text through iterative prediction:
- Fundamental operation: "What's the next word given previous text?"
- Trained on >1 trillion words from web pages/books

Pure max-probability leads to flat text:
 The best thing about AI is its ability to see through, and make sense of, the world around us, rather than panicking and ignoring. This is known as AI "doing its job" or AI "run-of-the-mill." Indeed,

- Pure max-probability leads to flat text:
 The best thing about AI is its ability to see through, and make sense of, the world around us, rather than panicking and ignoring. This is known as AI "doing its job" or AI "run-of-the-mill." Indeed,
- Solution: Introduce temperature

- Pure max-probability leads to flat text:
 The best thing about AI is its ability to see through, and make sense of, the world around us, rather than panicking and ignoring. This is known as AI "doing its job" or AI "run-of-the-mill." Indeed,
- Solution: Introduce temperature
- 0.8 optimal. Why 0.8? Empirical finding, not theory

- Pure max-probability leads to flat text:
 The best thing about AI is its ability to see through, and make sense of, the world around us, rather than panicking and ignoring. This is known as AI "doing its job" or AI "run-of-the-mill." Indeed,
- Solution: Introduce temperature
- 0.8 optimal. Why 0.8? Empirical finding, not theory
- Multiple runs create different outputs

- Pure max-probability leads to flat text:
 The best thing about AI is its ability to see through, and make sense of, the world around us, rather than panicking and ignoring. This is known as AI "doing its job" or AI "run-of-the-mill." Indeed,
- Solution: Introduce temperature
- 0.8 optimal. Why 0.8? Empirical finding, not theory
- Multiple runs create different outputs
- Beam Search

• Human-like text emerges from simple next-word prediction

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?
- No difference, since no built in facts

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?
- No difference, since no built in facts
- What to do?

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?
- No difference, since no built in facts
- What to do?
- Verifying Manually

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?
- No difference, since no built in facts
- What to do?
- Verifying Manually
- Grounding

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?
- No difference, since no built in facts
- What to do?
- Verifying Manually
- Grounding
- RAG

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?
- No difference, since no built in facts
- What to do?
- Verifying Manually
- Grounding
- RAG
- Chain of thought

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?
- No difference, since no built in facts
- What to do?
- Verifying Manually
- Grounding
- RAG
- Chain of thought
- MCP

- Human-like text emerges from simple next-word prediction
- No explicit "understanding" built in
- Hallucination?
- No difference, since no built in facts
- What to do?
- Verifying Manually
- Grounding
- RAG
- Chain of thought
- MCP
- Code Eval

Discovery vs Invention

- Discovery vs Invention
- Information disclosure(prompts,personal, commercial)

- Discovery vs Invention
- Information disclosure(prompts,personal, commercial)
- Bad data(MS twitter bot, reddit and google suggests)

- Discovery vs Invention
- Information disclosure(prompts,personal, commercial)
- Bad data(MS twitter bot, reddit and google suggests)
- Undermining programmers?

- Discovery vs Invention
- Information disclosure(prompts,personal, commercial)
- Bad data(MS twitter bot, reddit and google suggests)
- Undermining programmers?
- Geoffrey Hinton, Acemoglu

- Discovery vs Invention
- Information disclosure(prompts, personal, commercial)
- Bad data(MS twitter bot, reddit and google suggests)
- Undermining programmers?
- Geoffrey Hinton, Acemoglu
- Retrieval vs. Generation

- Opensource?
- Open weights

- Opensource?
- Open weights
- Finetunning

- Opensource?
- Open weights
- Finetunning
- \bullet Training -> closed source, 5M\$+

- Opensource?
- Open weights
- Finetunning
- Training -> closed source, 5M\$+
- GPU back of napkin calculations

- Opensource?
- Open weights
- Finetunning
- Training -> closed source, 5M\$+
- GPU back of napkin calculations
- GPU Nvidia market segmentation

- Opensource?
- Open weights
- Finetunning
- Training -> closed source, 5M\$+
- GPU back of napkin calculations
- GPU Nvidia market segmentation
- Usage -> still limited

- Opensource?
- Open weights
- Finetunning
- Training -> closed source, 5M\$+
- GPU back of napkin calculations
- GPU Nvidia market segmentation
- Usage -> still limited
- Quantization -> slow feasible

- Opensource?
- Open weights
- Finetunning
- Training -> closed source, 5M\$+
- GPU back of napkin calculations
- GPU Nvidia market segmentation
- Usage -> still limited
- Quantization -> slow feasible
- Smaller models

- Opensource?
- Open weights
- Finetunning
- Training -> closed source, 5M\$+
- GPU back of napkin calculations
- GPU Nvidia market segmentation
- Usage -> still limited
- Quantization -> slow feasible
- Smaller models
- Distillation

- Opensource?
- Open weights
- Finetunning
- Training -> closed source, 5M\$+
- GPU back of napkin calculations
- GPU Nvidia market segmentation
- Usage -> still limited
- Quantization -> slow feasible
- Smaller models
- Distillation
- Polling resources?

Perplexity?

- Perplexity?
- MMLU

- Perplexity?
- MMLU
- MMLU like in Farsi

- Perplexity?
- MMLU
- MMLU like in Farsi
- Livecoding Benchmark

- Perplexity?
- MMLU
- MMLU like in Farsi
- Livecoding Benchmark
- Chatbot Arena Explanation

Token Generation Process

- Text is chunked into tokens (words/subwords)
- Model estimates probability distribution over possible next tokens
- Selection involves randomness (temperature parameter)

Example of tokens: Deepseek

antidisestablishmentarianism noun

The doctrine or political position that opposes the withdrawal of state recognition of an established church; -- used especially concerning the Anglican Church in England. Opposed to disestablishmentarianism.

Example of tokens: Deepseek

Deepseek

ant idis establish ment arianism noun The doctrine or political position that opposes the withdrawal of state recognition of an established church; -- used especially concerning the Anglican Church in England. Opp osed to dis establish ment arianism.

Example of tokens: ChatGPT

GPT-4(o, o-mini, o1-preview, o1-mini)

ant idis establish ment arian ism noun The doctrine or political position that opposes the withdrawal of state recognition of an established church; -- used especially concerning the Anglic an Church in England. Opp osed to dis establish ment arian ism.

2nd Example of tokens

Kiyarash Fazeli

Apple

Sony

Joseph

Yousef

2nd Example of tokens



Deepseek

```
K iy ar ash F az eli Apple Sony Joseph Y ouse f
```

GPT

Probability in Action

At Each Step:

- Calculates probabilities for all possible next tokens
- Doesn't just pick highest probability
- Maintains creativity through probabilistic sampling

The Iterative Nature

- Each step feeds output back as input
- Context window grows with each iteration
- Surprisingly maintains coherence over long sequences

Why Does This Work?

- Emergent complexity from simple rules
- Massive neural network
- Captures linguistic patterns at multiple scales

Key Limitations

Important Caveats

- No true "understanding" of content
- Can't perform logical deductions
- Errors compound through iterations

Summary

- Statistical next-word prediction at scale
- Emergent complexity from simple iteration
- Combination of pattern recognition + controlled randomness

A Simple Language Model

Goldberg IPython Notebook

NNs = Differentiable Functions

Differentiable Functions

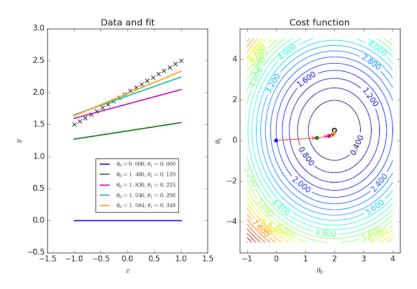
Training on Data + Cost

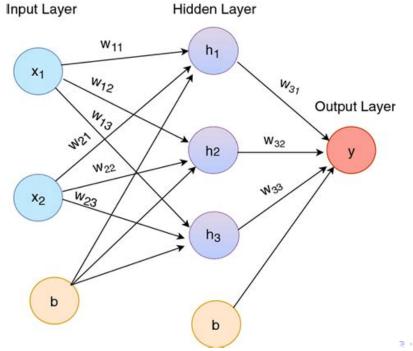
Input→Output Pairs Cost Minimisation

Random Init & Gradients

 $\mathsf{Random}\;\mathsf{Start}\;\to\;-\textit{Gradient}\;\mathsf{Steps}$

Example of Linear Regression





3Blue1Brown Visual Intuition Series

Emdedding

My Thesis Examples

Attention as Enriching Embedding

..

Result of Attention: Context Length

..

MCP

MCP