Text Generation - From Traditional LMs to LLMs

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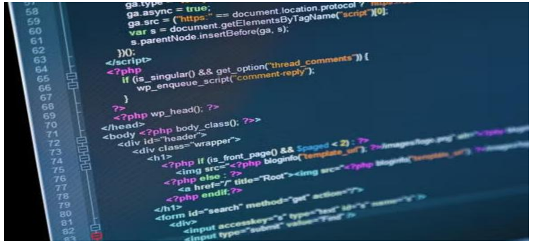
Text Generation and its Evolution

- Long Journey From Statistical Language Models (LMs) to Large Language Models (LLMs)
- Text Generation deals with the method of generating text by machines
    - Not natural text generation as humans
        - Synthetic Generation
    - Multiple Sources of Text

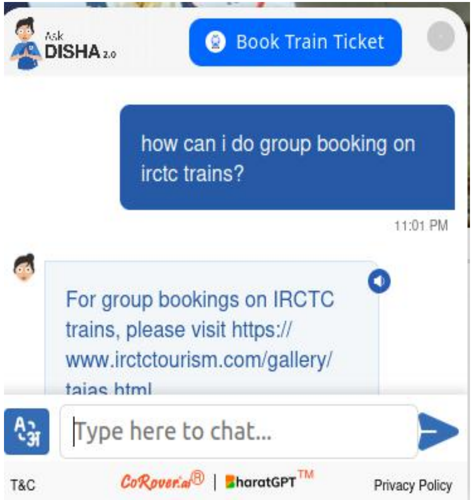


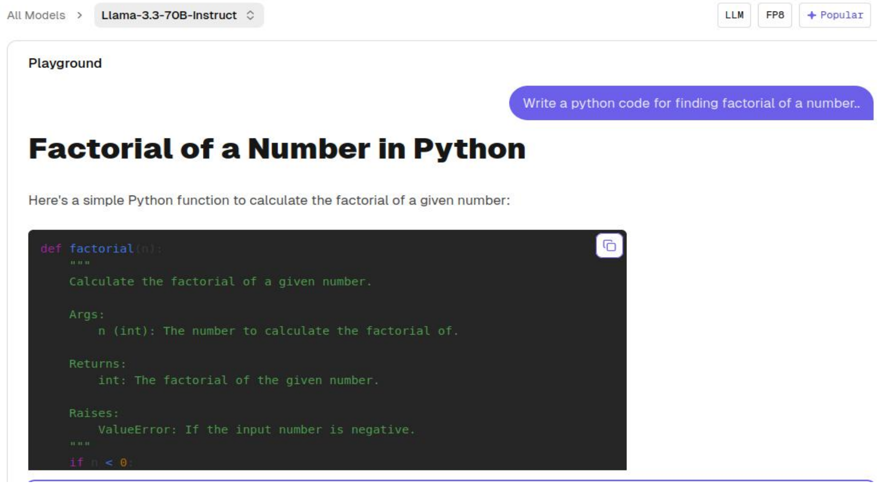
Key Milestones in the Evolution of Text Generation

- 1950s-1960s: Early Rule-Based Systems / Symbolic NLP (e.g., ELIZA)
    - Predefined rules, pattern matching, simple templates
    - Lacked understanding, couldn't generate truly novel or creative text
- 1980s-Early 2000s: Statistical Language Models (e.g., N-grams, HMMs)
    - Probabilistic models based on word frequencies and sequences from large corpora
    - Fluent and grammatically correct sentences than the rule based systems, but struggled with long-range dependencies and true semantic understanding
- Mid-2000s-Early 2010s: Neural Language Models (e.g., Feedforward Neural Networks, Word Embeddings like Word2Vec/GloVe)
    - Can "remember" past information in a sequence
    - Vanishing/exploding gradients, computational bottleneck due to sequential processing
- Late 2010s (Era of Transformers)
    - Demonstration of pre-training on huge datasets in an unsupervised manner
    - Capabilities of impressive zero-shot and few-shot learning capabilities
- Early 2020s - Present: Large Language Models (LLMs) / GPT-3, PaLM, Llama, Gemini, Claude, GPT-4/4o
    - Extreme scaling of parameters, training data, and computational power
    - Often combine pre-training with Reinforcement Learning from Human Feedback (RLHF)
    - Human-like performance in many language tasks as well as emergent abilities
        - coherent, contextually relevant, and diverse text across a vast range of tasks
            - creative writing, coding, summarization, conversation
    - Best model for text generation

What is Text Generation?

- The automatic creation of human-like text by a computer.
- Why is it important?
  - Several Applications
    - chatbots, content creation, summarization, translation, creative writing, coding assistance
  - Humans have always wanted machines to “think” and “write”.





Example

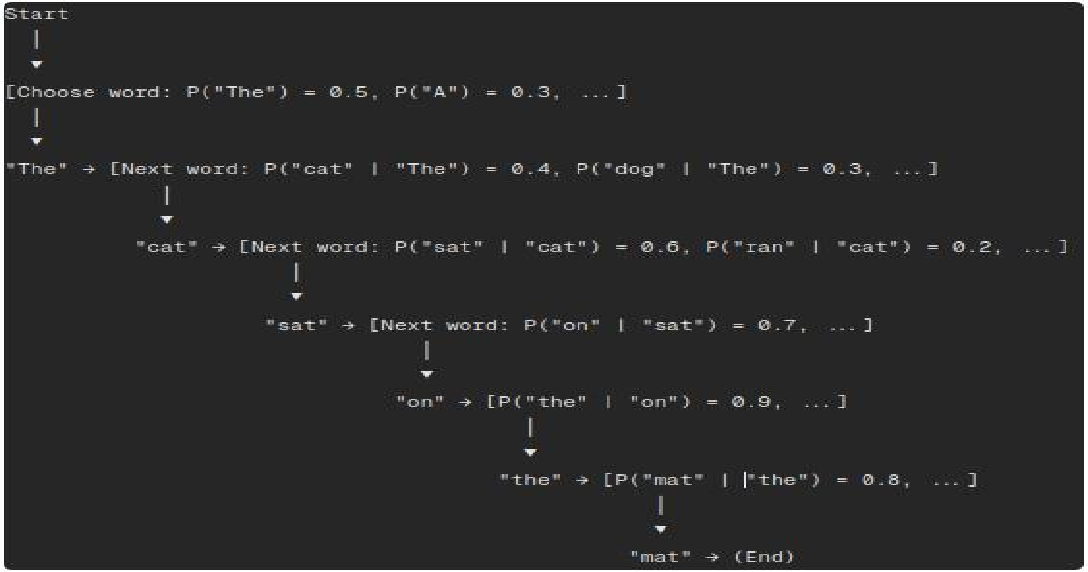
- There are 4 sentences, choose the best one.
  - he briefed to reporters on the chief contents of the statement
  - he briefed reporters on the chief contents of the statement
  - he briefed to reporters on the main contents of the statement
  - he briefed reporters on the main contents of the statement

Which is the best one and why?

- **he briefed reporters on the main contents of the statement**
  - This is the best sentence
    - *brief* is a transitive verb and requires an object
    - *main contents* is more **fluent** than *chief contents*
- “You shall know a word by the company it keeps”
  - Famous quote attributed to British linguist *J.R. Firth*
- This is the basis of language models

The Foundation: Language Models (LMs)

- What is a Language Model?
  - A model that assigns a probability to a sequence of words.
  - Using chain rule of Probability,
    - $P(w_1,w_2,...,w_n) = P(w_1) * P(w_2/w_1) * P(w_3/w_1,w_2) * ... * P(w_n/w_1,...,w_{n-1})$
  - Core idea for generation: Predict the next word given the previous words.



Early Approaches: N-gram Language Models

- The probability of the next word in a sequence of n words depends only on the previous “n-1” words
- Markov Assumption
  - First Order: the probability of the next word depends only on the previous word.
    - $P(W_n|W_{n-1})$
  - Second Order: the probability of the next word depends only on the previous word.
    - $P(W_n|W_{n-2},W_{n-1})$
- Using the Markov assumption, the probability of a sequence of n words can be further simplified
  - $P(w_1,w_2,...,w_n) = P(w_1)*P(w_2/w_1)*P(w_3/w_1,w_2)*...*P(w_n/w_1,...,w_{n-1})$ – *(No Markov Assumption)*
  - $P(w_1,w_2,...,w_n) = P(w_1)*P(w_2/w_1)*P(w_3/w_2)*...*P(w_n/w_{n-1})$ –*(With First Order Markov Assumption)*
  - $P(w_1,w_2,...,w_n) = P(w_1)*P(w_2/w_1)*P(w_3/w_1,w_2)*P(w_4/w_2,w_3)...*P(w_n/w_{n-2},w_{n-1})$ –*(With Second Order Markov Assumption)*

Types of Statistical LMs

- Unigram Model
  - Composed of unigrams or single tokens
  - $P(w_1,w_2,...,w_n) = P(w_1) * P(w_2) * P(w_3) * ... * P(w_n)$
  - All the words are independent of each other
    - Zeroth Order Markov Assumption
    - Very strong and weak assumption
- Bigram Model
  - Composed of bigrams or strings consisting of two tokens each
  - First Order Markov Assumption
  - $P(w_1,w_2,...,w_n) = P(w_1) * P(w_2/w_1) * P(w_3/w_2) * ... * P(w_n/w_{n-1})$
- Trigram Model
  - Composed of trigrams or strings consisting of three tokens each
  - Second Order Markov Assumption
  - $P(w_1,w_2,...,w_n) = P(w_1) * P(w_2/w_1) * P(w_3/w_1,w_2) * P(w_4/w_2,w_3) ... * P(w_n/w_{n-2},w_{n-1})$

How to Compute the Probabilities?

- Maximum Likelihood Estimation (MLE)
- Use relative frequency
  - $P(w_i|w_{i-1})=count(w_{i-1},w_i)/count(w_{i-1})$
  - This count is computed on a large corpus of data
    - For reliable estimation of probabilities
- Computationally Inexpensive and Easy
- Suffers from Sparsity Problem
  - Zero probabilities for unseen sequences
  - Smoothing Used to handle this
- Limited context window
  - Can't capture long-range dependencies
- Lack of generalization.

	i	want	to	eat
i	6	828	1	10
want	3	1	609	2
to	3	1	5	687
eat	1	1	3	1

Smoothed bigram counts from BeRP Corpus[1]

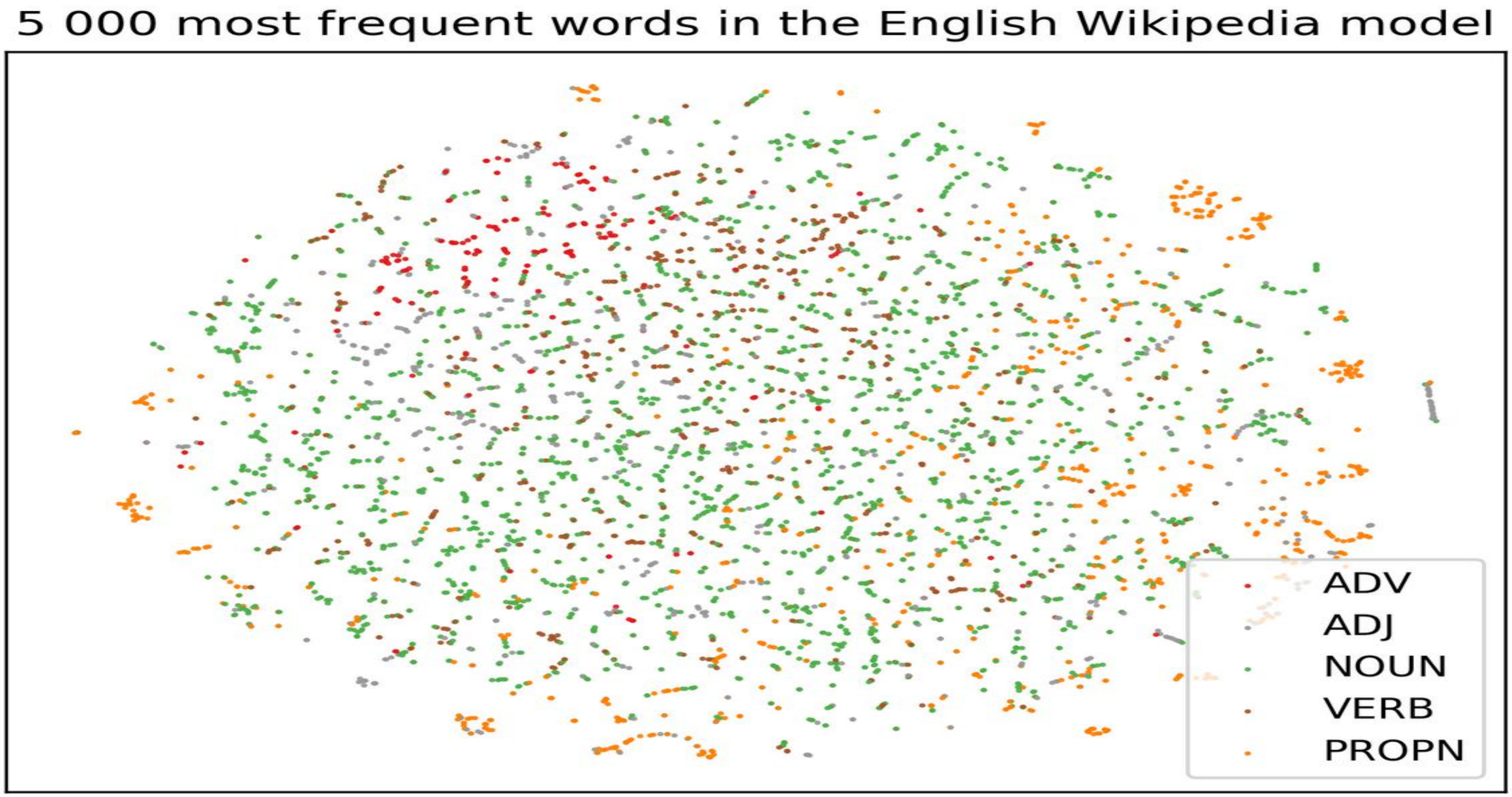
	i	want	to	eat
i	0.0015	0.21	0.00025	0.0025
want	0.0013	0.00042	0.26	0.00084
to	0.00078	0.00026	0.0013	0.18
eat	0.00046	0.00046	0.0014	0.00046

Smoothed bigram probabilities from BeRP Corpus[1]

Beyond N-grams: Introducing Neural Language Models

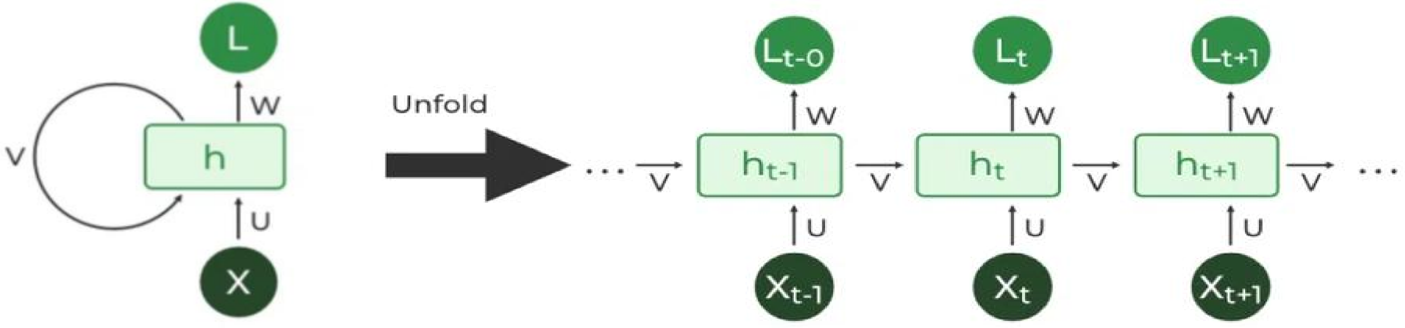
- Motivation for neural LMs
  - Overcome sparsity and capture longer dependencies
- Word Embeddings: A crucial step
  - Representing words as dense vectors in a continuous space
  - Capturing semantic relationships [2]
    - *India - Sachin + Australia = Pointing* [Word2vec model trained on GoogleNews]
    - *France: Paris:: India: New Delhi*
    - 3 most Similar words to *Computer*
      - *Microcomputer*
      - *Laptop*
      - *Mainframe*
  - Simple feed-forward Neural Networks were used for early word embedding

Word Vectors Visualization [2]



Recurrent Neural Networks (RNNs) for Text Generation

- How RNNs work?
  - Process sequences by maintaining a hidden state that carries information from previous steps

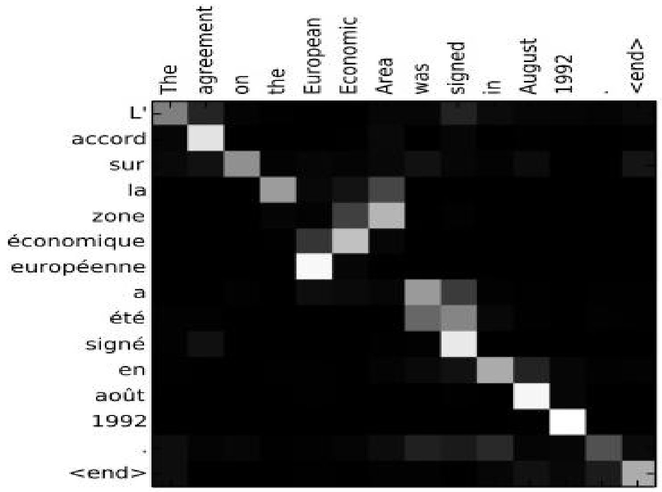


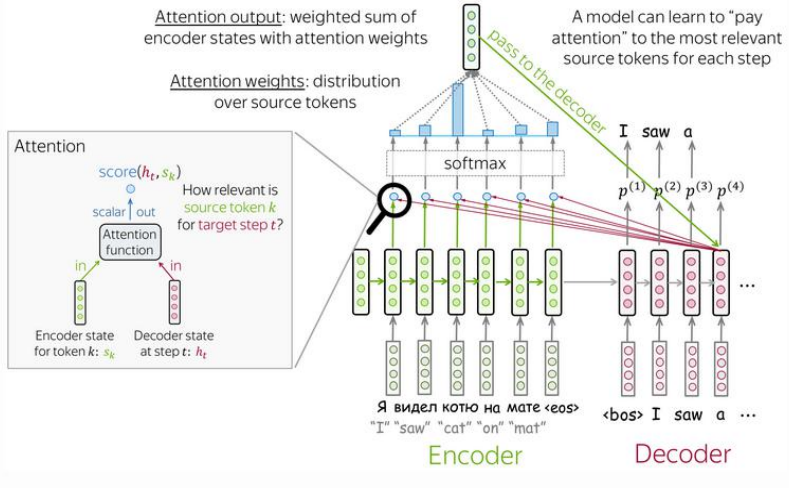
RNN Unfolding

- Vanishing/Exploding gradients
  - Difficulty learning very long-range dependencies
  - To alleviate this problems, LSTM/GRU are proposed using gating mechanism
- Slow training
- Lack of Parallelism

The Breakthrough: The Attention Mechanism

- Allows the model to "*focus*" on relevant parts of the input sequence when generating output
- Encoder-Decoder Architecture with Attention
- Resulted in improved performance in machine translation, summarization, and other sequence-to-sequence tasks





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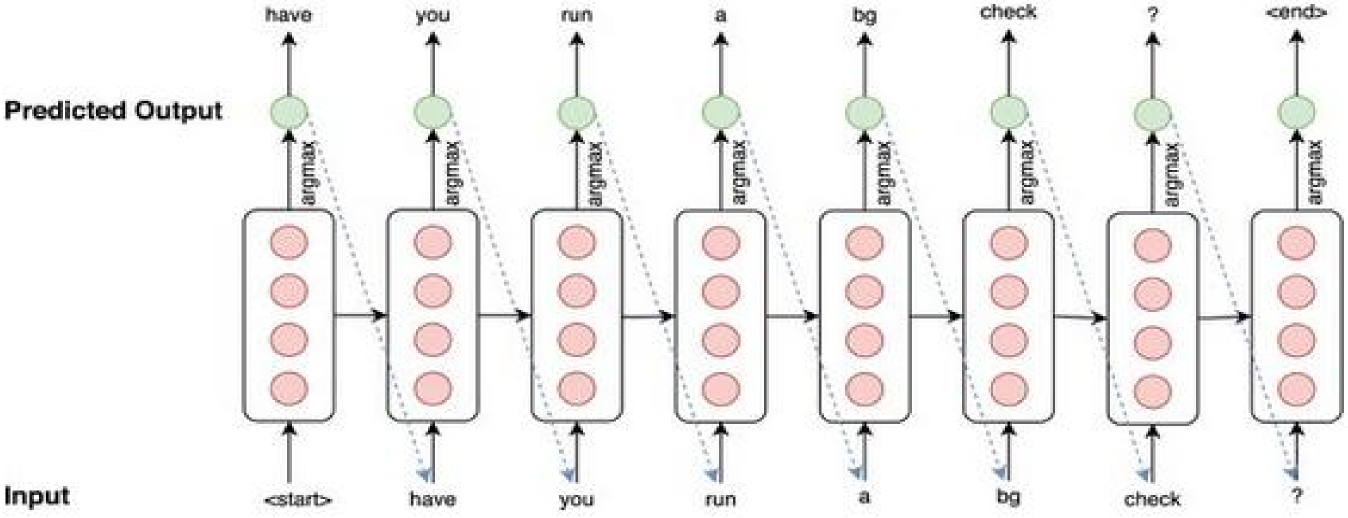
Just a Next Word Prediction Task

- Text Generation is a next word prediction task in a recursive manner
  - When do you stop generating?
    - After a fixed number of words
    - After the end sentence token is generated



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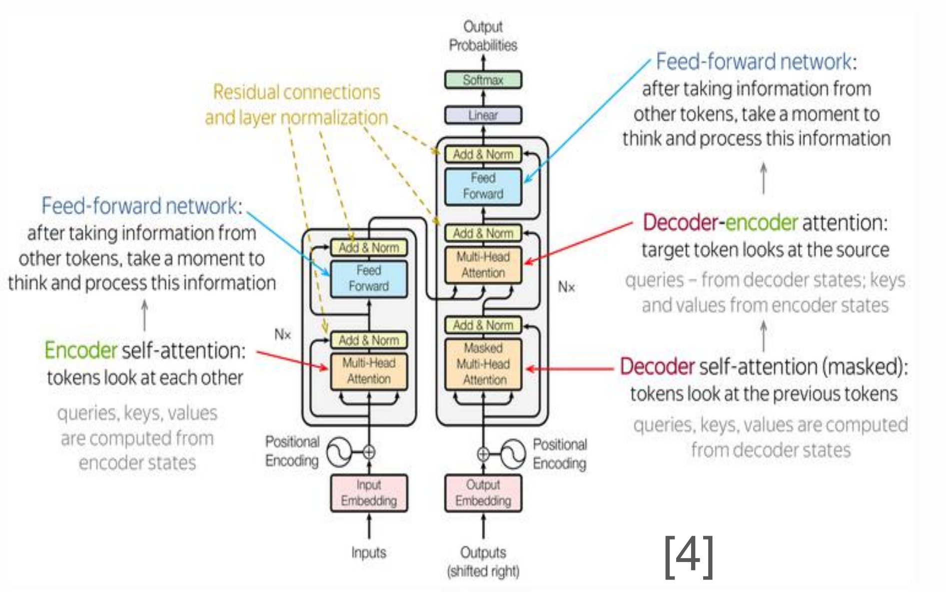
The Transformer Architecture: The New Paradigm

- Key Innovation: Self-Attention mechanism
  - allowing each word to attend to all other words in the same sequence
- Elimination of recurrence
  - Introduction of Parallelization
- Encoder and Decoder stacks
- Positional Encoding
  - How to retain word order information
- Introduction of Key, Query, Value



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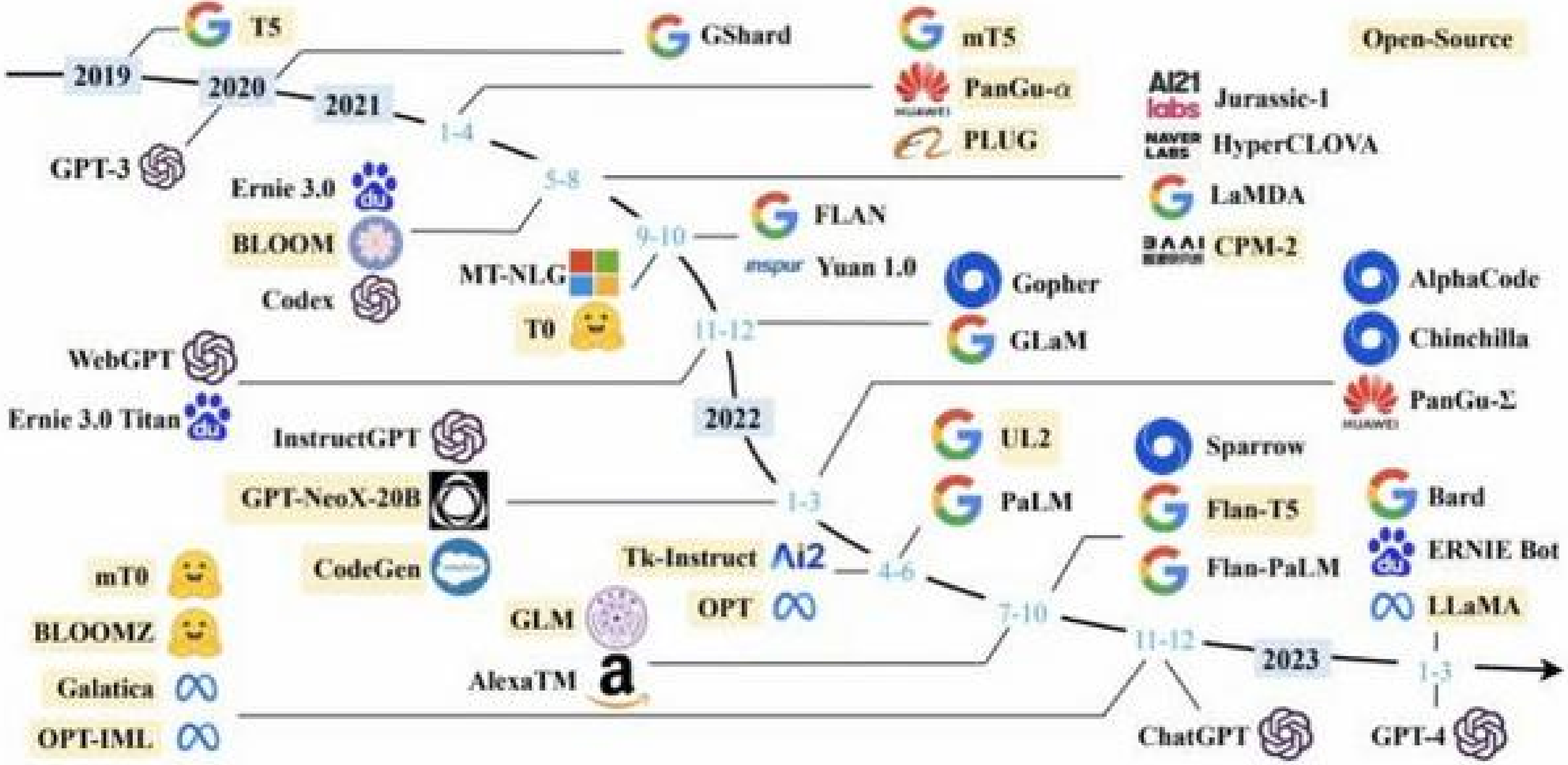
The Era of Large Language Models (LLMs)

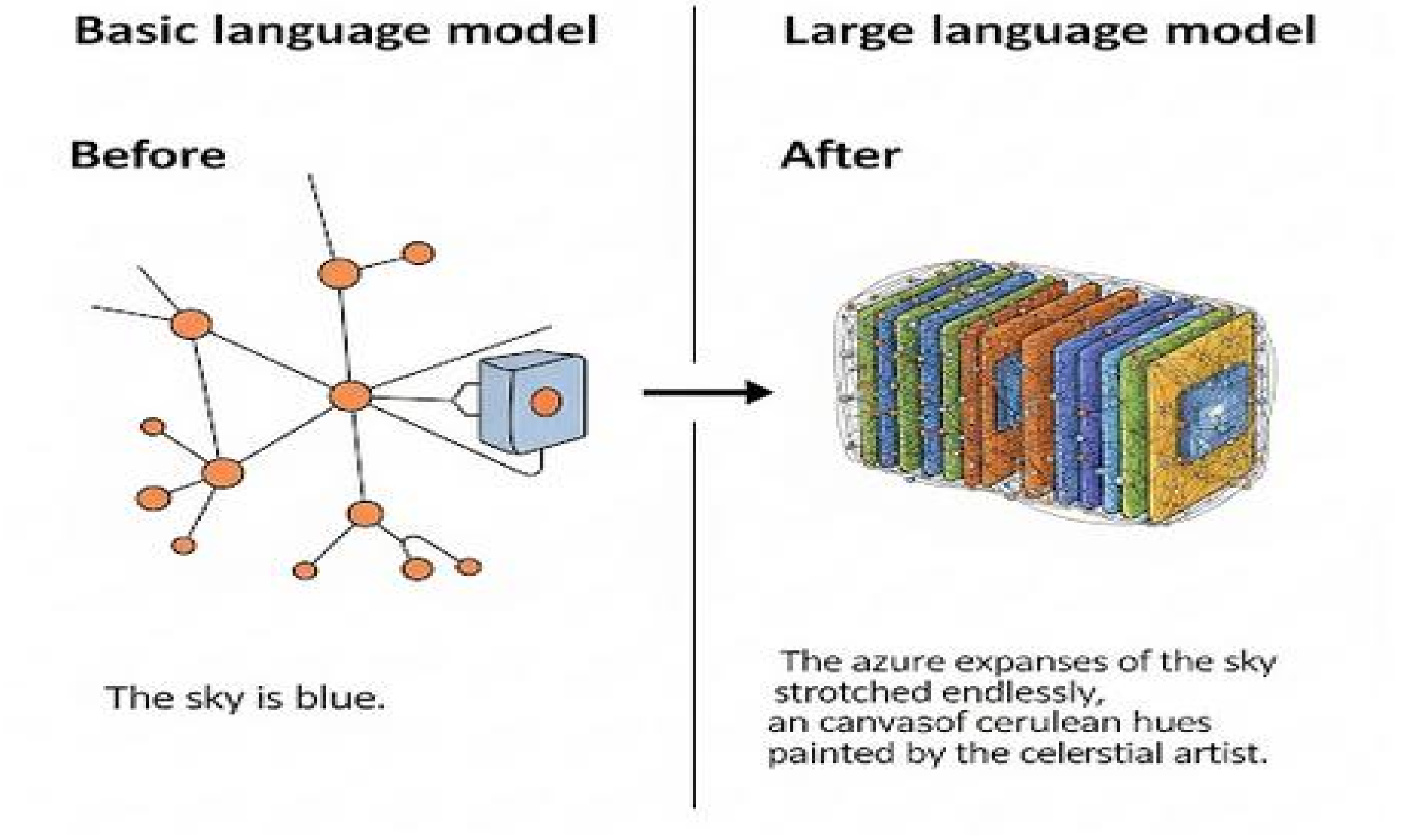
- Scaling Massively Up
  - Massive datasets (Common Crawl, web text, books)
  - Billions and Trillions of parameters
  - Enormous computational resources
- Pre-training and Fine-tuning Paradigm
  - Pre-training: Unsupervised learning on vast text data (next-word prediction, masked language modeling).
  - Fine-tuning: Supervised learning for specific downstream tasks (e.g., question answering, sentiment analysis).
  - Emergent Abilities: Capabilities that arise from scale (e.g., reasoning, code generation, summarization).

Timeline of LLMs [5]



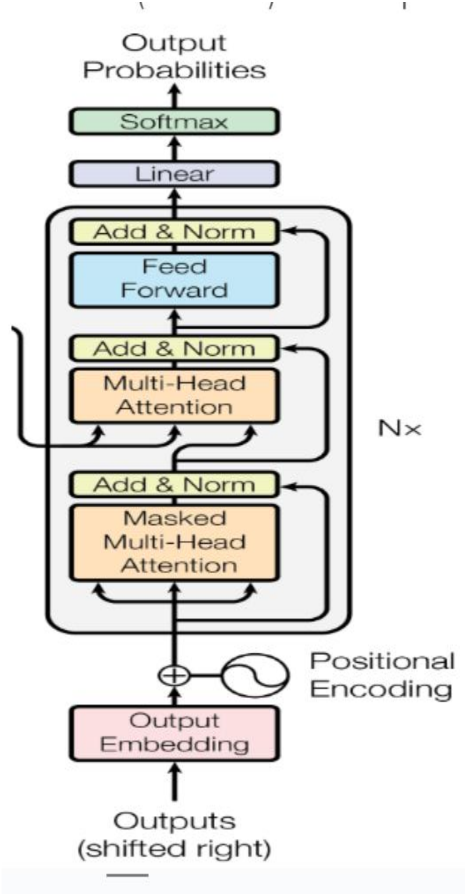
Very Very Competitive Field

Text Generation: Before and After [6]



How LLMs Generate Text: Decoding Strategies

- LLMs are Decoder-Only Models
- Autoregressive generation: One token at a time
- Decoding Strategies:
  - Greedy Search: Always pick the most probable next word
  - Beam Search: Keep track of multiple high-probability sequences
  - Sampling: Introduce randomness
    - Top-k
    - Nucleus sampling (p-sampling))
  - Temperature parameter for controlling diversity and creativity



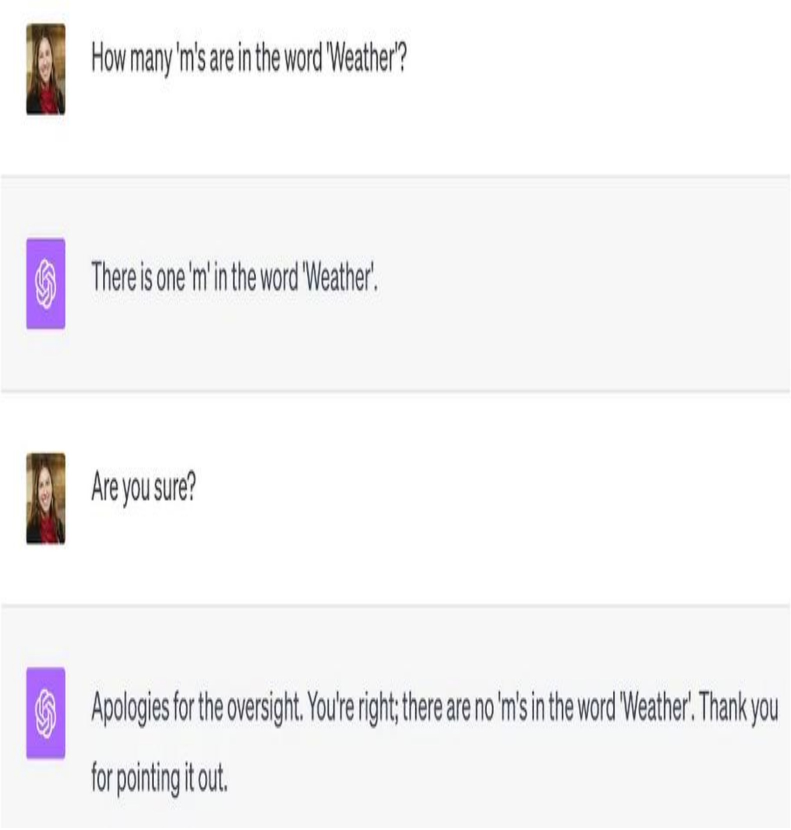
Key Characteristics and Capabilities of Modern LLMs

- Generalization
  - Perform well on a wide range of tasks
- Contextual Understanding
  - Long context windows (far better than Markov models)
- Few-shot/Zero-shot Learning
  - Ability to perform tasks with minimal or no examples
- Instruction Following
  - Responding to natural language prompts
- Reasoning and Problem Solving
  - Chain-of-thought prompting, Program-of-thought prompting
- Multimodality
  - Some LLMs are moving towards understanding images/audio

Challenges and Ethical Considerations of LLMs

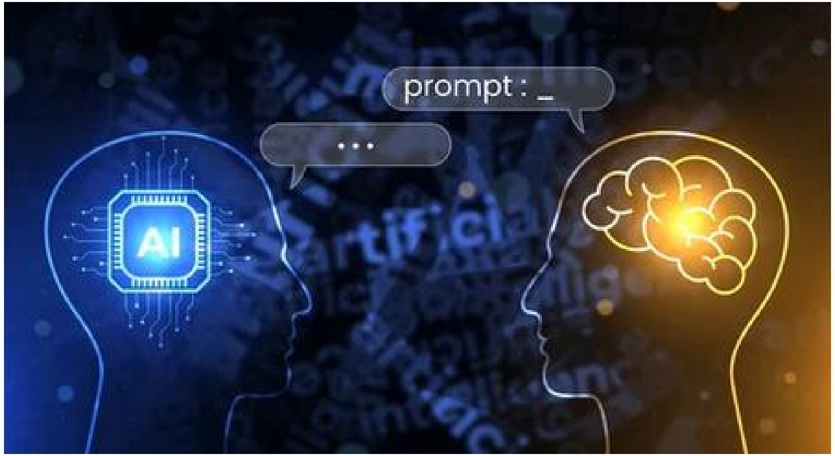
- Bias
  - Reflecting biases in training data
- Hallucination
  - Generating factually incorrect or nonsensical information
- Toxicity/Harmful Content Generation
- Computational Cost
  - Training and inference are very expensive
- Environmental Impact
- Data Privacy and Security
- The need for responsible AI development

Hallucination Example [7]



The Future of Text Generation

- Continued scaling of models and data
- Improved control with better explainability
- Addressing ethical concerns through research and regulation
- Personalized generation
- Multimodal LLMs becoming more prevalent
- Integration into more applications and workflows
- The role of human-in-the-loop



Conclusion and Key Takeaways

- Text generation has evolved from simple statistical methods to highly complex neural networks
- The Transformer architecture and the concept of scaling have revolutionized the field
- LLMs offer unprecedented capabilities but come with significant challenges.
- Responsible development and deployment are crucial for the future
- You can explore LLMs at https://app.hyperbolic.xyz/models/

Creative Future Lies Ahead…[8]

References

1. Speech and Language Processing, 2nd Edition in PDF format (complete and parts) by Daniel Jurafsky, James H. Martin
2. https://vectors.nlpl.eu/explore/embeddings/en/
3. https://www.geeksforgeeks.org/introduction-to-recurrent-neural-network/
4. https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html
5. https://www.nextbigfuture.com/2023/04/timeline-of-open-and-proprietary-large-language-models.html
6. https://gemini.google.com/
7. https://www.iguazio.com/glossary/llm-hallucination/
8. https://medium.com/@tehreemyounas/ai-as-a-catalyst-for-creativity-igniting-innovation-within-the-modern-world-36959bef2199
9. https://www.researchgate.net/publication/342609939_Developing_a_Twitter_bot_that_can_join_a_discussion_using_state-of-the-art_architectures