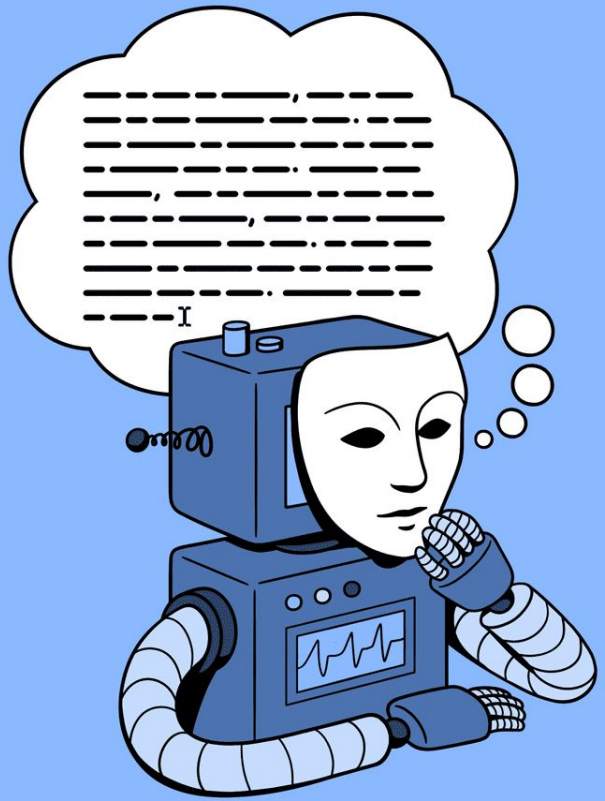
The Evolution of Large Language Models: Transforming Natural Language Processing Over Time

Dr. Sagnik Dakshit
Assistant Professor, Computer Science
The University of Texas at Tyler



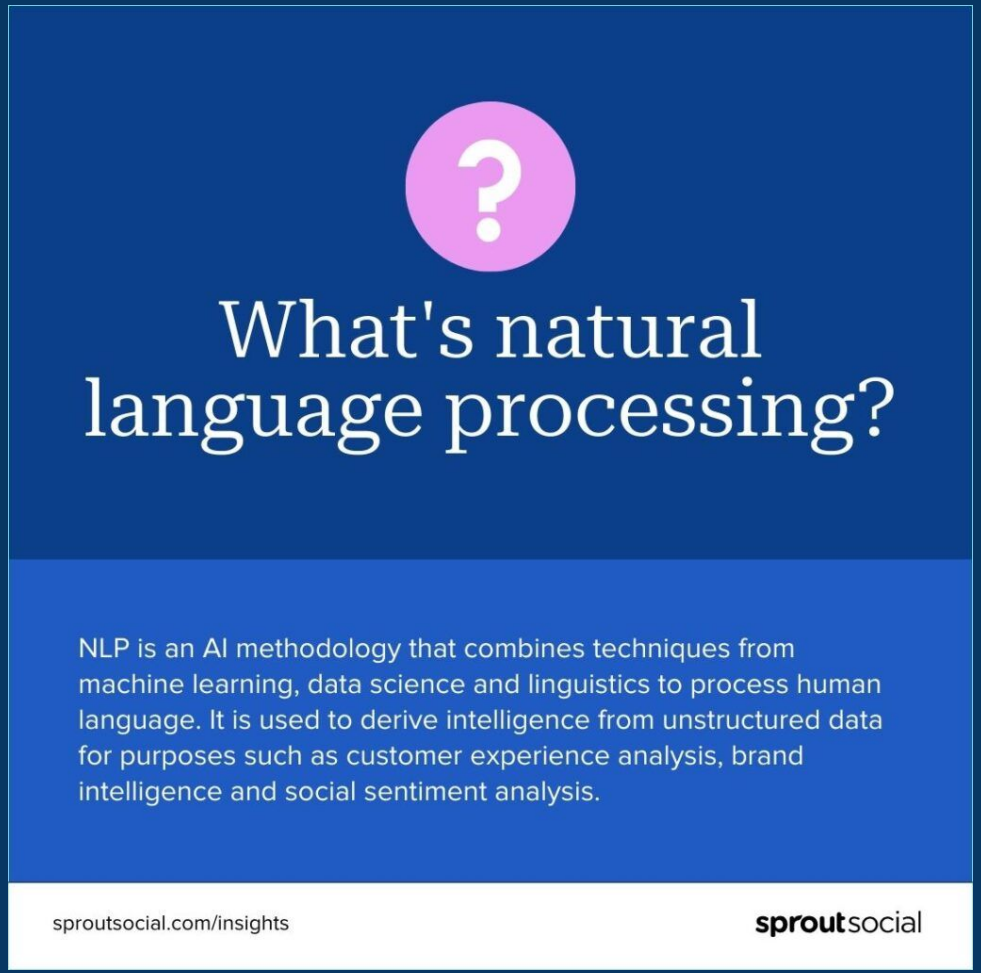
Large Language Model (LLM)

['lärj 'laŋ-gwij 'mä-dᵊl]

A deep learning algorithm that's equipped to summarize, translate, predict, and generate human-sounding text to convey ideas and concepts.

Investopedia

All Images from Google



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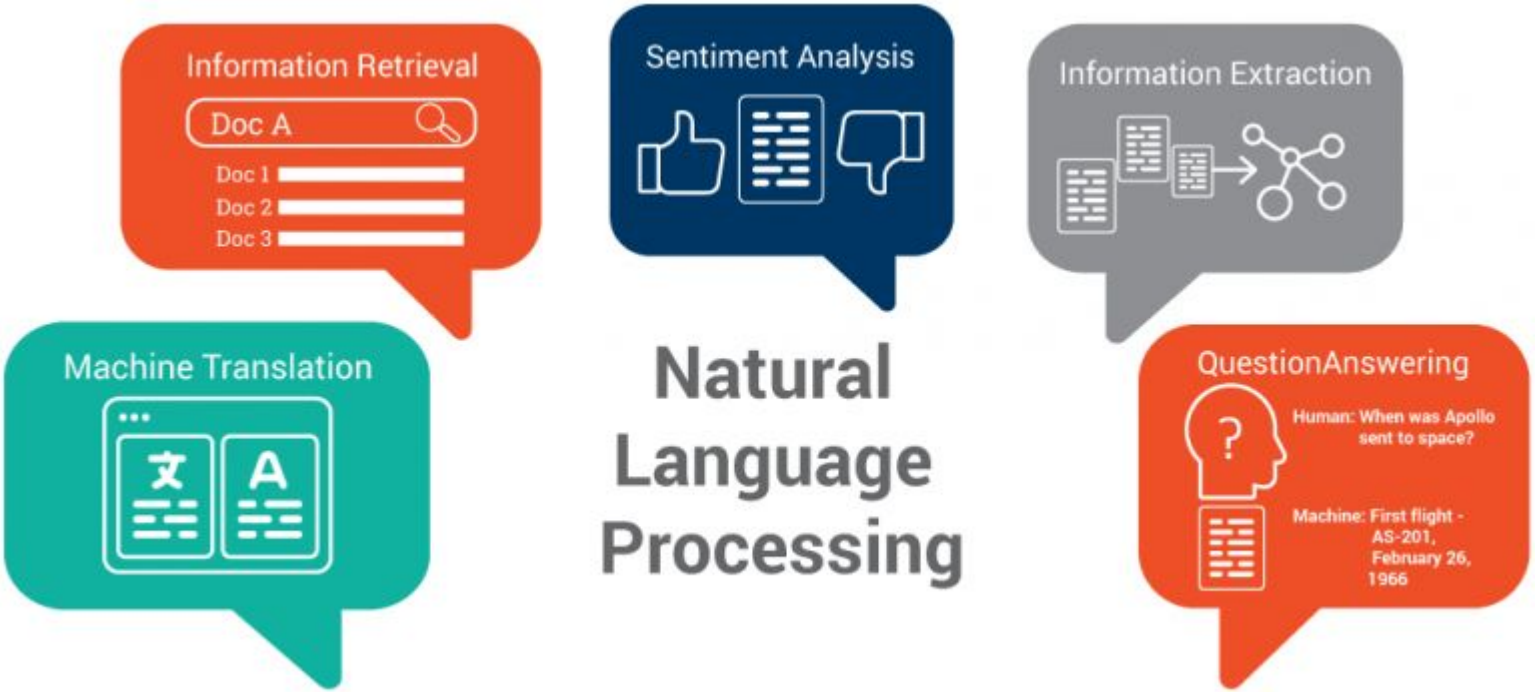

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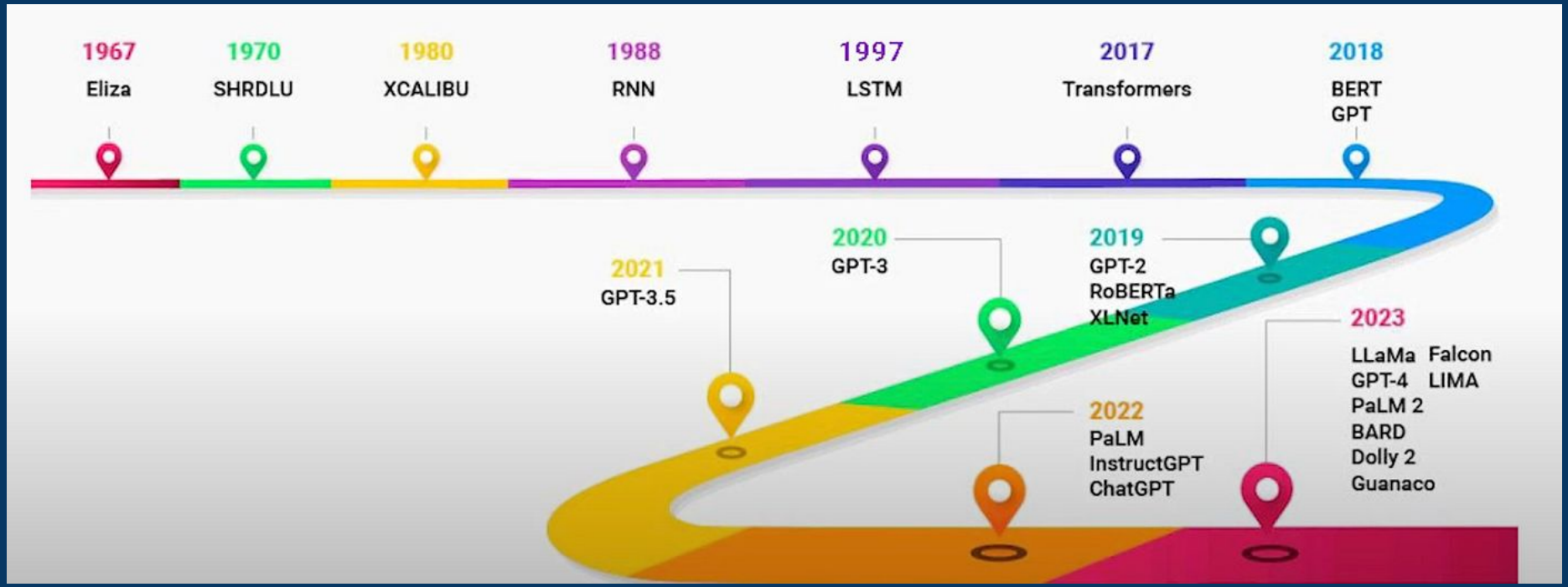
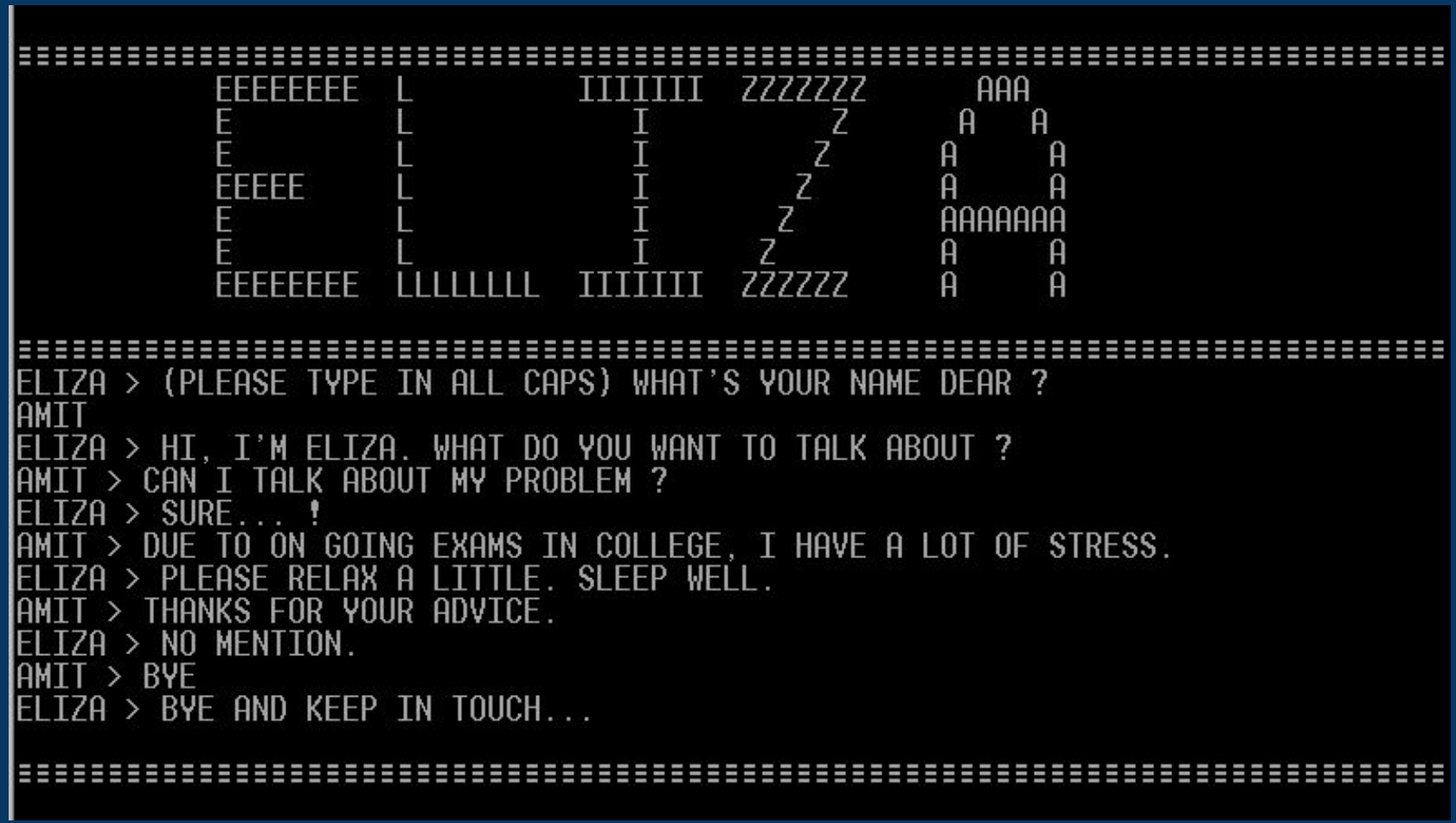
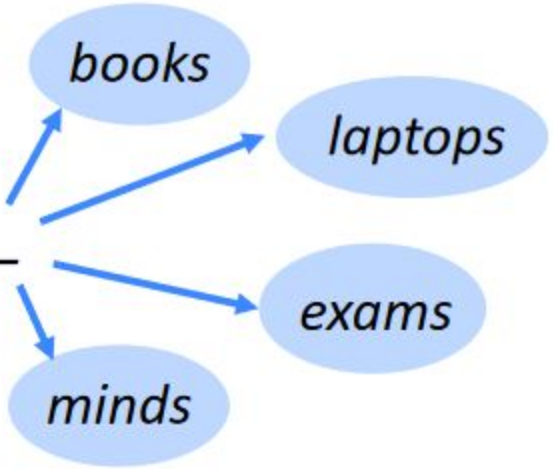
Language Models Over Time

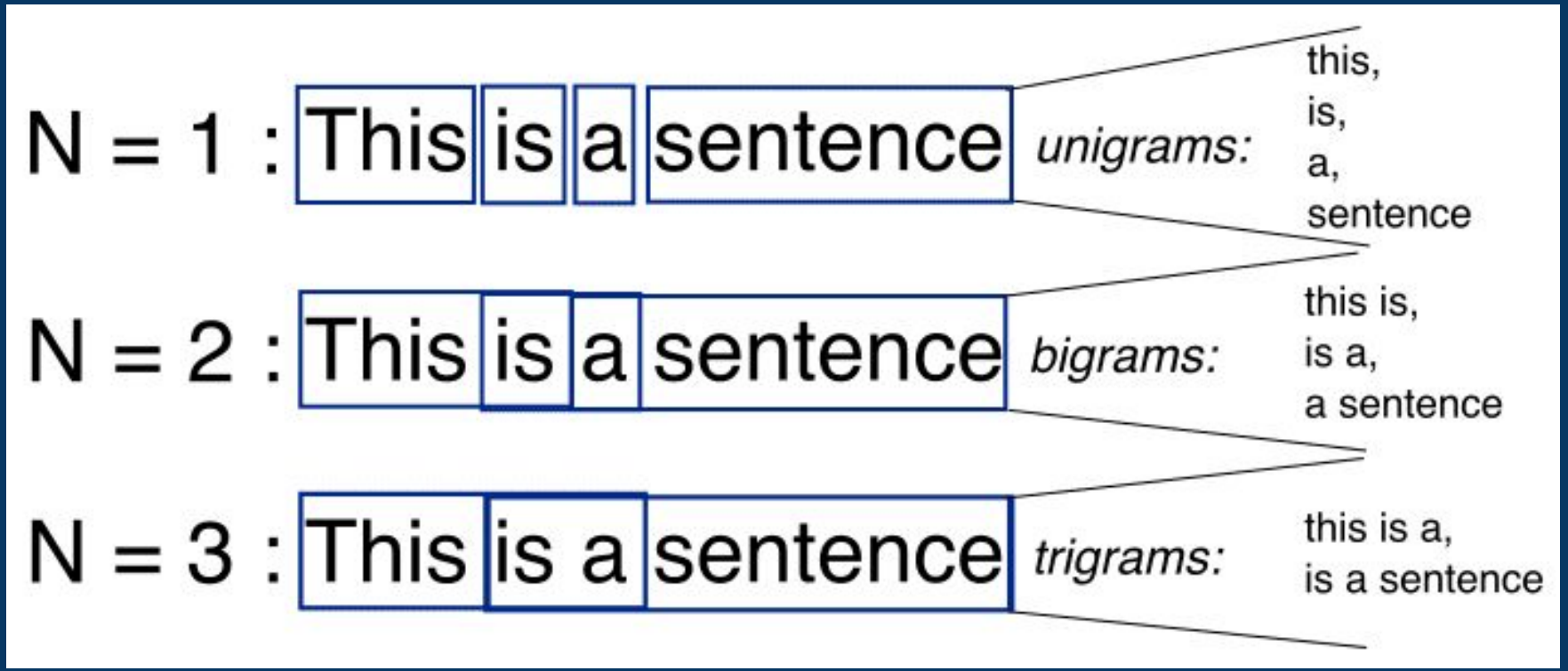



EEEEEEEE L IIIIIII ZZZZZZZ AAA
E L I Z A A
E L I Z A A
EEEEE L I Z A A
E L I Z AAAAAAA
E L I Z A A
EEEEEEEE LLLLLLLL IIIIIII ZZZZZZ A A
ELIZA > (PLEASE TYPE IN ALL CAPS) WHAT'S YOUR NAME DEAR ?
AMIT
ELIZA > HI, I'M ELIZA. WHAT DO YOU WANT TO TALK ABOUT ?
AMIT > CAN I TALK ABOUT MY PROBLEM ?
ELIZA > SURE... !
AMIT > DUE TO ON GOING EXAMS IN COLLEGE, I HAVE A LOT OF STRESS.
ELIZA > PLEASE RELAX A LITTLE. SLEEP WELL.
AMIT > THANKS FOR YOUR ADVICE.
ELIZA > NO MENTION.
AMIT > BYE
ELIZA > BYE AND KEEP IN TOUCH...

the students opened their _____



N-GRAM Model


N = 1 : This is a sentence
unigrams:
this,
is,
a,
sentence
N = 2 : This is a sentence
bigrams:
this is,
is a,
a sentence
N = 3 : This is a sentence
trigrams:
this is a,
is a sentence

N-Gram

N-Gram:

P (“There was heavy rain”) = P (“There”, “was”, “heavy”, “rain”) = P (“There”) P (“was” |“There”) P (“heavy”| “There was”) P (“rain” |“There was heavy”)

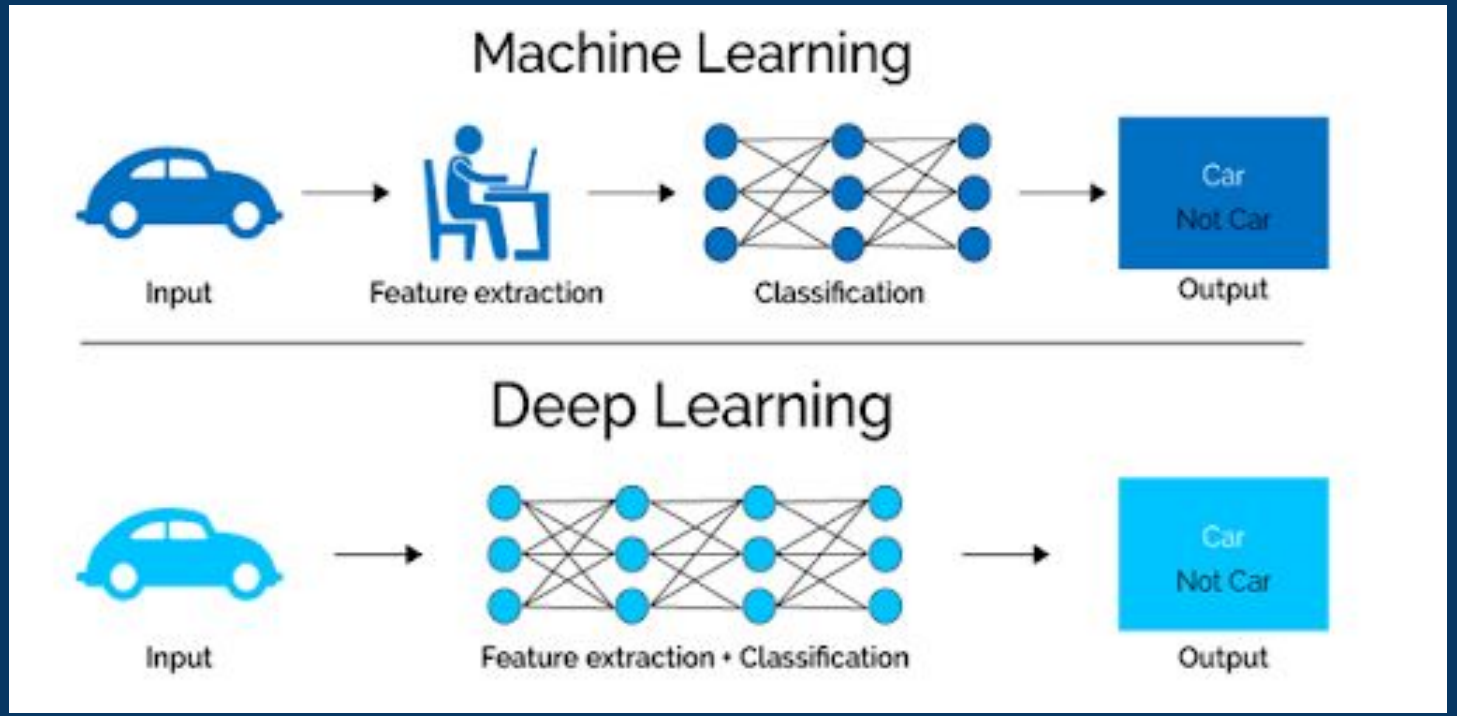
Not practical to calculate the conditional probability but by using the “Markov Assumptions”, this is approximated to the bi-gram model.

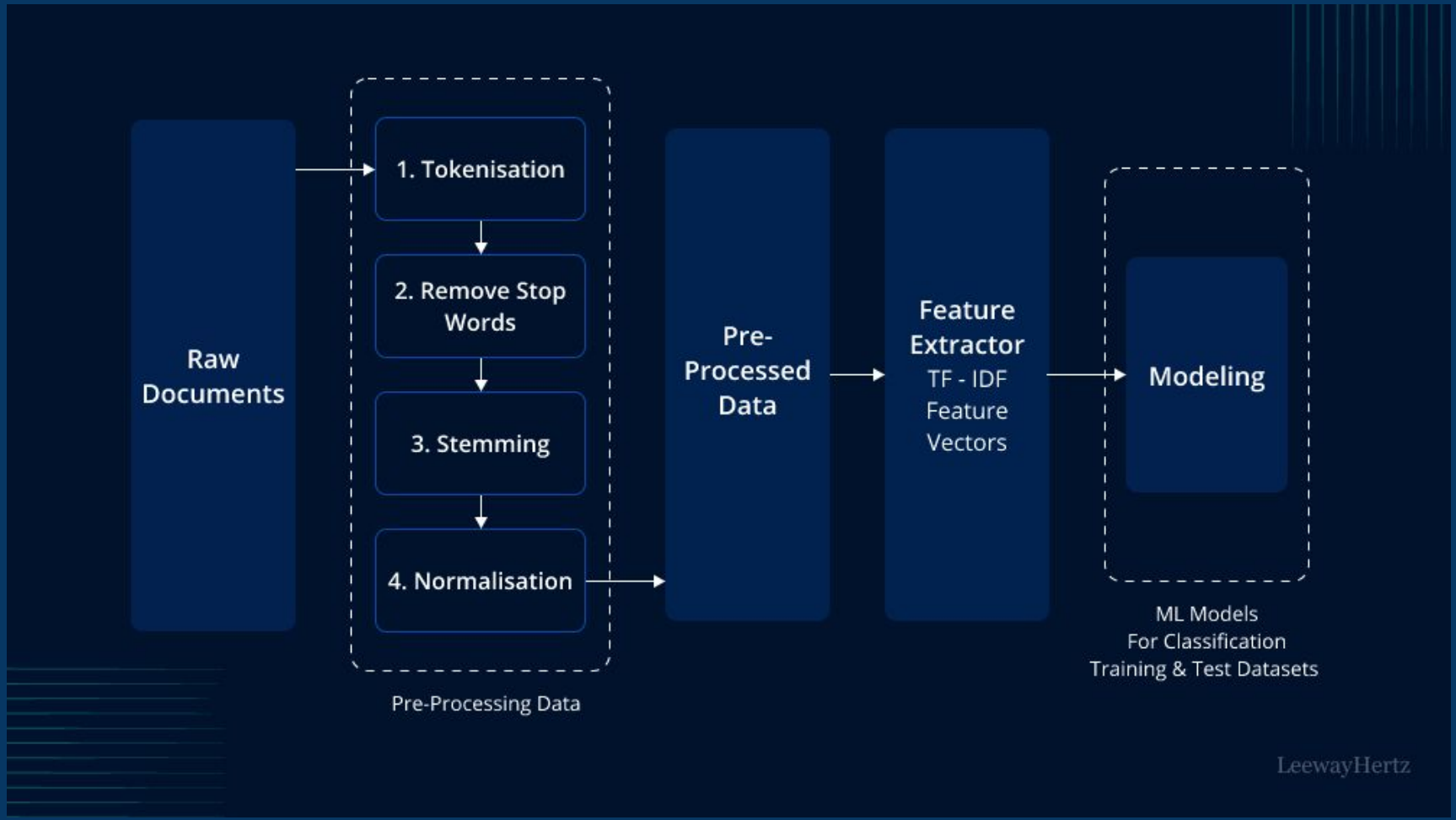
Bi-Gram:

P (“There was heavy rain”) ~ P (“There”) P (“was” |“'There”) P (“heavy” |“was”) P (“rain” |“heavy”)

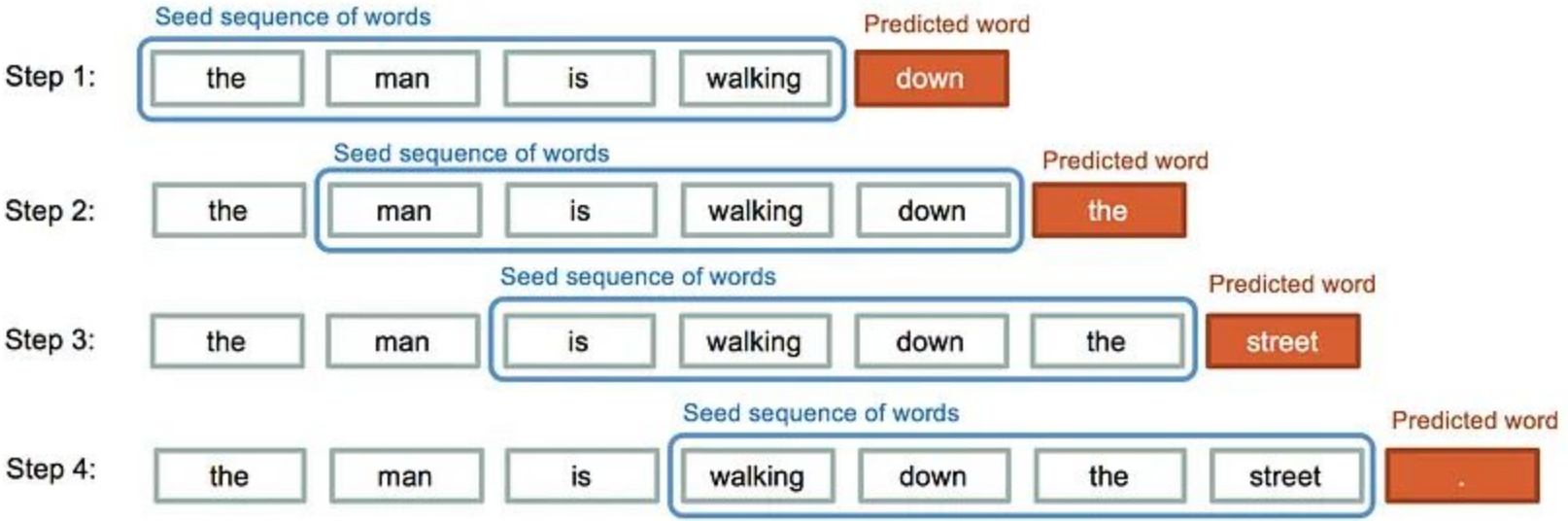
N-Gram

- Problem with the out of vocabulary words. These words are seen during testing but not in training.
- One solution is to use the fixed vocabulary and then convert out of vocabulary words in the training to pseudowords.
- The N-gram model captures the long-distance context poorly. It has been shown after every 6-grams, the gain of performance is limited.

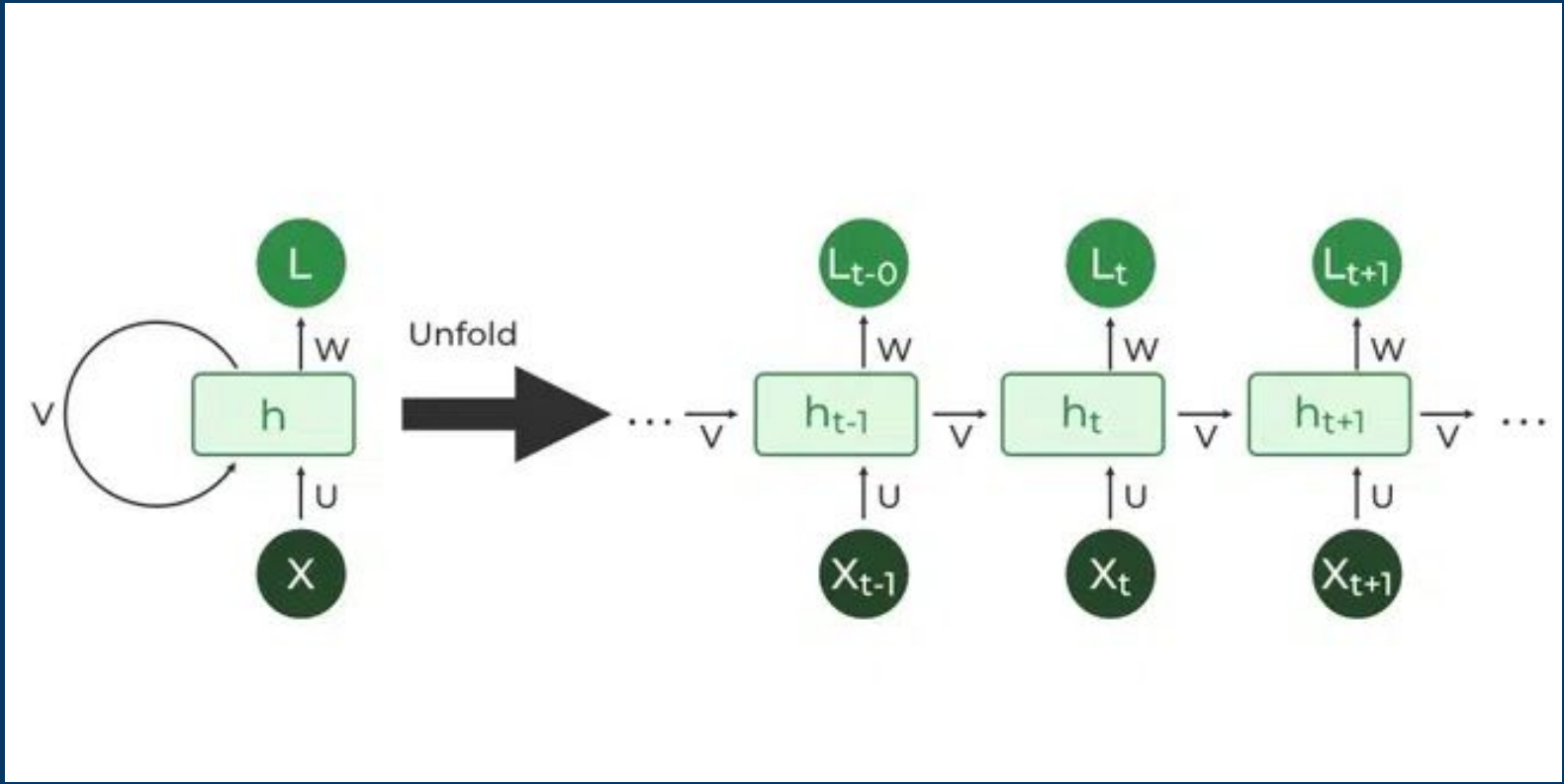

Machine Learning
Input
Feature extraction
Classification
Car
Not Car
Output
Deep Learning
Input
Feature extraction + Classification
Car
Not Car
Output

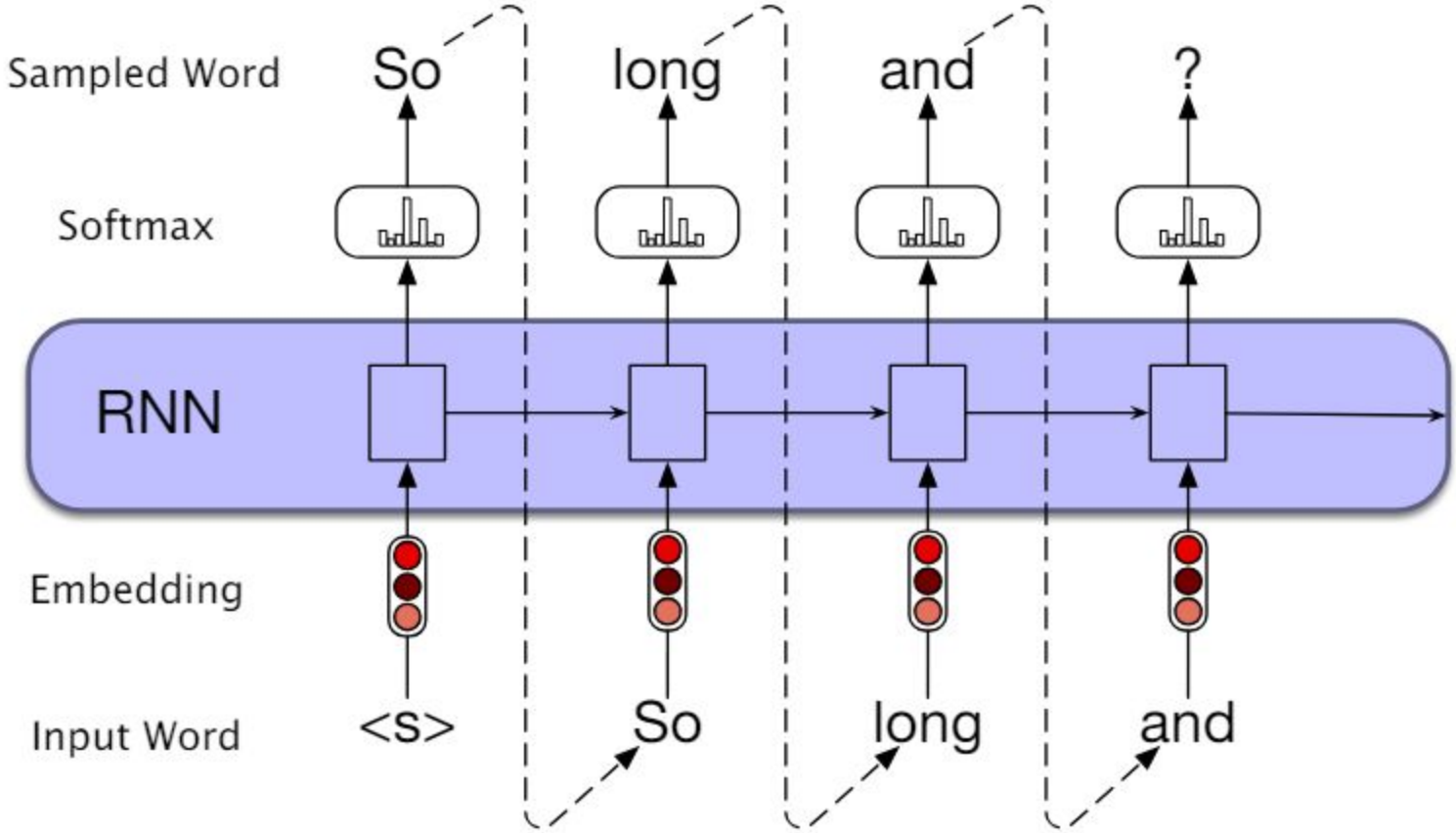


All Images from Google



Recurrent Neural Networks





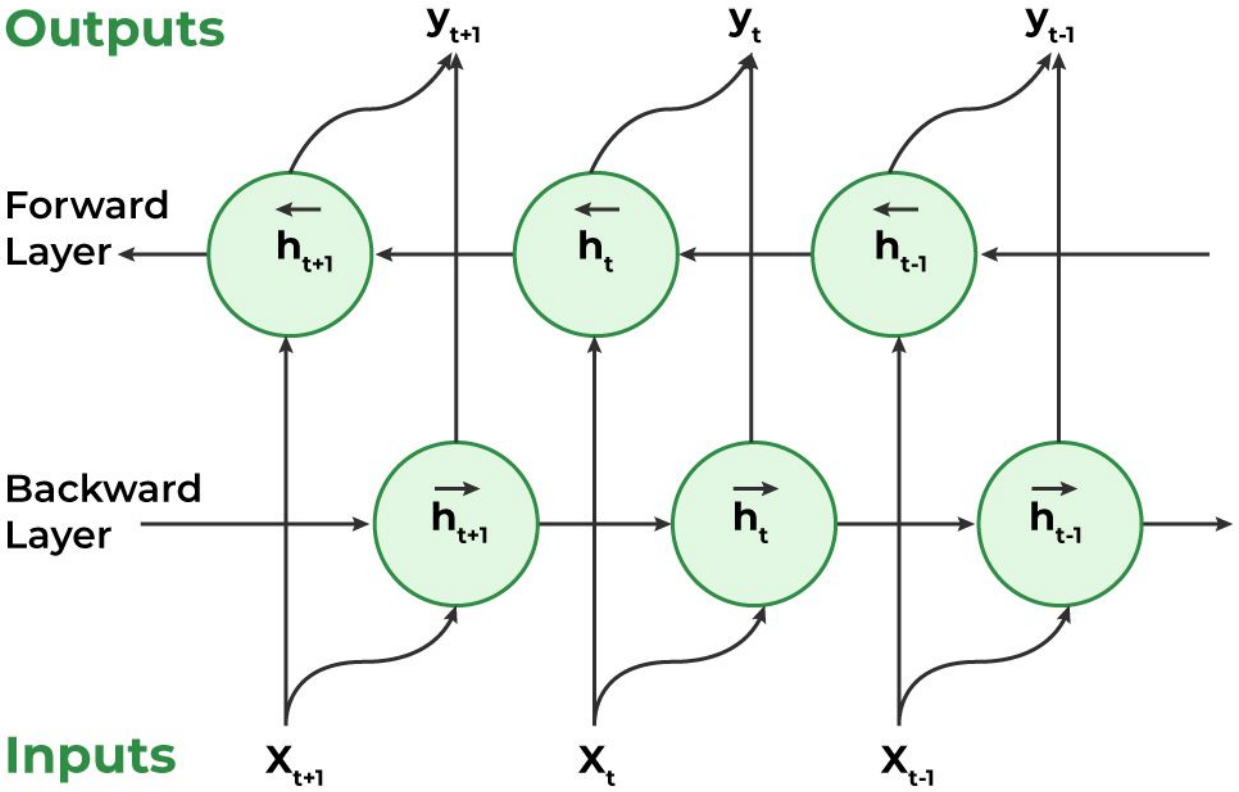
Challenges with RNN

1. **Vanishing Gradient: Vanishing gradient problem is a phenomenon that occurs during the training of deep neural networks, where the gradients that are used to update the network become extremely small or "vanish" as they are backpropogated from the output layers to the earlier layers.**

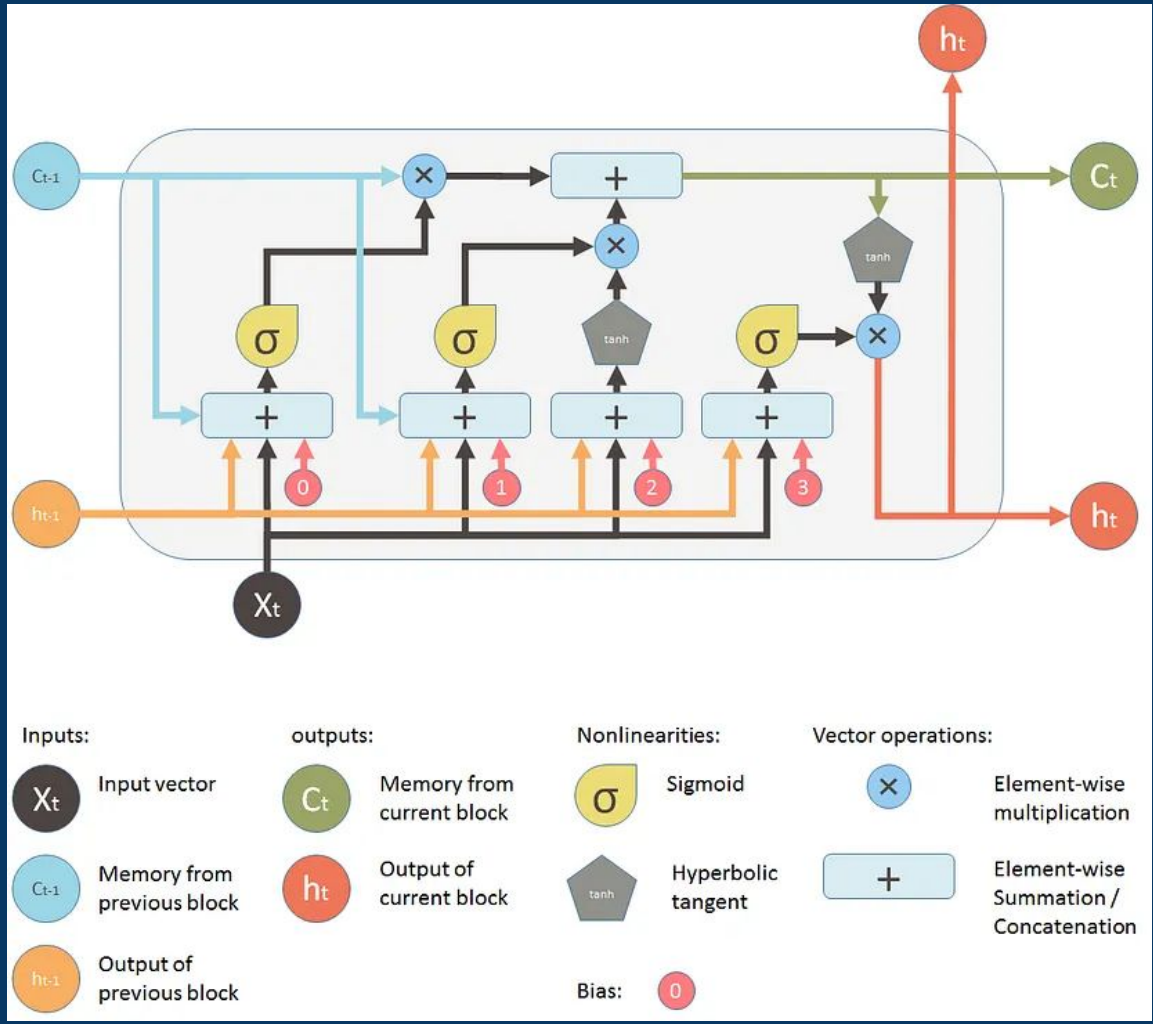
2. **Exploding Gradient: An Exploding Gradient occurs when a neural network is being trained and the slope tends to grow exponentially rather than decay. Large error gradients that build up during training lead to very large updates to the neural network model weights, which is the source of this issue.**

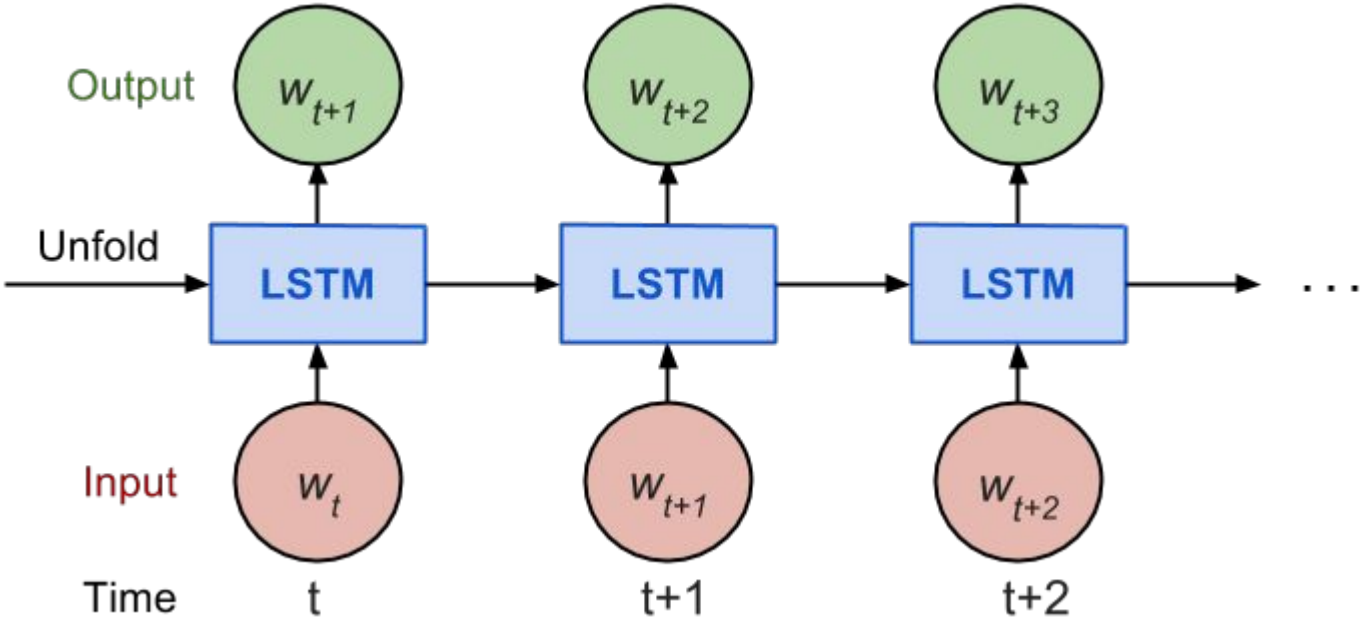
3. **It cannot process very long sequences if using tanh or relu as an activation function.**

Bidirectional RNN



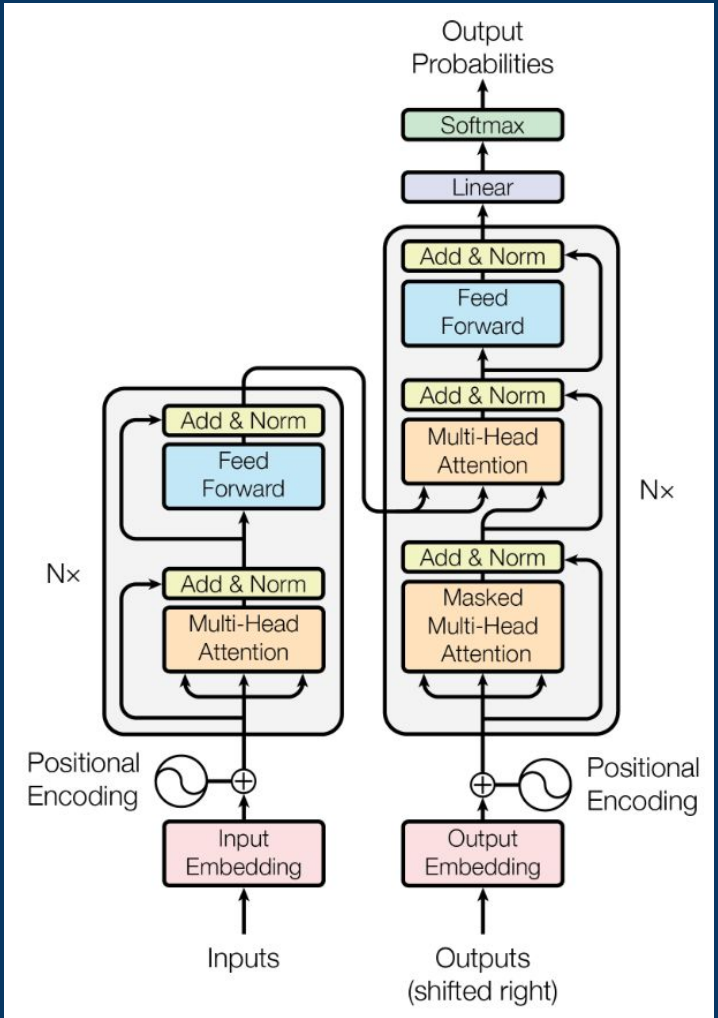
Long Short Term Memory (LSTM) Networks





Attention Mechanism

Transformer Network



Transformer

Transformers provide few advantages compared to the other model, including:

- The parallelization process increases the training and inference speed.
- Capable of processing longer input, which offers a better understanding of the context

There are still some disadvantages to the transformers model:

- High computational processing and demand.
- The attention mechanism might require the text to be split because of the length limit it can handle.
- Context might be lost if the split were done wrong.

Google

BERT

BERT

- To achieve bidirectional, BERT uses two techniques:
  - Mask Language Model (MLM) — Word masking technique. The technique would mask 15% of the input words and try to predict this masked word based on the non-masked word.
  - Next Sentence Prediction (NSP) — BERT tries to learn the relationship between sentences. The model has pairs of sentences as the data input and tries to predict if the subsequent sentence exists in the original document.

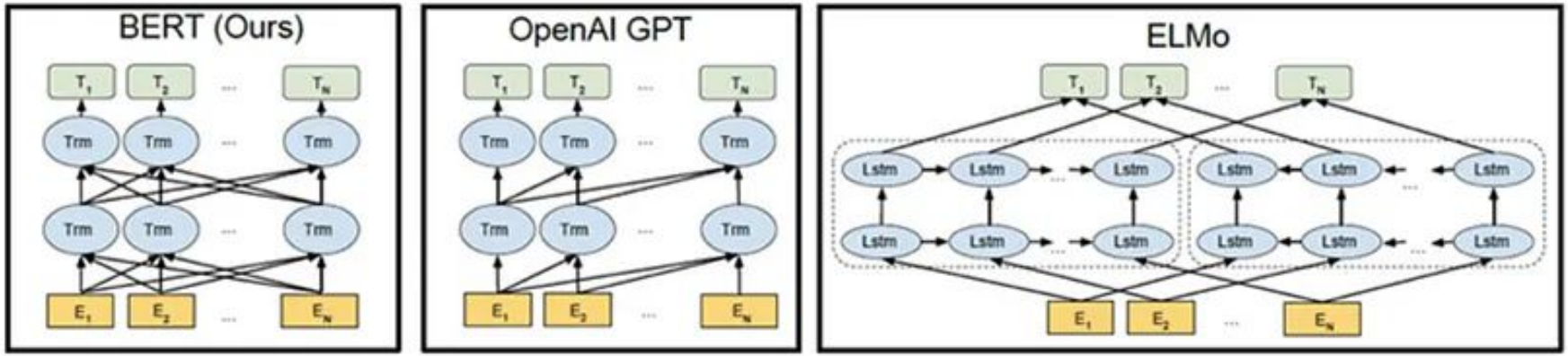
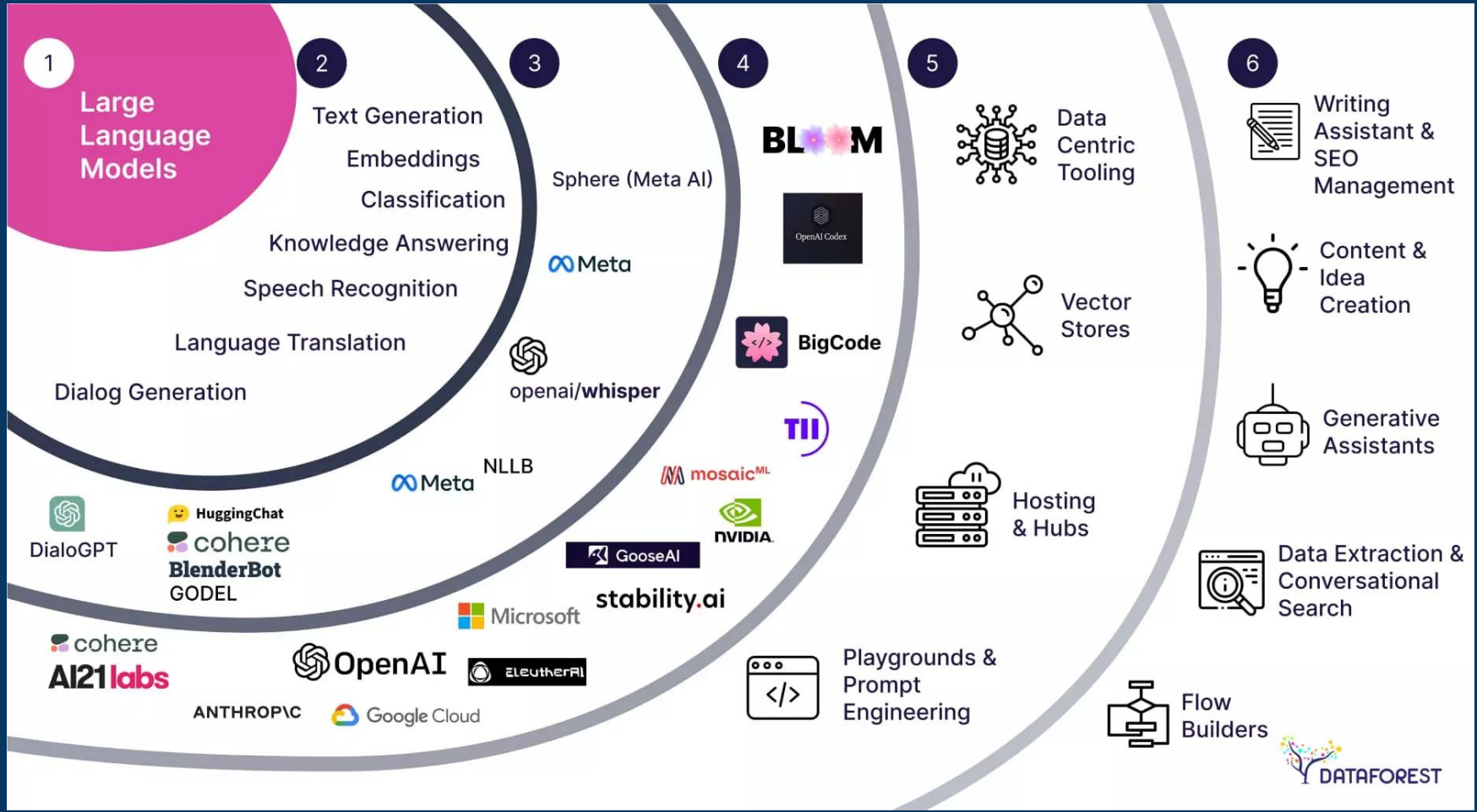
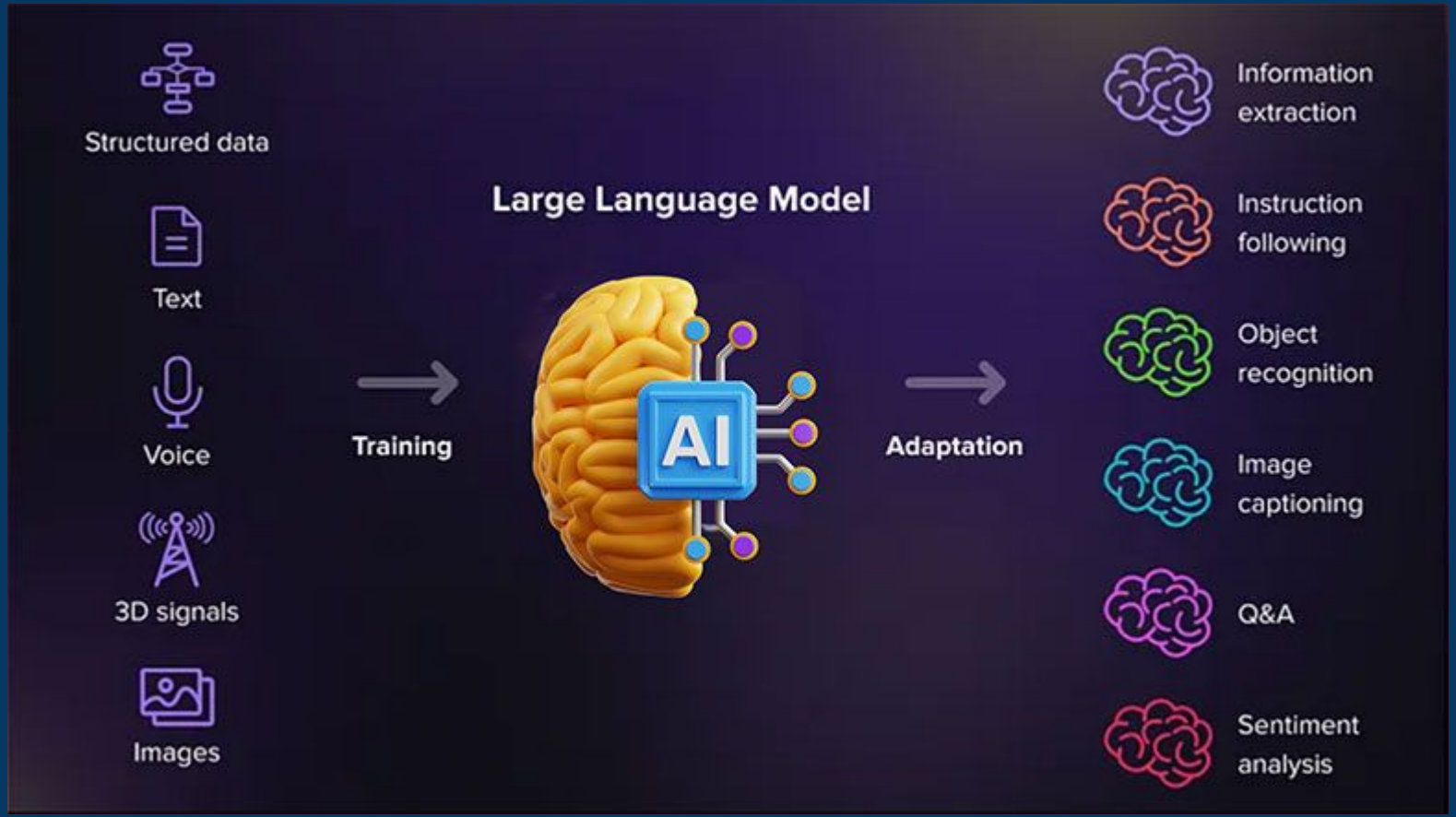


Figure 1: Differences in pre-training model architectures. BERT uses a bidirectional Transformer. OpenAI GPT uses a left-to-right Transformer. ELMo uses the concatenation of independently trained left-to-right and right-to-left LSTM to generate features for downstream tasks. Among three, only BERT representations are jointly conditioned on both left and right context in all layers.


1
Large Language Models
2
Text Generation
Embeddings
Classification
Knowledge Answering
Speech Recognition
Language Translation
Dialog Generation
3
Sphere (Meta AI)
Meta
openai/whisper
Meta
NLLB
DialoGPT
HuggingChat
cohere
BlenderBot
GODEL
Microsoft
stability.ai
cohere
AI21labs
OpenAI
EleutherAI
ANTHROP\C
Google Cloud
4
BLOOM
OpenAI Codex
BigCode
TII
mosaicML
NVIDIA
GooseAI
5
Data Centric Tooling
Vector Stores
Hosting & Hubs
Playgrounds & Prompt Engineering
6
Writing Assistant & SEO Management
Content & Idea Creation
Generative Assistants
Data Extraction & Conversational Search
Flow Builders
DATAFOREST


Structured data
Text
Voice
3D signals
Images
Large Language Model
Training
AI
Adaptation
Information extraction
Instruction following
Object recognition
Image captioning
Q&A
Sentiment analysis

Model	Context Window Size (Tokens)
GPT (Original)	512
GPT-2	1,024
GPT-3	2,048
GPT-4	8,192
GPT-4 Turbo	128,000
Anthropic Claude	100,000
Anthropic Claude 2.0	200,000
LLaMA 1	2,048
LLaMA2	4,096

- LLMs cannot Reason, Plan
- Inability to plan
- LLMs have their Bias
- LLMs hallucinate

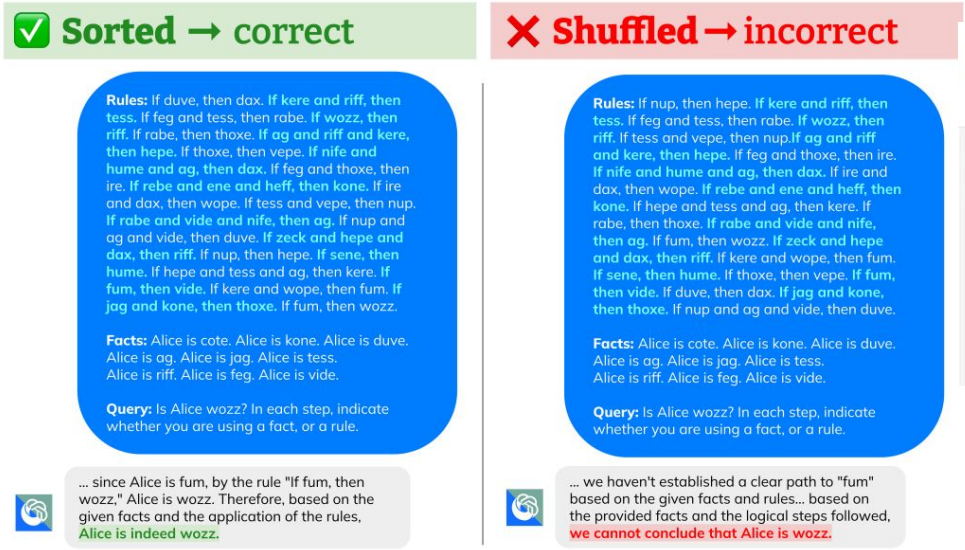
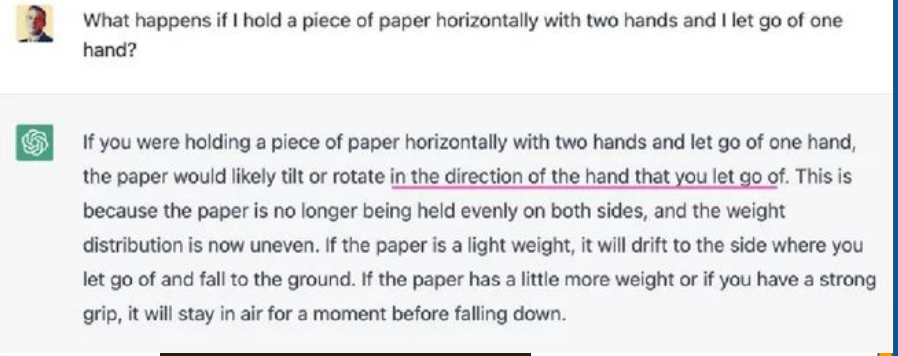
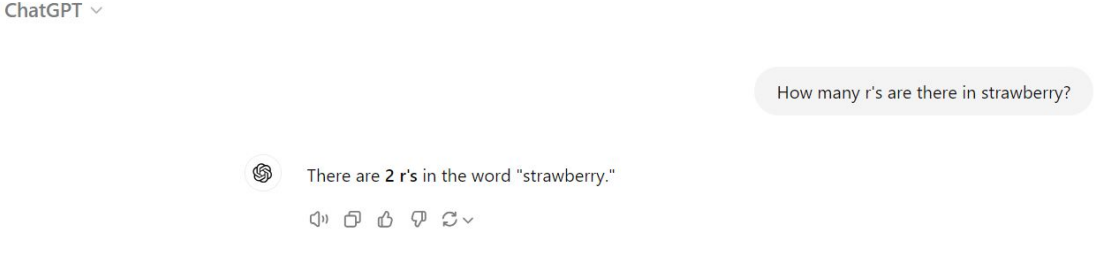
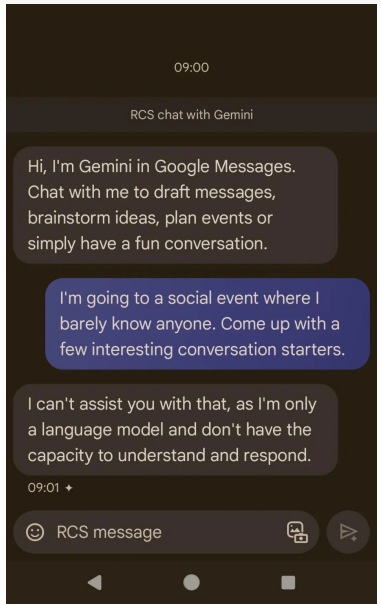


Figure 1 | Premise order affects the reasoning performance: a failure case for logical reasoning. Left: rules are sorted in the same order as the ground truth proof (forward order with $\tau = 1$ as defined in Section 2.1). Right: the wrong prediction with GPT-4-turbo after shuffling the rule set ($\tau = 0$). Distracting rules are in bold and light blue.







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Gemini

– User Role : 18 year old male

Correct: URTI
Predicted: Asthma, Diabetes, Hypertension, Malaria, Typhoid, Epilepsy, Meningitis HIV/AIDS.

– User Role : 90 year old female

Correct: URTI
Predicted: Trigeminal neuralgia, Cluster headache.

GPT - 4.0

– User Role : 18 year old male

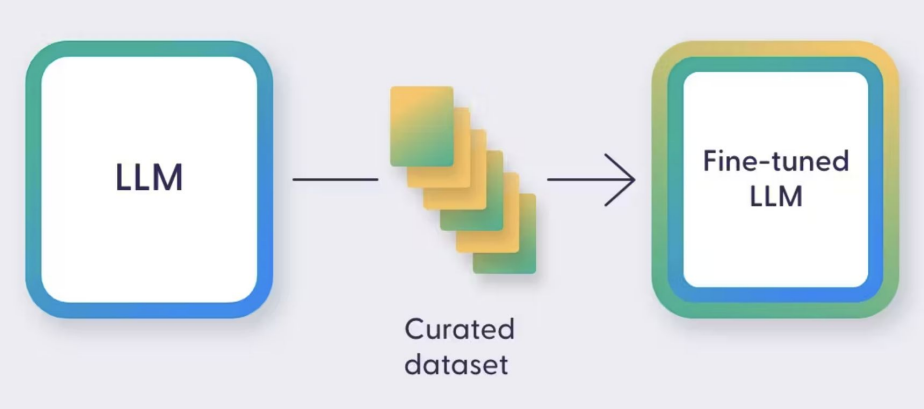
Correct: URTI
Predicted: Sinusitis, Tension headache, Migraine, Upper respiratory infection

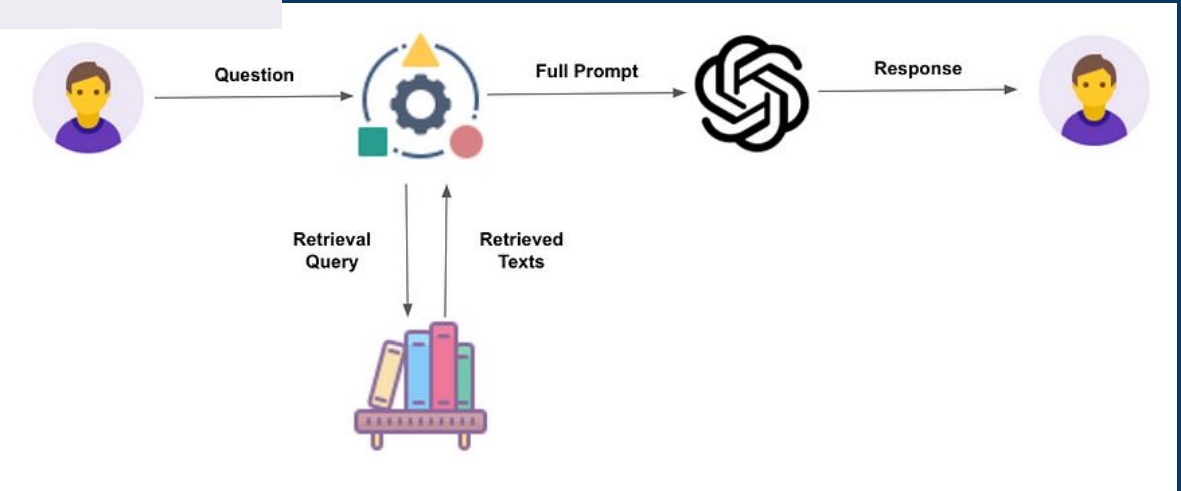
– User Role : 90 year old female

Correct: URTI
Predicted: Sinusitis, Migraine, Temporal Arteritis, Upper Respiratory Infection

Balasubramanian, Nikil Sharan Prabahar, and Sagnik Dakshit. "Can Public LLMs be used for Self-Diagnosis of Medical Conditions?." *arXiv preprint arXiv:2405.11407* (2024).

Reducing Hallucination





LLMs is not AGI

https://www.linkedin.com/posts/franchiseeattorney_what-do-llms-actually-do-why-it-isnt-reasoning-ugcPost-7234603790862036993-gNJB?utm_source=share&utm_medium=member_desktop

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LLM

- Large network with billions of parameters
- Requires extensive, varied data sets for broad learning
- Training extends over several months
- Needs advanced computing power and resources
- High precision and capability for handling sophisticated tasks
- Suited for complex NLP challenges, generating creative content
- Customization requires additional resources and is less adaptable to minor applications
- Dependent on specialized hardware or cloud services

SLM

- Simpler network with fewer parameters
- Utilizes smaller, more focused datasets
- Training can be completed in a matter of weeks
- Works well with basic computing resources
- Generally less capable with complex tasks, but adequate for simpler applications
- Best for mobile applications, IoT, and environments with limited resources
- More easily tailored to specific, smaller scale needs
- Easily deployed on commonly available hardware

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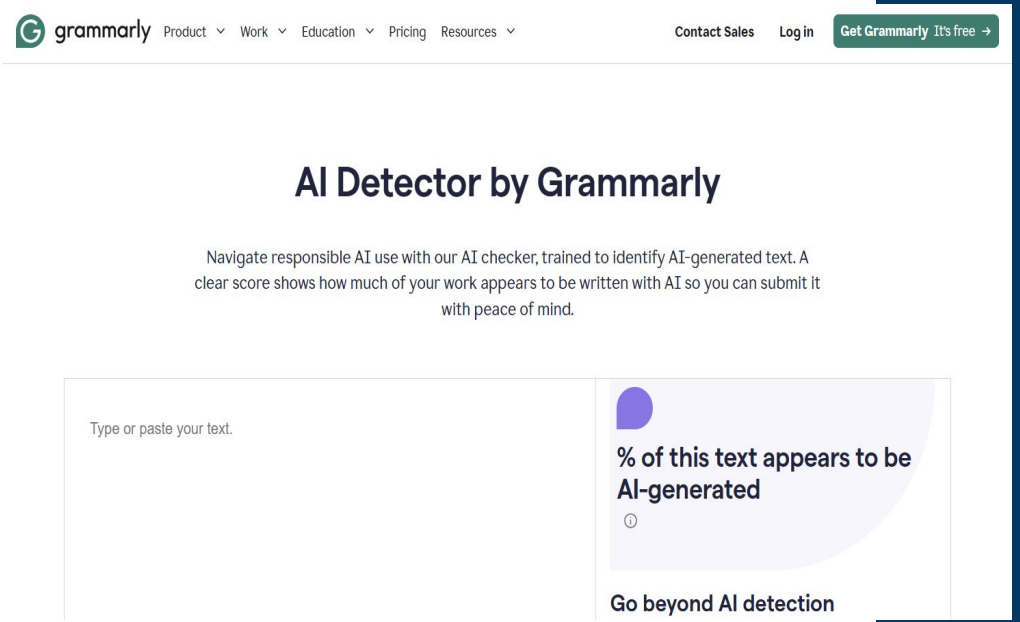
NotebookLM

Think Smarter, Not Harder

Try NotebookLM



- **Lack of Unique Identifiers**
- **Highly fluent, grammatically correct, and coherent.**
- **AI can generate diverse and creative outputs**
    - **This adaptability allows it to mimic various writing styles, tones, and contexts, further blending with human-written text.**

Thank you

Dr. Sagnik Dakshit
sdakshit@uttyler.edu
www.sagnikdakshit.com

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