Introduction to Large Language Models

Journey and Evaluation Parameters

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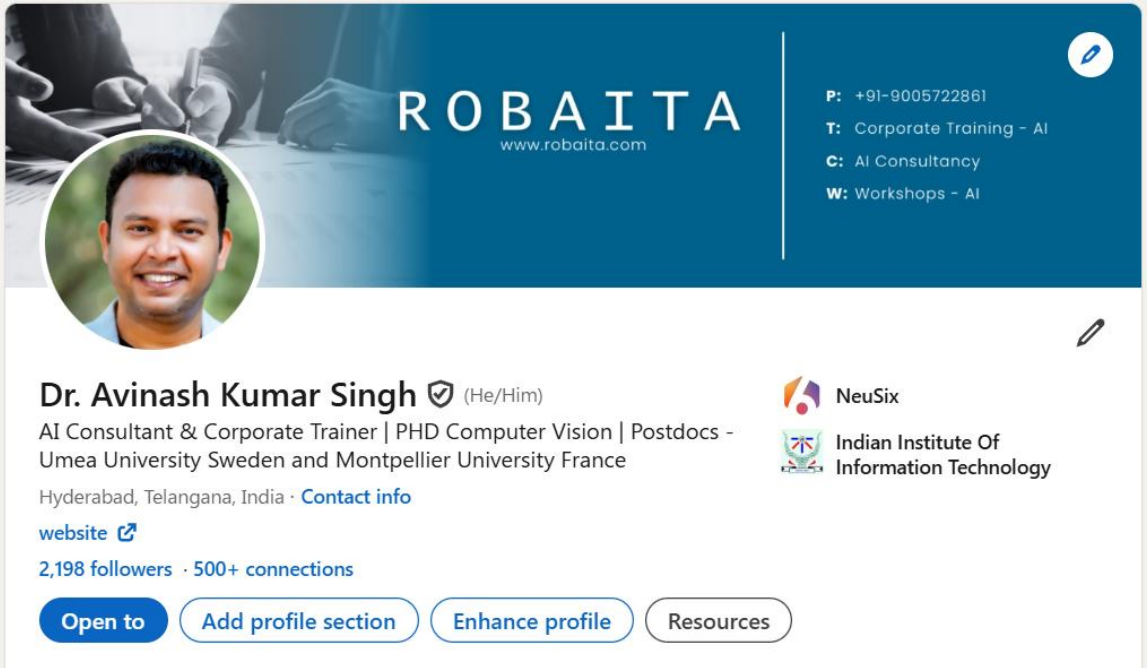
Dr. Avinash Kumar Singh

- ❑ **Possess** 15+ years of **hands-on expertise** in Machine Learning, Computer Vision, NLP, IoT, Robotics, and Generative AI.
- ❑ **Founded** Robaita—an initiative **empowering** individuals and organizations to **build, educate, and implement** AI solutions.
- ❑ **Earned** a Ph.D. in Human-Robot Interaction from IIIT Allahabad in 2016.
- ❑ **Received** postdoctoral fellowships at Umeå University, Sweden (2020) and Montpellier University, France (2021).
- ❑ **Authored** 30+ research papers in **high-impact** SCI journals and international conferences.
- ❑ Unlearning, learning, making mistakes …



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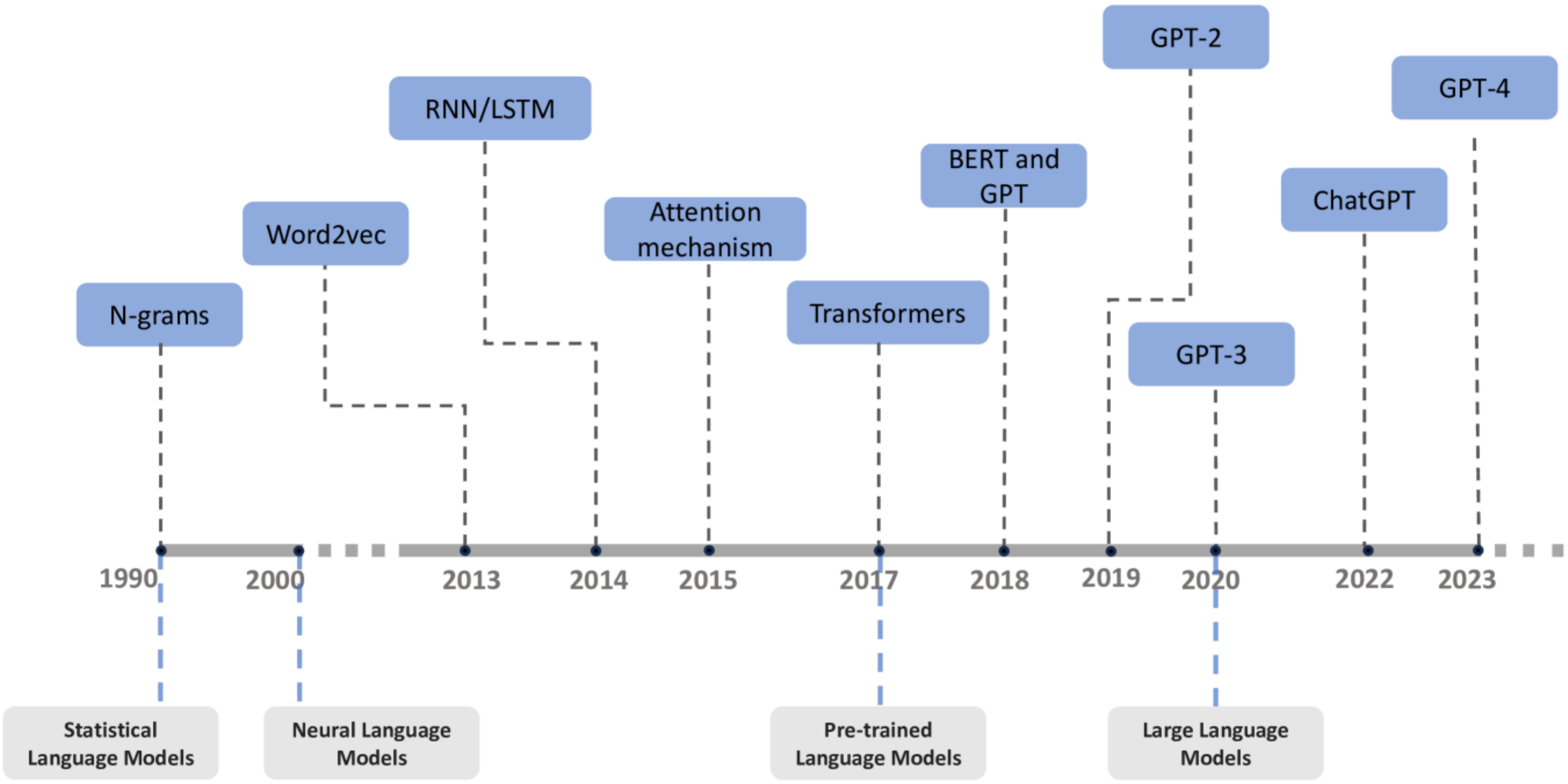
Things to be discussed

- What Are Large Language Models and How Do They Work?
- Popular LLMs and Benchmarks
- Evaluation Metrices:
    - Accuracy
    - Precision
    - Recall
    - F1-score
    - Confusion matrix interpretation
    - BLEU Score
    - ROUGE for language models, Perplexity (LLM-specific)
- Prompt Engineering

Language Models Journey



History, Development, and Principles of Large Language Models—An Introductory Survey, https://arxiv.org/html/2402.06853v1

Large Language Models

What is a Language Model

A language model is a probabilistic model that assigns a probability to a sequence of words and predicts the likelihood of the next word in a sentence, given the previous words.

Statistical Language Model (SLM):

A language model estimates the probability distribution over sequences of words. Given a sequence of words $w_1, w_2, w_3, \ldots, w_n$, a language model computes:

$$P(w_1, w_2, \ldots, w_n) = \prod_{i=1}^{n} P(w_i \mid w_1, \ldots, w_{i-1})$$

To calculate the probability of a sentence (or sequence of words),we multiply the conditional probability of each word given the previous words.

Chapter 3: N-gram Language Models , Jurafsky, D., & Martin, J. H. (2023). *Speech and Language Processing* (3rd ed. draft). Stanford University.
https://web.stanford.edu/~jurafsky/slp3/

Large Language Models

Predict the next word

I want to drink a hot cup of ____

Training Corpus

1. I want to drink a hot cup of coffee
2. Every morning, I drink a hot cup of coffee before work
3. He prefers a hot cup of tea in the evening
4. She needs a hot cup of coffee to wake up
5. After dinner, they drank a hot cup of tea
6. I always start my day with a hot cup of black coffee
7. On cold days, people enjoy a hot cup of cocoa
8. I want to drink a hot cup of coffee quickly
9. They like to have a hot cup of herbal tea after yoga
10. I usually order a hot cup of coffee at Starbucks

Large Language Models

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6. I always start my day with a hot cup of black coffee
7. On cold days, people enjoy a hot cup of cocoa
8. I want to drink a hot cup of coffee quickly
9. They like to have a hot cup of milk after yoga
10. I usually order a hot cup of coffee at Starbucks

Derivation

1. Expression to find the next word

$$P(w_1, \ldots, w_9) \approx \prod_{i=1}^{9} P(w_i \mid w_{i-2}, w_{i-1})$$

2. Chain rule of probability

$$P(w_1) \cdot P(w_2 \mid w_1) \cdot P(w_3 \mid w_1, w_2) \cdot P(w_4 \mid w_2, w_3) \cdot \cdots \cdot P(w_9 \mid w_7, w_8)$$

3. If we assume the next word is coffee

$$P(\text{"I want to drink a hot cup of coffee"}) = P(w_1, w_2, \ldots, w_9)$$

$$= P(w_1) \cdot P(w_2 \mid w_1) \cdot P(w_3 \mid w_1, w_2) \cdot \cdots \cdot P(w_9 \mid w_1, \ldots, w_8)$$

Phrase	Count	Probability
cup of coffee	5	= 5/10 (0.5)
cup of tea	2	= 2/10 (0.2)
cup of milk,	1	= 1/10 (0.1)
Total ("cup of X")	10	

4. The predicted word would be coffee

The Issues with Statistical Model

History, Development, and Principles of Large Language Models—An Introductory Survey

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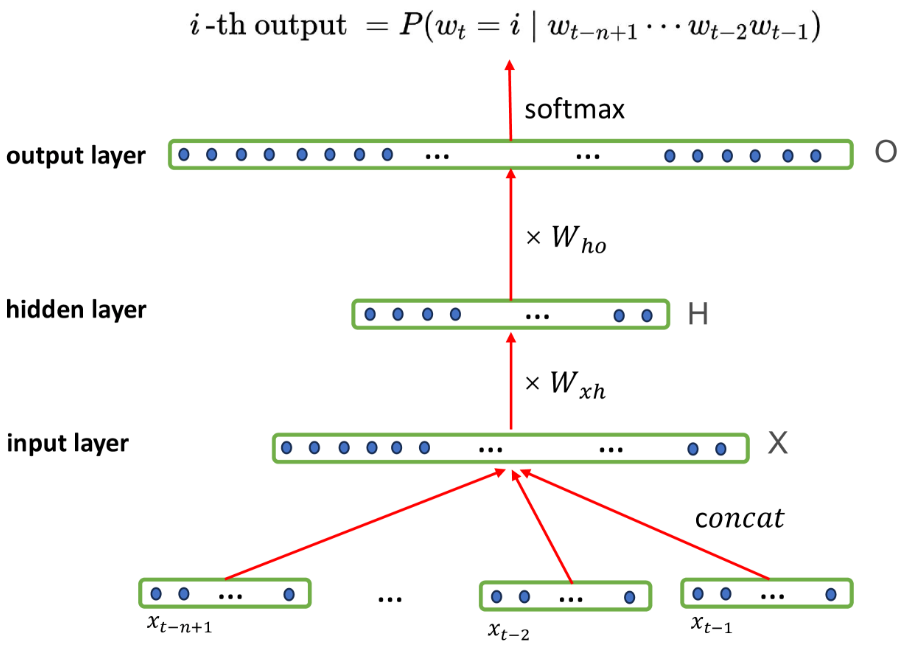
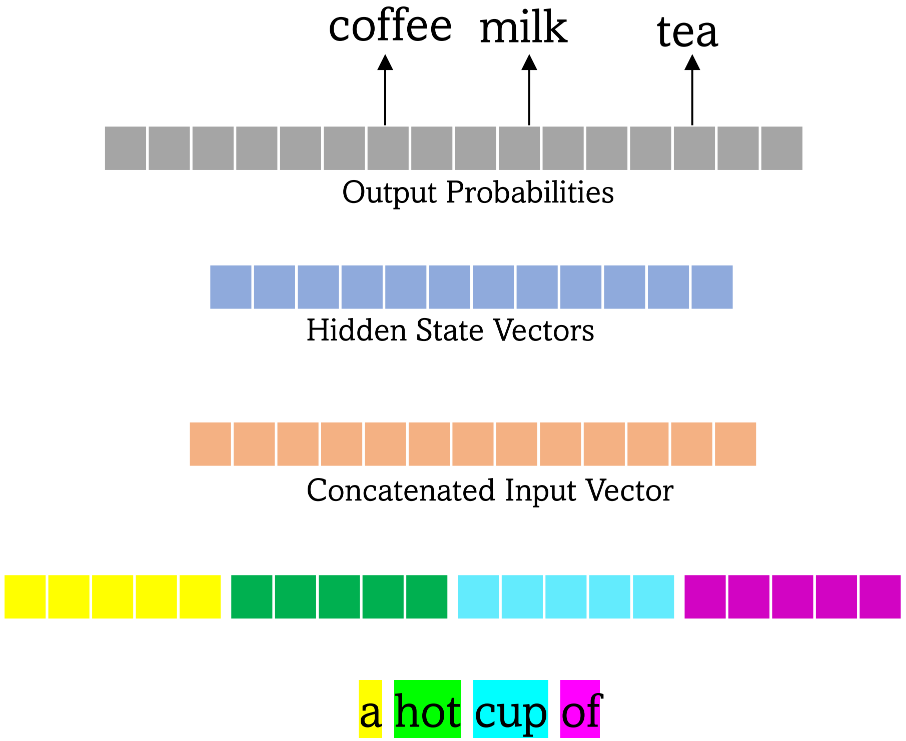
conditional probabilities, it is necessary to pre-compute and save $C(X)$required for the conditional probability computation, where X is a sentence of length n. The number of possible sentences X grows exponentially with the size of the vocabulary. For instance, with 1000 different words, there exist 1000^n potential sequences of length n. However, excessively large values of n pose storage limitations. Typically, n is confined to 2 or 3, causing each word to relate to only its first 1 or 2 preceding words, ultimately leading to a reduction in the model's accuracy.

Large Language Models

Neural Language Models

Neural Language Models: NLMs (Bengio et al., 2000; Mikolov et al., 2010; Kombrink et al., 2011) leverage neural networks to predict the probabilities of subsequent words within sequences. They effectively handle longer sequences and mitigate the limitations associated with small n in SLMs. Before delving into neural networks, let's grasp the concept of

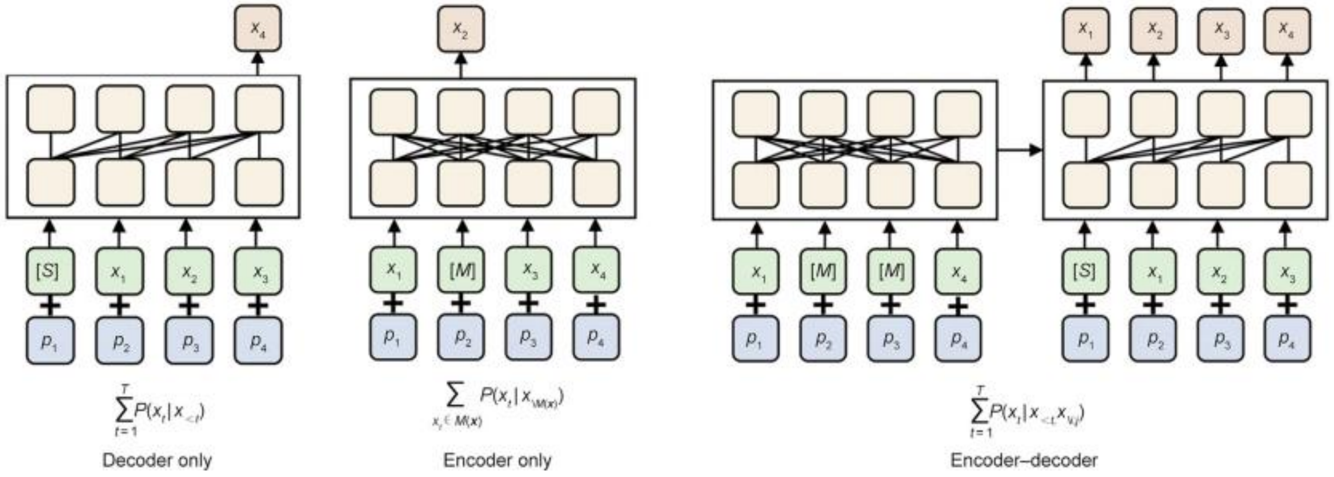




Large Language Models

Large Language Model

Pre-trained Language Model: PLMs undergo initial training using an extensive volume of unlabeled text, enabling them to grasp fundamental language structures such as vocabulary, syntax, semantics, and logic — a phase termed pre-training. Subsequently, this comprehensive language model can be applied to various NLP tasks like machine translation, text summarization, and question-answering systems. To optimize its performance, models need to be trained a second time on a smaller dataset customized for a specific downstream task — a phase known as fine-tuning. This is the "pre-training and fine-tuning" learning paradigm. We can use a visual example to understand the "pre-training and fine-tuning", as follows: in



GPT

BERT

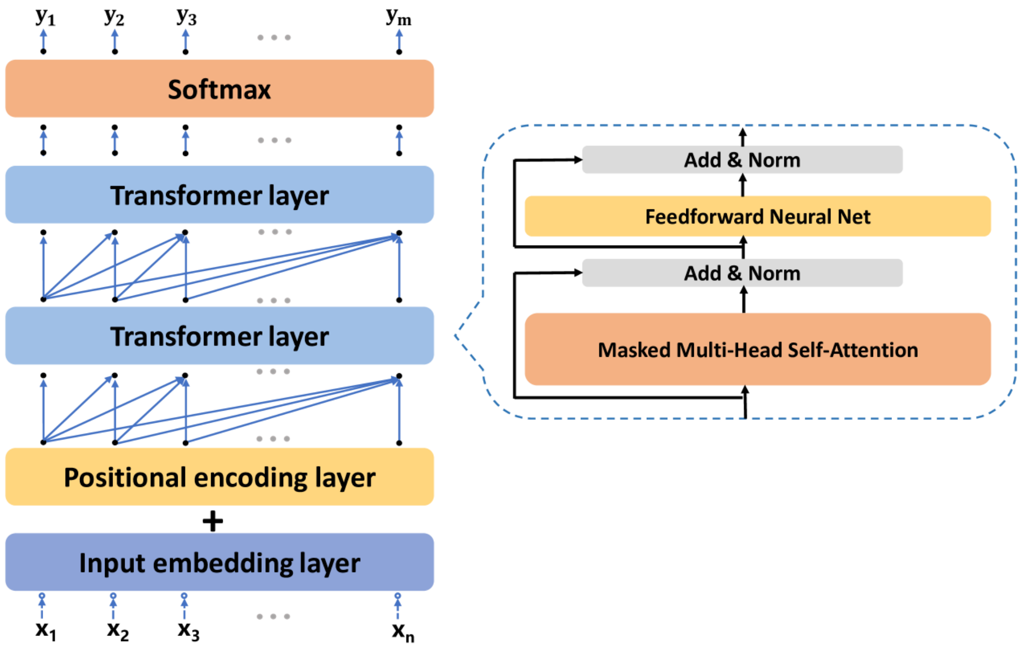
Bidirectional and Auto-Regressive Transformers (BART)

Wang, H., Li, J., Wu, H., Hovy, E., & Sun, Y. (2023). Pre-trained language models and their applications. *Engineering*, *25*, 51-65.

Large Language Models

"A Large Language Model is a transformer-based neural network trained to model the probability distribution over sequences of words or tokens, enabling tasks such as text generation, summarization, translation, and question answering."

- **Bommasani et al., 2021**, *On the Opportunities and Risks of Foundation Models*



Examples: GPT-4, BERT

LLaMA, Claude, Gemini, Mistral

Large Language Models

LLM Datasets

Dataset Name	Size	Dataset Information	Languages	URL
Common Crawl	Petabyte-scale	Web pages, blogs, news articles, forums	100+	https://commoncrawl.org
The Pile	825 GB	Academic papers, books, GitHub, StackExchange, Wikipedia, PubMed, etc.	Primarily English	https://pile.eleuther.ai
Wikipedia	~20 GB (English)	Encyclopedic articles	300+	https://dumps.wikimedia.org
OpenWebText2	~40 GB	High-quality content from web links in Reddit	Primarily English	https://github.com/EleutherAI/openwebtext2
RedPajama	~1.2 TB	Common Crawl, C4, Books, GitHub, Wikipedia, StackExchange	Primarily English	https://www.together.xyz/blog/redpajama
The Stack	3.1 TB	Source code from GitHub in 30+ programming languages	30+ (programming languages)	https://huggingface.co/datasets/bigcode/the-stack
arXiv + PubMed	10+ GB	Scientific papers in physics, math, medicine, biology	Primarily English	https://pubmed.ncbi.nlm.nih.gov/download https://www.kaggle.com/datasets/Cornell-University/arxiv

Large Language Models Evaluation

Total Cats = 6 +1

Total Dogs = 2 + 12

True Positive & True Negative: When Actual and Predicted values are same.

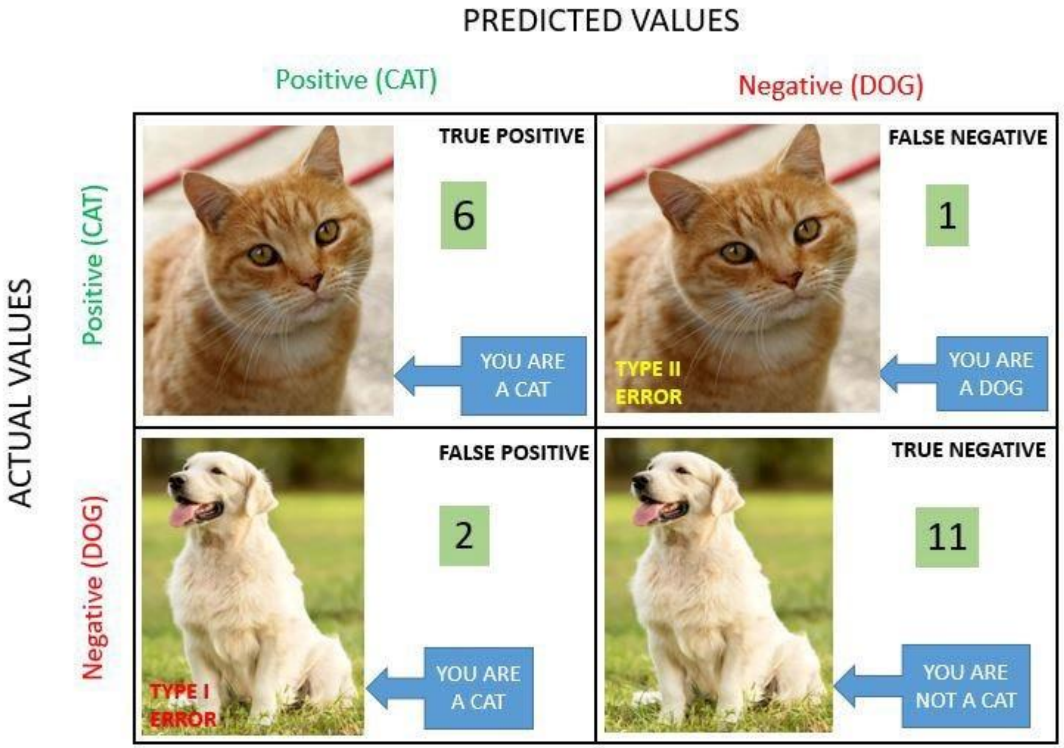
TP = 6, TN = 11

False Positive: When the actual Value was negative “dog” and the system predicted positive “cat “.

FP = 2

False Negative: When the actual value was “cat” and the system is predicted it “dog”

FN = 1



Confusion Matrix

Large Language Models Evaluation

TP = 6, TN = 11

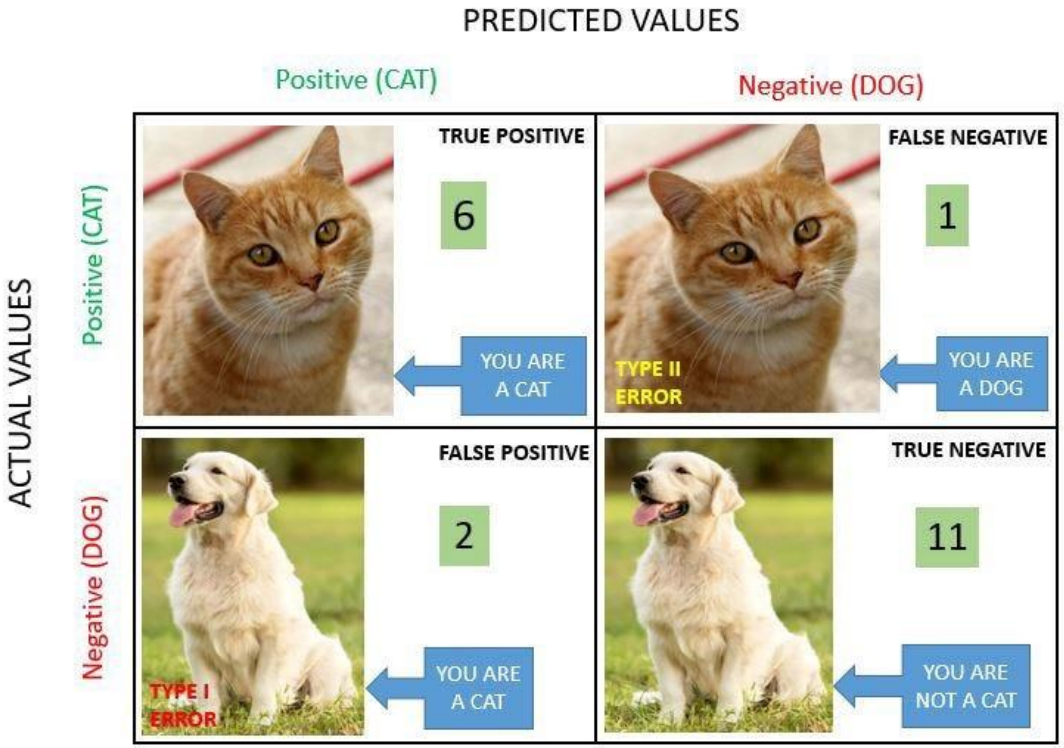
FP = 2, FN = 1

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + FP + FN}$$

$$Precision = \frac{\text{TP}}{\text{TP} + FP}$$

$$Recall = \frac{\text{TP}}{\text{TP} + FN}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall}$$



Confusion Matrix

Large Language Models Evaluation

BLEU (Bilingual Evaluation Understudy) – *compares n-gram overlaps between prediction and reference*

$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right).$$

Papineni, K., Roukos, S., Ward, T., & Zhu, W. J. (2002).

Let's calculate it for bigram

$$\text{BLEU-2} = \text{BP} \cdot \exp\left(\frac{1}{2}(\log p_1 + \log p_2)\right)$$

Actual: The cat is on the mat

Unigram: the, cat, is, on, the, mat

Bigram: the cat, cat is, is on, on the, the mat

Predicted: The cat sat on the mat

$$p1 = \frac{5}{6}$$

Unigram: the, cat, sat, on, the, mat

Bigram: the cat, cat sat, sat on, on the, the mat

$$p2 = \frac{3}{6}$$

$$BLEU - 2 = 1 * e^{\left(\frac{1}{2}\left(log\frac{5}{6} + log\frac{3}{6}\right)\right)}$$

$$\boxed{0.645}$$

BP stands for **Brevity Penalty**. It is used to penalize machine-generated text that is **too short** compared to the reference

BLEU score is precision-oriented (counts how many n-grams match), but without a length penalty, a model could **cheat** by just outputting short sequences.

BP solves this by lowering the BLEU score when the generated output is shorter than the reference.

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{(1-\frac{r}{c})} & \text{if } c \leq r \end{cases}$$

Large Language Models Evaluation

ROUGE (Recall-Oriented Understudy for Gisting Evaluation) Score

Lin, C.-Y. (2004).
ROUGE: A Package for Automatic Evaluation of Summaries

ROUGE (Recall-Oriented) is used in summarization. The most common are:

- **ROUGE-1**: Overlap of unigrams

$$\textbf{ROUGE-1(Precision)} = 5/6,\ \textbf{ROUGE-1(Recall)} = 5/6,\ \textbf{ROUGE-1(F1)} = \frac{2 * \frac{5}{6} * \frac{5}{6}}{\frac{5}{6} + \frac{5}{6}}$$

- **ROUGE-2**: Overlap of bigrams

$$\textbf{ROUGE-2(Precision)} = 3/6,\ \textbf{ROUGE-1(Recall)} = 3/6,\ \textbf{ROUGE-1(F1)} = \frac{2 * \frac{3}{6} * \frac{3}{6}}{\frac{3}{6} + \frac{3}{6}}$$

- **ROUGE-L**: Longest Common Subsequence (LCS)

  Longest Sequence (5) = The cat [mismatch/gap] on the mat

$$\textbf{ROUGE-L(Precision)} = 5/6,\ \textbf{ROUGE-1(Recall)} = 5/6,\ \textbf{ROUGE-1(F1)} = \frac{2 * \frac{5}{6} * \frac{5}{6}}{\frac{5}{6} + \frac{5}{6}}$$

Some Benchmarks

Model	MMLU	HumanEval	GSM8K	TruthfulQA
GPT-4	86.40%	88.00%	94.00%	59.00%
Claude 2	81.60%	71.00%	88.00%	58.00%
Gemini 1.5 Pro	84.00%	83.00%	92.00%	62.00%
Claude 3 Opus	88.70%	90.00%	95.00%	68.00%
GPT-3.5	70.00%	48.10%	57.10%	47.00%
LLaMA 2 70B	79.00%	67.00%	83.00%	52.00%
Mixtral 8x7B	84.10%	74.00%	87.00%	58.50%
Mistral 7B	70.00%	55.00%	65.00%	47.00%
Command R+	75.20%	60.50%	78.00%	53.10%
Gemma 7B	65.00%	45.00%	58.00%	41.00%

MMLU (Massive Multitask Language Understanding)
- **What it tests:** Knowledge and reasoning across 57 academic subjects like history, law, math, medicine, etc.
- **Use case:** Checks how well a model performs on real-world, high school to graduate-level exams.

HumanEval
- **What it tests:** Code generation and reasoning.
- **Use case:** Given a prompt (like a function definition), the model needs to generate correct Python code that passes test cases.

GSM8K (Grade School Math 8K)
- **What it tests:** Basic arithmetic and word problem-solving.
- **Use case:** Models solve grade-school level math problems using step-by-step reasoning.

TruthfulQA
- **What it tests:** The ability to give **truthful** answers, especially in tricky or misleading questions.
- **Use case:** The model is asked questions where giving a common but false answer is easy (e.g., urban myths).

Thanks for your time