Getting Started with Llama3.2

Lucas Soares

12-02-2024

Methodology Notes

Methodology Notes

1. Presentation Block

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2. Notebook Demo

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3. Quick Q&A + Summary

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4. Optional Exercise During Q&A

Methodology Notes

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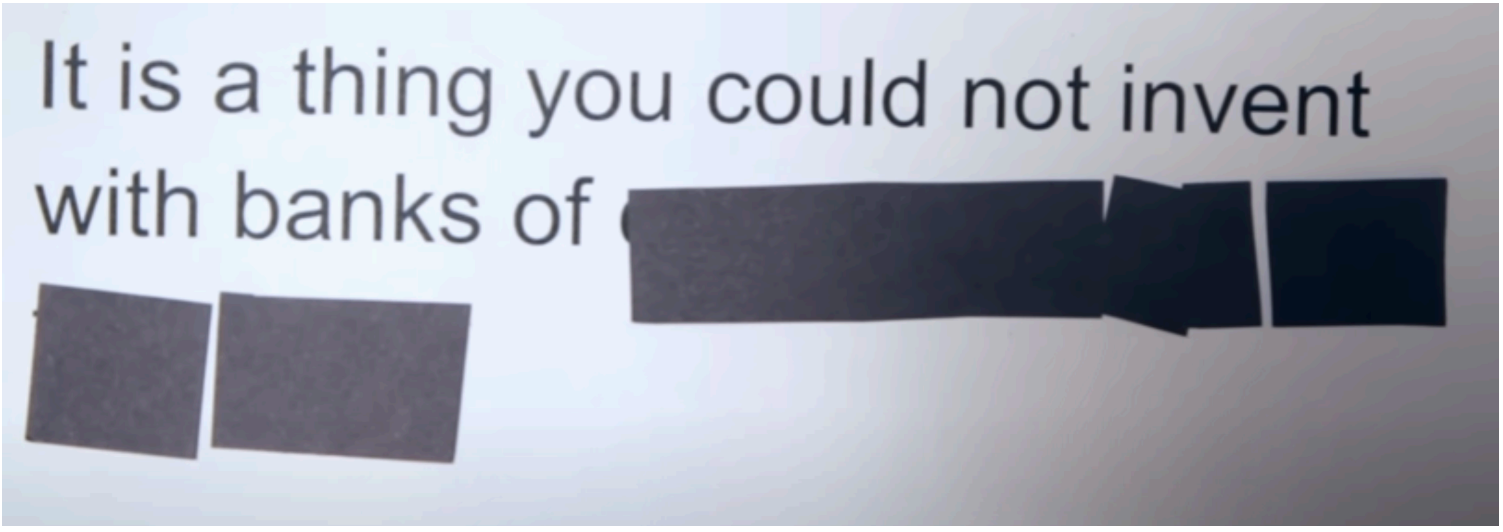
3. Quick Q&A + Summary
4. Optional Exercise During Q&A
5. Repeat

LLMs Predict the Next Word



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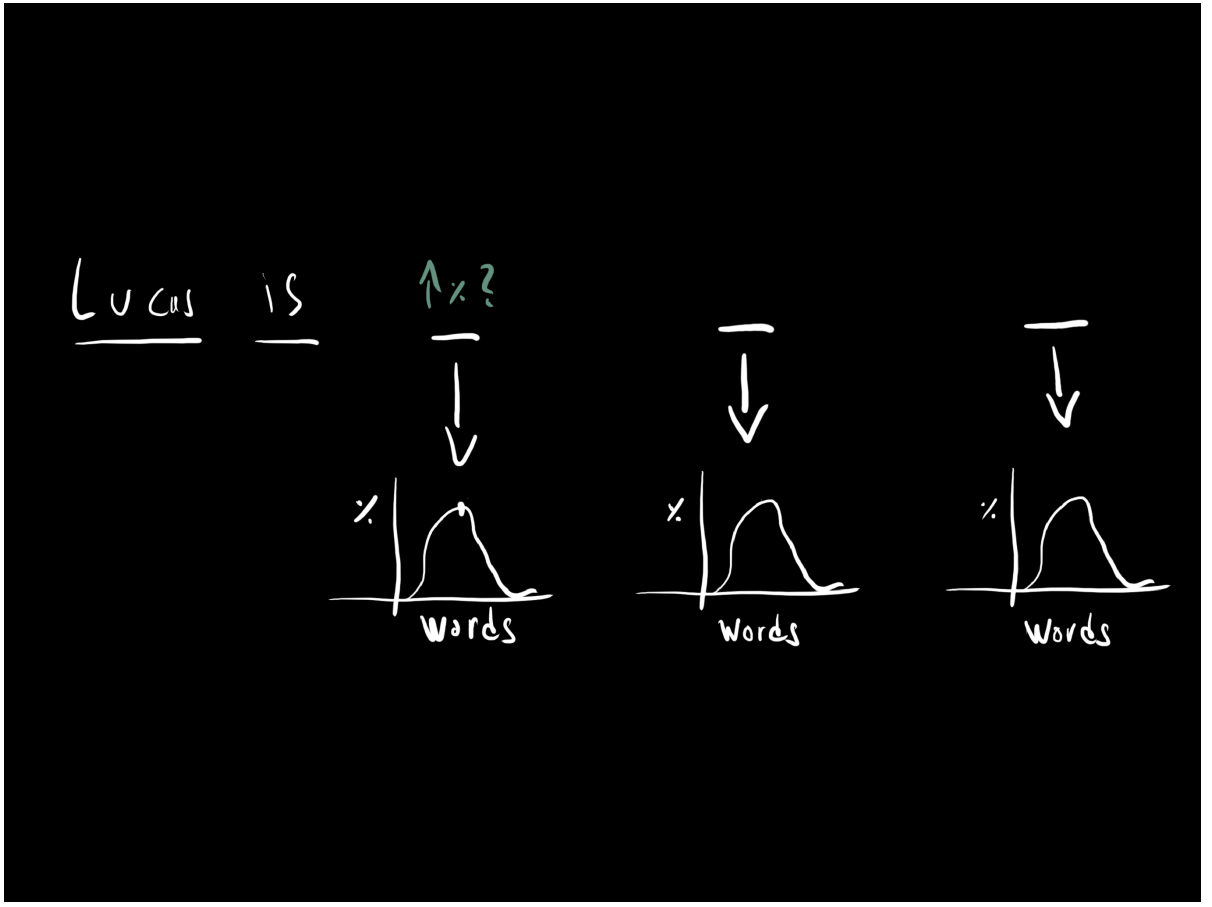

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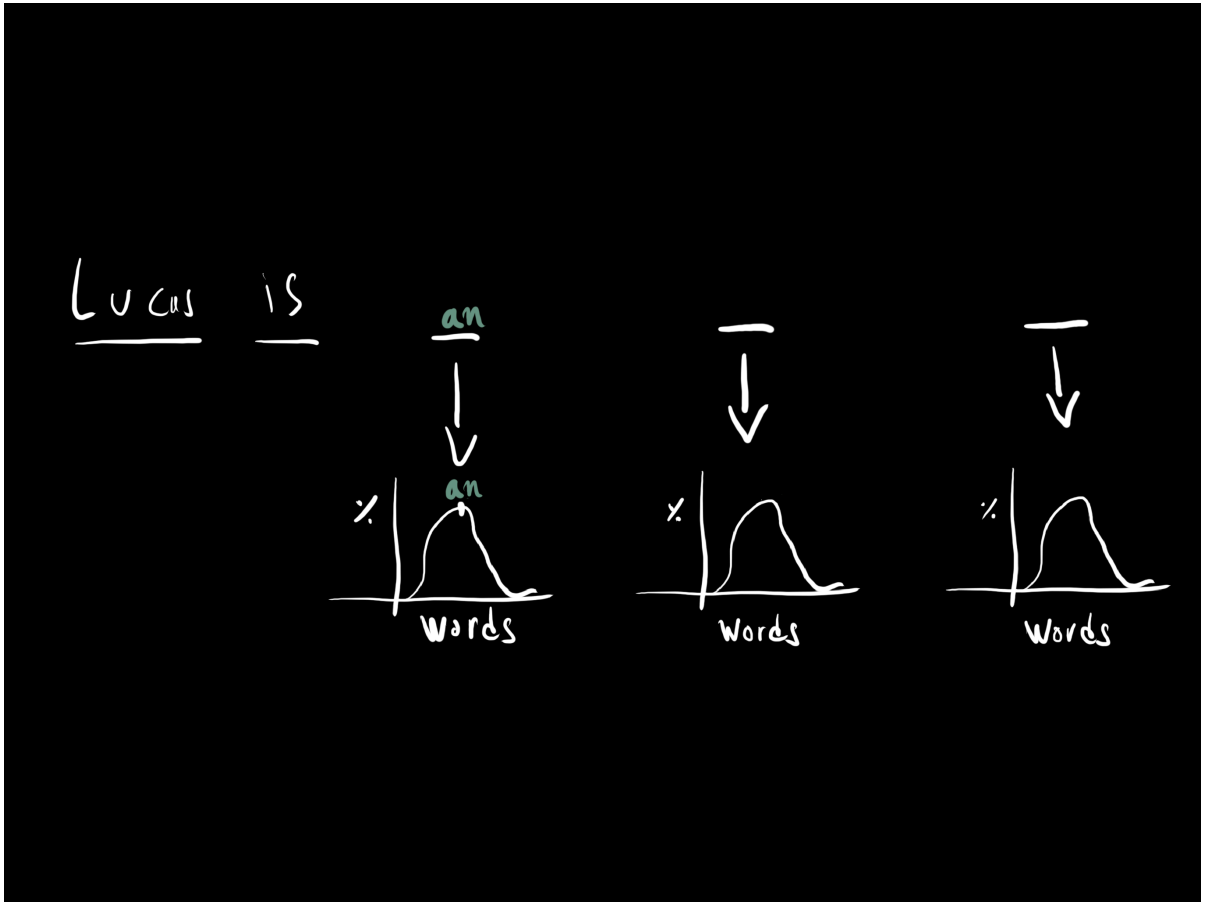

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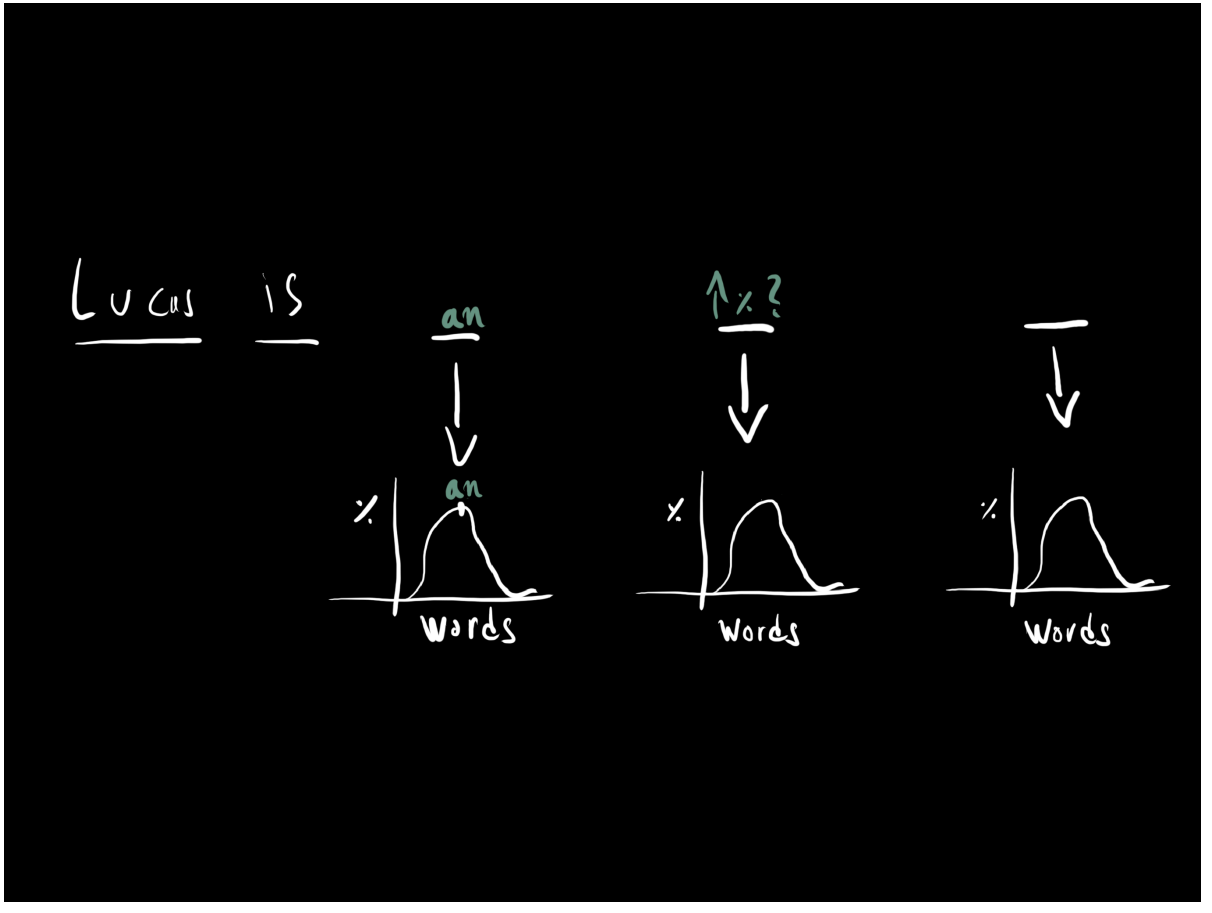

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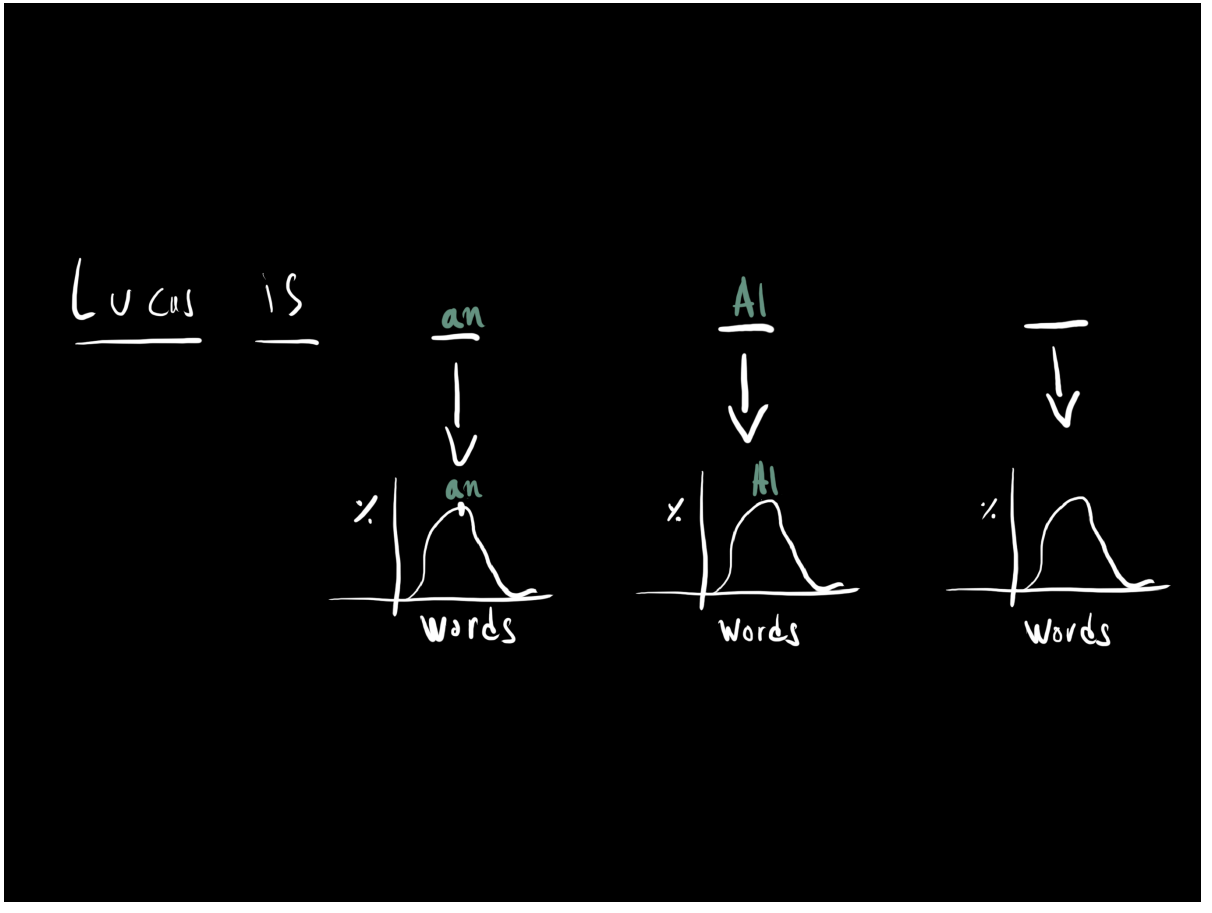

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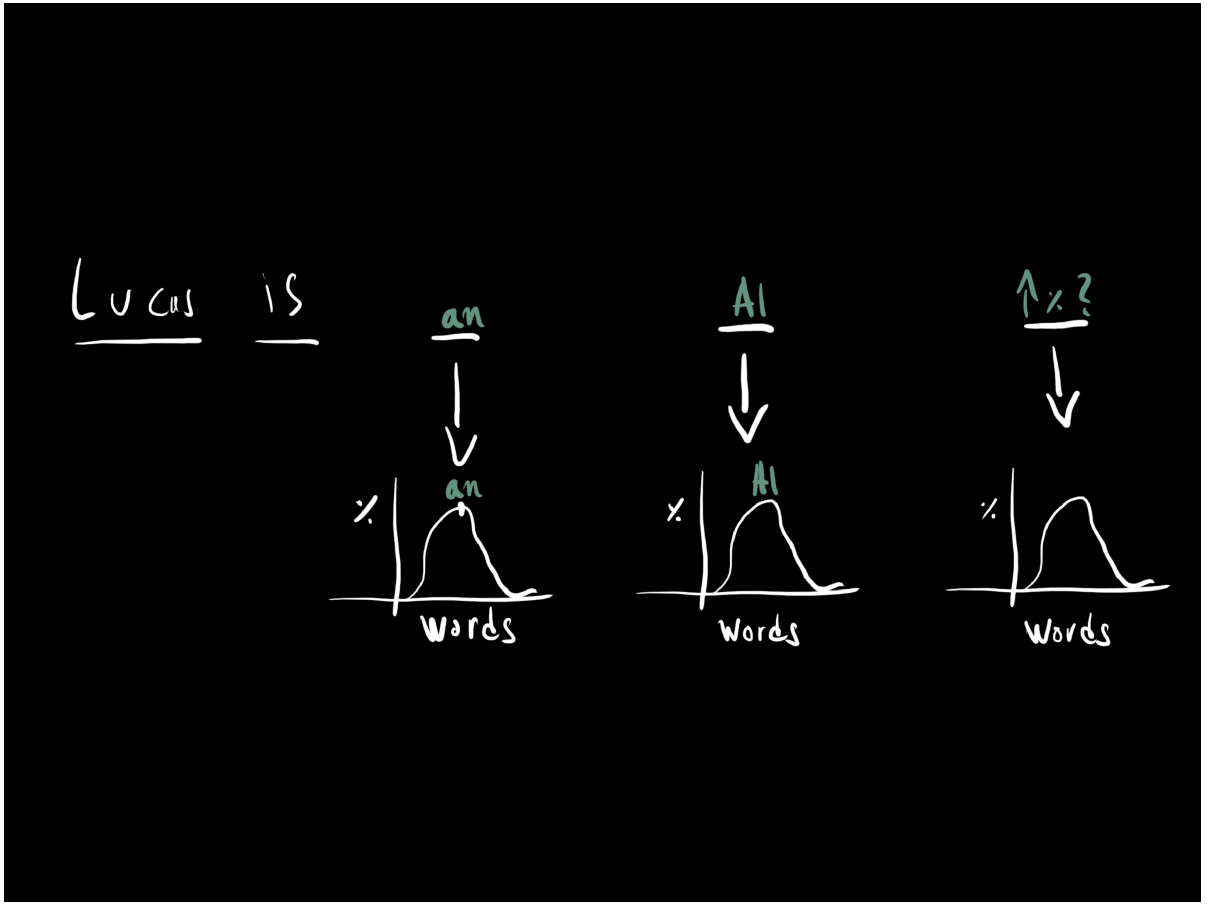
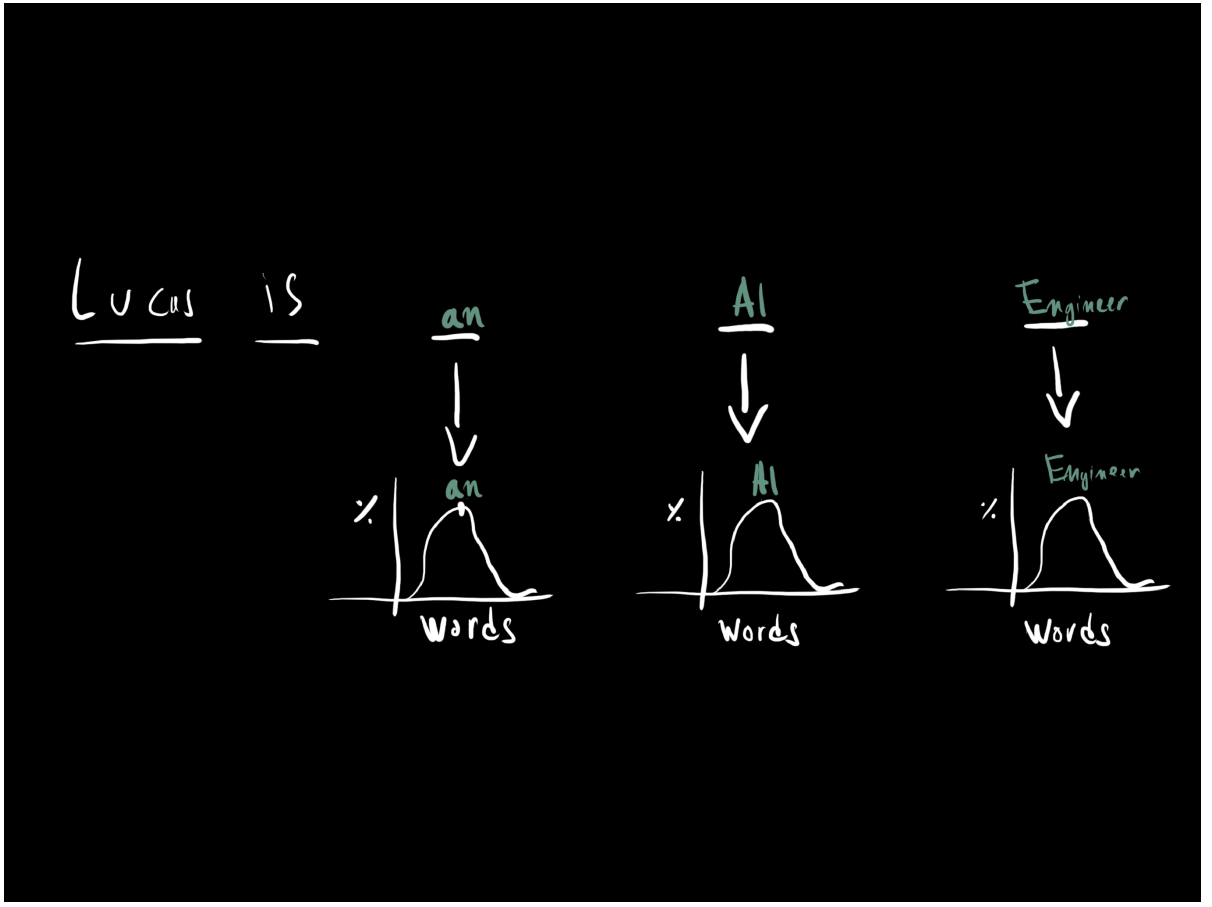
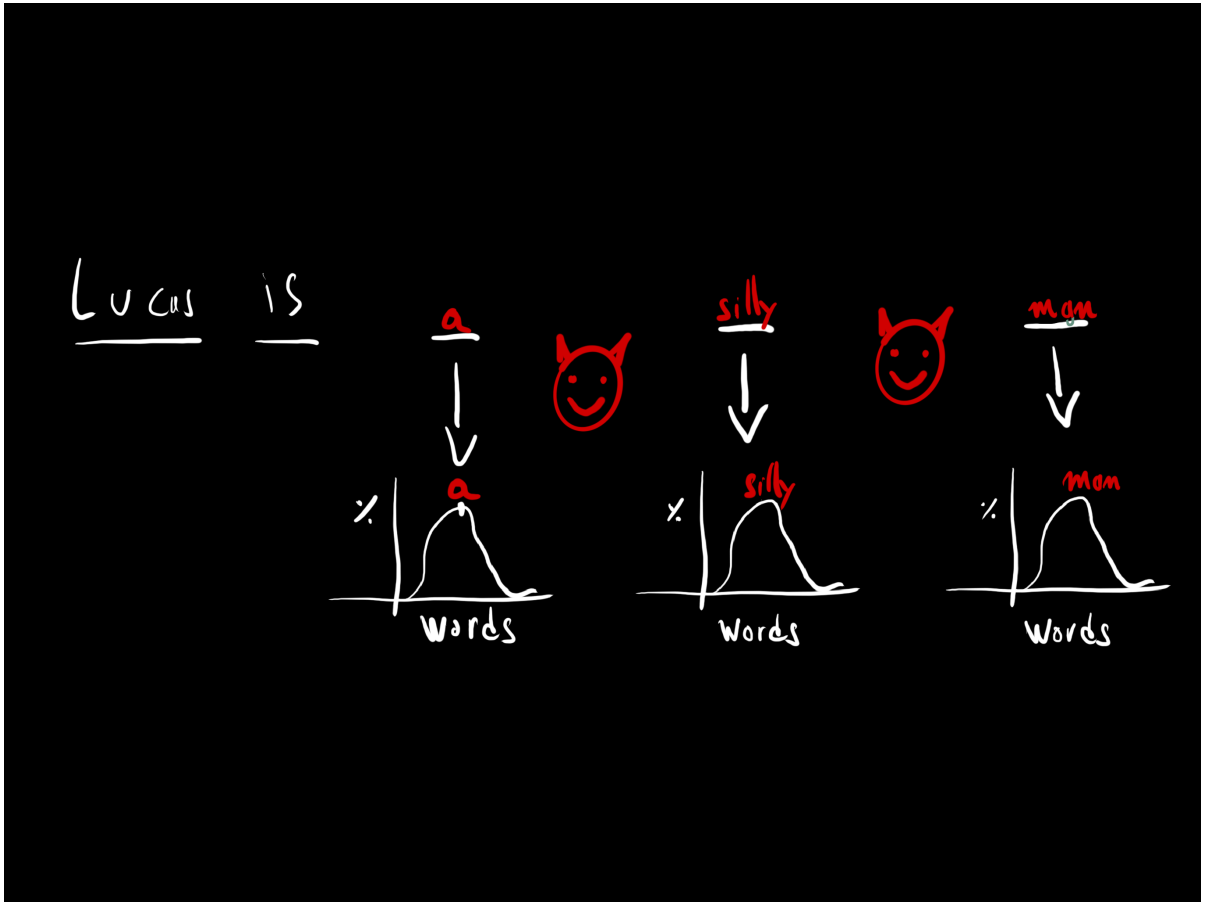
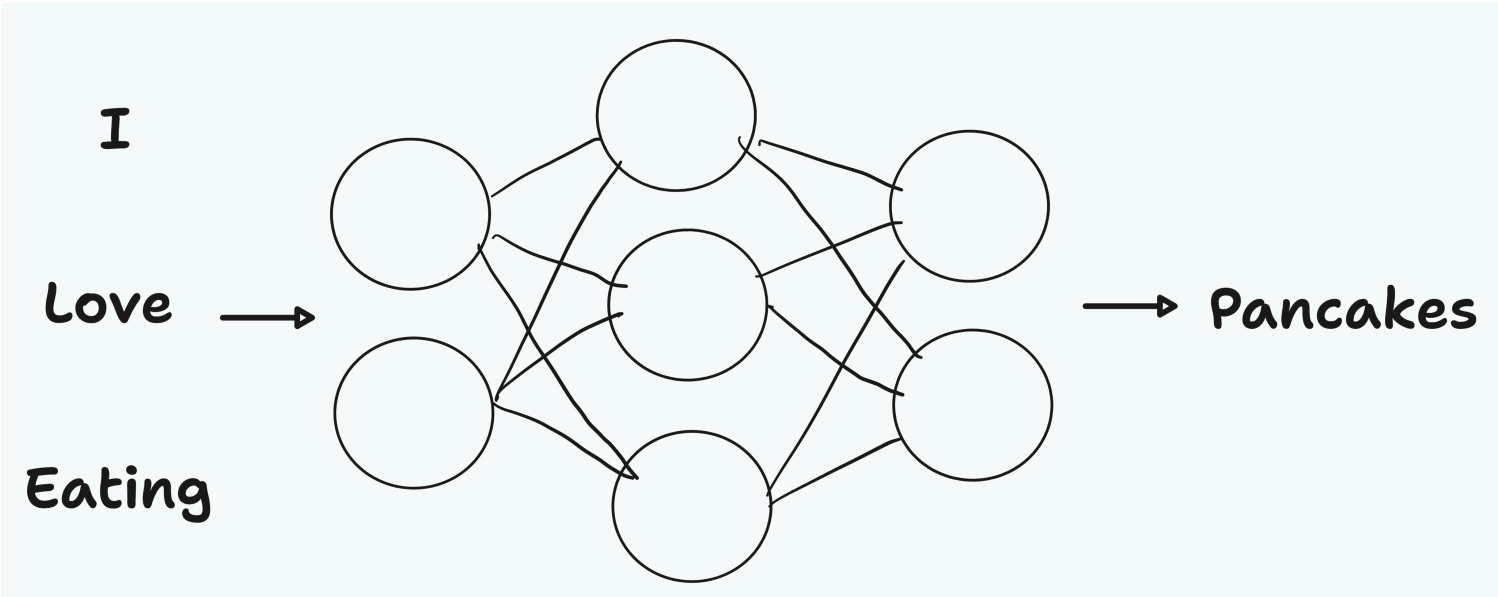


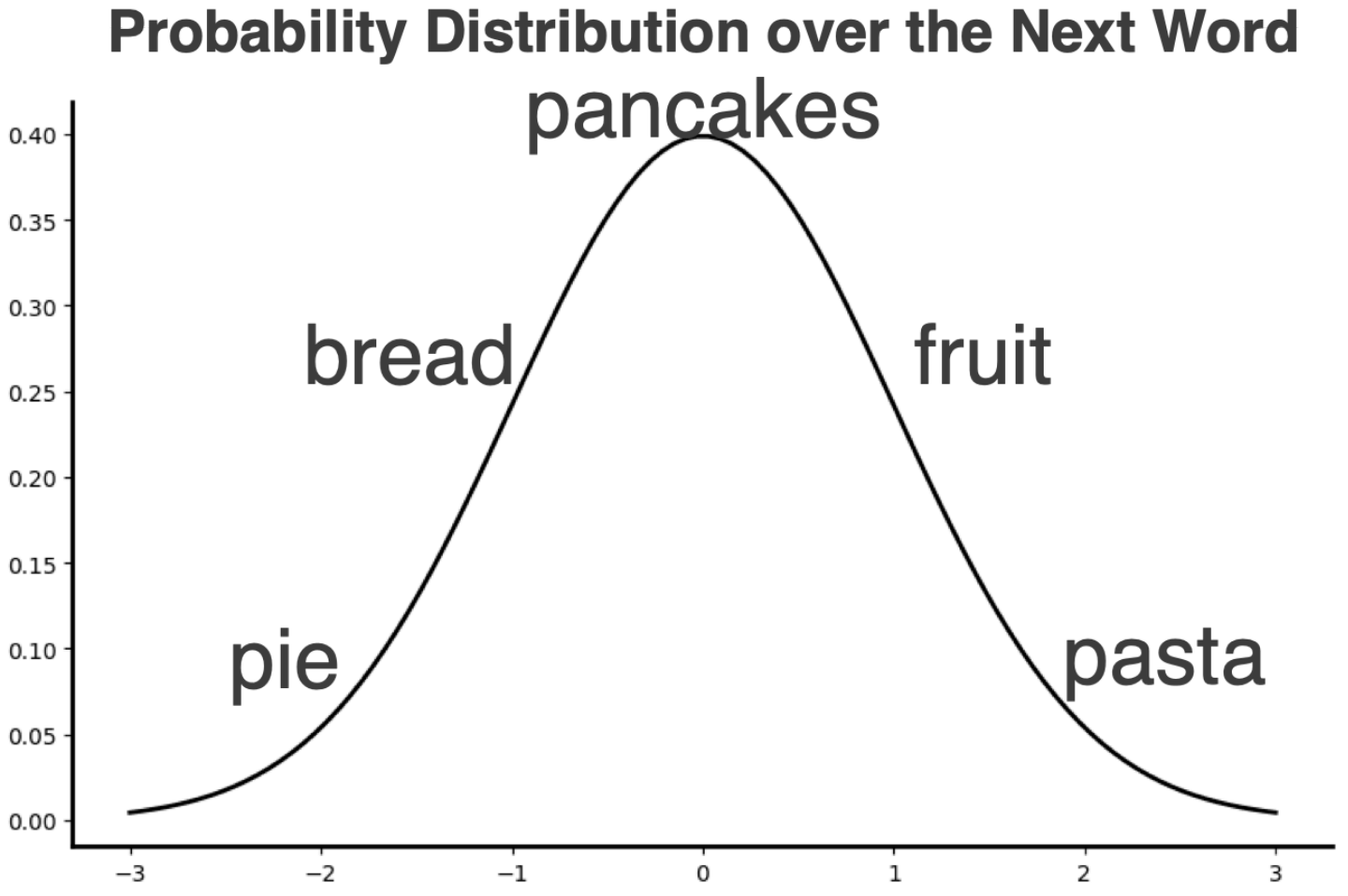
LLMs Predict the Next Word



LLMs Predict the Next Word




I
Love
Eating
Pancakes


Probability Distribution over the Next Word
pancakes
bread
fruit
pie
pasta
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−3
−2
−1
0
1
2
3

Introduction to Llama 3.2

Llama 3.2: Revolutionizing edge AI and vision with open, customizable models

September 25, 2024 • 15 minute read

Llama3.2 Release

- LLM Released by Meta in July of 2024

Llama3.2 Release

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- Open source with a Commercial license (just like Llama2 & Llama3)

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- Llama 3.2 Repo

Incredible Performance in 4 sizes

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Incredible Performance in 4 sizes

- Llama3.2 is OPEN SOURCE
- Released in 4 sizes: 1B, 3B for text and 11B & 90B for the vision models.

Incredible Performance in 4 sizes

- Llama3.2 is OPEN SOURCE
- Released in 4 sizes: 1B, 3B for text and 11B & 90B for the vision models.
- Incredible evaluation performances for all models.

Lightweight instruction-tuned benchmarks

Category / Benchmark	Llama 3.2 1B	Llama 3.2 3B	Gemma 2 2B IT (measured)	Phi-3.5-mini IT (measured)
General — MMLU (5-shot)	49.3	63.4	57.8	**69.0**
Open-rewrite eval (0-shot, rougeL)	**41.6**	40.1	31.2	34.5
TLDR9+ (test, 1-shot, rougeL)	16.8	**19.0**	13.9	12.8
IFEval	59.5	**77.4**	61.9	59.2
Tool Use — BFCL V2	25.7	**67.0**	27.4	58.4
Nexus	13.5	**34.3**	21.0	26.1
Math — GSM8K (8-shot, CoT)	44.4	77.7	62.5	**86.2**
MATH (0-shot, CoT)	30.6	**48.0**	23.8	44.2
Reasoning — ARC Challenge (0-shot)	59.4	78.6	76.7	**87.4**
GPQA (0-shot)	27.2	**32.8**	27.5	31.9
Hellaswag (0-shot)	41.2	69.8	61.1	**81.4**
Long Context — InfiniteBench/En.MC (128k)	38.0	63.3	—	39.2
InfiniteBench/En.QA (128k)	20.3	19.8	—	11.3
NIH/Multi-needle	75.0	84.7	—	52.7
Multilingual — MGSM (0-shot, CoT)	24.5	**58.2**	40.2	49.8

Let's not forget Llama 3.1!

Llama 3.1 8B & 70B

Category / Benchmark	Llama 3.1 8B	Gemma 2 9B IT	Mistral 7B Instruct	Llama 3.1 70B	Mixtral 8x22B Instruct	GPT 3.5 Turbo
General MMLU (0-shot, CoT)	73.0	72.3 (5-shot, non-CoT)	60.5	86.0	79.9	69.8
MMLU PRO (5-shot, CoT)	48.3	-	36.9	66.4	56.3	49.2
IFEval	80.4	73.6	57.6	87.5	72.7	69.9
Code HumanEval (0-shot)	72.6	54.3	40.2	80.5	75.6	68.0
MBPP EvalPlus (base) (0-shot)	72.8	71.7	49.5	86.0	78.6	82.0
Math GSM8K (8-shot, CoT)	84.5	76.7	53.2	95.1	88.2	81.6
MATH (0-shot, CoT)	51.9	44.3	13.0	68.0	54.1	43.1
Reasoning ARC Challenge (0-shot)	83.4	**87.6**	74.2	94.8	88.7	83.7
GPQA (0-shot, CoT)	32.8	-	28.8	46.7	33.3	30.8
Tool use BFCL	76.1	-	60.4	84.8	-	**85.9**
Nexus	38.5	30.0	24.7	56.7	48.5	37.2
Long context ZeroSCROLLS/QuALITY	81.0	-	-	90.5	-	-
InfiniteBench/En.MC	65.1	-	-	78.2	-	-
NIH/Multi-needle	98.8	-	-	97.5	-	-
Multilingual Multilingual MGSM (0-shot)	68.9	53.2	29.9	86.9	71.1	51.4

Llama 3.1 405B Rivals Closed Source Models

Category / Benchmark	Llama 3.1 405B	Nemotron 4 340B Instruct	GPT-4 (0125)	GPT-4 Omni	Claude 3.5 Sonnet
General MMLU (0-shot, CoT)	88.6	78.7 (non-CoT)	85.4	**88.7**	88.3
MMLU PRO (5-shot, CoT)	73.3	62.7	64.8	74.0	**77.0**
IFEval	**88.6**	85.1	84.3	85.6	88.0
Code HumanEval (0-shot)	89.0	73.2	86.6	90.2	**92.0**
MBPP EvalPlus (base) (0-shot)	88.6	72.8	83.6	87.8	**90.5**
Math GSM8K (8-shot, CoT)	**96.8**	92.3 (0-shot)	94.2	96.1	96.4 (0-shot)
MATH (0-shot, CoT)	73.8	41.1	64.5	**76.6**	71.1
Reasoning ARC Challenge (0-shot)	**96.9**	94.6	96.4	96.7	96.7
GPQA (0-shot, CoT)	51.1	-	41.4	53.6	**59.4**
Tool use BFCL	88.5	86.5	88.3	80.5	**90.2**
Nexus	**58.7**	-	50.3	56.1	45.7
Long context ZeroSCROLLS/QuALITY	**95.2**	-	**95.2**	90.5	90.5
InfiniteBench/En.MC	**83.4**	-	72.1	82.5	-
NIH/Multi-needle	98.1	-	**100.0**	**100.0**	90.8
Multilingual Multilingual MGSM (0-shot)	**91.6**	-	85.9	90.5	**91.6**

Llama3.1 Technical Details

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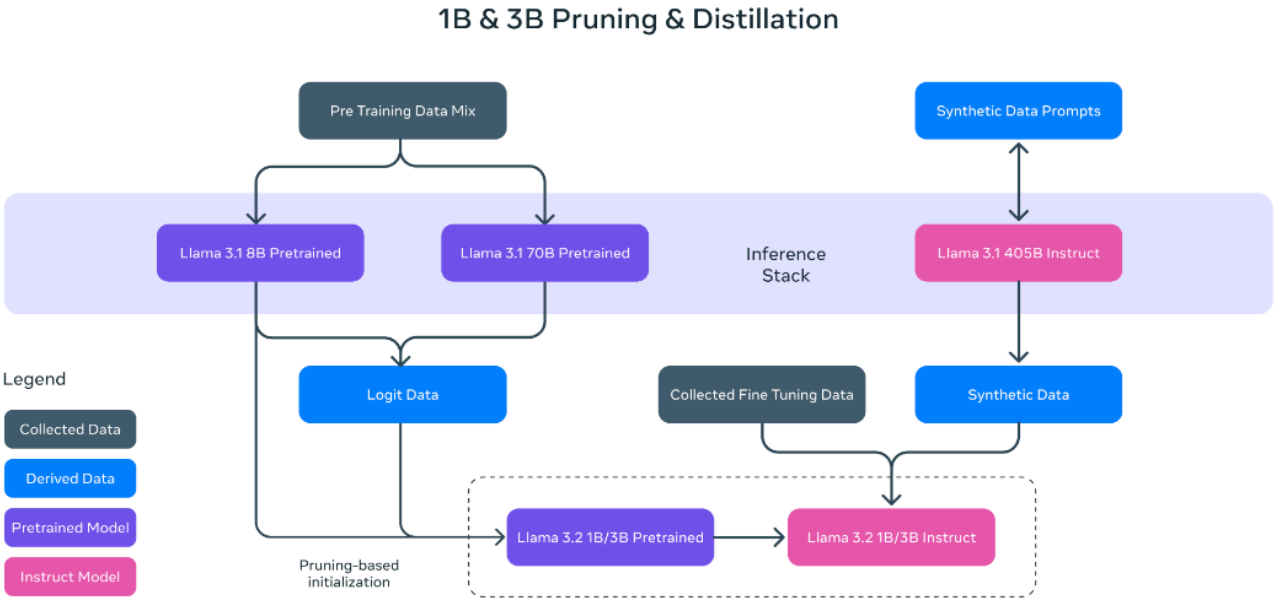
- Context length: 128k tokens
- System level approach for responsible development

Meta AI Llama3.2 Release Blog Post

From Llama 3.1 to Llama 3.2 with Knowledge Distillation & Pruning



[Meta AI Llama3.2 Release Blog Post]

Training Llama 3.2 Vision Models

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1. Architecture Adaptation:
    - Integrated image processing capabilities while preserving text abilities through adapter weights, cross-attention layers, and frozen language model parameters.

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2. Training Pipeline:
    - Built upon Llama 3.1 models through pretraining on image-text pairs followed by domain-specific fine-tuning.
3. Post-Training Alignment:
    - Enhanced model safety and performance through supervised fine-tuning with rejection sampling and safety-focused data.

Notebook Demo - Introduction to Llama3.2

Query Your Docs Locally with Llama3.2

- Need for LLMs with access to context-relevant data.

Query Your Docs Locall with Llama3.2

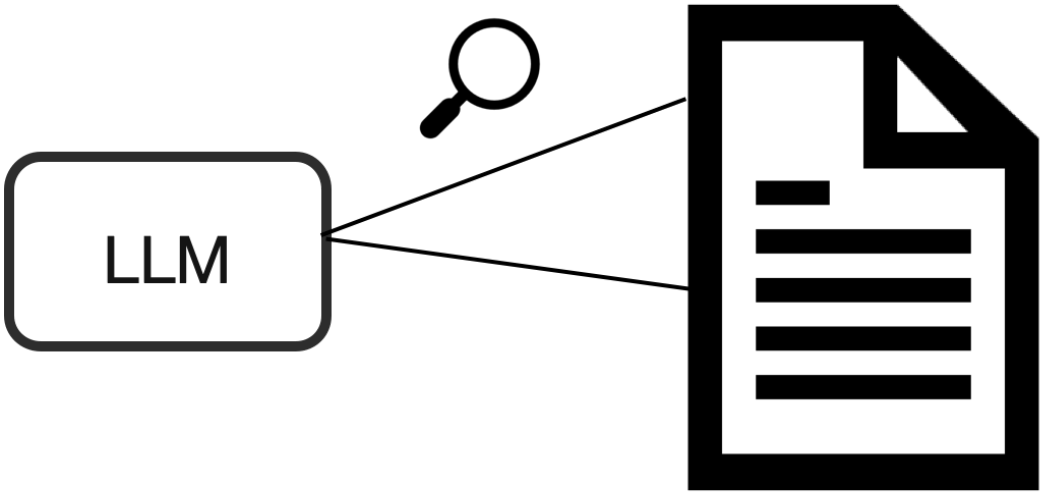
- Privacy concern with closed source LLMs.

Query Your Docs Locall with Llama3.2

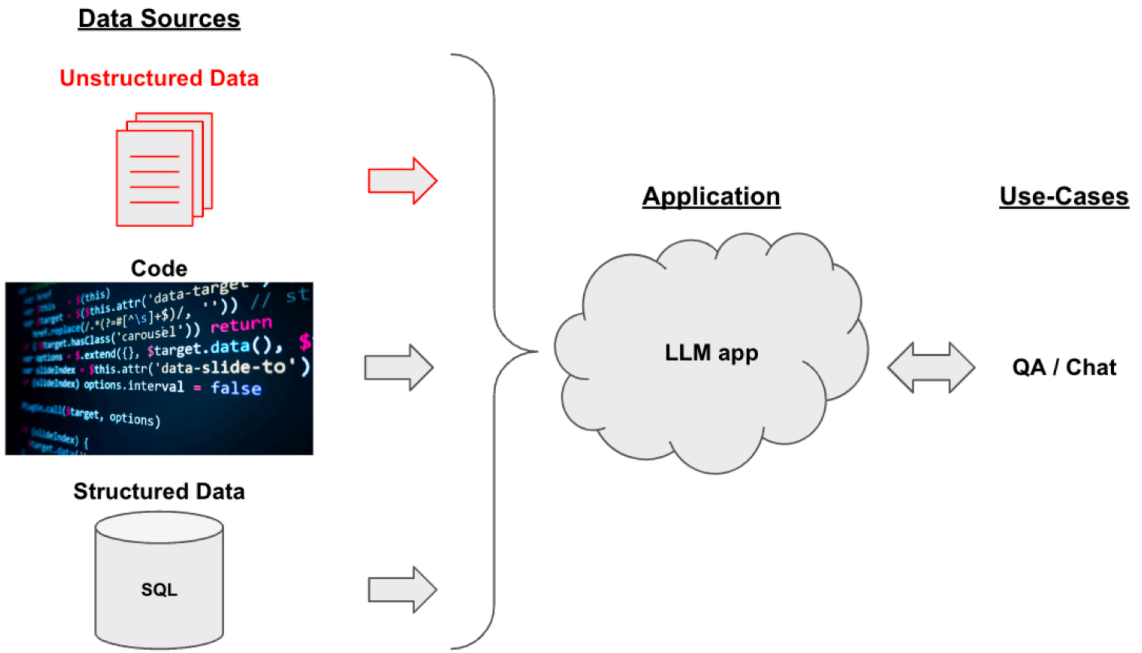
- Solution? Llama3.2!

RAG with Llama3.2

- RAG - Retrieval Augmented Generation



RAG with Llama3.2



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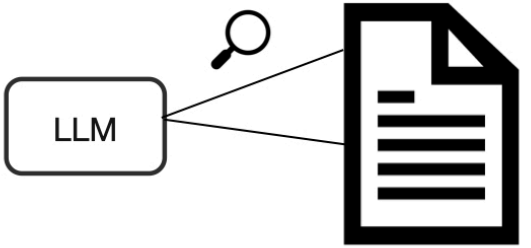
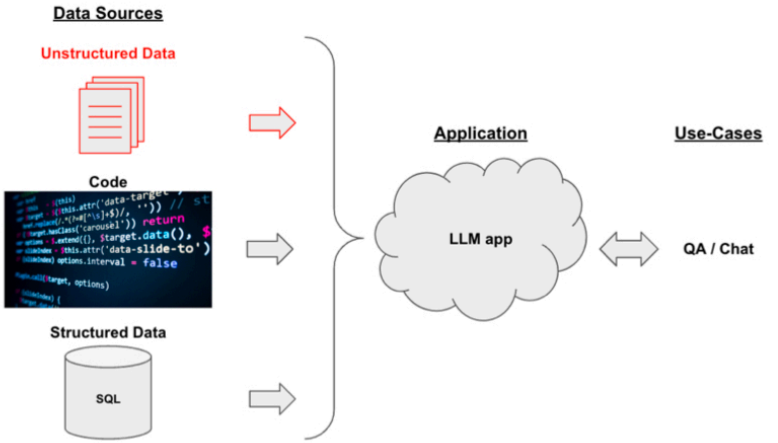


Langchain Docs

RAG - Retrieval Augmented Generation



[Langchain Docs]

- RAG - Retrieval Augmented Generation
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Langchain Docs

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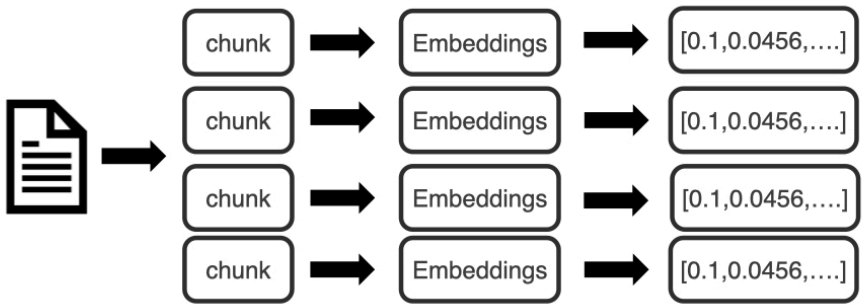
- **Embeddings**: capture content and meaning



Langchain Docs

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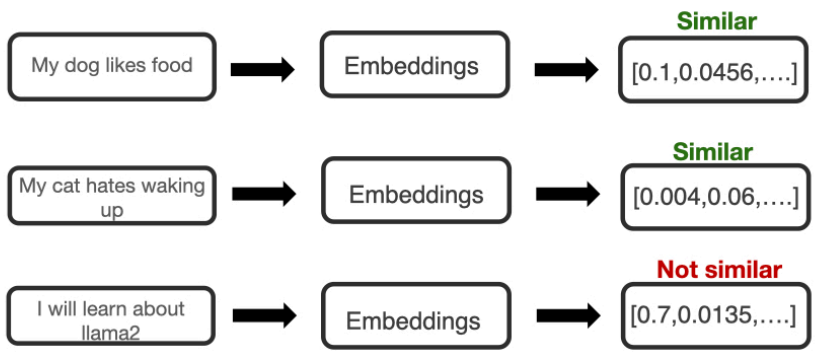

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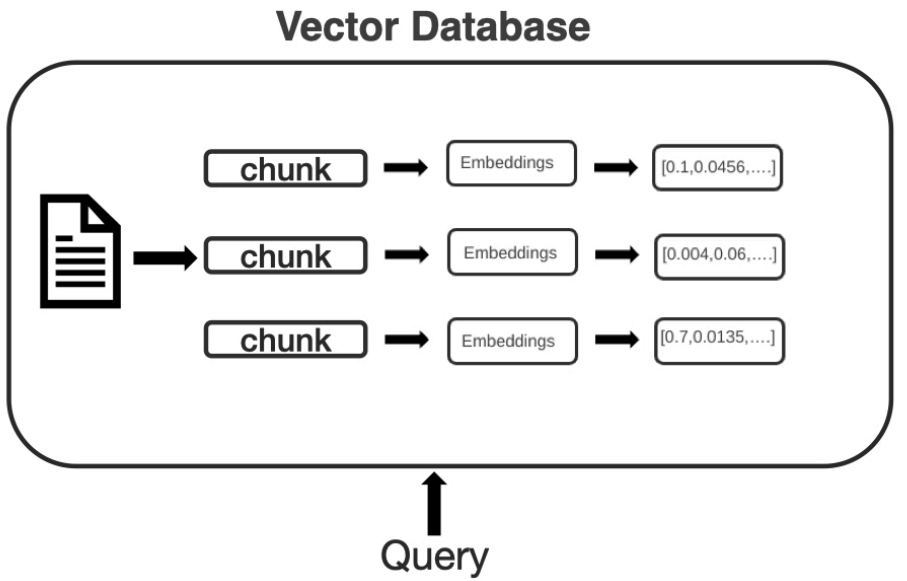
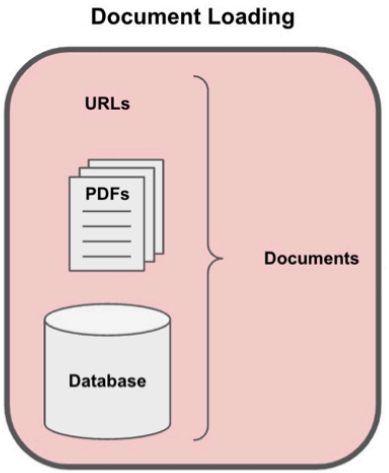


Langchain Docs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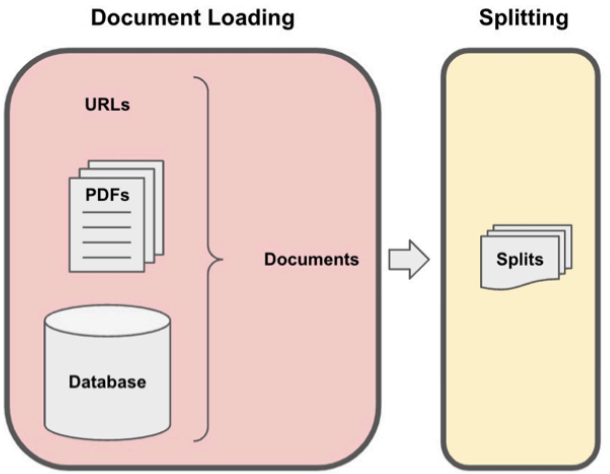
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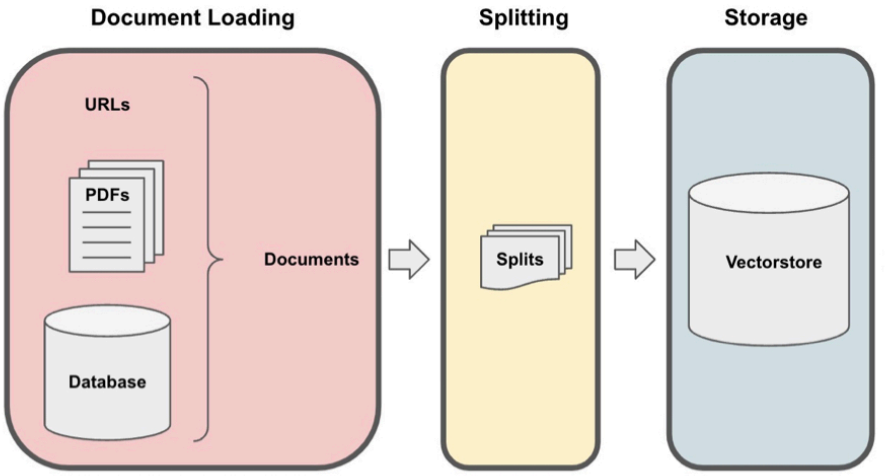
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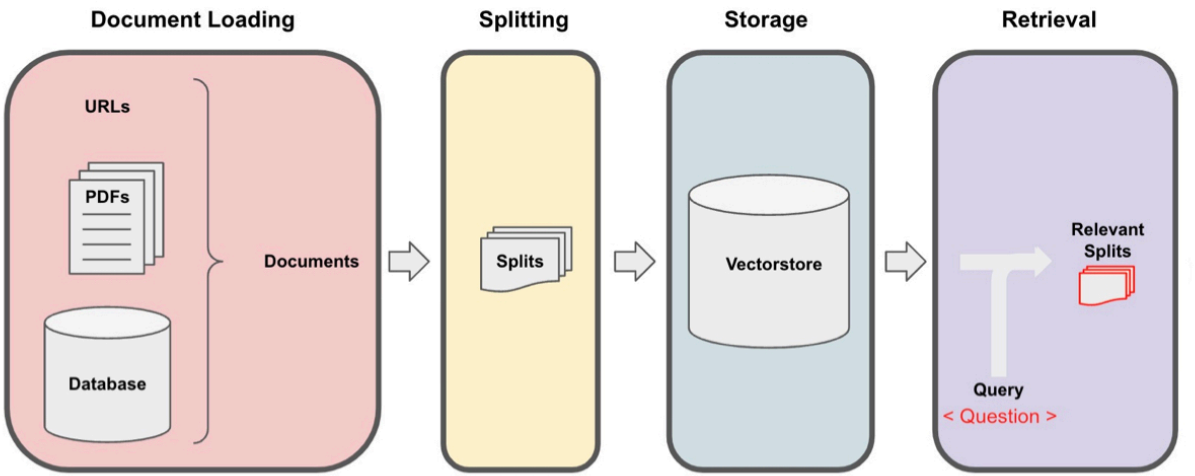
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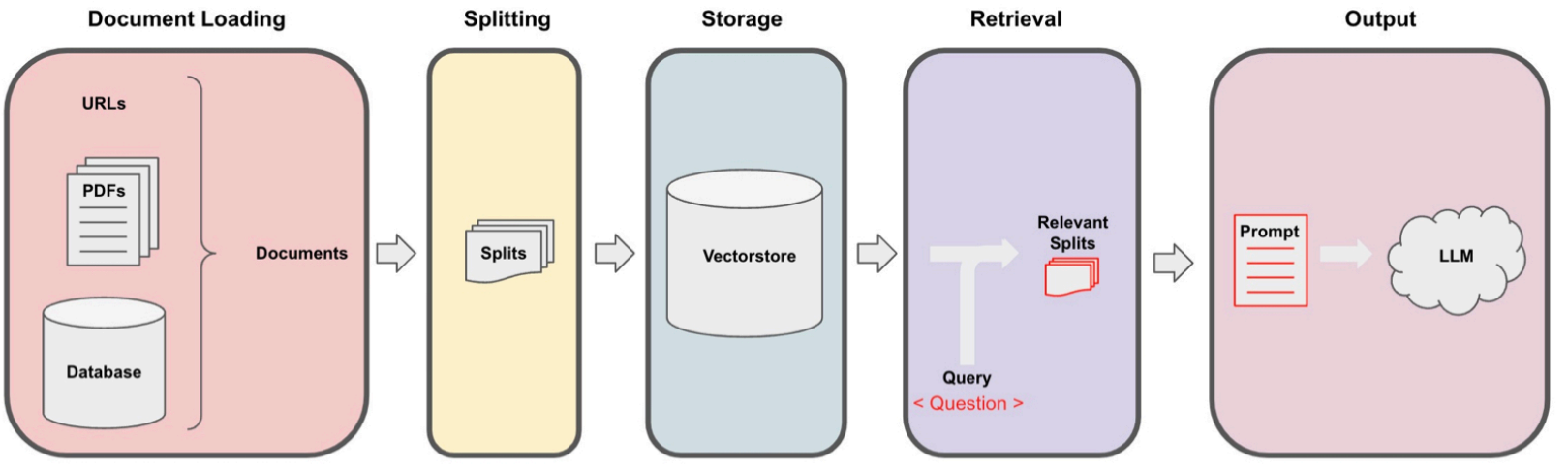
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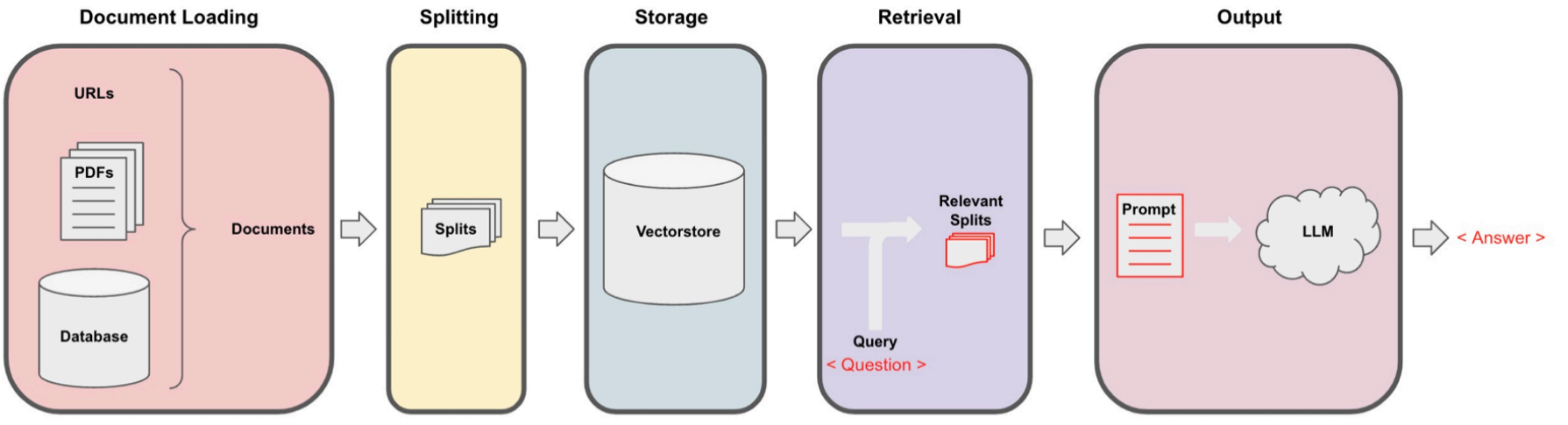
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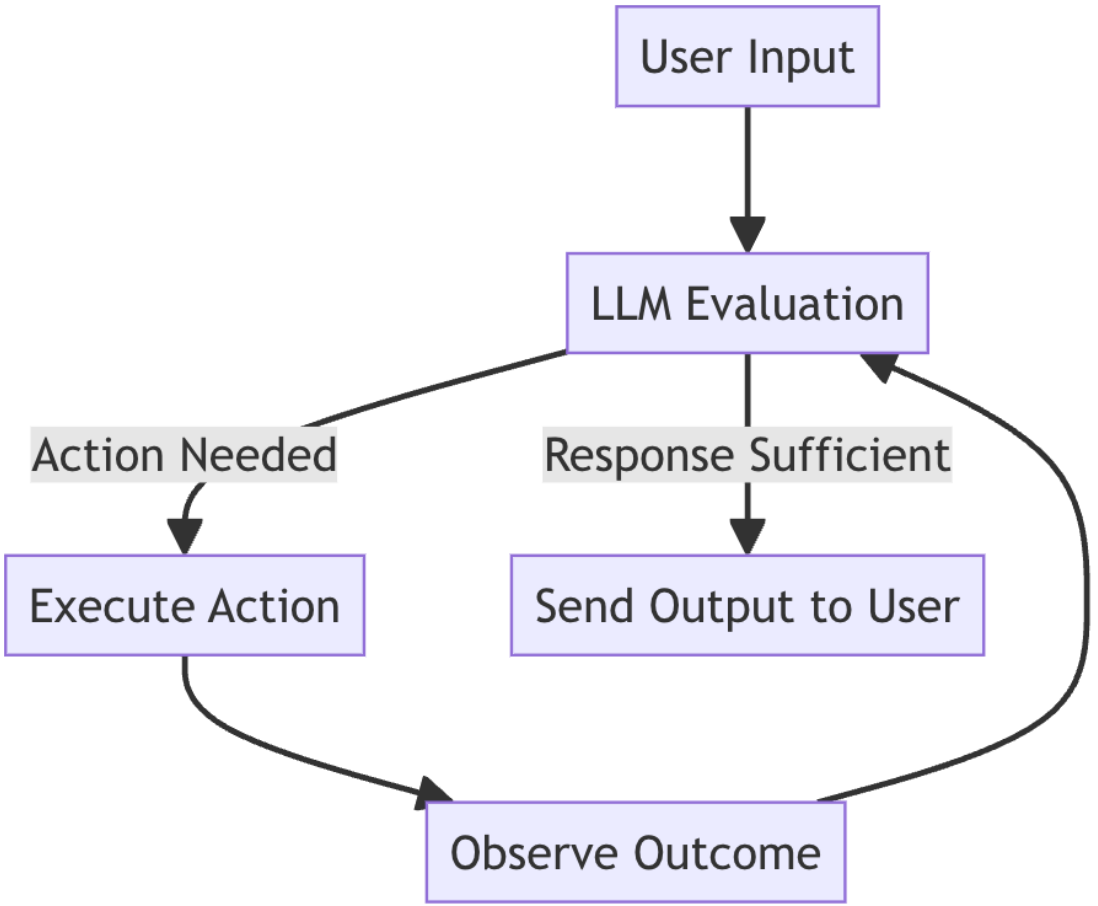
Notebook Demo - Local RAG with Llama 3.2

Q&A / Break

Local Agents with Llama 3.2

Local Agents with Llama 3.2



Explanation of the agent loop in cognitive architectures.

Practical Use Case: Customer Support Agent

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- **Scenario**: An LLM-powered customer support agent.

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- **User Input**: Customer asks about order status.

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Practical Use Case: Customer Support Agent

- **Scenario**: An LLM-powered customer support agent.
- **User Input**: Customer asks about order status.
- **LLM Decision**: Determines if it can provide the status directly or if it needs to fetch data from the database.
- **Action Taken**: If data fetch is needed, the agent queries the database and updates the user with the order status.

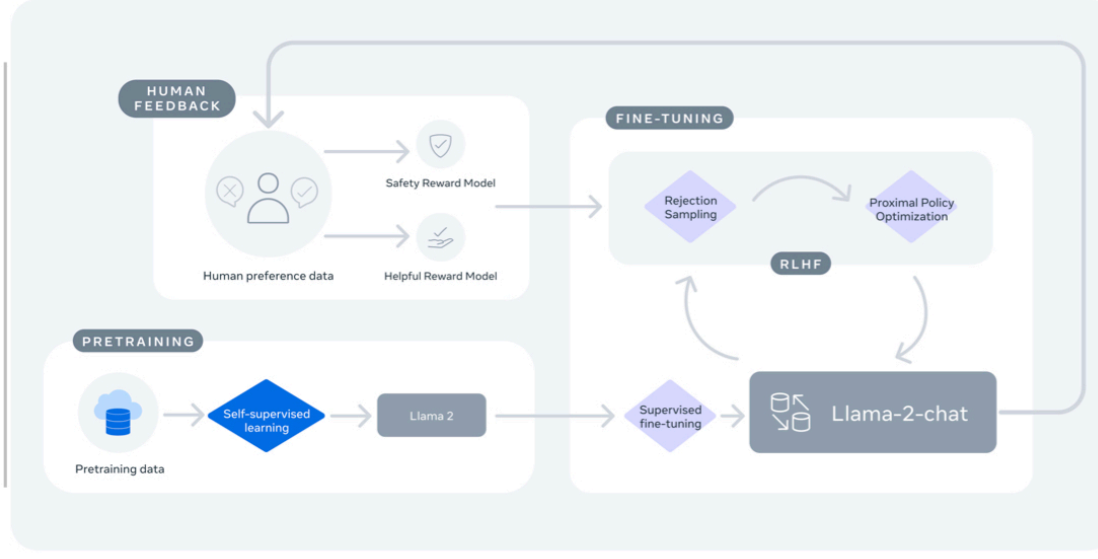
Practical use case of LLM agents in customer support.

Notebook Demo - Tool Calling and local agents with Llama 3.2

Q&A / Break

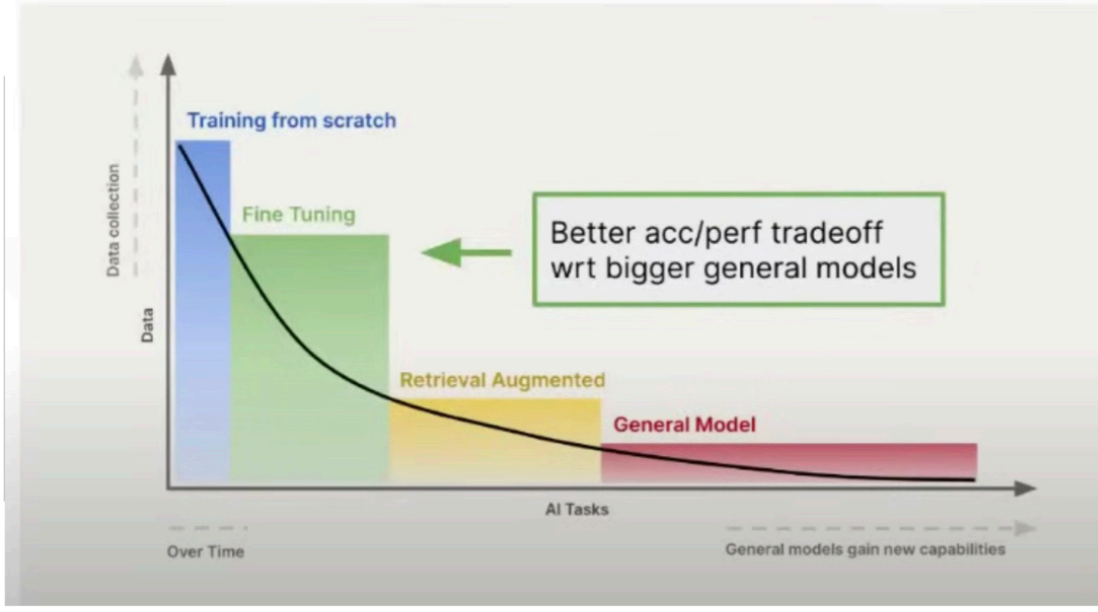
Fine Tunning Llama3.2

What is Fine Tuning?



LLama2 Paper

- What is Fine Tuning?
- Why Fine Tune?



[Efficient Fine-Tuning for Llama-v2-7b on a Single GPU]

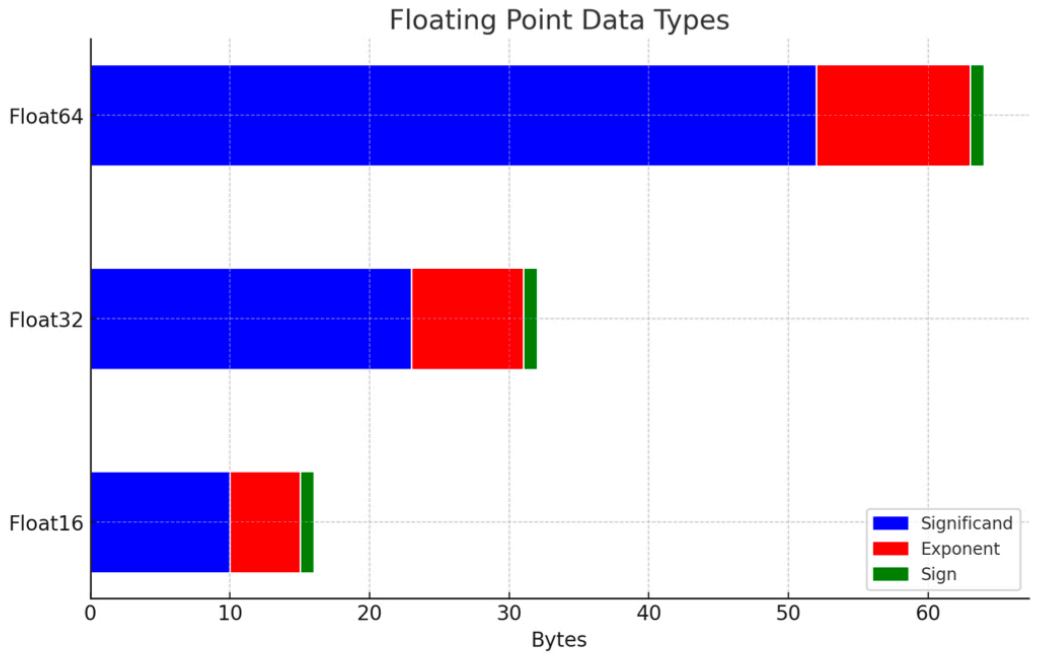
- What is Fine Tuning?
- Why Fine Tune?
- Memory cost of LLMs: parameters, gradients, optimiser states

The Memory Bottleneck: GPU comparison

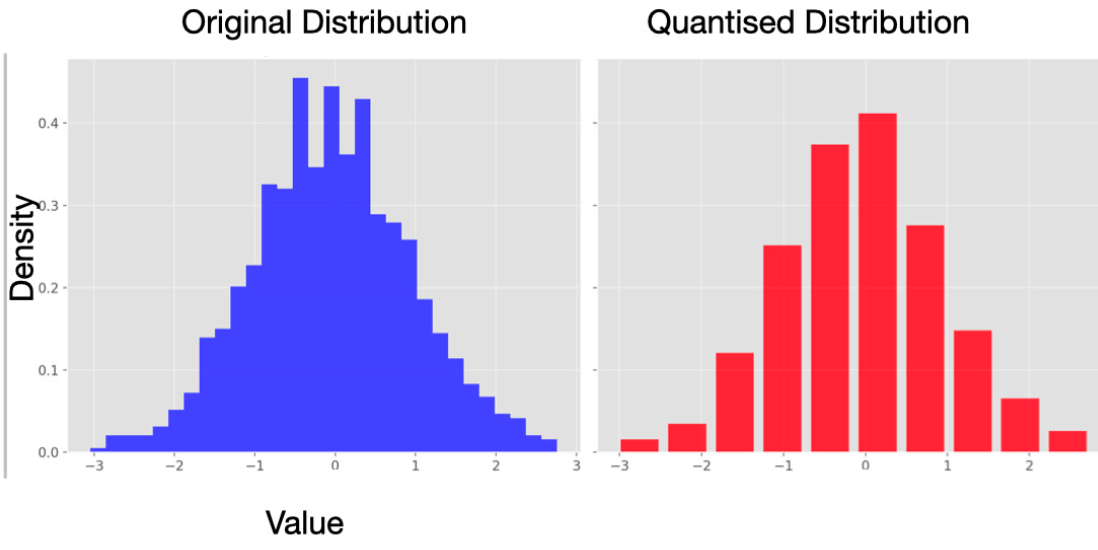
GPU	Tier	$ / hr (AWS)	VRAM (GiB)
H100	Enterprise	12.29	80
A100	Enterprise	5.12	80
V100	Enterprise	3.90	32
A10G	Enterprise	2.03	24
T4	Enterprise	0.98	16
RTX 4080	Consumer	N/A	16

Problem - Loading Params

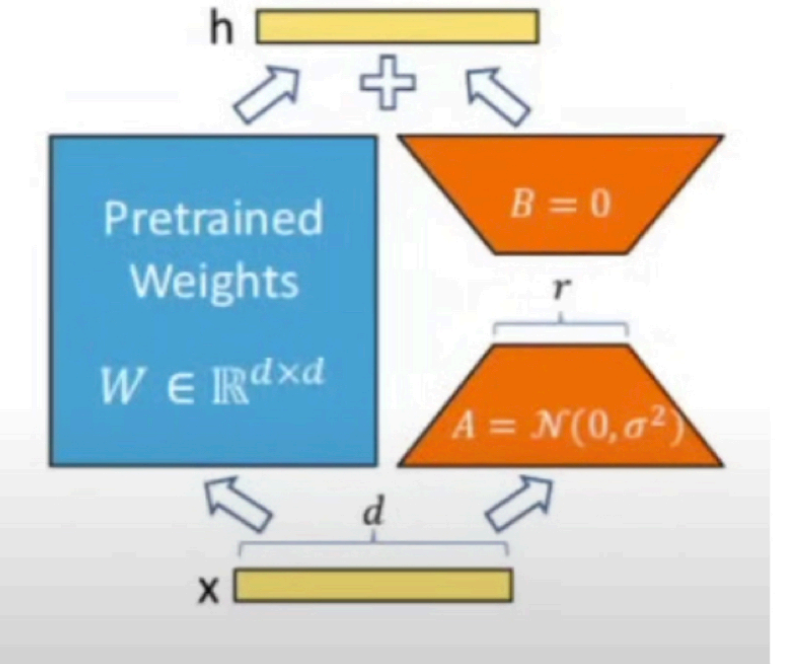
Solution - Half Precision



- Problem - Loading Params
  Solution - Half Precision
- Problem - Loading Gradients
  Solution - Quantization



- Problem - Loading Params
  Solution - Half Precision
- Problem - Loading Gradients
  Solution - Quantization
- Problem - Loading Optimizer States
  Solution - LoRA, QLora



Lora Paper

Notebook Demo - Fine-Tuning Llama3.1 - Walkthrough