RSAConference™2024

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THE ART OF POSSIBLE

SESSION ID: PDP-M06

IP Protection & Privacy in LLM: Leveraging Fully Homomorphic Encryption

#RSAC

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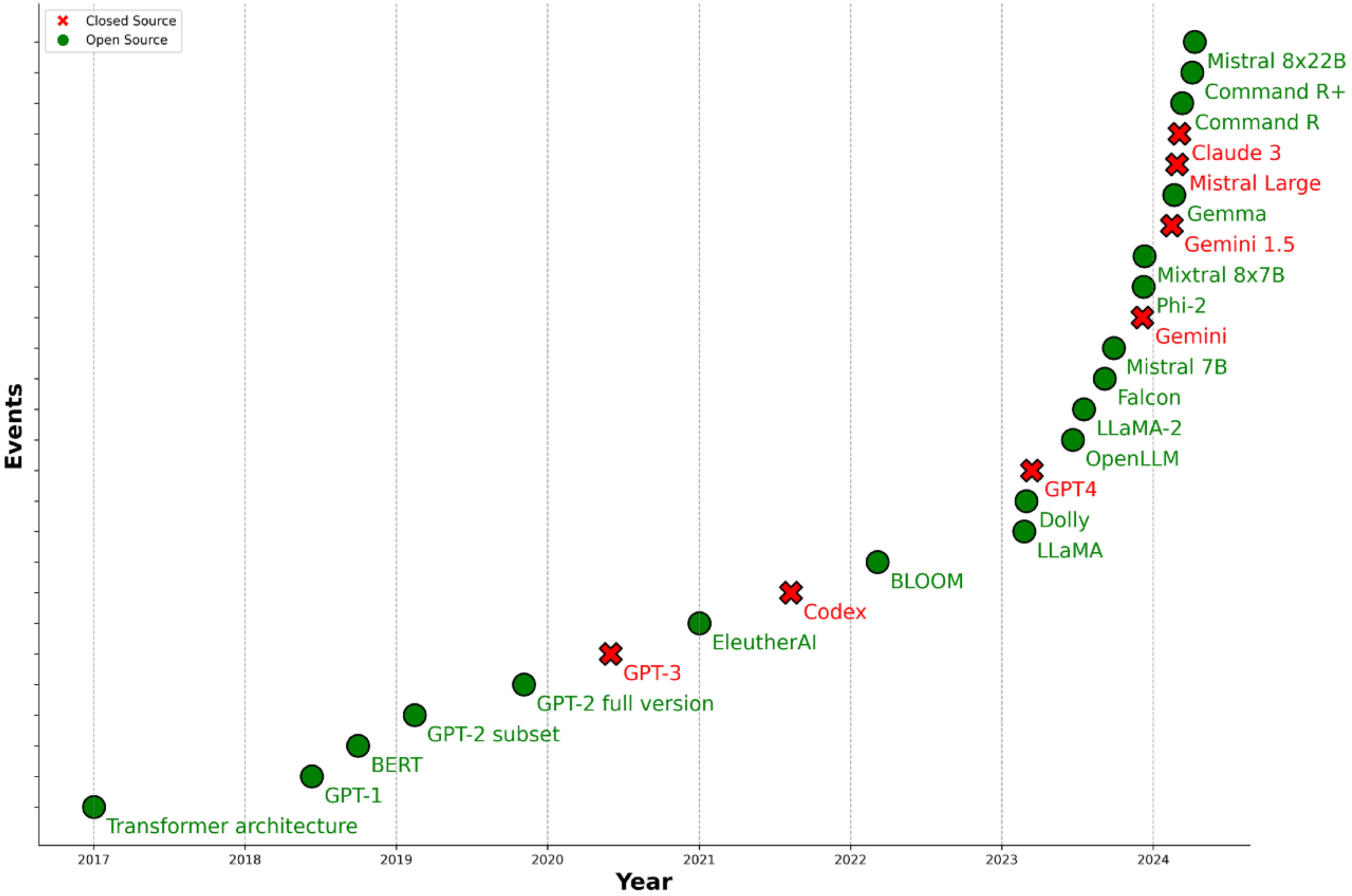
The Rising Importance of Large Language Models (LLM)



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Intellectual Property Privacy Concerns in LLM

- Accessing LLMs and Preserving IP
  - Serving LLM through a paid API (Claude, ChatGPT, Gemini, Copilot)
- This makes the **user's privacy at risk**

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LLM SaaS Deployment: Convenience vs. Privacy

- Accessing LLM while preserving user's privacy:
  - 1. Build your own LLMs (too expensive)
  - 2. Building upon free for commercial use LLMs (not state of the art)
  - 3. Deploy proprietary LLM on-premise (leak of IP)

Rank	🤖 Model	License
1	GPT-4-1106-preview	Proprietary
2	GPT-4-0125-preview	Proprietary
3	Bard (Gemini Pro)	Proprietary
4	GPT-4-0314	Proprietary
5	GPT-4-0613	Proprietary
6	Mistral-Large-2402	Proprietary
7	Claude-1	Proprietary
8	Mistral Medium	Proprietary
9	Qwen1.5-72B-Chat	Qianwen LICENSE
10	Claude-2.0	Proprietary
11	Mistral-Next	Proprietary
12	Gemini Pro (Dev API)	Proprietary
13	Claude-2.1	Proprietary
14	Mixtral-8x7b-Instruct-v0.1	Apache 2.0
15	GPT-3.5-Turbo-0613	Proprietary

Our Goal

Use LLMs while preserving IP and user's privacy.

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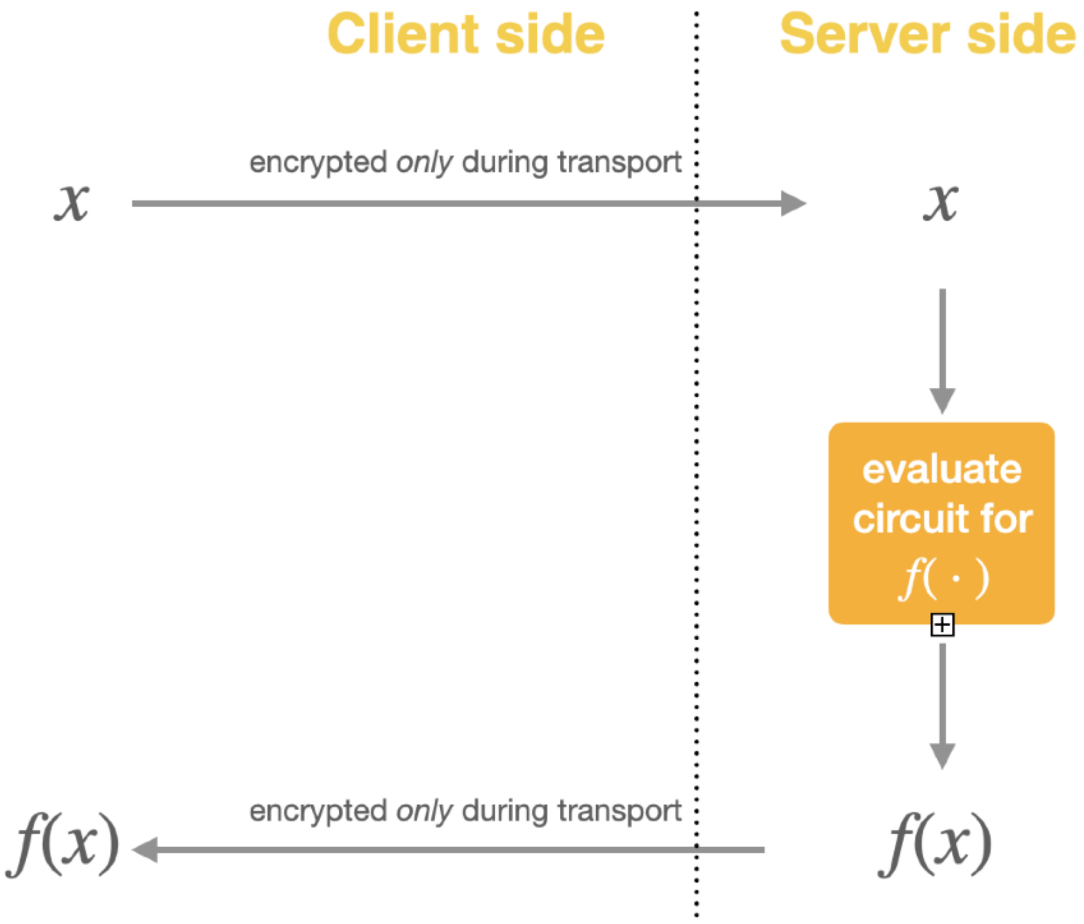
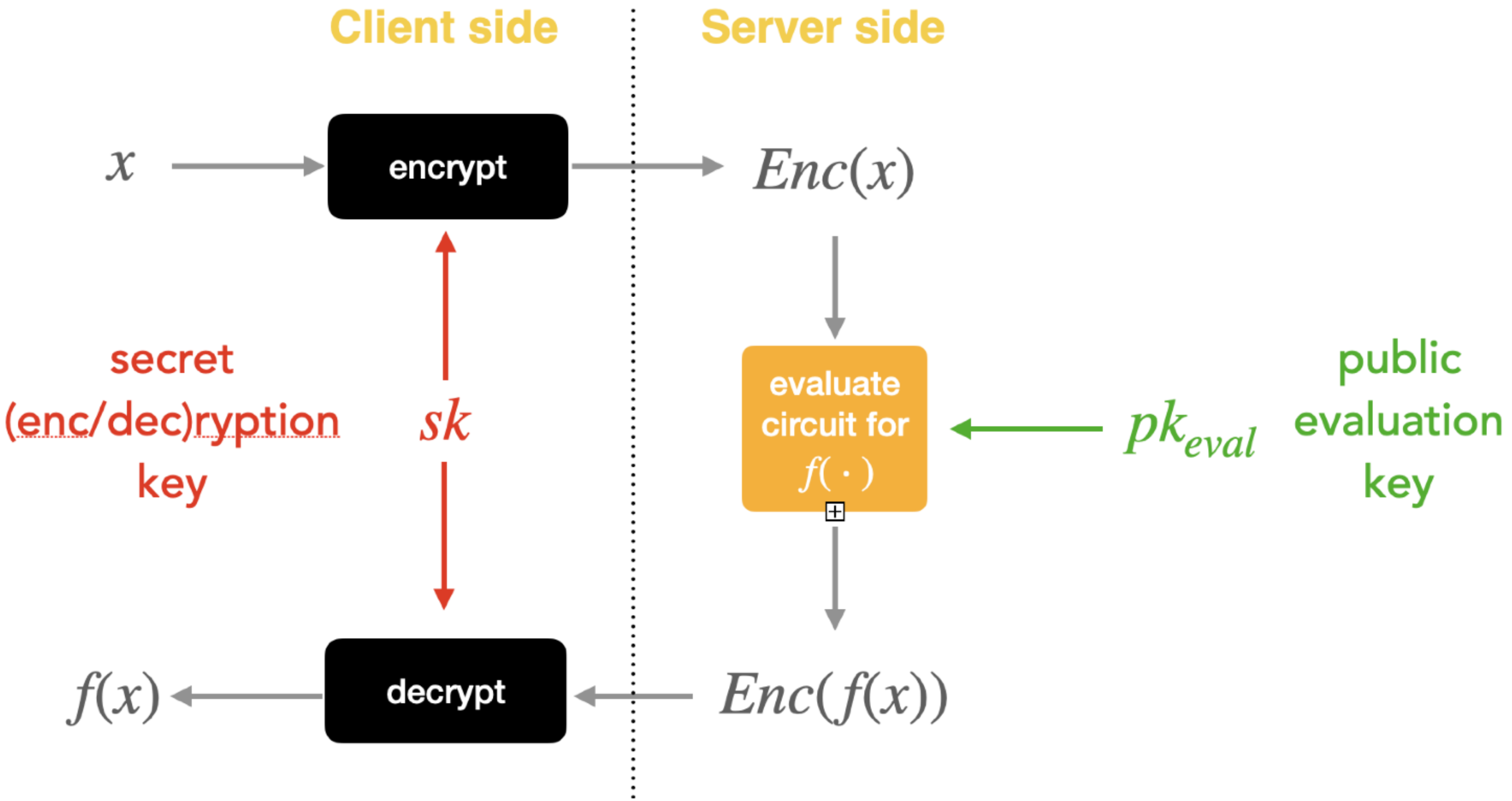
Fully Homomorphic Encryption

Today Data is Only Encrypted During Transport



With FHE, Data is Encrypted Also While Processed



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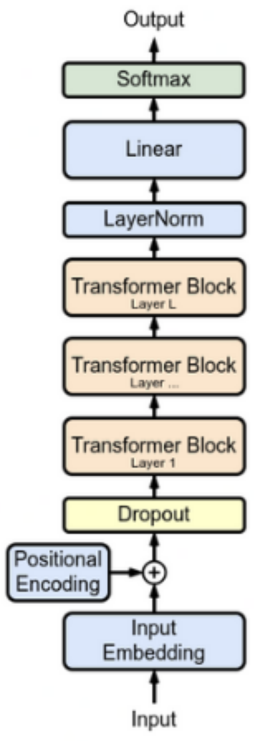
Leveraging FHE in LLMs

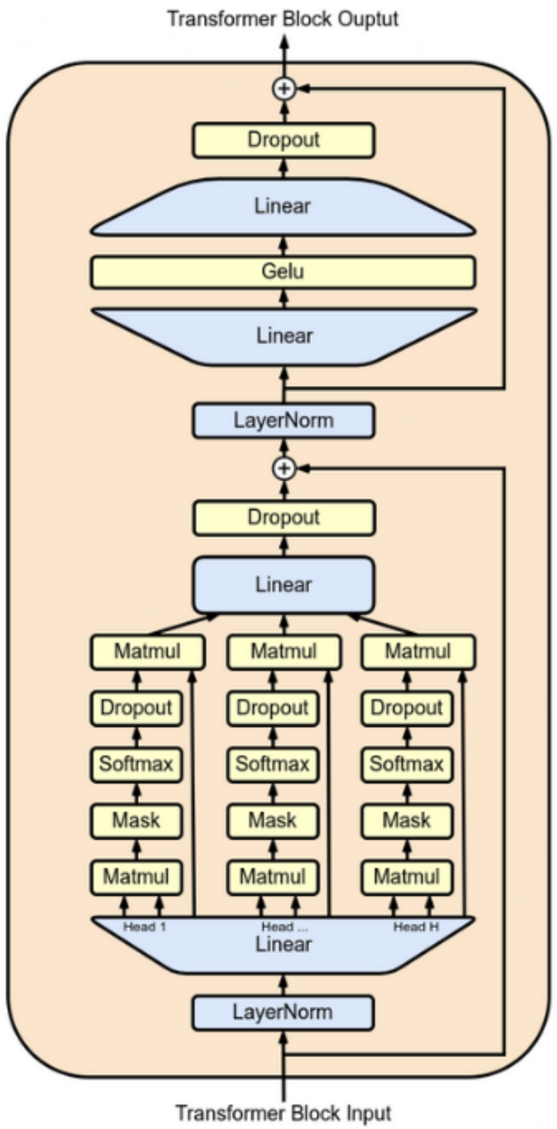
Our Open-Source Experiments

huggingface.co/blog/encrypted-llm

Transformers as Large Language Models

- Main operations:
  - Embedding
  - Feed-Forward
  - Attention

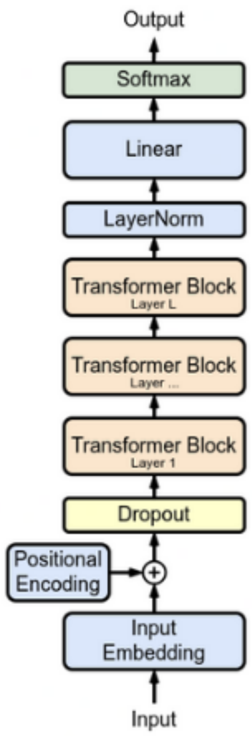


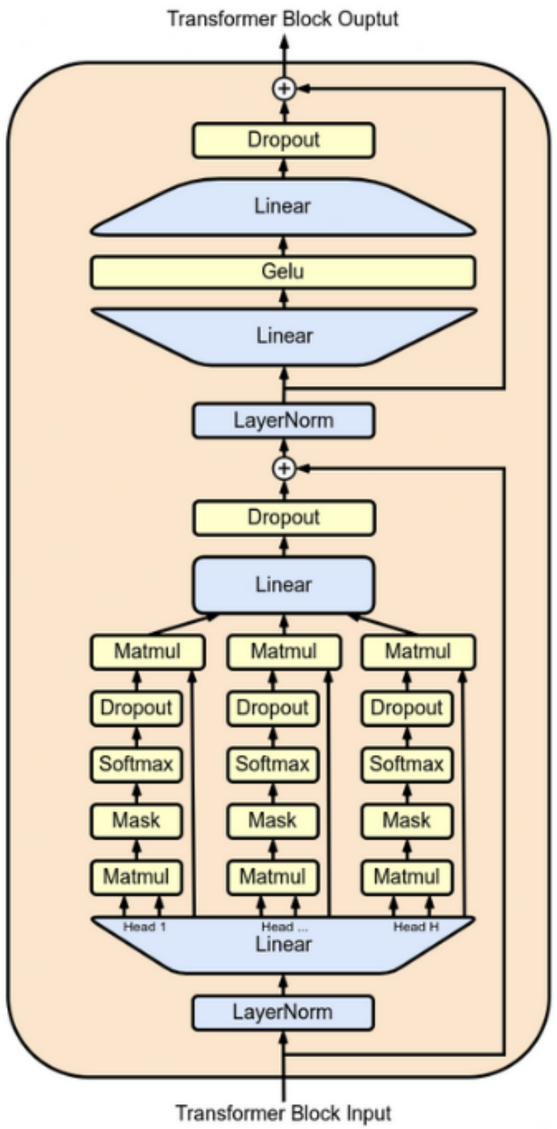


Transformers as Large Language Models

- Main operations:
  - **Embedding**
  - Feed-Forward
  - Attention

$$\mathrm{Embedding}_i = \mathrm{E}[i]$$





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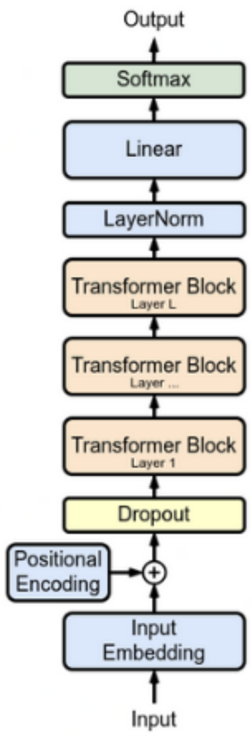
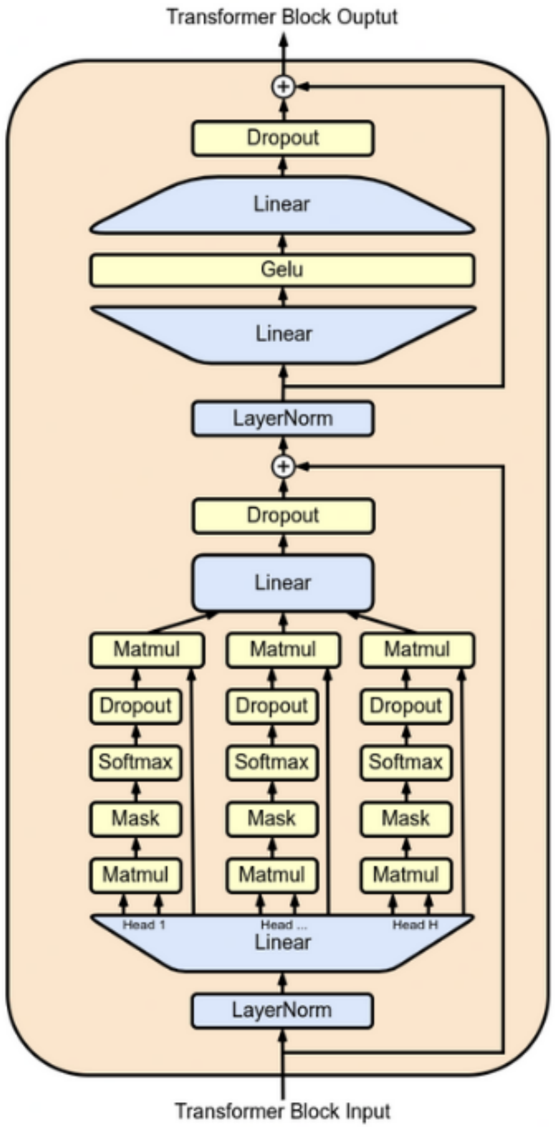
Transformers as Large Language Models

- Main operations:
  - **Embedding** ✓ FHE (ms)
  - Feed-Forward
  - Attention

$$\text{Embedding}_i = \text{E}[i]$$

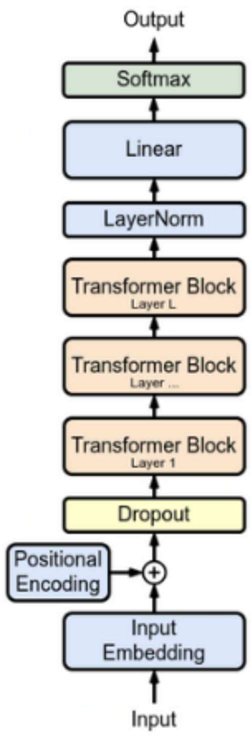


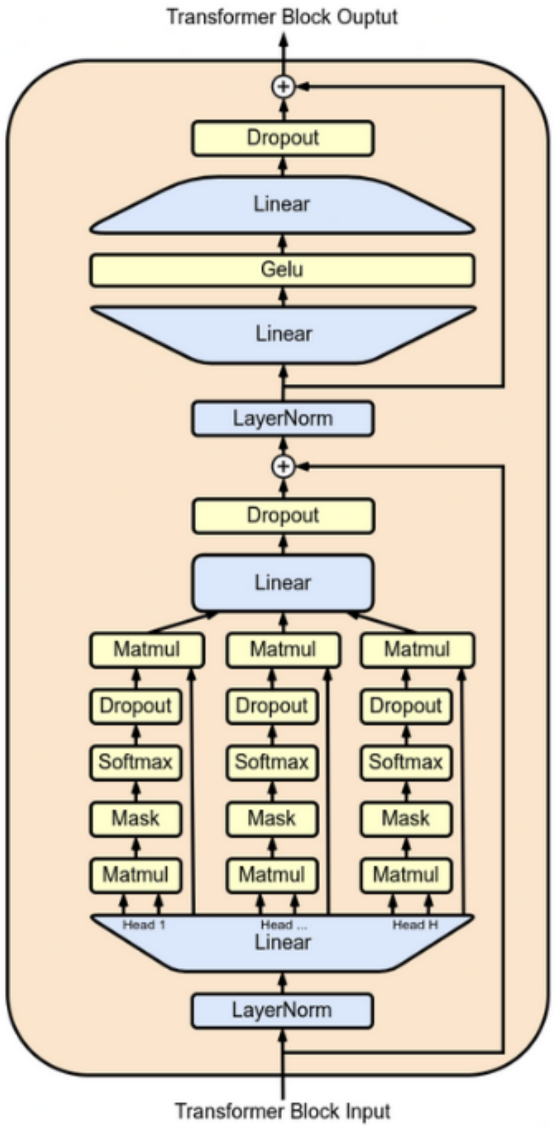


Transformers as Large Language Models

- Main operations:
  - Embedding ✓ FHE (ms)
  - **Feed-Forward**
  - Attention

$$\mathrm{FFN}(x) = F(xW_1 + b_1)W_2 + b_2$$





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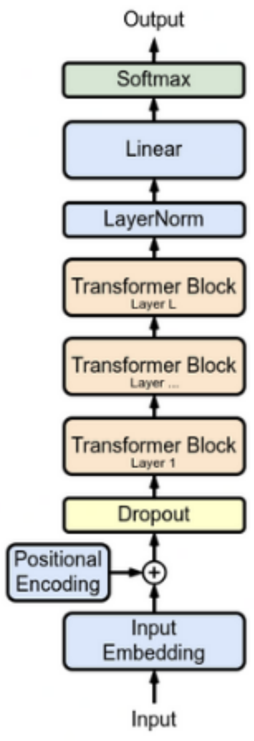
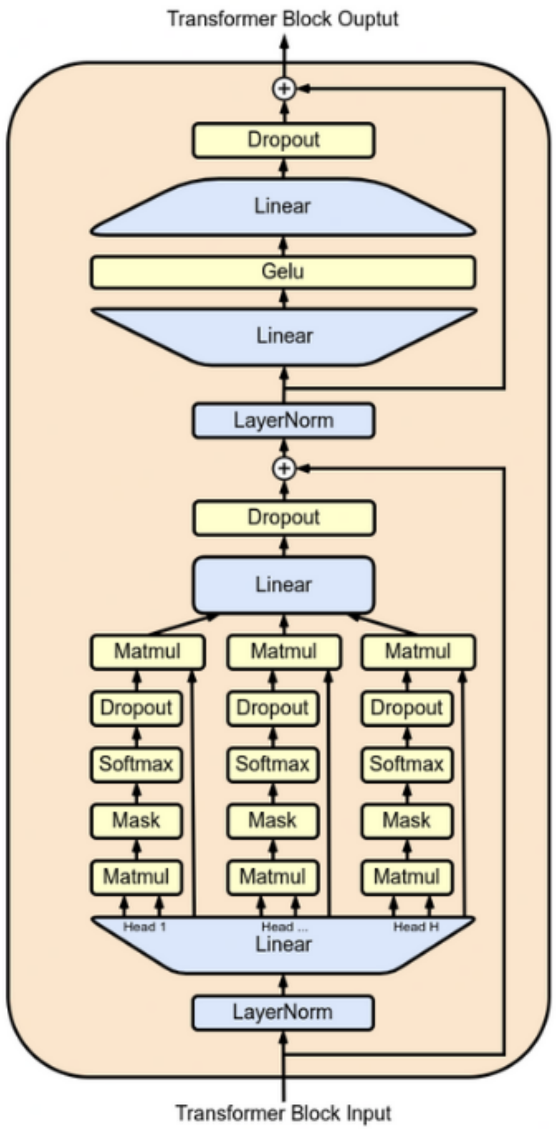
Transformers as Large Language Models

- Main operations:
  - Embedding ✓ FHE (ms)
  - **Feed-Forward** ✓ FHE (s)
  - Attention

$$\mathrm{FFN}(x) = F(xW_1 + b_1)W_2 + b_2$$

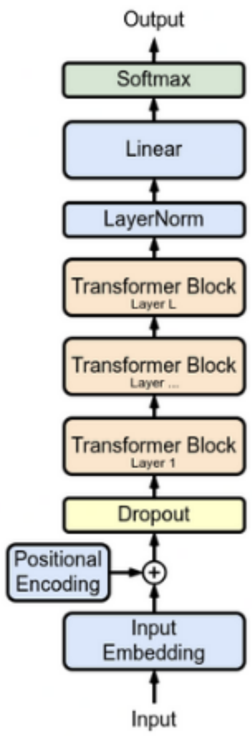


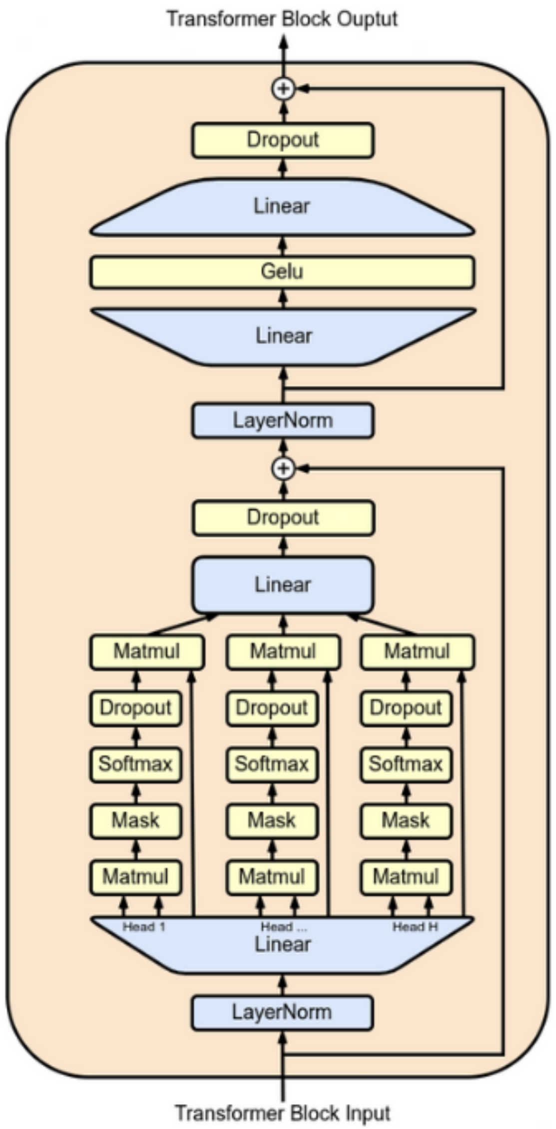


Transformers as Large Language Models

- Main operations:
  - Embedding ✓ FHE (ms)
  - Feed-Forward ✓ FHE (s)
  - **Attention**

$$Q = XW_Q$$
$$K = XW_K$$
$$V = XW_V$$
$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$





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Transformers as Large Language Models

- Main operations:
  - Embedding ✓ FHE (ms)
  - Feed-Forward ✓ FHE (s)
  - **<u>Attention</u>** ✓ FHE (m/h)

$$Q = XW_Q$$
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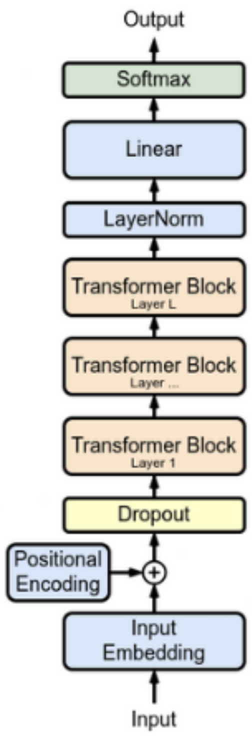
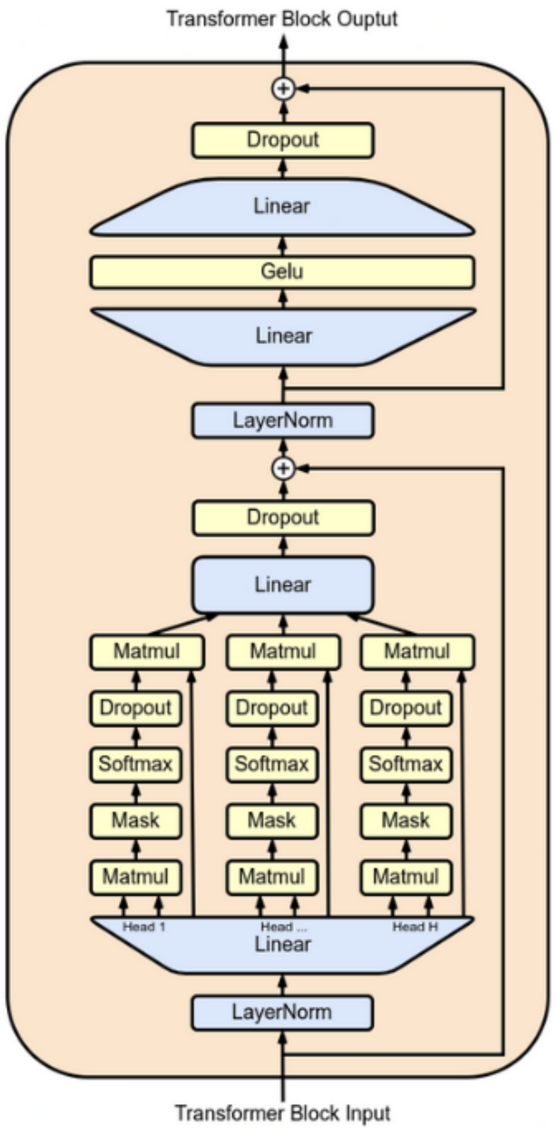
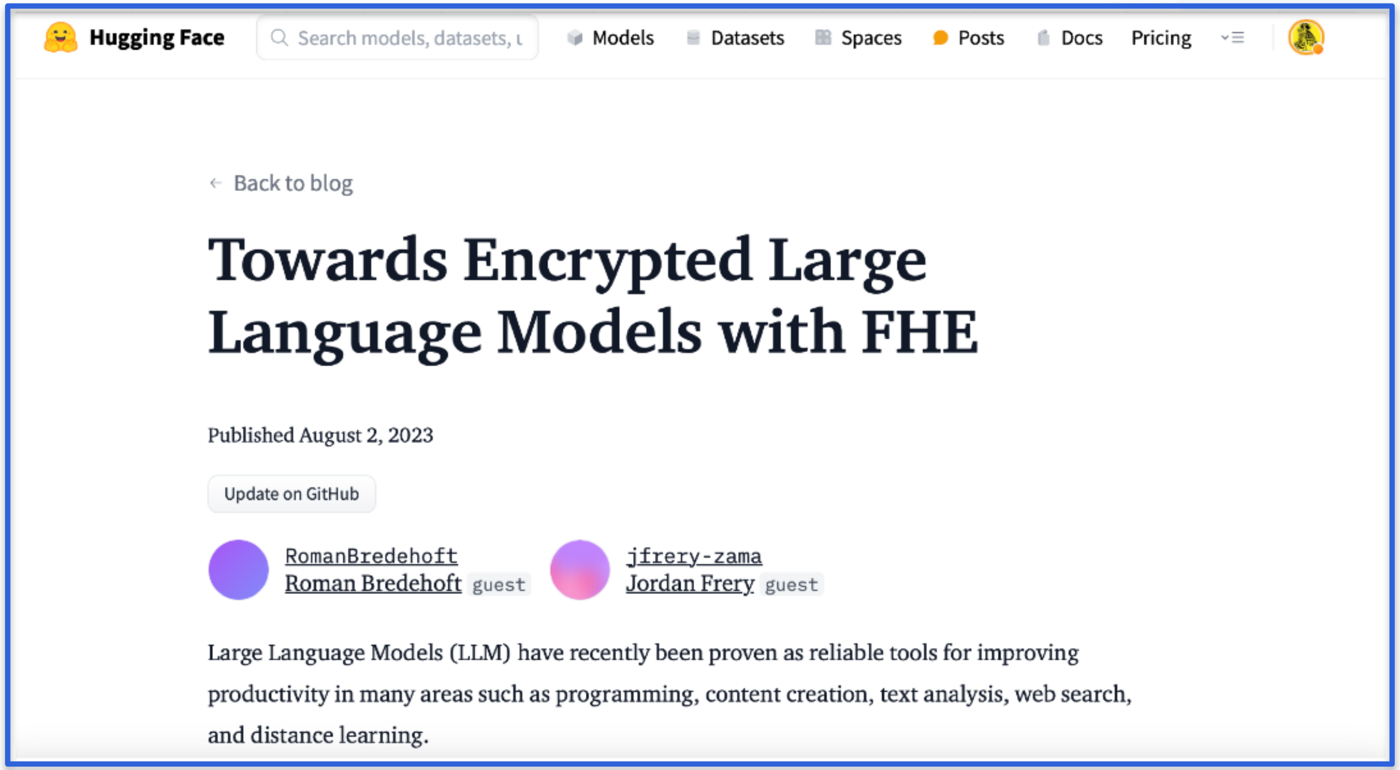
$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$





Read the Full Blog Post and Open-Source Code

huggingface.co/blog/encrypted-llm



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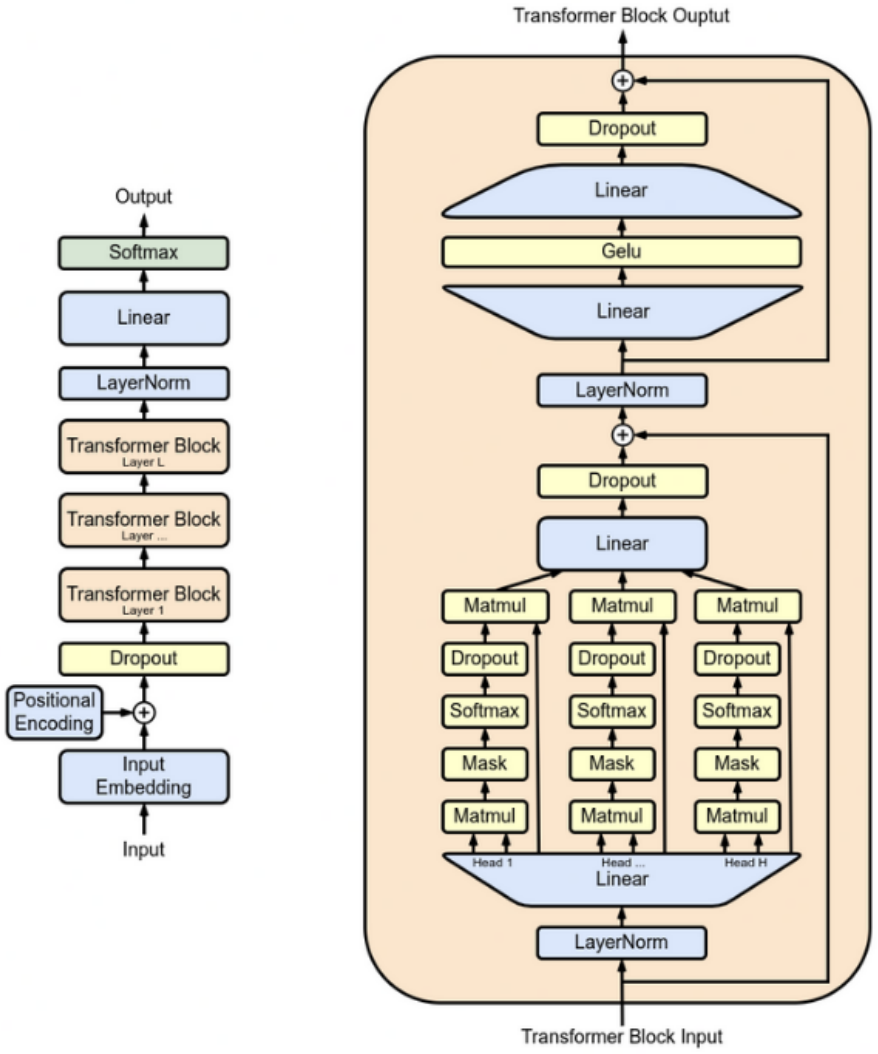
Hybrid Models

Faster Implementations

LLM User's Privacy And IP preserving

- Where is the Intellectual Property (IP) located?
  - Neural network parameters (weights/biases)
- Parameter distribution in google/gemma-7b:
  - Embedding -> 9.21%
  - Feed-Forward -> 71.55%
  - Attention -> 15.93%
  - Remaining -> 3.31%



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LLM User's Privacy And IP preserving

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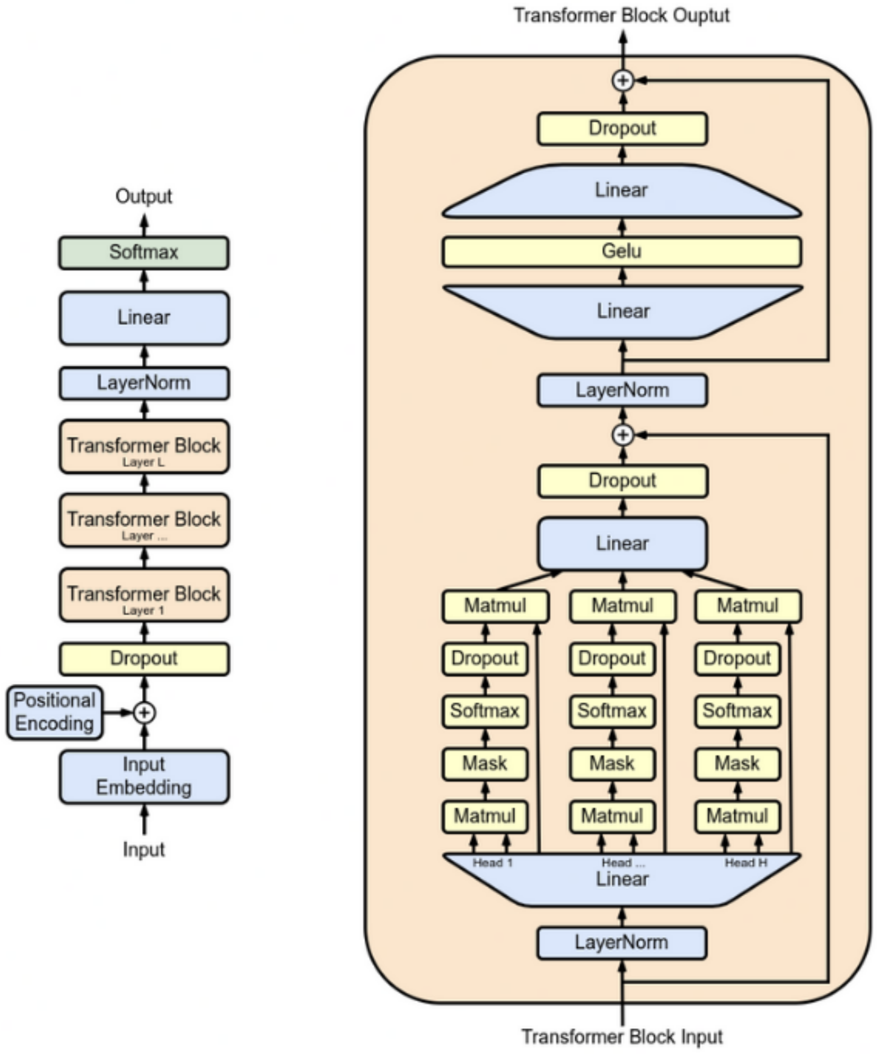
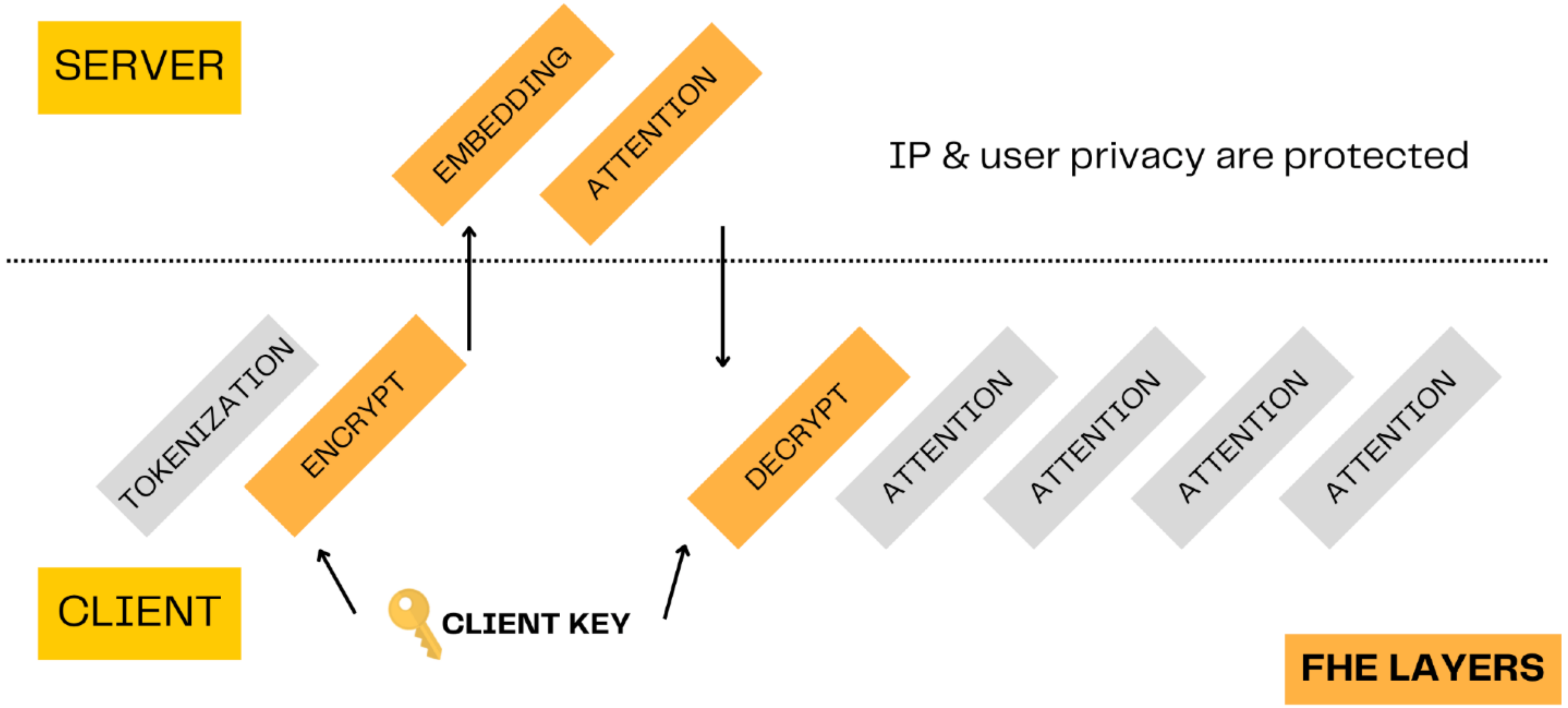


Hybrid Model Principle



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Demo

"Apply" Slide

- Next week you should:
  - Identify AI systems in your company who need privacy:
    - for your customers (their personal data)
    - for your company (your assets)
- In the first three months following this presentation you should:
  - Prototype protection one of these AI systems with FHE
  - Get help from discord.fhe.org
- Within six months you should:
  - Have moved your most critical AI systems to FHE (or other PETs)

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Appendix: Glossary

In the document:

- **FHE**: fully homomorphic encryption
- **ms**: milli seconds
- **s**: seconds
- **m/h**: minutes or hours

For LLM technical slides (Slides 11-17):

- Embedding, Feed-Forward, Attention and Softmax are described in Wikipedia or LLM technical papers
- F, W1, W2, Q, K, V, W_Q, W_K, W_V and X are matrices
- x, b_1, b_2 are vectors
- M^T stands for transposition of a matrix M
- d_k is the dimension of Q and K