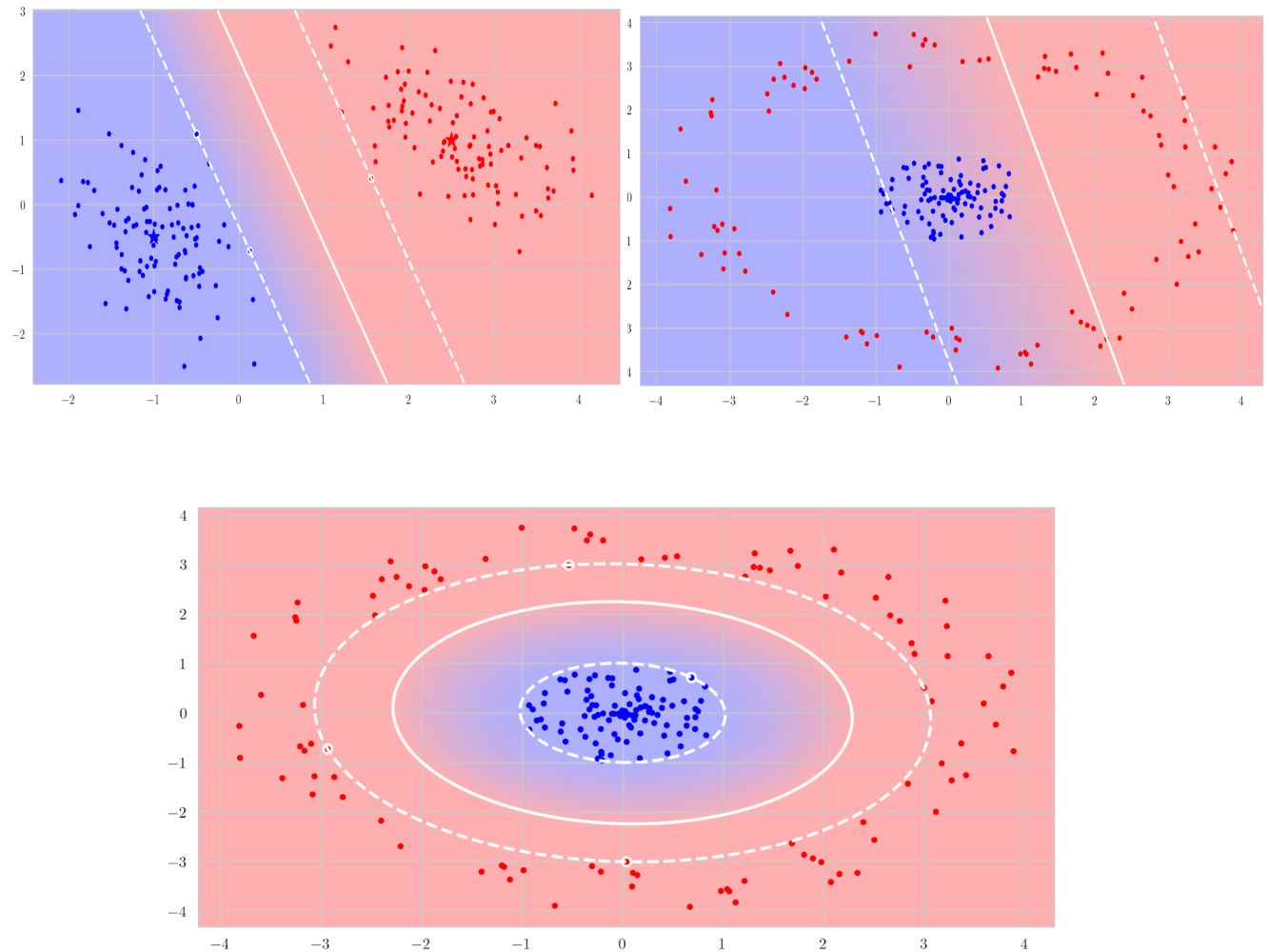


# "Beyond Transformers: Exploring Modern AI Architectures"

 *From Transformers to State Space Models (SSMs), Mamba, Jamba, Zamba, Bamba, Mamba-2, Zyptra, FlashAttention, and Beyond*

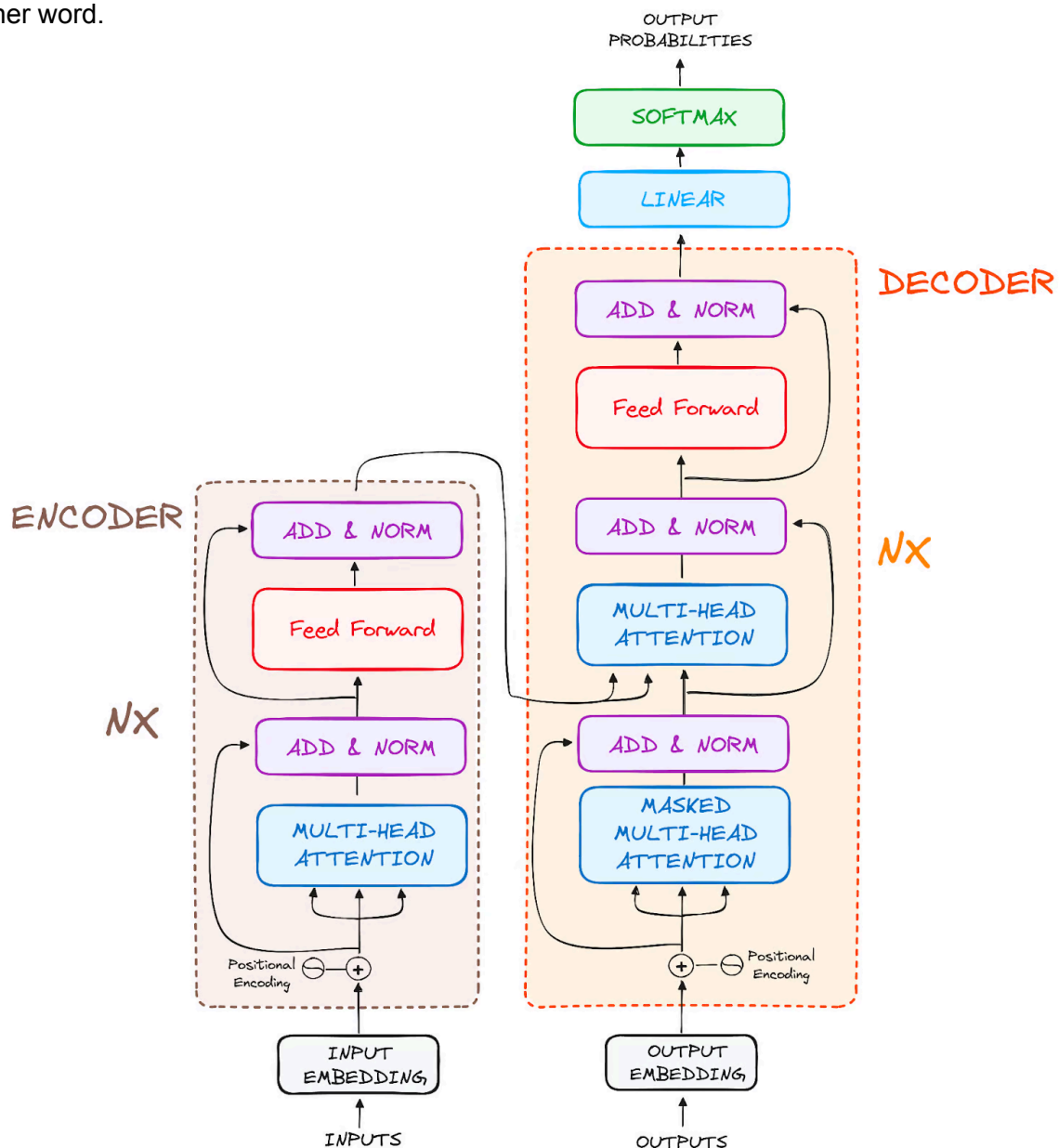


# Transformers – The Standard Approach

## 🧠 How do Transformers work?

- **Self-Attention:** Every word compares itself with every other word.
- **Advantages:** Excellent at capturing relationships in text.
- **Limitations:**
  - **Slow for long sequences.**
  - **High memory usage.**

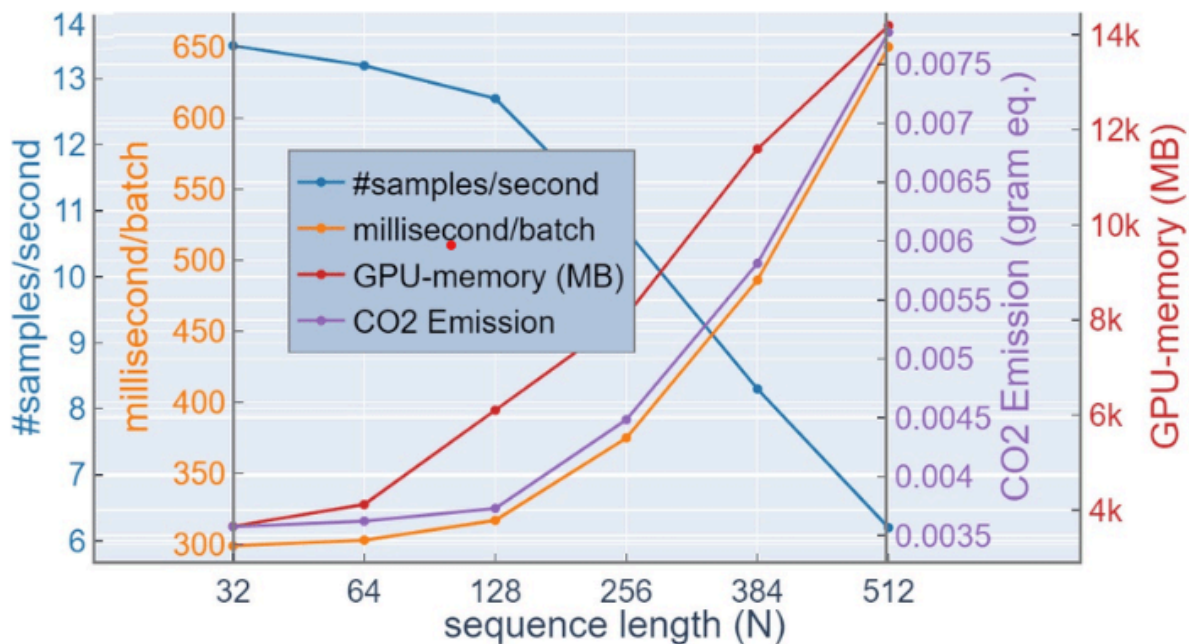
📌 *Example:* Processing an entire book is inefficient because every word interacts with every other word.



# The Challenge – Processing Long Sequences

💡 Why is this important?

- AI models need to handle **long texts, time-series data, audio, and genomics**.
- **Transformers (like GPT-4) struggle with long sequences** due to **quadratic complexity ( $O(N^2)$ )**.
- **Inefficiency in handling extremely long contexts**



# FlashAttention – Optimizing Transformers

## ⚡ What is FlashAttention?

- An optimization technique for Transformers to reduce memory usage.
- Speeds up computation but still follows self-attention( $O(N^2)$ ).
- Used in models like GPT-4 and Claude.

FlashAttention vs. standard attention memory usage.

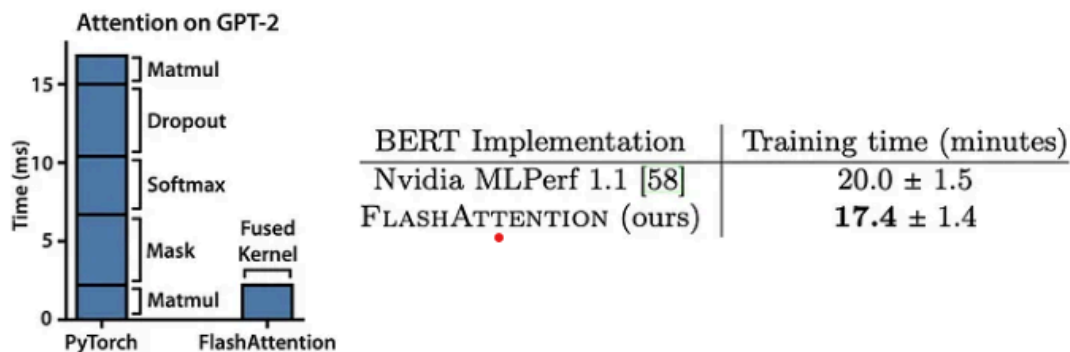


Figure 4: A comparison between a standard-attention and flash attention. (Left) Flash attention delivers a 7.6x Speedup over the PyTorch implementation. (Right) Flash attention is 15% faster over an Nvidia implementation that set the training speed record for MLPerf 1.1.

Vanilla Attention	Flash Attention
<ol style="list-style-type: none"> <li>Matmul_op (Q,K) <ol style="list-style-type: none"> <li>Read Q,K to SRAM</li> <li>Compute matmul <math>A=Q \times K</math></li> <li>Write A to HBM</li> </ol> </li> <li>Mask_op <ol style="list-style-type: none"> <li>Read A to SRAM</li> <li>Mask A into A'</li> <li>Write A' to HBM</li> </ol> </li> <li>Softmax_op <ol style="list-style-type: none"> <li>Read A' to SRAM</li> <li>Softmax A' into A''</li> <li>Write A'' to HBM</li> </ol> </li> </ol>	<ol style="list-style-type: none"> <li>Read Q,K to SRAM</li> <li>Compute <math>A = Q \times K</math></li> <li>Mask A into A'</li> <li>Softmax A' into A''</li> <li>Write A'' to HBM</li> </ol>

Figure 3: A comparison between standard attention (left) and flash attention (right). This comparison leverages three operations (matmul, mask, softmax) only. Other operations (e.g., dropout) are omitted for presentation purposes.

# State Space Models (SSMs) – A Different Approach

## 🧩 What are SSMs?

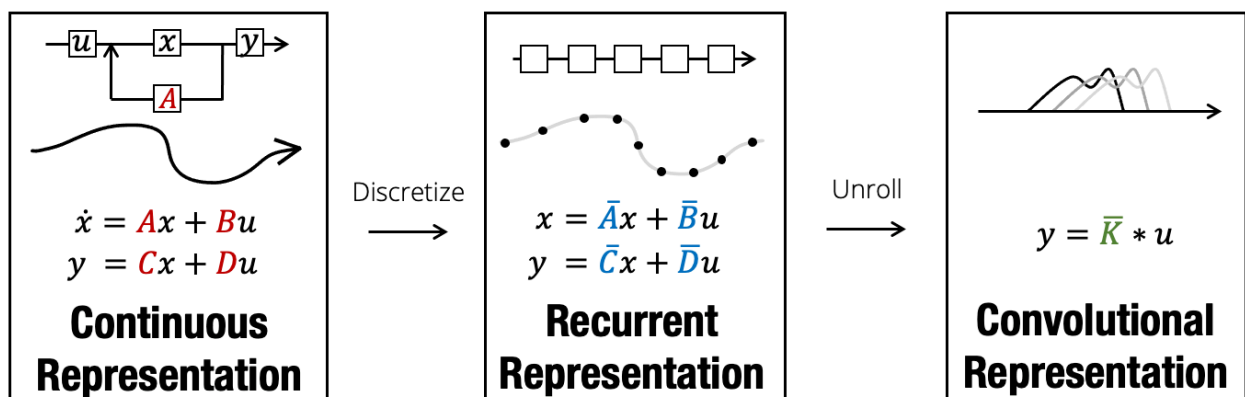
- Instead of self-attention, **SSMs track hidden states over time.**
- Used in **control systems, time-series forecasting, and deep learning.**
- **More efficient for long sequences** because they **don't compare every token.**

📌 Think of it like summarizing key points instead of remembering every word.

✅ **Linear Scaling:** ✅ **Memory Efficiency:** ✅ **Parallelized Training:** ✅ **Handles Long-Range Dependencies:** Unlike RNNs, SSMs can capture **long-term information** without vanishing gradients

**Discretization** is one of, if not the most important point in SSM. All the efficiency of this architecture lies in this step, since it enables us to **pass from the continuous view of the SSM to its two other views: the recursive view and the convolutive view.**

*If there's one thing to remember from this, it's this.*



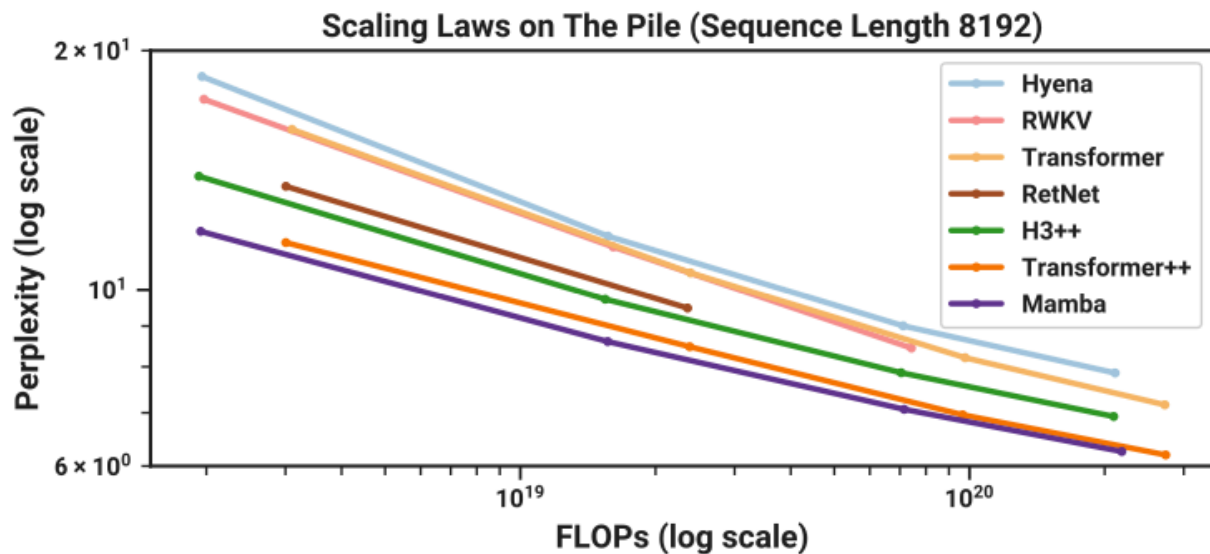
# Mamba – An Alternative to Transformers

## 🦩 What is Mamba?

- Inspired by SSMs but designed for deep learning.
- Processes sequences in  $O(N)O(N)$  (linear) instead of  $O(N^2)O(N^2)$  (quadratic).
- More efficient for long-sequence tasks like genomics, audio, and language.
- Does not use self-attention but structured state updates.

📌 Think of it like tracking important points in a discussion instead of listening to everything at once.

*Mamba vs. Transformer efficiency comparison chart.*



# Expanding on Mamba & Emerging Innovations

## Variants of Mamba

- ✓ **Jamba** – Hybrid model **blending Transformer-like properties** for performance boost.
- ✓ **Zamba** – Optimized for audio and genomics, excelling in **domain-specific tasks**.
- ✓ **Zyphra** – Enhances sequence processing, **ideal for long-context applications**.
- ✨ **Bamba** – A further optimized **variant of Mamba** with efficiency refinements.
- ✨ **Mamba 2** – An improved, next-gen version with enhanced stability & scalability.

## Others

- ◆ **EfficientVMamba** – Introduces Atrous Selective Scan, **enabling lightweight deployment** & better global-local feature extraction.
- ◆ **Cobra** – Extends Mamba into a **multi-modal AI for vision-language reasoning**, achieving faster inference.
- ◆ **SiMBA** – A simplified Mamba-based model with **EinFFT for stable scaling**, excelling in vision & time-series tasks.

 **Explore more:** [GitHub - state-spaces/mamba](https://github.com/state-spaces/mamba)

 ***The Potential Transformer Replacement: Mamba:***

[https://medium.com/@zilliz\\_learn/the-potential-transformer-replacement-mamba-f982a9d2aa12](https://medium.com/@zilliz_learn/the-potential-transformer-replacement-mamba-f982a9d2aa12)

 ***Mamba Will Never Beat the Transformer:***

<https://nathanpaull.substack.com/p/mamba-will-never-beat-the-transformer-24-03-08>





