The i3-200M Model: A Hybrid Architecture for Efficient and Effective Language Modeling

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Abstract

The pursuit of efficient and high-performing large language models (LLMs) has led to the exploration of novel architectures beyond the traditional Transformer. This paper introduces the **i3-200M Model** (also known as Redherring), a novel hybrid architecture designed to leverage the strengths of both recurrent/state-space models and attention mechanisms. The i3-200M uniquely combines RWKV-style time-mixing with Mamba state-space dynamics in its initial layers for efficient sequence processing, followed by standard multi-head attention in deeper layers for complex global dependency capture. With approximately 170 million parameters, the model achieves a final training loss of 1.6 and a perplexity of 5.2 on its diverse pre-training corpus. This hierarchical hybrid approach demonstrates a compelling balance between computational efficiency and modeling capacity, offering a promising direction for developing resource-conscious LLMs.

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1. Introduction

The Transformer architecture [1] has dominated the field of natural language processing, driving the success of modern LLMs. However, its quadratic complexity with respect to sequence length, due to the self-attention mechanism, presents significant challenges for long-context modeling and deployment on resource-constrained hardware. This limitation has spurred research into alternative, sub-quadratic architectures, notably the Recurrent Neural Network (RNN) revival through models like RWKV [2] and the introduction of State Space Models (SSMs) like Mamba [3].

The i3-200M model is a direct response to this architectural trade-off. It proposes a **hierarchical hybrid** design that integrates the linear-complexity benefits of RWKV and Mamba for local and temporal processing with the global context-capturing power of the Transformer's attention mechanism.

Our main contributions are:

1. The introduction of a novel **RWKV-Mamba Hybrid Block** for efficient sequence processing in the lower layers.

2. A **hierarchical architecture** that strategically places recurrent/state-space blocks before full attention blocks to optimize for both speed and performance.
3. Demonstration of competitive performance (Perplexity 5.2) with a modest parameter count (~170M) and highly efficient training dynamics.

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2. Related Work

The i3-200M model builds upon three foundational architectural concepts: the Transformer, RWKV, and Mamba.

2.1. The Transformer Architecture

The Transformer [1] relies entirely on the self-attention mechanism, which allows for parallel computation and direct modeling of dependencies between any two tokens, regardless of their distance. While powerful, the $O(N^2)$ complexity of attention, where N is the sequence length, is a major bottleneck.

2.2. Recurrent Architectures (RWKV)

RWKV (Receptance Weighted Key Value) [2] re-casts the Transformer's input-to-output mapping into a recurrence, achieving $O(N)$ complexity. It replaces the self-attention block with two linear-complexity modules: **Time-Mixing** and **Channel-Mixing**. The Time-Mixing block handles temporal dependencies, effectively providing a form of long-term memory while maintaining fast, constant-time inference.

2.3. State Space Models (Mamba)

Mamba [3] introduces the concept of **Selective State Spaces (SSMs)**. It addresses the limitations of prior SSMs (like S4) by making the state-space parameters input-dependent, which allows the model to selectively propagate or forget information based on the input content. This mechanism grants Mamba $O(N)$ complexity and superior performance on long-range dependency tasks compared to non-selective SSMs.

2.4. Hybrid Models

The idea of combining different architectures is gaining traction. Models like Jamba [4] have successfully integrated Mamba blocks with Transformer layers using a Mixture-of-Experts (MoE) approach. The i3-200M differs by employing a **sequential, hierarchical** hybrid structure, specifically integrating RWKV and Mamba into a single block, and then

stacking these hybrid blocks with full attention blocks. This is a unique approach to balancing the strengths of recurrent/state-space models (efficiency, local patterns) and attention (global context).

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3. i3-200M Architecture

The i3-200M model is a 16-layer language model with a total of **169.85 million parameters**.

3.1. Hybrid Block Design

The core innovation is the **RWKV-Mamba Hybrid Block**, which is used in the first 10 layers. This block combines RWKV-style time-mixing with Mamba state-space dynamics.

Component	Function	Rationale
RWKV Time-Mixing	Efficiently processes temporal information and short-range dependencies.	Provides linear complexity and constant-time inference.
Mamba State-Space	Selectively models temporal dependencies and long-range context.	Enhances the model's ability to capture relevant information over long sequences.
Feed-Forward Network	Standard 4x expansion FFN.	Provides non-linearity and increases model capacity.

3.2. Hierarchical Layering

The model employs a hierarchical structure across its 16 layers:

- **Layers 1-10: RWKV-Mamba Hybrid Blocks (Recurrent/Conv)**
  - Focus: Efficient processing of local and temporal patterns.
  - Complexity: Linear $O(N)$.
- **Layers 11-16: Full Attention Blocks**
  - Focus: Capturing global dependencies and complex relationships across the entire sequence.
  - Complexity: Quadratic $O(N^2)$.

This design is motivated by the hypothesis that lower layers primarily learn local features and grammar, which can be handled efficiently by recurrent/state-space mechanisms. The higher layers then integrate these features into a global context using the more powerful, albeit more expensive, full attention mechanism.

Model Statistics:

Statistic	Value
Total Parameters	~169.85M
Total Layers	16 (10 Hybrid + 6 Attention)
Hidden Dimension (d_{model})	512
Attention Heads	16
State Dimension (d_{state})	32
Max Sequence Length	256
Vocabulary Size	32,000 (BPE Tokenization)

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4. Training Methodology

4.1. Pre-training Data

The i3-200M model was pre-trained on a diverse corpus to ensure robust language understanding and generation capabilities. The datasets used include:

- **TinyStories**: Focuses on narrative structure and simple storytelling.
- **TinyChat**: Provides conversational dynamics and dialogue structure.
- **High-Quality English Sentences**: Contributes linguistic diversity and grammatical correctness.
- **Wikitext**: Adds general knowledge and factual context.

This multi-dataset approach is a key improvement over the earlier i3-22M model, which was trained solely on TinyChat.

4.2. Configuration and Optimization

The model was trained using the following configuration:

- **Training Steps**: 250 iterations.
- **Batch Size**: 4 (with gradient accumulation).
- **Optimizer**: AdamW with gradient clipping (max norm: 1.0).
- **Learning Rate**: 4e-4 (with warmup and cosine decay schedule).
- **Hardware**: NVIDIA P100 (16GB VRAM).
- **Training Time**: Approximately 1-2 hours.

4.3. Memory Efficiency

The training process incorporated several memory-optimized techniques, crucial for training a model of this size on limited hardware:

- **Streaming Vocabulary Building**: The vocabulary was built without storing the full text in memory.
- **Vocabulary Caching**: The built vocabulary was cached for reuse.
- **Automatic Memory Cleanup**: Intermediate data was automatically cleaned up to manage VRAM usage.

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5. Experiments and Results

The i3-200M model was evaluated based on its final training loss and perplexity.

5.1. Performance Metrics

Metric	Initial	Final
Training Loss	~10.0	**1.6**
Perplexity	~4000+	**5.2**

The low final perplexity of 5.2 indicates a strong capacity for language modeling and prediction on the training distribution.

5.2. Comparison with Previous Models

The i3-200M represents a significant scaling and architectural refinement over its predecessors, the i3-22M and i3-80M.

Feature	i3-22M	i3-80M	i3-200M (This Model)
Parameters	22.6M	82.77M	**169.85M**
Architecture	24 Hybrid Layers (Pure Hybrid)	10 Hybrid + 6 Attention	**10 Hybrid + 6 Attention**
Hidden Dimension	512	512	**512**
Vocabulary Size	4,466	35,560	**32,000**
Training Dataset	TinyChat only	TinyStories + TinyChat + HQ Sentences	**TinyStories + TinyChat + HQ Sentences + Wikitext**
Final Loss	~2.0	~2.0	**1.6**
Final Perplexity	7.29-9.70	7.29-10.0	**5.2**
Attention Layers	None	6 Full Attention Layers	**6 Full Attention Layers**

The i3-200M achieves a substantial reduction in both final loss (1.6 vs. ~2.0) and perplexity (5.2 vs. 7.29-10.0) compared to the i3-80M, despite only doubling the parameter count. This improvement is attributed to the expanded and more diverse training corpus, as well as the refined hybrid block design.

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6. Conclusion and Future Work

The i3-200M model successfully demonstrates the viability of a hierarchical hybrid architecture for language modeling. By combining the linear-complexity efficiency of RWKV-Mamba blocks with the global context capabilities of full attention layers, the model achieves strong performance metrics (Perplexity 5.2) with a moderate size and highly efficient training.

Limitations of the current model include its limited context window (256 tokens) and training on English text only.

Future work will focus on:

1. Scaling the model size and context window to further evaluate the performance ceiling of the hierarchical hybrid design.
2. Exploring the optimal ratio of hybrid blocks to attention blocks for various downstream tasks.
3. Expanding the training corpus to include multilingual data.

References

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