MOSS: Multi-Modal Representation Learning on Sequential Circuits

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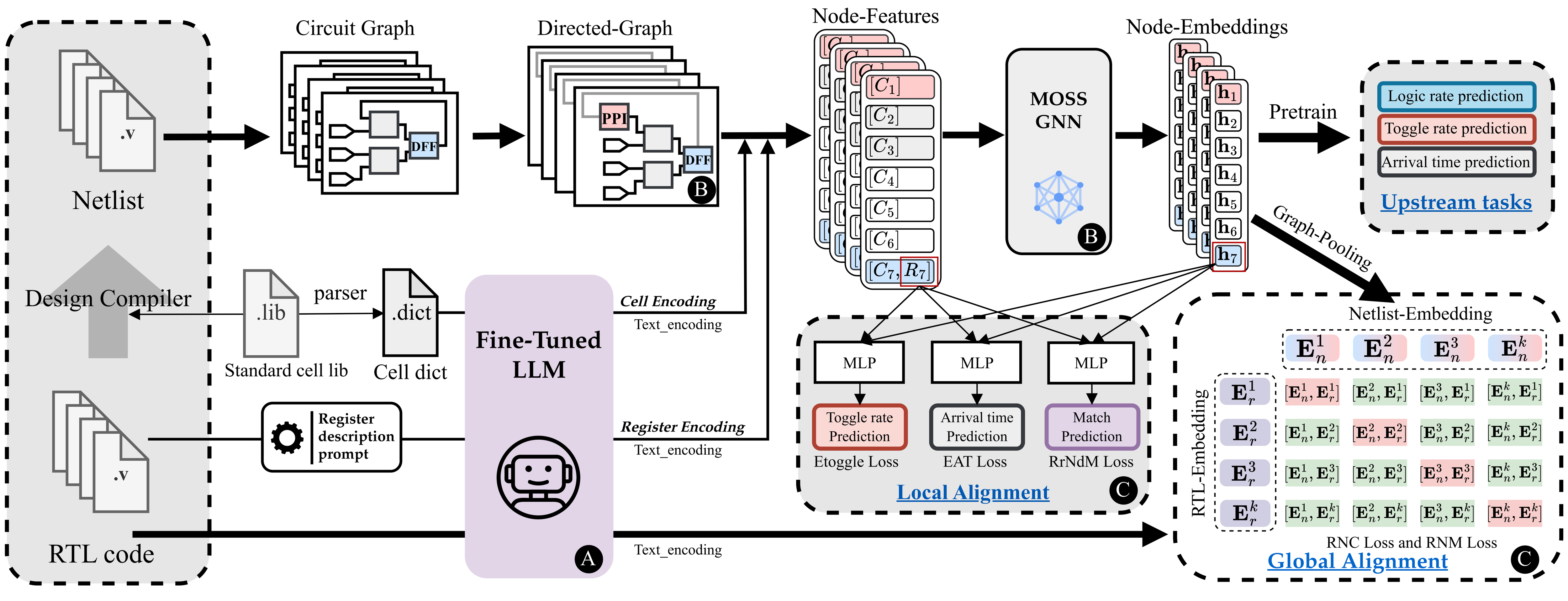


Figure 1. Overview of the MOSS framework

Introduction

- Deep learning has significantly advanced Electronic Design Automation (EDA), with circuit representation learning emerging as a key area
- Existing methods use either LLMs for RTL analysis or GNNs for netlist modeling
- Challenges: GNNs face difficulties with sequential circuits:
  - Long-range information dependencies
  - Insufficient functional supervision
  - Limited generalization capability

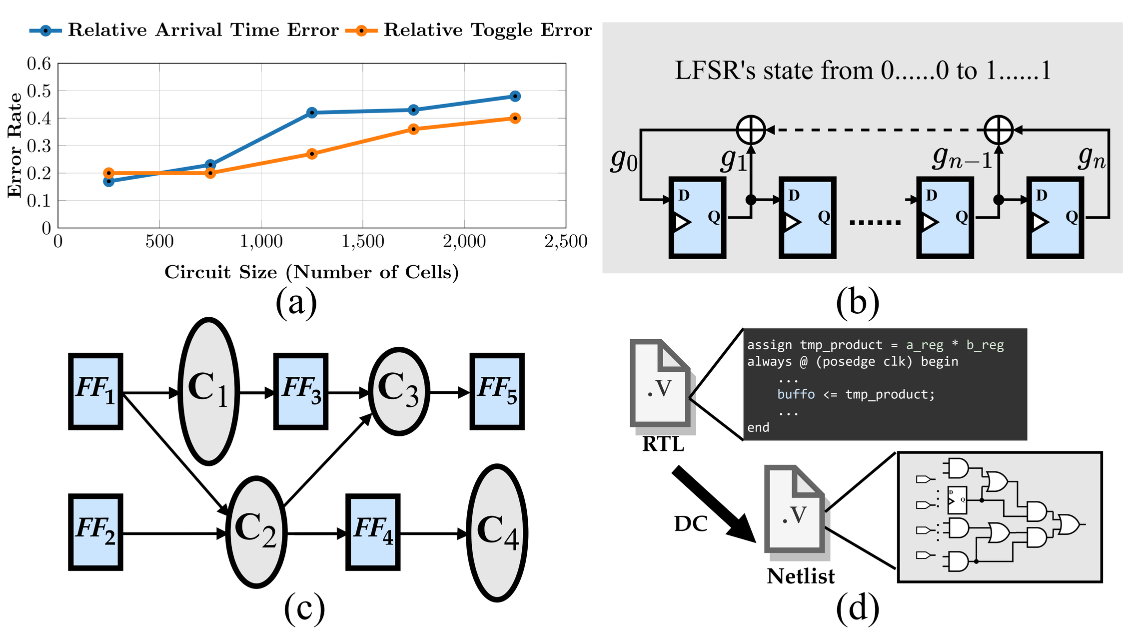


Figure 2. Challenges and motivations for sequential circuit representation learning

Our Solution: MOSS

- Integrates GNNs with LLMs for sequential circuit modeling
- Enhances DFF node features with LLM embeddings from RTL
- Introduces adaptive aggregation and two-phase propagation
- Achieves **95.2%** accuracy in arrival time prediction

Problem Formulation

Sequential circuits modeled as directed graphs $G = (V, E)$:

- V: circuit components (logic gates, DFFs)
- E: component connections

Goal: Learn node embeddings $\mathbf{H} \in \mathbb{R}^{|V|\times d}$ that encode both structural and temporal features:

$$\mathbf{H} = f(G, \mathbf{X}, \mathbf{T}) = f(V, E, \mathbf{X}, \mathbf{T}) \quad (1)$$

where $\mathbf{X}$ represents structural features and $\mathbf{T}$ represents temporal features.

Key Tasks:

- Toggle rate/Power prediction
- Arrival time prediction
- Functional equivalence checking

MOSS Framework Overview

Key Components:

1. **LLM-Enhanced Node Features:** Fine-tuned LLM generates contextual embeddings for DFF nodes
2. **Graph Construction:** Netlist represented as directed graph with adaptive aggregators
3. **Local & Global Alignment:** Multi-task learning with specialized loss functions

Technical Innovations

1. LLM Fine-Tuning and Feature Enhancement

- Fine-tuned Yi-Coder-9B-Chat on 31,701 RTL descriptions
- Extract contextual embeddings for registers and logic cells
- Mean pooling to aggregate token embeddings

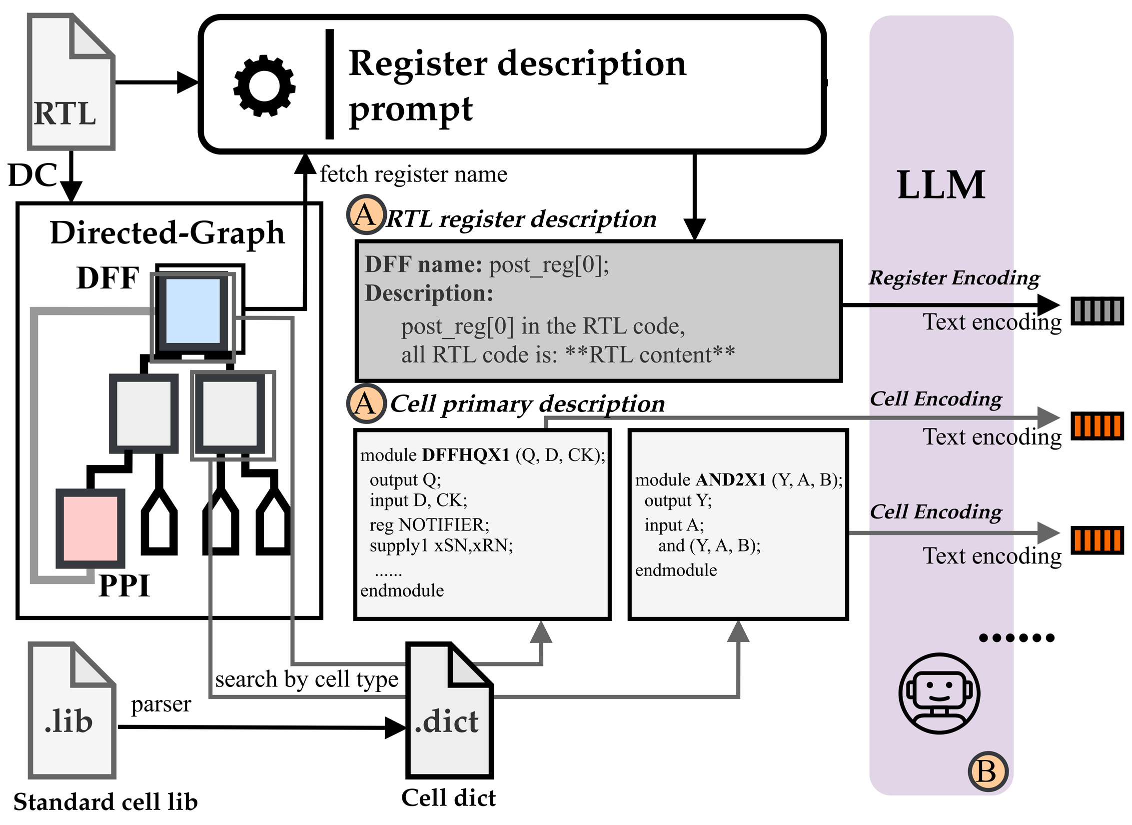


Figure 3. LLM feature extraction process

2. Adaptive Aggregator Design

- DBSCAN clustering based on LLM embeddings
- Different attention-based aggregators for each cell category
- Automatically adapts to various cell types

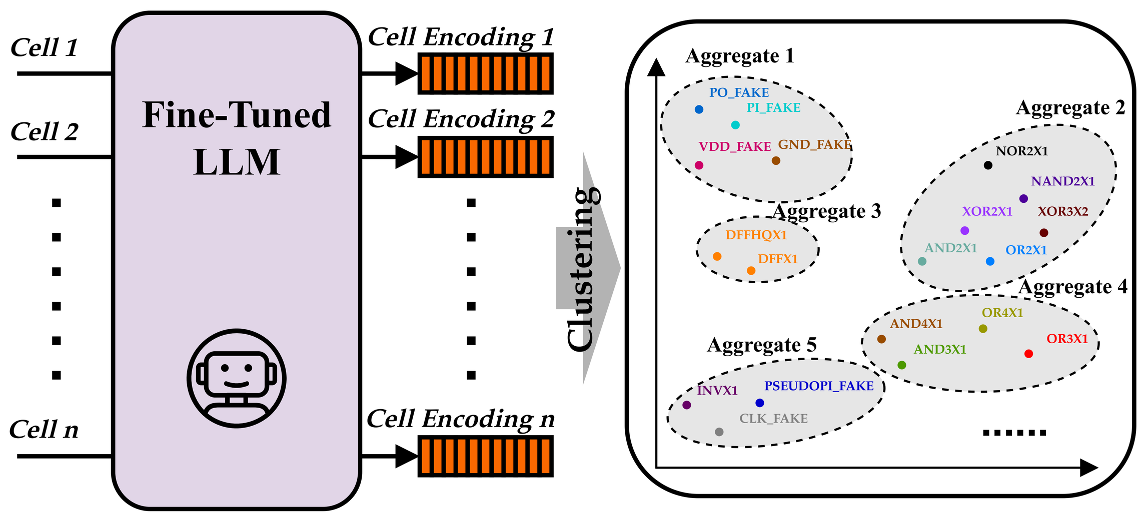


Figure 4. Adaptive aggregator with clustering

3. Two-Phase Propagation Mechanism

- **Phase 1:** Forward propagation from PIs to DFFs
- **Phase 2:** Turnaround propagation for feedback loops
- Asynchronous updates to model signal propagation

Experimental Results

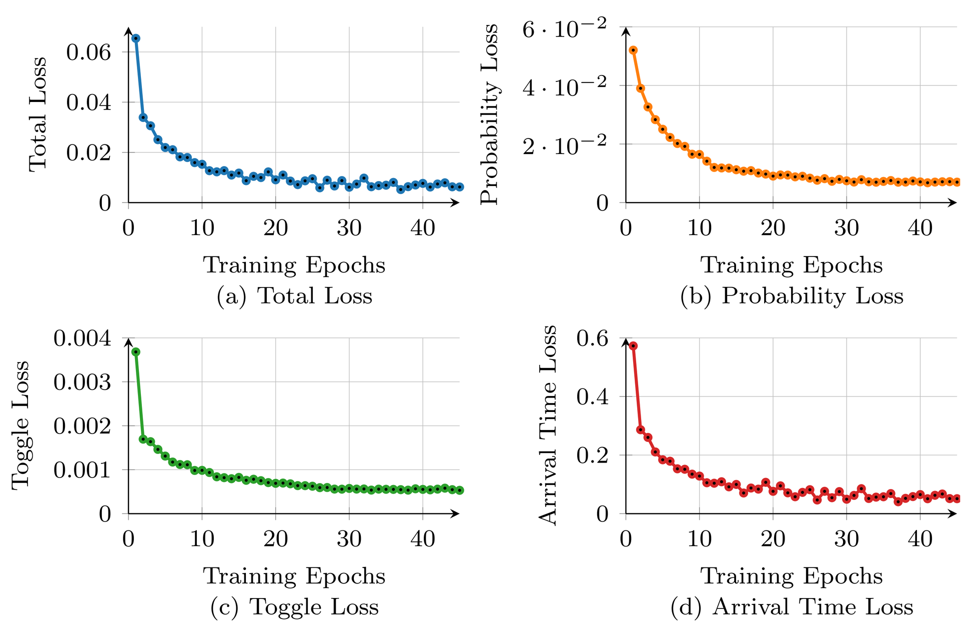
Dataset: 31,701 RTL designs synthesized with Synopsys DC
Circuit sizes: 100 to 5,000 cells

Table 1. Performance comparison on various metrics (%)

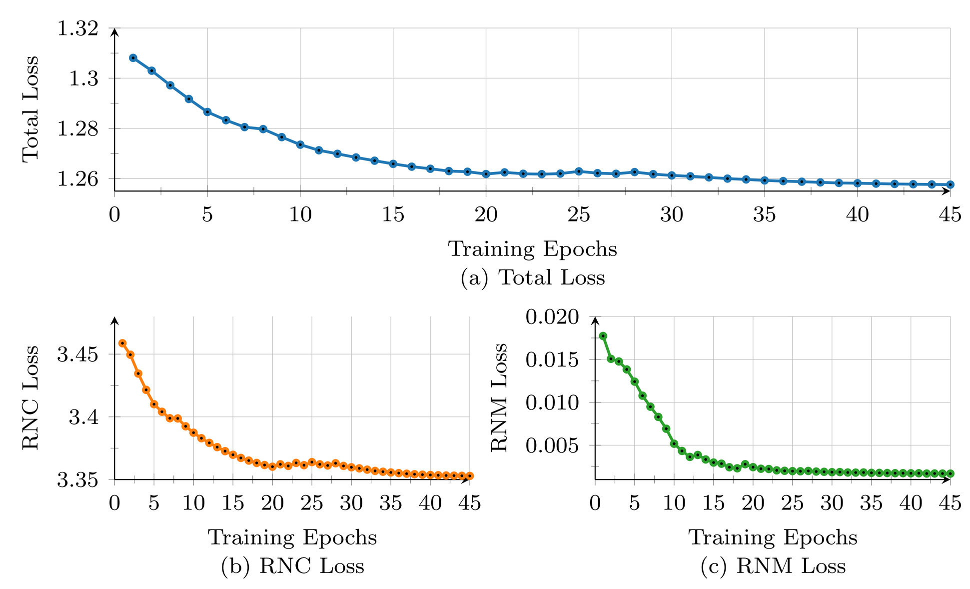
Circuit	DeepSeq2			MOSS w/o FAA			MOSS w/o AA			MOSS w/o A			**MOSS**		
	ATP	TRP	PP	ATP	TRP	PP	ATP	TRP	PP	ATP	TRP	PP	ATP	TRP	PP
max_selector	81.4	78.7	94.6	47.0	75.8	88.6	82.3	85.2	94.5	95.4	89.4	99.9	**95.6**	**90.5**	**99.9**
pipeline_reg	77.6	83.6	91.4	52.2	63.6	63.4	80.5	88.3	90.2	94.2	92.1	94.1	**94.5**	**92.4**	**94.6**
mult_16x32	57.6	66.6	80.1	19.3	40.1	54.1	75.2	72.3	85.4	93.9	84.8	91.5	**94.3**	**87.9**	**93.5**
Average	79.1	76.4	88.4	45.6	57.1	75.1	80.3	81.0	90.7	94.9	87.0	95.1	**95.2**	**87.5**	**96.3**

Key Findings:

- MOSS achieves 95.2% accuracy in arrival time prediction and leads with 96.3% accuracy for power prediction.
- Significant improvement on larger circuits (e.g., mult_16x32: 94.3% vs 57.6%)
- Superior performance in functional equivalence checking (93.7% average)



(a) Pre-training losses



(b) Alignment losses

Figure 5. Training loss curves showing effective convergence

Ablation Study Results:

- LLM features crucial: MOSS w/o FAA drops to 45.6% ATP
- Alignment important for FEP: 93.7% → 26.6% without alignment
- Adaptive aggregator improves all metrics

Conclusion

- **First multimodal framework** combining GNNs and LLMs for sequential circuits
- **Novel techniques:** LLM-enhanced DFF features, adaptive aggregation, two-phase propagation
- **Superior performance:** Experimental results show that MOSS significantly boosts accuracy for tasks like toggle rate and arrival time prediction——95.2% arrival time prediction accuracy
- **Addresses key challenges:** Long-range dependencies and functional supervision
- **Future impact:** Opens new directions for AI-driven EDA research and multimodal EDA prediction

Acknowledgements

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