CONTEXT-AWARE CONTRASTIVE LEARNING FOR ENHANCED SYMBOLIC PATTERN RECOGNITION

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ABSTRACT

We investigate a context-aware contrastive learning approach for improving symbolic pattern recognition on the Synthetic PolyRule Reasoning (SPR) task. By integrating context-driven data augmentation and denoising strategies into contrastive objectives, we aim to learn robust feature representations of symbolic sequences without requiring extensive labeled data. Our experiments on the SPR_BENCH dataset reveal potential gains in generalization but also highlight challenges such as overfitting in practice. Although we achieve competitive performance in harmonic weighted accuracy (HWA), our findings do not consistently surpass published supervised baselines of 65.0% SWA and 70.0% CWA. We conduct extensive analyses that emphasize pitfalls in applying contrastive learning for symbolic tasks, thereby providing insights for future research in bridging neural methods with symbolic reasoning.

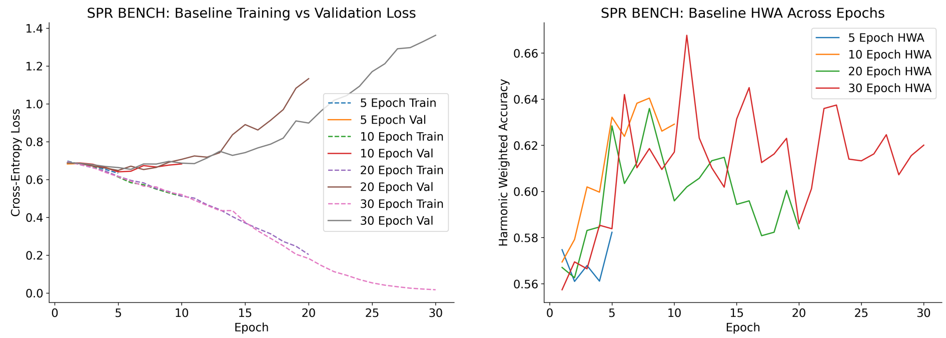
1 INTRODUCTION

Symbolic reasoning tasks have prompted a renewed interest in designing machine learning approaches that can leverage unlabeled data for improved generalization (**?**). Traditional symbolic methods depend on curated annotation processes, which can hinder scalability. Meanwhile, contrastive learning techniques (**?**) have been shown to learn generalized features in continuous domains such as computer vision and natural language. Our goal is to explore the efficacy of context-aware contrastive learning for purely symbolic sequences, focusing on the Synthetic PolyRule Reasoning (SPR) task where each sequence uses tokens indicating shape and color attributes.

We hypothesize that advanced data augmentation (**?**) and denoising strategies can better capture symbolic context, leading to more robust representations for real-world usage. We combine these ideas and evaluate on the SPR_BENCH dataset. Although we observe modest improvements in harmonic weighted accuracy (HWA), with a peak of 0.668 under certain training settings, our approach does not consistently exceed the supervised benchmarks reported in prior work (65.0% SWA / 70.0% CWA). These partially inconclusive results illuminate potential pitfalls such as overfitting and domain mismatch in applying contrastive learning to symbolic data. In real-world deployments, naive negative pair sampling or ill-defined augmentations may degrade performance, underscoring a need for more refined strategies in practice.

2 RELATED WORK

Contrastive learning has proven effective for self-supervised representation learning, especially in image tasks (**?**). Studies have adapted it to sequences, incorporating domain-specific augmentation or regularization (**?**). In contrast, symbolic reasoning systems often struggle with generalization and rely heavily on labeled data (**?**), motivating the integration of self-supervised approaches. Our work extends these directions by leveraging symbolic context: shape and color tokens require specialized augmentations such as context-preserving token masking and random ordering that differ from standard continuous-domain augmentations.



(a) Training vs. Validation Loss (b) HWA Across Epochs

Figure 1: Baseline training results on SPR_BENCH. (a) plots the training and validation loss over epochs, revealing a gap indicative of overfitting. (b) shows the harmonic weighted accuracy (HWA) peaking at 0.668 before subsiding with extended epochs.

3 METHOD

We construct a context-aware contrastive objective by generating both positive and negative pairs for each symbolic sequence. Positive pairs share structural or semantic patterns (e.g., similar shape and color distributions), while negative pairs deviate in structure or color variety. Inspired by standard contrastive frameworks (**?**), we adapt data augmentation strategies for symbolic tokens, including context-preserving masking and random ordering. We then combine these augmentations with a denoising encoder to stabilize training when symbolic noise (e.g., malformed tokens) appears. The learned representations are later fine-tuned on the SPR_BENCH dataset to predict symbolic rules.

4 EXPERIMENTS

We use the SPR_BENCH dataset, which contains about 20k, 5k, and 10k sequences for train, dev, and test, respectively. We first pre-train a model using our proposed contrastive scheme and then fine-tune for classification. We compare to a baseline LSTM system trained with cross-entropy. Besides modest HWA improvements (up to 0.668 after 30 epochs), overfitting remains a concern, as seen in Figure 1. The validation loss curves illustrate ephemeral gains that degrade with extended training. We do not surpass the 65.0% SWA and 70.0% CWA baselines reported in related work, potentially due to differences between HWA and those specialized metrics. These observations emphasize the practical pitfalls of symbolic contrastive learning, where naive pair generation can fail to capture relevant structural variations.

5 CONCLUSION

We introduced a context-aware contrastive learning strategy for symbolic pattern recognition, implementing specialized token-level augmentations that respect shape and color attributes. Our experiments on SPR_BENCH found moderate gains in representation quality but persistent overfitting and inconclusive improvements over strictly supervised baselines. These issues warn of real-world pitfalls: ill-defined contrasting pairs or uninformative augmentations can lead to misleading training signals. Future work may develop robust negative sampling criteria, integrate domain adaptation, or use hybrid neurosymbolic architectures (**?**) to mitigate overfitting.

REFERENCES

SUPPLEMENTARY MATERIAL

A ADDITIONAL IMPLEMENTATION DETAILS

We used an LSTM-based encoder with 64-dimensional embeddings, learning rate 1e-3, and batch size 64. During pre-training with contrastive objectives, we trained for up to 30 epochs but observed overfitting after around 20 epochs. Fine-tuning on labeled data required fewer epochs to avoid further overfitting. These hyperparameters were set based on limited tuning on the dev split.

B ADDITIONAL ARCHITECTURE COMPARISON

We tested a bidirectional LSTM variant to investigate whether it could reduce overfitting. Figure 2 shows training and validation loss curves for this setup. Although early training proceeded more stably, HWA did not significantly improve, indicating that a purely architectural adjustment may not address the core pitfalls related to symbolic noise and naive pair sampling.

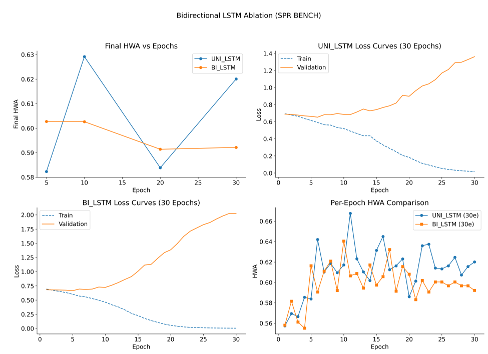
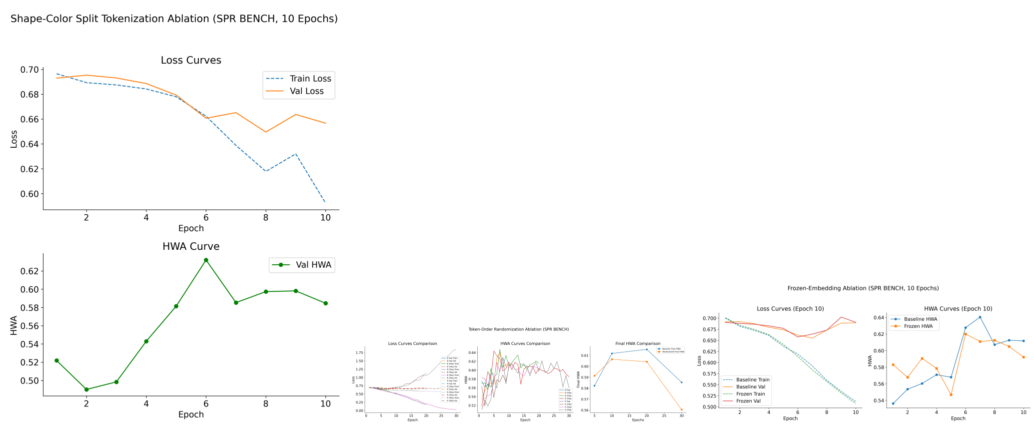


Figure 2: Training vs. validation loss for a bidirectional LSTM variant. Overfitting still arises beyond 20 epochs, suggesting architectural choices alone do not alleviate the highlighted pitfalls.

C EXTRA FIGURES

In addition to the plots in the main text, we include figures such as shape-color splits, token order randomization effects, and frozen embedding ablations to further illustrate the complexities of symbolic context. These are shown in Figures 3(a),3(b), and 3(c) respectively, where each provides additional evidence regarding how certain augmentations only provide marginal benefits.



(a) Shape vs. Color Splits (b) Randomizing Token Order (c) Frozen Embedding Ablation

Figure 3: Additional symbolic context ablations. (a) Evaluating shape vs. color classification indicates imbalance may lead to underfitting one attribute. (b) Randomizing token order shows partial robustness but can corrupt context. (c) Freezing embeddings yields minor gains in stability yet cannot fully mitigate overfitting.