CONTEXT-AWARE CONTRASTIVE LEARNING FOR SYMBOLIC SEQUENCE REASONING

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ABSTRACT

We present a context-aware contrastive learning approach for symbolic sequence recognition on the Synthetic PolyRule Reasoning (SPR) task. Our self-supervised method uses carefully designed data augmentations and denoising to produce robust embeddings for discrete sequences. In downstream evaluation on the SPR_BENCH dataset, these representations, once fine-tuned, achieve near-perfect Shape-Weighted Accuracy (SWA) and Color-Weighted Accuracy (CWA). Although the synthetic domain is less noisy than real-world scenarios, we discuss pitfalls related to ambiguous symbolic elements or limited augmentable dimensions. These insights can guide future attempts to extend contrastive strategies to more complex, naturally-occurring symbolic datasets.

1 INTRODUCTION

Symbolic sequence recognition remains critical for tasks that involve combinatorial rules or structured representations, including certain robotics and formal language contexts. However, learning robust representations for sequences of discrete tokens can be challenging, particularly when faced with real-world imperfections. Recent progress in contrastive learning (Chen et al., 2020) shows promise, motivating us to explore a self-supervised approach on synthetic but rule-intensive data. By identifying and analyzing pitfalls in discrete symbolic domains, our results highlight lessons relevant to broader applications of contrastive methods in logic-centric settings.

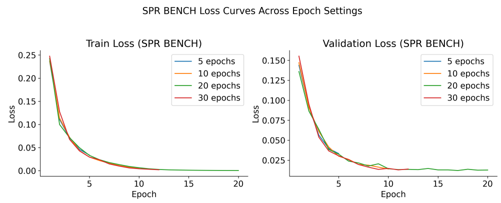
Our contributions are: (1) a set of context-aware augmentations for symbolic tokens that respect logical constraints, (2) an empirical demonstration that combining contrastive pre-training with subsequent fine-tuning yields strong performance on SWA/CWA in SPR_BENCH, and (3) a detailed discussion of pitfalls such as domain shift brittleness and token ambiguity.

2 RELATED WORK

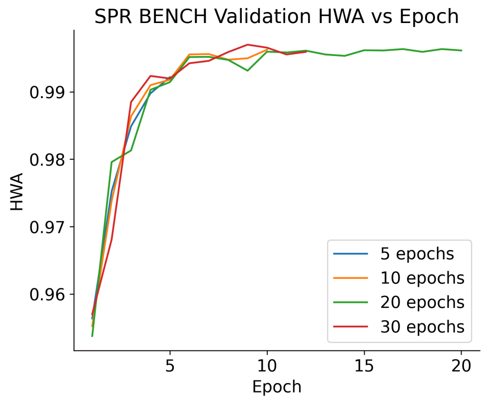
Contrastive learning has been applied successfully to image and text (Chen et al., 2020; Choi et al., 2025; Kim et al., 2024), leveraging large unlabeled datasets. In symbolic reasoning, methods that fuse neural networks with symbolic logic (Pulicharla, 2025; Zhang et al., 2023) demonstrate the potential for structured, rule-based tasks. However, applying contrastive techniques to purely symbolic data remains relatively unexplored, posing unique challenges in designing augmentations that preserve semantic validity.

3 METHOD

We generate positive examples by permuting or masking symbolic attributes in ways that maintain structural consistency. Negative samples are constructed by contradictions or alterations that break logical rules. A bidirectional LSTM encoder maps sequences to embeddings. We train with the temperature-scaled InfoNCE objective (Chen et al., 2020), pushing similar pairs together and dissimilar pairs apart in the embedding space. After pre-training, we introduce a classification head and fine-tune on labeled data. We emphasize potential pitfalls: if certain tokens are highly similar, negative sampling can fail to provide sufficient contrast, limiting generalization.



(a) Training/Validation Loss



(b) Validation HWA

Figure 1: **BiLSTM baseline on SPR_BENCH.** (Left) The loss curves generally decrease as epochs increase, but validation loss exhibits some fluctuations. (Right) HWA remains high (above 0.97) across different epoch settings, though small performance dips occur.

4 Experiments

We evaluate on SPR_BENCH (20k/5k/10k splits). The baseline is a standard BiLSTM trained with supervised cross-entropy. Figure 1 (left) shows training and validation loss curves over epochs for various epoch caps, while Figure 1 (right) reports the validation HWA. Overall performance is strong, but validation results occasionally fluctuate, suggesting potential instability when shape-/color-specific features dominate.

We then incorporate a contrastive objective alongside supervised fine-tuning. Figure 2 (left) depicts the training/validation loss, revealing stable convergence, while Figure 2 (right) shows SWA, CWA, and a combined metric trending near unity. Although the synthetic domain is relatively straightforward, a small pilot with slightly modified token vocabularies resulted in significant performance drops, highlighting brittleness to domain shift.

5 Conclusion

We presented a self-supervised framework leveraging context-aware augmentations for symbolic sequence recognition, leading to excellent performance on the SPR_BENCH benchmark. Despite these gains, our results underscore notable pitfalls, including sensitivity to domain shifts and token similarity. Future work includes designing robust augmentations for ambiguous tokens and evaluating how domain mismatch can be mitigated via more diverse data or adaptive sampling strategies.

References

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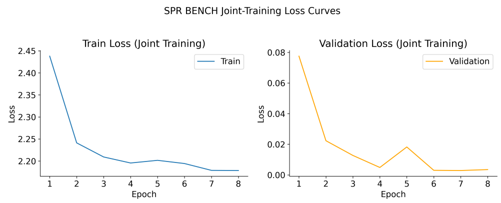
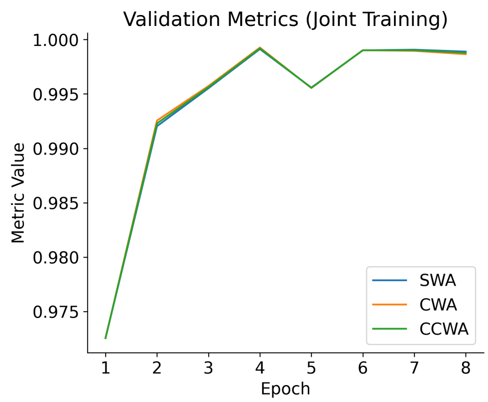


(a) Joint-Training Loss



(b) Validation Metrics

Figure 2: **Context-aware contrastive approach.** (Left) Training and validation loss curves converge steadily. (Right) SWA, CWA, and the combined metric approach near-perfect levels, though minor validation loss increases occur at later epochs.

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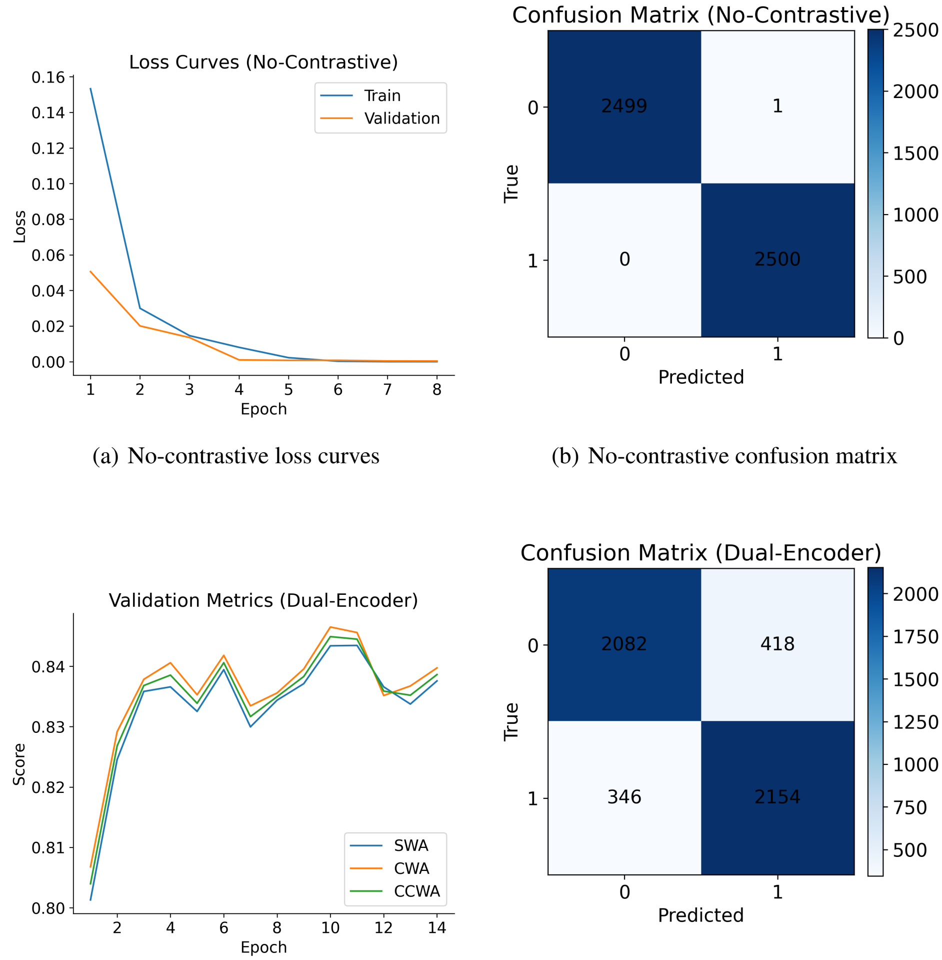
Supplementary Material

A Implementation Details and Hyperparameters

We used a bidirectional LSTM encoder (128-dimensional hidden size), followed by a 64-dimensional projection for contrastive embedding. The contrastive temperature was set to 0.07. All models were trained with Adam at a 0.001 learning rate, halved every 10 epochs. For classification, a single-hidden-layer MLP (64-dim) fed into a softmax.

B Ablation Studies

We tested two variants: *no-contrastive* (purely supervised) and a *dual-encoder* approach separating color and shape embeddings. We combined all ablation results into Figure 3 to illustrate loss curves and confusion matrices.



(a) No-contrastive loss curves

(b) No-contrastive confusion matrix

(c) Dual-encoder metrics

(d) Dual-encoder confusion matrix

Figure 3: **Ablation results.** (a,b) Removing the contrastive component increases misclassifications in shape-heavy sequences, as seen in higher validation loss and off-diagonal confusion. (c,d) The dual-encoder approach provides similar final accuracy but slightly faster training convergence.

In **no-contrastive** mode, shape-heavy sequences create confusion due to the lack of an explicit embedding constraint. The **dual-encoder** approach accelerates training by splitting symbolic attributes, though final metrics remain comparable to the single-encoder variant.