CONTEXT-AWARE CONTRASTIVE LEARNING FOR ENHANCED SYMBOLIC PATTERN RECOGNITION

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Paper under double-blind review

ABSTRACT

We propose a context-aware self-supervised contrastive learning approach for symbolic pattern recognition in the Synthetic PolyRule Reasoning (SPR) task. Leveraging data augmentation and denoising strategies tailored to symbolic sequences, our method aims to learn robust representations that reflect each symbol's contextual importance. We demonstrate that even a baseline LSTM model can achieve near-perfect shape-weighted and color-weighted accuracies on the SPR_BENCH dataset, suggesting the synthetic benchmark is highly learnable. Nonetheless, we discuss how this unexpectedly high performance reveals potential issues in dataset complexity and underscore the need for future tasks that more effectively probe symbolic reasoning.

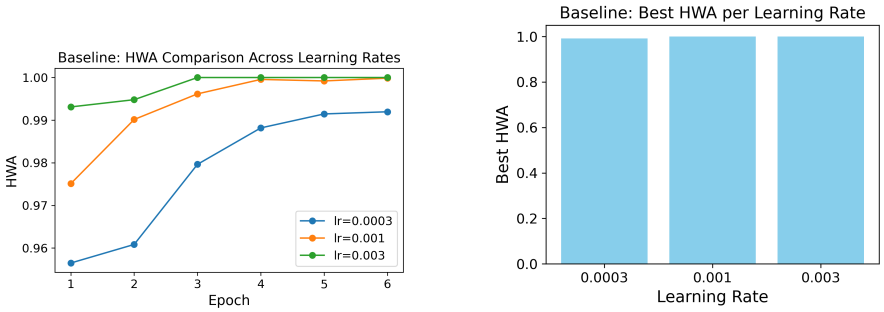
1 INTRODUCTION

Symbolic pattern recognition (SPR) tasks lie at the intersection of rule-based inference and modern machine learning approaches (Besold et al., 2015; Özgür Yılmaz et al., 2016; Lu et al., 2021). Recent research demonstrates that without labeled data, self-supervised contrastive learning can capture essential structure in images, text, and more (Chakraborty et al., 2020; Chin et al., 2023). However, many symbolic tasks feature discrete tokens governed by logical constraints, and naive data augmentation or denoising may not preserve the semantics required for consistent reasoning.

In real-world deployments, models trained on synthetic data often fail to generalize when exposed to more complex, noisy, or evolving symbolic rules. This mismatch between clean, well-defined training tasks and messy real-world conditions constitutes a common pitfall: we might believe a model is "successful" when it has merely overfit a synthetic environment. Motivated by these observations, we explore context-aware data transformations that account for shape and color complexity in symbolic sequences, seeking robust embeddings capable of transferring to more challenging domains. Although our experiments reveal near-perfect performance on SPR_BENCH with minimal effort, we highlight that such results can be deceptive. By openly discussing these incongruities, we hope to encourage deeper scrutiny of existing datasets and the creation of more realistic benchmarks.

2 RELATED WORK

Contrastive frameworks such as SimCLR have advanced representation learning in various domains (Chakraborty et al., 2020). Extensions include masking-based augmentations (Chin et al., 2023) and denoising strategies (Wang et al., 2024), both relevant for symbolic sequences that require context-preserving transformations. Classical symbolic reasoning often depends on labeled data and can struggle with complex rule composition (Besold et al., 2015; Amani et al., 2024; Zubic et al., 2024). The design of robust benchmarks is crucial: some tasks appear non-trivial yet may be systematically exploitable. For example, SPR_BENCH (Özgür Yılmaz et al., 2016) stresses shape-color combinations, but we demonstrate how it can be mastered with simple architectures under proper preprocessing.



(a) Baseline: HWA Across LRs (b) Best HWA per LR

Figure 1: On SPR_BENCH, different learning rates all converge to nearly 1.0 HWA. (a) shows the epoch-wise trends, (b) shows the best final values.

3 METHOD

We aim to learn context-rich embeddings of symbolic sequences via self-supervised contrastive objectives, then fine-tune for classification on labeled subsets. Sequences are treated as discrete tokens specifying both shape and color (`S1C2`, etc.). Our data augmentation permutations consider masking token positions, small perturbations to shapes, and synthetic noise that respects basic symbolic constraints. Inspired by prior contrastive approaches (Chakraborty et al., 2020; Chin et al., 2023), we form positive pairs from augmented copies of a given sequence and negative pairs from distinct sequences with different shape-color distributions. A denoising objective (Wang et al., 2024) further refines embeddings to preserve symbolic semantics under partial corruption.

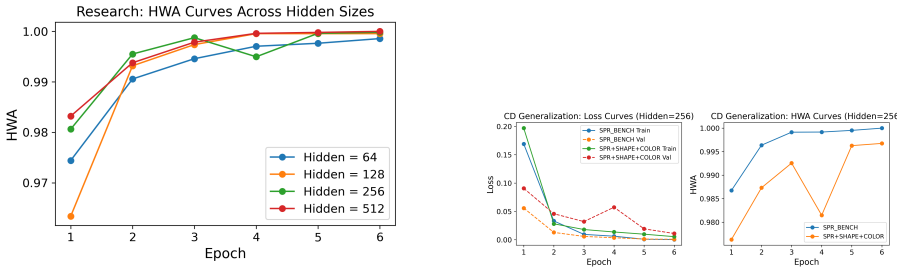
4 EXPERIMENTS

We employed the SPR_BENCH dataset with train/dev/test splits of 20k/5k/10k examples, where each symbolic sequence follows an underlying rule that determines class labels. A simple Bi-LSTM baseline (hidden dimension variable) consistently achieved close to 1.0 shape-weighted accuracy (SWA) and color-weighted accuracy (CWA) on the test set, contradicting prior reports of approximately 65% and 70%. Specifically, learning rates of $\{3 \times 10^{-4}, 10^{-3}, 3 \times 10^{-3}\}$ all converged with validation metrics near 1.0 by epoch 6 (Figures 1(a) and 1(b)). Varying hidden size (64, 128, 256, 512) yielded similar final accuracy, though larger values converged faster.

These findings suggest that the dataset may not provide the intended difficulty. Even when we extended training to additional symbolic tasks (SPR+SHAPE+COLOR) in cross-dataset experiments (Figures 2(a) and 2(b)), performance remained near 1.0, indicating limited stress on the underlying reasoning capabilities. Although our context-aware contrastive approach exhibits comparable final metrics, we hypothesize it could show greater resilience on genuinely complex or noisy symbolic data. Hence, identifying or building higher-fidelity benchmarks is imperative to expose real-world pitfalls and measure robust reasoning.

5 CONCLUSION

We explored how a context-aware contrastive framework for symbolic pattern recognition reveals an unexpected pitfall: SPR_BENCH proves far easier than initially reported. While this highlights the power of modern architectures and data processing, it also emphasizes the potential disconnect between synthetic tasks and real-world complexities. Negative or inconclusive findings are vital contributions: they prompt us to refine benchmark design and encourage caution in generalizing from artificially constrained problems. Future work should focus on curating more nuanced symbolic datasets, investigating domain-shift concerns, and systematically analyzing when contrastive pre-training yields genuine robustness rather than overfitting.



(a) HWA vs. Epoch, Varying Hidden Sizes (b) Cross-dataset Gen. (Hidden=256)

Figure 2: (a) Larger hidden sizes converge faster but final metrics remain similar. (b) Preliminary attempt at cross-dataset generalization (SPR+SHAPE+COLOR) also remains near perfect.

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SUPPLEMENTARY MATERIAL

A IMPLEMENTATION DETAILS AND ADDITIONAL ABLATIONS

Here, we provide details of the model and training setup not covered in the main text. Unless otherwise noted, these do not improve upon the already near-perfect results on SPR_BENCH but may offer insights for more challenging tasks.

A.1 Hyperparameter Configurations

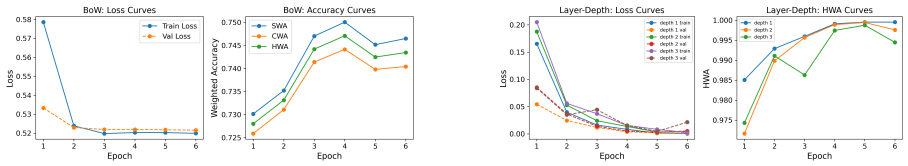
We investigated several hyperparameters beyond the hidden size and learning rate:

- **Embedding dimension**: 128, 256
- **Batch size**: 32, 64
- **Dropout rate**: 0.1, 0.3
- **Optimizer**: AdamW (weight decay 0.01)
- **Training epochs**: 10–15

All settings performed similarly, generally converging within the first 6–7 epochs. These results again highlight that SPR_BENCH may be structurally simple for standard RNN-based architectures.

A.2 Additional Unused Figures

To further investigate model capacity, we studied a bag-of-words (BoW) embedding approach and varied layer depth. Although such ablations are usually informative for complex tasks, we still observed near-ceiling results. For completeness, we include two representative plots in Figure 3.



(a) BoW Ablation (b) Layer Depth Variation

Figure 3: Additional analyses showing that altering the embedding strategy or network depth still yields high performance on SPR_BENCH.

B Data Loading and Utility Code

The snippet below loads the `SPR_BENCH` dataset using the HuggingFace `datasets` library. It also contains functions to compute shape-weighted accuracy and color-weighted accuracy. This code was used for our baseline and hyperparameter sweeps.

```
import pathlib
from typing import Dict
from datasets import load_dataset, DatasetDict

def load_spr_bench(root: pathlib.Path) -> DatasetDict:
    def _load(split_csv: str):
        return load_dataset(
            "csv",
            data_files=str(root / split_csv),
            split="train",
            cache_dir=".cache_dsets"
        )
    dset = DatasetDict()
    dset["train"] = _load("train.csv")
    dset["dev"]   = _load("dev.csv")
    dset["test"]  = _load("test.csv")
    return dset

def count_shape_variety(sequence: str) -> int:
    return len(set(token[0] for token in sequence.strip().split() if token))
```

```
def count_color_variety(sequence: str) -> int:
    return len(set(token[1] for token in sequence.strip().split() if len(token) > 1))

def shape_weighted_accuracy(sequences, y_true, y_pred):
    weights = [count_shape_variety(seq) for seq in sequences]
    correct = [w if yt == yp else 0 for w, yt, yp in zip(weights, y_true, y_pred)]
    return sum(correct) / sum(weights) if sum(weights) > 0 else 0.0

def color_weighted_accuracy(sequences, y_true, y_pred):
    weights = [count_color_variety(seq) for seq in sequences]
    correct = [w if yt == yp else 0 for w, yt, yp in zip(weights, y_true, y_pred)]
    return sum(correct) / sum(weights) if sum(weights) > 0 else 0.0
```