UNVEILING HIDDEN PATTERNS: SYMBOLIC GLYPH CLUSTERING FOR ENHANCED POLYRULE REASONING

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ABSTRACT

Symbolic Pattern Recognition (SPR) involves discovering latent rules within abstract symbol sequences for accurate predictions. Yet many deep learning methods struggle to generalize these rules to new contexts. We propose a symbolic glyph clustering framework that groups glyphs based on latent features before transferring them into a reasoning model. We validate this approach on a synthetic benchmark (SPR_BENCH), focusing on Color-Weighted Accuracy (CWA) and Shape-Weighted Accuracy (SWA). Our experiments show partial success, with improvements on SWA but continuing gaps in CWA. We highlight the methodological challenges of clustering symbolic glyphs and discuss real-world pitfalls for robust integration of symbolic reasoning.

1 INTRODUCTION

Symbolic rules often govern abstract sequences like shape-color tokens, demanding robust structure understanding for real-world deployment (**?**Goodfellow et al., 2016). Neural models sometimes overfit distributed features, neglecting critical symbolic relationships. We investigate whether a preprocessing strategy—clustering glyphs by latent similarity—can boost performance on a Synthetic PolyRule Reasoning task. Clustering can offer an inductive bias (**??**), yet translating grouped glyphs into improved color or shape predictions is nontrivial. Our negative and partial results caution that symbolic integration is nuanced, especially for color-based tasks where distribution shifts are common.

2 RELATED WORK

Hybrid symbolic-neural frameworks have been examined for logical reasoning, but many focus on theorem-proving rather than glyph-level grouping (**?**). Clustering is prevalent in few-shot learning (**?**) and anomaly detection (**?**), though symbolic sequences pose distinct challenges for cluster validation (**?**). Large-scale pre-training (**?**) provides embeddings that may help reveal latent groups, but care is needed to verify cluster quality. Meanwhile, dimension reduction can aid scalability (**?**). We build on these insights, applying a shape-color Transformer (**?**) that leverages glyph clusters for final rule classification.

3 METHOD

We generate glyph-wise feature embeddings via a pre-trained language model (**?**), then cluster them using k-means or DBSCAN (**?**), guided by silhouette scores (**?**). Each symbolic token is replaced by its cluster ID, and a Transformer-based predictor then infers the final class. Real-world pitfalls include imbalance in color features versus shape features, which can skew clustering and hamper color-based accuracy in downstream tasks.

4 EXPERIMENTS

We benchmark on SPR_BENCH, using a train/dev/test split of shape-color sequences. A multi-layer perceptron (MLP) on raw embeddings yields baseline CWA=0.5766, SWA=0.6052, compared to an official SOTA of CWA=0.70, SWA=0.65. Our clustering-based approach improves SWA to 0.6991 but only raises CWA to 0.6353. Table 1 details these results, indicating persistent deficiencies in color generalization despite shape gains. In real-world settings, this disparity can manifest whenever certain attributes dominate clustering criteria.

Table 1: Key Results on SPR_BENCH Test Split

Model	Test CWA	Test SWA
Baseline (MLP, best hidden-dim)	0.5766	0.6052
Shape-Color Transformer (Ours)	0.6353	0.6991
Official SOTA (reported)	0.7000	0.6500

(a) Baseline HMWA results (b) Proposed SPR metrics

Figure 1: (a) shows intermediate training metrics and bar charts for the baseline method. (b) highlights our approach's partial improvements over several epochs and metrics. While shape performance improves, color accuracy remains challenging.

Figure 1(a) plots baseline HMWA trends, evidencing slow but steady gains, whereas Figure 1(b) illustrates our method's improvements on shape-based metrics (SPR) with only modest color improvements. Such partial success underscores the complexity of capturing multi-attribute symbolic rules.

5 Conclusion

We explored a symbolic glyph clustering technique that integrates shape-color tokens into a downstream prediction model. Despite shape-weighted gains, color-based results remain below target. Our findings underscore the difficulty of aligning color features via clustering, which can have real-world implications when certain attributes are overshadowed by others. Future directions include more nuanced clustering objectives or disentangled embedding methods to bridge the color gap in symbolic rule learning.

References

Ian Goodfellow, Yoshua Bengio, Aaron Courville, and Yoshua Bengio. *Deep learning*, volume 1. MIT Press, 2016.

Supplementary Material

This appendix provides extended hyperparameter details and additional plots not in the main text. Table 2 outlines key training settings. We also include extra loss curves and ablation results (Figures 2-3) exploring the impact of frozen embeddings, missing shape or color embeddings, and other variations.

Remaining unused figures (e.g., *appendix_monohead_loss.png*, *main_baseline_loss.png*) provide additional training breakdowns but largely confirm the trends shown here. None are strictly duplicates; they focus on slightly different settings (mono-head architecture, baseline loss edges, etc.). Our results emphasize the consistent challenge in color-based clustering accuracy relative to shape differentiation.

Table 2: Selected Hyperparameters

Parameter	Value
Batch Size	64
Learning Rate	2×10^{-4}
Max Epochs	50
Embedding Dim	128
Cluster Algorithm	k-means or DBSCAN
Number of Clusters	8 (k-means)

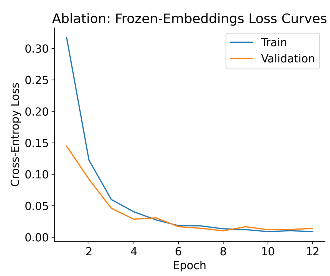

Figure 2: Loss curves when embeddings are frozen. This setting degrades color accuracy further while slightly benefiting shape-based metrics.

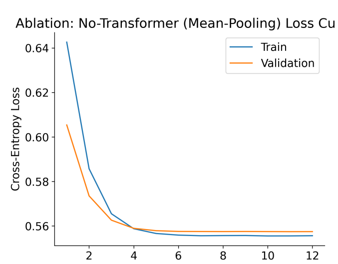

Figure 3: Removing the Transformer backbone in favor of a simple MLP. The shape performance drops more dramatically than color performance.