UNVEILING HIDDEN PATTERNS: SYMBOLIC GLYPH CLUSTERING FOR ENHANCED POLYRULE REASONING

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ABSTRACT

Symbolic Pattern Recognition (SPR) often involves deciphering latent rules from sequences of abstract glyphs. We investigate whether clustering glyphs based on latent feature representations can reveal hidden structure and improve reasoning performance. We propose a pipeline that uses pre-trained embeddings, clusters glyphs using K-means, then feeds the clustered representations into a neural reasoning model. Experiments on a synthetic SPR benchmark show partial improvements, particularly for shape-focused metrics, yet fail to surpass the state of the art on color-based tasks. The findings highlight the challenges and potential pitfalls in applying clustering to symbolic reasoning.

1 INTRODUCTION

Many real-world tasks involve abstract, symbolic manipulations, but neural models often struggle when symbols do not follow conventional text distributions. Synthetic datasets such as SPR_BENCH facilitate controlled evaluation (**?**). Our focus is symbol clustering for improved reasoning. We hypothesize that grouping glyphs by shared features can reveal interpretable patterns. This can have implications for neural-symbolic integration (**??**) and for bridging latent representations with more explicit structure (Goodfellow et al., 2016).

We present a clustering-based approach for PolyRule reasoning: (1) latent feature extraction, (2) glyph grouping, and (3) aggregated reasoning. Despite observing strong performance on shape-dependent metrics, our approach underperforms on color-weighted tasks. These mixed results underscore the challenges of balancing multiple symbolic attributes.

2 RELATED WORK

Symbolic clustering has been explored in few-shot learning (**?**) and unsupervised object representation tasks (**?**), though prior studies have focused on visual or textual data rather than abstract glyphs. Dimensionality reduction (e.g., PCA) is often applied to mitigate computational costs when clustering large feature sets (**?**). We rely on K-means (**?**) and validate cluster quality using silhouette scores (**?**). Our work expands on neural-symbolic methodologies (**??**) by focusing on a novel symbolic domain with color and shape attributes. Clustering high-entropy symbols can be ambiguous (**?**), leading to possible pitfalls in real-world deployments.

3 METHOD

We load sequences from SPR_BENCH, each symbol composed of shape and color tags, then tokenize them with a pre-trained model (e.g., BERT) (**?**) or simple ID lookups. We optionally reduce dimensionality (**?**) before clustering. K-means assigns each symbol to a cluster, producing a label used alongside the raw shape and color embeddings. A neural reasoning module (e.g., a BiLSTM) sums or concatenates embeddings, averages token representations, and classifies the rule. We train with cross-entropy on the labeled sequence, keeping the best checkpoint by validation loss.

(a) Baseline Dimension Tuning (b) Enhanced BiLSTM + Clustering

Figure 1: Key experiment results on SPR_BENCH. Left: minor gains from higher embedding dimensions. Right: BiLSTM plus glyph clustering improves shape-based metrics but struggles with color attributes.

4 Experiments

We first compare a baseline model with embedding dimensions of 4–64. Validation scores increase slightly for higher dimensions, but test metrics remain around 0.63–0.68 for color and shape. We then incorporate clustering. On the test set, shape-weighted accuracy (SWA) reaches 0.70, surpassing a 0.65 benchmark. However, color-weighted accuracy (CWA) remains at 0.635, short of the 0.70 state of the art. Figure 1(a) shows baseline tuning, and Figure 1(b) presents results for the enhanced BiLSTM.

All experiments use the Adam optimizer with a learning rate of 2e-4, batch size of 32, and up to 100 training epochs. Early stopping with patience of 5 is applied based on validation loss. We observe that clustering helps capture certain shape attributes yet introduces confusion on color tasks, possibly due to the high variability in color embeddings.

5 Conclusion

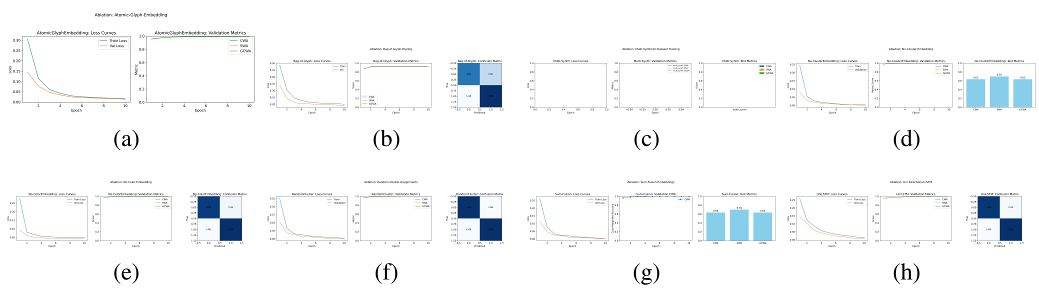
Symbolic glyph clustering for reasoning shows promise in revealing latent shape structure, but it does not universally enhance performance across color attributes. The partial success underscores the need for robust multi-attribute representations that effectively capture color and shape. Future work may incorporate alternative distance metrics or more specialized clustering approaches to accommodate diverse symbolic properties. These findings reveal the importance of reporting challenges and negative outcomes in symbolic pattern recognition, aligning with the workshop's goal of fostering open discussion.

References

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

Supplementary Material

This section provides further details and additional analyses that could not be included in the main text due to space constraints. We also include ablation studies examining alternative embedding and clustering strategies. Figure 2 presents their results. In these experiments, we consider variations such as removing color embeddings, using random cluster assignments, or adopting atomic glyph embeddings. We observe that removing color embeddings degrades performance on color-based tasks, confirming the difficulty of capturing multi-attribute features. Random clustering notably harms reasoning accuracy across all measures.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 2: Ablation studies for various configurations: (a) atomic glyph embeddings; (b) bag-of-glyph approach; (c) multi-synth training; (d) no cluster embedding; (e) no color embedding; (f) random clustering; (g) summation-based fusion; (h) unidirectional LSTM.