ViRel: Unsupervised Visual Relations Discovery with Graph-level Analogy

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Introduction

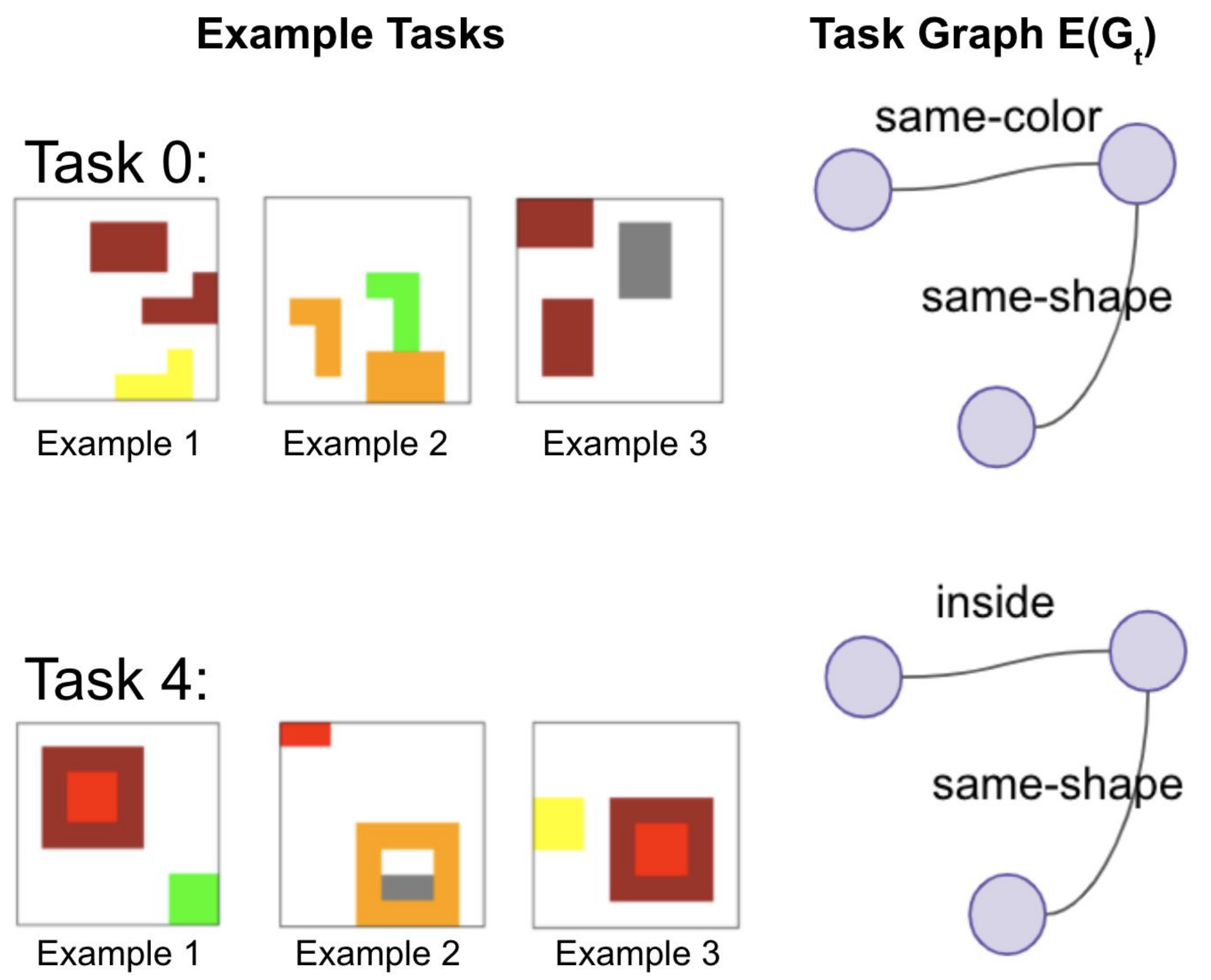
- Visual relations form the basis of understanding our compositional world, as relationships between visual objects capture key information in a scene.
- We tackle learning and discovering relations without supervision, where relation types and labels are not known *a priori*
- In contrast, when relations are learned with predefined labels in a supervised context, this limits us to settings which depend on those seen relations

Problem Statement

- Input: [*16 x 16 x 9 x n]* images, and no knowledge of objects, nor relation types, nor underlying graph per example
- The goal: Infer the global relation types
- Graph *E(*g_i*)* of each image x_i
- Relational graph structure *E(*G_t*)* for each task *t*
  - Requires identifying relation $e_{k,l}$ between object pairs
  - Metric: Relation Classification Accuracy %

Dataset: BabyARC

- Collection of images (observations) x_i
- Each image x_i belongs to some known task *t* ∈ *T*.
- Each task *t* has an unknown unique task graph G_t *= (V, E),* where nodes V are objects and edges E are the corresponding relations
- All of its corresponding images share this common relational subgraph *E(*G_t*)*
- Objects in x_i part of relational subgraph: "core" objects Not part of relational subgraph: "distractor" objects



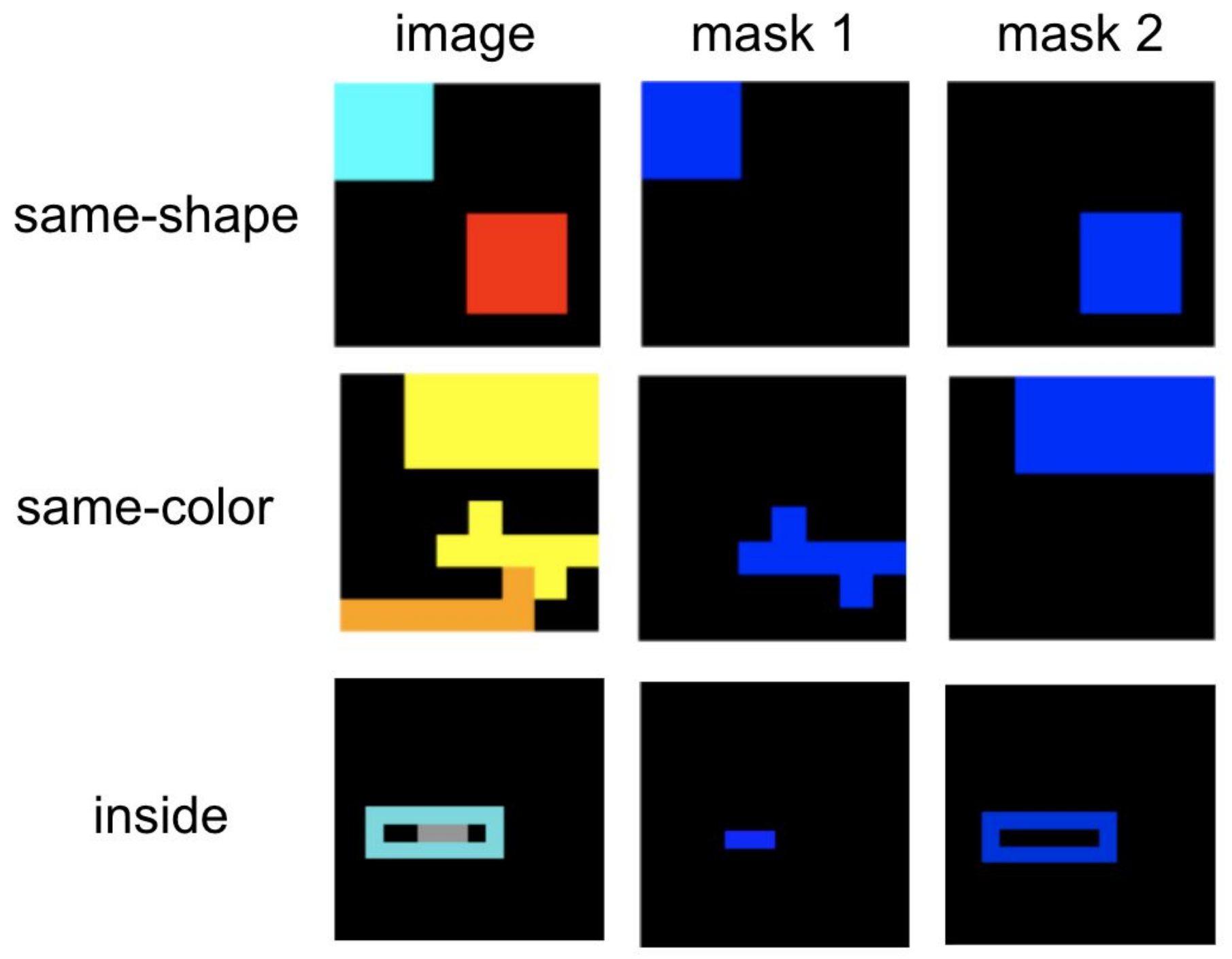


Figure 1. The relations in dataset, 'same-shape', 'same-color', 'inside'

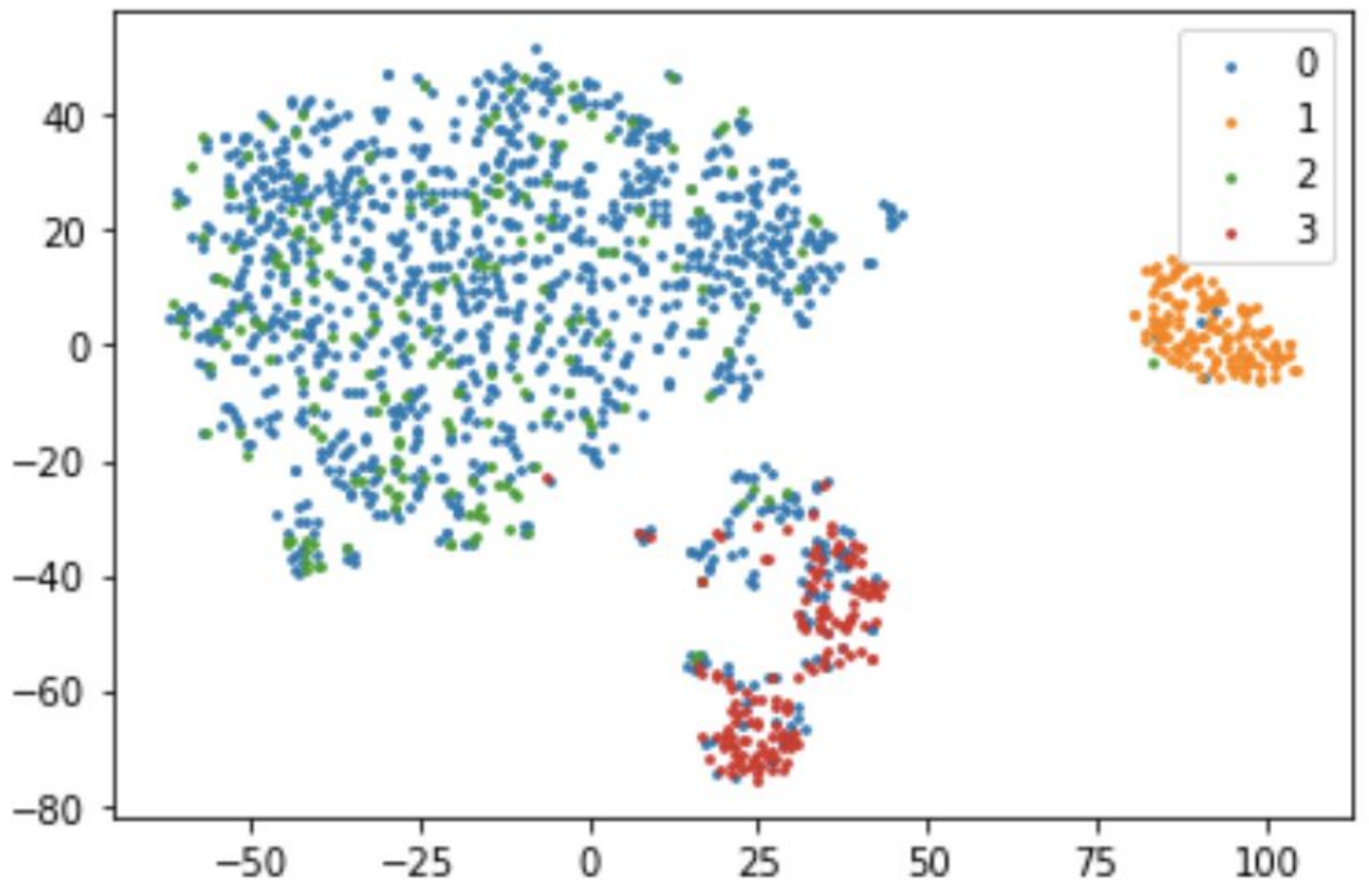
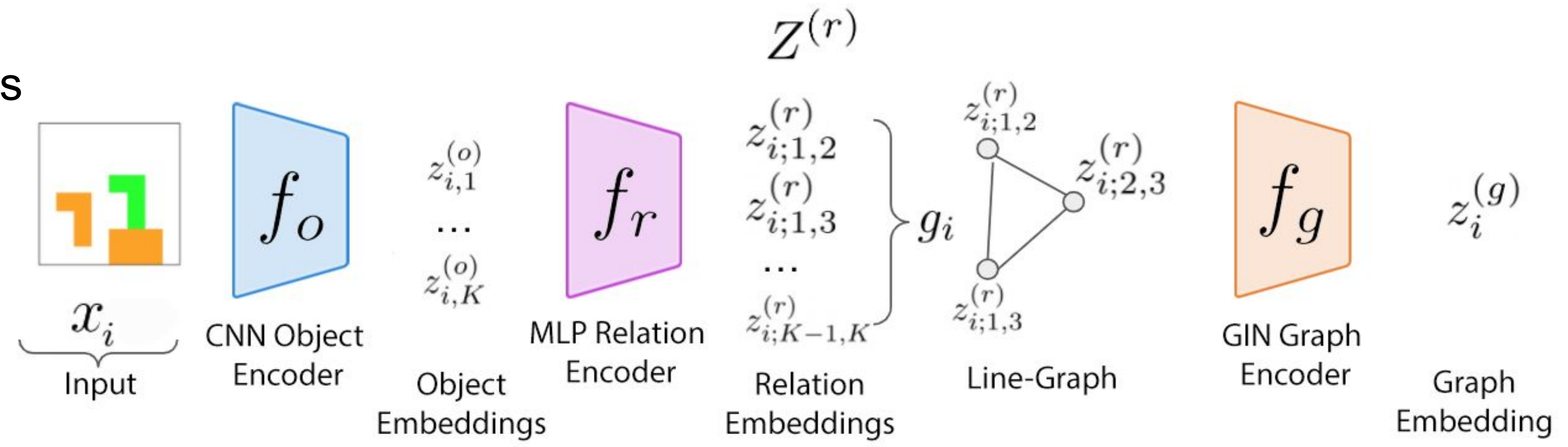


Figure 2. t-SNE visualization of relation embeddings. 0 is 'none', 1 is 'inside', 2 is 'same-color', 3 is 'same-shape

Methods



- Each image x_i is represented as latent graph g_i after CNN + MLP, becomes $z_i^{(g)}$ after graph isomorphism network (GIN)
- Two types of loss functions to train CR-GNN architecture (above)
  - Contrastive objective

$$\mathcal{L}_{\text{contrastive}} = \sum_{i,j \in \text{same-task}} ||f_g(g_i) - f_g(g_j)||_2$$

$$+ \sum_{k,m \in \text{diff-task}} \max(0, \eta - ||f_g(g_k) - f_g(g_m)||_2$$

    - graph representation $f_g(g_i)$ should be similar within the task (intra-task loss), and should be different between different tasks (inter-task loss). *η* is margin hyperparameter
  - Classification objective

$$\mathcal{L}_{\text{classify}} = \sum_{\forall i \in n} \mathcal{L}_{CE}(\text{Linear}(f_g(g_i)), y)$$

    - standard cross-entropy loss, between the true task ID *y* against the predicted task ID
- Additional regularizer: Information Bottleneck (IB)
  - Constraints information between input and relation embedding

$$\mathcal{L}_{\text{IB}} = \mathcal{I}(X; Z^{(r)})$$

Results

Table 1. Relation classification accuracy for 2-3 core objects

Method	# Distractors		
	0	1	0-2
Classify	0.923	0.926	0.946
Classify + IB	0.919	0.918	0.901
Contrastive	**0.959**	0.961	0.954
Contrastive + IB	0.952	**0.963**	**0.957**
Best	**0.959**	**0.963**	**0.957**

Table 2. Relation classification accuracy for 2-4 core objects

Method	# Distractors		
	0	1	0-2
Classify	0.956	0.955	0.965
Classify + IB	0.960	0.962	0.959
Contrastive	**0.965**	0.971	0.965
Contrastive + IB	0.960	**0.973**	**0.971**
Best	**0.965**	**0.973**	**0.971**

- Apply *k*-means clustering to assign cluster labels to each of the learned relation embeddings
- Model performance is similar between both objectives
  - Contrastive objective performing slightly better
- No accuracy degradation due to varying the number of introduced distractor objects, in all cases
- Overall slight improvement with more tasks in 2-4 core objects setting compared to 2-3 core objects
- Model infers the global relation types, as the *t*-SNE visualization shows clustering of relation embeddings by same relation label, shown in Figure 2

Conclusion / Future Work

- Our method achieves above 95% accuracy in relation classification, discovers the relation graph structure for most tasks, and further generalizes to unseen tasks with more complicated relational structures
- Limitation: model only learns the necessary relation representations needed to distinguish between the given tasks, such as overlapping clusters in Figure 2
- Future work is expanding towards more datasets, potentially CLEVR generation with graph structure