Predicate Logic Network: Vision Concept Formation

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Abstract

Although deep learning has shown good performance in many fields, it still lacks the most basic human intelligence, which we often called the ability to draw inferences about other cases from one instance. Therefore, how to empower model with logical reasoning ability has received much attention. Thus, we propose neural predicate networks, a model that combines deep learning methods with first-order logic. It converts visual tasks into first-order logic problems by deconstructing them into objects, concepts and relations. Then, achieve first-order logic differentiable by learning logical predicates as neural networks. Finally, the differentiable model can be trained by back propagation to simulate the formation of concepts in the human brain and solve the problem. Experimental results on two image concept classification datasets demonstrate the effectiveness and advantages of our approach.

Keywords

Neural Network, Neural-Symbolic, Cognitive AI

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What is Neural-Symbolic Learning

Deep learning needs system 1 to system 2 transformation, where

system 1 represents intuitive, fast, unconscious, non-linguistic, and habitual;

system 2 representsslow, logical, sequential, conscious, linguistic, algorithmic, planning, and reasoning.

—— special lecture of NIPS 2019, Yoshua Bengio

The motivation for this paper

- Human concepts are not given by the outside world and unchanging as knowledge in a symbolic system, but are constantly changing in their experience

- Children do not need to learn knowledge like deep learning methods, Rather, it is possible to reason about unseen things through existing concepts

Therefore, we want the model to be able to both learn from the data through neural networks and to reason with the help of symbolic logic.

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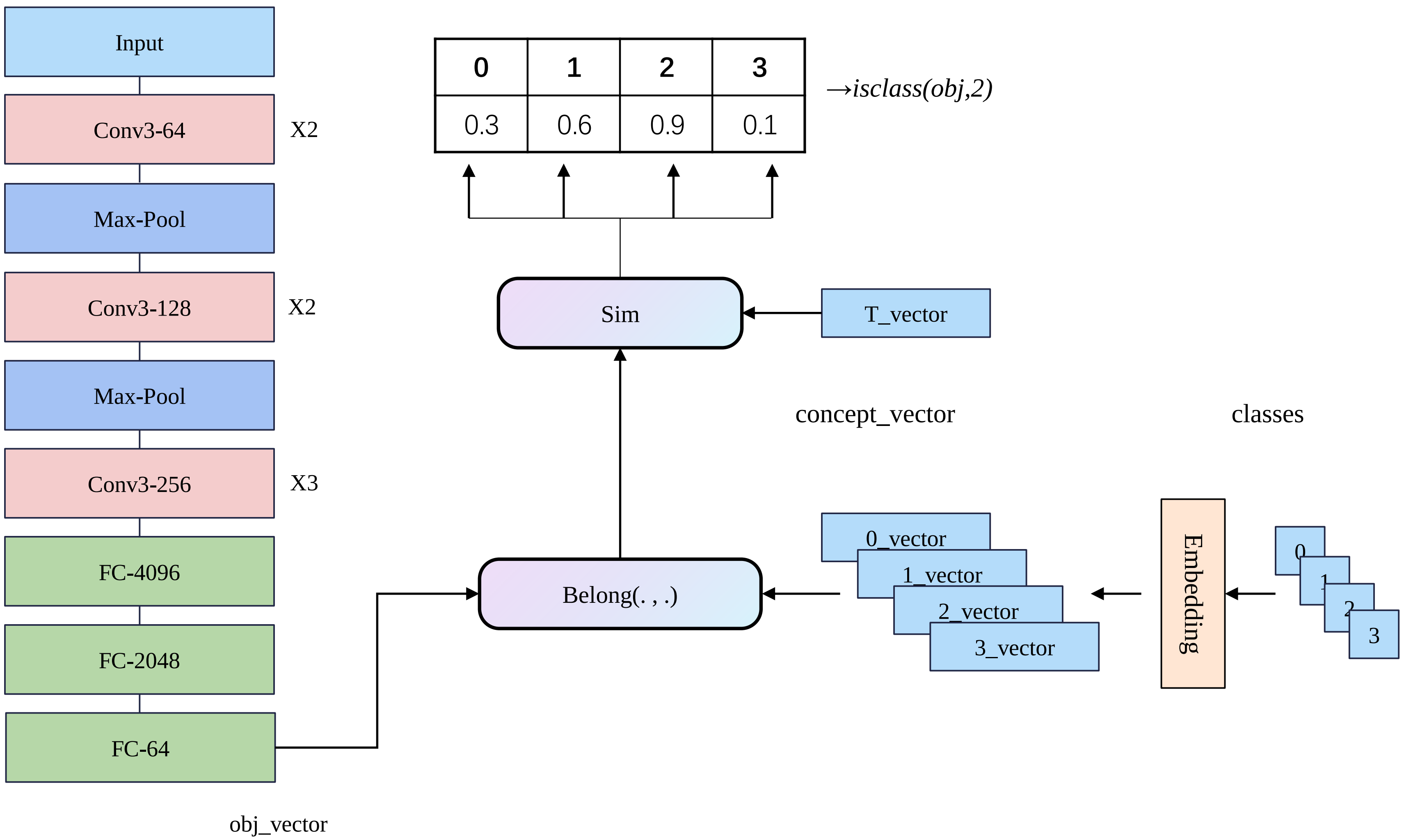
The framework of the model

$$\forall obj.\ belong(obj, concept_0) \rightarrow isclass(obj, 0)$$



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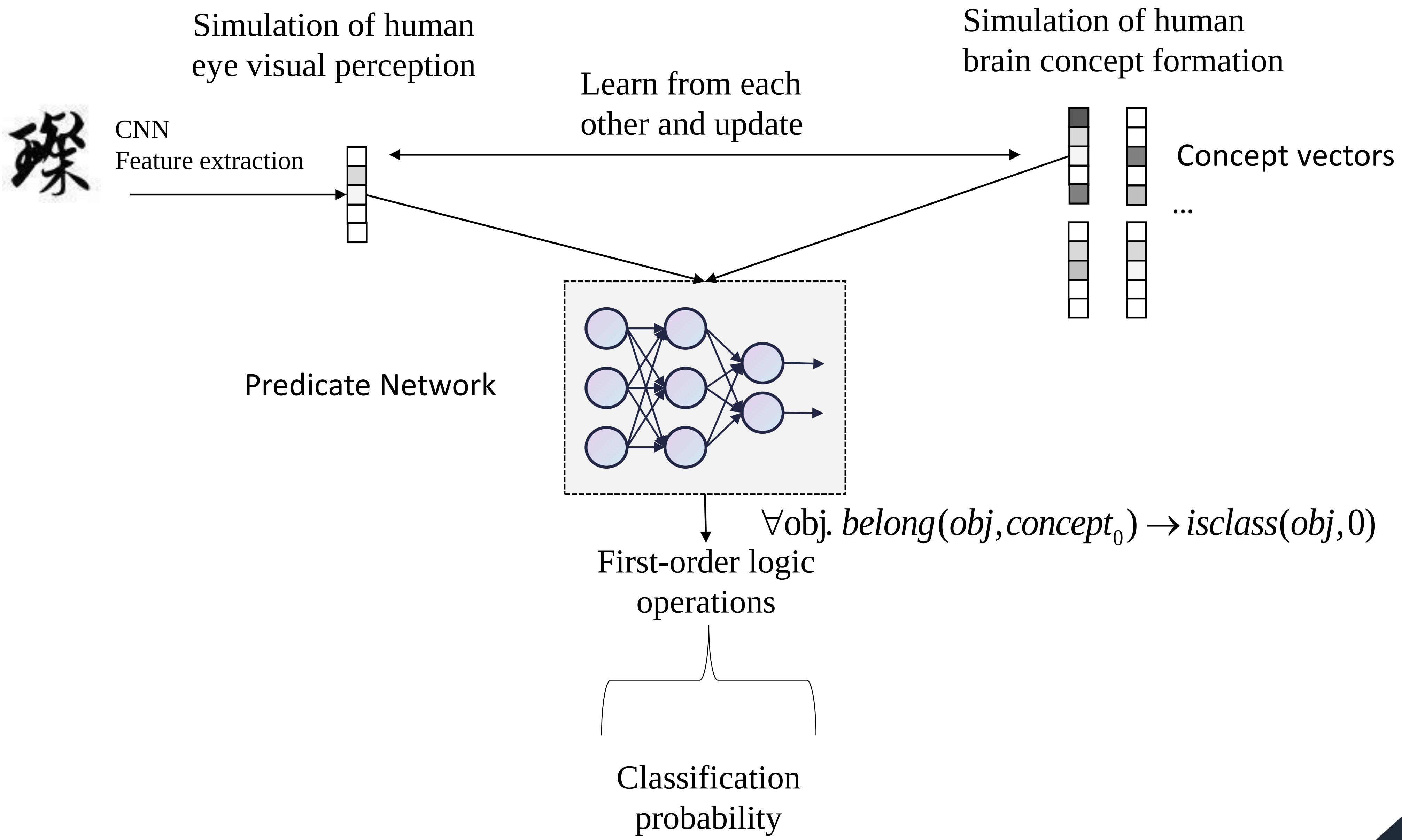
The abstract running process



Experiment Settings 1

Shape Recognition

The training data does not contain right triangles, the test data has only right triangles, and the model is expected to infer the unknown from the known

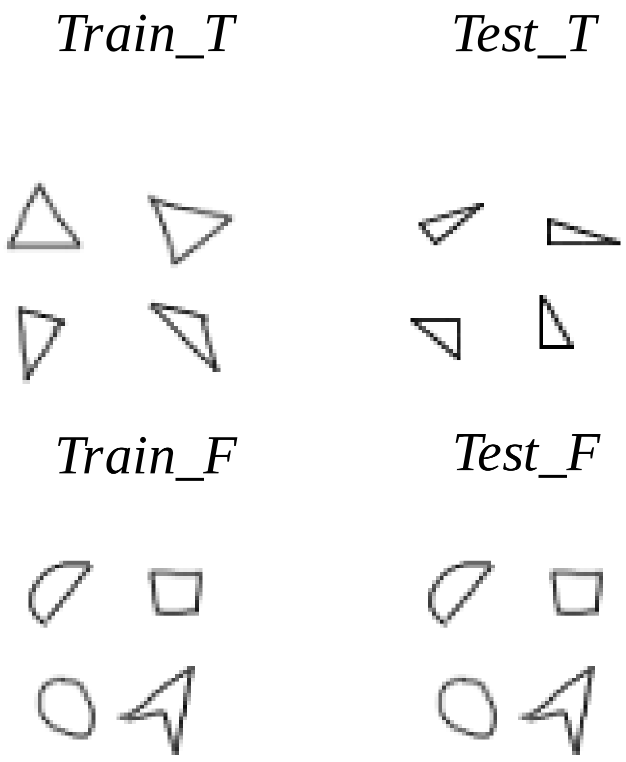


Table 1. Experimental results of each model on the triangular concept dataset

	Train Data			Test Data		
	Acc	Recall	Precision	Acc	Recall	Precision
LeNet5	**1**	**1**	**1**	0.7733	0.7340	0.8567
VGG5	**1**	**1**	**1**	0.8067	0.7837	0.8500
NPN	0.9978	0.9978	0.9978	**0.8333**	**0.8057**	**0.8767**

Experiment Settings 2

Calligraphy Recognition
All the words in the test data do not appear in the training data, font style is a concept that difficult to describe

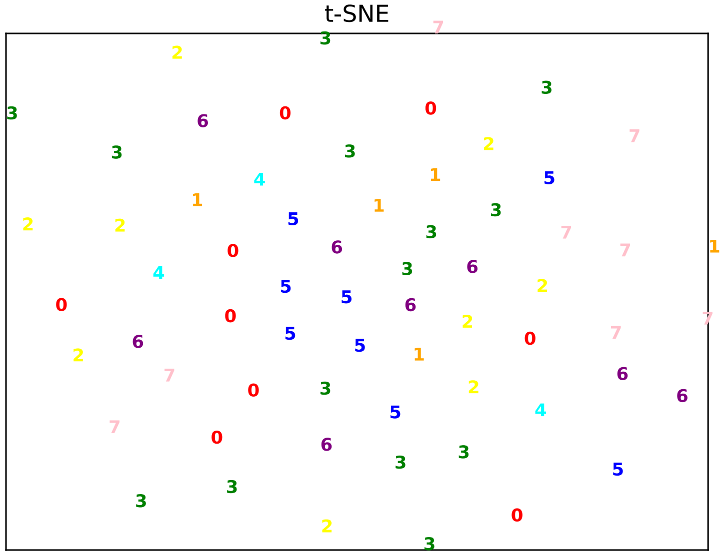
Table 3. Experimental results of each model on the Chinese calligraphy style dataset

	Calligraphy style-4		Calligraphy style-8	
	TrainAcc	TestAcc	TrainAcc	TestAcc
AlexNet8	0.9824	0.9685	0.9727	0.9520
VGG10	0.9932	0.9757	0.9899	0.9588
VGG13	0.2499	0.2487	0.1369	0.1338
VGG16	0.2499	0.2484	0.1369	0.1338
ResNet18	0.9936	0.3300	0.9947	0.1666
NPN	**0.9966**	**0.9886**	**0.9977**	**0.9858**

Table 4. Experimental detail of each model on the Chinese calligraphy style test set

		Calligraphy style-4			Calligraphy style-8		
		Recall	Precision	F1	Recall	Precision	F1
1	AlexNet8	0.9807	0.9742	0.9774	0.9711	0.9513	0.9611
	VGG10	**0.9881**	0.9737	0.9808	0.9102	0.9639	0.9363
	ResNet18	0.2470	0.3310	0.2829	0.1573	0.1381	0.1471
	NPN	0.9874	**0.9852**	**0.9863**	**0.9814**	**0.9757**	**0.9785**
2	AlexNet8	**0.9955**	0.9911	0.9933	0.9800	0.9881	0.9840
	VGG10	0.9882	0.9874	0.9878	0.9845	0.9666	0.9755
	ResNet18	0.2036	0.2712	0.2326	0.2036	0.1554	0.1763
	NPN	0.9948	**0.9956**	**0.9952**	**0.9948**	**0.9933**	**0.9940**
3	AlexNet8	0.9702	0.9796	0.9749	0.9613	0.8984	0.9288
	VGG10	0.9798	0.9879	0.9838	0.9889	0.9595	0.9740
	ResNet18	0.6008	0.3648	0.4540	0.3246	0.2859	0.3040
	NPN	**0.9903**	**0.9911**	**0.9907**	**0.9948**	**0.9795**	**0.9871**
4	AlexNet8	0.9955	0.997	0.9962	0.9889	0.9933	0.9911
	VGG10	0.9852	0.9926	0.9889	0.9697	0.9791	0.9744
	ResNet18	0.2520	0.2932	0.2710	0.1574	0.2171	0.1825
	NPN	**0.9963**	**0.9985**	**0.9974**	**0.9985**	**0.9978**	**0.9981**
5	AlexNet8				0.9829	0.9857	0.9843
	VGG10				0.9772	0.9581	0.9676
	ResNet18				0.1211	0.1214	0.1212
	NPN				**0.9957**	**0.9887**	**0.9922**
6	AlexNet8				0.9993	0.9992	0.9992
	VGG10				0.9985	**1**	0.9992
	ResNet18				0.1375	0.3483	0.1972
	NPN				**1**	**1**	**1**
7	AlexNet8				0.9600	0.9554	0.9577
	VGG10				0.9736	0.9419	0.9575
	ResNet18				0.1472	0.1679	0.1569
	NPN				**0.9760**	**0.9839**	**0.9799**
8	AlexNet8				0.8825	0.9692	0.9238
	VGG10				0.9217	0.9439	0.9327
	ResNet18				0.2195	0.1553	0.1819
	NPN				**0.9579**	**0.9774**	**0.9676**

t-SNE visualization



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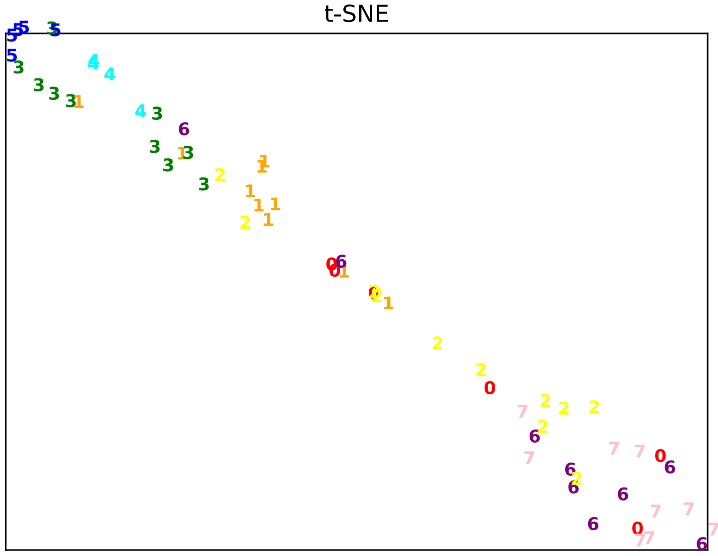

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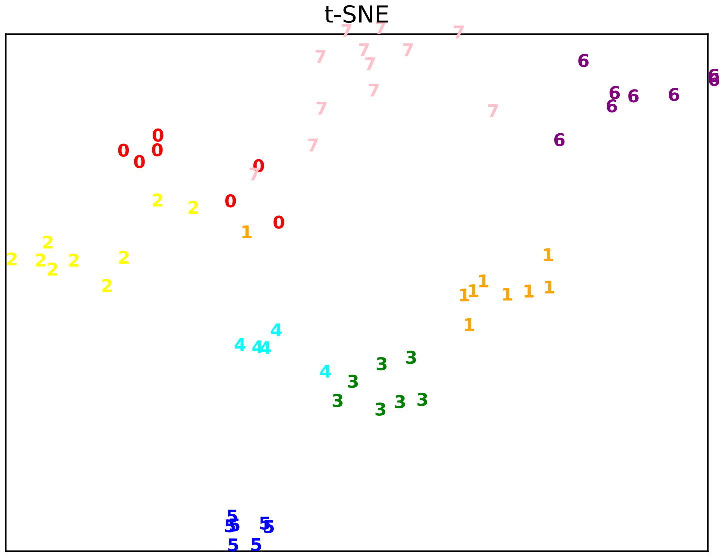

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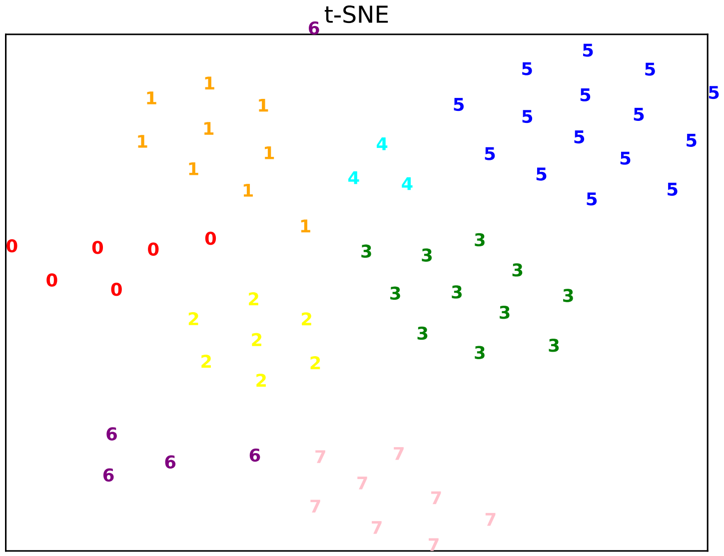
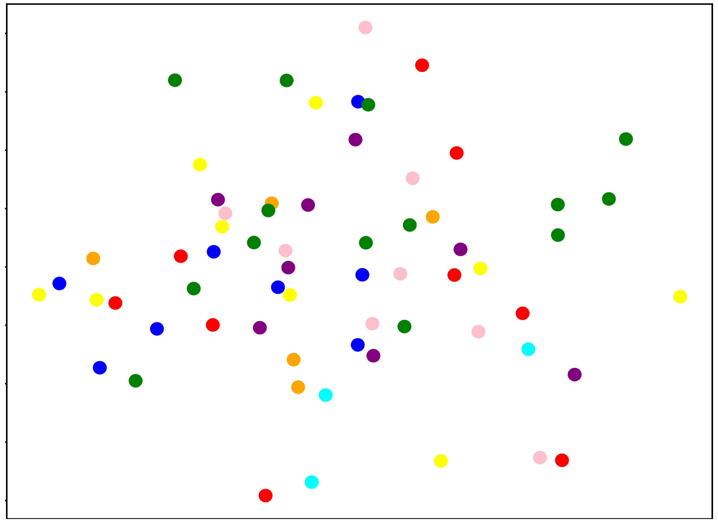


Batch 2000

PCA visualization



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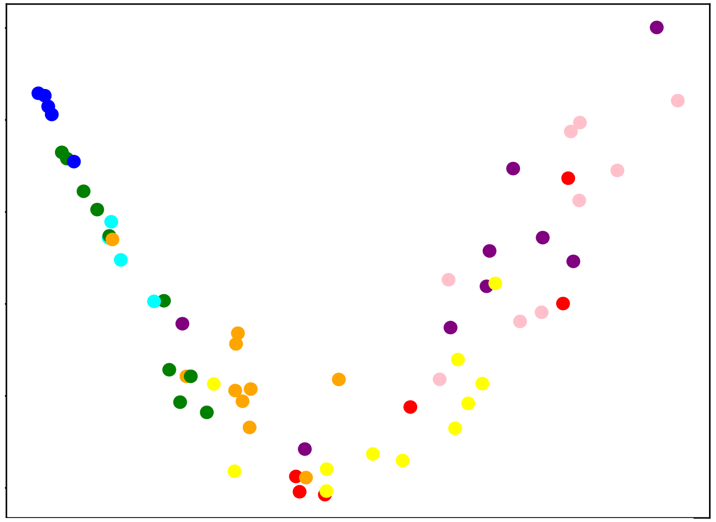

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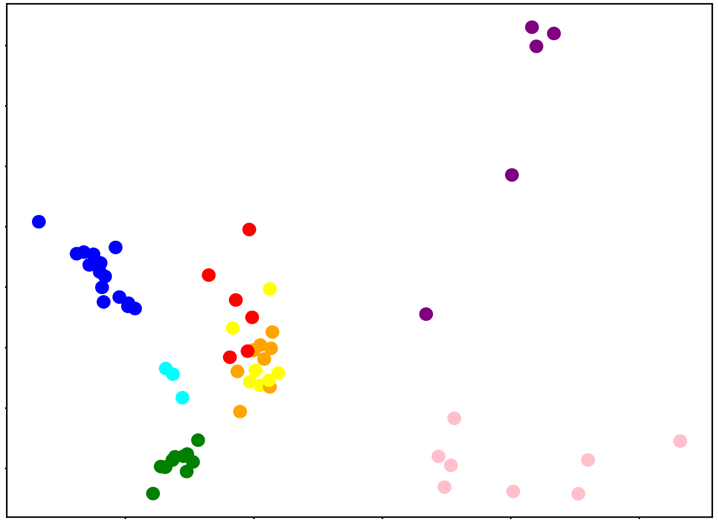

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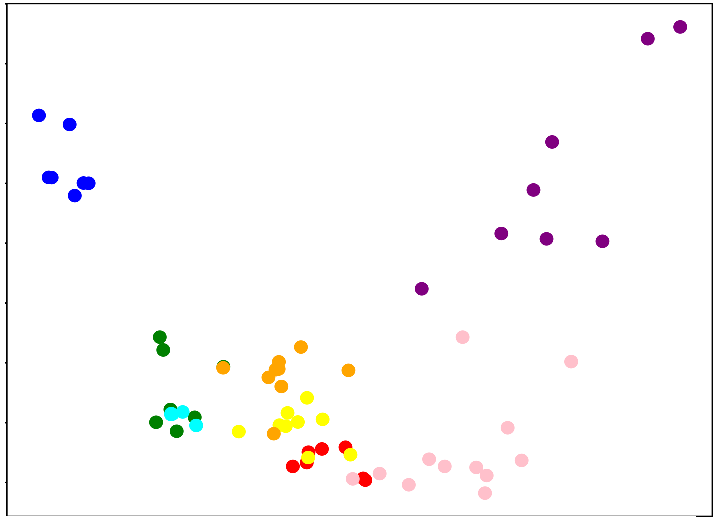

Batch 2000

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Future Work

Future Work

- Visual Reasoning
- Explainable
- Cross-domain knowledge transfer

THANKS!