Unsupervised Neural Representation Learning

Agenda

- Recap
- Does a fixed program help the vision system?
  - Hypothesis
  - Experimental Results
- Behavioral Keypoint Extraction for Shape World
- Next Steps

Recap

- *Paper Roadmap*: The perception component provides an information bottlebeck. The symbolic component allows us to inject prior knowledge. Moreover, we can learn both components simultaneiously.
- *Experiments*: Cartesian product of 2 perception engines and 2 datasets:
    - Behavioural KPD - Mice domain
    - Behavioural KPD - Shape-world domain
    - Slot Attention - Shape-world domain
    - (**Ill-posed**) Slot Attention - Mice domain
- TODO from last week:
    - Do we learn better neural representations with fixed prior knowledge?
        - Experimental results.
    - BKPD model's performamce on shapeworld?
        - Unknown behaviour of BKPD network on more than 2 objects.

Fixed Symbolic Rules

- Pure DNN based approaches struggle to disassociate shapes with colors.
  - The (shape, color) pairs in training is different from (shape, color) pairs in testing.
  - Sample 1 on next slide shows an effect of this disassociation on a purely neural model (with no rules).
- **Hypothesis**: Given a fixed transition function, can a hybrid neurosymbolic model produce better reconstructions and converge faster than a purely symbolic model.
  - Three models (reconstructiong $(s_i, a_i) \rightarrow (s_{i+1})$):
    - A vanilla resnet autoencoder
    - A slot attention based autoencoder (with an MLP for the transition layer)
    - A slot attention based autoencoder (with a fixed symbolic program for the transition layer)
  - Compare metrics between these models.

Experiments (1 object fixed dataset)

\# Experiment 1

Methodology:

Train a slot autoencoder.

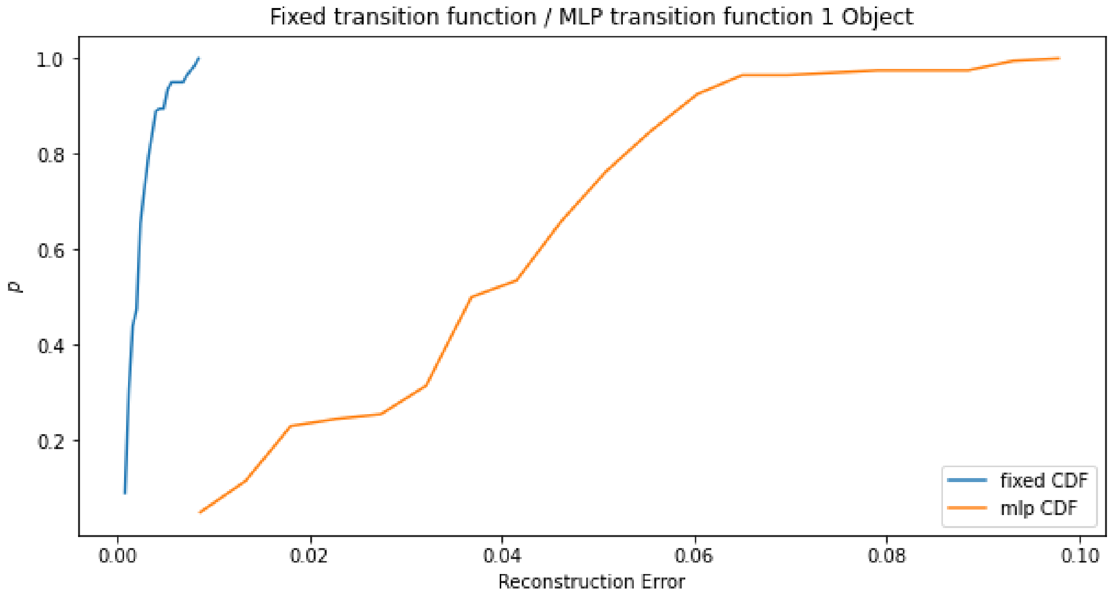
```
(img) --[Slot Enc]--> (x, y, shape, color) --[Slot Dec]--> (img)
```

Generate a dataset based on fixed transition function `T`.

Finetune two more networks using pretrained weights

1. with MLP as transition function
2. with `T` as transition function

Test on 200 unseen (shape, color) pairs.



MLP: Mean reconstruction error `0.0378`

```
(img_{i}) --[Slot Enc]--> (x, y, shape, color) -[MLP]-> (?x, ?y, ...) --[Slot Dec]--> (img_{i+1})
```

fixed: Mean reconstruction error `0.0024`

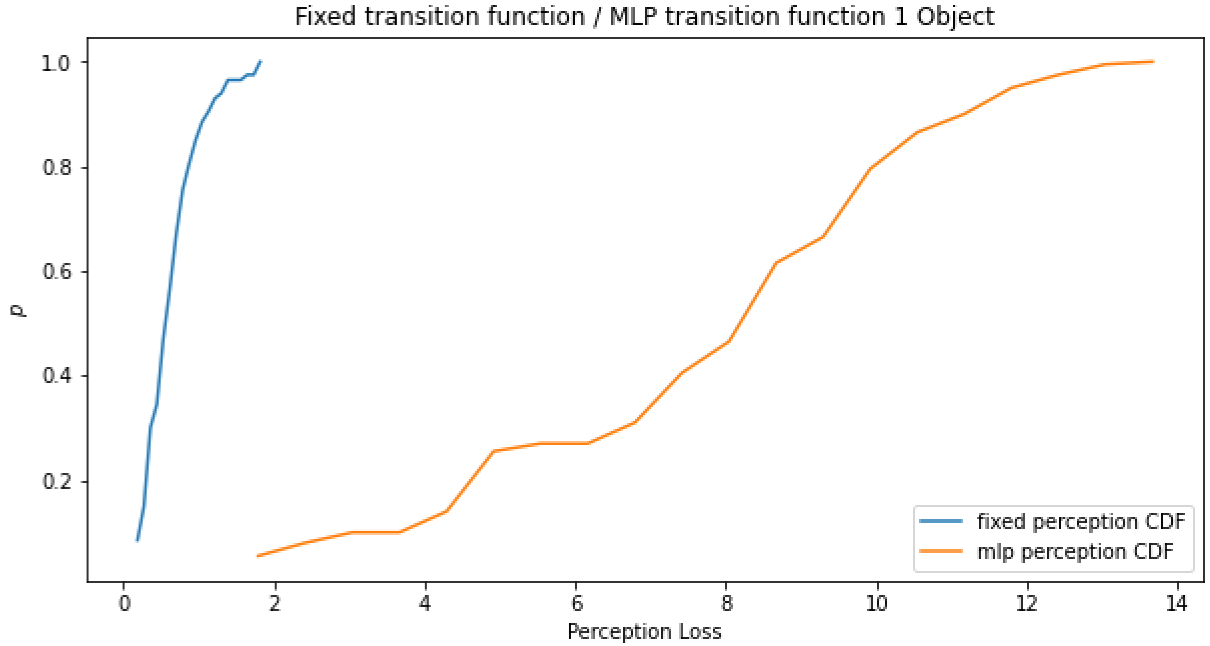
```
(img_{i}) --[Slot Enc]--> (x, y, shape, color) -[T]-> (x+1, y, ...) --[Slot Dec]--> (img_{i+1})
```

Experiments (1 object fixed dataset)

MLP mean perception error: `7.588`

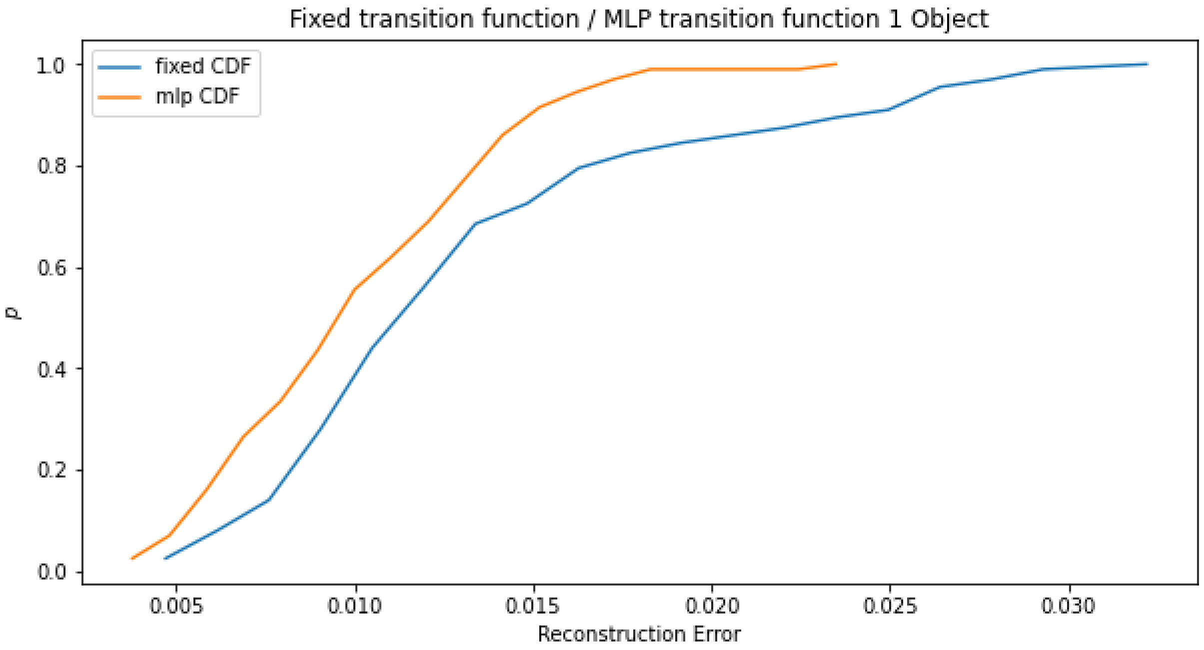
Fixed mean perception error: `0.616`

w/ perception loss:

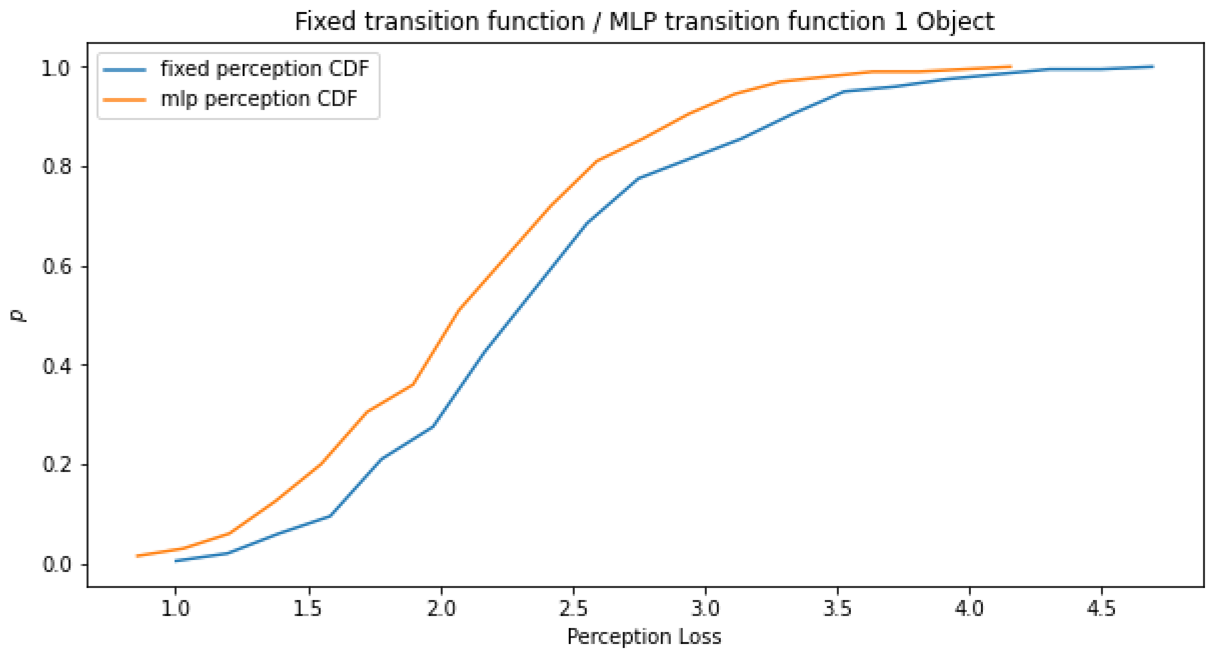


Experiments (3 object fixed dataset)

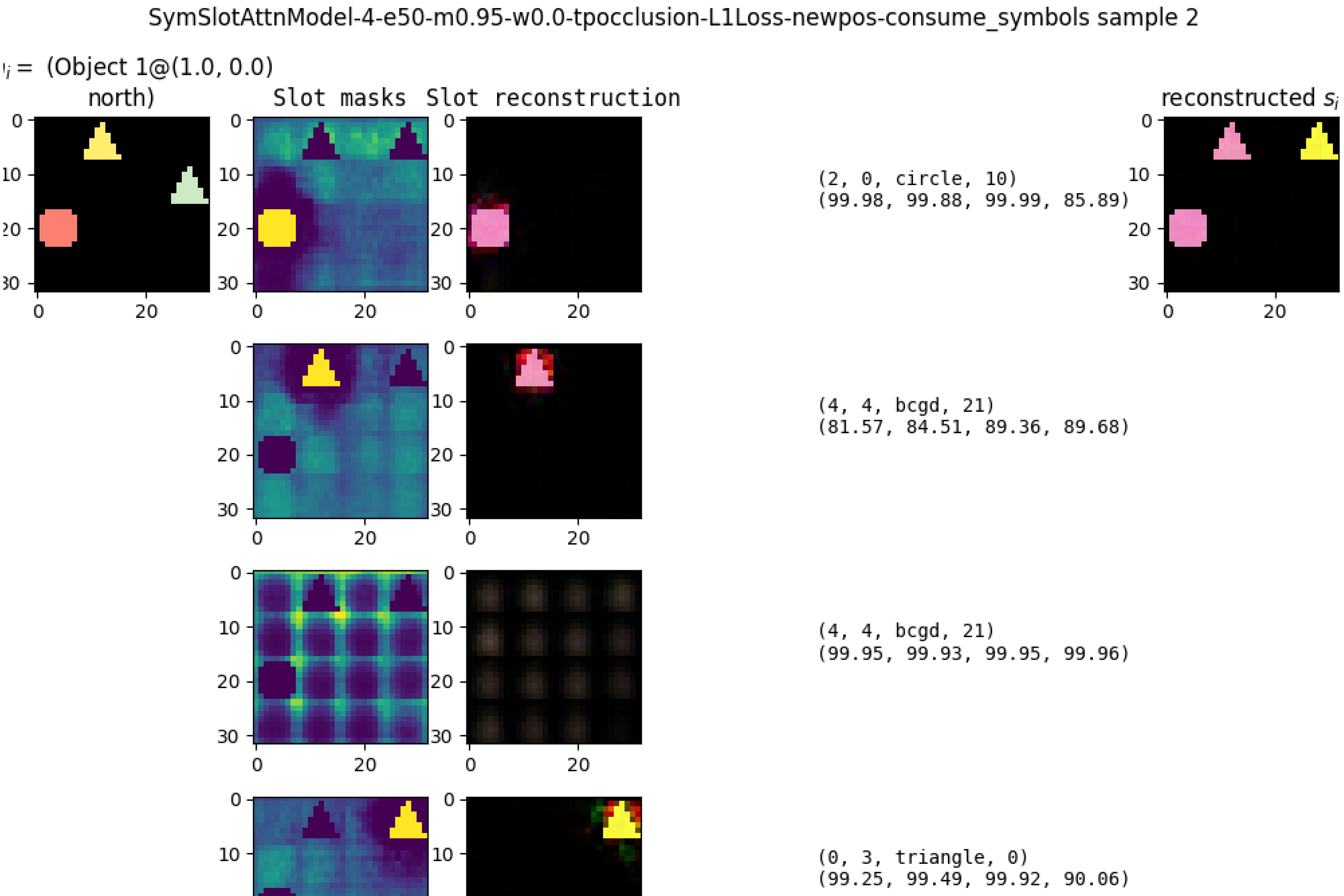
w/ perception loss:



Experiments (3 object fixed dataset)



- The test dataset introduces colors the model has never seen before.



Next Steps

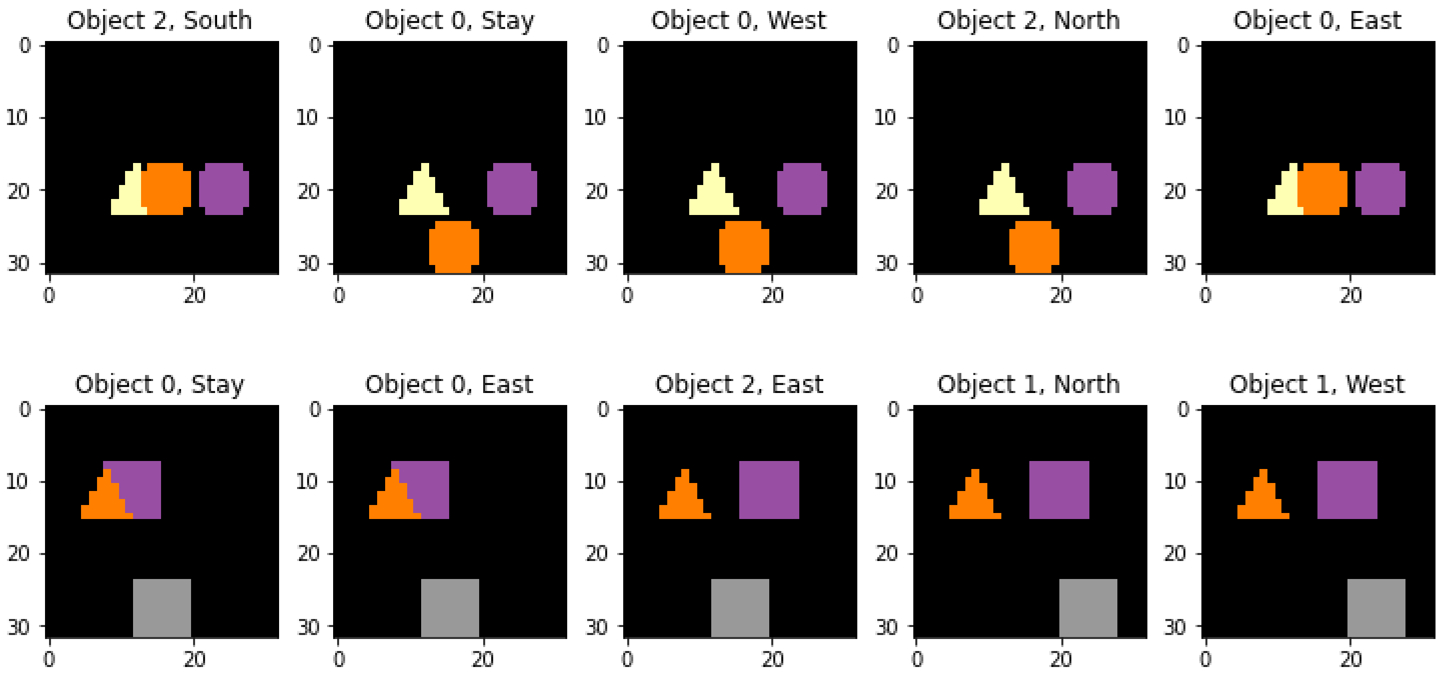
- The code for Behavioral KPD + Shapeworld compiles but takes 3+ days to finish 10 epochs. I need to run this on a larger machine and distribute compute across GPUs.
- I want to do one final check and train with lesser colors.

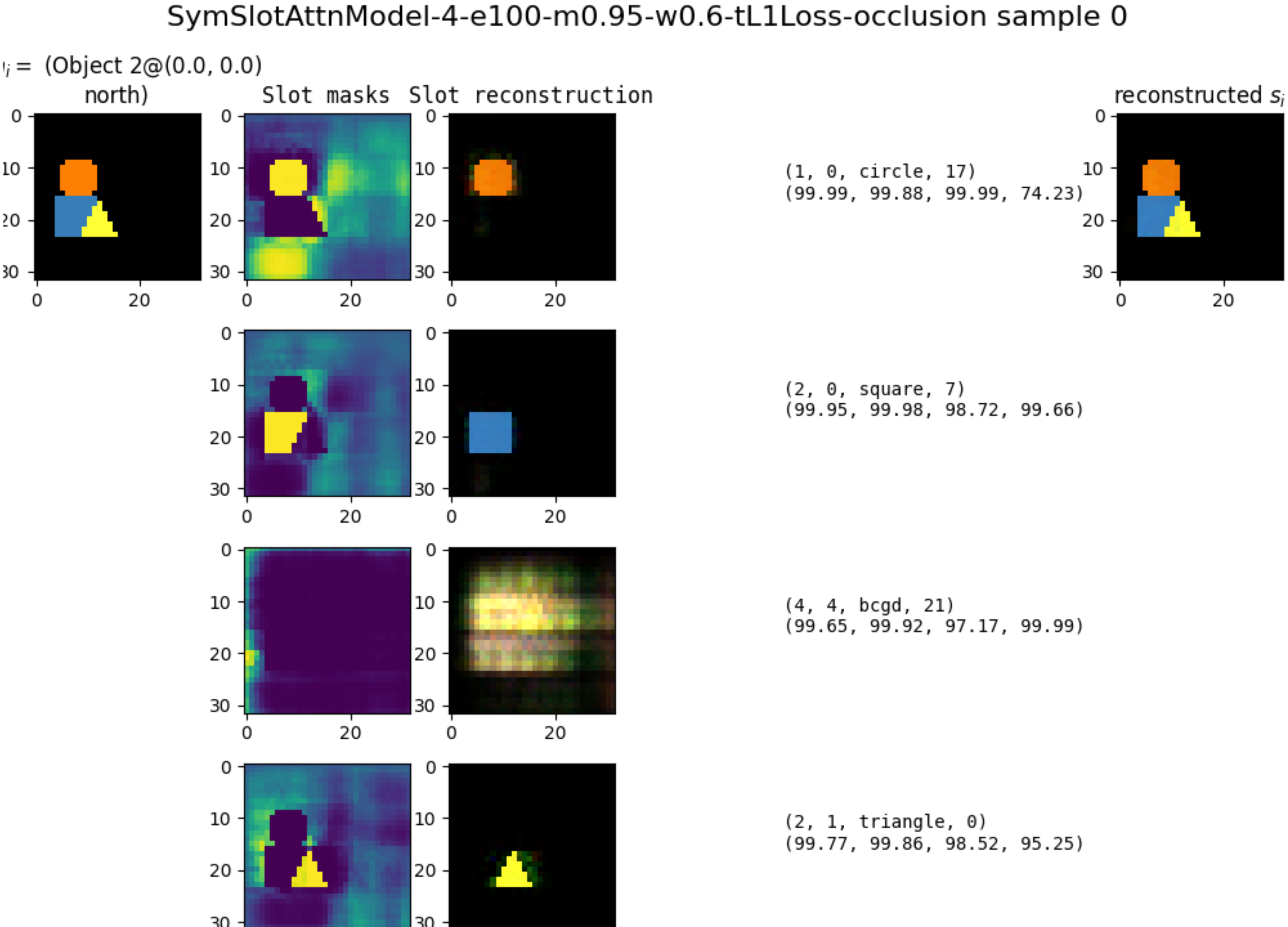
Previous Slides

Agenda:

- Recap
- How does slot attention handle occlusion:
  - Dataset
  - Results
- Do symbolic rules "help" the vision system.
- Next Steps

Slot Attention - Occlusion Dataset




SymSlotAttnModel-4-e100-m0.95-w0.6-tL1Loss-occlusion sample 0
(Object 2@(0.0, 0.0)
north)
Slot masks
Slot reconstruction
reconstructed s_i
(1, 0, circle, 17)
(99.99, 99.88, 99.99, 74.23)
(2, 0, square, 7)
(99.95, 99.98, 98.72, 99.66)
(4, 4, bcgd, 21)
(99.65, 99.92, 97.17, 99.99)
(2, 1, triangle, 0)
(99.77, 99.86, 98.52, 95.25)

Fixed Symbolic Rules

- Pure DNN based approaches struggle to disassociate shapes with colors.
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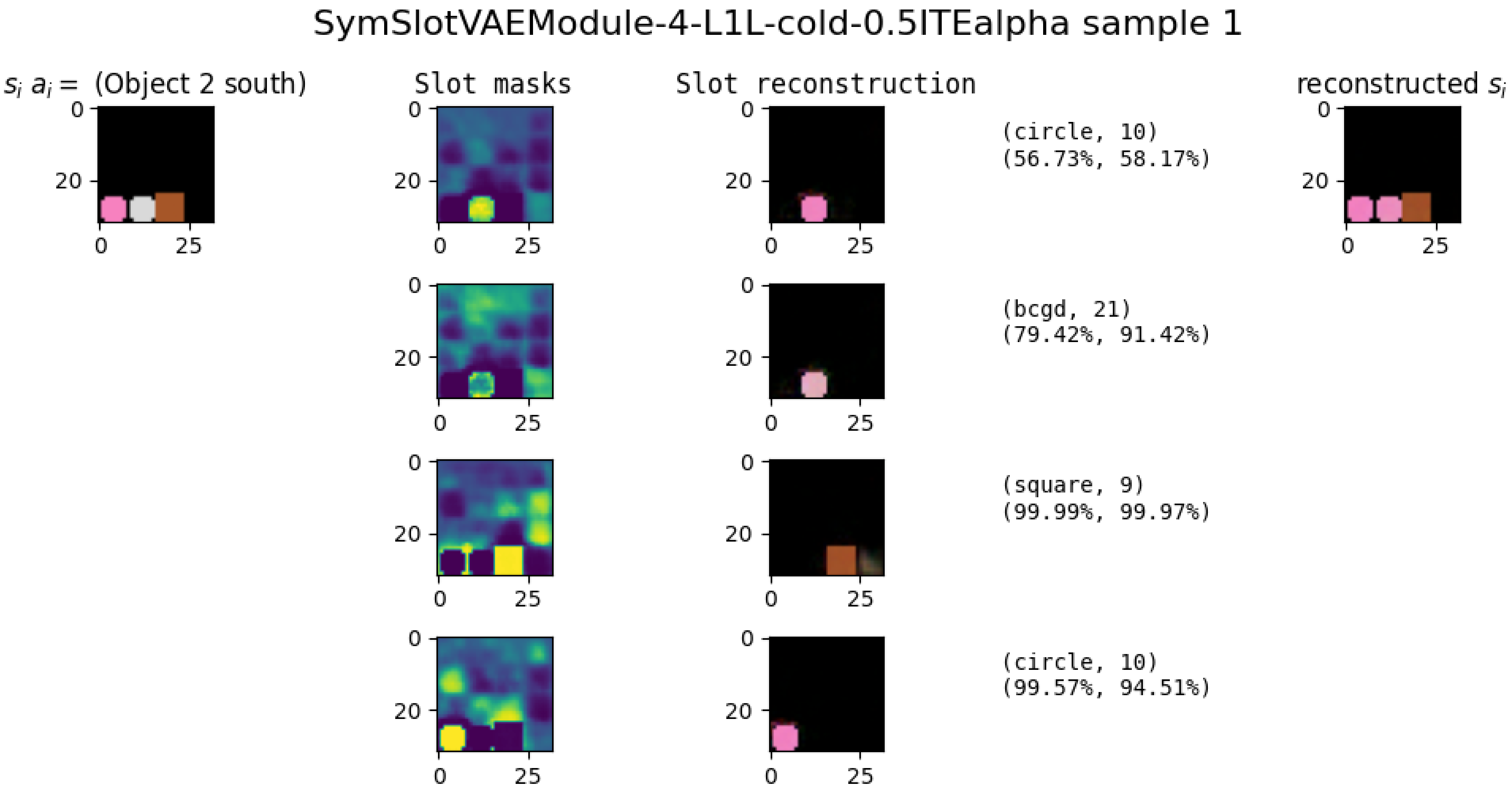
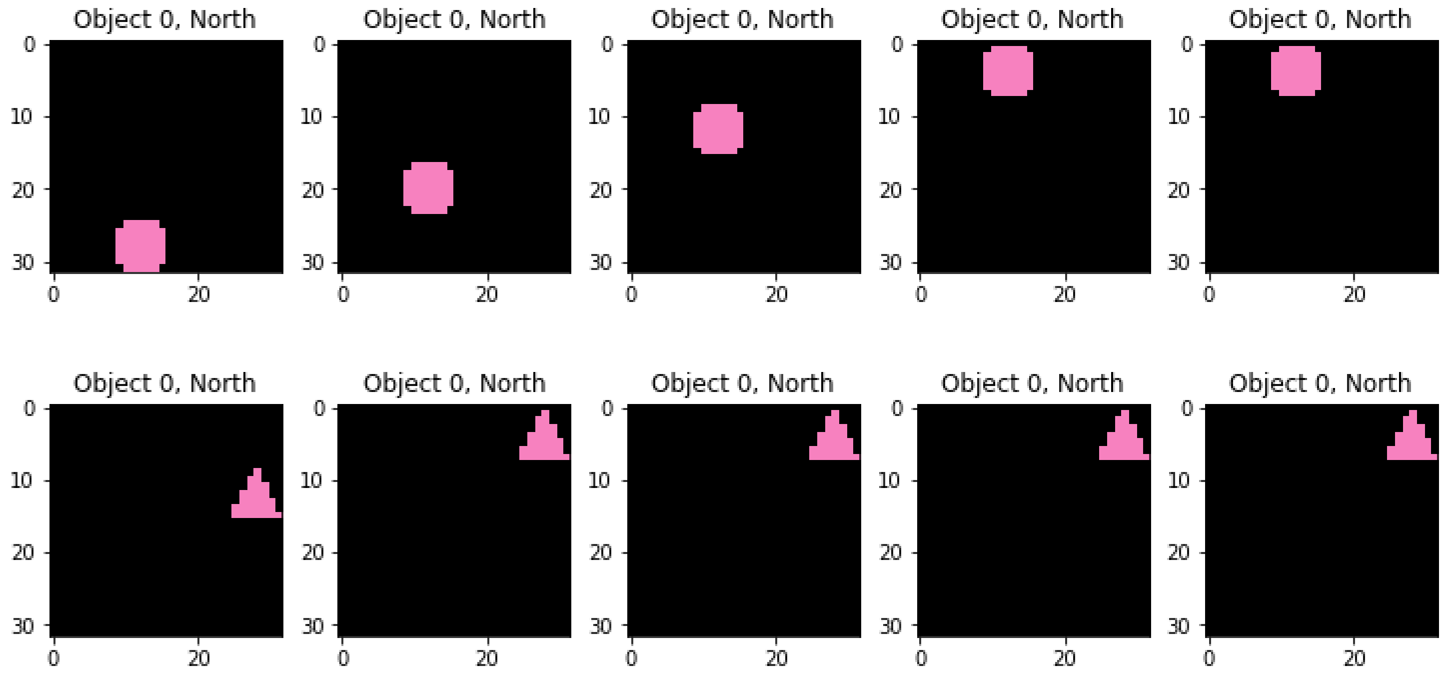
  - Sample 1 on next slide shows an effect of this disassociation on a purely neural model (with no rules).
- Hypothesis: Given a fixed transition function, can a hybrid neurosymbolic model produce better reconstructions and converge faster than a purely symbolic model.
  - Three models:
    - A vanilla resnet autoencoder reconstructiong $(s_i, a_i) \rightarrow (s_{i+1})$
    - A slot attention based autoencoder (with an MLP for the transition layer) reconstructiong $(s_i, a_i) \rightarrow (s_{i+1})$
    - A slot attention based autoencoder (with a fixed symbolic program for the transition layer) reconstructiong $(s_i, a_i) \rightarrow (s_{i+1})$

Sample 1


SymSlotVAEModule-4-L1L-cold-0.5ITEalpha sample 1
s_i a_i = (Object 2 south)
Slot masks
Slot reconstruction
reconstructed s_i
(circle, 10)
(56.73%, 58.17%)
(bcgd, 21)
(79.42%, 91.42%)
(square, 9)
(99.99%, 99.97%)
(circle, 10)
(99.57%, 94.51%)

Dataset

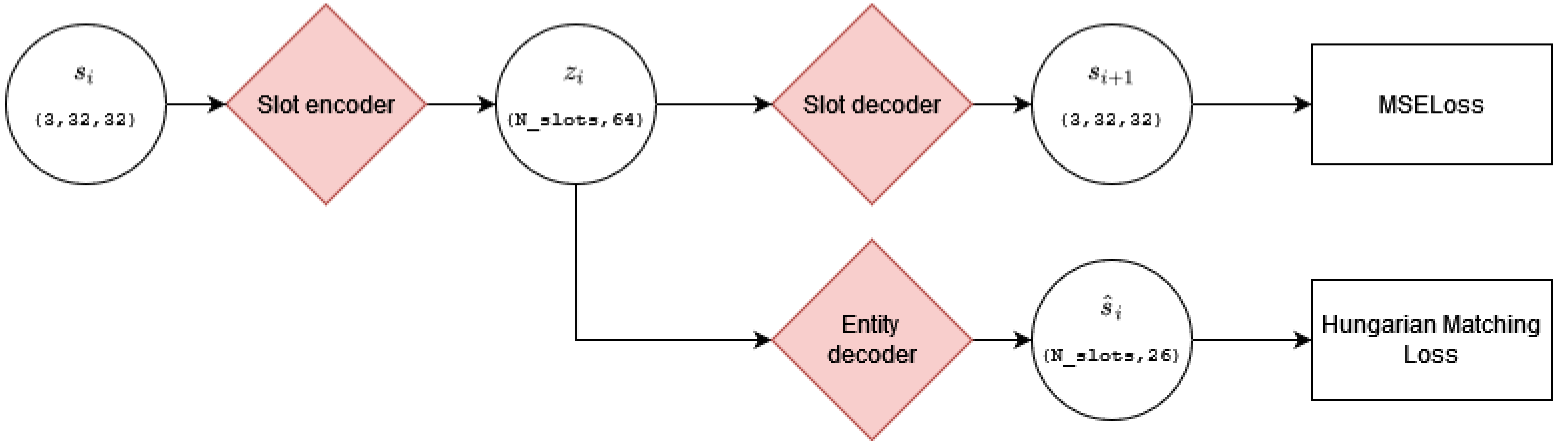


Next steps

- Slot Attention w/ Occlusion on mice domain.
  - MABE Videos.
- Results for the symbolic rule hypothesis.

Slides from Last Week

Slot Attn Decoder



Changes

[Submitted on 15 Jun 2019 (v1), last revised 24 Apr 2020 (this version, v6)]

Deep Set Prediction Networks

Yan Zhang, Jonathon Hare, Adam Prügel-Bennett

Current approaches for predicting sets from feature vectors ignore the unordered nature of sets and suffer from discontinuity issues as a result. We propose a general model for predicting sets that properly respects the structure of sets and avoids this problem. With a single feature vector as input, we show that our model is able to auto-encode point sets, predict the set of bounding boxes of objects in an image, and predict the set of attributes of these objects.

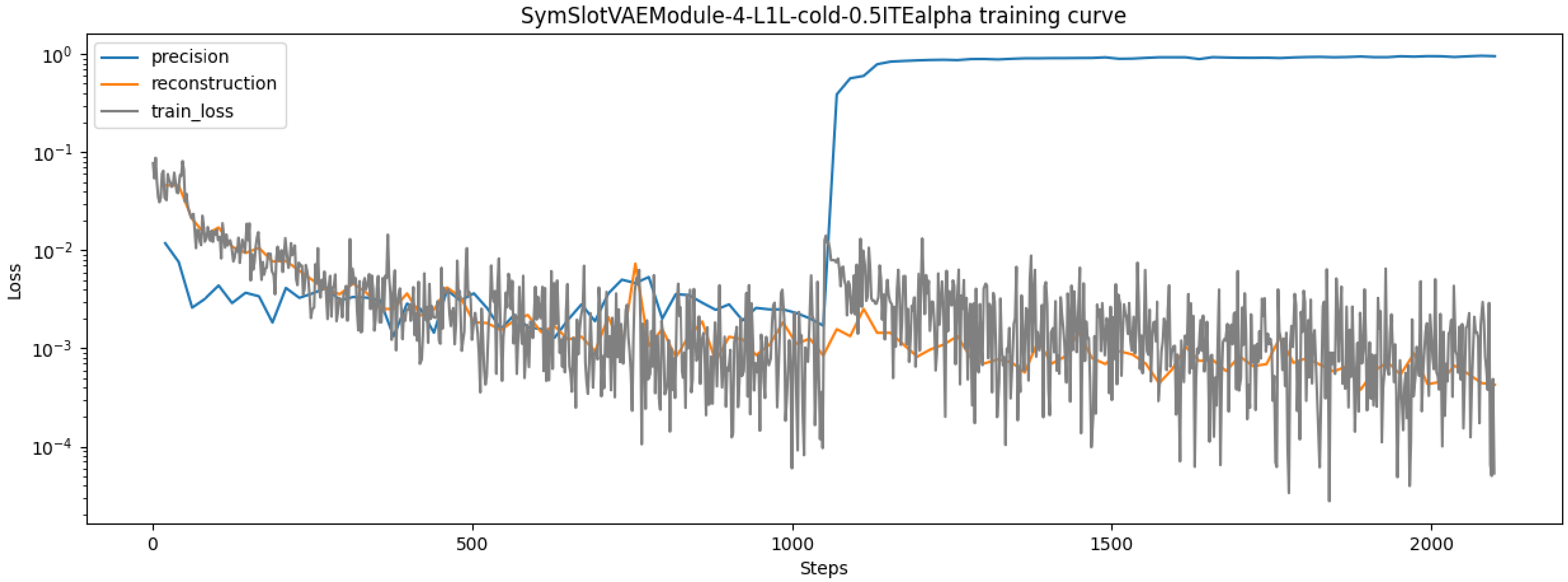
Comments:	Appendix C contains an erratum
Subjects:	**Machine Learning (cs.LG)**; Machine Learning (stat.ML)
Journal reference:	Advances in Neural Information Processing Systems 32 (NeurIPS 2019)
Cite as:	arXiv:1906.06565 **[cs.LG]**
	(or arXiv:1906.06565v6 **[cs.LG]** for this version)

Changes:

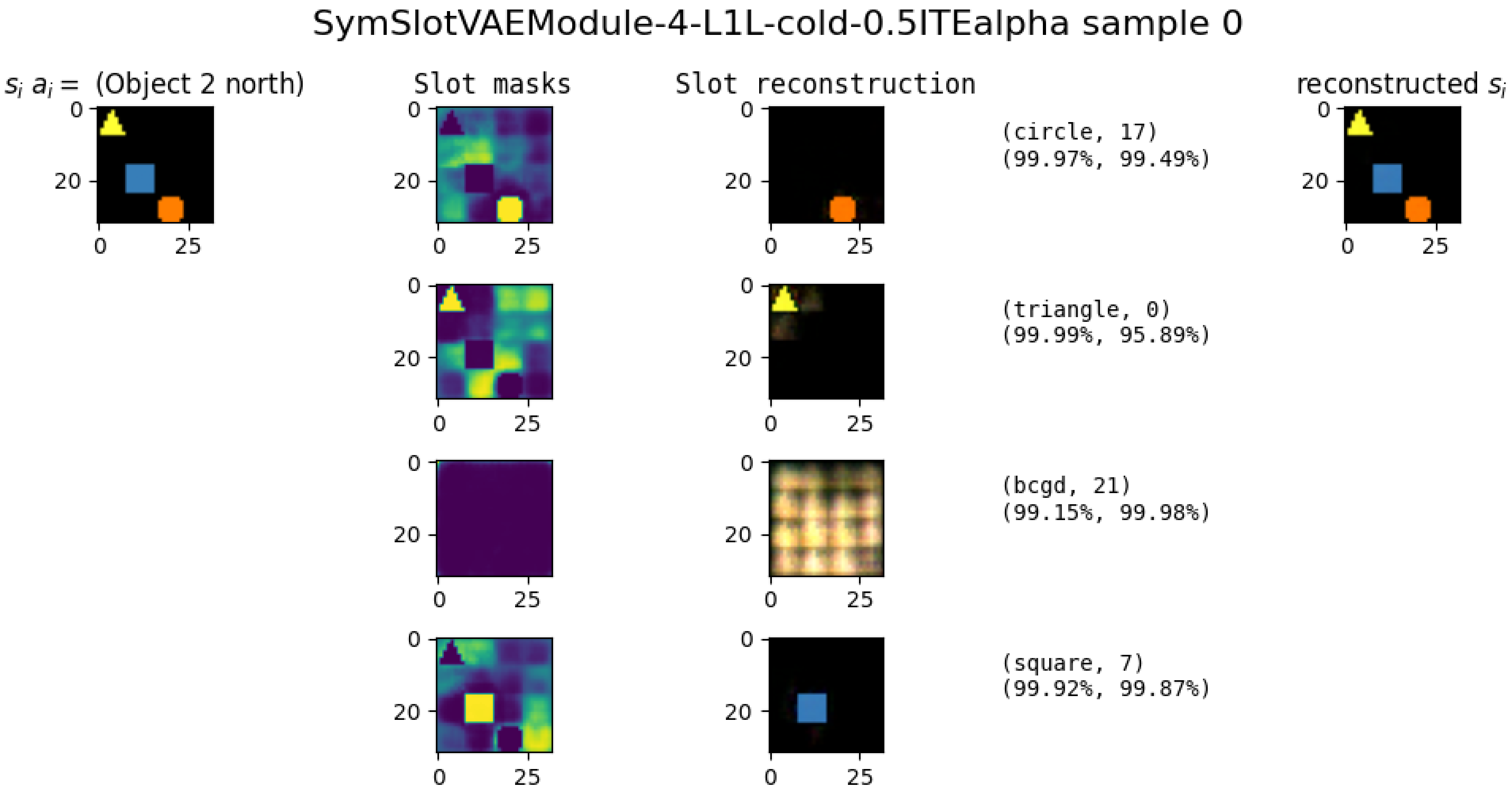
- Use smoothL1 loss instead of L1 loss.
- Use the same loss function for matching and backprop.

Slot Attn Decoder

Training Curve

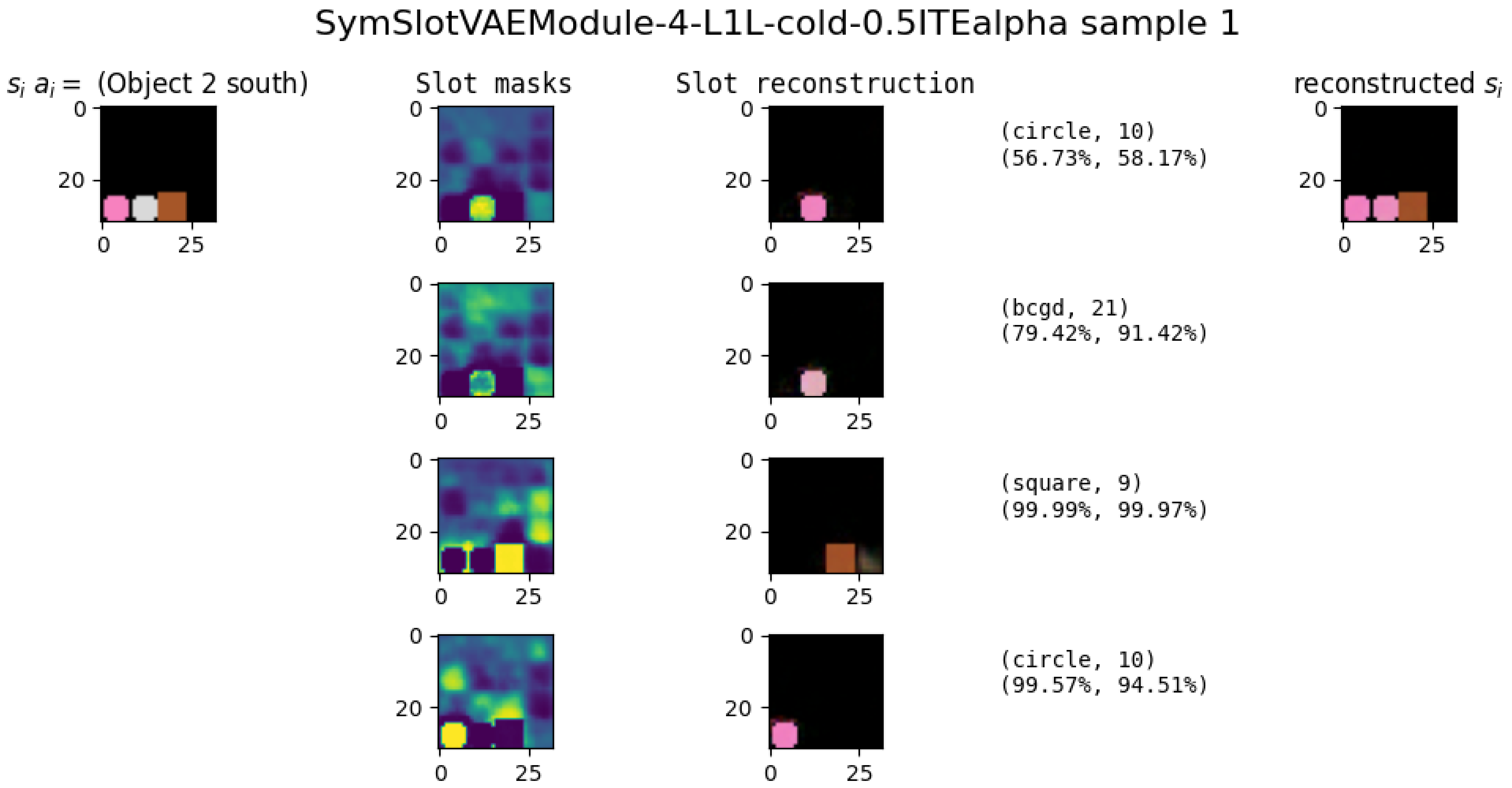


Sample 0

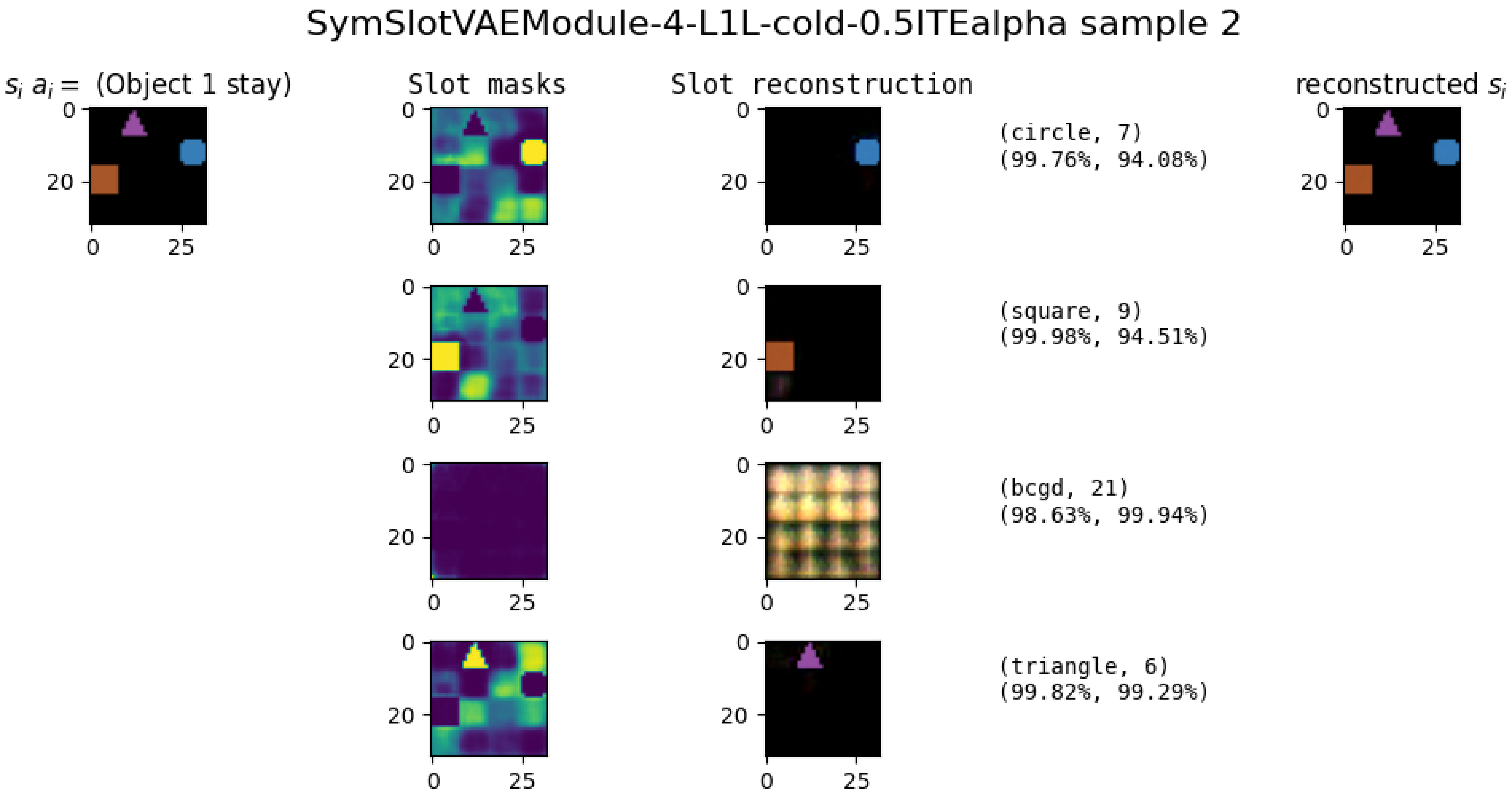


SymSlotVAEModule-4-L1L-cold-0.5ITEalpha sample 0
s_i a_i = (Object 2 north)
Slot masks
Slot reconstruction
reconstructed s_i
(circle, 17)
(99.97%, 99.49%)
(triangle, 0)
(99.99%, 95.89%)
(bcgd, 21)
(99.15%, 99.98%)
(square, 7)
(99.92%, 99.87%)

Sample 1


SymSlotVAEModule-4-L1L-cold-0.5ITEalpha sample 1
s_i a_i = (Object 2 south)
Slot masks
Slot reconstruction
reconstructed s_i
(circle, 10)
(56.73%, 58.17%)
(bcgd, 21)
(79.42%, 91.42%)
(square, 9)
(99.99%, 99.97%)
(circle, 10)
(99.57%, 94.51%)

Sample 2


SymSlotVAEModule-4-L1L-cold-0.5ITEalpha sample 2
s_i a_i = (Object 1 stay)
Slot masks
Slot reconstruction
reconstructed s_i
(circle, 7)
(99.76%, 94.08%)
(square, 9)
(99.98%, 94.51%)
(bcgd, 21)
(98.63%, 99.94%)
(triangle, 6)
(99.82%, 99.29%)

Dealing with multiple objects

```
S0: s_i |> (enc) |> (slot)                                                     (dec) |> s_{i+1}
S1:                          |> (entitiy dec) |> (a_i) |> (???) |>
```

dPads

- Given a differentiable DSL, dPads aims to derive a program that maps an input stream to an output stream.
- $$\arg\min_{\theta,\alpha} \mathbb{E}_{\mathbf{i},\mathbf{o}\in D}[l(P(\mathbf{i};\alpha,\theta),o)] + c(\alpha)$$
- alpha is a program derivation graph

DSL

Inputs:

```
pos :: [int, int]
color :: int
shape :: {circ, sq, tri}
slot :: [color, shape, pos]
```

Multi column template.

- Recap
- Failure Cases of SA on `poccluded-shapeworld` domain.
- Does a fixed program help the vision system?
    - Hypothesis
    - Experimental Results (Model 1)
    - Experimental Results (Model 2)
    - Experimental Results (Model 3)
- Behavioural Keypoint Extraction for Shape World
- Next Steps

```
pos :: [int, int]
color :: int
shape :: {circ, sq, tri}
slot :: [color, shape, pos]
```

```
pos :: [int, int]
color :: int
shape :: {circ, sq, tri}
slot :: [color, shape, pos]
```

```
pos :: [int, int]
color :: int
shape :: {circ, sq, tri}
slot :: [color, shape, pos]
```