Latent Predictive Learning: Modeling Neuronal Selectivity in Sensory Networks

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INCM Project

Aim

- To evaluate the effectiveness of Latent Predictive Learning (LPL) in producing invariant representations
- Effectiveness in dynamic settings (SNNs)
- This work further extends LPL to auditory stimuli to assess its generalizability and limitations.

Motivation

Challenges in Artificial Neural Networks:

- Limitations of backpropagation in biological systems
- Difficulty in creating invariant object representations
- Can we develop a learning mechanism that mimics biological neural networks?
- How can we prevent representational collapse?
- If yes, Can we generalize for multi-modal inputs?

Latent Predictive Learning (LPL) Framework

Combined Learning Rule:

$$\Delta W = \eta \cdot (\Delta W_{\text{hebbian}} + \Delta W_{\text{predictive}})$$

$$\Delta W_{\text{hebbian}} = \alpha \cdot x^T \cdot y_{\text{true}}$$

$$\Delta W_{\text{predictive}} = \beta \cdot x^T \cdot (y_{\text{pred}} - y_{\text{true}})$$

Hyperparameters:

- $\alpha = 0.1$
- $\beta = 0.01$

Architecture of the simulated CNN

1. **Deep Neural Network (DNN):**
   - Convolutional Neural Network
     - 2 convolutional layers
     - ReLU activation
     - 2 fully connected layers
   - Dataset: MNIST
     - 60,000 training images
     - 10,000 testing images

Experimental Configurations for testing neuronal selectivity

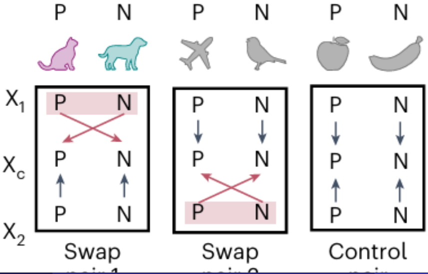
To check for the effectiveness of the cnn to mimic neuronal selectivity in IT Cortex of primates.

2. Synthetic Moving MNIST Dataset:

- Sequences with preferred (P) and non-preferred (N) digits
- Swap and non-swap conditions
- 500 sequences, 20 frames per sequence

  Selectivity (S) was computed as:

$$S = P_{\text{response}} - N_{\text{response}}$$



Spiking Neural Network (SNN) Architecture

Network Composition:

- 100 Excitatory Neurons
- 25 Inhibitory Neurons

Synaptic Connections:

- Input Synaptic Weights W_{input}:
    - Random initialization
    - Bounded between 0 and 5

Signal Simulation:

- Input: Sinusoidal waveforms
- Encoding: Poisson spike train statistics
- Simulation Duration: 100,000 ms
- Time Step: 1 ms

Objective: Classify speakers using audio data from the LibriSpeech dataset. **Dataset Preparation:**

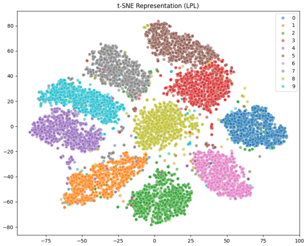
- **Dataset:** LibriSpeech train-clean-100 and test-clean subsets.
- Custom PyTorch Dataset class for loading and preprocessing audio samples.
- Initial experiments conducted on 5 speakers, extended to 41 for scalability.

Preprocessing Pipeline:

- Convert waveforms to Mel-spectrograms and amplitude values to decibels.
- Resize inputs to **224×224 pixels** for consistency.
- Normalize data for uniformity across the dataset.

Results: Disentangled Representations

Visualization Techniques: t-SNE and PCA analysis



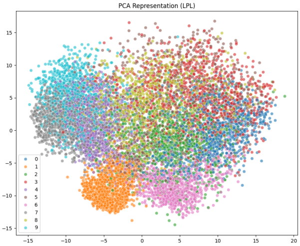


Figure: Representations with LPL Rule: t-SNE and PCA

Key Findings:

- Well-separated clusters in embedding space
- Effective disentanglement of input images and clear distinction between different digit representations

Disentangled Representations (Continued)

[Loss and Accuracy during Training]

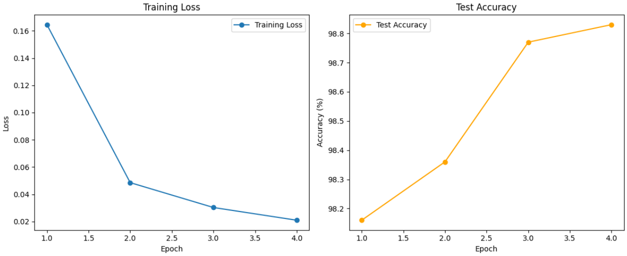
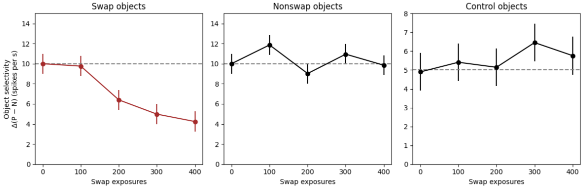


Figure: Training Loss and Accuracy

Key Findings :

- The training shows consistent improvement in loss reduction and accuracy.

Neuronal Selectivity Experiment



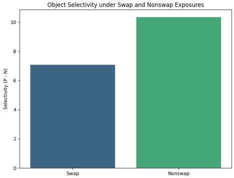


Figure: Selectivity analysis for the IT cortex experiment in primates (Comparison and Barplot)

Swap Condition:

- Significant reduction in neuronal selectivity
- Decreased responses to preferred stimuli
- Increased responses to non-preferred stimuli

Non-swap Condition:

- Stable neuronal selectivity and Preserved temporal associations

Neuronal Selectivity Experiment (Continued)

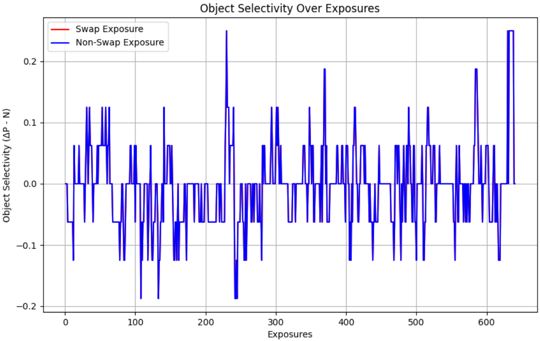


Figure: Selectivity analysis for the IT cortex experiment in primates

Spiking Neural Network Experiment

Challenges in Applying LPL to SNNs:

- Weak weight selectivity
- Less effective neuronal activity compared to original study

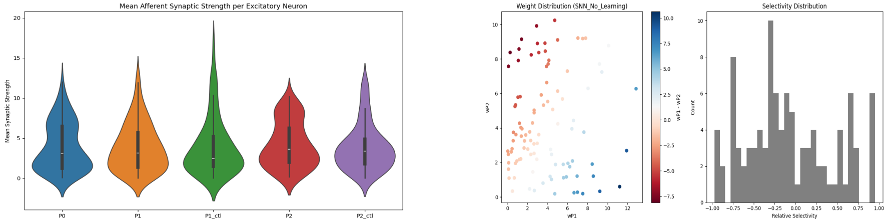


Figure: Results when LPL was used with spiking neural networks

Potential Reasons:

- Complex network dynamics
- Need for further parameter tuning

Evaluation on Audio Dataset

- Accuracy on audio data: **20%**, below expectations.
- Model performed significantly better on visual data.
- Results include:
  - Training loss and accuracy metrics.
  - t-SNE and PCA plots to analyze feature disentanglement in low-dimensional space.

Findings : Performance on audio data indicates room for improvement.

Conclusion

Key Contributions:

- Successful modeling of neuronal selectivity changes
- Produced disentangled representations
- Demonstrated superiority over:
  - Hebbian learning
  - BCM
- A plausible model to model learning in brain without back propagation.

Future Work:

- Explore more complex datasets with large size
- Apply to real-world scenarios

References

- Li & DiCarlo (2008)
- Halvagal & Zenke (2023)
- Illing et al. (NeurIPS 2021)

Code : GitHub Repository