Learning Predictive Filters

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Introduction

- How would a system intend on only keeping information maximally predictive of the future filter its input?
- We analytically derive the optimal predictive filters for Gaussian stimuli by modifying [1] and [2].
- We learn the optimal predictive filters for non-Gaussian naturalistic movies.
- We examine the role of prediction in the retina and compare our predictive filters to measured filters in salamander retina.

Machine learning interpretation:
We want to learn models with low complexity that generalize well to future data.

Neuroscience interpretation:
Neural circuits should allocate resources to encode bits that will be useful for the future.

Predictive Information Bottleneck

Problem:

\[ \min I(\hat{X}; \hat{Y}) - \beta I(Y; \hat{X}) \]

Beta parameterizes the tradeoff between complexity and accuracy.

System:

\[ x_{t+1} = Ax_t + \eta \]
\[ y_{t+1} = Cx_{t+1} + Dz_{t+1} + \xi \]

We learn the linear filters \( C = \beta x_{t+1} + Dz_{t+1} + \xi \) as a function of how many bits we can keep.

Analytical Results

\[ \min_{H(\beta)} (1 - \beta) \log[H(\beta)X]^T + \beta \log[H(\beta)X]^T + I] \]
\[ \hat{Y} = H(\beta)\hat{X} \]

Learning predictive filters for naturalistic movies

Predictive Filters in the Retina

Linear-Nonlinear model

\[ \hat{Y} = H(\beta)\hat{X} \]

Real vs. Optimal filters

Stimulus

Conclusions

- Neural systems and machine learning models have common goals of being generalizable with low complexity.
- The predictive information bottleneck provides a model-free way of quantifying this objective.
- The critical values of \( \beta \) provide an expectation for the different information-processing regimes we expect to find in natural systems.