Low-Rank Nonlinear Decoding of μ-ECoG from the Primary Auditory Cortex

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Overview

- Problem : Neural decoding from parallel neural measurements in awake rats
- Challenge in learning decoders:
  - Large dimensionality of raw data due to high sampling rate
  - Limited number of training samples
- Contribution: novel neural decoder with low-rank structure in first hidden layer

Background

Previous work in neural decoding:

- Linear and non-linear mapping of the neural response to to auditory spectrogram
- Linear neural decoders like SVMs for behavioral task classification
- Canonical correlation analysis (CCA) to measure the correlation between the stimulus and the responses.

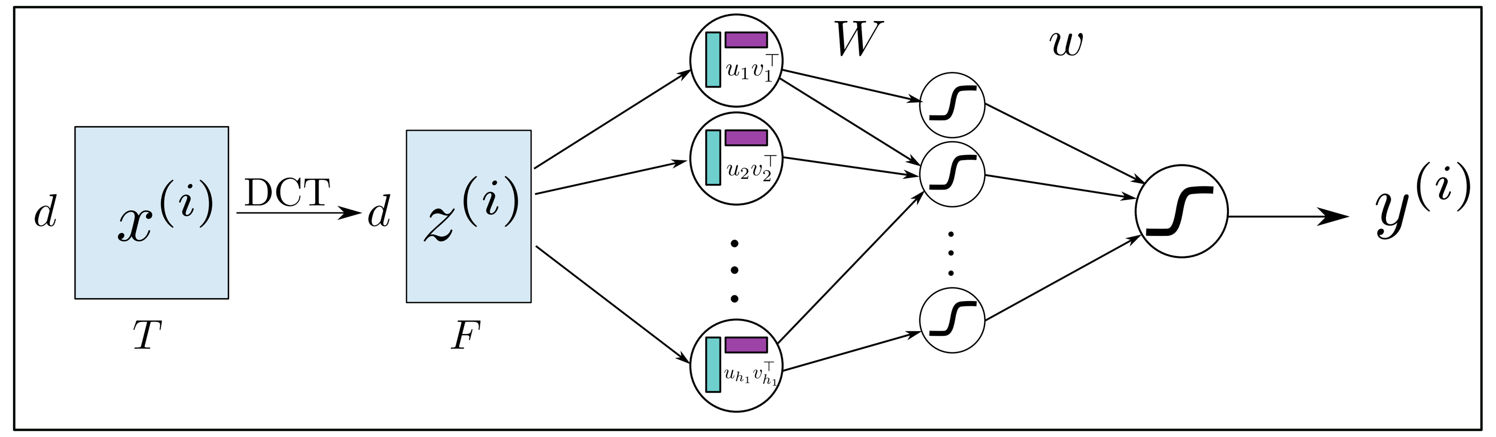
Challenge in parallel neural measurements: High dimensionality of the raw data

- Two key novel properties in our work:
  - DCT preprocessing stage to reduce sampling rate
  - Low-rank structure in the first hidden layer of neural decoder

Problem Formulation

- Decoding stimuli y_i from d dimensional neural response from some area of brain
- $X^i \in R^{T\times d}$ is the response to y_i in time window of length T
- N input-output sample pairs $\{(X^1, y^1), (X^2, y^2), \dots, (X^N, y^N)\}$
- Problem: learn a decoder to map X to y
  - Response y can be discrete or continues
- We present regression problem for scalar target y
- Challenge: High-dimensionality of X
  - Large number of parameters
  - Even linear decoders need $O(dT)$ coefficient

Model



- First stage: DCT
  - low pass filtering (F first component in the frequency domain is remained)
- Next stage: Neural network

$$Z_{1j} = u_j^T Z_0 v_j + b_{1j} \qquad j = 1, \dots, h_1$$
$$Z_{2j} = \sigma\left(w_{2j}^T Z_1 + b_{2j}\right) \quad j = 1, \dots, h_2$$
$$\hat{y} = \sigma\left(w_3^T Z_2 + b_3\right)$$

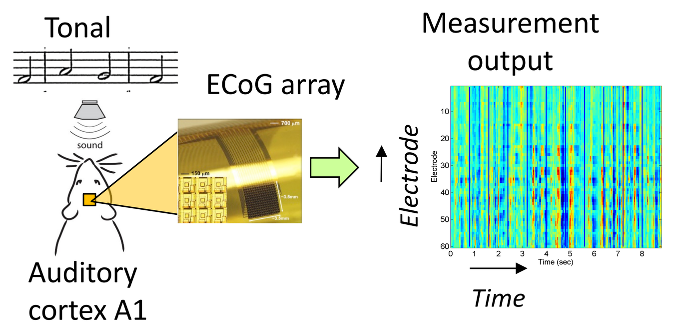
- First layer based on low rank projections
  - Reduces number of parameters
- Motivation for low-rank model :
  - Suppose

$$Z_0 \approx \sum_{k=1}^{h_1} \alpha_k u_{ki} v_{kf} \qquad i = 1, 2, \dots, d \quad \text{and } f = 1, 2, \dots, F$$

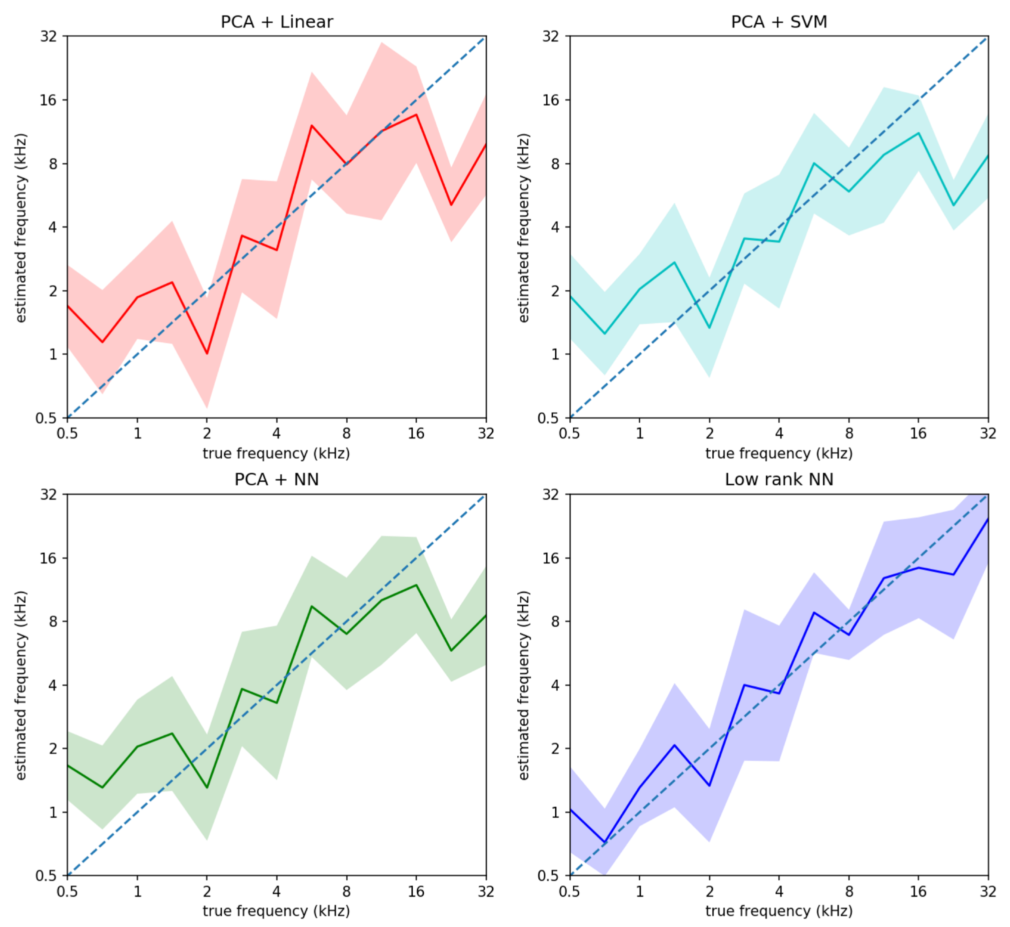
  - $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_{h_1})$ latent variables caused by stimulus y
  - u_{ki} , v_{kf} are responses of α_k over measurement channel index i and frequency index f
  - Estimation of y: first estimate α from Z_0 and then estimate y
  - $Z_0 = G(\alpha) \Rightarrow \hat{\alpha} = (G^T G + \gamma I)^{-1} G^T (Z_0)$
    - regularized least square estimate for given Z_0
  - Due to separability we have: $\hat{\alpha}_k = \sum_{j=1}^{h_1} W_{2,kj} u_j^T Z_0 v_j + b_{2k}$
  - Thus we can recover the latent variables under a linear low-rank output model

Results

- Data
  - Recordings from a high resolution μECoG array from A1 area of auditory cortex in awake rats.
  - $420\ \mu m$ spacing and 8x8 grid
  - Frequency tones were played for $50\ ms$
  - Recorded signal are down sampled at $2\ kHz$
  - 390 tones in each experiment
  - 61 channels and $T = 160$ samples
  - $F = 256$ (we choose 55 first components), 10 low rank units and 4 hidden units in the next layer



- Decoder Performances:
  - **PCA + Linear**: top p PCs of the network is used for regression, $p+1$ parameters, ℓ_1 and ℓ_2 regularization
  - **PCA + SVM**: top p PCs of the network is used for regression, $p+1$ parameters (Linear and Radial basis functions are used for SVM)
  - **PCA+NN**: top p PCs of the input followed by a NN,$(p+2)n_h + 1$ parameters, ℓ_2 regularization is used for weights



Method	R-squared score	RMSE
PCA+Linear	0.484	0.179
PCA+SVM	0.476	0.181
PCA+NN	**0.510**	0.174
Low-Rank +NN	**0.761**	0.121

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