Neural Network Metrics for Viterbi Decoding in Molecular Communication Channels

Peter Hartig

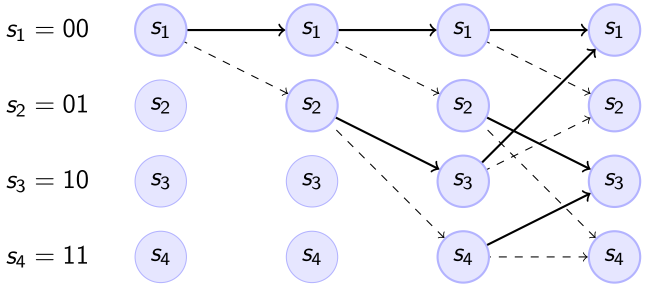
December 16, 2019

Outline

Viterbi Setup

Maximum Likelihood sequence decoding can be formalized as

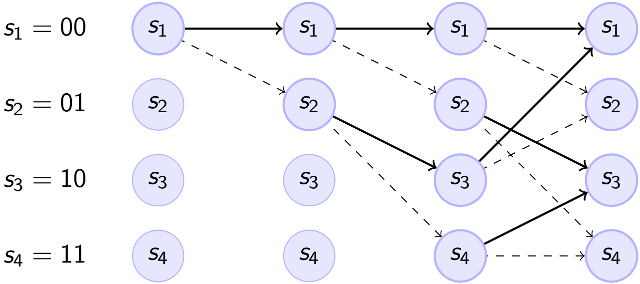
$$
\begin{aligned}
&\underset{\mathbf{x}}{\text{maximize}} \quad Pr(\mathbf{y}|\mathbf{x}) \\
&\underset{\mathbf{x}}{\text{maximize}} \quad \prod_{\mathrm{i}=1}^{\mathrm{N}} Pr(y_{\mathrm{i}}|\mathbf{x}) \\
&\underset{\mathbf{x}}{\text{minimize}} \quad \sum_{\mathrm{i}=1}^{\mathrm{N}} -log(Pr(y_{\mathrm{i}}|\mathbf{x}))
\end{aligned}
\tag{5}
$$



Viterbi Setup Continued

Each state change is decided by the metric $Pr(y_i|\mathbf{x})$. In a linear channel with length l impulse response , this metric becomes $Pr(y_i|\mathbf{x}_{i-l}^{i})$.

Example with channel impulse response length 2 and constellation size 2



Example with channel impulse response length 2 and constellation size 2.

Incorporating Neural Net into Viterbi Decoding

Problem 1

Viterbi algorithm requires distribution $Pr(y_i|\mathbf{x}_{i-l}^{i})$ (or its parameters).

- ### Solution

  Have Neural Network learn $Pr(y_i|\mathbf{x}_{i-l}^{i})$

Problem 2

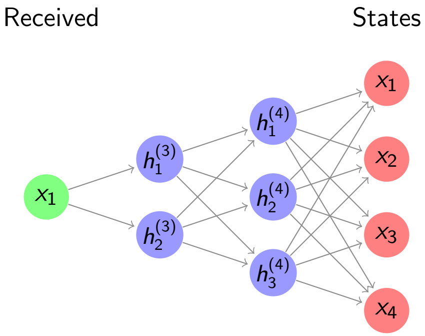
Generating training data $Pr(y_i|\mathbf{x}_{i-l}^{i})$ requires knowledge of the channel and its (current) parameters.

- ### Solution

  Decompose $Pr(y_i|\mathbf{x}_{i-l}^{i})$ into

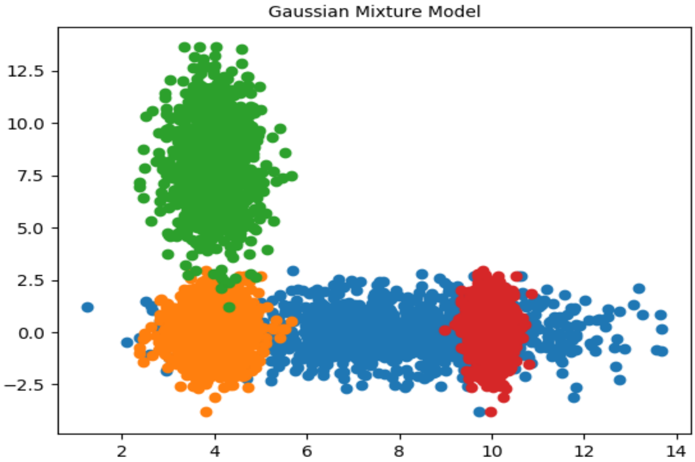
$$Pr(y_i|\mathbf{x}_{i-l}^{i}) = \frac{Pr(\mathbf{x}_{i-l}^{i}|y_i)Pr(y_i)}{Pr(\mathbf{x}_{i-l}^{i})} \tag{6}$$

Metrics for $Pr(x_{\mathrm{i-l}}^{\mathrm{i}}|y_{\mathrm{i}})$



Metrics for $Pr(y_i)$

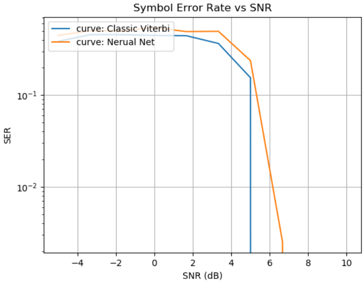
Gaussian Mixture Model using Expectation-Maximization algorithm



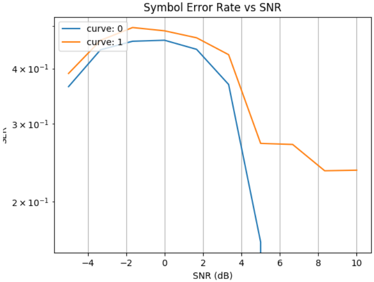
Outline

Detection Performance

Without ISI

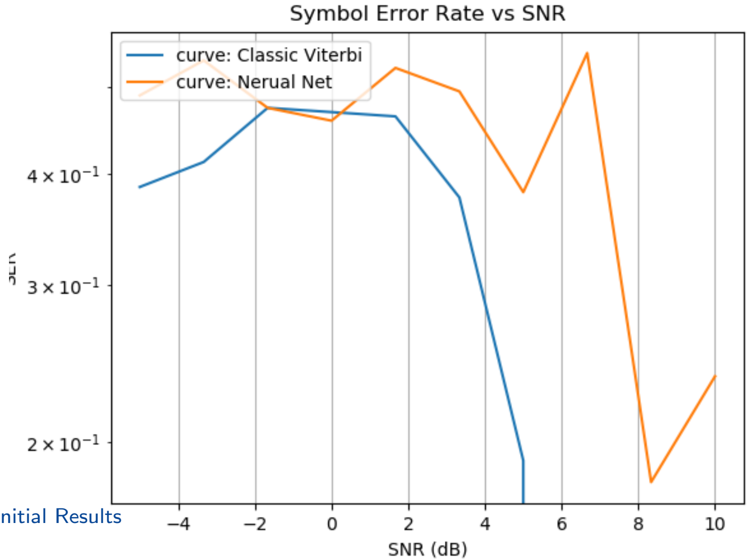


With ISI



Detection Performance

Reduced Training data



Next Steps

- Improve Neural Net Performance
- Apply to a sampled molecular communications channel.
  - Estimate matched filter
- Generate training data for molecular communications channel and test "transfer learning" to real data.