

Neural Network Metrics for Viterbi Decoding in Molecular Communication Channels

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Outline

Background

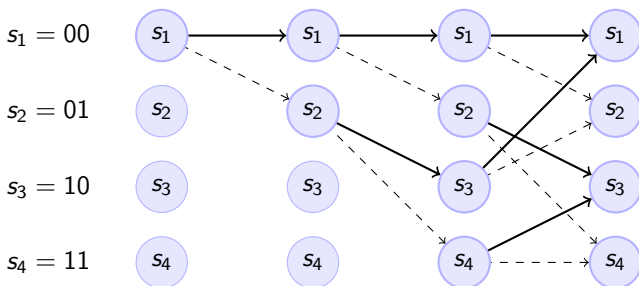
Initial Results

Viterbi Setup

Maximum Likelihood sequence decoding can be formalized as

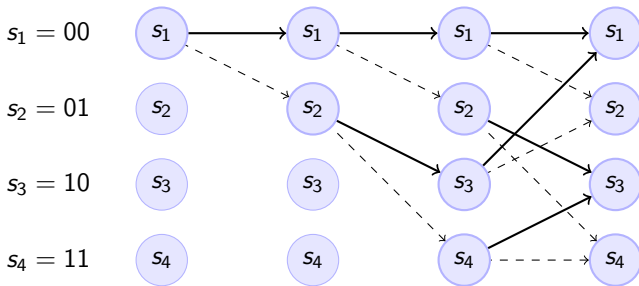
$$\begin{aligned} & \underset{\mathbf{x}}{\text{maximize}} && Pr(\mathbf{y}|\mathbf{x}) \\ & \underset{\mathbf{x}}{\text{maximize}} && \prod_{i=1}^N Pr(y_i|\mathbf{x}) \end{aligned} \tag{5}$$

$$\underset{\mathbf{x}}{\text{minimize}} \quad \sum_{i=1}^N -\log(Pr(y_i|\mathbf{x}))$$



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 $Pr(y_i|\mathbf{x}_{i-1}^i)$.



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

Incorporating Neural Net into Viterbi Decoding

Problem 1

Viterbi algorithm requires the distribution $Pr(y_i|\mathbf{x}_{i-1}^i)$.

► Solution

Have a neural network learn $Pr(y_i|\mathbf{x}_{i-1}^i)$.

Problem 2

Generating training data $Pr(y_i|\mathbf{x}_{i-1}^i)$ requires knowledge of the channel and its (current) parameters.

► Solution

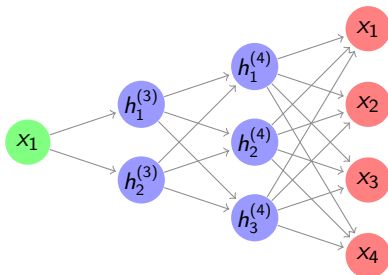
Decompose $Pr(y_i|\mathbf{x}_{i-1}^i)$ into

$$Pr(y_i|\mathbf{x}_{i-1}^i) = \frac{Pr(\mathbf{x}_{i-1}^i|y_i)Pr(y_i)}{Pr(\mathbf{x}_{i-1}^i)} \quad (6)$$

Metrics for $Pr(x_{i-1}^i | y_i)$

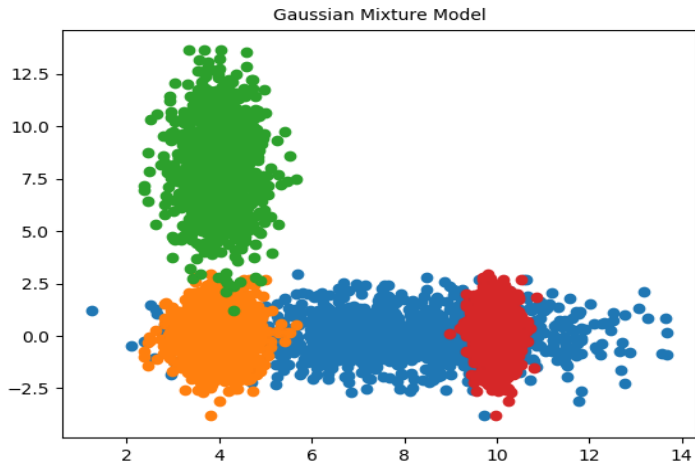
Received

States



Metrics for $Pr(y_i)$

Gaussian Mixture Model using Expectation-Maximization algorithm



Outline

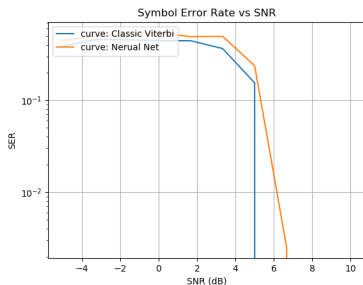
Background

Initial Results

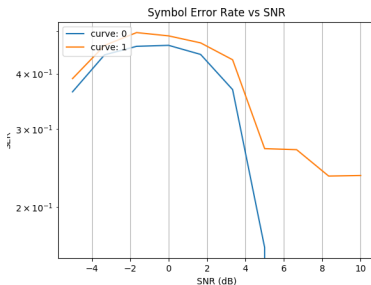
Initial Results

Detection Performance

Without ISI

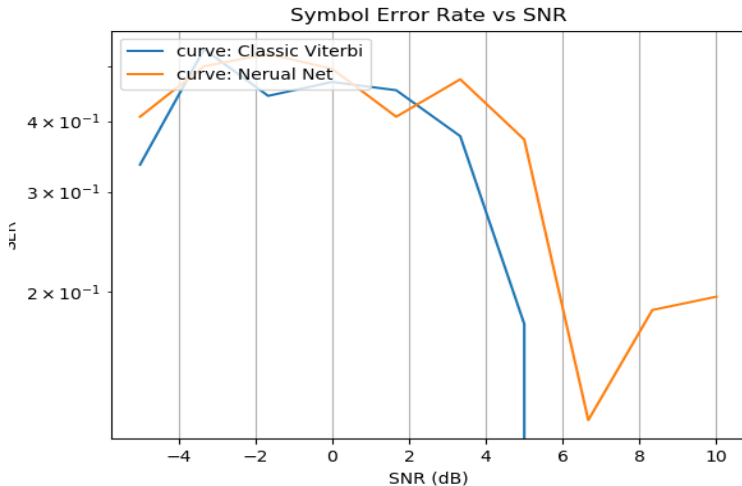


With ISI



Detection Performance

Reduced Training data (100 vs. 1000 symbols)



Next Steps

- ▶ Improve decoding performance with neural net.
- ▶ Apply to a sampled molecular communications channel.
 - Estimate matched filter
- ▶ Generate training data for molecular communications channel and test "transfer learning" to real data.

Thank You.

Questions or Comments?