Neural Network Metrics for Viterbi Decoding in Molecular Communication Channels

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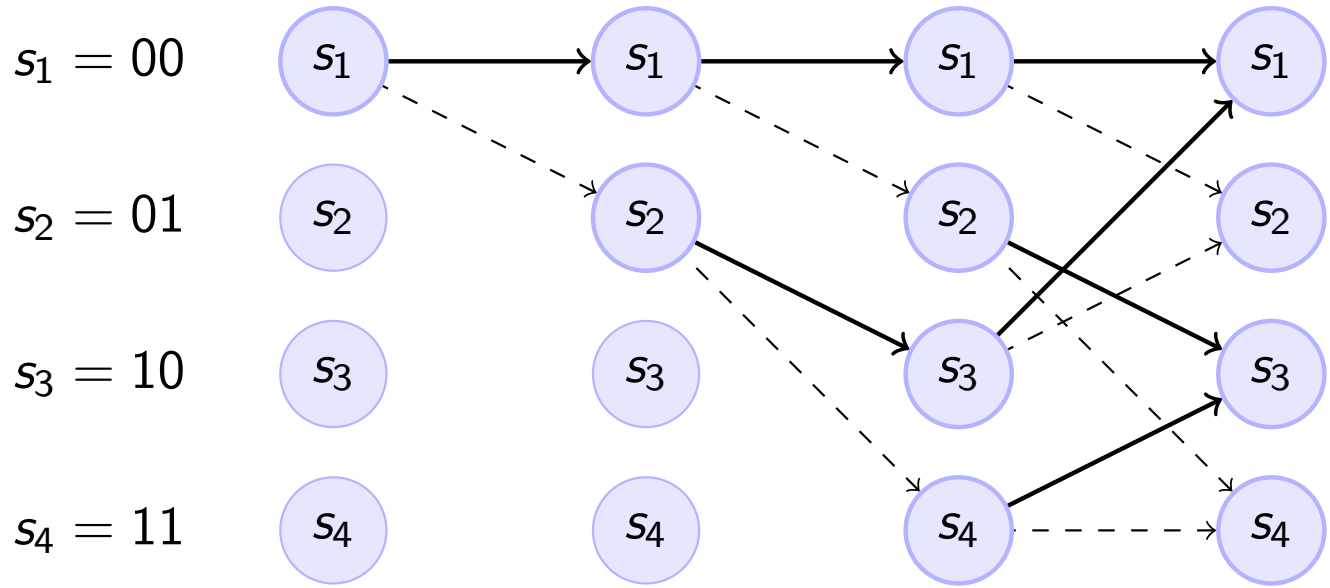
Outline

Viterbi Setup

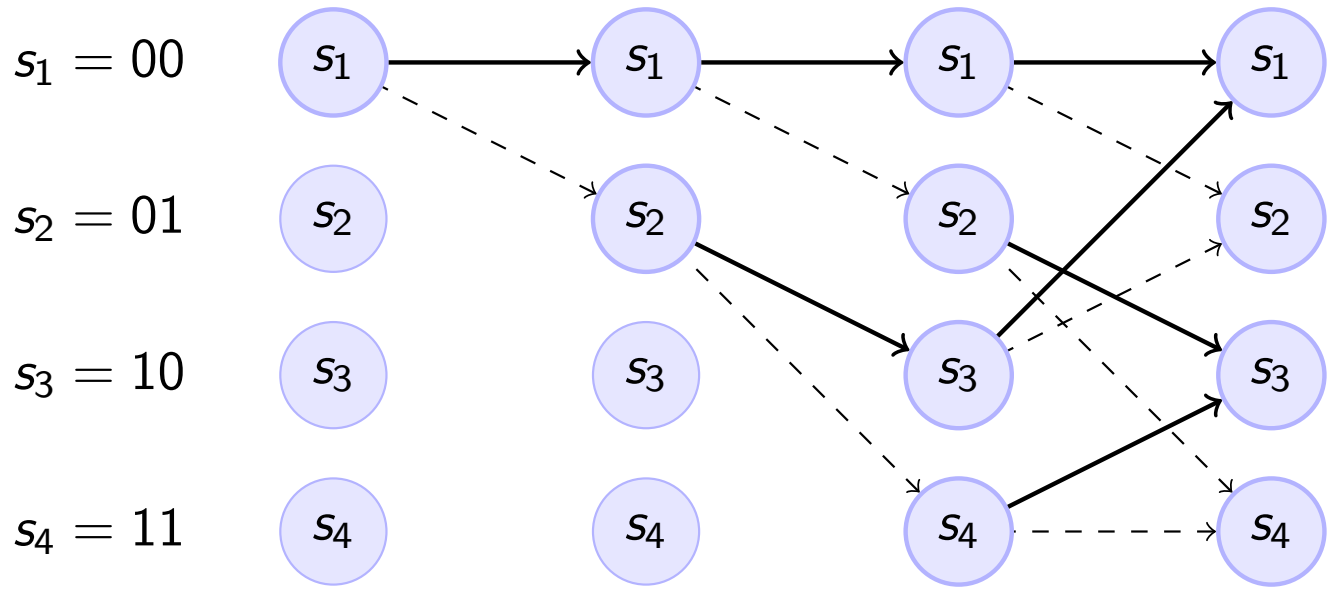
Maximum Likelihood sequence decoding can be formalized as

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



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.

Incorporating Neural Net into Viterbi Decoding

Problem 1

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

Solution

Have a 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

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

▶

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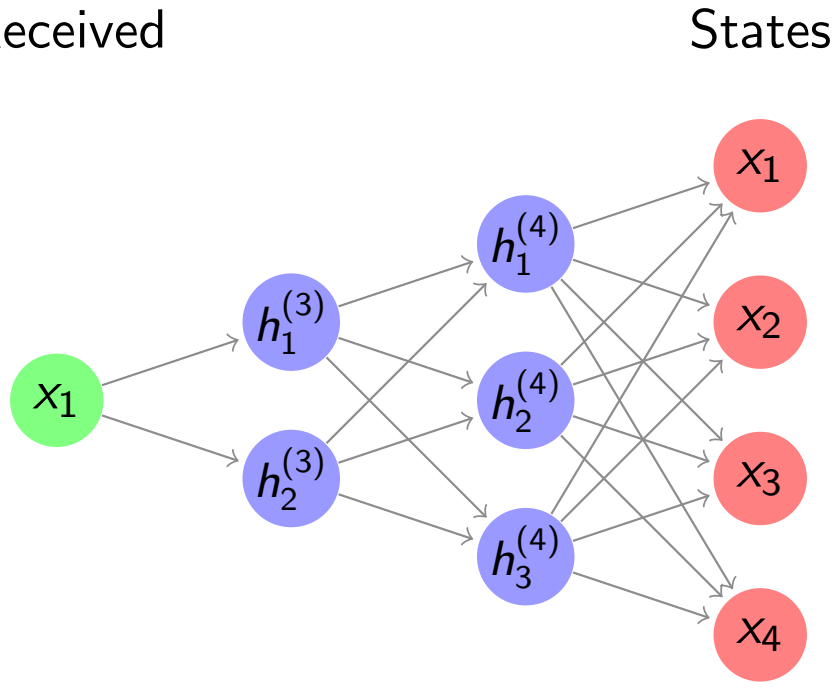
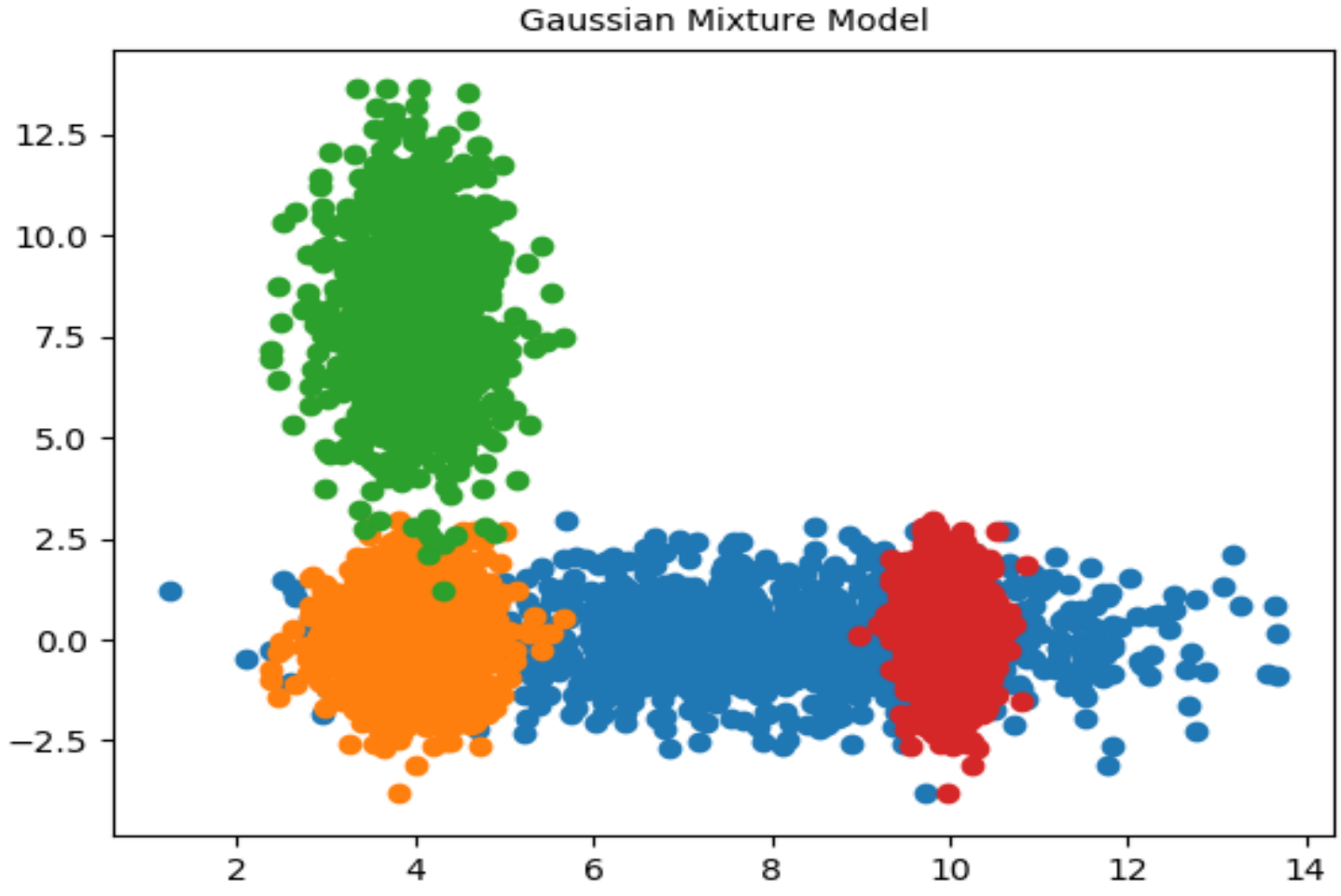
Metrics for $Pr(x^{i}_{i-1}|y_i)$



Metrics for $Pr(y_i)$

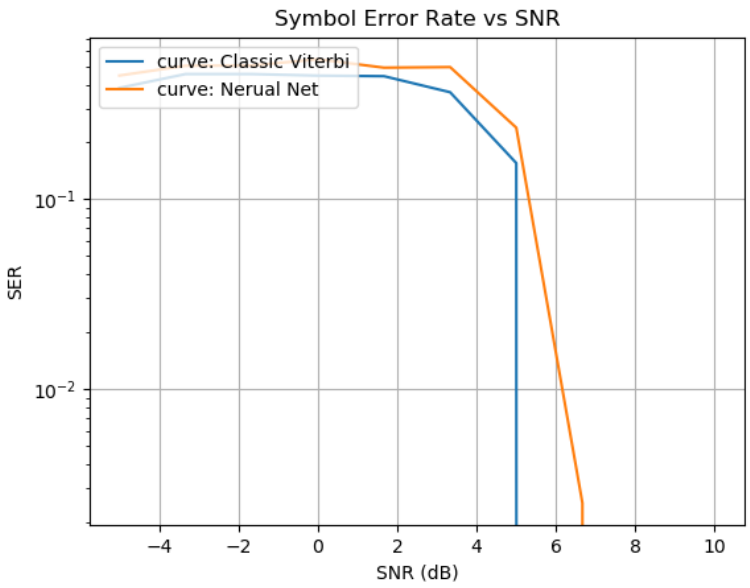
Gaussian Mixture Model using Expectation-Maximization algorithm



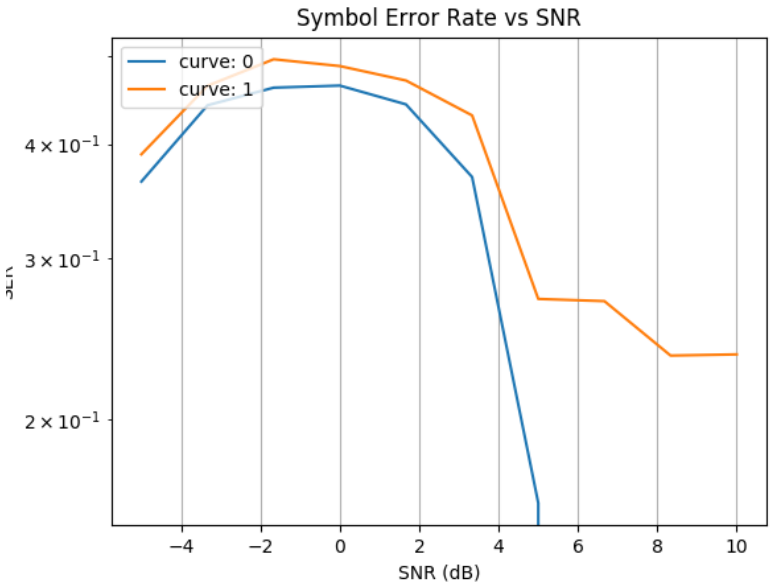
Outline

Detection Performance

Without ISI

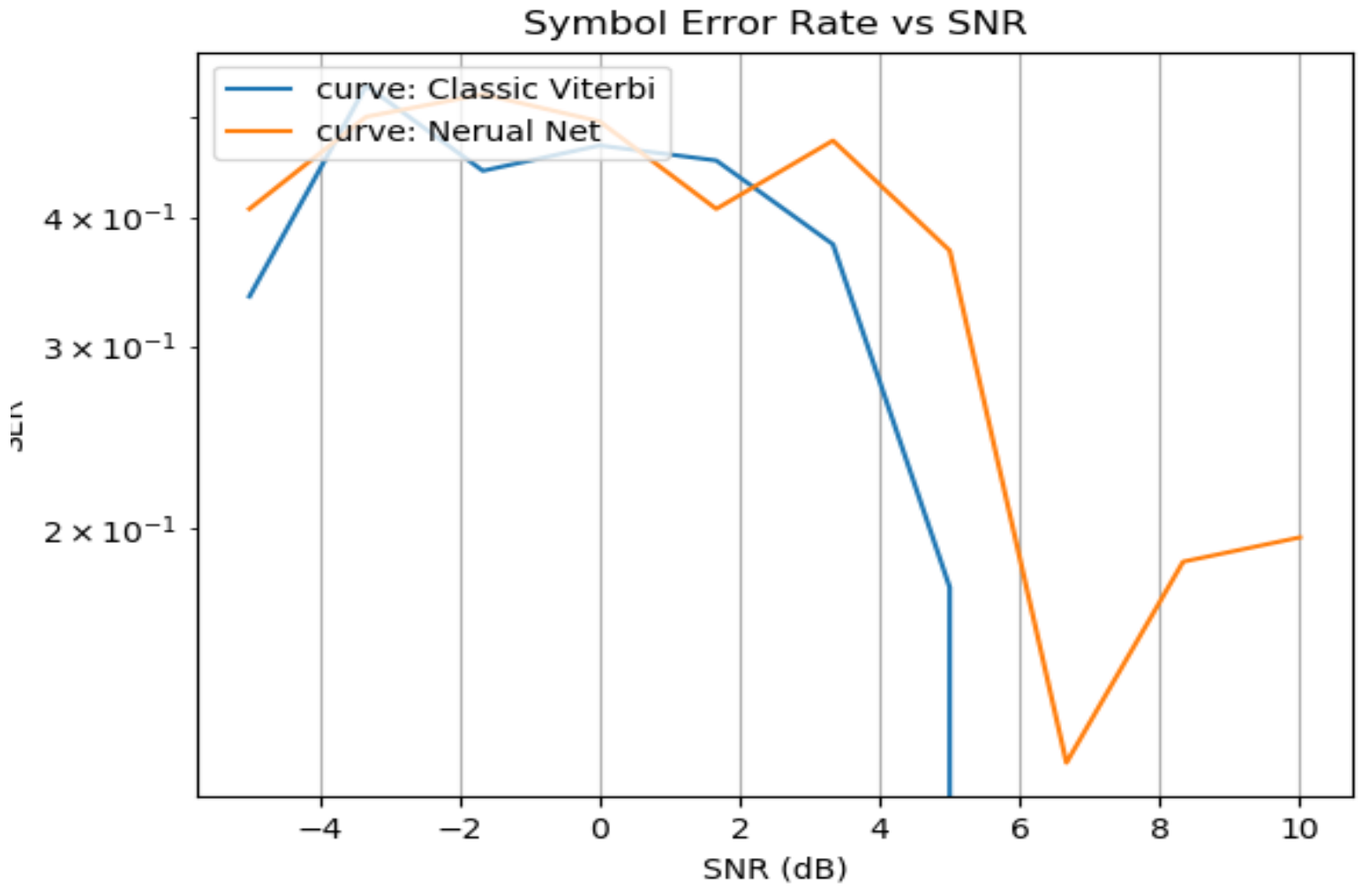


With ISI



Detection Performance

Reduced Training data (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?