Neural Network Metrics for Viterbi Decoding in Molecular Communication Channels

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Outline

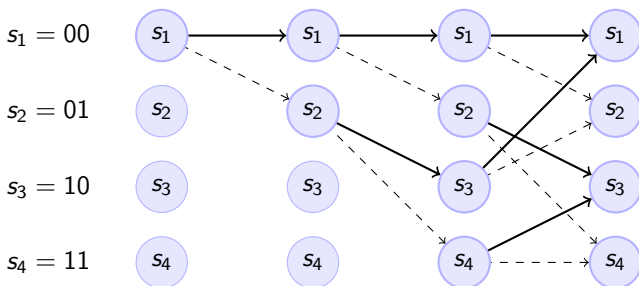Background

Initial Results

Viterbi Setup

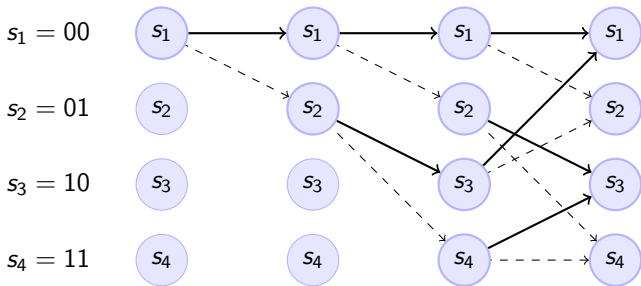Maximum Likelihood sequence decoding can be formalized as

$$\underset{\mathbf{x}}{\text{maximize}} \quad Pr(\mathbf{y}|\mathbf{x})$$
$$\underset{\mathbf{x}}{\text{maximize}} \quad \prod_{i=1}^{N} Pr(y_i|\mathbf{x}) \tag{5}$$
$$\underset{\mathbf{x}}{\text{minimize}} \quad \sum_{i=1}^{N} -log(Pr(y_i|\mathbf{x}))$$

$s_1 = 00$

$s_2 = 01$

$s_3 = 10$

$s_4 = 11$

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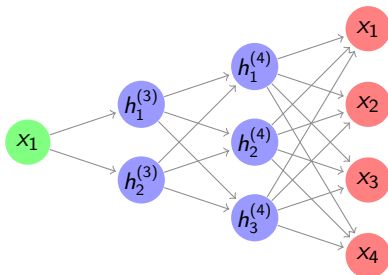
▶ Solution
Decompose $Pr(y_i|\mathbf{x}_{i-1}^i)$ into

$$Pr(y_i|\mathbf{x}_{i-1}^i) = \frac{Pr(\mathbf{x}_{i-1}^i|y_i)Pr(y_i)}{Pr(\mathbf{x}_{i-1}^i)} \tag{6}$$
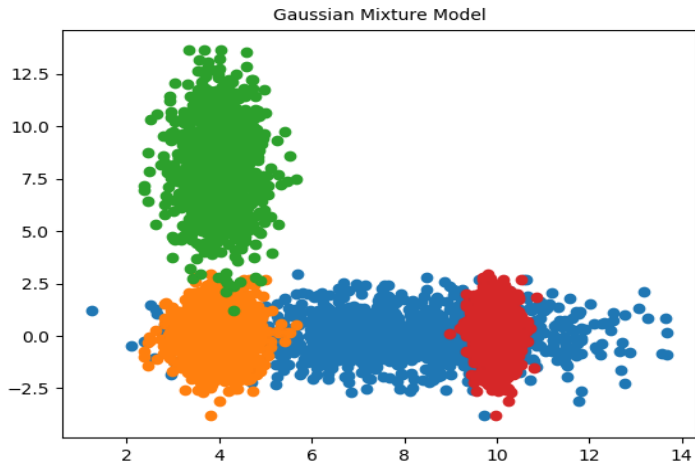
Metrics for $Pr(x_{i-1}^i | y_i)$

Metrics for $Pr(y_i)$

Gaussian Mixture Model using Expectation-Maximization algorithm

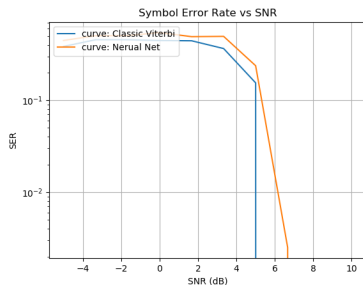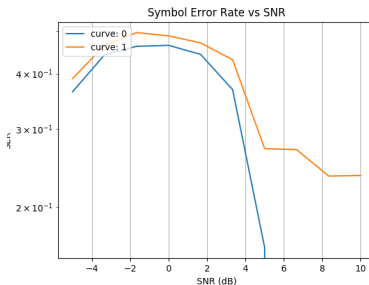Gaussian Mixture Model

Outline

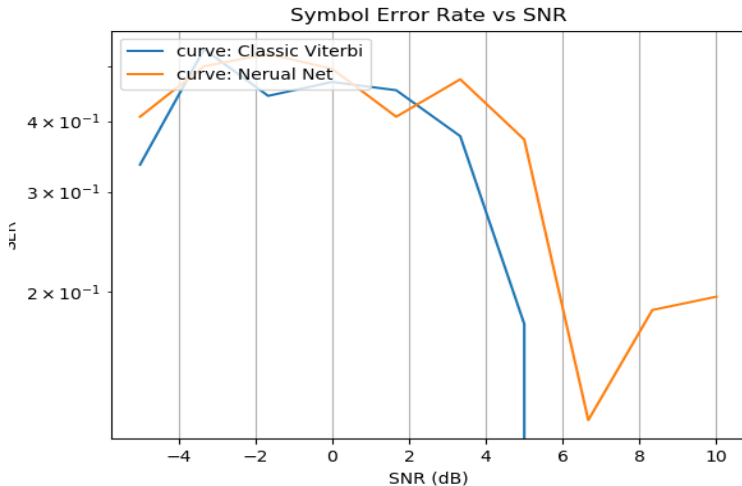# Detection Performance

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?