

# **Neural Network Metrics for Viterbi Decoding in Molecular Communication Channels**

Peter Hartig

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# Outline

Background

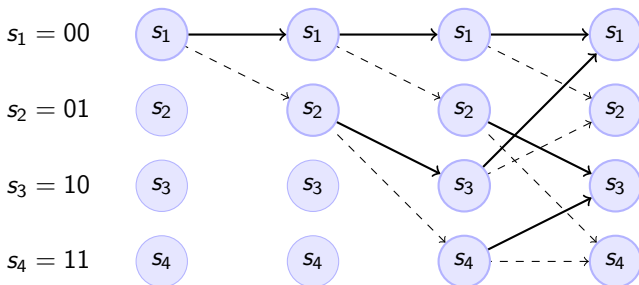
Initial Results

## Viterbi Setup

Maximum Likelihood sequence decoding can be formalized as

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

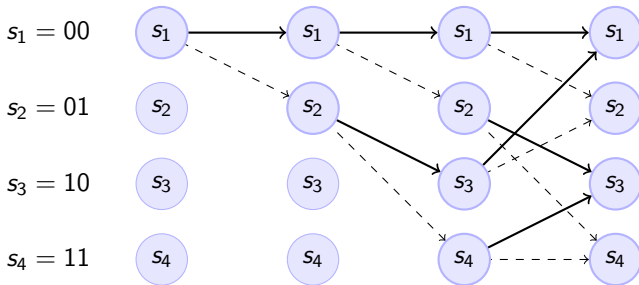
$$\underset{\mathbf{x}}{\text{minimize}} \quad \sum_{i=1}^N -\log(Pr(y_i|\mathbf{x}))$$



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

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

### ► Solution

Have 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

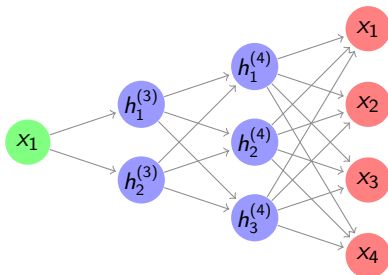
Decompose  $Pr(y_i|\mathbf{x}_{i-1}^i)$  into

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

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

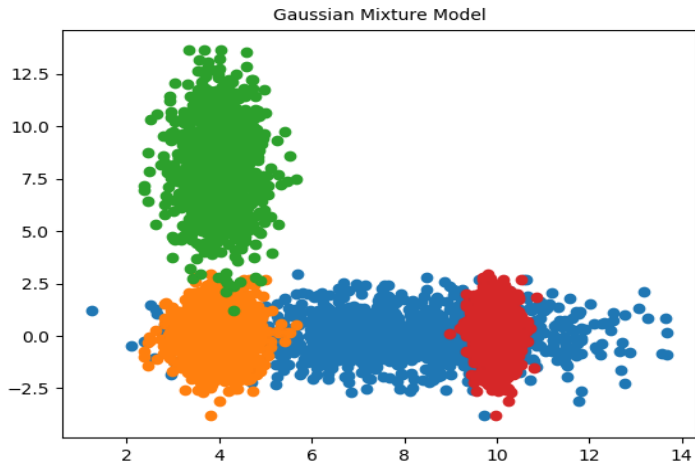
Received

States



## Metrics for $Pr(y_i)$

Gaussian Mixture Model using Expectation-Maximization algorithm



# Outline

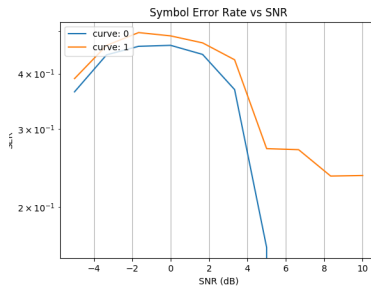
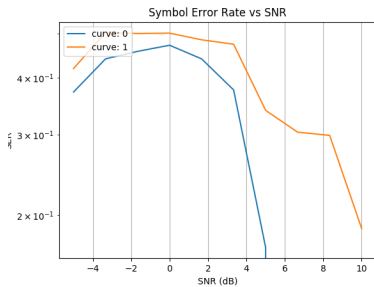
Background

Initial Results

Initial Results



# Detection Performance



## Next Step

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