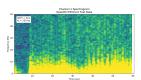
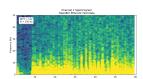
Adam Jump Salisbury University

January 18, 2018

### WHY ARE WE INTERESTED?

- ► Brain Computer Interfacing
- ► Accessibility
- ► Applications in Artificial Intelligence
- ► Prediction of Chaotic Time Series





#### Preliminary Information

- ► *Electroencephalography*: the measurement of neuronal function given by the *ionic gradient* of neuronal membranes
- ► *The Neuron*: Composed of a cell body (*Soma*), signal receptors (*Dendrites*), and signal transmitters (*axon*)
- ► Excitatory Postsynaptic Potentials (ESP) and Inhibitory Postsynaptic Potentials (ISP)

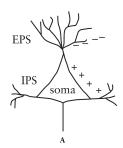


Figure: Sample Neuron

# ARTIFICIAL NEURAL NETWORKS (ANNS)

- ► *ANN*: information processing system composed of *perceptrons*
- ► *Directed Graph*: ANNs are represented using directed graphs and adjacency matrices

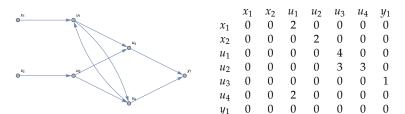


Figure: Sample Network and Network Structure

### TRANSLATION FROM THE TIME DOMAIN

▶ 8 electrodes giving us row vectors,

$$f(t) = (x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8),$$
$$x_i = x(t + i\tau)$$

▶ Utilizing the *Discrete Fourier Transform*,

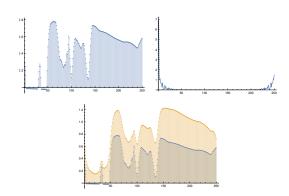
$$F_n = \sum_{k=0}^{N-1} X_k \cdot e^{-2\pi i n k/N}$$

Multiplying by low and high pass filters,

$$\frac{t}{\tau+t}, \frac{\tau}{t+\tau}$$

# FREQUENCY DOMAIN

► Why look at frequency?



## TIME-FREQUENCY DOMAIN (WAVELETS)

► The individual wavelet defined as,

$$\psi^{a,b}(x) = |a|^{-1/2} \psi\left(\frac{x-b}{a}\right)$$

▶ which gives,

$$W_{\psi}(f)(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right) dt$$

### ARTIFACT REMOVAL AND RETURN TO LINEARITY

- ► For all f(t) we want to find  $\mathbf{M}$  such that  $f(t)\mathbf{M} = \mathbf{s}$  where all  $\mathbf{s}$  are maximally independent
- ► Generally referred to as an *independent component analysis* and used in unsupervised machine learning

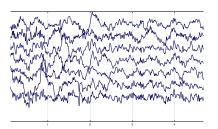
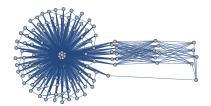


Figure: Processed Time-Series Data

### CHAOTIC TIME-SERIES PREDICTION

- ► Nonlinear autoregressive exogenus model (NARX)
- ► Algebraically stated as  $y(t) = N[y_{t-1}, y_{t-2}, y_{t-3}, \dots, u_t, u_{t-1}, \dots] + \epsilon_t$



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