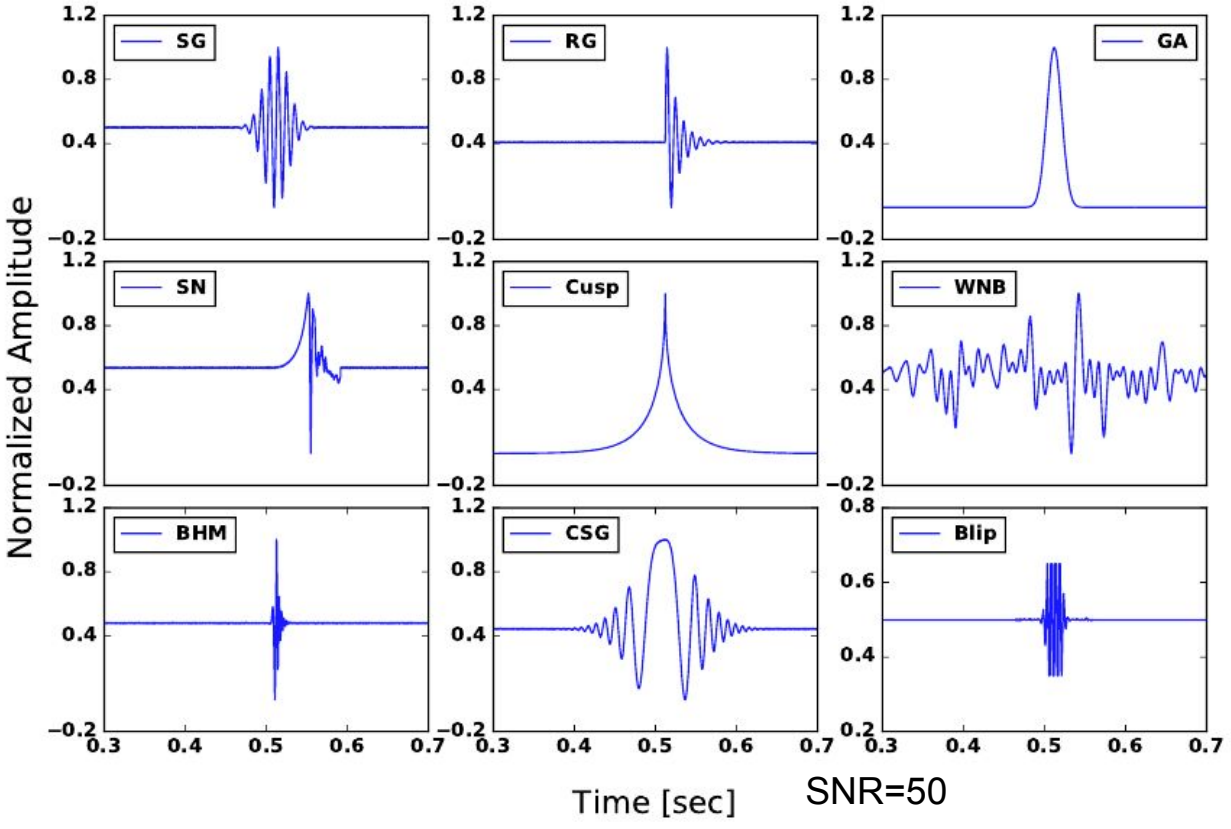
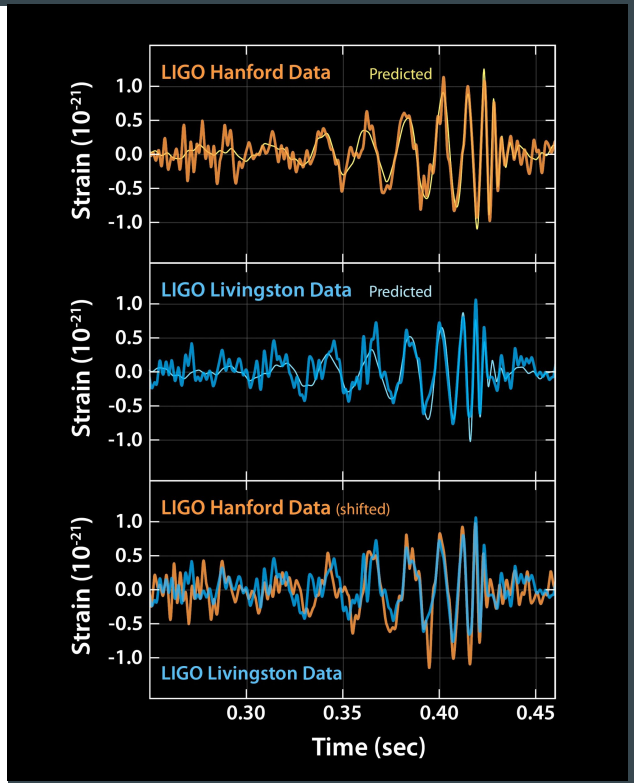
Selection of the right Feature is Crucial for reliable prediction

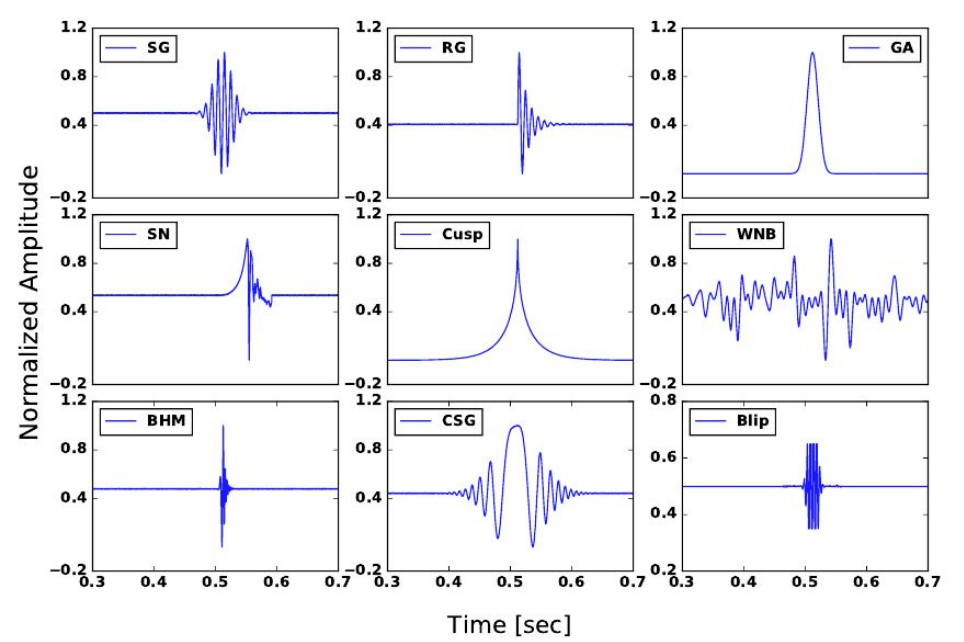
Identification of Glitches in LIGO data

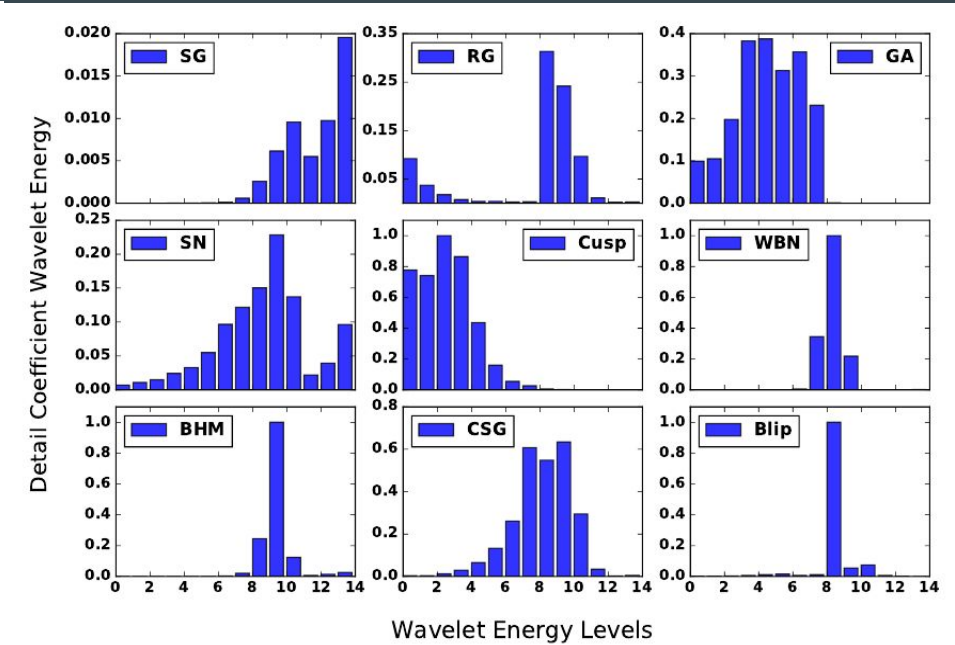




Nikhil Sheelu

Identification of Glitches in LIGO data

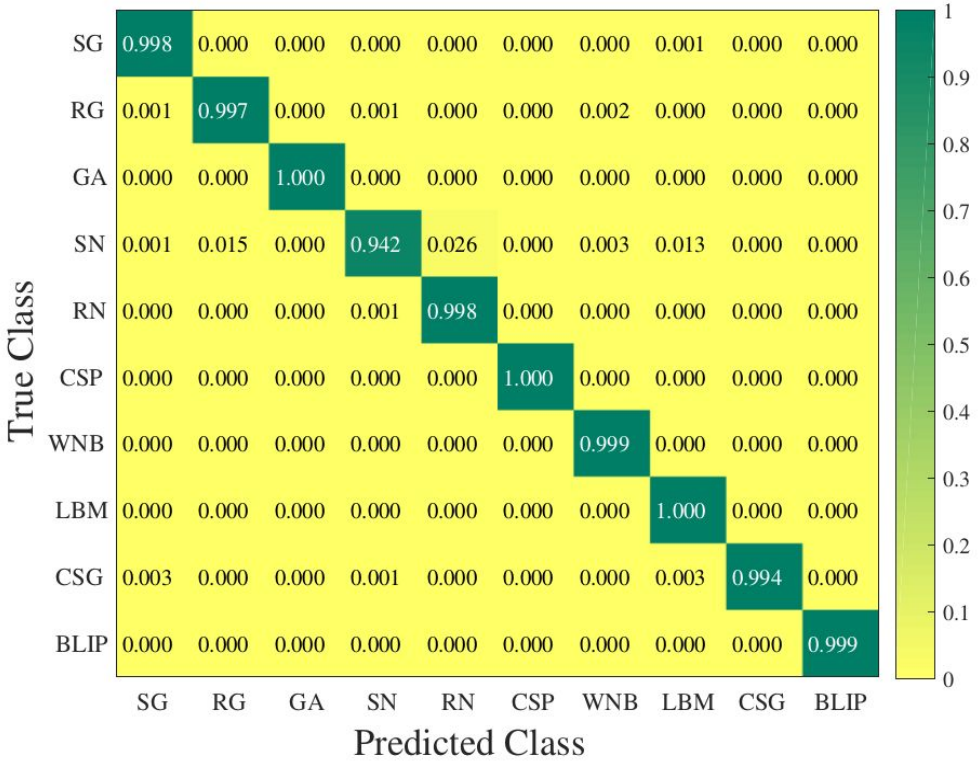




Identification of Glitches in LIGO data

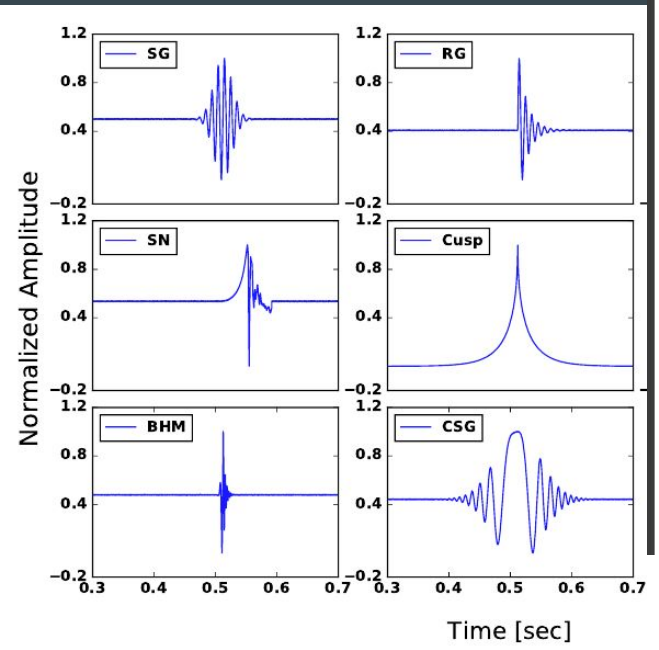
Nikhil Sheelu

Name	Total	Train.	TP	FP	Preci.	Sensi.	Speci.
SG	5000	552	4991	22	0.99	0.99	1.00
RG	5000	311	4984	16	0.99	0.99	1.00
GA	5000	155	5000	0	1.00	1.00	1.00
SN	745	313	702	14	0.98	0.94	1.00
RN	5000	114	4992	19	0.99	0.99	1.00
CSP	5000	14	5000	0	1.00	1.00	1.00
WNB	10000	421	9994	15	0.99	0.99	1.00
LBM	5000	586	4999	31	0.99	1.00	0.99
CSG	5000	378	4969	0	1.00	0.99	1.00
BLIP	4100	153	4097	0	1.00	0.99	1.00



Identification of Glitches in LIGO data

Nikhil Sheelu



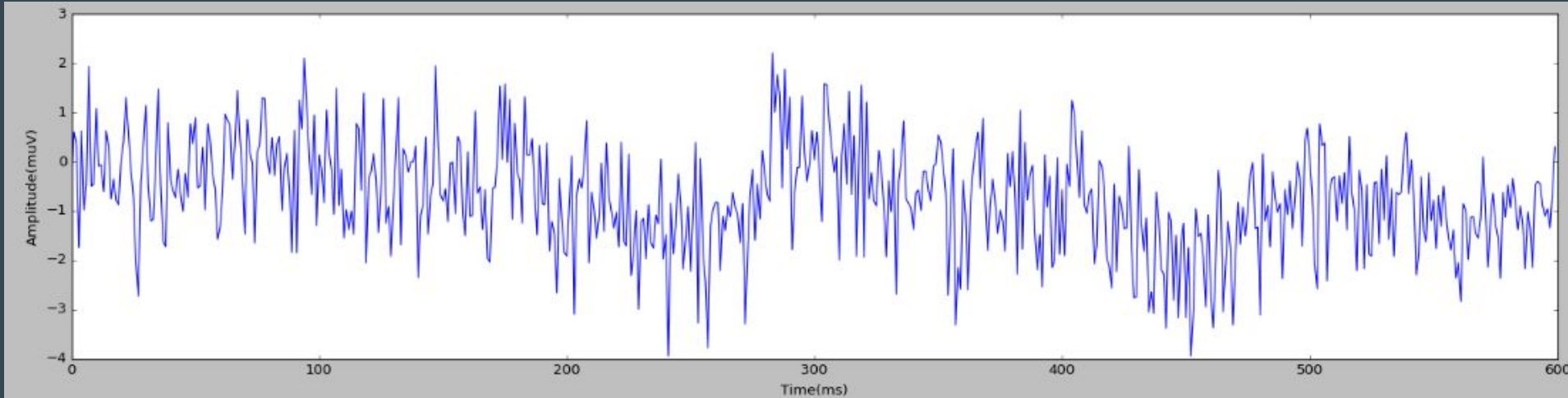
First Successful ML application on transients using LIGO data

https://arxiv.org/abs/1609.07259

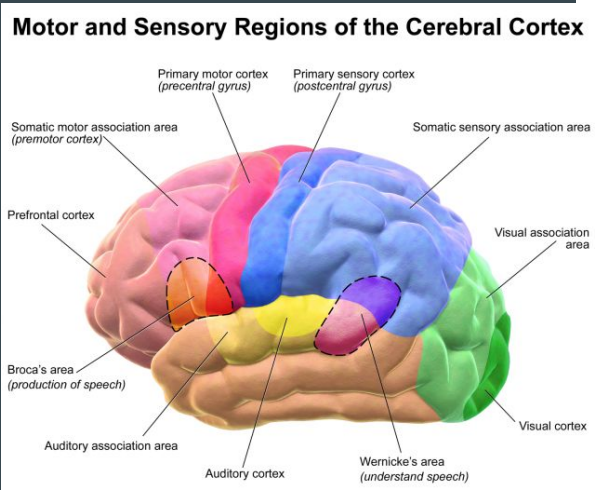
Selection of the right Feature is Crucial for reliable prediction

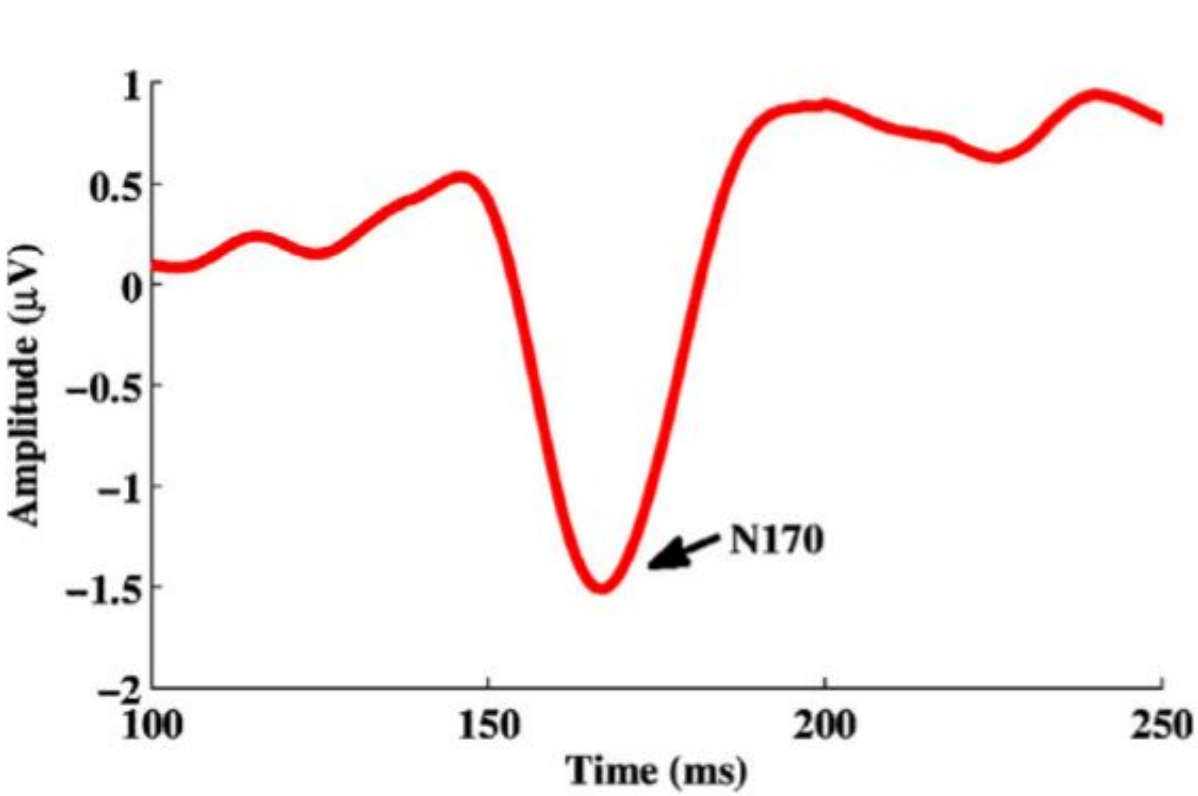
Detection of Event Related Potential N170 in EEG data

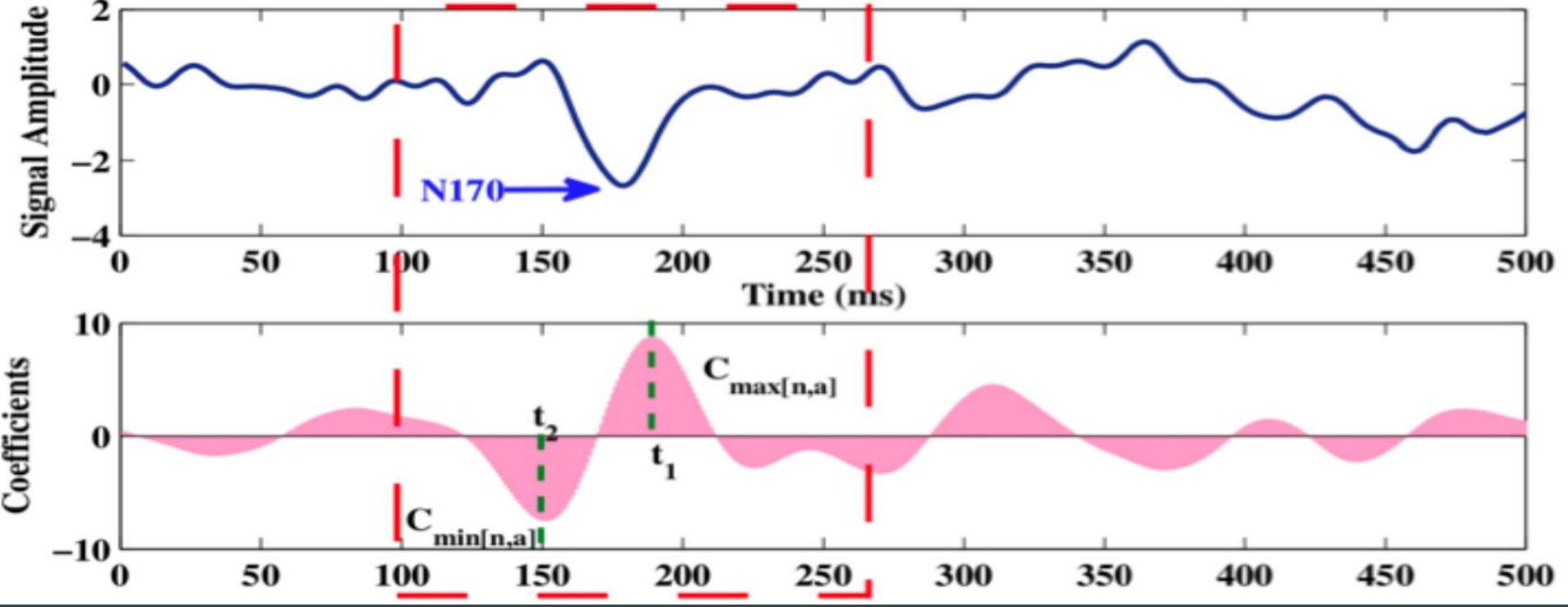
Work Done in Collaboration with Rochester University



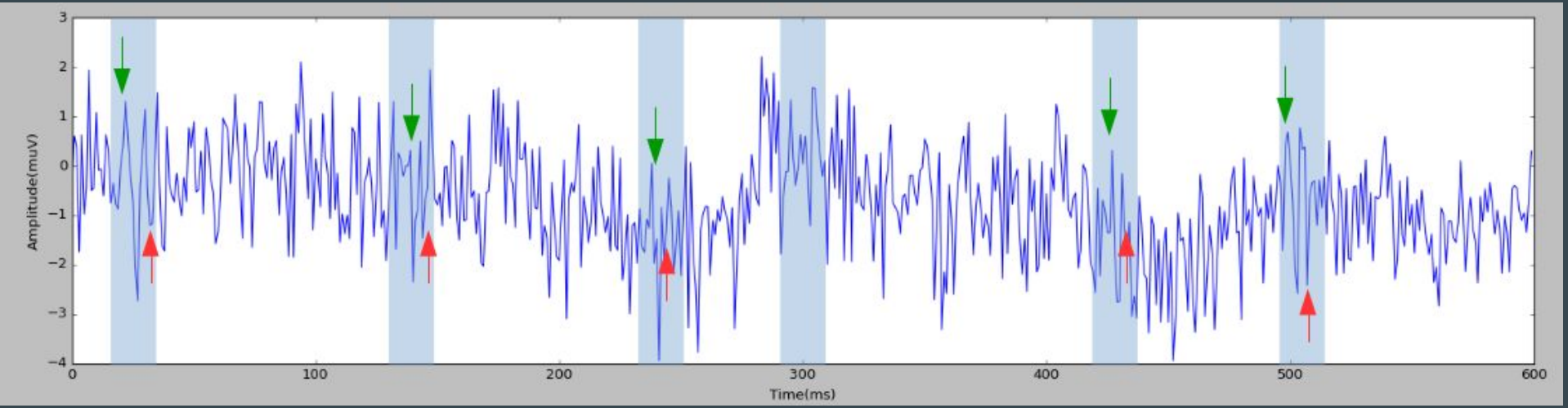
Selection of the right Feature is Crucial for reliable prediction







Arun Kumar found that Asymmetries in wavelet coefficients can be used to efficiently identify N170 locations.

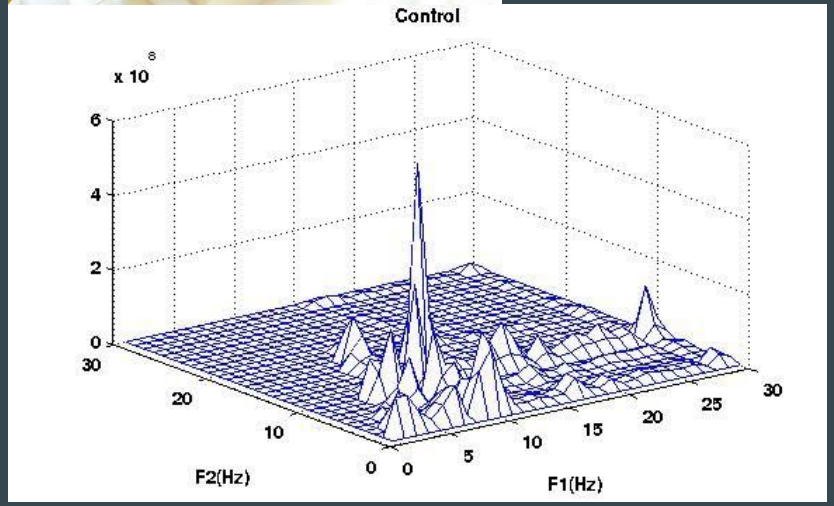


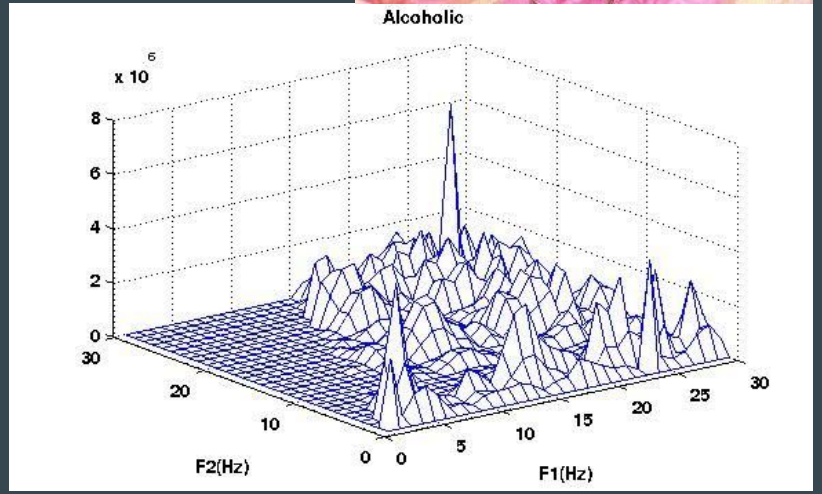
Aniyan, A. K., Philip, N. S., Samar, V. J., Desjardins, J. A., & Segalowitz, S. J. (2014).,
A wavelet based algorithm for the identification of oscillatory event-related potential components.
Journal of neuroscience methods, *233*, 63-72.

Bispectrum Analysis of EEG of Alcoholics

Arun Kumar

Deepthi R





Can Machines make logical/magical selection of

Features

(anything that leads to right conclusions)

to answer a given query?

What about CNN and Deep Learning?

Works well on image data

CNN can be used for Automated Feature Creation

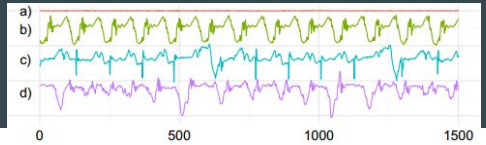
CNN can be used for Automated Feature Creation

On the flip side,
Convolutional Nets produce several thousands of features.

This affects the generalisation ability of the classifier

CNN can be used for Automated Feature Creation

Can we design an algorithm to trim down the number of features without causing performance degradation ?



Time Series Classification Using Multi-Channels Deep Convolutional Neural Networks

Yi Zheng[1,2], Qi Liu[1], Enhong Chen[1], Yong Ge[3], and J. Leon Zhao[2]

[1] University of Science and Technology of China
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[2] City University of Hong Kong, Hong Kong
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[3] The University of North Carolina at Charlotte
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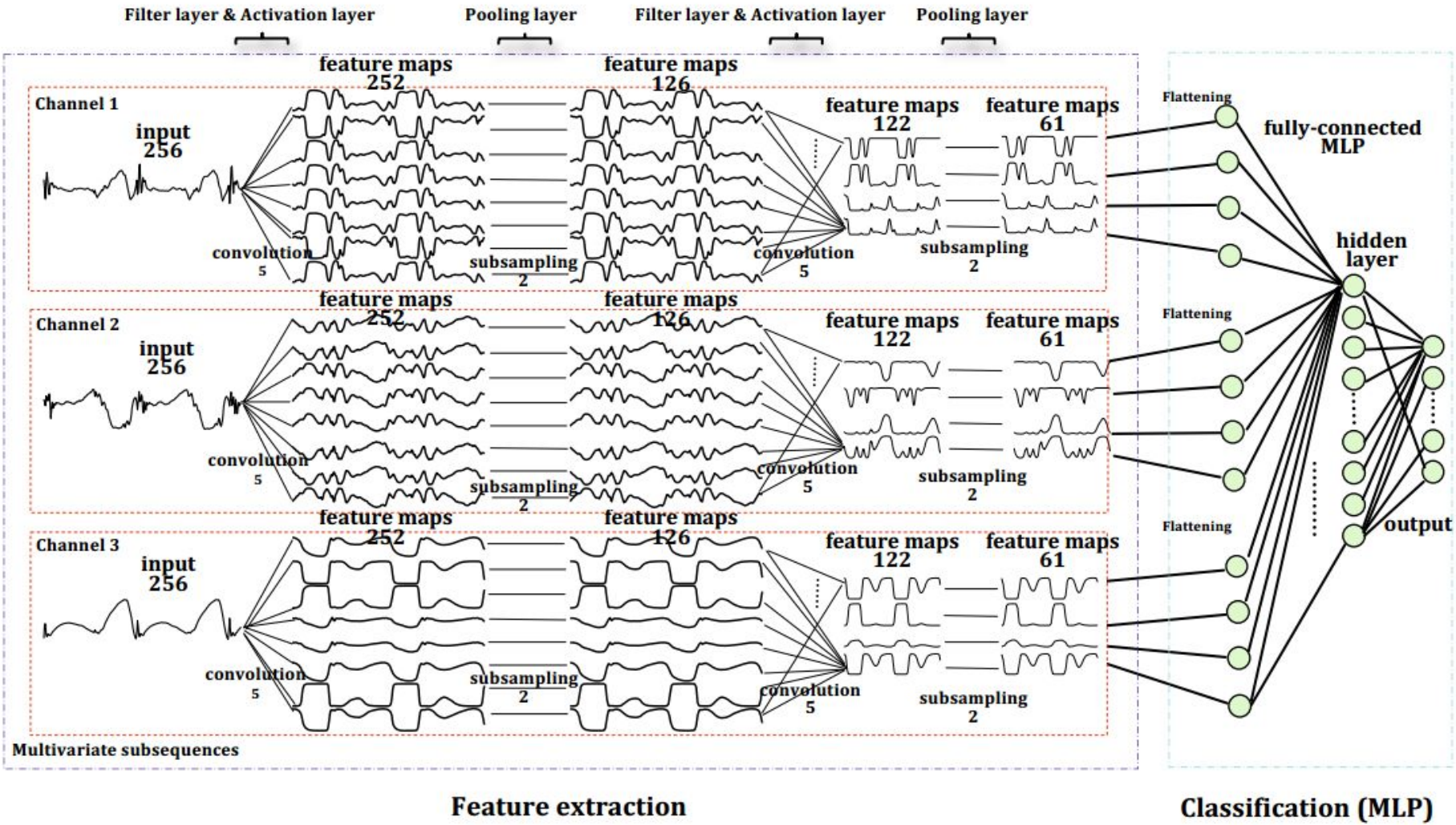
F. Li et al. (Eds.): WAIM 2014, LNCS 8485, pp. 298–310, 2014.


Filter layer & Activation layer
Pooling layer
Filter layer & Activation layer
Pooling layer
Channel 1
input
256
feature maps
252
feature maps
126
feature maps
122
feature maps
61
convolution
5
subsampling
2
convolution
5
subsampling
2
Channel 2
input
256
feature maps
252
feature maps
126
feature maps
122
feature maps
61
convolution
5
subsampling
2
convolution
5
subsampling
2
Channel 3
input
256
feature maps
252
feature maps
126
feature maps
122
feature maps
61
convolution
5
subsampling
2
convolution
5
subsampling
2
Multivariate subsequences
Flattening
Flattening
Flattening
fully-connected
MLP
hidden
layer
output
Feature extraction
Classification (MLP)

Deep neural networks for time series prediction with applications in ultra-short-term wind forecasting

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E-mail: mladen.dalto@fer.hr.

Abstract—The aim of this paper is to present deep neural network architectures and algorithms and explore their use in time series prediction. Existing and novel input variable selection algorithms and deep neural networks are applied for ultra-short-term wind prediction. Since gradient-based optimization starting from random initialization often appears to get stuck in poor solutions, recent research effort aimed at training methods for such deep networks is summarized. Shallow and deep neural networks coupled with two input variable selection algorithms are compared on a ultra-short-term wind prediction task. Initial results show that deep neural networks outperform shallow ones. Depth adds additional computational cost and input variable selection use reduces it.

Keywords—Deep Neural Networks, Input Variable Selection, ultra-short-term, wind forecasting

Is this is perhaps the direction we should move on?

Or should we think of something different?....

Thank You