EEG Processing for Neural Interactive Machine Learning

Leslie Blaha, Gerges Dib, Kayla Duskin, Katie Porterfield, Johnathan Cree, Jesse Johns, Gianluca Longoni, Bharat Medasani, Jonathan Suter
{Leslie.Blaha, Gerges.Dib, Kayla.Duskin, Johnathan.Cree, Jesse.Johns, Gianluca.Longoni, Jonathan.Suter}@pnnl.gov
Pacific Northwest NATIONAL LABORATORY

Overview

Neural interactive machine learning (NIML) is about developing an effective interface for human-machine interaction that leverages the unique pattern-recognition abilities of the human brain. Directly measured brainwave data and operator interactions support both unsupervised and semi-supervised data analytics to enhance image and audio data processing.

Motivations

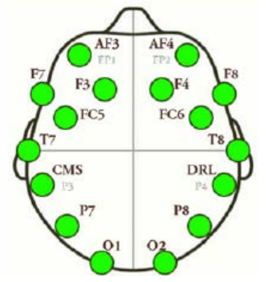
- Machine learning cannot fully replace human pattern recognition
- Data-intensive environments increasingly require effective human-machine interfaces
- Leverage the strengths of human beings and modern computational power

Table of Aptitudes		
High data throughput	✓	✗
Great attention span	✓	✗
Intuitive pattern recognition	✗	✓
Small training data set	✗	✓
Contextual understanding	✗	✓
Can handle ambiguity	✗	✓

Present work scope

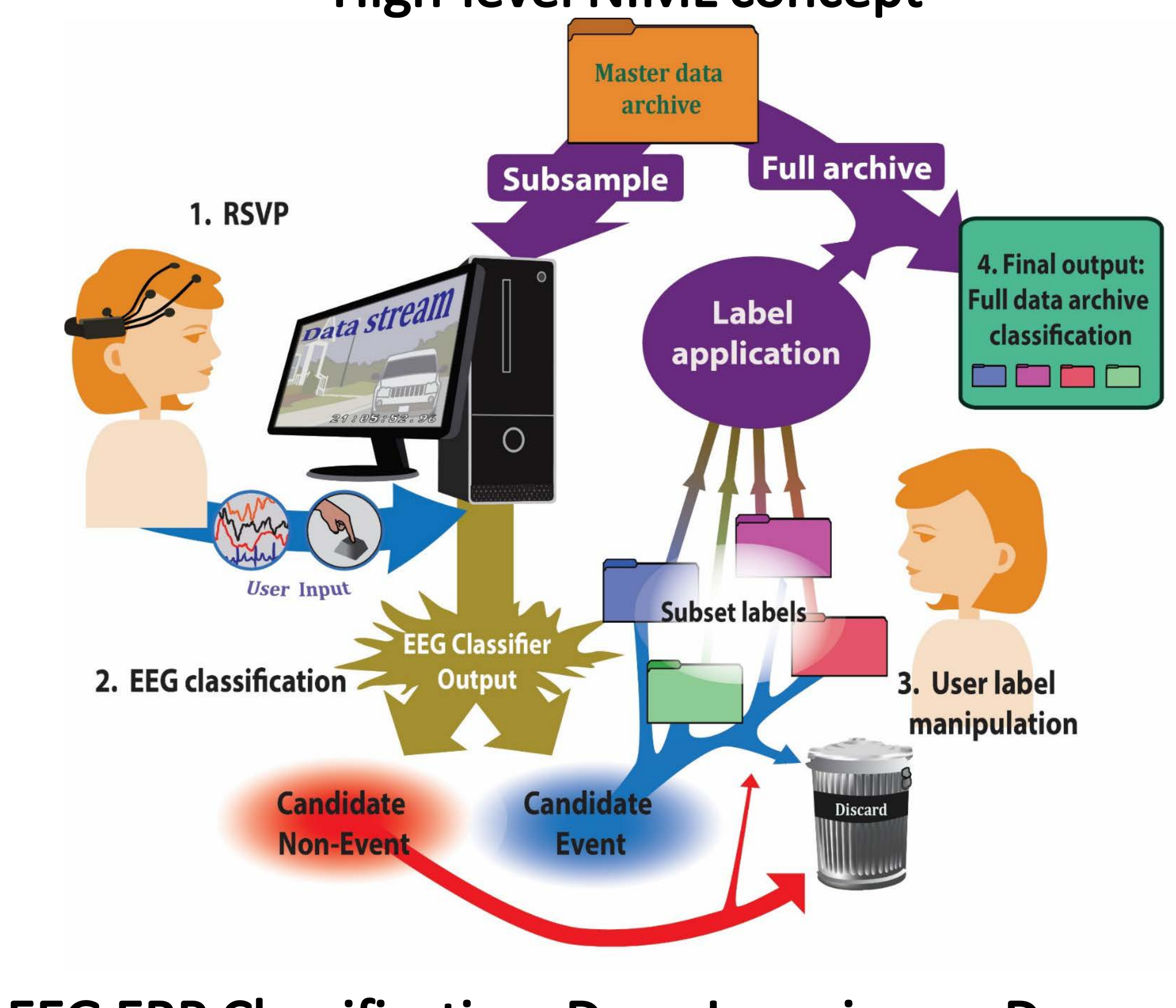
- Develop intuitive user interface
- Evaluating existing ML pipelines
- Comparing home-grown data with publically available archives

Equipment



- Emotiv Epoc portable EEG is being used to validate data processing with consumer-grade equipment.
- Low-density systems are more practical and portable, easy to wear, and offer Bluetooth connectivity.

High-level NIML concept



EEG ERP Classification: Deep Learning on Dense-Caps

Data using high-density EEG cap* was used to test neural network classification algorithms. The goal of this analysis was to obtain a classification model with minimal pre-processing and signal processing applied on the raw EEG data. This would allow its implementation in a real-time/streaming setting and integration into NIML.

RSVP experiments: Satellite image clips of London, with superimposed target airplane mages were shown to eight participants (15 total sessions) in RSVP mode. Images were presented at 12/s in 4.1 s bursts. About 500 bursts were shown in each session. 40% of bursts contained targets. EEG data collected using BIOSEMI Active View 2 system with 256 electrodes.

Preprocessing: A minimal pre-processing pipeline was used to clean the raw EEG data. Each session was segmented into individual bursts of length 1050 samples (4.1 s time). The preprocessing steps used are as follows:

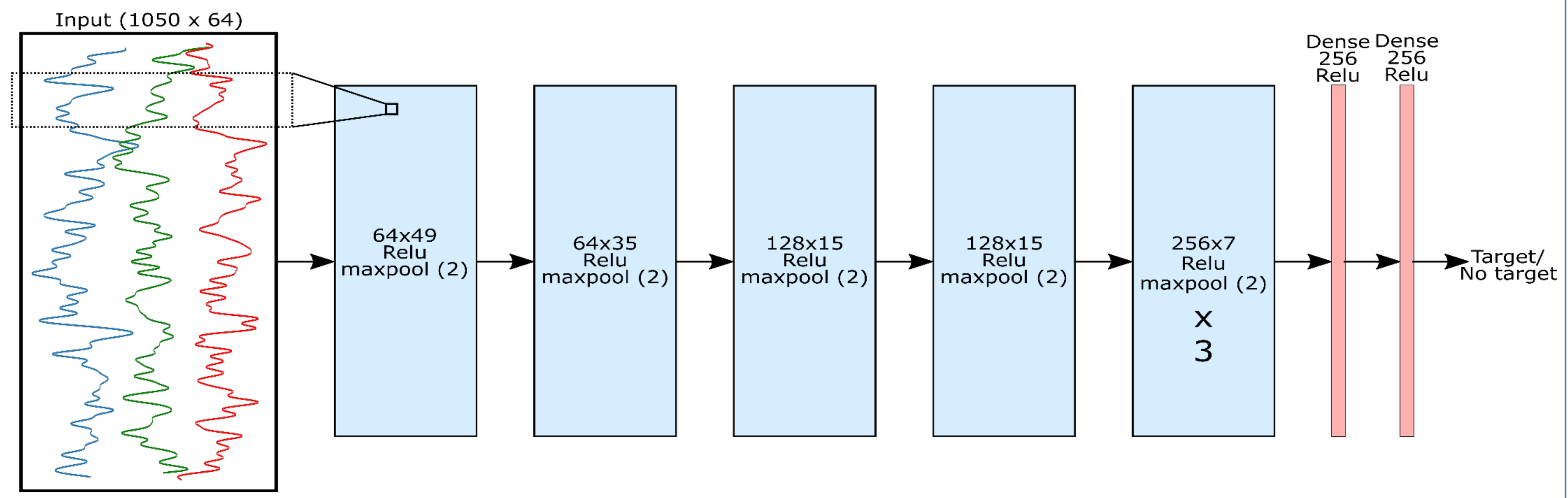
- Removal of linear trends in the time series of each channel,
- Detection of bad channels in each session using an entropy metric,
- Interpolation of detected bad channels in each session,
- Re-reference channels by subtracting the average of all channels.

Neural Network Architectures

Two types of convolutional neural network architectures were trained and validated. The validation scheme implemented here was to train the network on all but one session, and validate on the held-out session. Thus a total of 14 validation folds were run. (Note session 9 had bad data and was not used.)

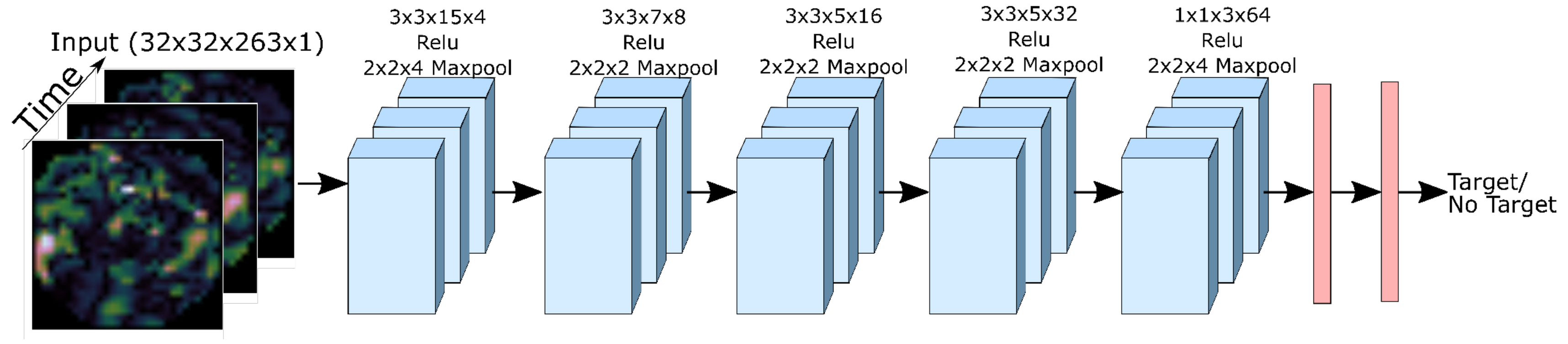
1-D Convolutional Network

Network input was filtered using 20 Hz 4th order Butterworth low pass. Number of electrodes down-sampled to 64. Convolution computed in time dimension. The 64 electrodes are treated as different channels. Trained using stochastic gradient descent (SGD) with a 0.075 learning rate, 0.0015 weight decay, dropout in dense layers, and early stopping.



3-D Convolutional Network

The advantage of 3-D convolution is that spatial structure is also considered (in addition to temporal structure). The time dimension was mean-reduced by a factor of 4. The electrode locations were projected onto a 2-D plane and a 32x32 image was formed at each reduced time point. The network was trained similarly to the 1-D configuration but with 0.15 learning rate.



Classification Results

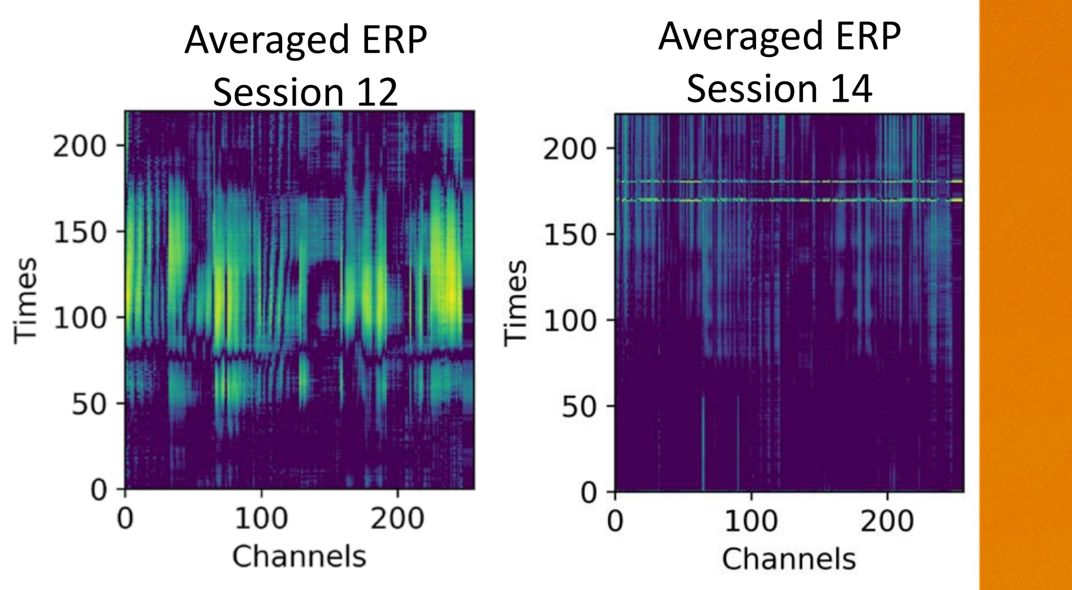
We report the accuracy of target classification based on the **area under curve (AUC)** metric. Validation results on each session for the two networks compared with the work of Bigdely-Shamlo* show similar accuracy. However, the advantage of the deep learning approach is that no feature extraction is required to obtain those results.

Classification Results (cont'd)

Session	1	2	3	4	5	6	7	8	10	11	12	13	14	15	median
Conv1D	0.90	0.92	0.89	0.88	0.90	0.89	0.78	0.92	0.83	0.71	0.91	0.87	0.71	0.80	0.88
Conv3D	0.87	0.93	0.92	0.84	0.88	0.87	0.82	0.95	0.86	0.71	0.84	0.84	0.69	0.80	0.84
Shamlo*	-	-	-	0.89/ 0.92	0.78	0.84	-	-	-	-	0.95	-	0.56	0.88	0.86

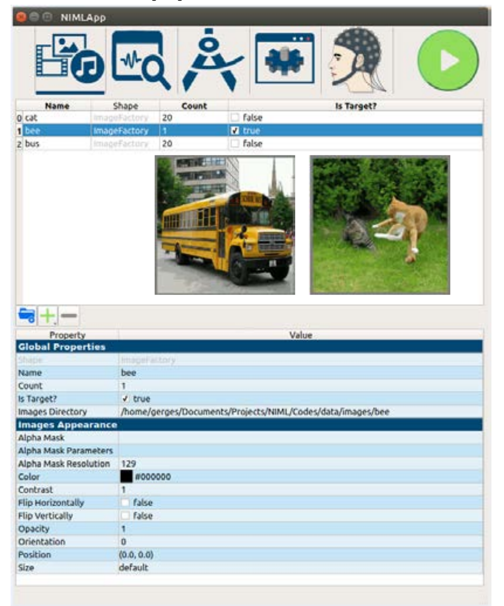
Note: Training scheme & across-session validation scheme may be slightly different than Bigdely-Shamlo.

Session 14 shows poor performance across all models, while session 12 shows good performance. We looked at the averaged ERP signals for those two sessions across all bursts, for each channel to visualize if data quality is affecting this accuracy. The figures show ERP intensity much higher for session 12 indicating data quality is a factor and must be handled appropriately.

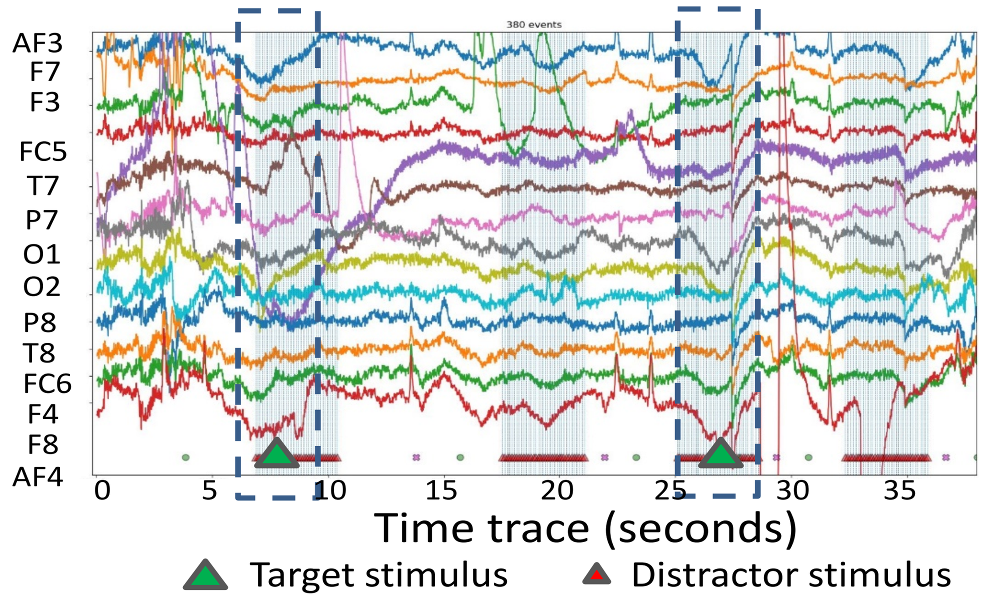


Experiments using Emotiv Epoc and next steps

NIMLApp User interface



RSVP stimulus: signal analysis



Test sequence

1. Noise characterization (eyeblinks, facial expressions, etc.)
2. Mixed language character recognition
3. Where's Waldo?
4. Application-specific datasets

Next Steps

- Integrate neural networks for low-density headset data classification
- Investigate optimal experimental conditions for low-density EEG
- Expand beyond binary (interesting/not interesting) classification

* We would like to acknowledge Nima Bigdely-Shamlo for providing us with this data.

N. Bigdely-Shamlo et al., "Brain activity-based image classification from rapid serial visual presentation," IEEE Trans. on NSRE, 16(5):432–441, Oct. 2008.