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PNNL-31540

Neural Interactive Machine Learning

Final Report: Compilation of presentation material

June 2021

Jonathan D Suter
Johnathan V Cree
Jesse M Johns
Gianluca Longoni

U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
under Contract DE-AC05-76RL01830

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Pacific Northwest National Laboratory
Richland, Washington 99354

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

Overview

Neural interactive machine learning (NIML) is about developing a more effective interface for human-machine interaction that leverages the unique pattern-recognition abilities of the human brain. Directly measured brainwave data and operator interactions to 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
- We believe we can leverage the strengths of human beings and modern computational power

Benefits

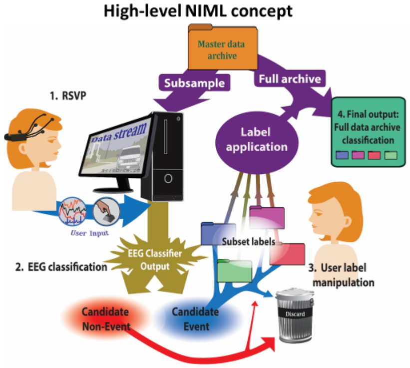
- Balancing work-load between human and machine
- Improving throughput on large datasets
- Create framework for training ML with human expertise
- Identification of poorly-understood targets
- Supporting trust in ML classification outcomes

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

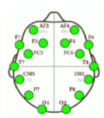
Present workscope

- Develop intuitive user interface
- Evaluating existing ML pipelines
- Comparing home-grown data with publically available archives
- Characterization of noise sources and smoothing/pre-filtering requirements

High-level NIML concept



Equipment



- Emotiv Epoc test system is being used to validate data processing with consumer-grade equipment
- Low-density systems (only 14 electrodes) are more practical and portable than high density (up to 256 electrodes)
- Consumer-grade system is easy to wear and offers Bluetooth connectivity

Example high-density system

(from "Management of Epilepsy – Research, Results and Treatment" ISBN 978-953-307-680-5)

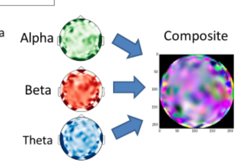
EEG Classification: Deep Learning on Dense-Caps

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. The pre-processing used in classification algorithms included:

- Removal of linear trends in the time series of each channel
- Detection of bad channels in each session using an Entropy metric.
- Interpolation of bad channels in each session.
- Re-reference channels by subtracting the average of all channels.
- Apply a 20 Hz 4th order Butterworth low pass filter

PCA spatial classification

- Previously published data used for reconstruction
- Alpha, beta, and theta frequency bins spatially resampled
- RGB composite fed into classifier



AUC evaluation metric

We are currently studying accuracy results using the area under curve (AUC) metric obtained using the minimal data preprocessing pipelines listed here. The results will be used to downselect for integration into NIML.

Architecture
1-D convent
1-D resnet
3-D convent
3-D resnet
LSTM

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

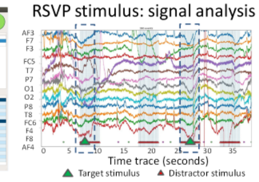
Experiments using Emotiv Epoc

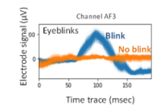
Test sequence:

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

NIMLApp User interface

RSVP stimulus: signal analysis





Characterization of noise sources

- Muscle-related signals come from close to the scalp
- Signals manifest very differently at different electrode locations

Next Steps

- Fully characterize low-density headset strengths/weaknesses
- Continue to evaluate EEG signal processing techniques
- Investigate electrode scalp positioning
- Investigate optimal experimental conditions for low-density EEG
- Expand beyond binary (interesting/not interesting) classification

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NiML

Neural Interactive Machine Learning

Jonathan D. Suter
Engineer, Applied Physics Group

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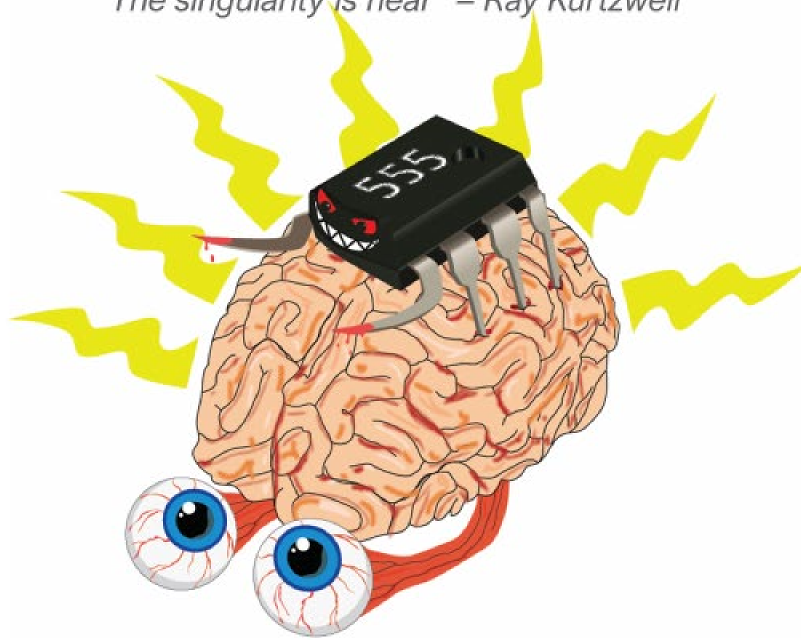
Big Picture Thoughts

"The singularity is near" – Ray Kurtzweil



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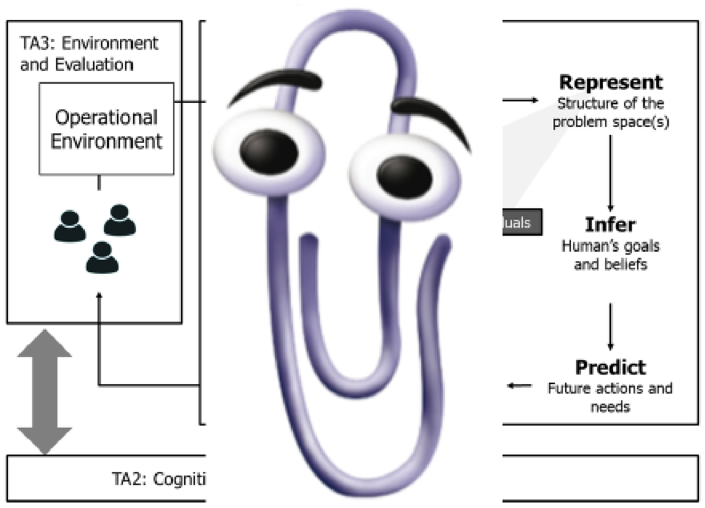
Need: Human Machine Teaming beyond Alexa

2019 DARPA ASIST* BAA



*ASIST = Artificial Social Intelligence for Successful Teams

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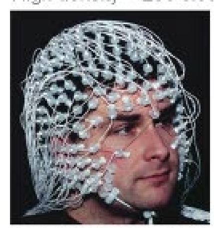
Why NIML?

- EEG gets at the fundamentals of human interest and intent.
- EEG yields extremely rich data sets.

High density – 256 electrodes



(from "Management of Epilepsy – Research, Results and Treatment" ISBN 978-953-307-680-5)

vs.

Low density – 14 electrodes

Emotiv Epoc – consumer grade BCI

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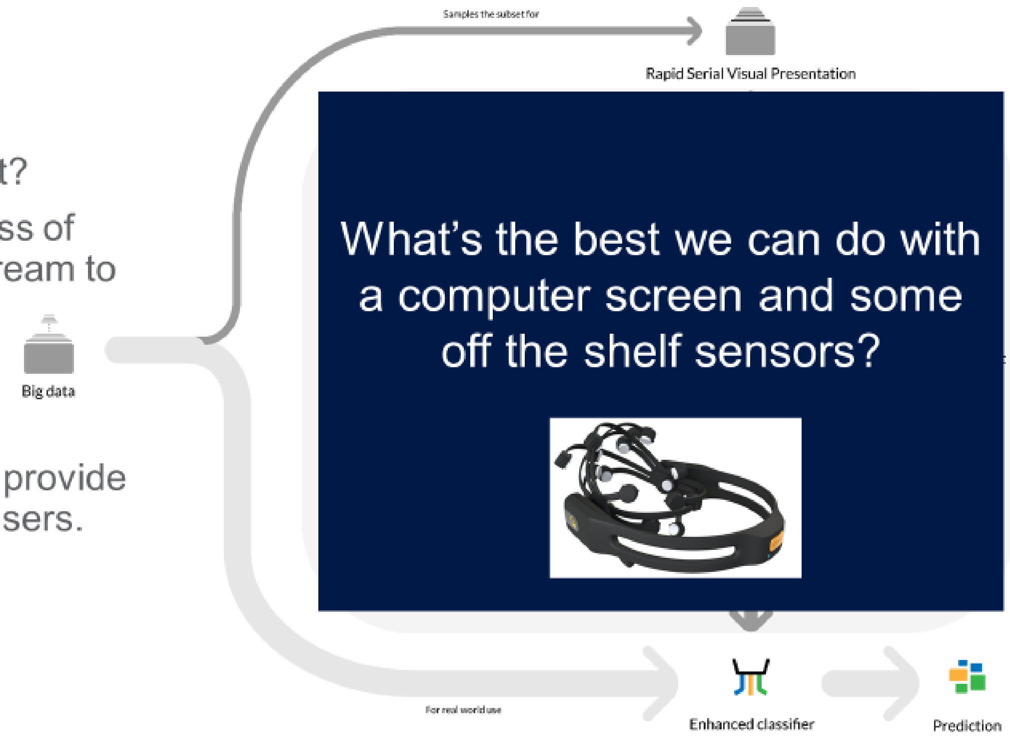
Approach

A reasonable subset?

1. Study effectiveness of EEG as a sensor stream to train ML.

2. Use ML output to provide useful feedback to users.



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Benefits

Use cases:

1. Tool/workflow recommendations.
2. Facilitate information flow in dynamic teams.
3. Easier target searching in big data.

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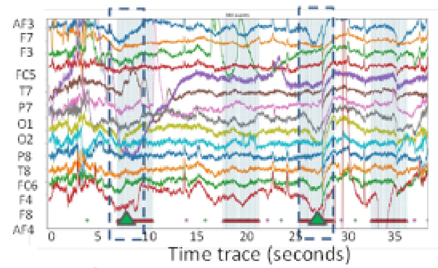
Implementation

Scope:

1. Select publicly available data, test ML pipelines.
2. Collect in-house data and compare.
3. Test some very specific questions.
4. Build feedback GUI and vet.

1. Load stimulus data

2. Human subjects testing



3. Collect and analyze data

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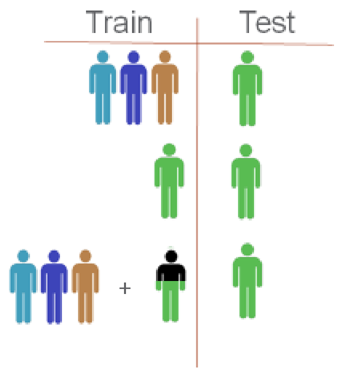
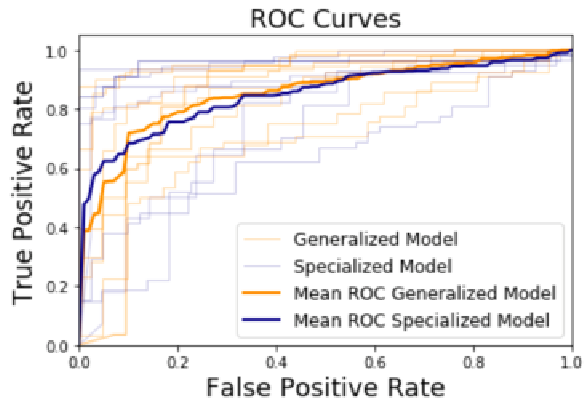
Key Discoveries

1. Cross-subject trainability seems feasible



Our CNN classifier can generalize ERP signatures across subjects



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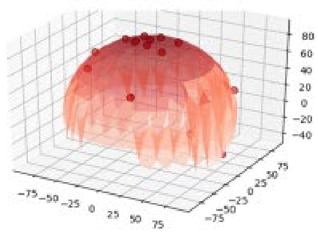
Key Discoveries

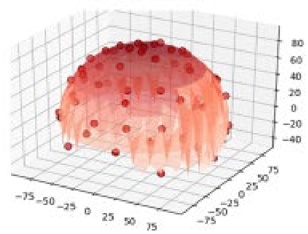
2. Feasibility of using "low-density" EEG systems

# Electrodes	AUC
256	0.910
128	0.909
64	0.910
32	0.902
16	0.822
8	0.806

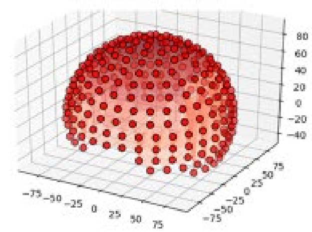
16 Electrodes



64 Electrodes



256 Electrodes



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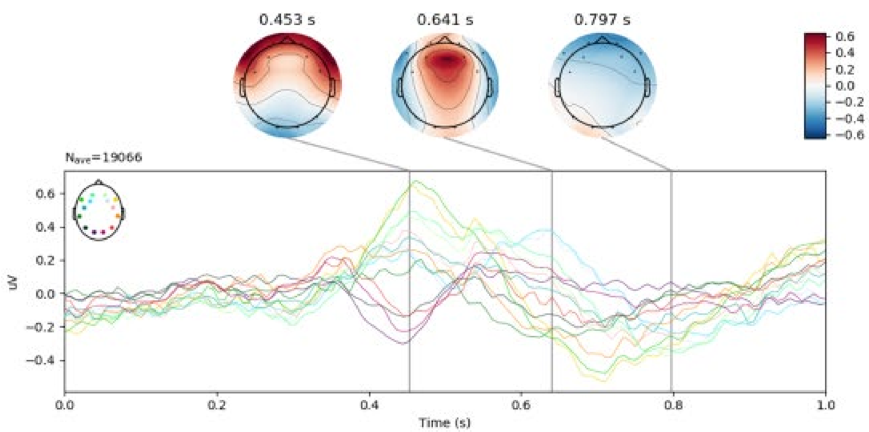
Key Discoveries

3. Being signature agnostic may provide best outcomes.



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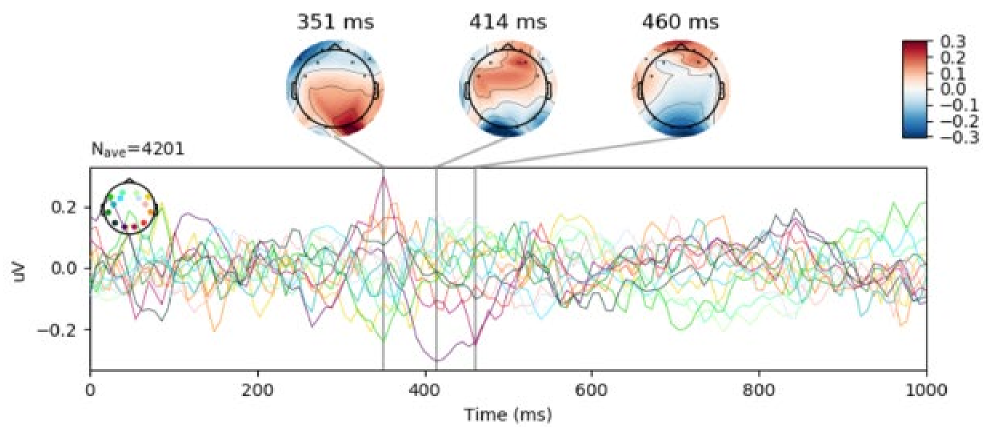
Key Discoveries

4. Sub-conscious recognition hypothesis is not supported



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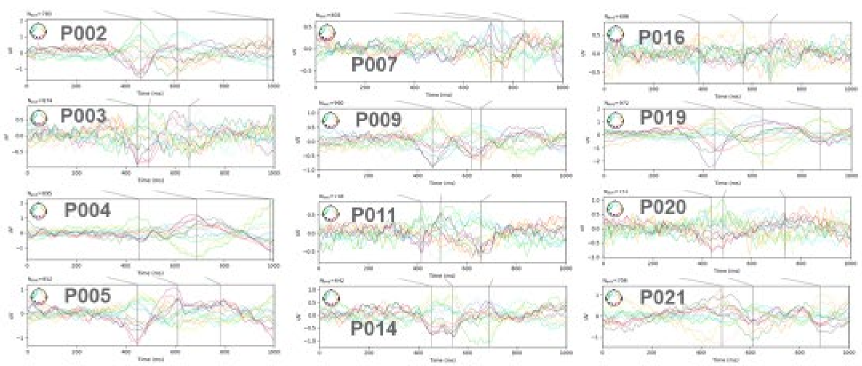
Key Discoveries

5. Near real-time EEG-based classification is not quite there.

Averaged responses = approximately 800



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Competition

Question: If this is so great, why is no one else doing it?

Answer: they are

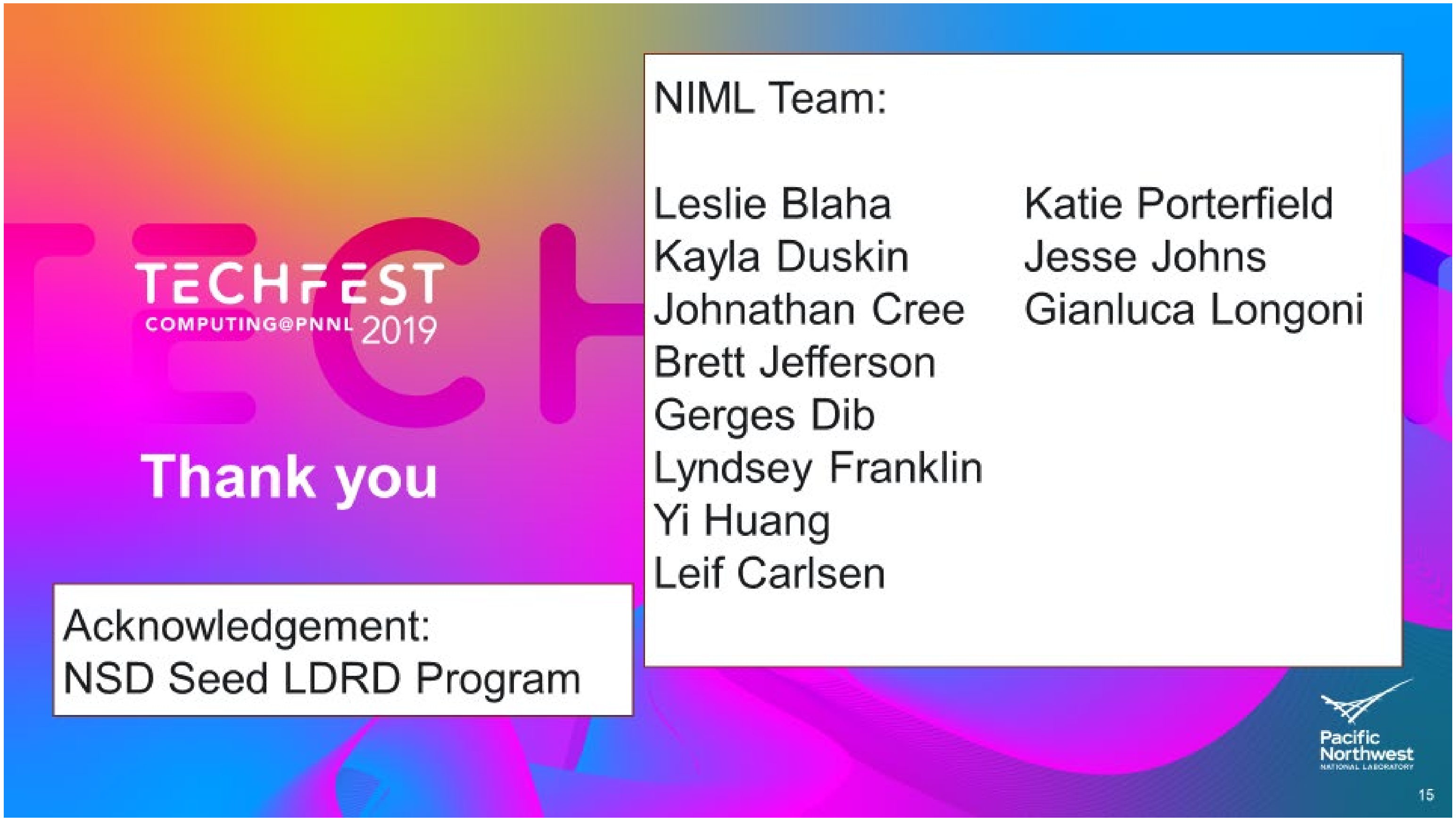
Why us?

- We are a matrixed organization.
- Strategic interest in HMT is increasing here.

Conclusions

- This is still a huge challenge and will not be solved soon
- There are opportunities to use EEG beyond current state-of-the-art
- ML on EEG signals is very difficult
- Future advancements will need to employ multiple types of sensor streams

Continuing challenge:
Building user feedback GUI.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Kayla Duskin
Johnathan Cree
Brett Jefferson
Gerges Dib
Lyndsey Franklin
Yi Huang
Leif Carlsen
Katie Porterfield
Jesse Johns
Gianluca Longoni
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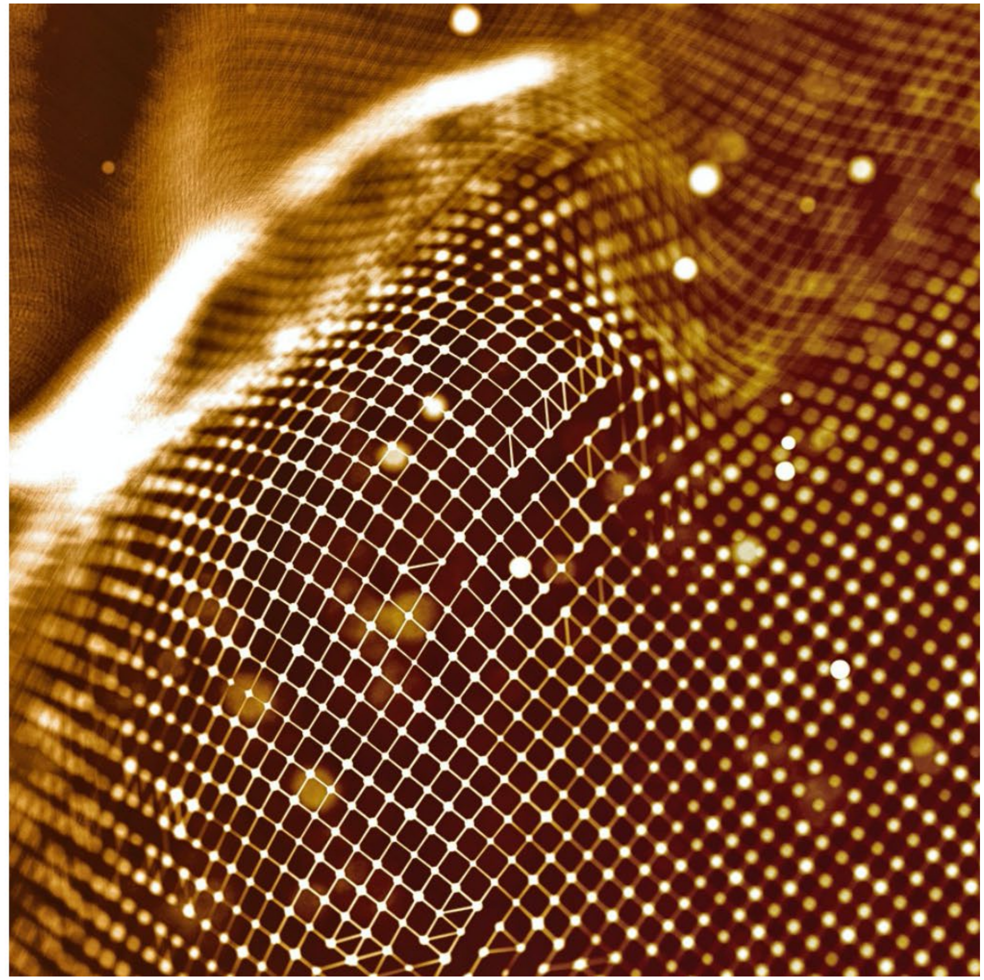
NiML

Jonathan Suter

NSD LDRD Symposium
June 12th, 2019



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Neural Interactive Machine Learning

Driving question: how can we use biometric data to build better human-machine interfaces?

Origins:

Why NIML?

- EEG gets at the fundamentals of human interest and intent.
- EEG yields extremely rich data sets.

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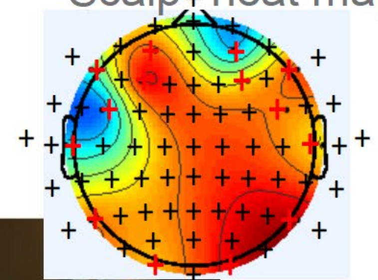
Quick note on EEG

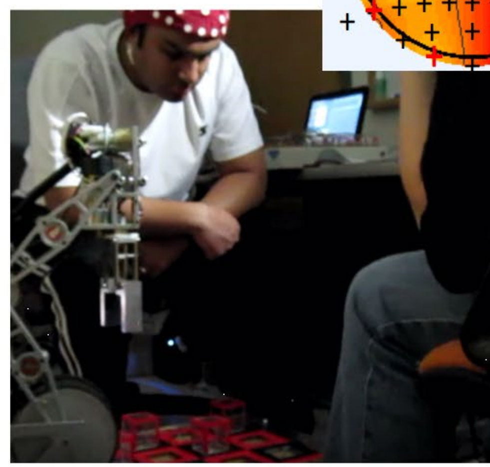
EEG = electroencephalography
Frequency bands: 0.5-40 Hz

Strengths:
- Real-time data stream
- Accesses sensory responses and emotion
- Extensive literature background

Weaknesses:
- Skull gets in the way
- Donning equipment takes time
- Signals lack specificity

Scalp "heat map"

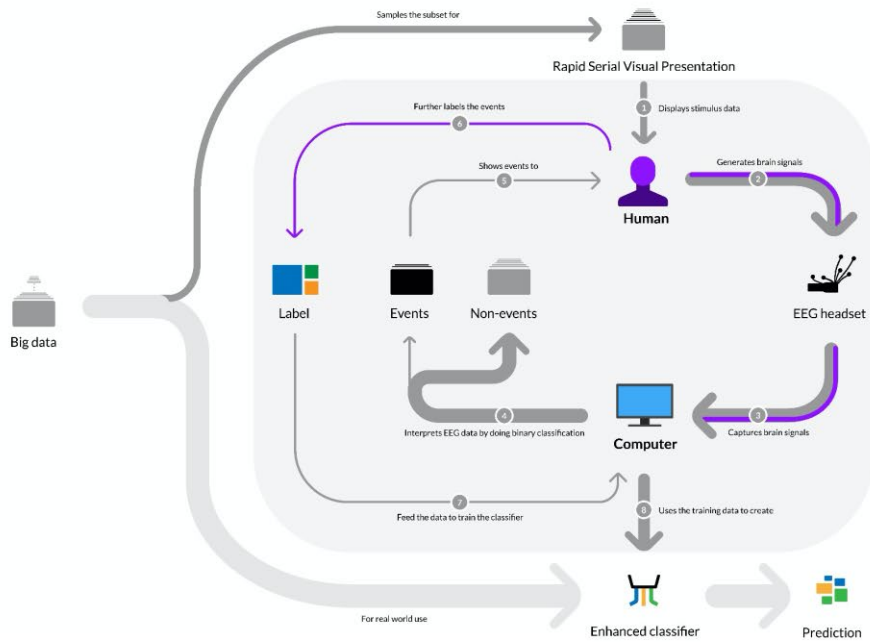




UIUC EEG
checkers demo

Idealized NIML framework

In short, it's complicated.



Building a Team

PI: Jonathan Suter – sensors and data analytics

Key staff:

Leslie Blaha – Human factors
Kayla Duskin – ML/DL
Johnathan Cree – Sensors, hardware/software
Brett Jefferson – data analysis, human factors
Gerges Dib – GUI, software, ML
Leif Carlsen – GUI, demo

Role players and advisors:

Katie Porterfield – ML
Bharat Medasani – lit review
Jesse Johns – ML/GUI
Gianluca Longoni - ML
Lyndsey Franklin – testing support
Yi Huang – testing support, data vis
Jonah Cullen – data analysis

Collaborators:

LAS – Brian Kritzstein and Ken Thompson
Naval Research Lab – Leslie Blaha

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Scope

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2. Collect in-house data and compare.
3. Test some very specific questions.
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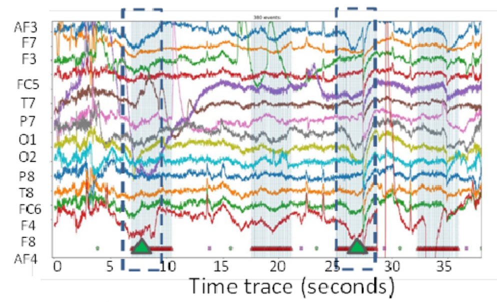

3. Collect and analyze data

NIML – things we hope to learn

- How effective are ML pipelines on EEG data?
- Practical constraints of using EEG for human-machine teaming?
- Can we use the features we've observed to flag targets without pre-training?
- How fast can we perform classification?
- How different are EEG signatures from one user to another?
- Can we see subconscious recognition?

Note on Competition

Question: If this is so great, why is no one else doing it?

Answer: they are

Why us?

- We are a matrixed organization.
- Strategic interest in HMT is increasing here.

Who Cares About This?

- NIML's first incarnation was an NA-22 proposal

"Alternative data analysis."

- Other sponsors
  - DARPA
  - CTTSO
  - DHS
  - Intelligence community – LAS tie-in

Proposals submitted based on this project so far ~ 5 and counting

Potential Impact

Broadly: lessening the burden of data-intensive tasks on human beings

- Path to overcoming some of ML's limitations
- Cognitively-informed data facilitation
- Workflow recommenders
- Broad human-machine teaming interest areas

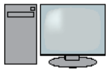


Table of Aptitudes		
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Great attention span	✓	✗
Intuitive pattern recognition	✗	✓
Small training data set	✗	✓
Contextual understanding	✗	✓
Can handle ambiguity	✗	✓

Progress: Technical Output

- Poster at Cog-Sci 2018:

- Poster at NIPS 2019 sub-conference:

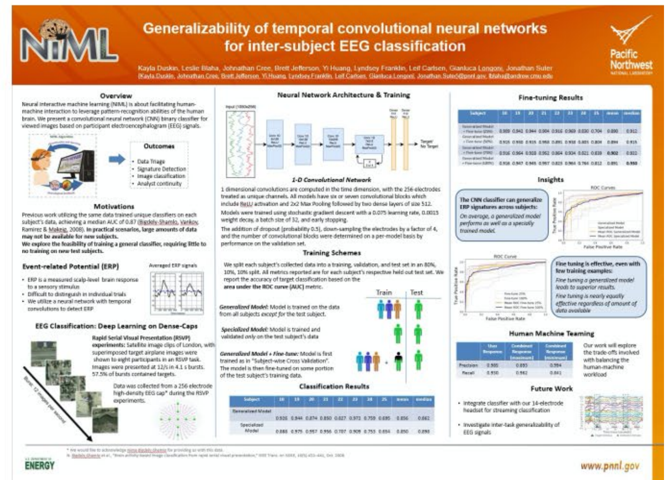
  "Generalizability of temporal convolutional neural networks for inter-subject EEG classification"

- Joint publication in preparation with LAS:

  "Analyst workflows of the future

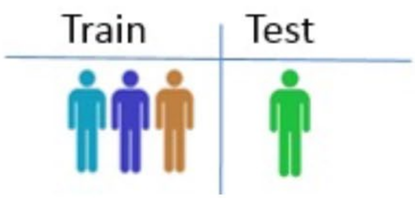
- Joint publication in preparation with NRL:

  "Temporal Convolutional Neural Networks for Generalizing EEG Classification"

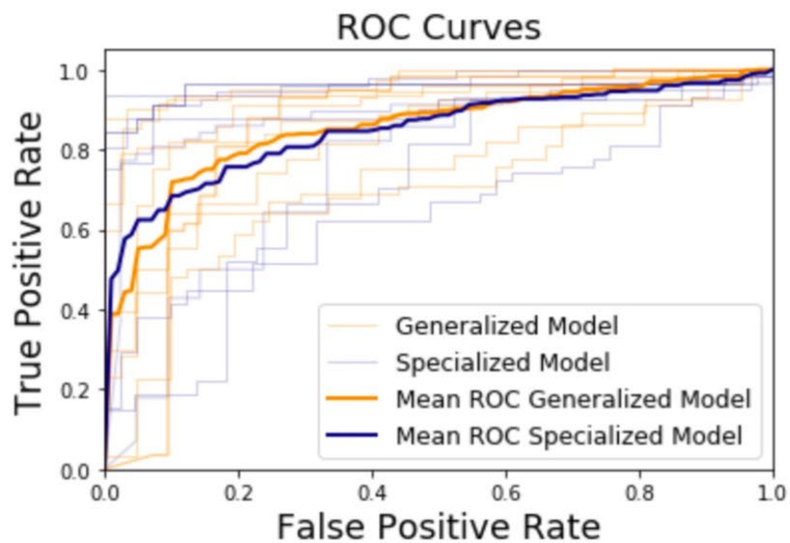


Progress: Innovation

- Generalizable user-based training looks feasible



Our CNN classifier can generalize ERP signatures across subjects

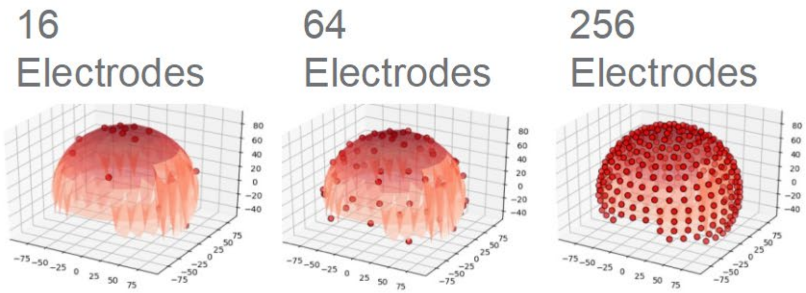


Progress: Innovation (cont.)

- "Comfortable" EEG headsets could actually be a viable tool of the trade

Emotiv Epoc – consumer grade BCI

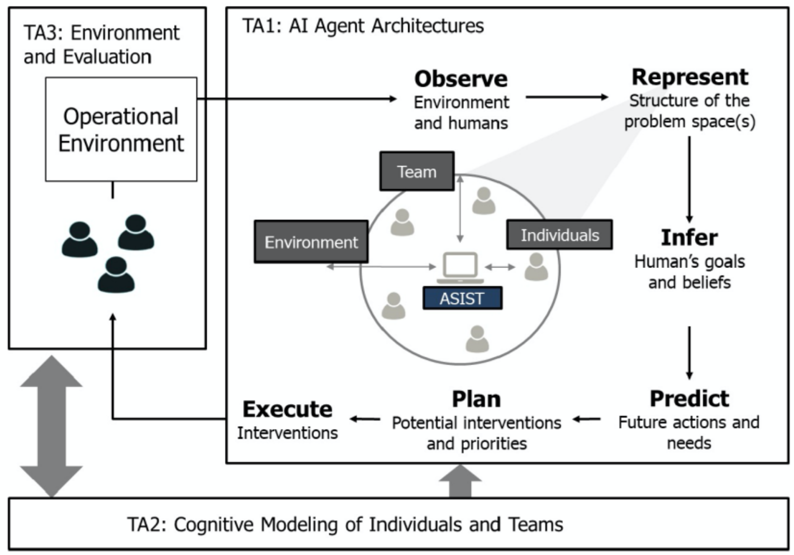
High density – 256 electrodes



# Electrodes	AUC
256	0.910
128	0.909
64	0.910
32	0.902
16	0.822
8	0.806

Progress: Innovation (cont.)

- We can provide value-added by advising on sensor inputs



Progress: Humbling Discoveries

General statement: EEG data is more complicated than expected.

- EEG cannot be used to identify specific stimulus images
  Response: binary interesting/not-interesting may be enough
- Signature identification based on known EEG waveforms is not as useful as expected
  Response: there are signatures, just not the ones we expected
- Real-time EEG response classification is still out of reach
  Response: technical maturity of EEG + orthogonal sensing modalities
- Subconscious image recognition is very faint
  Response: you can't win them all

Progress: Pivots

Original objective: This project is about using EEG to find signatures in data.

Pivot #1: This project is about training ML faster using human input.

Pivot #2: This project is about short-cutting ML training using human input.

Pivot #3: This project is about human-machine teaming platforms of the future.

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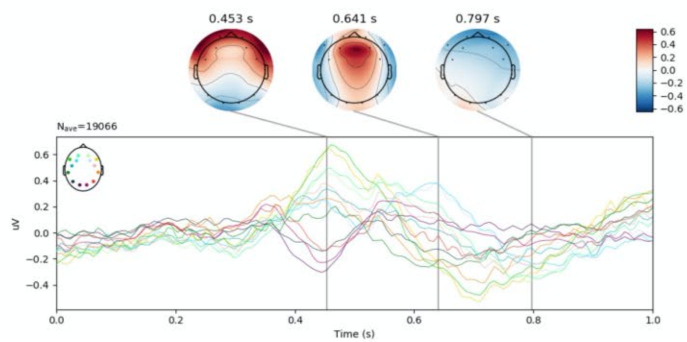
Takeaways so far

- NIML has evolved a great deal
- EEG data is challenging but fascinating
- Primary goal seems doable, but….



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Organizational benefits

- Introducing a highly multidisciplinary team
- Additional visibility with LAS
- Building a custom interface tool (NIMLApp)
- Collecting a carefully curated high-quality EEG dataset
- Developing Dr. Suter as a PI
- Providing exposure for multiple staff to ML
- Development of junior staff (Gerges, Brett, Katie, Kayla, Jonah, Yi)

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Looking forward

1. Continued analysis of our data

2. Assemble publications – dependent on outcomes of point 1

3. Further develop and mature NIML demo

4. Business development, strategic teaming, offsite assignments, etc.

Conclusions

- This is still a huge challenge and will not be solved soon
- There are opportunities to use EEG beyond current state-of-the-art
- ML on EEG signals is very difficult
- Future advancements will need to employ multiple types of sensor streams
- Human-machine teaming will require very multi-disciplinary teams

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