Classification of EEG During Imagined Mental Tasks by Forecasting with Elman Recurrent Neural Networks

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Outline

Electroencephalography

Electroencephalography (EEG) is a technique for measuring brain activity using an array of electrodes placed on the surface of a subject's scalp.

Brain-Computer Interfaces

- There many uses for EEG, both clinical and research
- Today, we are interested in Brain-Computer Interfaces (BCI)
- BCI establish a direct channel of communication between brain and machine
- Bypasses ordinary motor based communication
- BCI can be used in assistive technology:
  - operate computers, wheelchairs, telephones, et cetra
- Reestablish communication for those with Locked-in Syndrome
- May eventually be used in everyday devices

EEG classification is difficult

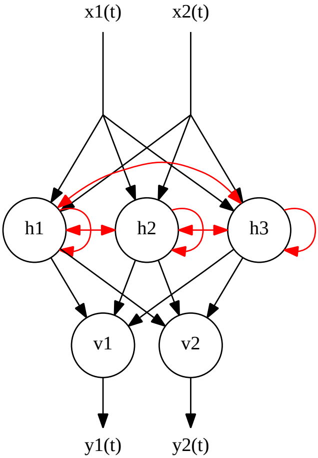
- Useful and exciting, but not easy
- Low signal to noise ratio:
  - Microvolt signals
  - Ocular & muscular artifacts
  - Noise from external electronics
- The brain is complex!
  - Billions of neurons
  - Trillions of connections
  - Recurrent & Stateful
- EEG is complex and patterns are both spatial (intra-electrode) and temporal

Current approaches

- Current classification rates are not high enough
- Often rely on power spectrum estimates
- Do not readily capture some patterns
  - Phase differences
  - Short term ordering of events
- We propose using Recurrent Neural Networks
  - Here, we investigate Elman Nets in particular

Elman Networks

- Elman Networks have two layers
- Hidden layer:
  - fully connected to inputs
  - sigmoidal transfer functions
  - full recurrent connections
- Visible layer:
  - fully connected to hidden layer and outputs
  - linear transfer function
  - no recurrent connections
- Long history and, relatively, well studied [1]
- Universal approximators of Finite State Machines [2]



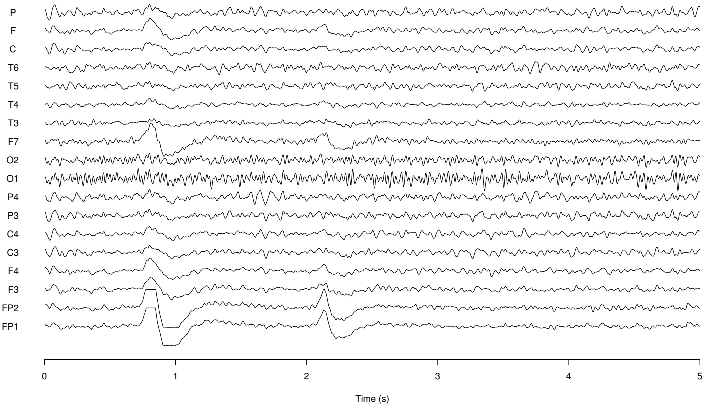
Training Elman Networks

- Gradient Descent using Scaled Conjugate Gradients (SCG) [3]
- Gradient estimated using Truncated, Batch-Mode, Back-Propagation Through Time (BPTT) [4, 5]
  - Recurrent connections unrolled into feedforward network
  - Unrolling truncated after some timesteps back
  - Gradient accumulated over entire sequence

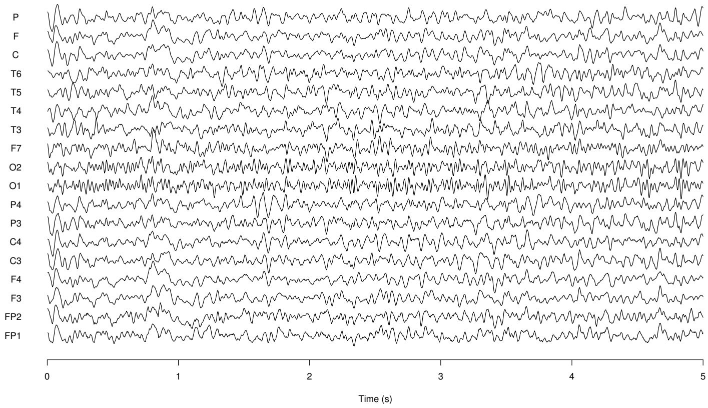
EEG Collection

- Classify EEG during imagined mental tasks
  - Imagined motor task
  - Arithmetic task
- Simple dataset for now
- Three subjects
  - Subject-A and Subject-B: Able bodied, mid-twenties, in laboratory setting
  - Subject-C: Quadriplegia, spinal legion at C4, mid-twenties, at home
- 256 samples per second
- Hardware Analog Bandpass filter: 1.5-34Hz
- Maximum Noise Fraction Filter [6, 7]
- Standardize to zero mean unit variance

Raw EEG



Preprocessed EEG



Forecasting EEG

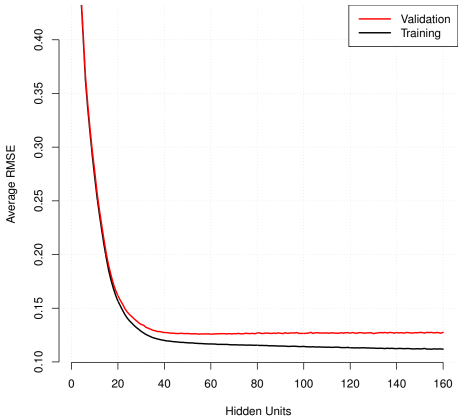
- First, we consider forecasting EGG a single step ahead
- One input per channel
- One output per channel
- Minimize MSE between current output and next signal value

Parameter Selection

- Three parameters to tune manually
  - Steps unrolled for BPTT
  - Training epochs
  - Hidden units
- Steps unrolled fixed at 20
- Training epochs fixed at 250
- Little improvement with larger values
- Regularization controlled by limiting hidden units
  - Smaller networks are much faster
  - Early stopping doesn't work quite as well

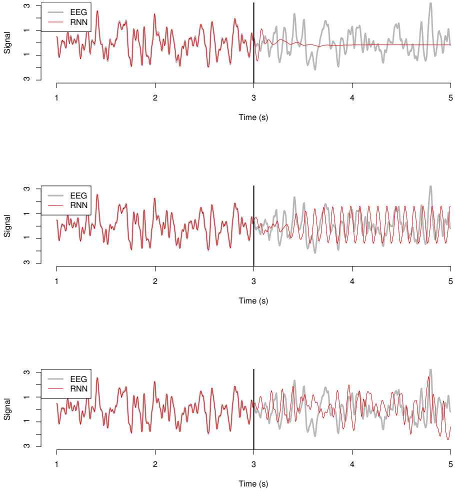
Forecasting EEG

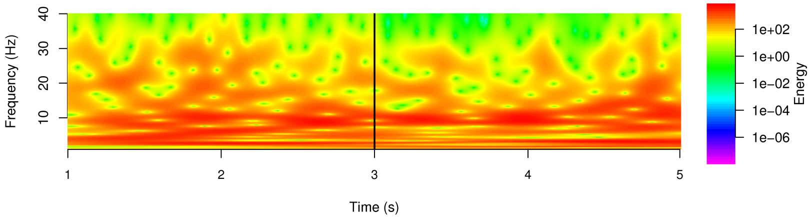
- Forecasting error vs hidden units
- Six-fold cross validation
- Separates around 15-20
- Levels off around 40
- Only slight over-fitting



Iterated Models

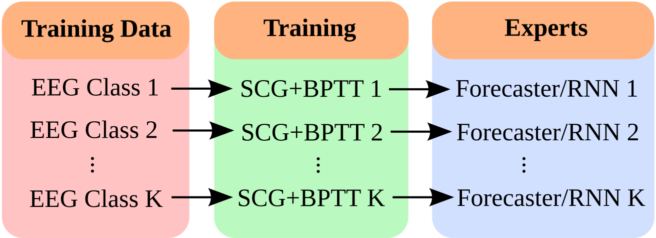
- Placing feedback loop between the output and input
- Forms an autonomous, iterated system
- This gives insight into the temporal information learned
- To the right: 20, 40 and 160 hidden units




Frequency (Hz)
10
20
30
40
1
2
3
4
5
Time (s)
1e+02
1e+00
1e−02
1e−04
1e−06
Energy

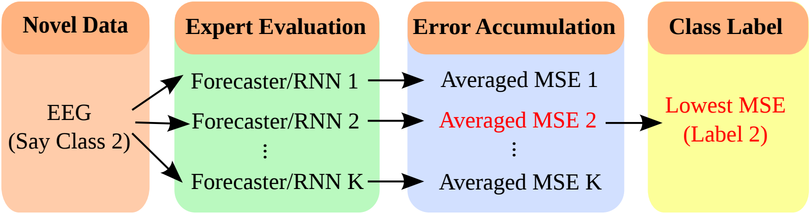
Classification via Forecasting

- Generative approach to classification
  - Separate RNN trained to model each class
  - Model by forecasting a single step ahead
  - Each network is an expert on its class



Classification via Forecasting

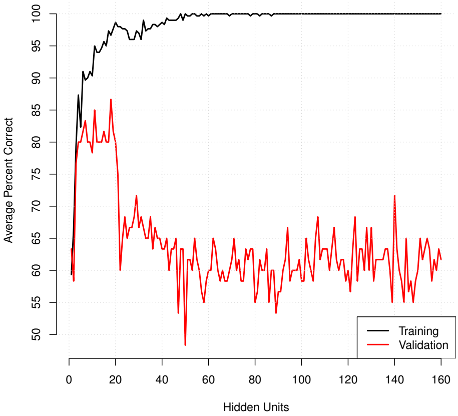
- Novel EEG is labeled by
  - apply each forecaster/expert to new EEG
  - average error over a short window
  - select label associated with model that produced lowest error



- Similar to Gupta, Oeda and Coyle [8, 9, 10]

Classification of EEG

- Classification accuracy vs hidden units
- Decisions made every second
- Six-fold cross validation
- Over-fit after 10-20 hidden units



Hidden Unit Contradiction

- We have a paradox:
  - Best modeling error with ≈ 50 hidden units
  - Richest iterated dynamics with > 150 hidden units
  - Highest classification accuracy with $\approx 10 - 20$ hidden units
- Conjecture:
  - Simple, short-term patterns seem more discriminative
  - Complex, long-term patterns seem to contribute to forecasting error but are not discriminative

Classification Accuracy

	NH	Training	Validation	Test
Subject-A	18	96.7%	86.7%	80.0%
Subject-B	10	100.0%	85.0%	57.9%
Subject-C	16	99.3%	90.0%	94.6%

Table: Average Classification Accuracy

- Subject-A performs well
- Subject-B performs poorly on test partition, possibly lost concentration?
- Subject-C performs very well
- Recall that Subject-C is disabled and data was recorded at home

Bitrates

	NH	Training	Validation	Test
Subject-A	18	47.3bpm	26.0bpm	16.7bpm
Subject-B	10	60.0bpm	23.4bpm	1.1bpm
Subject-C	16	56.5bpm	31.9bpm	41.8bpm

Table: Average Bitrate

- decisions are made at one second intervals
- bitrates are more comparable, fair and describe user experience better [11, 12]
- state-of-the-art is somewhere around 10-40bpm

Thanks!

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