Brain Computer Interface to Assistive Robots

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Overview of Presentation

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  - Overview
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  - Raw EEG
  - Dataset
  - Preprocessing
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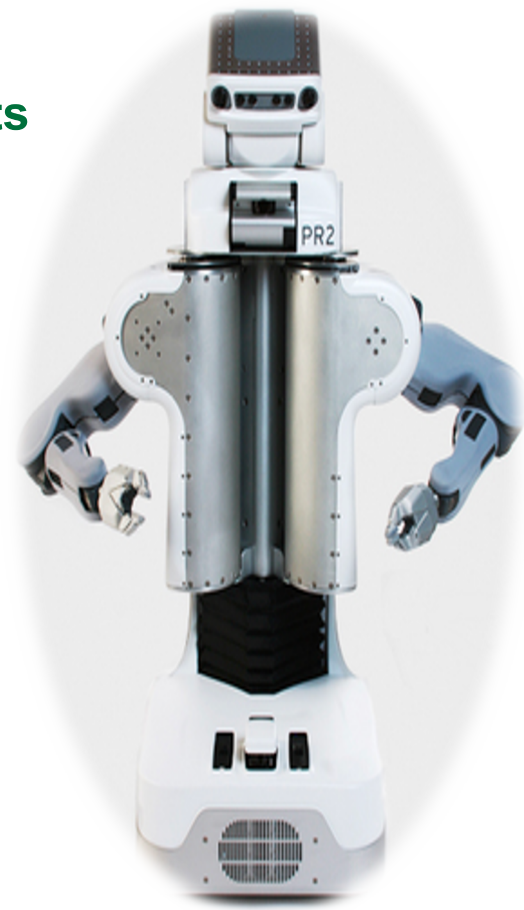

- System Integration
- Self Learning
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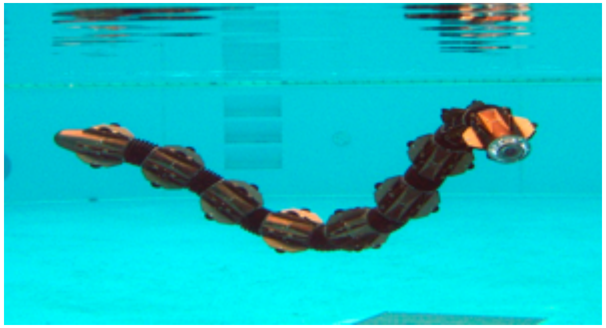
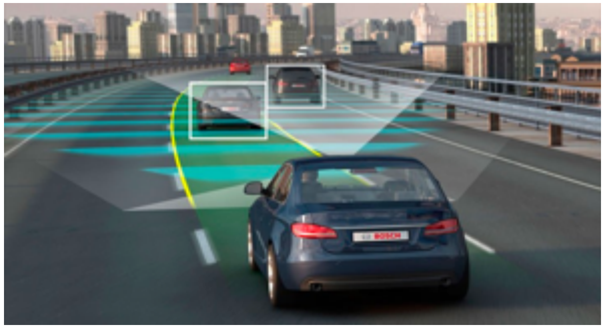
Robots

A machine (programmable by a computer) capable of carrying out a complex series of actions automatically or with guidance.





Categories

- **Application it is used : Medical, Industry**
- **Based on mobility : locomotive, legged**
- **Level of robotics : washing machine to laptop**
- **Size of robot: nanorobot**
- **Programmable**
- **Etc…**

Assistive Robots

A branch of robotics that assists people with physical disabilities with physical interaction.





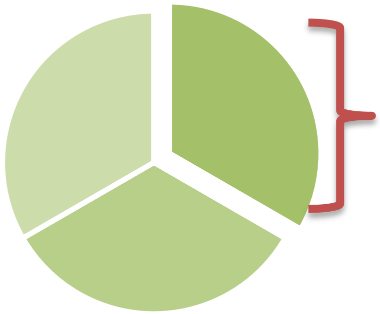
Human Robot Interaction :

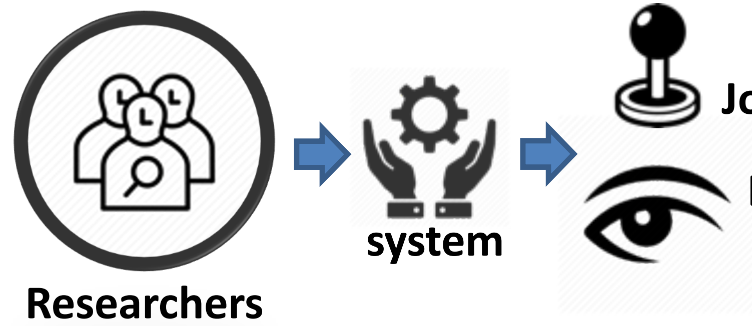
A study of interactions between humans and robots, with contribution from brain computer interaction, artificial intelligence, robotics, natural language understanding, design and social sciences.

Interaction or the exchange of information can be verbally or non-verbally

Communication

Motivation





Locked-in syndrome

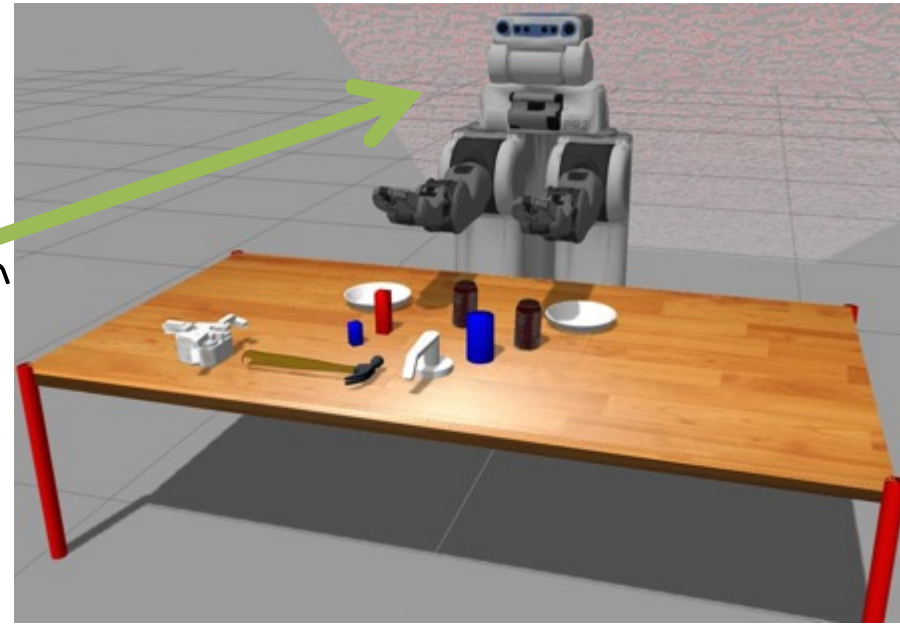
- **Complete loss of control over their voluntary muscles where patients are unable to speak and move but are conscious and can think and reason.**

Examples: Stroke, severe cerebral palsy, motor neuron disease, ALS

- Our research focus is on patients who are affected by Locked-In Syndrome and to help physically challenged people to achieve **greater independence by making technologies such as BCI/HRI** accessible which provides an alternative communication bridge between human brain and robot/computer.

Overview of Work

EEG decoding system

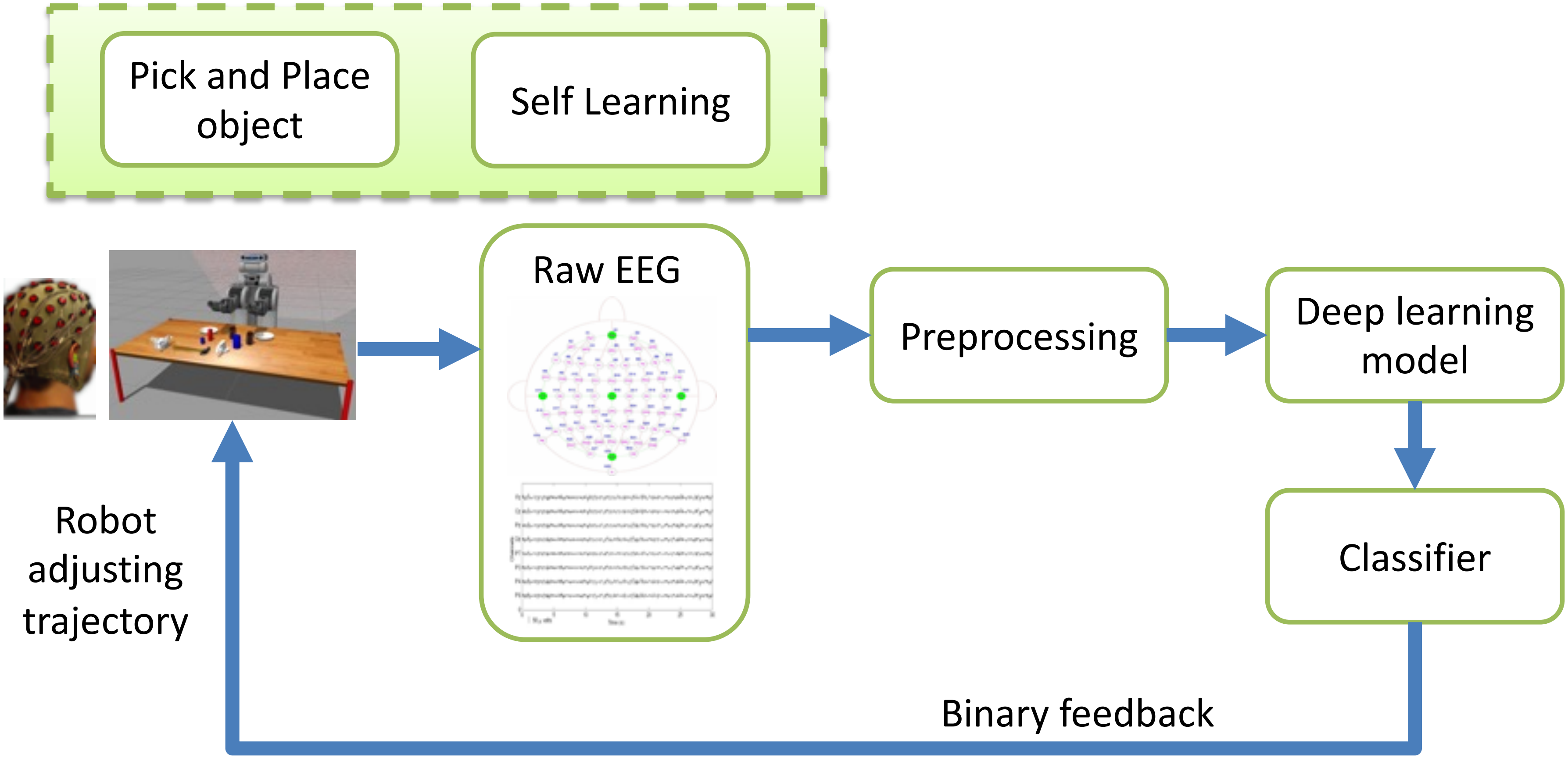


Trajectory Correction

Pick and Place Objects

Online Classification learner

Block Diagram

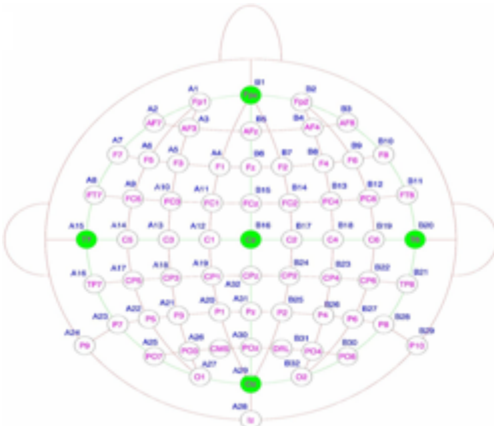


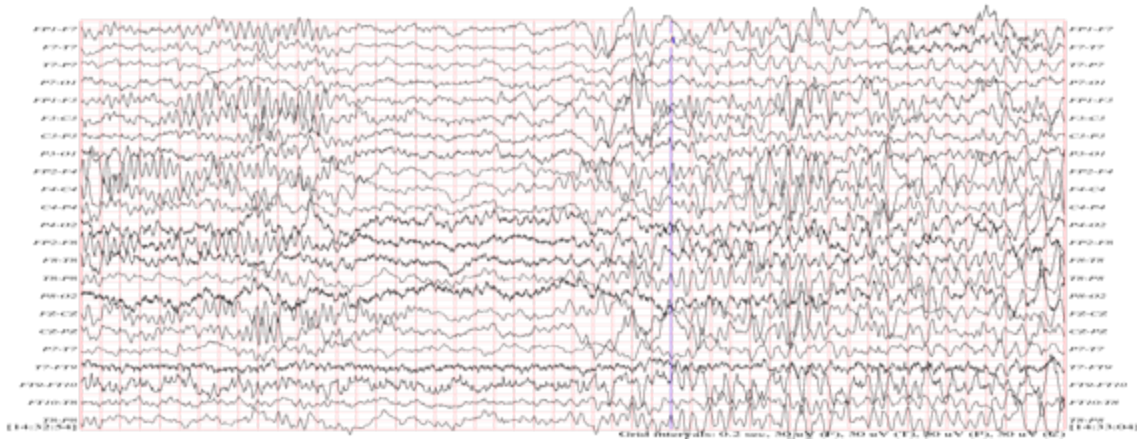
ErrP Classification

Raw EEG

Electroencephalography (EEG):

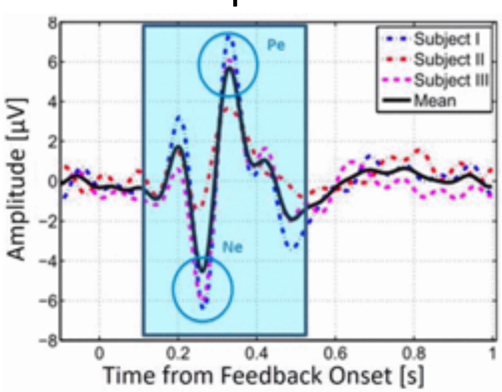
A group of electrical potentials generated by neural activities in human brain.





Event Related Potential:

Derivative of EEG which are produced by human brain in response to external stimuli or specific event



P50 wave
N100 or N1 wave
P200 or P2 wave
N200 or N2 wave
N300 wave
P300 wave

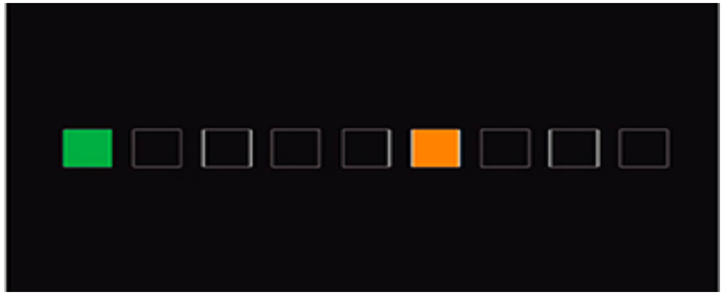
N400 wave
Movement related cortical potentials
Contingent negative variation
Post imperative negative variation

Categorized according to latency and amplitude after the stimulus

<u>Error Related Potential:</u> Characterized by an initial positive peak occurring at 200ms and large negative between 200-250ms and positive peak

Dataset

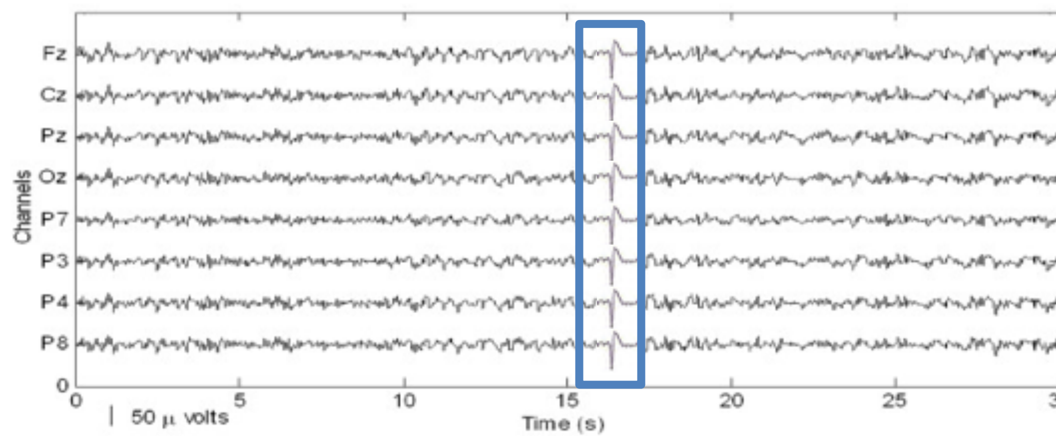
Experiment Protocol



P_{err}	Subject 1	2	3	4	5	6
20%	51	50	54	211	628	643
40%	-	-	54	211	628	643

Dataset of 64 electrode system			
6 subjects	2 events	10 trails	120 datasets

- 64 electrode data was recorded as per 10/20 International system
- 6 subjects of mean age about 27.83$\pm$2.23 separated by several weeks
- Error related potentials were elicit when the user monitors the behavior of an external device upon, he or she has no control



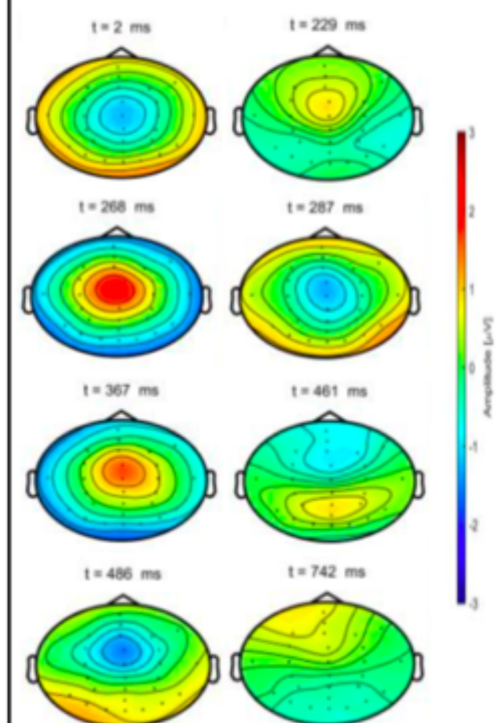
R. Chavarriaga, A. Sobolewski, and J. d. R. Milln, "Errare machinale est: the use of error-related potentials in brain-machine interfaces," Frontiers in Neuroscience, vol. 8, p. 208, 2014.

Preprocessing

Raw data → Common average reference filter (CAR) → Band pass filter 1Hz to 10Hz → Electrode Selection FCz & Cz

EEG signals | **Spatially Filtered** | **Remove noise**

As most variation is at the region of Anterior Cingulate Cortex (ACC), hence 2 out of 64 were selected from that region



Spatiotemporal maps

Dataset → 70% Training; 10% Validation; 20% Testing

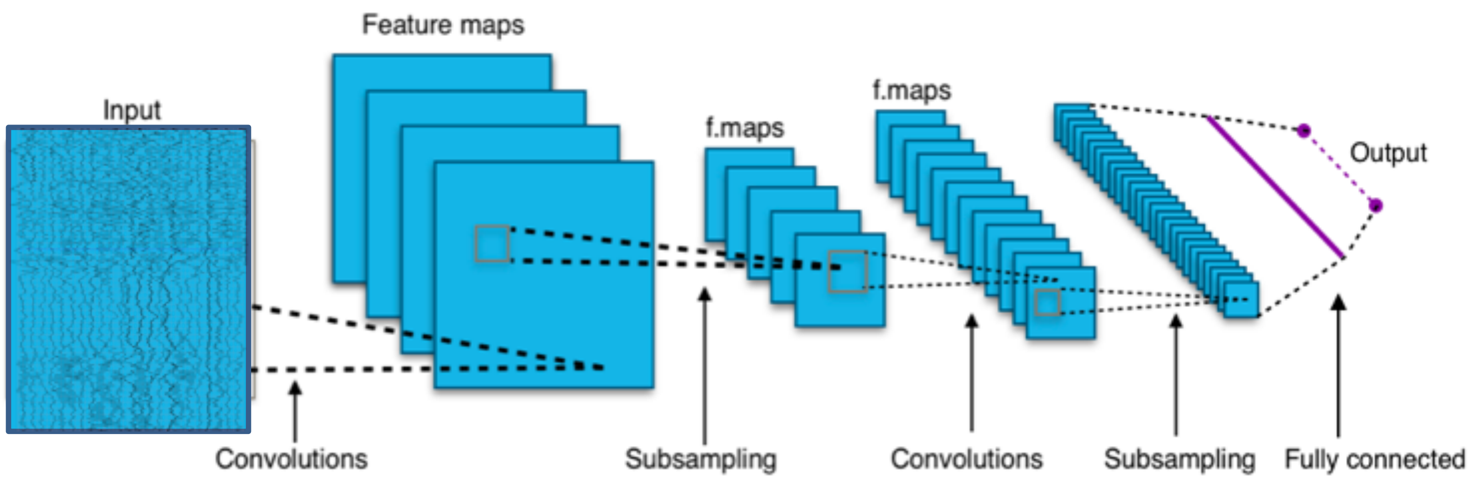
Delorme, Arnaud, and Scott Makeig. "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis." *Journal of neuroscience methods* 134, no. 1 (2004): 9-21.

Classifier

Convolutional Neural Networks

- ANNs that can learn **local patters** in data using convolutions
- Architectures varies from shallow to deep with multiple layers
- Advantage of using CNNs are they are well suited for end to end learning
- These architectures have outperformed in the field of computer vision, speech processing, yet new to EEG signals classification

Layers: Convolution layer, pooling layer, ReLU activation, Fully Connected, Batch Normalization and Drop out layer



Moon, Seong-Eun, Soobeom Jang, and Jong-Seok Lee. "Convolutional neural network approach for EEG-based emotion recognition using brain connectivity and its spatial information." In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 2556-2560. IEEE, 2018.

Results

Layer	stage	kernel	filters
Input	-	-	0
Convolution	1	2x64	16
Convolution	2	1x64	32
ReLU activation	2		0
Max Pooling	2	1x2	0
Convolution	3	1x32	32
ReLU activation	3		0
Max Pooling	3	1x2	0
Convolution	4	1x16	64
ReLU activation	4		0
Max Pooling	4	1x2	0
Fully Connected	5	2	2
Softmax activation	5		0
Total Learnable Parameter : 239938			

CNN Architecture

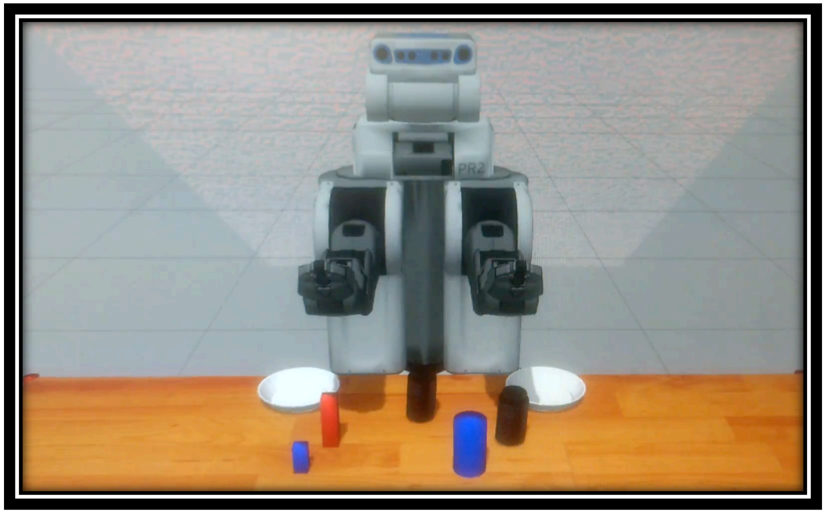
Case 1: Train Session 1 and Test Session 2
Case 2: Train Session 2 and Test Session 1

Sub	Case 1	Case 2
1	87.62%	85.35%
2	80.13%	82.77%
3	79.40%	80.01%
4	78.46%	83.28%
5	70.92%	78.59%
6	78.76%	76.46%

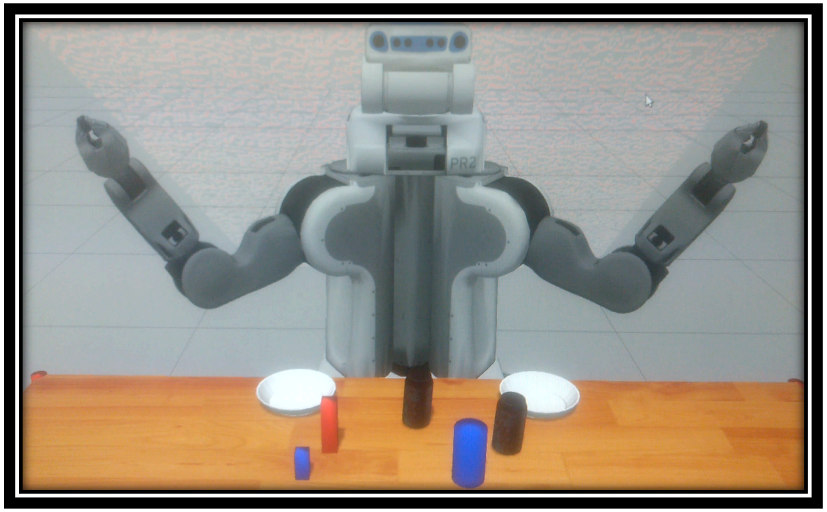
Overall Accuracy
86.1 % for both cases

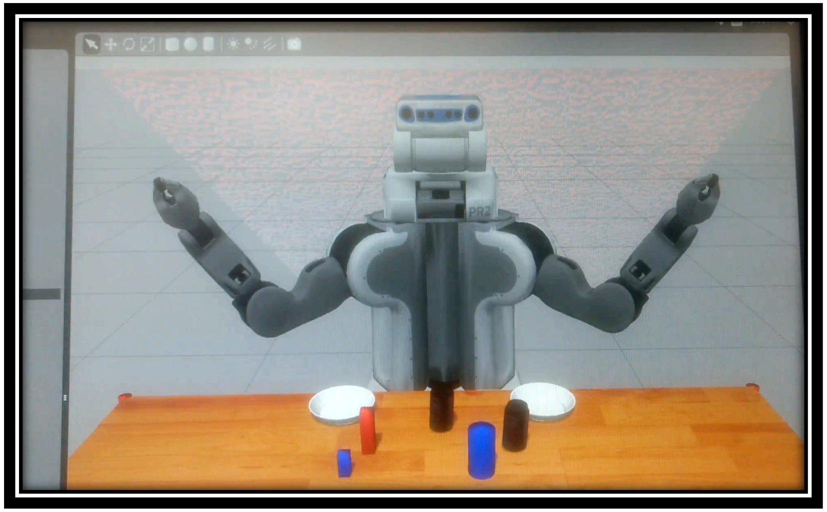
Integration

Initial Position



ErrP :
Trajectory Correction





No ErrP : No Correction

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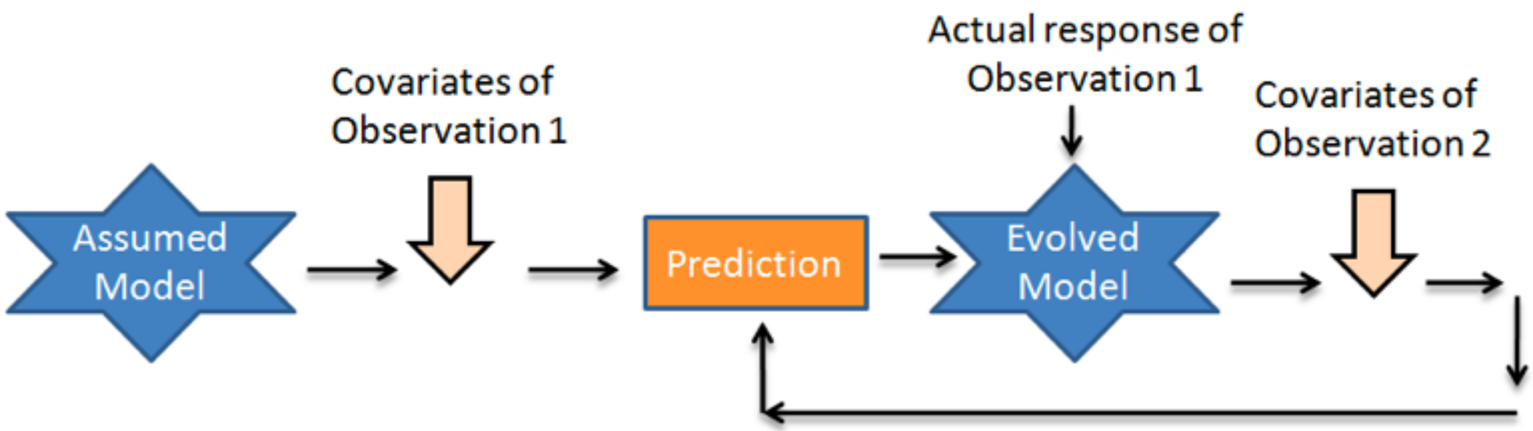
Self Learning

Online Machine Learning

- Type of machine learning in which data becomes available in a sequential order
- Online learning is used when its computationally infeasible to train over the entire dataset
- Used in situations where it is necessary for the algorithm to dynamically adapt to new patterns in the data
- Disadvantage is it is prone to catastrophic interference which can be addressed by increment learning approaches



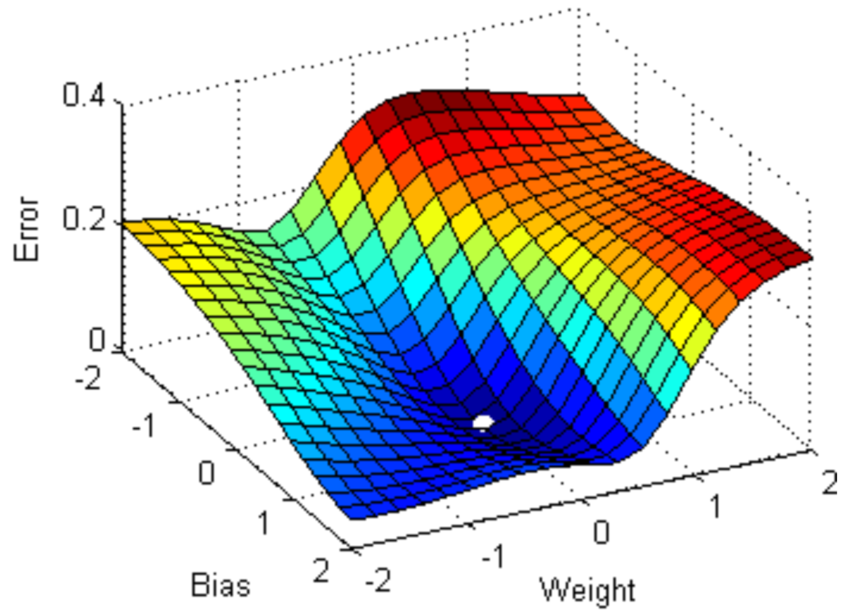
https://www.analyticsvidhya.com/blog/2015/01/introduction-online-machine-learning-simplified-2/

Stochastic Gradient Descent

- Iterative method for optimizing a differentiable function
- It is stochastic because samples are randomly selected instead of a single group
- SGD performs parameter update for each training example individually

$$\theta = \theta - \eta . \nabla_{\theta} J(\theta;\, x^{(i)}; y^{(i)})$$

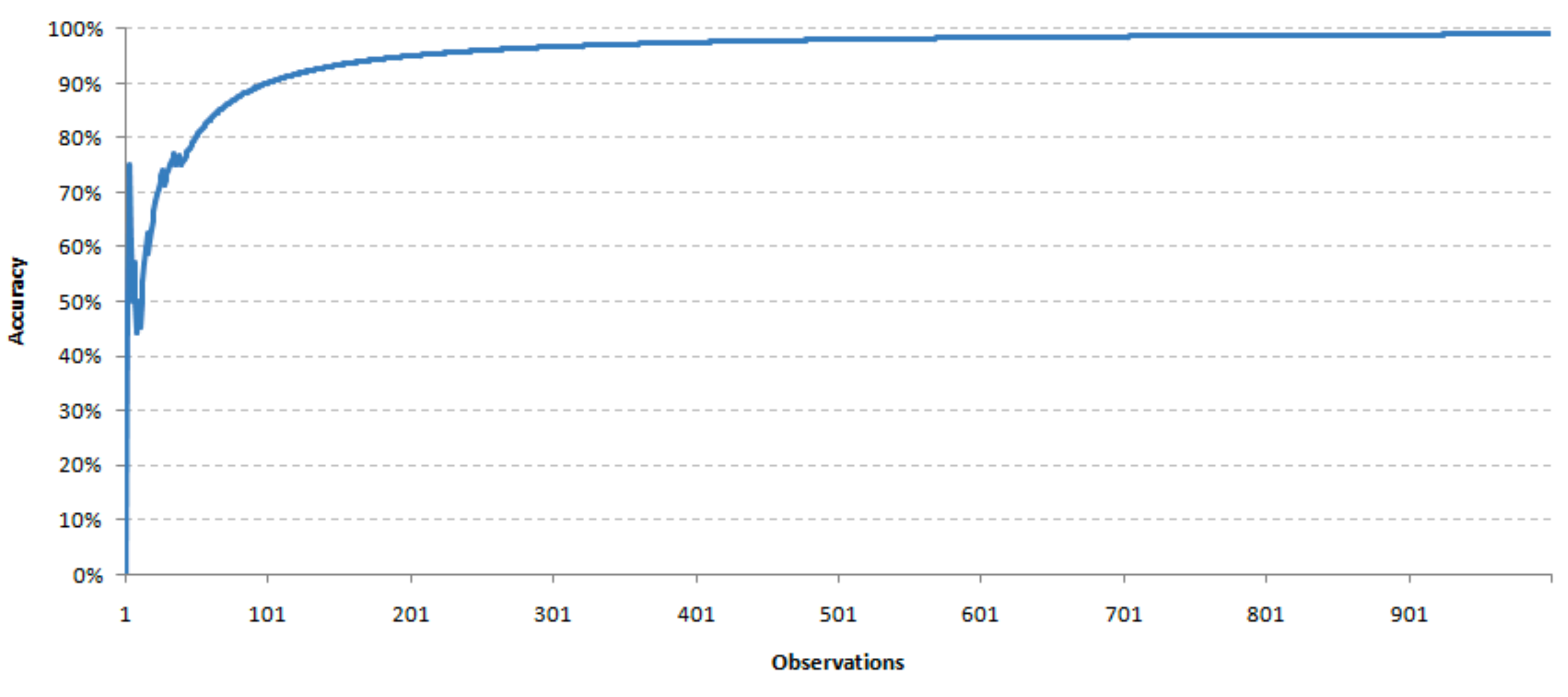
$\boldsymbol{\theta}$	**Weight update**
$\boldsymbol{\eta}$	**Learning rate**
$\mathbf{x^{(i)}}$	**Input example**
$\mathbf{y^{(i)}}$	**Target example**



*H. Robinds and S. Monro, "A stochastic approximation method," Annals of Mathematical Statistics, vol. 22, pp. 400–407, 1951.

Results

Examples of input data:



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Conclusion and Future Work

1. Integration for Real Time
2. Navigation
3. Multi task system

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Thank you