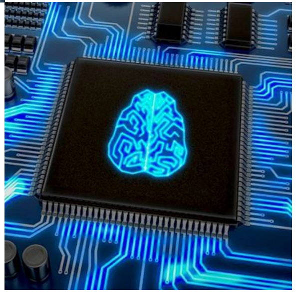
Evolving Neural Networks

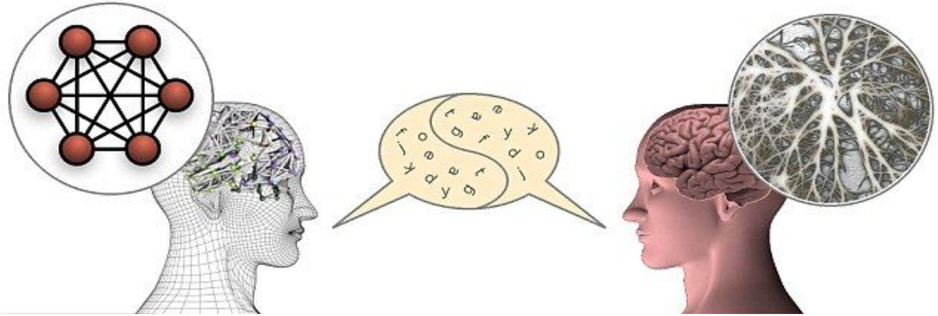
towards Self-referential Universal Learners

Aritra Sarkar
Research Intern, TCS Innovation Labs
PhD Candidate, Quantum and Computer Engineering, TU Delft
Promoters: Sounak Dey (TCS-RI), Dr. Koen Bertels (TU Delft)

Motivation

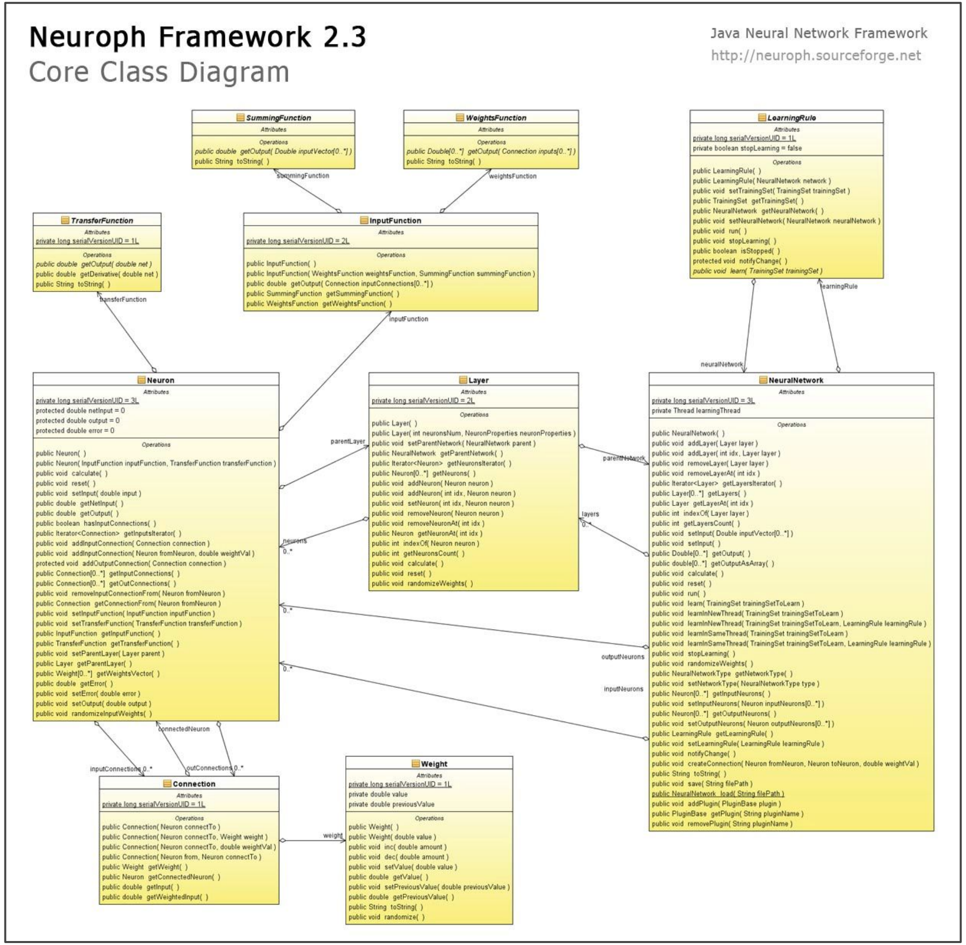
- Learn how the brain works
- Develop bio-inspired hardware
- Evaluate efficiency of bio-inspired learning models
- Apply bio-inspired computing to artificial intelligence
  - Broad domain exploration
  - Algorithm Design
  - Proof-of-concept Implementation





System design choices

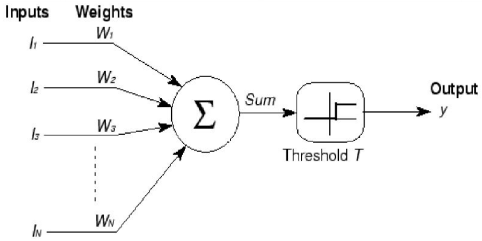
- Physical Platforms
- Neuron Models
- Network Architecture
- Software Tools
- Applications



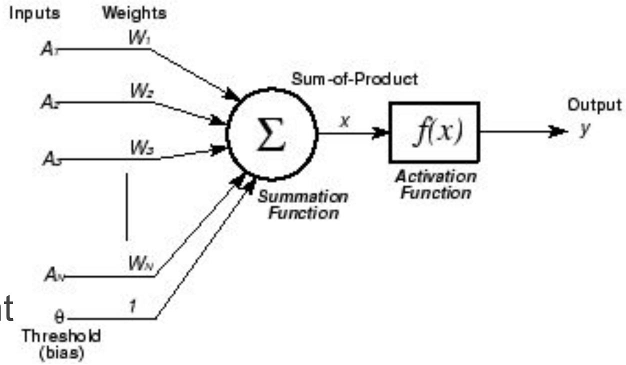
Physical Platforms

- Neuromorphic Chips
  - SpiNNaker, Loihi (Intel), TrueNorth (IBM), SyNAPSE (DARPA)
  - Specialised Accelerator for Neural Network Simulation
  - Costly, promised of memristor based
  - Still huge gap between processing power w.r.t. Human Brain (10^{11} neurons, 10^{15} synapses)
- Supercomputing Platforms
  - HPC with distributed processing (Hadoop/Spark framework)
  - GP-GPU based parallel processing
- PC CPU
  - Proof-of-concept Simulation
- Microprocessors
  - Not suitable, needs centralised control

Neuron Models



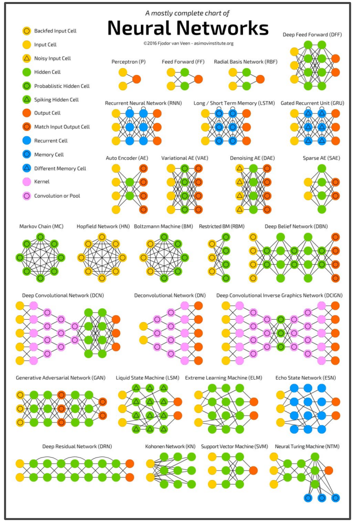
- Generation 1 (McCulloch–Pitts Neuron)
  - Weighted sum with step threshold
  - Only binary outputs
- Generation 2
  - Weighted sum plus bias input to a function (logistic, tanh, etc)
  - Gives real-valued outputs
  - Universal Turing Machine with 1 Hidden layer
  - Training by Backpropagation and Stochastic Gradient Descent



- Generation 3 (Spiking Neural Networks)
  - Hodgkin-Huxley Model, Izhikevich, Spike Response Model, Integrate-and-Fire, Leaky IF
  - Difficult to train due to non-differentiable nature of asynchronous spike events
  - Training by Spike Time Dependent Plasticity, ReSuMe, Backpropagation, SGD, etc.
  - Requires less neurons for learning, good for capturing temporal information
  - Computationally equivalent in power to ANN, more complex simulation

Network Architectures

- Very specialised and diversified (also in brain)
- Some popular ones
    - Multi-Layer Perceptron, Convolution NN, Recurrent NN (LSTM), Generative Adversarial Networks, Self Organising Map (Kohonen Nets), Capsule Networks, Associative Memory, Deep Belief Networks (Restricted Boltzmann Machine), Deep Auto-Encoders
- Shallow vs. Deep variants
    - Complexity of patterns



Research question:

What if the network can select the best architecture by itself?

Software Tools

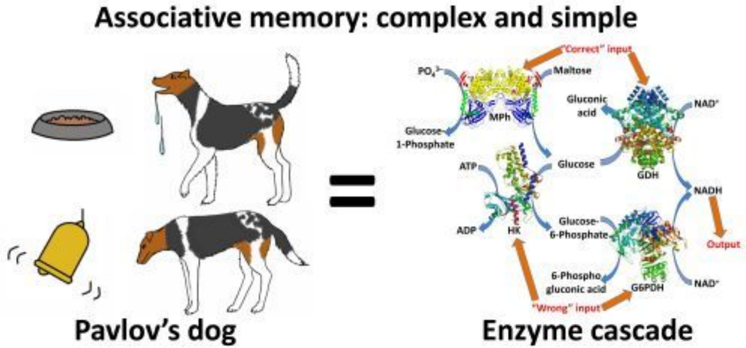
- Platforms
  - ErSatz, H2O, Data Graphlab, etc..
- Software Libraries
  - TensorFlow, Theano, Torch, Caffe, DeepMat, DeepLearning4j, Keras, etc..
- Neural Modelling
  - Brain2, NEST, Nengo, Neuroph, Encog, Neural, etc..

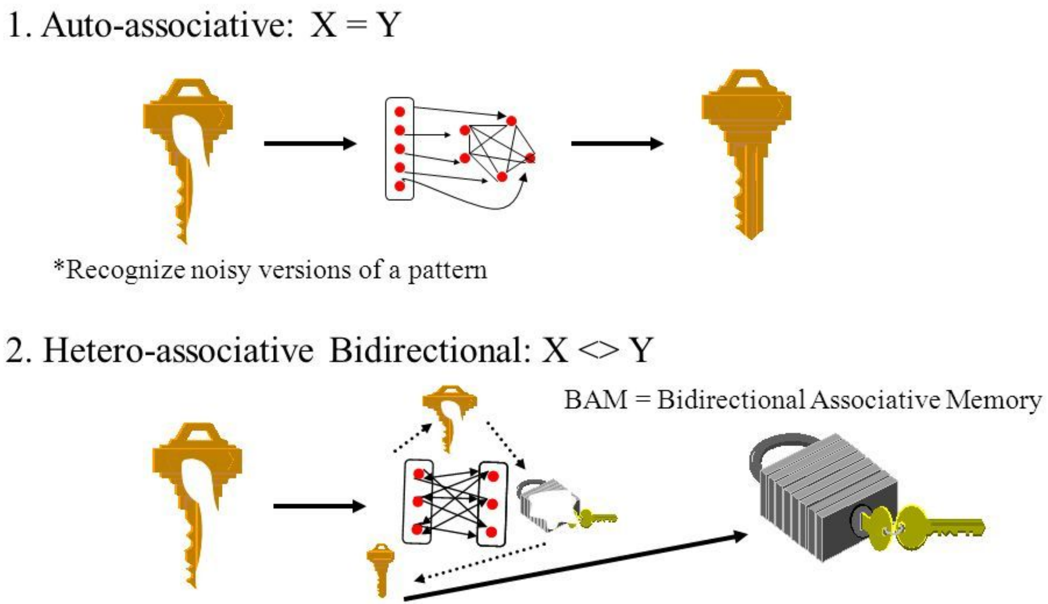
- Native Python Code
  - Tedious to code but useful in learning phase, everything customisable (hyperparameter)
  - Extensible with TensorFlow + Brian2/NEST

Applications

- Object List to Environment Classification (based on patent filed)
  - Associative Memory Evolution
- Design of a general Neuro-Evolution algorithm

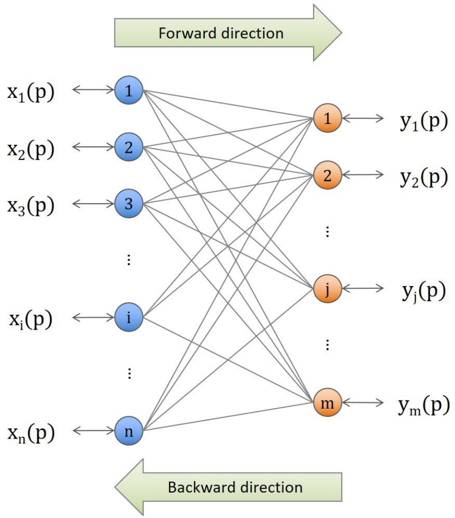
1. Associative Memory

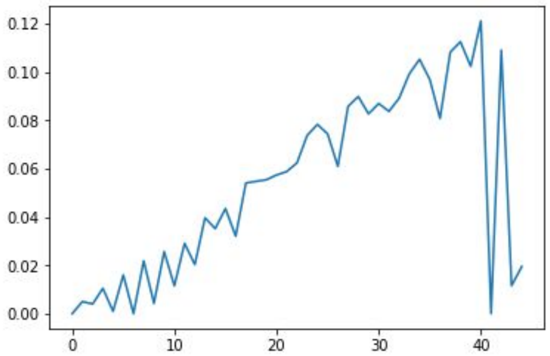




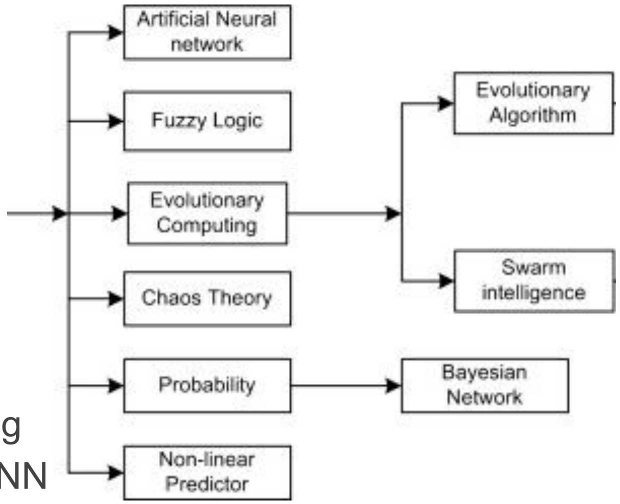
1. Associative Memory Evolution

- Input a stream of scenes (online learning)
  - Each timestep: SceneID, Probability of known objects
  - Set of known objects can expand over time
  - If SceneID is 0, Network predicts unknown scene
    - If variance with known scenes are low, new SceneID
- 2 Layer Network
  - Input Layer: Object IDs
  - Output Layer: Scene IDs
  - Number of neurons can expand in both layers
- Proof-of-concept in Python NB
  - Adjustment of variance threshold needs to be done
  - Works for non-complex associations.
    - Deep Belief Network required for more complex correlations.



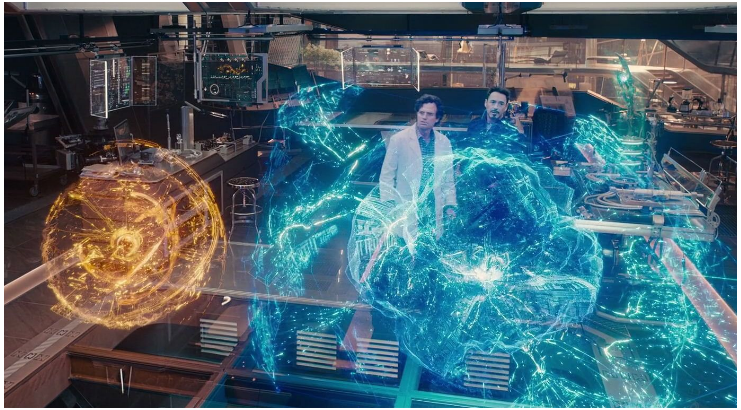


2. Neuro-Evolution



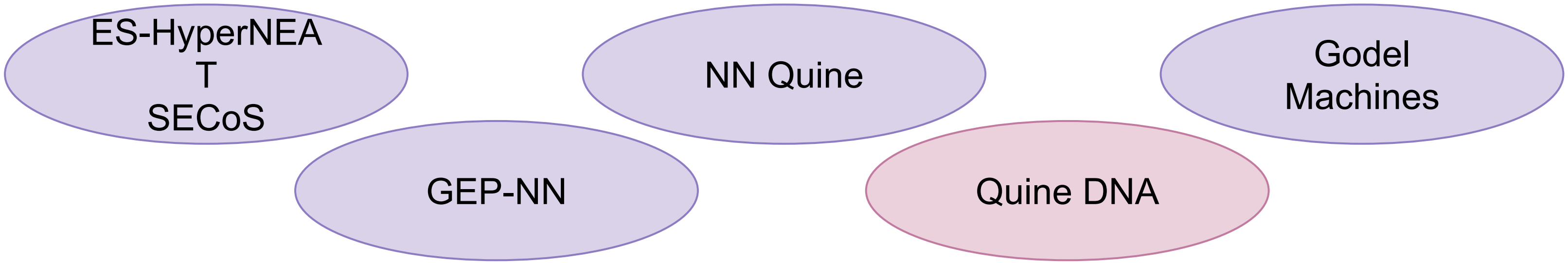
- Hard-computing vs. Soft-computing
  - Sub-optimal solution is acceptable
  - Access to intermediate partial solutions
  - Machine Learning
    - Learn with data without explicit formal logic programming
    - Classification, Regression, Naive Bayes, k-NN, SVM, ANN
  - Evolutionary Computation
    - Survival of the fittest individuals; population in generations
    - Genetic Algorithm, Genetic Programming, Gene Expression Programming, Swarm Algos.
  - Merging the 2 ideas
    - Same Neural Network rewires for different tasks or changing environment
    - Biological inspiration - Neural Plasticity
    - Useful in Online/Incremental Learning, Continual/Lifelong Learning, Transfer Learning
    - Topology and Weight Evolving Artificial Neural Network (TWEANN)

2. Reviving AGI



- Components of Human Intelligence (Learning)
  - Large number of neurons
  - Plasticity in both number, weights and topology
  - Power efficiency (10^{-15} J/op)
  - Spiking neuron based
  - Cell death (weight transfer)
- Indirect encoding in DNA (Evolution)
  - Impact of environment (semi-supervised, reinforcement)
    - Deductive logic is a limiting tautology case of inductive logic
  - # neurons = 10^{11}, # synapses = 10^{15}, # genes = 10^{5}
- Narrow AI vs. Artificial General Intelligence (AGI)
  - AIXI, Gödel Machine

Future Work: Neuro-Evolution on Quine



Risi, Sebastian, and Kenneth O. Stanley. "An enhanced hypercube-based encoding for evolving the placement, density, and connectivity of neurons." Artificial life 18.4 (2012): 331-363.

Uber AI Labs

Watts, Michael, and Nik Kasabov. "Simple evolving connectionist systems and experiments on isolated phoneme recognition." Combinations of Evolutionary Computation and Neural Networks, 2000 IEEE Symposium on. IEEE, 2000.

Auckland Univ. of Tech.

Ferreira, Candida. "Designing neural networks using gene expression programming." Applied soft computing technologies: The challenge of complexity. Springer, Berlin, Heidelberg, 2006. 517-535.

Gepsoft

Chang, Oscar, and Hod Lipson. "Neural Network Quine." arXiv preprint arXiv:1803.05859 (2018).

Columbia Univ.

Schmidhuber, Jürgen. "Gödel machines: Fully self-referential optimal universal self-improvers." Artificial general intelligence. Springer, Berlin, Heidelberg, 2007. 199-226.

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