LECTURER: Nghia Duong-Trung

DEEP LEARNING

UNIT 5.2

Further Network Architectures

STUDY GOALS

– After completing this unit you will be able to ...

… describe what generative adversarial networks (GANs) are and how to train them.

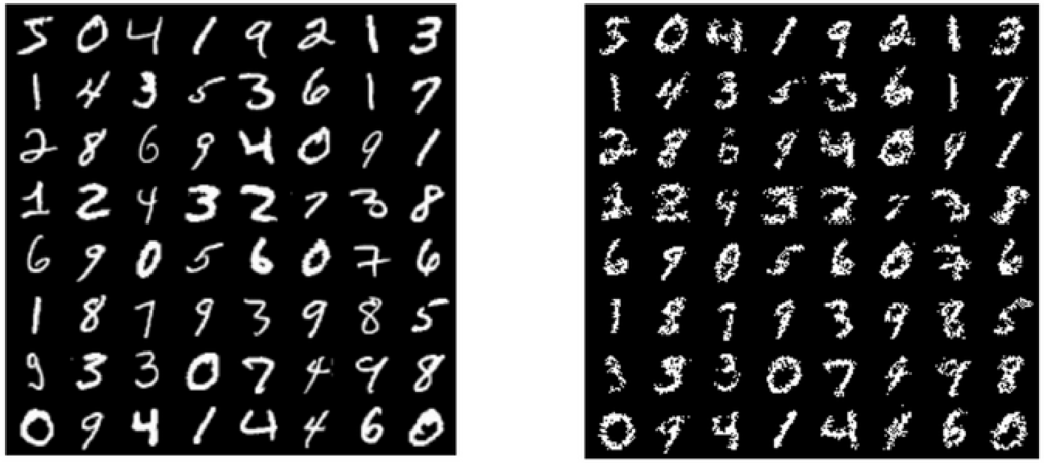
… build and train autoencoders and variational autoencoders (VAEs).

… explain what restricted Boltzmann machines (RBMs) are and how they are used for recommender systems.

… understand potential evolutions in deep learning in the form of capsule and spiking neural networks.

RESTRICTED BOLTZMANN MACHINES (RBMS)

- Boltzmann Machines can be applied on two types of problems i.e., learning and searching.
  - Learning: When Boltzmann Machines are employed in learning, they try to derive important features from the input, reconstruct this input, and render it as output by parallel updating of weights. It is essential to note that during this learning and reconstruction process, Boltzmann Machines also might learn to predict or interpolate missing data.

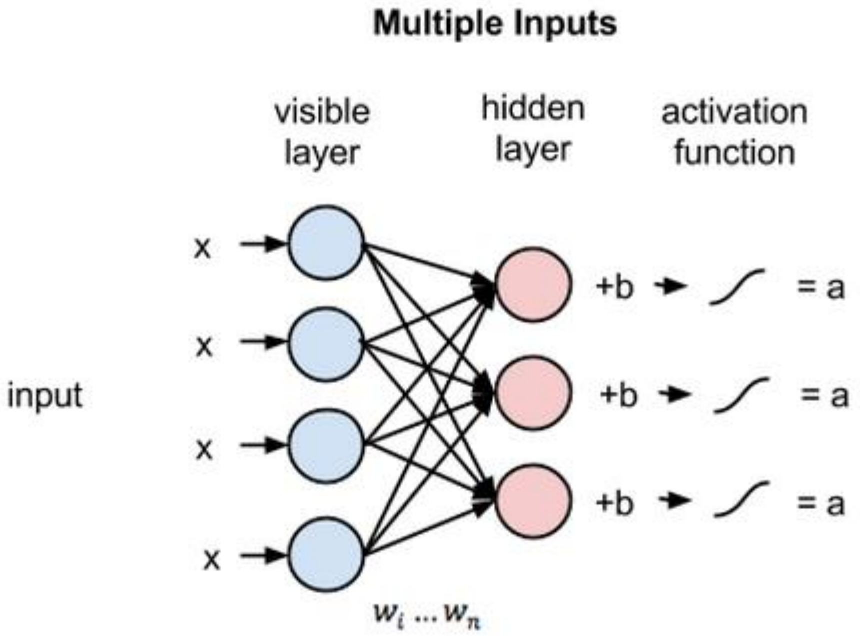


  - Searching: The architecture and working of Boltzmann Machines suit well to solve a constraint satisfaction problem (searching for a solution which can satisfy all constraints), even when it has weak constraints. A problem having weak constraints tries to obtain an answer which may be close enough to the answer which completely satisfies all the constraints i.e., the answer need not completely satisfy all the constraints.

https://blog.paperspace.com/beginners-guide-to-boltzmann-machines-pytorch/

RESTRICTED BOLTZMANN MACHINES (RBMS)

- RBMs are shallow, two-layer neural nets that constitute the building blocks of deep-belief networks.
- The first layer of the RBM is called the visible, or input layer, and the second is the hidden layer.
- Each circle in the graph above represents a neuron-like unit called a node, and nodes are simply where calculations take place. The nodes are connected to each other across layers, but no two nodes of the same layer are linked.
- Restriction: there is no intra-layer communication.
- As in this machine, there is no output layer.



http://wiki.pathmind.com/restricted-boltzmann-machine

- Because the weights of the RBM are randomly initialized, the difference between the reconstructions and the original input is often large.
- In RBM there are two phases through which the entire RBM works:
  - 1st Phase: In this phase, we take the input layer and using the concept of weights and biased we are going to activate the hidden layer.
  - 2nd Phase: As we don’t have any output layer. Instead of calculating the output layer, we are reconstructing the input layer through the activated hidden state.
    - Feed Backward Equation:

      Error = Reconstructed Input Layer-Actual Input layer

      Adjust Weight = Input*error*learning rate

- There are mainly two types of Restricted Boltzmann Machine (RBM) based on the types of variables they use:
  - Binary RBM: In a binary RBM, the input and hidden units are binary variables. Binary RBMs are often used in modeling binary data such as images or text.
  - Gaussian RBM: In a Gaussian RBM, the input and hidden units are continuous variables that follow a Gaussian distribution. Gaussian RBMs are often used in modeling continuous data such as audio signals or sensor data.

- Hyperparameters for Boltzmann Machines.
  - Weight Initialization: Proper initialization of weights can save a lot of time as it can optimize the time required to learn those weights, which is the whole idea of training a network.
  - Visible and Hidden Units:
    - The number of inputs is the feature that is explicitly given to the network.
    - The number of hidden features has to be optimally chosen to make the network grasp a majority of features.
    - Each of these layers has its own transform function to process the inputs and pass them onto the next layer.
  - Regularization: Through regularization, a network's chance of overfitting is pulled away. Whenever the model overfits or learns large weights, it is penalized as it helps in reducing the weights to an acceptable level.

https://blog.paperspace.com/beginners-guide-to-boltzmann-machines-pytorch/

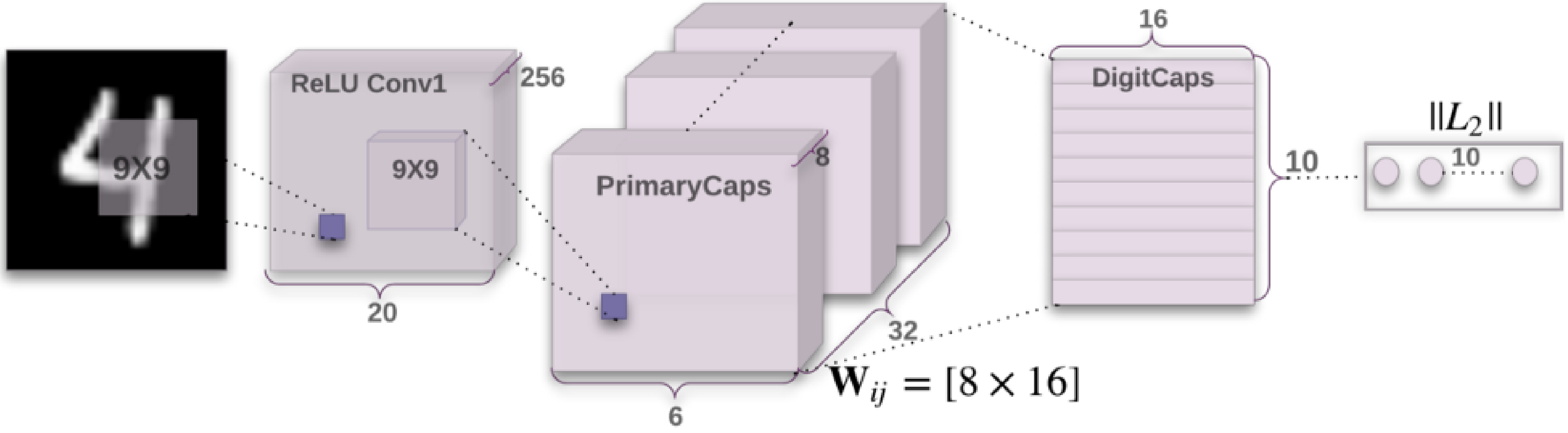
TRANSFER TASK

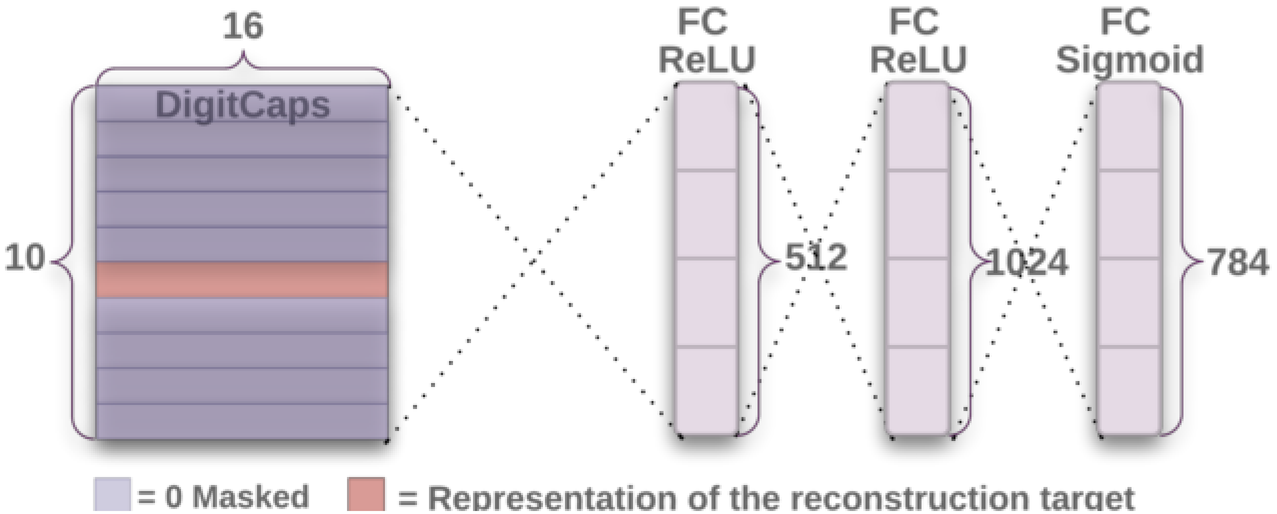
- Notebook AE > 04. Restricted Boltzmann Machines.ipynb

CAPSULE NETWORKS (CAPSNETS) (2011)

- The main idea is to replace neurons (which have a scalar output) with capsules (which have a vector output).
- In the context of image processing, each capsule in a trained CapsNet should theoretically correspond to a viewpoint-independent representation of an object learned from training images, with the capsule output encoding how that object is rendered in a given image.

CAPSULE NETWORKS (CAPSNETS) (2011)

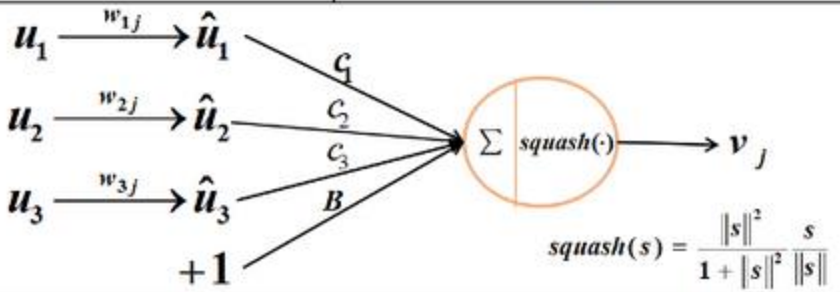


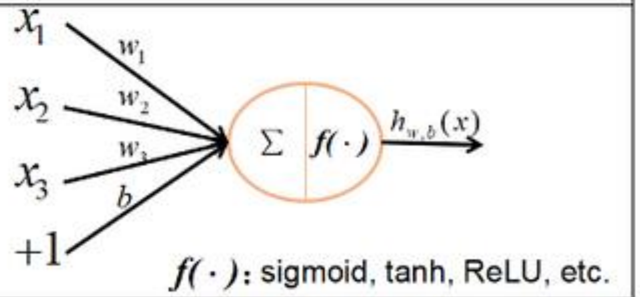


https://blog.paperspace.com/capsule-networks/

CAPSULE NETWORKS (CAPSNETS) (2011)

		capsule	VS. traditional neuron
Input from low-level neurons/capsules		vector(u_i)	scalar(x_i)
Operations	Linear/Affine Transformation	$\hat{u}_{j\|i} = W_{ij} u_i + B_j$ (Eq. 2)	$a_{j\|i} = w_{ij} x_i + b_j$
	Weighting Summation	$s_j = \sum_i c_{ij} \hat{u}_{j\|i}$ (Eq. 2)	$z_j = \sum_{i=1}^{3} 1 \cdot a_{j\|i}$
	Non-linearity activation	$v_j = squash(s_j)$ (Eq. 1)	$h_{w,b}(x) = f(z_j)$
output		vector(v_j)	scalar(h)

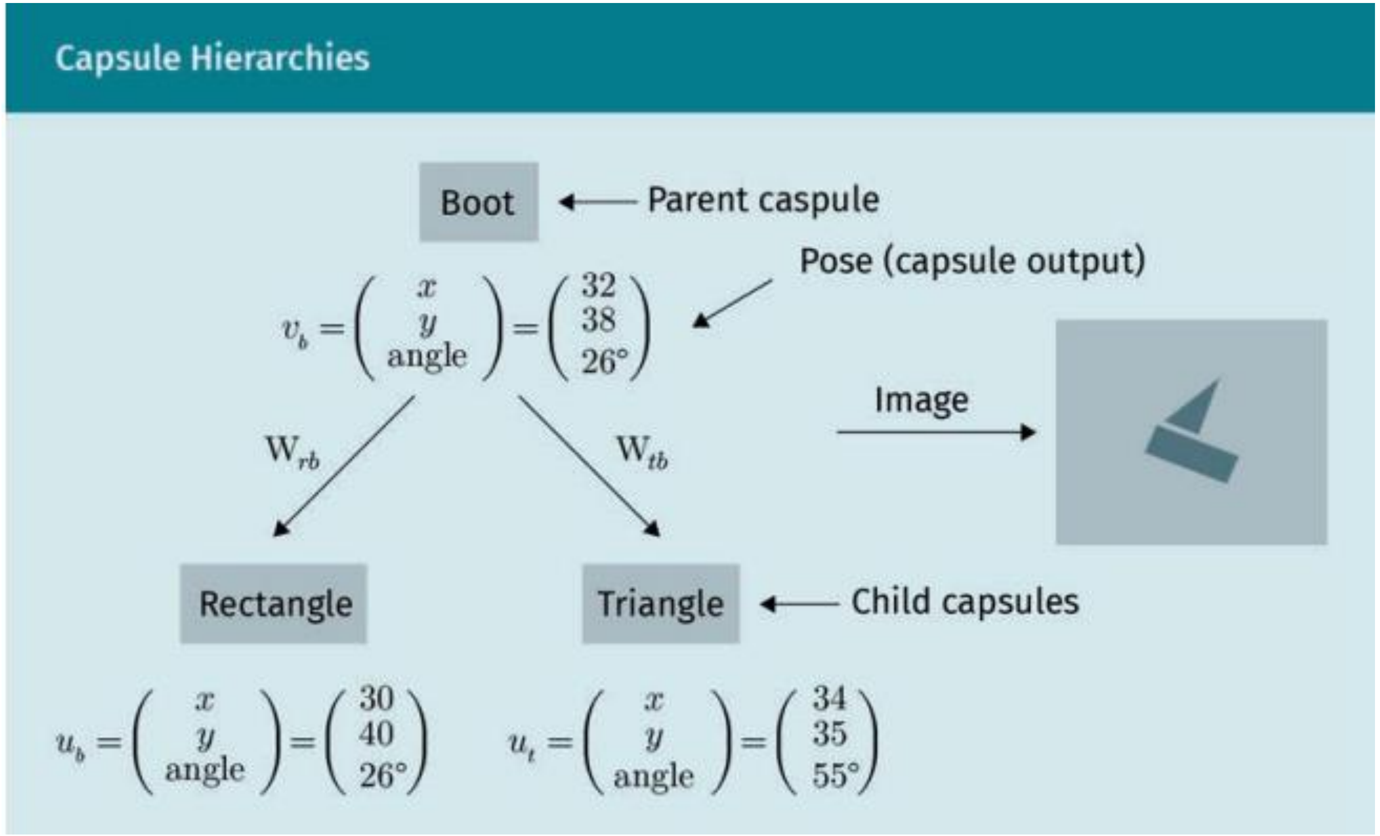




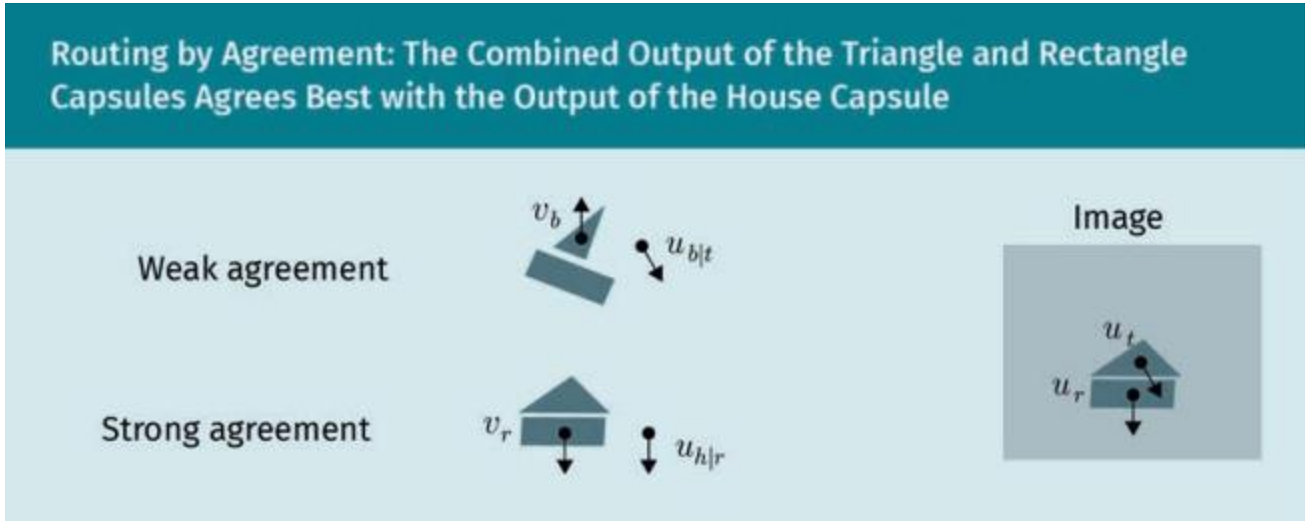
Capsule = New Version Neuron!
vector in, vector out VS. scalar in, scalar out

https://github.com/naturomics/CapsNet-Tensorflow/?ref=blog.paperspace.com

- Viewpoint Independent Representations and Hierarchies.



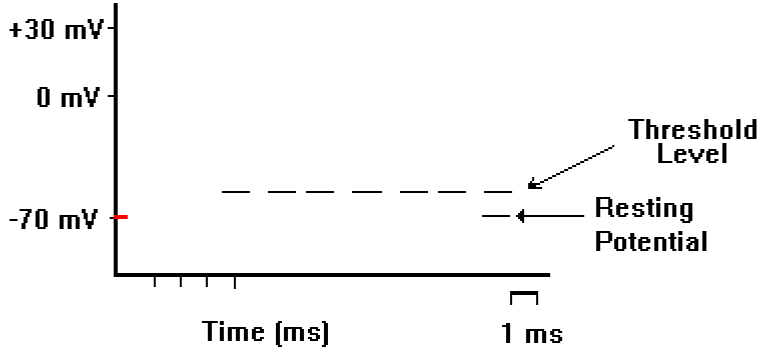
- Dynamic Routing by Agreement



SPIKING NEURAL NETWORKS (SNN) (1995)

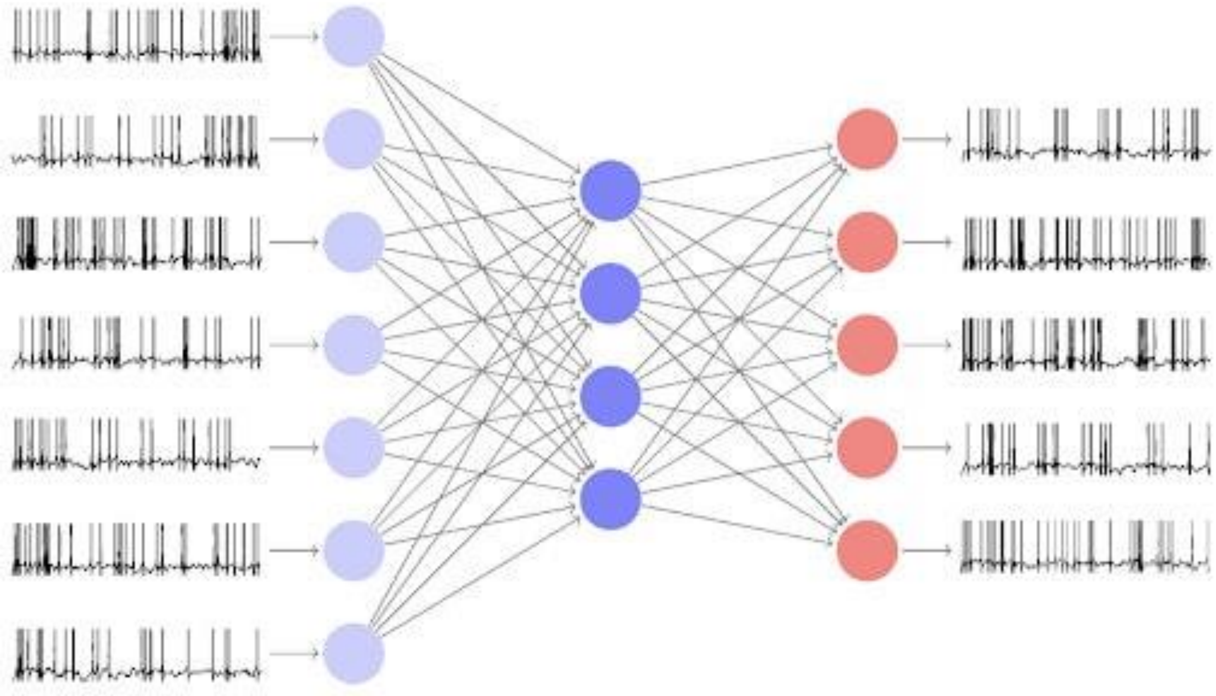
- The key difference between a traditional ANN and SNN is the information propagation approach.
- SNN tries to more closely mimic a biological neural network. This is why instead of working with continuously changing in time values used in ANN, SNN operates with discrete events that occur at certain points of time. SNN receives a series of spikes as input and produces a series of spikes as the output (a series of spikes is usually referred to as spike trains).

1. At every moment of time each neuron has some value that is analogous to the electrical potential of biological neurons;
2. The value in a neuron can change based on the mathematical model of a neuron, for example, if a neuron receives a spike from the upstream neuron, the value might increase or decrease;
3. If the value in a neuron exceeds some threshold, the neuron will send a single impulse to each downstream neuron connected to the initial one;
4. After this, the value of the neuron will instantly drop below its average. Thus, the neuron will experience the analog of a biological neuron's refractory period. Over time the value of the neuron will smoothly return to its average.



https://cnvrg.io/spiking-neural-networks/

- How to train a SNN?
  - Unfortunately, as of today, there is no effective supervised interpretable learning method that can be used to train an SNN. The key concept of SNN operations does not allow the use of classical learning methods that are appropriate for the rest of NNs. Still, scientists are searching for an optimal method.
  - This is the reason why training an SNN might be a tough task.



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REVIEW STUDY GOALS

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SESSION 5.2

Further Network Architectures

1. Select the correct option?

Statement 1: Boltzmann machines are non-deterministic generative Deep learning models with 3 types of nodes: visible, hidden and output nodes.
Statement 2: Boltzmann machines fall into the class of Unsupervised learning.

A. Both the statements are TRUE.
B. Statement A is TRUE, but statement B is FALSE.
C. Statement A is FALSE, but statement B is TRUE
D. Both the statements are FALSE.

2. Select the correct option.

Statement 1: RBM is ‘restricted’ to have only the connections between the visible and the hidden units.
Statement 2. RBM performs discriminative learning similar to what happens in a classification problem.
Statement 3: If number of visible nodes = nV, number of hidden nodes = nH, then number of connections in RBM = nV* nH

A. True, True, True.
B. True, False, True.
C. False, False, True.
D. True, False, False.