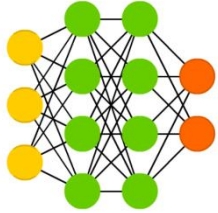
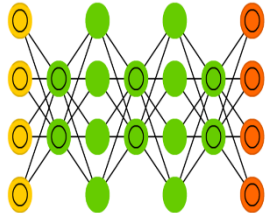


Deep Learning CSI_7_DEL

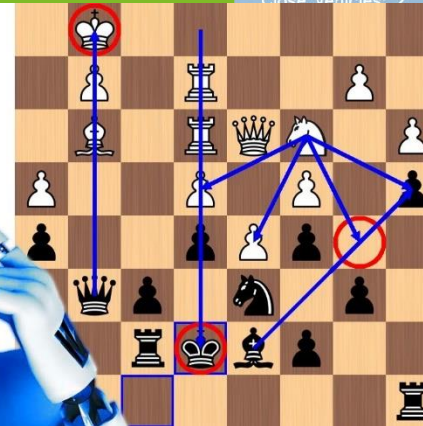
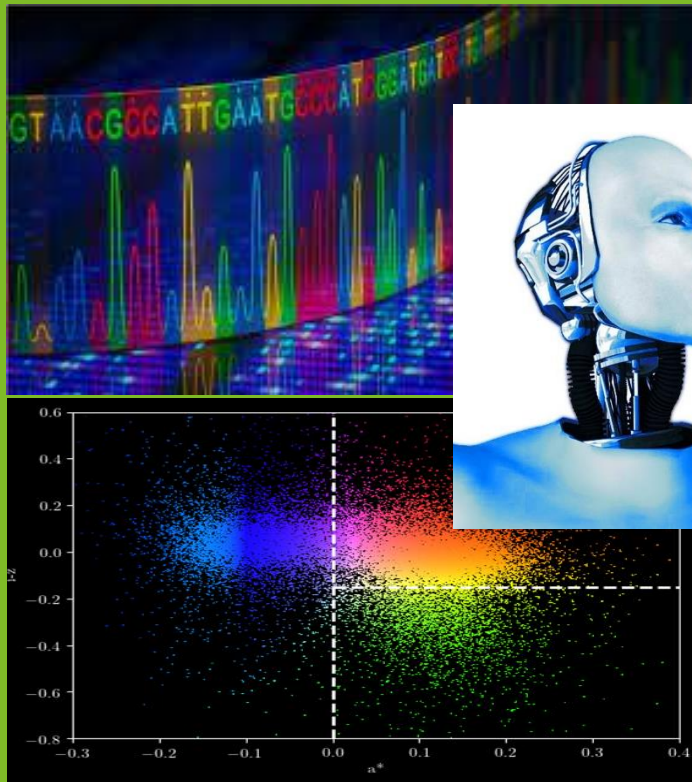
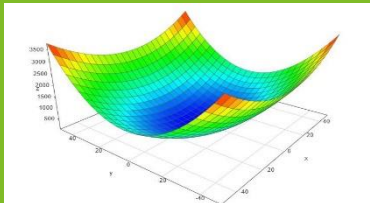
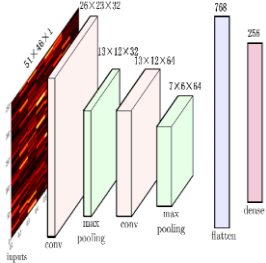
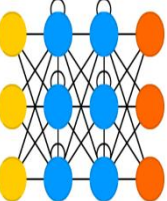
Deep Feed Forward (DFF)



Deep Belief Network (DBN)



Recurrent Neural Network (RNN)



Week 8: Restricted Boltzmann Machine (RBM)

Lecture points

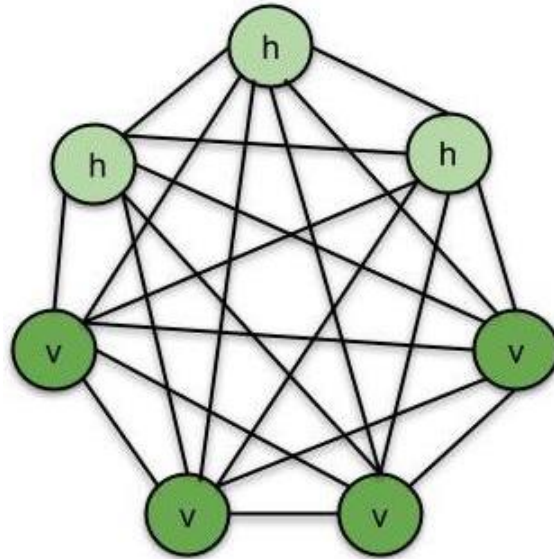
- Boltzmann Machine.
- Restricted Boltzmann Machine
- RBM applications.
- Gibbs Sampling
- Contrastive Divergence

Boltzmann Machine

- Unsupervised **Generative** Deep Learning models.
- Introduced by Geoffrey Hinton and Terry Sejnowski in [1985](#)
- Learns the probability distribution over a set of inputs.
- An energy-based model
- Only binary input and output is allowed

Boltzmann Machine

- **Boltzmann distribution** used in the sampling distribution (Ludwig Boltzmann)
- Contains two types of neurons: **hidden and visible**.
- Each neuron is connected to the other (**bidirectional connections**)



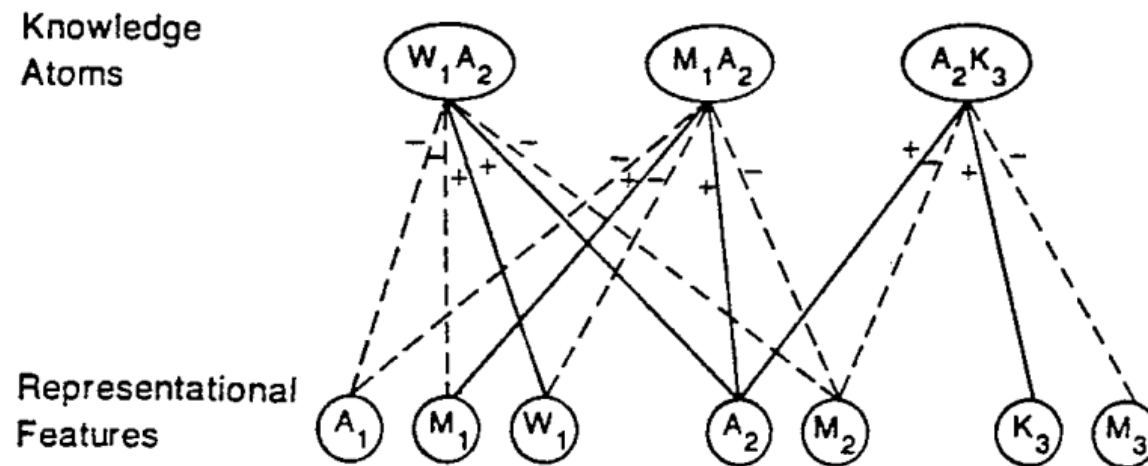
v= visible neurons **h**= hidden neurons

Types of Boltzmann

- Restricted Boltzmann Machines (RBM)
- Deep Belief Networks (DBN)
- Deep Boltzmann Machines (DBM)

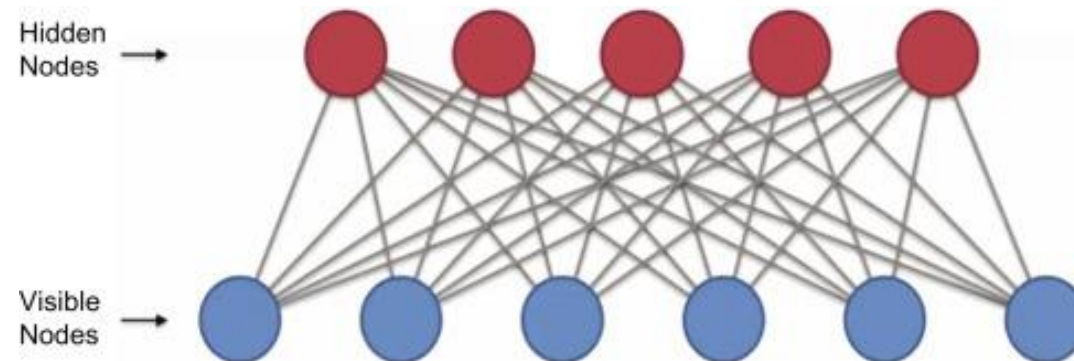
Restricted Boltzmann Machines

- First introduced under the name “Harmonium model” by Smolensky ([1986](#))
- Traditional Boltzmann Machine has connections growing exponentially.
- Unidirectional graphical model.
- Used to build Deep Belief Networks and Deep Boltzmann Machine



RBM: Architecture

- Shallow two-layer neural network.
- **Visible** neurons **only connects** to **hidden** neurons
- **Hidden** neurons **only connects** to **visible** neurons
- Each hidden neuron represents a data feature or pattern



RBM Applications

- Commonly used in **unsupervised** classification of images, text, voice etc.
- Heals the curse of dimensionality
- Pattern recognition and features extraction. (Autoencoders)
- Solve **imbalanced data** problem (One class dominates the other classes in the training data).
- **Noisy label problems** (Some observations in the training data contain wrongly assigned label).

Conditional RBM for recommender system

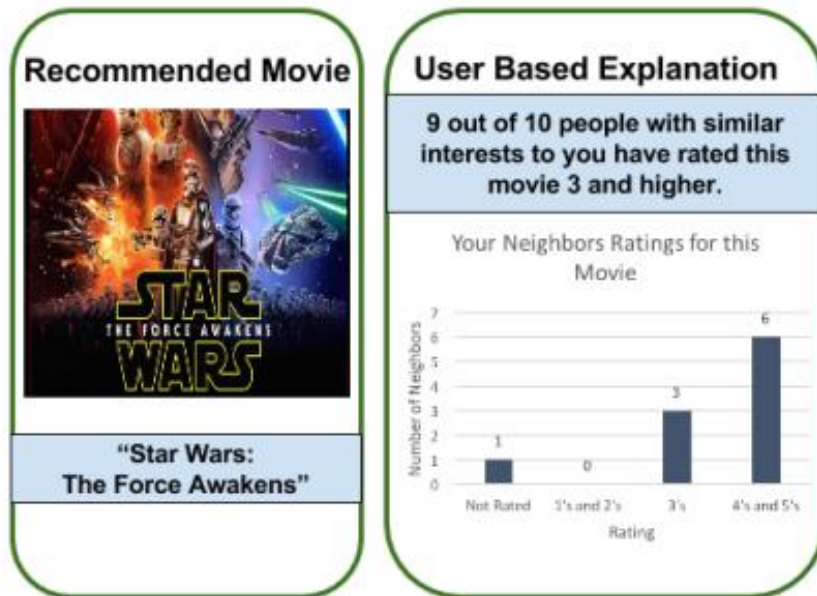


Figure 1. An example of a user-based neighbor style explanation for a recommended item.

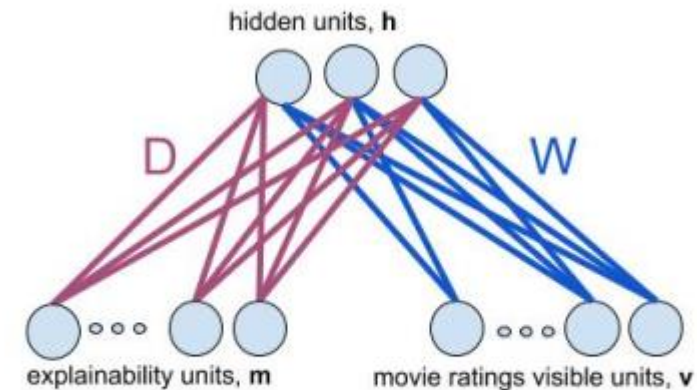


Figure 2. Conditional RBM for explainability.

RBM: Hidden and Visible units

- For any given hidden or visible neuron, to set any state The weighted combination of all input needs to be calculated.
- In For any hidden unit h_i , he probability P that h_i can be turn on can be computed as follow:

$$P(h_i = 1) = \frac{1}{1 + e^{-z_i}} \quad (\text{a sigmoid basically also called partition function})$$

z_i represents the sum of all input combinations:

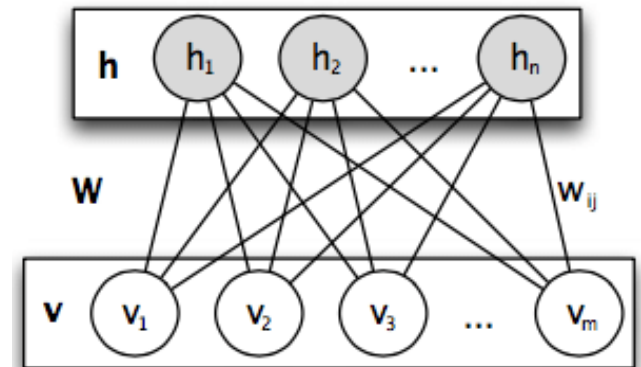
$$z_i = \sum_j w_{ji} v_j + b_i$$

Where w_{ji} is the weight connection between the visible and the hidden neurons and b_i is the bias added to the visible neuron.

- Similarly, for any visible unit v_i , he probability P that v_i can be turn on can be computed as follow:

$$P(v_i = 1) = \frac{1}{1 + e^{-y_i}}$$

Where $y_i = \sum_j w_{ji} v_j + b_i$



Energy function

- RBM is energy-based model
- Analogous to the **cost function** in other neural networks.
- The training algorithm attempts to minimize the energy function
- **Low energy** translates to **high probability** (High accuracy)
- Standard energy function with biases a_i , b_i and weights w_{ji} :

$$\begin{aligned} E(v, h) &= - \sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} w_{ij} v_i h_j \\ &= -a^T v - b^T h - v^T W h \end{aligned}$$

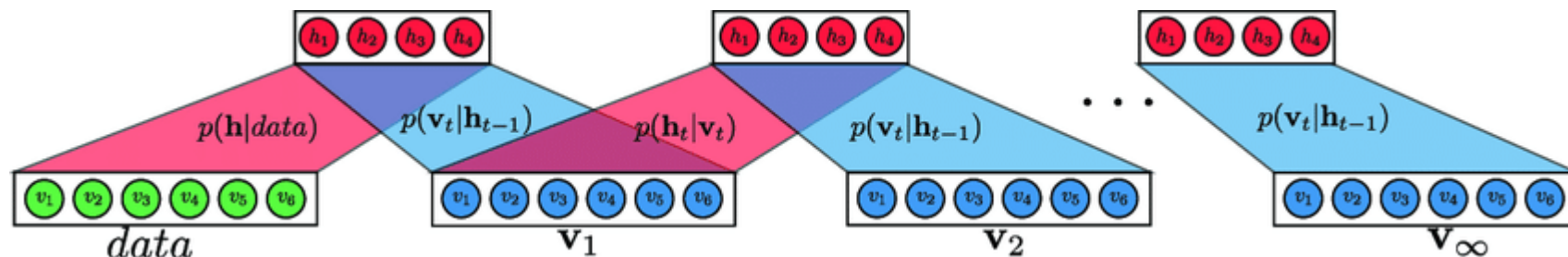


RBM Training

- RBM are trained using Stochastic Gradient Descent (SGD).
- There are two training steps
- Gibbs sampling
- Contrastive divergence.

Gibb sampling

- The search technique used in the training for RBM is called Gibbs sampling.
- A variant of Markov chain Monte Carlo method (MCMC) introduced by German and German ([1984](#))
- Gibbs sampling calculates two parts:
 - **Part one** $P(v_i = 1 | h) = \frac{1}{1 - e^{-(w_{ij}h_j + a_i)}} = \sigma(\sum_j w_{ij}h_j + a_i)$
 - **Part two:** $P(h_i = 1 | v) = \frac{1}{1 - e^{-(w_{ij}h_j + b_i)}} = \sigma(w_{ij}h_j + b_i)$



Gibbs sampling steps

Step 1: Initialize a matrix $Q=0$ where the estimates will be stored.

Step 2: Pick a random vector v .

Step 3: Repeat for N The following:

$$\text{Sample } h \sim p(h|v) = \sigma(b + W^T v)$$

$$\text{Sample } v \sim p(v|h) = \sigma(a + Wh)$$

$$Q \leftarrow Q + vh^T$$

Step 4: End results $\Rightarrow E(v_i, h_i) \approx \frac{1}{N} Q$

Usually, Gibbs sampling tends to be slow.



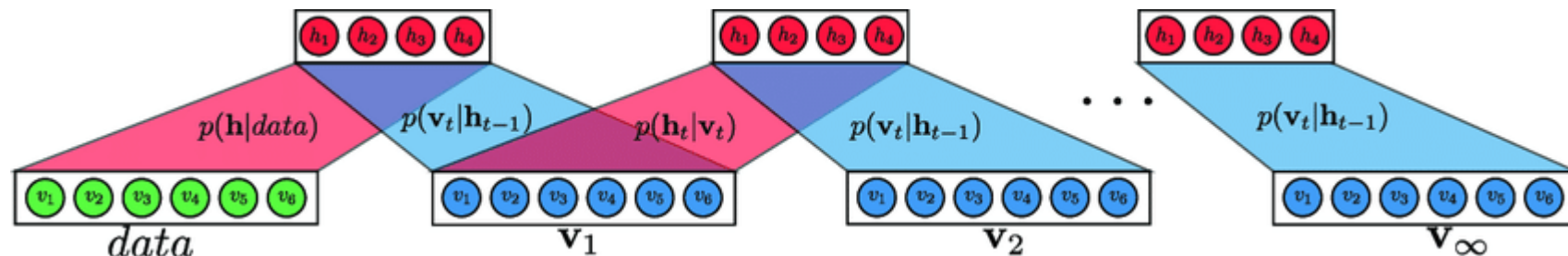
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Contrastive Divergence

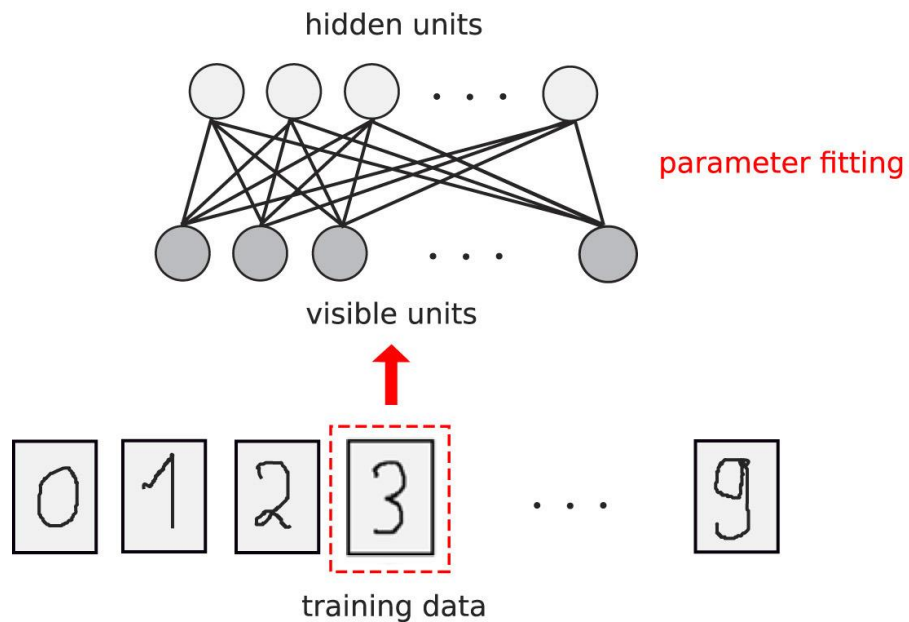
- A Markovian chain training technique used to learn the gradients of RBM
- The goal is to optimize weights and minimize the energy function.
- The weight values are updated during the contrastive divergence.

$$\Delta W = \mathbf{v}_0 \otimes p(\mathbf{h}_0 | \mathbf{v}_0) - \mathbf{v}_k \otimes p(\mathbf{h}_k | \mathbf{v}_k)$$
$$W_{new} = W_{old} + \Delta W$$

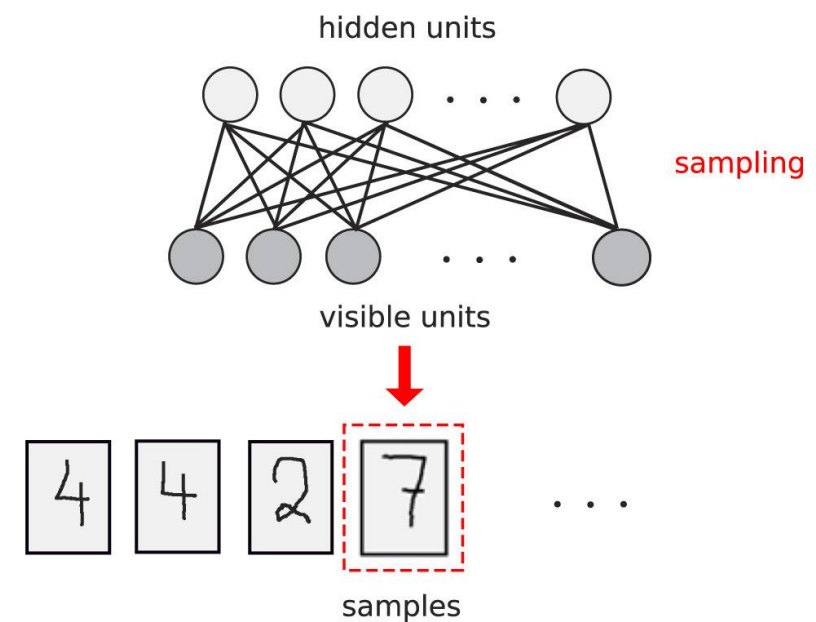


Learning and generating samples

learning



generating



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Training

- Finally, The gradient of the log likelihood of p with respect to w_{ij} connections between hidden and visible neuros can be calculated.

$$\frac{\partial \log p(v)}{\partial w_{ij}} = \langle v_i h_j \rangle^0 - \langle v_i h_j \rangle^\infty$$

- Where $\langle v_i h_j \rangle$ is the average over many generated samples



Summary

- RBM networks are energy-based.
- Learn the probability distribution of a given input.
- Use Markovian techniques for learning and generating samples (Gibbs sampling and contrastive divergence)
- Useful for recognising patterns, curse of dimensionality and recommender systems.

Questions & Answers



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