Artificial Neural Network:

Building a machine or autonomous mechanism endowed with intelligence is an ancient dream of researchers from diverse areas of sciences and engineering.
The applications involving systems

- Analysis of images acquired from artificial satellites.
- Speech and writing pattern classification.
- Face recognition with computer vision.
- Control of high-speed trains.
- Stocks forecasting on the financial market.
- Anomaly identification on medical images.
- Automatic identification of credit profiles for clients of financial institutions.
- control of electronic devices and appliances, such as washing machines, microwave ovens, freezers, coffee machines, frying machines, video cameras, and so on.

Fundamental Theory:

Artificial neural networks are computational models inspired by the nervous system of living beings. They have the ability to acquire and maintain knowledge (information-based) and can be defined as a set of processing units, represented by artificial neurons, interlinked by a lot of interconnections (artificial synapses), implemented by vectors and matrices of synaptic weights.

Key Features:

1. **Adapting from experience**
2. **Learning capability**

3. **Generalization capability**-network can generalize the acquired knowledge through learning
4. **Data organization-**pattern Recognized
5. **Fault tolerance-** high connections among themselves (layers)
6. **Distributed storage-** store the previous Data- synaptic weights
7. **Facilitated prototyping-** easily prototyped into hardware

1st historical experiment was done in 1949,

Hebb's rule:

The first method for training artificial neural networks is Hebb's rule and was based on hypothesis and observations of neurophysiologic nature.
The Perceptron model stirred interest due to its capability of recognizing simple patterns. Widrow and Hoff (1960) developed a network called ADALINE, which is short for ADAptive LINEar Element. Later on, the MADALINE, the Multiple ADALINE was proposed. It consisted of a network whose learning is based on the Delta rule, also known as LMS (Least Mean Square) learning method.

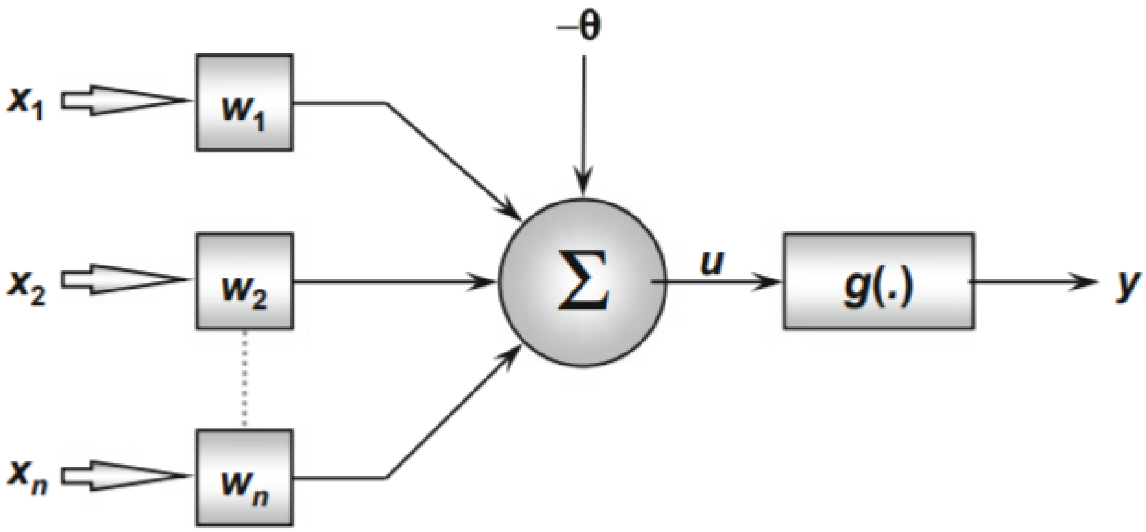
Potential Application Areas of ANN:

a. Universal curve fitting
b. Process control
c. Pattern recognition/classification
d. Data clustering
e. Prediction system
f. System optimization
g. Associative memory

Artificial Neuron

The artificial neural network structures were developed from known models of biological nervous systems and the human brain itself.
The artificial neurons used in artificial neural networks are nonlinear, usually providing continuous outputs, and performing simple functions, such as gathering signals available on their inputs, assembling them according to their operational functions, and producing a response considering their innate activation functions

The most simple neuron model that includes the main features of a biological neural network—parallelism and high connectivity—was proposed by **McCulloch and Pitts** (1943), and still is the most used model in different artificial neural network architectures.



In this model,

1. The multiple input signals coming from the external environment (application) are represented by the set {x1, x2, x3, …, xn}
2. The weighing carried out by the synaptic junctions of the network are implemented on the artificial neuron as a set of synaptic weights {w1, w2, …, wn}
3. output of the artificial cellular body, denoted by u, is the weighted sum of its inputs

Elements:

a. **Input signals** **(x1, x2, …, xn)**
b. **Synaptic weights** **(w1, w2,…, wn)**
c. **Linear aggregator(sigma):**gathers all input signals weighted by the synaptic weights to produce an activation voltage
d. **Activation threshold or bias (Θ):**a variable used to specify the proper threshold that the result produced by the linear aggregator should have to generate a trigger value toward the neuron output.
e. **Activation potential (u):** e difference between the linear aggregator and the activation threshold
f. **Activation function (g):** whose goal is limiting the neuron output within a reasonable range of values, assumed by its own functional image

g. **Output signal (y):** the final value produced by the neuron given a particular set of input signals

Results using the McCulloch and Pitts,

$$u = \sum_{i=1}^{n} w_i \cdot x_i - \theta$$

$$y = g(u)$$

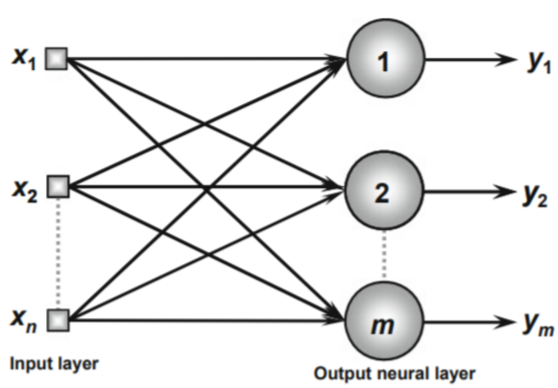
Steps:

1. Present a set of values to the neuron, representing the input variables.
2. Multiply each input of the neuron to its corresponding synaptic weight.
3. Obtain the activation potential produced by the weighted sum of the input signals and subtract the activation threshold.
4. Applying a proper activation function to limit the neuron output.
5. Compile the output by employing the neural activation function in the activation potential.

Main Architectures of Artificial Neural Networks:

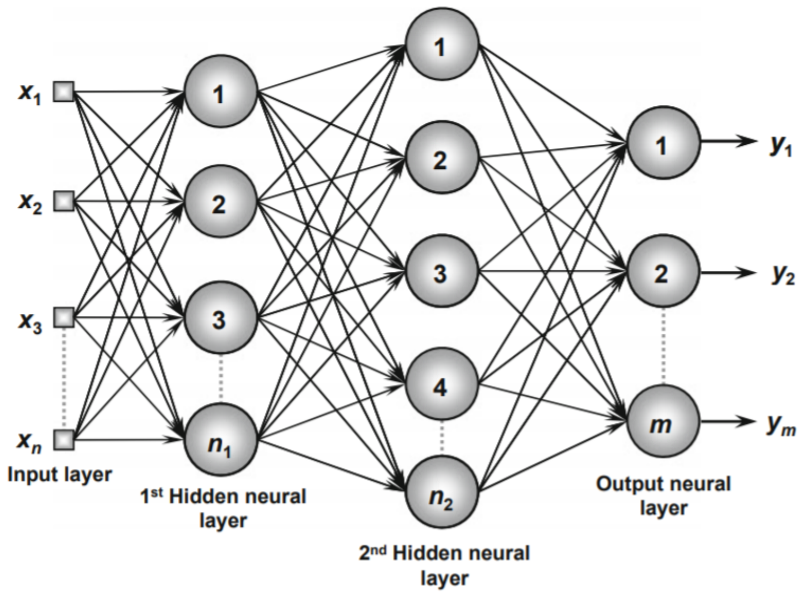
1. Single-Layer Feedforward Architecture:

This artificial neural network has just one input layer and a single neural layer, which is also the output layer. Figure illustrates a simple-layer feedforward network composed of n inputs and m outputs.
The information always flows in a single direction (thus, unidirectional), which is from the input layer to the output layer.



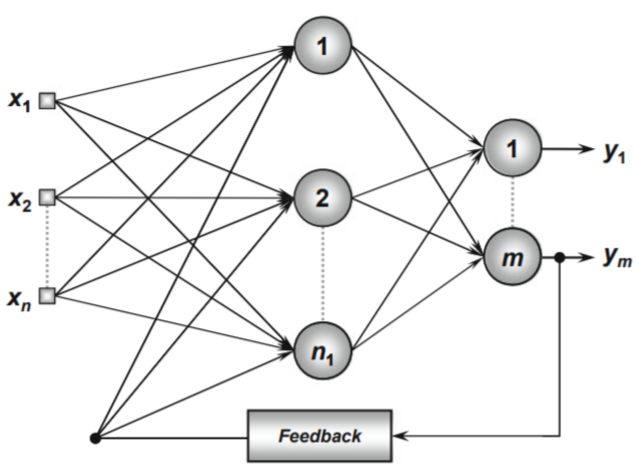
2. Multiple-Layer Feedforward Architectures:

Feedforward networks with multiple layers are composed of one or more hidden neural layers. They are employed in the solution of diverse problems, like those related to function approximation, pattern classification, system identification, process control, optimization, robotics, and so on.



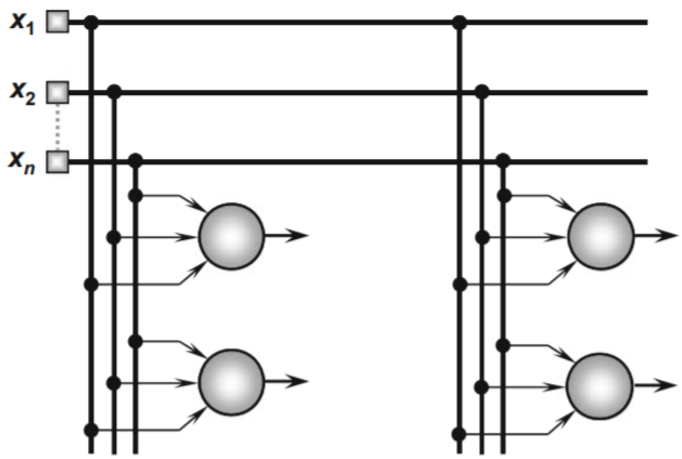
3. Recurrent or Feedback Architecture:

In these networks, the outputs of the neurons are used as feedback inputs for other neurons. The feedback feature qualifies these networks for dynamic information processing, meaning that they can be employed on time-variant systems, such as time series prediction, system identification and optimization, process control, and so forth.



4. Mesh Architectures:

The main features of networks with mesh structures reside in considering the spatial arrangement of neurons for pattern extraction purposes, that is, the spatial localization of the neurons is directly related to the process of adjusting their synaptic weights and thresholds. These networks serve a wide range of applications and are used in problems involving data clustering, pattern recognition, system optimization, graphs, and so forth.



Training Processes and Properties of Learning:
One of the most relevant features of artificial neural networks is their capability of learning from the presentation of samples (patterns), which expresses the system behavior.

1. **Supervised Learning:**
2. **Unsupervised Learning:**

Statistical Model:

SIM: Simple index model - Sharpe's Model -

Markowitz model: This tells us about the correlation between each security.
Drawback- Too much calculation- get to know the correlation between each of the securities.

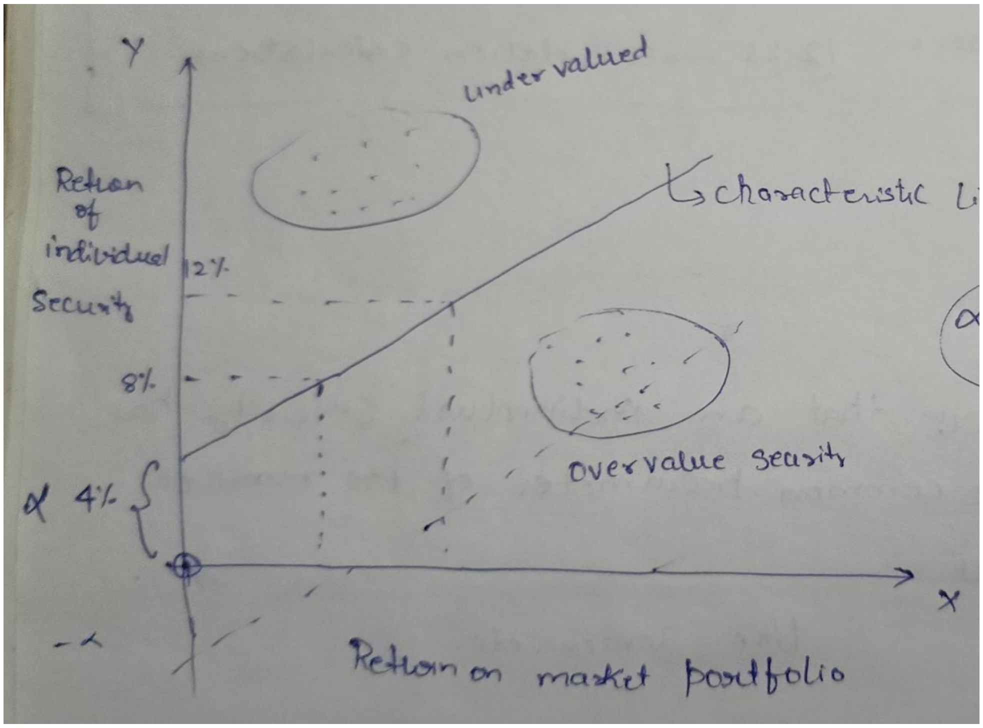
So, for n securities, we have n(n-1)/2 - no. of calculations

So to avoid too many calculations we prefer Sharpe's Model
- Sharpe's model favors that individual security has a relationship with one common parameter of the market, generally it is the Index of Market

Basic Concept:
1. **Market Portfolio:** Securities are related to the index.
2. **Systematic Risk:** Risk rise from macro factor- market-wide factor, which implies there is no control on them. All security having the same. E.g. Like RBI increases interest on securities.
3. **Unsystematic Risk:** Risk arises from micro factors, Company-wide factors. It particularly depends on the company. E.g. Maruti Suzuki buys a machine to build the engine.
4. **Residual error return:** Rise from extraordinary events

Characteristics Line:
Represent decomposition of risk and return into its component.
Also used to calculate estimated return and risk of portfolio or security

1. Market-wide component od return and risk- systematic component
2. Company-wide component of return and risk - unsystematic component.
3. Random return



Abstract: construct an optimal portfolio, Taking BSE SENSEX as market performance index and considering daily indices along with the daily prices of sampled securities for the period of April 2001 to March 2011.
The proposed method formulates a unique cut-off rate and selects those securities to construct an optimal portfolio whose excess return to beta ratio is greater than the cut-off rate.
To get the proportion of stock to be invested on to get maximum portfolio (max return with minimum risk).

-**Diversification:** All investors invest in multiple securities rather than in a single security, to get the benefits from investing in a portfolio consisting of different securities.

Objective:
1. To get an insight into the idea embedded in Sharpe's Single Index Model.
2. To construct an optimal portfolio empirically using the Sharpe's Single Index Model.
3. To determine the return and risk of the optimal portfolio constructed by using Sharpe's Single Index Model.

Terminologies:

1. Ri = Return on security i (the dependent variable)
2. Rm = Return on market index (the independent variable)
3. αi = Intercept of the best fitting straight line of Ri on Rm drawn on the Ordinary Least Square (OLS) method or 'Alpha Value'. It is that part of security i's return which is independent of market performance.
4. β i = Slope of the straight line (Ri on Rm) or 'Beta Coefficient'. It measures the expected change in the dependent variable (Ri) given a certain change in the independent variable (Rm) i.e.

$$\frac{dR_i}{dR_m}$$

5. ei = random disturbance term relating to security i
6. Wi = Proportion (or weights) of investment in securities of a portfolio.

σ_{ei}^2 = unsystematic risk (in terms of variance) of security i

R_p = Portfolio Return

σ_p^2 = Portfolio Variance (risk)

β_p = Portfolio Beta

e_p = Expected value of all the random disturbance terms relating to portfolio.

σ_{ep}^2 = Unsystematic risk of the portfolio

i = $1, 2, 3, \ldots\ldots\ldots\ldots, n$

Mathematical Model:
From the SIM model, let's take return with respect to securities

$$R_i = \alpha_i + \beta_i R_m + e_i$$
,

Rm - market return,
ɑi- non-systematic return
Risk:

$$\sigma_i^2 = \beta_i^2 \sigma_m^2 + \sigma_{ei}^2$$

1st part- systematic
2nd part- non-systematic

Return & Risk of the portfolio under Sharpe's model:

Return: Rp = Σwiai + Bp.Rm
Risk: = (Bp^2 + σp^2)+ Σwi^2.σei^2 -- systematic + Non-systematic

Perceptron Algorithm:
https://colab.research.google.com/drive/1xDJ9UW54E4Xo-wwBqfk9aFXuY-OcGiwQ?usp=sharing

ARIMA Model:
Here is the code related to this
https://colab.research.google.com/drive/1qKeWkq_RCbNv-suVjbzl3te4Yic63Ts0?usp=sharing