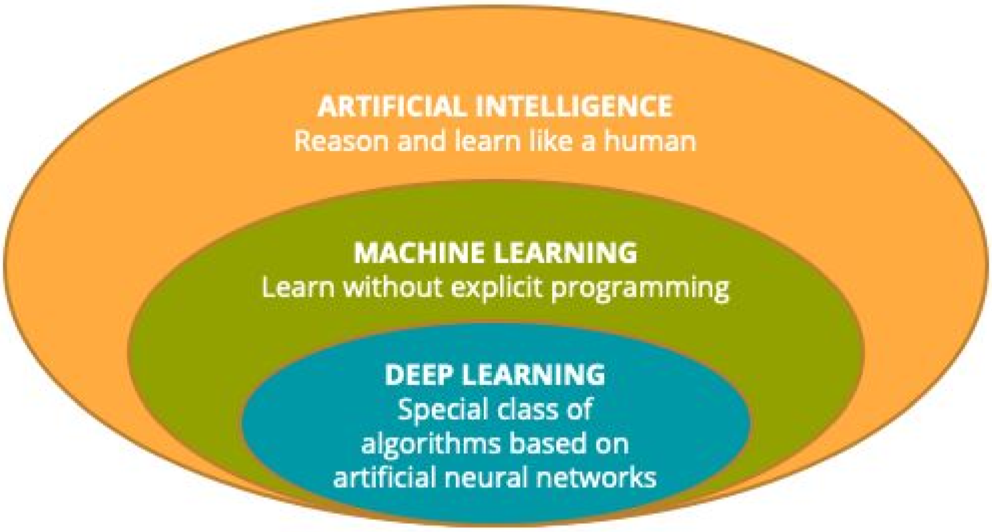
Applications of Machine Learning



Classical ML vs Deep Learning

- *Deep Learning > Classical ML*
  - Best-in-class performance
  - Scales effectively with data
  - No need for feature engineering
  - Adaptable and transferable
- *Classical ML > Deep Learning*
  - Works better on small data
  - Financially and computationally cheap
  - Easier to interpret

Deep learning

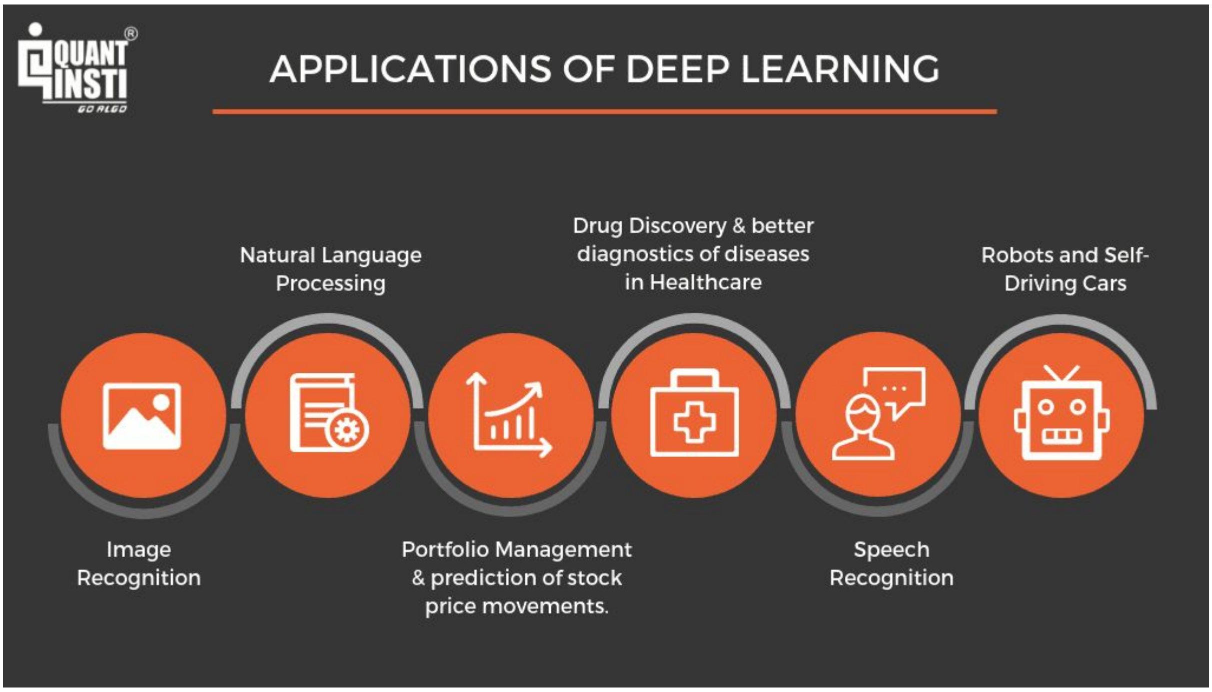
- **Deep learning** (also known as **deep structured learning**) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised.

❑ Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

Advantages of Deep Learning

- Maximum utilization of unstructured data
- Elimination of the need for feature engineering
- Ability to deliver high-quality results
- Elimination of unnecessary costs
- Elimination of the need for data labeling

Applications of Deep Learning



Specialized Cases of Model Training

Specialized cases of model training

Specific variations of the generic classes can be treated individually

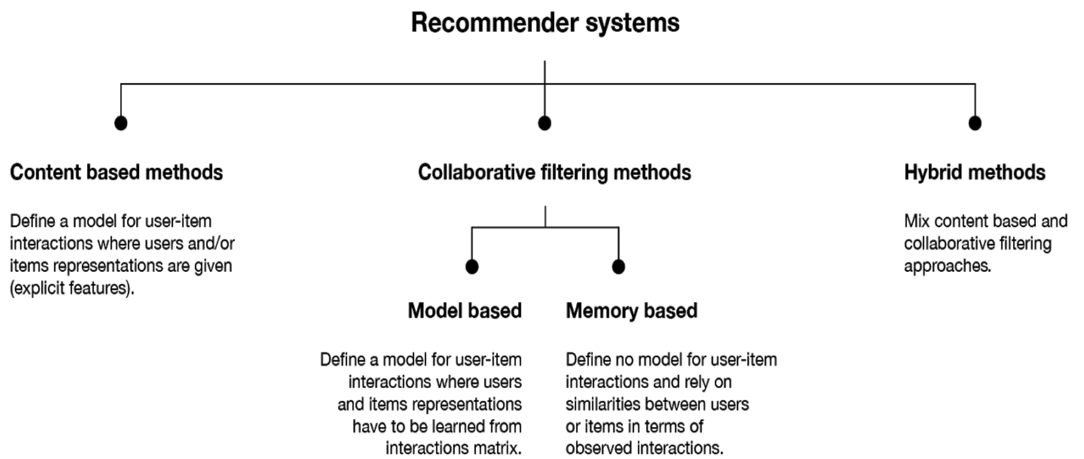
Specialized case	Approach
Similarity Learning	Supervised
Text Classification	Supervised (classification)
Feature Learning	Supervised (classification) Unsupervised (clustering)
Anomaly Detection	Supervised (classification) Unsupervised (clustering)
Forecasting	Supervised

Similarity Learning

- Similarity learning is an area of supervised machine learning in artificial intelligence.
- It is closely related to regression and classification, but the goal is to learn a similarity function that measures how similar or related two objects are.
- Similarity learning is used in information retrieval for learning to rank, in face verification or face identification and in recommendation systems.
- Also, many machine learning approaches rely on some metric. This includes unsupervised learning such as clustering, which groups together close or similar objects.
- It also includes supervised approaches like the K-nearest neighbor algorithm which rely on labels of nearby objects to decide on the label of a new object.

Recommender Systems

- A **recommender system** is a subclass of information filtering system that seeks to predict the "rating" or "preference" a user would give to an item.
- Recommender systems usually make use of either or both collaborative filtering and content-based filtering.
- Collaborative filtering approaches build a model from a user's past behavior as well as similar decisions made by other users. This model is then used to predict items (or ratings for items) that the user may have an interest in.
- Content-based filtering approaches utilize a series of discrete, pre-tagged characteristics of an item in order to recommend additional items with similar properties.



Feature Learning

- In machine learning, **feature learning** is a set of techniques that allows a system to automatically discover the representations needed for feature detection or classification from raw data.
- This replaces manual feature engineering and allows a machine to both learn the features and use them to perform a specific task.
- Feature learning is one of the machine learning techniques that can be done in both *supervised* and *unsupervised* ways.

- In supervised feature learning, features are learned using labeled input data. Examples include supervised neural networks, multilayer perceptron and (supervised) dictionary learning.
- In unsupervised feature learning, features are learned with unlabeled input data. Examples include k-means clustering, principal component analysis, autoencoders, matrix factorization and various forms of clustering.

Applications of Feature Learning

- ❑ Image classification
- ❑ Image search
- ❑ Feature Embedding

Anomaly Detection

Anomaly Detection is the technique of identifying rare events or observations which can raise suspicions by being statistically different from the rest of the observations.
It can be done in the following ways –

1. **Supervised Anomaly Detection:** This method requires a labeled dataset containing both normal and anomalous samples to construct a predictive model to classify future data points. The most commonly used algorithms for this purpose are supervised Neural Networks, Support Vector Machine learning, K-Nearest Neighbors Classifier, etc.
2. **Unsupervised Anomaly Detection:** This method does require any training data and instead assumes two things about the data ie Only a small percentage of data is anomalous and Any anomaly is statistically different from the normal samples. Based on the above assumptions, the data is then clustered using a similarity measure

and the data points which are far off from the cluster are considered to be anomalies.

Forecasting Algorithms

- ARIMA-Autoregressive Integrated Moving Average
- Multivariate Regression
- Prophet
- ForecastTCNs
- RNNs(Recurrent Neural Networks)