Learning Paradigms in Machine Learning

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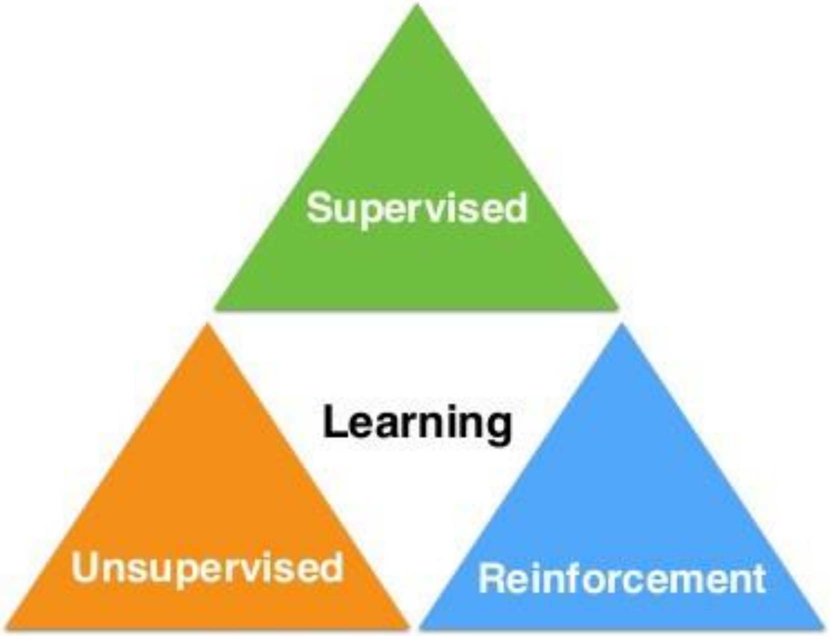
Learning Paradigms

- **Learning Paradigms** states a particular pattern on which something or someone learns.
- How a machine learns when some data is given to it, its pattern of approach for some particular data.
- There are three basic types of learning paradigms widely associated with machine learning, namely
    - **Supervised Learning**
    - **Unsupervised Learning**
    - **Reinforcement Learning**
    - **Semi Supervised Learning**

Learning Paradigms

- Labeled data
- Direct feedback
- Predict outcome/future

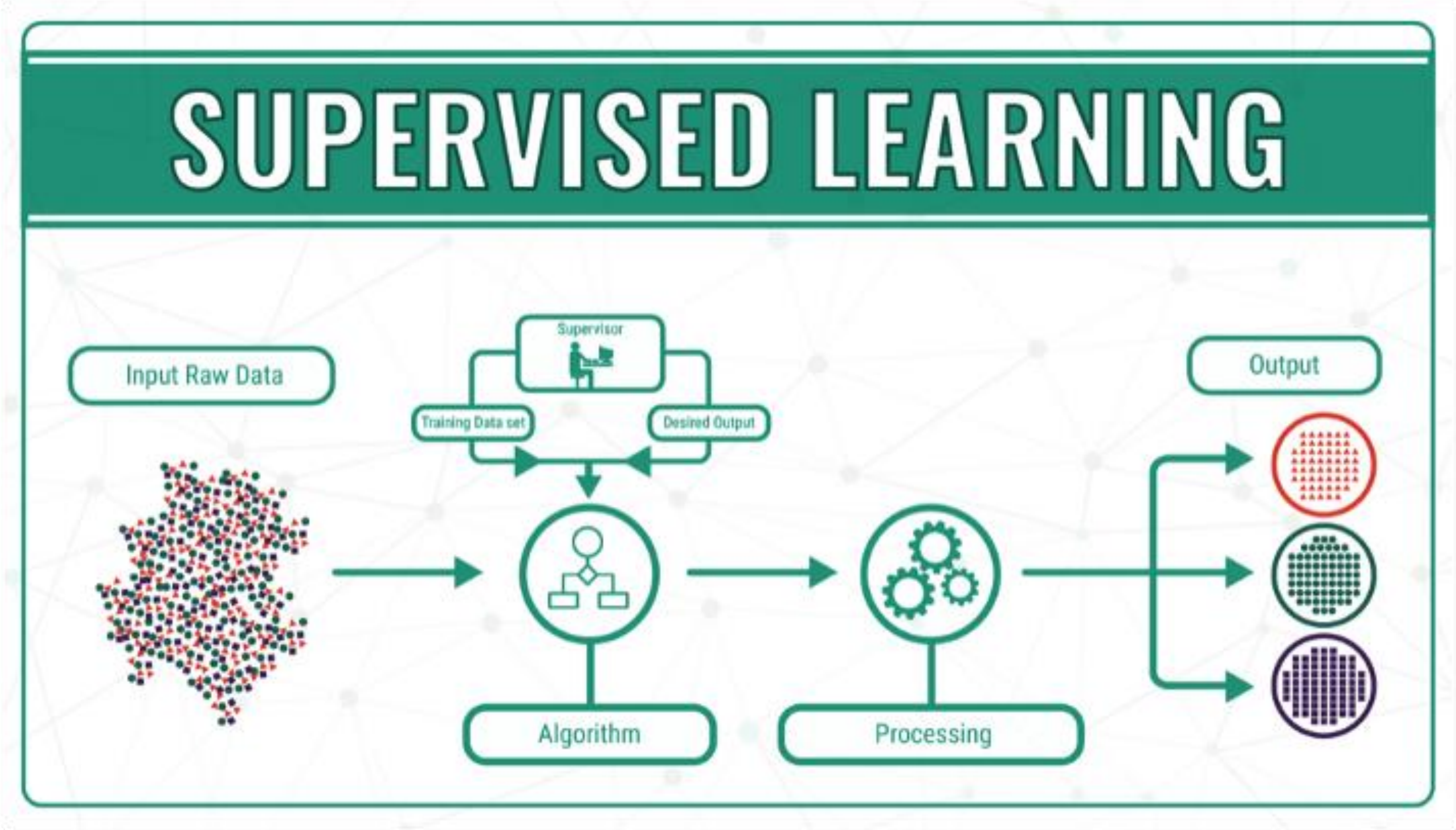


- No labels
- No feedback
- “Find hidden structure”

- Decision process
- Reward system
- Learn series of actions

Learning Paradigms

- **Supervised Learning**
  - *Supervised learning is a machine learning task in which a function maps the input to output data using the provided input-output pairs.*



Learning Paradigms

- **Supervised Learning**

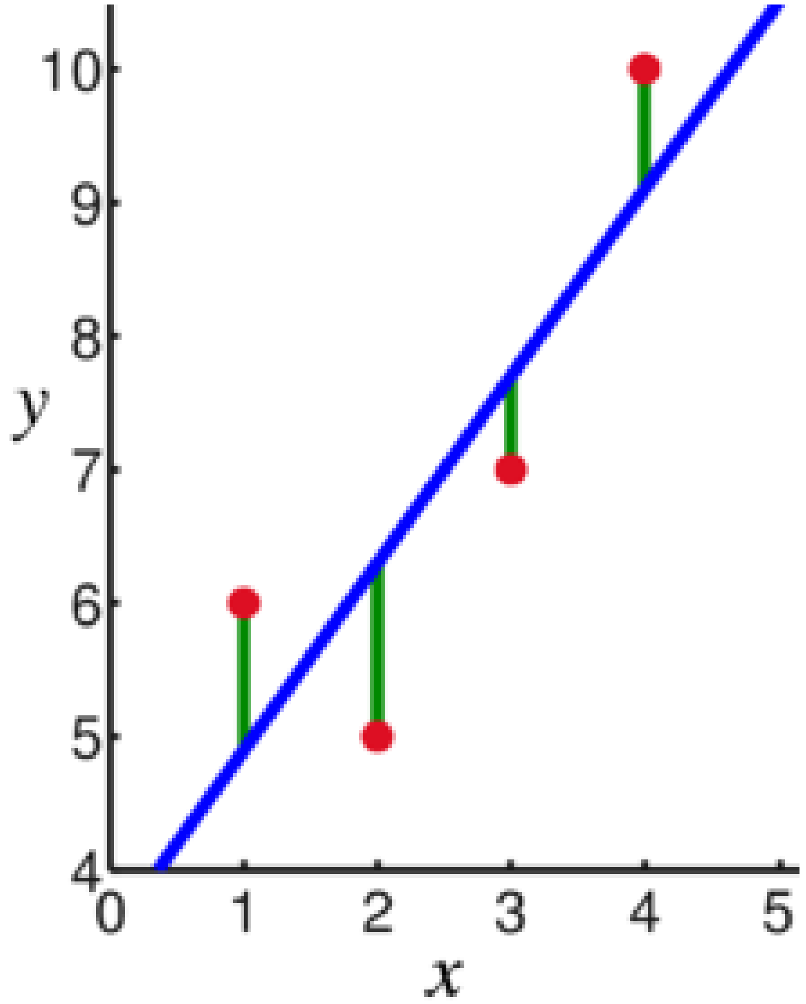
- In this type of learning, both the input and output (usually in the form of labels) are provided to the machine to learn from it.

- What the machine does is that it generates a function based on this data, which can be anything like a simple line, to a complex convex function, depending on the data provided.

- This is the most basic type of learning paradigm, and most algorithms we learn today are based on this type of learning pattern. Some examples of these are:

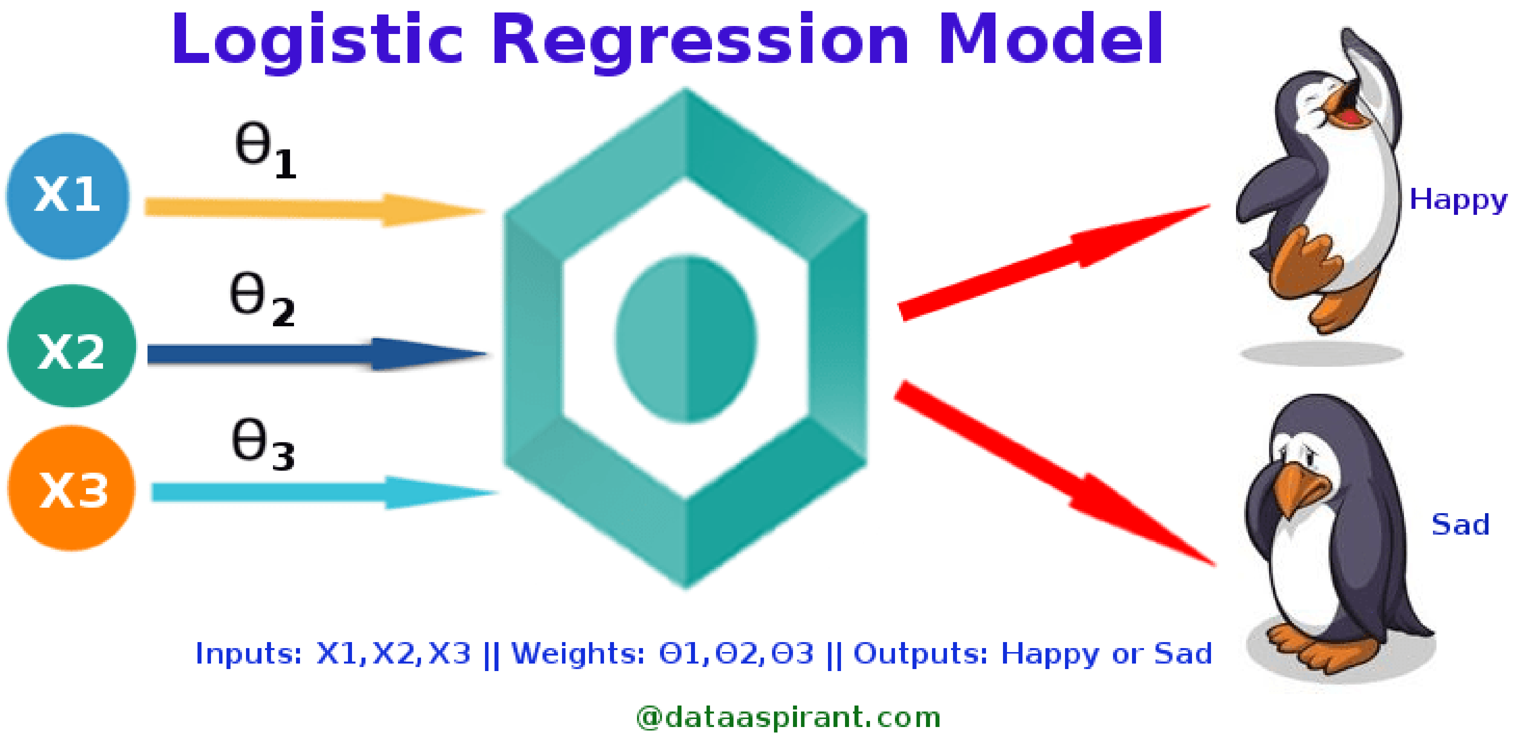
Learning Paradigms

- **Supervised Learning**
  - Some examples of these are:
  - **Linear Regression (the simple Line Function!)**



Learning Paradigms

- **Supervised Learning**
  - Some examples of these are:
  - **Logistic Regression (0 or 1 logic, meaning yes or no!)**

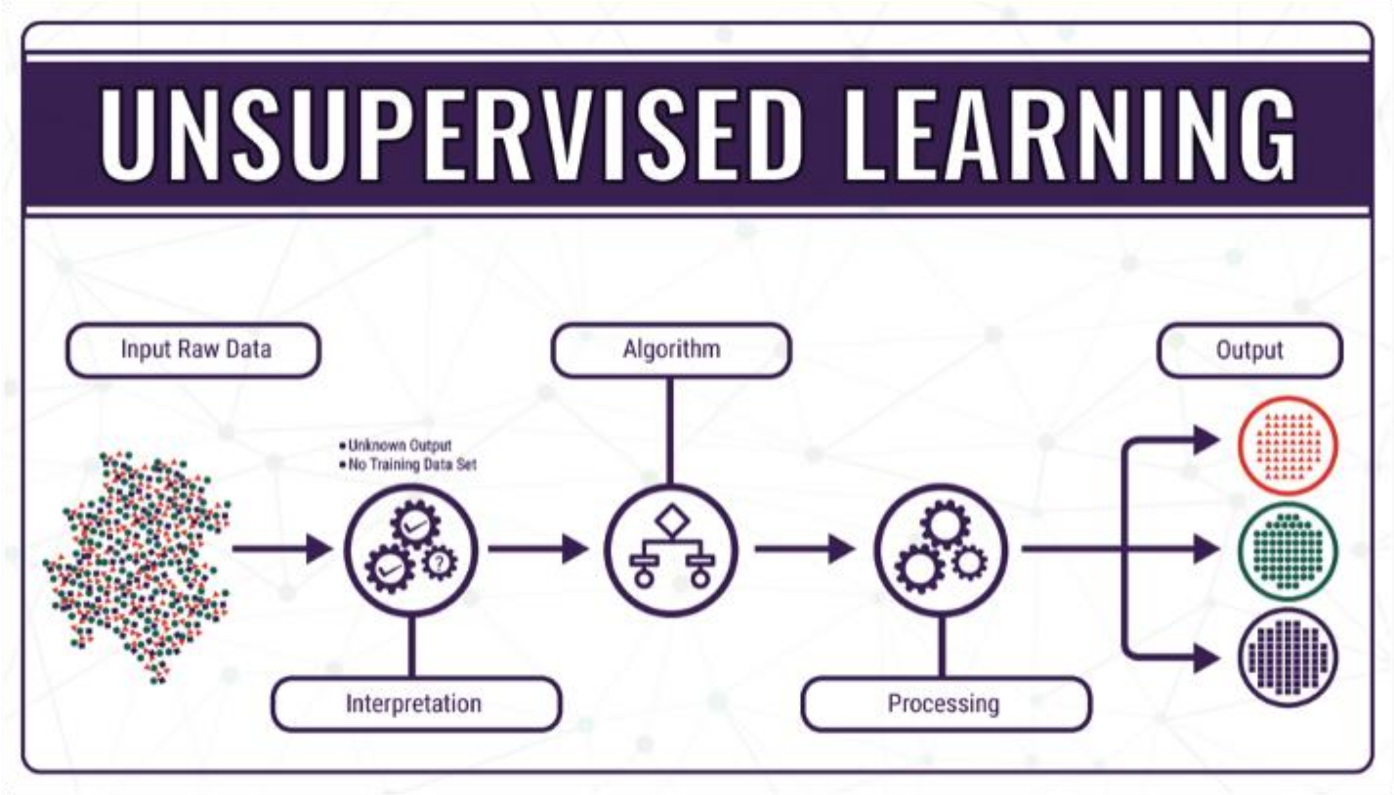


Learning Paradigms

- **Supervised Learning**
- Some practical examples of the same are :
  - **Classification:** Machine is trained to classify something into some class.
    - Classifying whether a patient has disease or not
    - Classifying whether an email is spam or not
  - **Regression:** Machine is trained to predict some value like price, weight or height.
    - Predicting House/Property Price
    - Predicting Stock Market Price

Learning Paradigms

- **Unsupervised Learning**
- *The machine is provided with just the input to develop a learning pattern. It is basically Learning from no results!!*



Learning Paradigms

- **Unsupervised Learning**

- The machine has to recognize a pattern in the given input, and develop an learning algorithm accordingly.

- **“The machine learns through observation & find structures in data”**.

- This is still a very unexplored field of machine learning, and big tech giants like Google and Microsoft are currently researching on development in it.

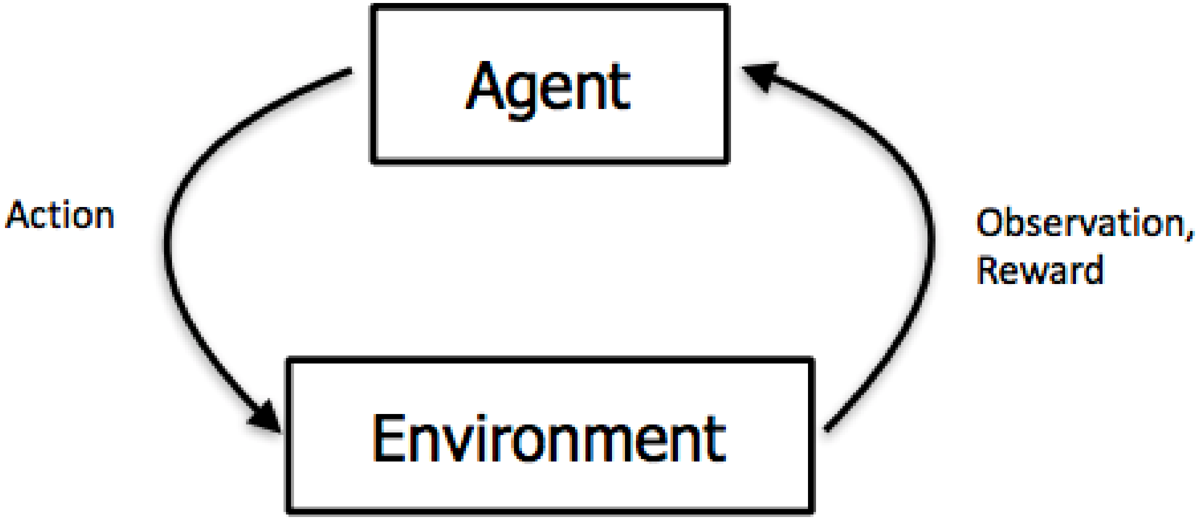
- **Clustering:** A clustering problem is where you want to discover the inherent groupings in the data
    - such as grouping customers by purchasing behavior

- **Association:** An association rule learning problem is where you want to discover rules that describe large portions of your data
    - such as people that buy X also tend to buy Y

Learning Paradigms

- **Reinforcement Learning**

- *It allows machines and software agents to automatically determine the ideal behavior within a specific context, in order to maximize its performance.*



Learning Paradigms

- **Reinforcement Learning**
  - There is an excellent analogy to explain this type of learning paradigm, **“training a dog”.**
  - This learning paradigm is like a dog trainer, which teaches the dog how to respond to specific signs, like a whistle, clap, or anything else.
  - Whenever the dog responds correctly, the trainer gives a reward to the dog, which can be a “Bone or a biscuit”.
  - A variety of different problems can be solved using Reinforcement Learning.

Learning Paradigms

- **Reinforcement Learning**

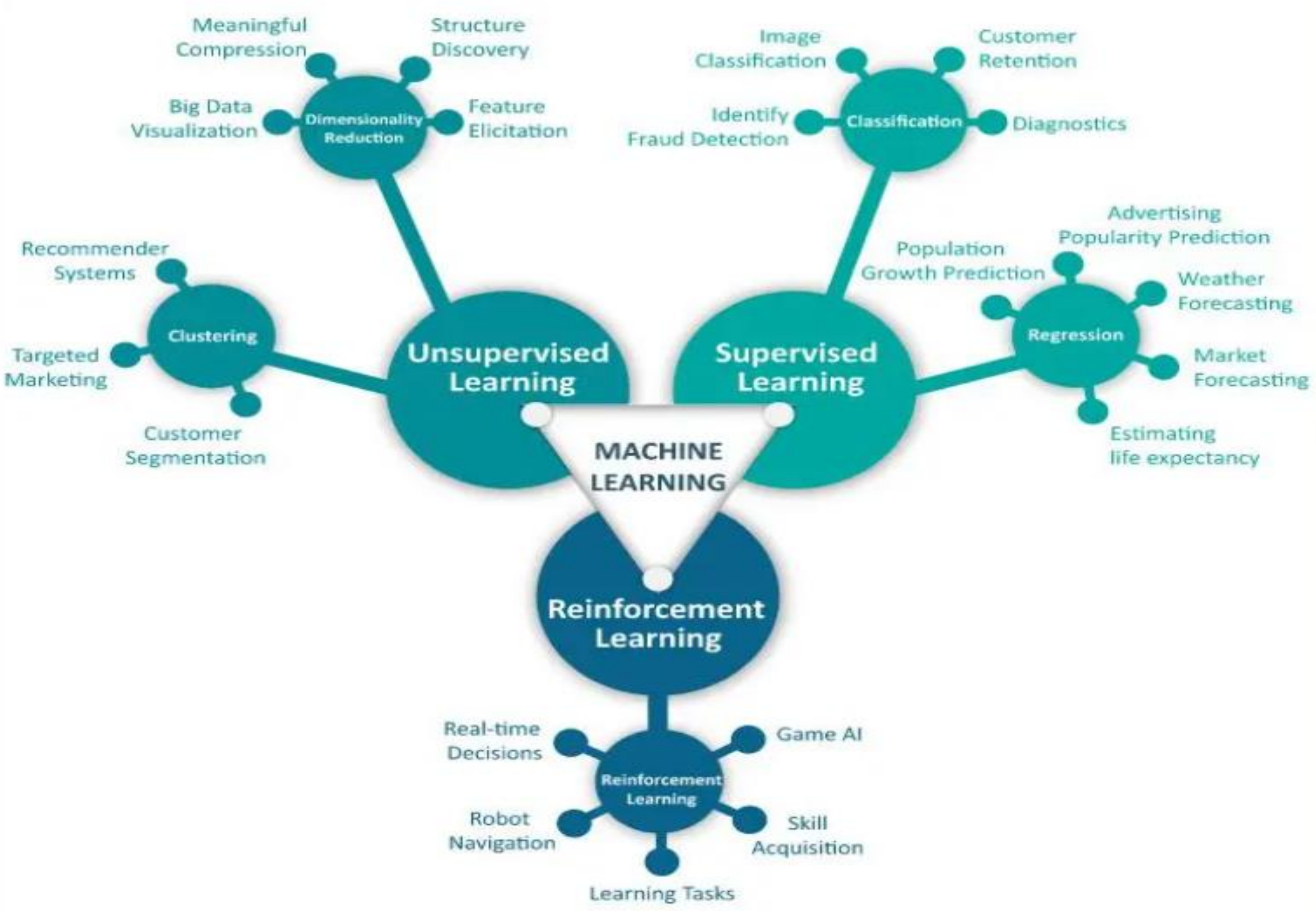
- Because RL agents can learn without expert supervision, the type of problems that are best suited to RL are complex problems where there appears to be no obvious or easily programmable solution.

- Two of the main ones are:

- ***Game playing*** — determining the best move to make in a game often depends on a number of different factors, hence the number of possible states that can exist in a particular game is usually very large.

- ***Control problems*** — such as elevator scheduling. Again, it is not obvious what strategies would provide the best, most timely elevator service. For control problems such as this, RL agents can be left to learn in a simulated environment and eventually they will come up with good controlling policies.

Learning Paradigms



Learning Paradigms

- **Semi Supervised learning**
- Semi-supervised learning (SSL) is a machine learning approach that falls between supervised and unsupervised learning.
- It uses a small amount of labeled data along with a large amount of unlabeled data to improve learning performance.
- **Key Characteristics**
  1. **Mix of Labeled & Unlabeled Data**: Uses a small subset of labeled data and a large amount of unlabeled data.
  2. **Bridges Supervised & Unsupervised Learning**: Uses labeled data for guidance while leveraging patterns in the unlabeled data.
  3. **Cost-Effective**: Reduces the need for large labeled datasets, which can be expensive and time-consuming to create.

Learning Paradigms

- **Semi Supervised learning**

- **Common Approaches in SSL**

1.Self-Training:

1. The model is first trained on the labeled data.
2. It then predicts labels for the unlabeled data.
3. The most confident predictions are added to the training set.

2.Consistency Regularization:

1. Encourages the model to produce consistent outputs for similar inputs, even with small perturbations.

3.Graph-Based Methods:

1. Uses graph structures where labeled and unlabeled samples are connected to propagate label information.

4.Generative Models (e.g., Variational Autoencoders, GANs):

1. Generate synthetic data to help the model learn better representations.

Learning Paradigms

- **Semi Supervised learning**
- **Why Use Semi-Supervised Learning?**
  - In real-world scenarios, labeled data is often limited because:
  - **Labeling is expensive and time-consuming** (e.g., medical diagnosis, speech transcription).
  - **A vast amount of unlabeled data is available** but cannot be used directly in supervised learning.
  - SSL helps by using **a small labeled dataset** to guide learning from **a large pool of unlabeled data**, improving model accuracy without requiring massive manual labeling efforts.

Learning Paradigms

- **Semi Supervised learning**
- **How Semi-Supervised Learning Works**
  - **Assumptions in SSL**
  - For SSL to work effectively, certain assumptions are made:
    1. **Smoothness Assumption**: Similar data points should have similar labels.
    2. **Cluster Assumption**: Data points tend to form clusters, and points in the same cluster likely share the same label.

  Manifold Assumption: High-dimensional data lies on a lower-dimensional manifold, making it possible to generalize from fewer labeled examples.
- **General Workflow of SSL**
  1. Train a model using labeled data.
  2. Use the trained model to predict labels for the unlabeled data.
  3. Select high-confidence predictions and add them to the training set.
  4. Retrain the model with both real and pseudo-labeled data.
  5. Repeat the process iteratively.

Learning Paradigms

- **Semi Supervised learning**
  - Techniques in Semi-Supervised Learning
  - **Self-Training**
    - A model is trained on labeled data.
    - It predicts labels for the unlabeled data.
    - High-confidence predictions are added to the labeled dataset for retraining.
    - Iteratively improves performance.
    - 🔹 *Example:* A spam classifier trained on 1,000 labeled emails can label 10,000 unlabeled emails, reinforcing its learning.
  - **Co-Training**
    - Two models are trained on different subsets of features.
    - Each model labels some unlabeled data for the other.
    - This mutual reinforcement improves learning.
    - 🔹 *Example:* A webpage classification model could use both **text content** and **hyperlinks** as independent feature sets for co-training.

Learning Paradigms

- **Semi Supervised learning**
  - Techniques in Semi-Supervised Learning
  - **Consistency Regularization**
    - Assumes that small perturbations in input data shouldn't change the model's predictions.
    - The model is trained to produce **consistent** outputs under noise or data augmentation.
    - 🔹 *Example:* In image classification, adding random transformations (rotation, blurring) should not change the predicted label.
  - **Graph-Based SSL**
    - Constructs a graph where nodes are data points and edges represent similarity.
    - Labeled data propagates labels to similar unlabeled data.
    - 🔹 *Example:* Social network analysis, where a few labeled users help classify others based on network structure.
  - **Generative Models**
    - Uses models like Variational Autoencoders (VAEs) or Generative Adversarial Networks (GANs) to generate synthetic labeled samples.
    - 🔹 *Example:* In medical imaging, GANs can create synthetic X-rays with labeled conditions, improving disease detection.

Learning Paradigms

- **Semi Supervised learning**
  - **Advantages of Semi-Supervised Learning**
    - ✅ **Reduces Labeling Costs** – Uses a small amount of labeled data efficiently.
✅ **Improves Accuracy** – Unlabeled data helps generalization.
✅ **Works in Real-World Scenarios** – Ideal when labeling is expensive or time-consuming.

Learning Paradigms

- **Semi Supervised learning**
  - **Applications of Semi-Supervised Learning**
    - **Computer Vision**
      - Image recognition with limited labeled images (e.g., **Google Photos**).
      - Object detection in **autonomous driving** (self-driving cars).
    - **Natural Language Processing (NLP)**
    - **Sentiment analysis** with limited labeled reviews.
    - **Spam detection** where only a few emails are manually labeled.
    - **Healthcare & Medical Diagnosis**

Learning Paradigms

- **Semi Supervised learning**
  - **Applications of Semi-Supervised Learning**
    - **Medical imaging** (MRI, X-rays) with limited labeled data.
    - **Drug discovery** by learning patterns in molecular structures.
    - **Speech & Audio Recognition**
    - **Speech-to-text models** (e.g., Google Assistant, Siri) trained on limited labeled speech samples.
    - **Music genre classification** with sparse labeled data.
    - **Cybersecurity**
    - **Fraud detection** using few known fraud cases and many unknown transactions.
    - **Malware detection** by learning from a mix of labeled and unlabeled software files.

Learning Paradigms

- **Semi Supervised learning**
  - **Challenges & Limitations of SSL**
    - ⚠️ **Incorrect Pseudo-Labeling** – If the model assigns wrong labels to unlabeled data, it can reinforce mistakes. ⚠️ **Sensitive to Data Assumptions** – Assumptions like smoothness or clustering may not hold in all cases. ⚠️ **Computational Cost** – Some methods (e.g., graph-based SSL) can be computationally expensive.


THANK
YOU