Introduction to Machine Learning

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What is Machine Learning?

- Machine learning is the process of extracting knowledge from data and lies at the **intersection of statistics, artificial intelligence, and computer science**.
- Its also known as predictive analytics or statistical learning, it is widely used in everyday applications like :
  - GUESS??

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  - facial recognition, and
  - product suggestions.
- Major websites like Facebook and Netflix heavily rely on machine learning.

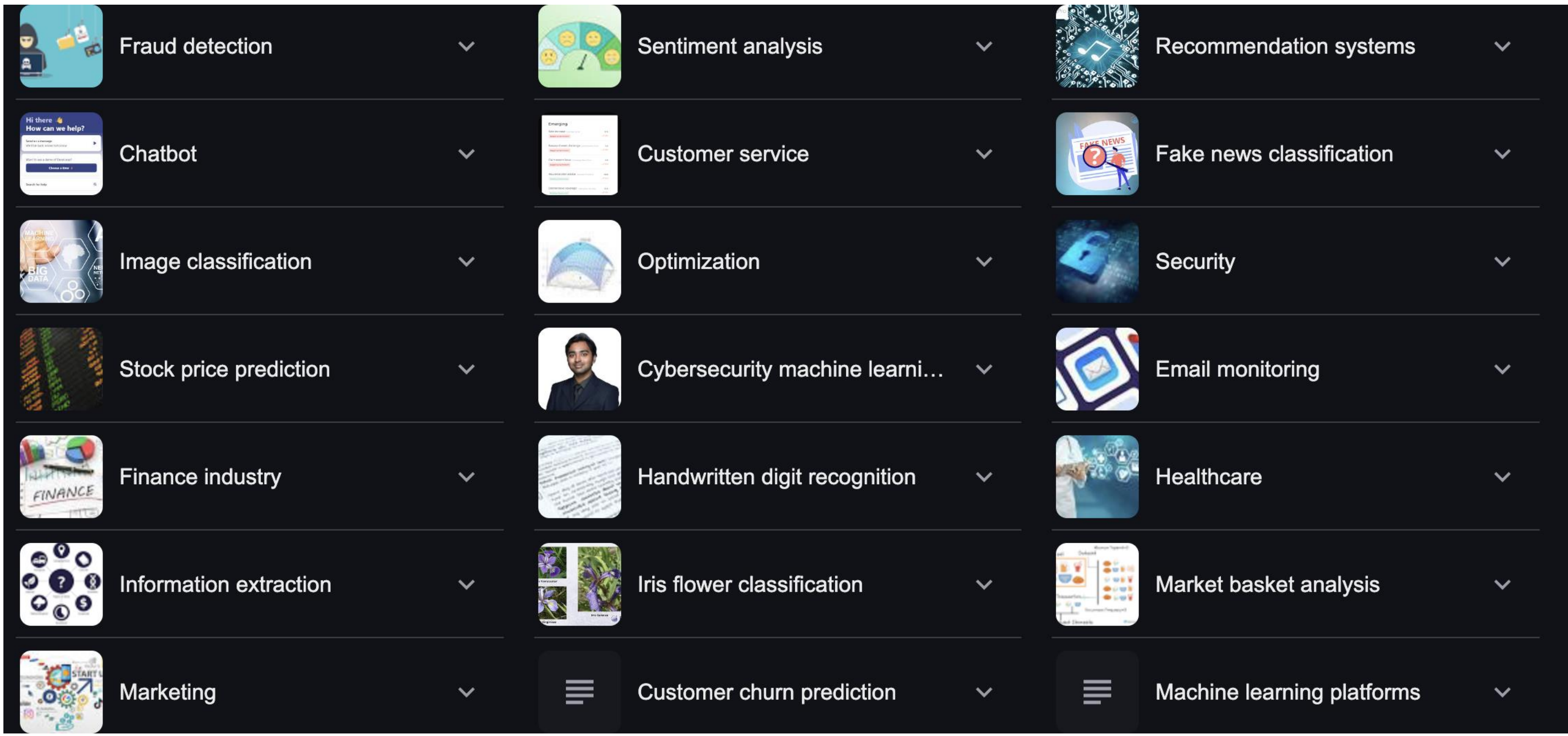
Scientific Research

- It plays a significant role in scientific research, aiding in discoveries in astronomy, genetics, and medicine.
- Even small-scale projects can benefit from machine learning.
  - GUESS?

1. Machine learning models can predict **sales trends and forecast future demand**, helping businesses optimize inventory and marketing strategies.
2. Identifying **customers at risk** of leaving can allow businesses to take proactive measures to retain them.
3. **Grouping customers based on their behaviour** and preferences can enable targeted marketing campaigns and personalized product recommendations.
4. Analysing **customer feedback** and social media mentions can provide insights into customer sentiment and **satisfaction levels.**
5. Identifying **suspicious transactions** and patterns can help businesses protect themselves from fraudulent activity.
6. **Automating customer service interactions** through chatbots can improve efficiency and customer satisfaction.
7. **Suggesting** relevant products or services based on user behavior can **enhance the customer experience.**
8. **Identifying unusual patterns** or events in data can help businesses detect potential problems or threats early on.
9. Using machine learning models to analyze images can be used for various applications such as **object detection, face recognition, and activity recognition.**
10. **Analysing text data** can be used for various tasks, such as sentiment analysis, topic modeling, and translation.
11. **Forecasting the failure of equipment** based on sensor data can help businesses plan for repairs and minimize downtime.
12. Predicting **optimize logistics**, **predict demand**, and **improve supply chain efficiency.**
13. Predicting the **quality of wine based** on various features can help winemakers optimize their production process.

1. **Sales Prediction:** Machine learning models can predict sales trends and forecast future demand, helping businesses optimize inventory and marketing strategies.
2. **Customer Churn Prediction**: Identifying customers at risk of leaving can allow businesses to take proactive measures to retain them.
3. **Customer Segmentation:** Grouping customers based on their behavior and preferences can enable targeted marketing campaigns and personalized product recommendations.
4. **Sentiment Analysis**: Analyzing customer feedback and social media mentions can provide insights into customer sentiment and satisfaction levels.
5. **Fraud Detection:** Identifying suspicious transactions and patterns can help businesses protect themselves from fraudulent activity.
6. **Chatbots:** Automating customer service interactions through chatbots can improve efficiency and customer satisfaction.
7. **Personalized Recommendations:** Suggesting relevant products or services based on user behavior can enhance the customer experience.
8. **Anomaly Detection:** Identifying unusual patterns or events in data can help businesses detect potential problems or threats early on.
9. **Image Recognition and Analysis:** Using machine learning models to analyze images can be used for various applications such as object detection, face recognition, and activity recognition.
10. **Natural Language Processing (NLP):** Analyzing text data can be used for various tasks, such as sentiment analysis, topic modeling, and translation.
11. **Predictive Maintenance:** Forecasting the failure of equipment based on sensor data can help businesses plan for repairs and minimize downtime.
12. **Supply Chain Optimization:** Machine learning models can optimize logistics, predict demand, and improve supply chain efficiency.
13. **Wine Quality Prediction**: Predicting the quality of wine based on various features can help winemakers optimize their production process.

Scientific Research



Why Machine Learning?

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Why is Machine Learning Important?

Automates Tasks

- ML can handle repetitive, time-consuming tasks without human intervention.
- Example: Email filtering, data entry, customer service chatbots.

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Improves Decision-Making

- ML helps businesses and individuals make better decisions by uncovering patterns in large datasets.
- Example: Risk assessment in finance, medical diagnosis support, personalized marketing.

Enhances Efficiency and Accuracy

- ML systems often outperform traditional methods in speed, accuracy, and scalability.

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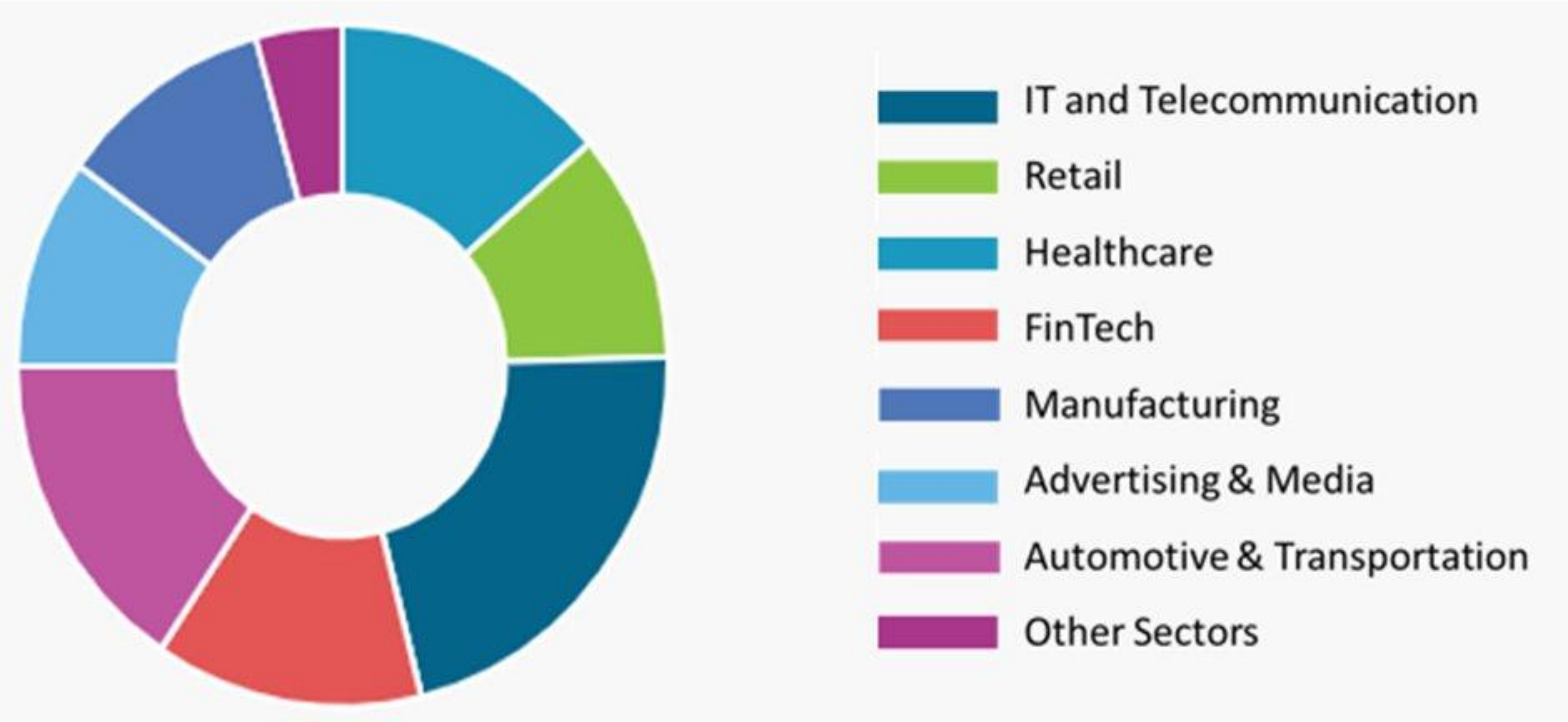
Global Machine Learning Market Share, 2021



Key Concepts in ML

1. Data:

- **Definition:** Raw facts, figures, and other information used to train ML models.
- **Types:** Structured (e.g., databases) and unstructured (e.g., images, text).
- **Importance:** ML models learn from data; the quality and quantity of data significantly impact model performance.

Key Concepts in ML

2. Algorithms:

- Definition: Sets of rules or instructions that guide the learning process and enable models to make predictions.
- Types: Supervised (predictive, e.g., regression, classification), unsupervised (exploratory, e.g., clustering, dimensionality reduction), and reinforcement learning (trial-and-error, e.g., game playing).
- Examples: Linear regression, decision trees, neural networks.

Key Concepts in ML

3. Models:

- Definition: Learned representations of patterns and relationships within the data, built by algorithms.
- Role: Models use the learned patterns to make predictions on new, unseen data.
- Types: Can be simple (e.g., a linear equation) or complex (e.g., a neural network).

Key Concepts in ML

4. Training:

- Definition:
- The process of feeding a model with data so it can learn patterns and make predictions.
- Process:
- Algorithms adjust their parameters based on the training data to minimize prediction errors.
- Goal:
- To create a model that can generalize well to unseen data and make accurate predictions.

Key Concepts in ML

5. Predictions:

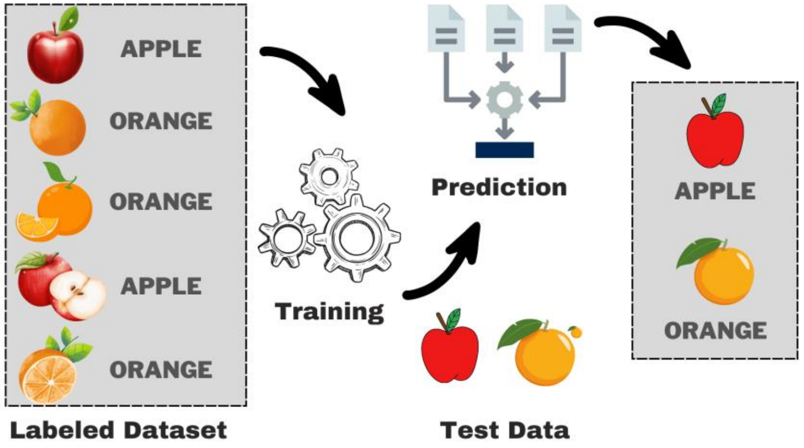
- Definition: The outputs generated by a model after it has been trained and used to make inferences on new data.
- Types: Can be numerical (e.g., price prediction), categorical (e.g., image classification), or other formats.
- Purpose: To help solve problems, make decisions, or understand trends in data.

Problems Machine Learning Can Solve

- The most successful kinds of machine learning algorithms are those that automate decision-making processes by generalizing from known examples.

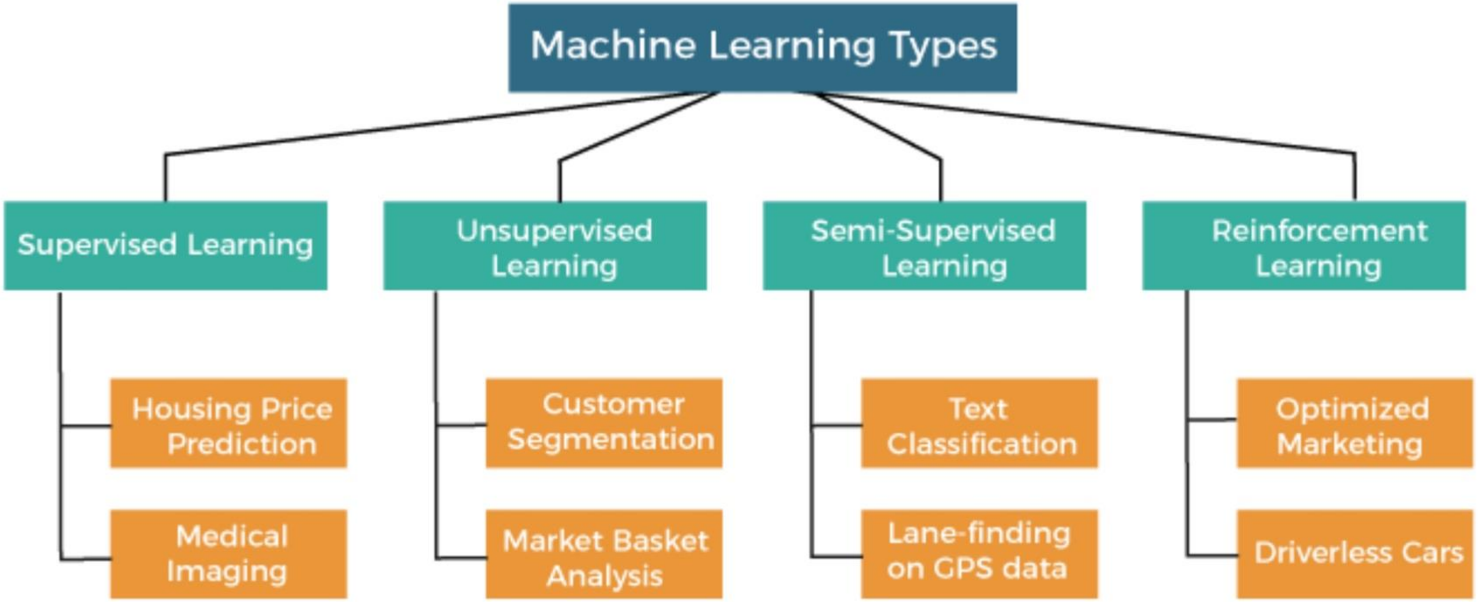
Known Examples to Accurate Predictions

- The user provides the algorithm with pairs of inputs and desired outputs, and the algorithm finds a way to produce the desired out-put given an input.



Its able to create an output for an input it has never seen before without any help from a human.

Types of Machine Learning



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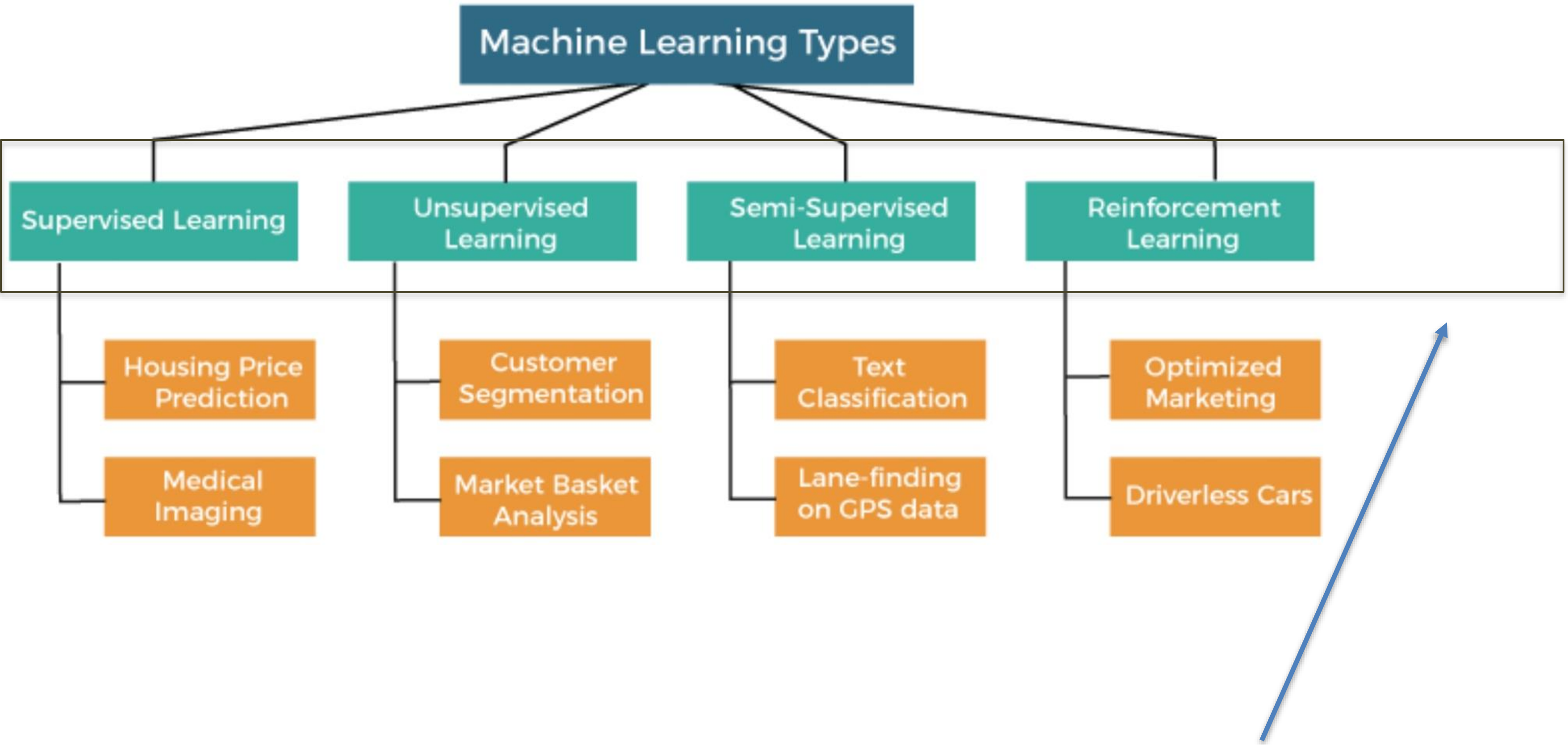


We will focus on these 4 types

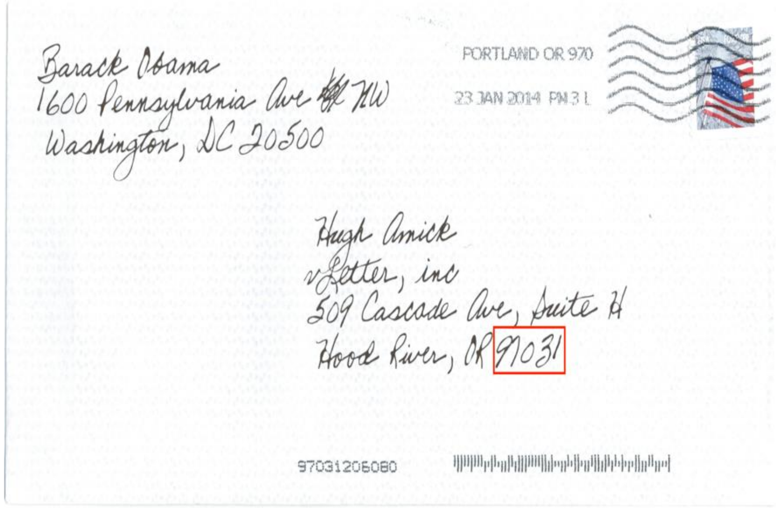
Supervised Learning

- Machine learning algorithms that learn from input/output pairs are called supervised learning algorithms because a “teacher” provides supervision to the algorithms in the form of the desired outputs for each example that they learn from.
- Your application can be formulated as a supervised learning problem, if you are able to create a dataset that includes the desired outcome, machine learning will likely be able to solve your problem.

Examples of Supervised Learning

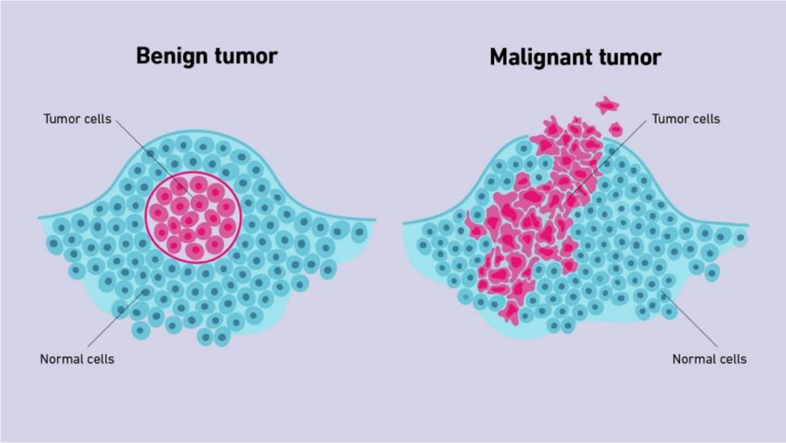
- Identifying the zip code from handwritten digits on an envelope or money in cheque.

- Here the input is a scan of the handwriting, and the desired output is the actual digits in the zip code.
- To create a dataset for building a machine learning model, you need to collect many envelopes.
- Then you can read the zip codes yourself and store the digits as your desired outcomes.



Examples of Supervised Learning

- Determining whether a tumor is benign based on a medical image:
  - Here the input is the image, and the output is whether the tumor is benign.
  - To create a dataset for building a model, you need a database of medical images.
  - You also need an expert opinion, so a doctor needs to look at all of the images and decide which tumors are benign and which are not.
  - It might even be necessary to do additional diagnosis beyond the content of the image to determine whether the tumor in the image is cancerous or not.



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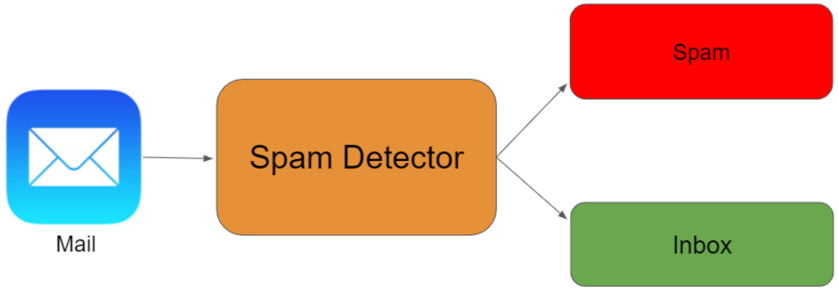
- Detecting fraudulent activity in credit card transactions :
  - Here the input is a record of the credit card transaction, and the output is whether it is likely to be fraudulent or not. Assuming that you are the entity dis- tributing the credit cards, collecting a dataset means storing all transactions and recording if a user reports any transaction as fraudulent.

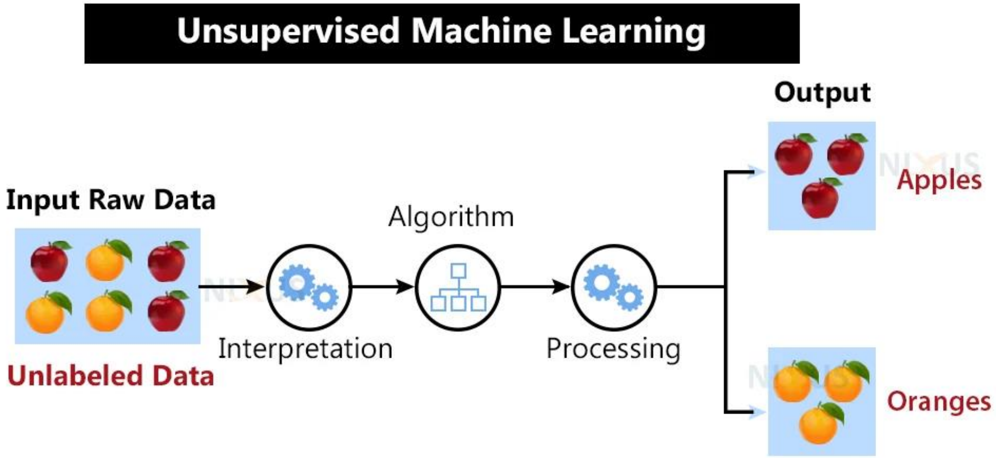
Spam Classification

- Using machine learning, the user provides the algorithm with a large number of emails (which are the input), together with information about whether any of these emails are spam (which is the desired output).
- Given a new email, the algorithm will then produce a prediction as to whether the new email is spam



Unsupervised Learning

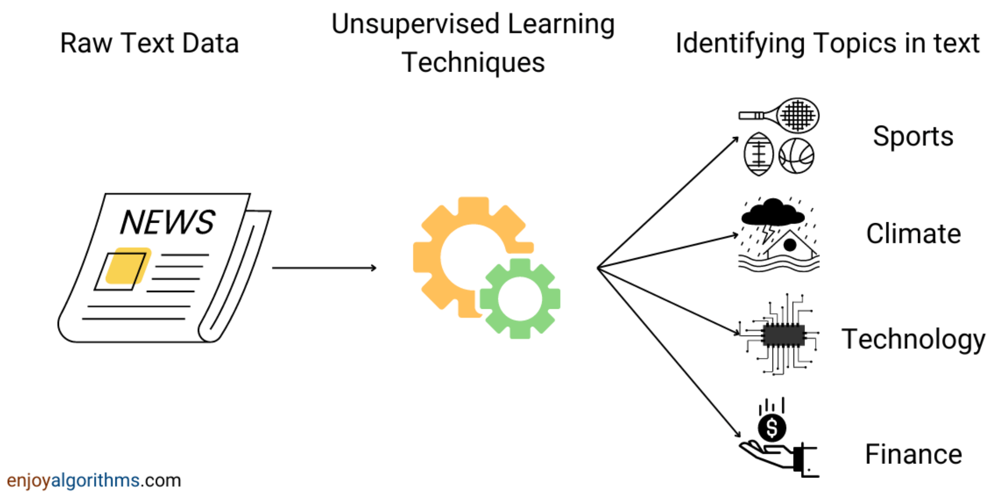
- In unsupervised learning, only the input data is known, and no known output data is given to the algorithm.
- **Goal:**
  - The primary goal is to uncover inherent patterns and relationships within the data, such as identifying natural groupings or clusters, finding correlations between variables, or reducing the complexity of the data.
- While there are many successful applications of these methods, they are usually harder to understand and evaluate.



Examples of unsupervised learning

Identifying topics in a set of blog posts:

- If you have a large collection of text data, you might want to summarize it and find prevalent themes in it. You might not know beforehand what these topics are, or how many topics there might be. Therefore, there are no known outputs.



Examples of unsupervised learning

Segmenting customers into groups with similar preferences

- Given a set of customer records, you might want to identify which customers are similar, and whether there are groups of customers with similar preferences.

Examples of unsupervised learning

Detecting abnormal access patterns to a website:

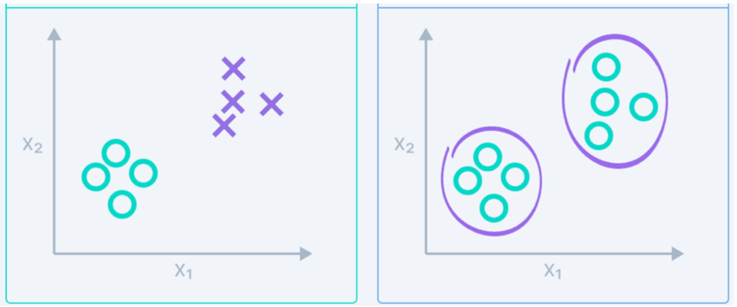
- To identify abuse or bugs, it is often helpful to find access patterns that are different from the norm.
- Each abnormal pattern might be very different, and you might not have any recorded instances of abnormal behaviour.
- Because in this example you only observe traffic, and you don't know what constitutes normal and abnormal behaviour.

Differences between Supervised and Unsupervised

?

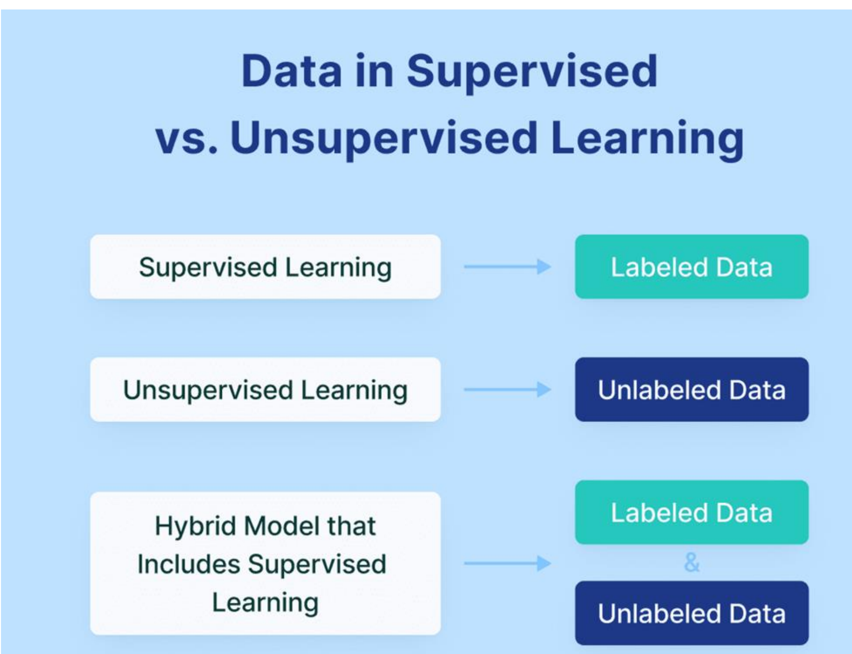
Differences

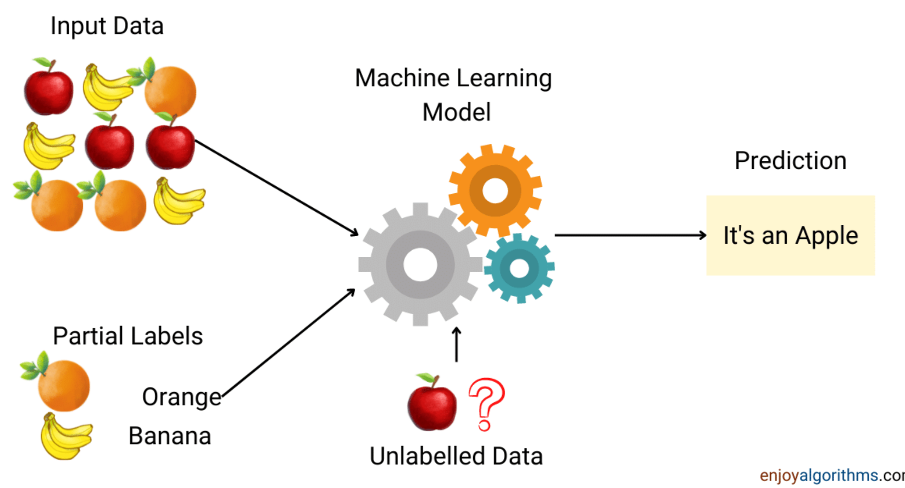
Supervised learning	Unsupervised learning
Input data is labeled	Input data is unlabeled
Has a feedback mechanism	Has no feedback mechanism
Data is classified based on the training dataset	Assigns properties of given data to classify it
Divided into Regression & Classification	Divided into Clustering & Association
Used for prediction	Used for analysis
Algorithms include: decision trees, logistic regressions, support vector machine	Algorithms include: k-means clustering, hierarchical clustering, apriori algorithm
A known number of classes	A unknown number of classes



Semi-Supervised Learning

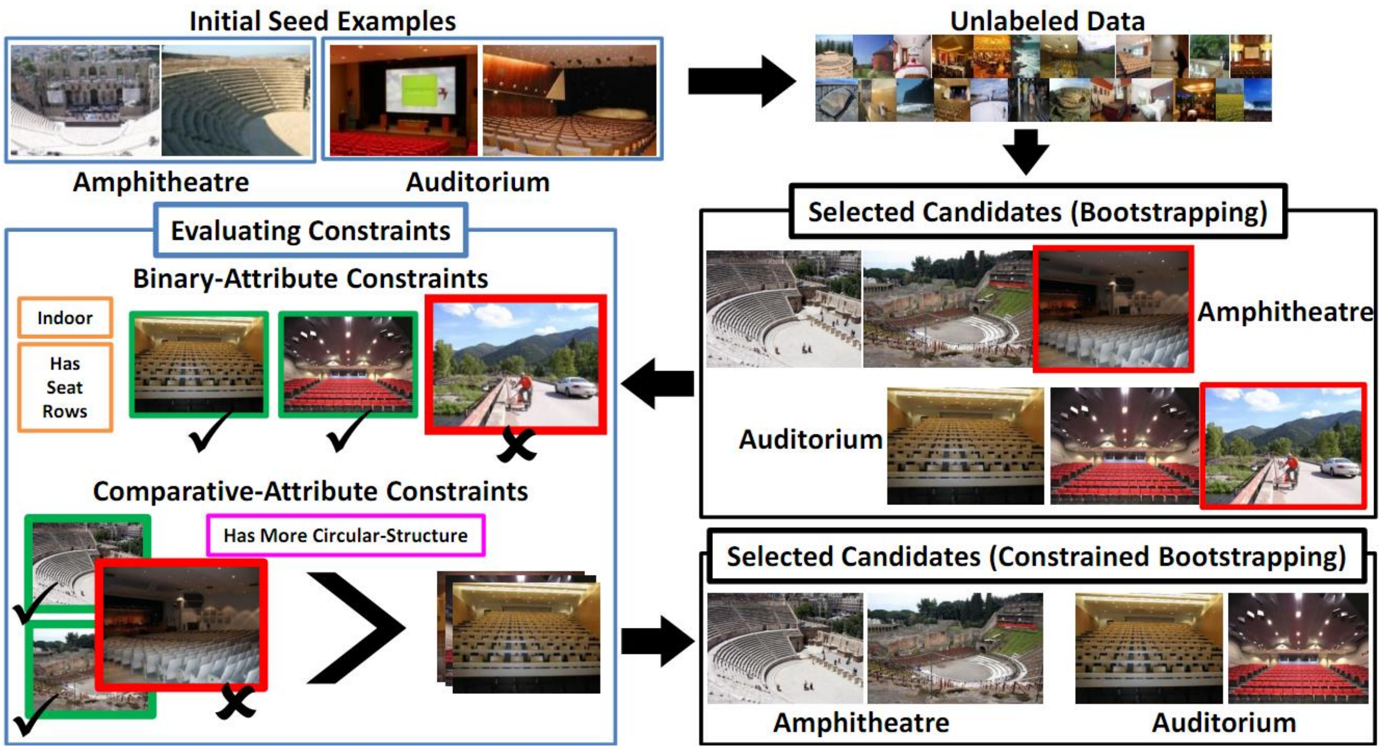
- Semi-supervised learning combines supervised and unsupervised learning by using both labeled and unlabeled data to train artificial intelligence (AI) models for a particular tasks.
- Semi-supervised learning methods are especially relevant in situations where obtaining a sufficient amount of labelled data.





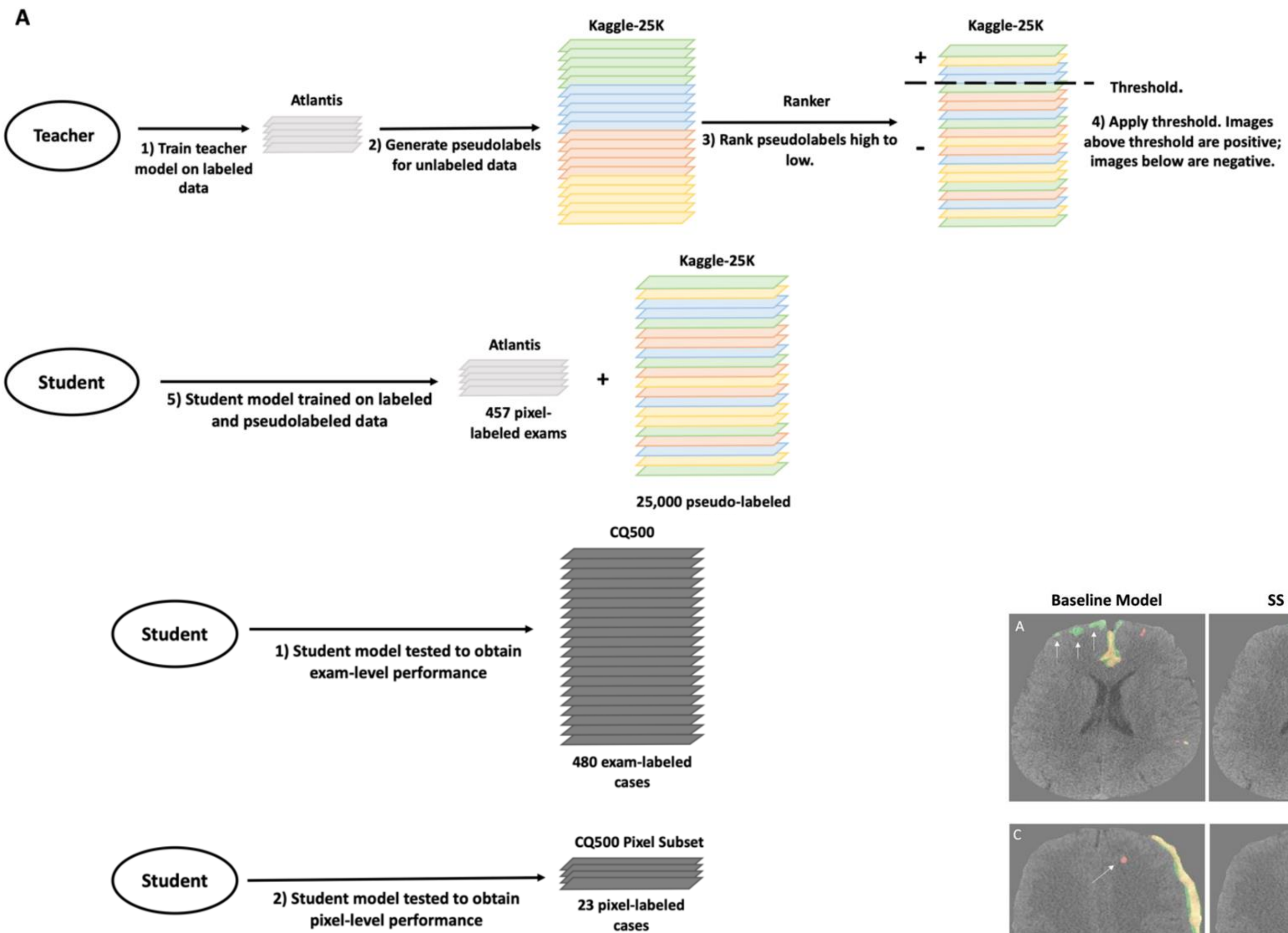
semi-supervised learning for scene categorization

- Strong interactions that often exist between scene categories.
- Such as the common attributes shared across categories as well as the attributes which make one scene different from another



https://videolectures.net/videos/eccv2012_shrivastava_attributes

Semi-supervised Learning for Generalizable Medical Image Hemorrhage Detection and Segmentation



Schematic of the semi-supervised Noisy Student approach. Each color signifies data from a different institution.

A) Workflow at training time,
B) Workflow at test time as the student model is evaluated on both dataset

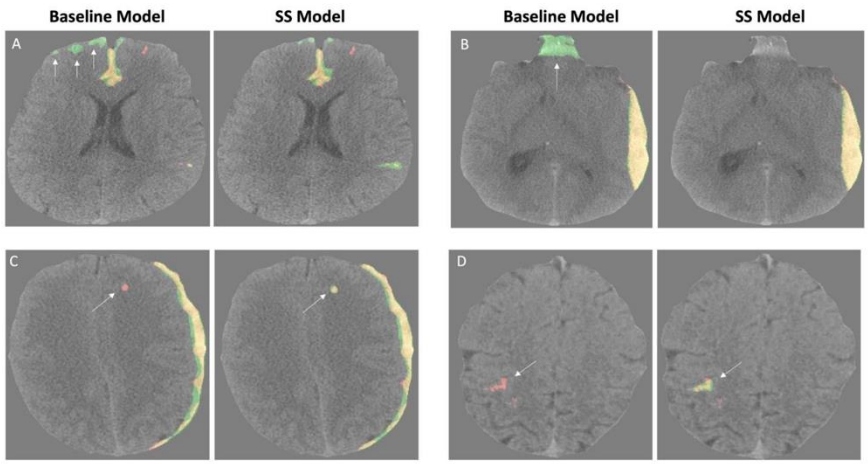


Figure 3. Visualization of model predictions on the validation set using the baseline and semi-supervised (SS) models. Red is the reference standard label, green is the model's positive prediction, and yellow is the overlap. These are axial CT images obtained without contrast.

https://arxiv.org/pdf/2105.00582

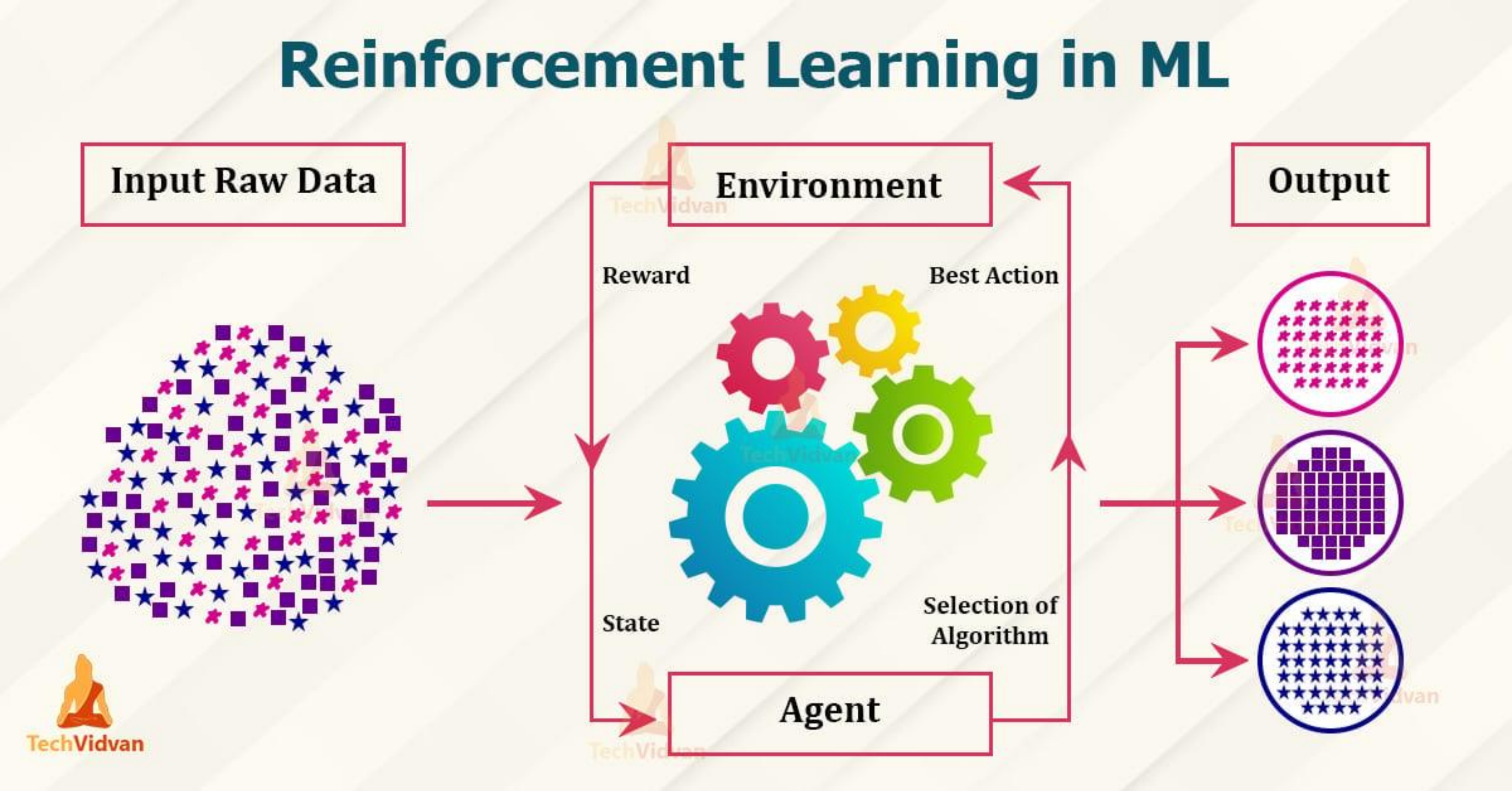
Supervised vs Semi-supervised Learning

Key Differences:

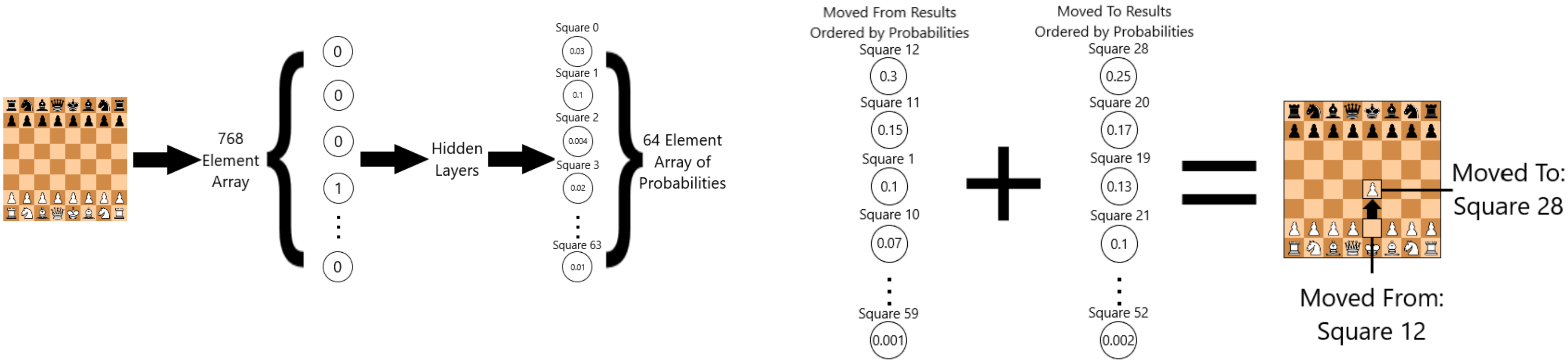
Aspect	Supervised Learning	Semi-supervised Learning
Data Used	Uses **only labeled data**	Uses **both labeled and unlabeled data**
Training Focus	Trained fully on labeled examples	Initially trained on labeled data, then refined with unlabeled data
Labeling Cost	Requires a large amount of labeled data	Can perform well with a small amount of labeled data and a lot of unlabeled data
Handling of Unlabeled Data	Not used at all	Leverages unlabeled data for more accurate predictions
Complexity	Easier to implement but needs more labeled data	More complex but cost-effective when labeled data is scarce
Example	Image classification with all images labeled	Text classification with few labeled reviews and many unlabeled ones

Reinforcement Learning

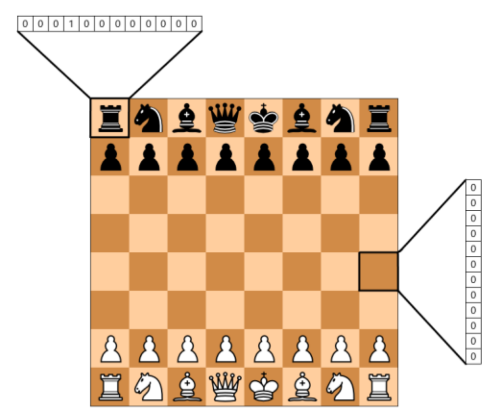
- The essence of Reinforcement Learning is based on learning through environmental interaction, as well as through adapting to, learning from, and calibrating future decisions based on mistakes.
- Agents learn by interacting with an environment and receiving rewards.



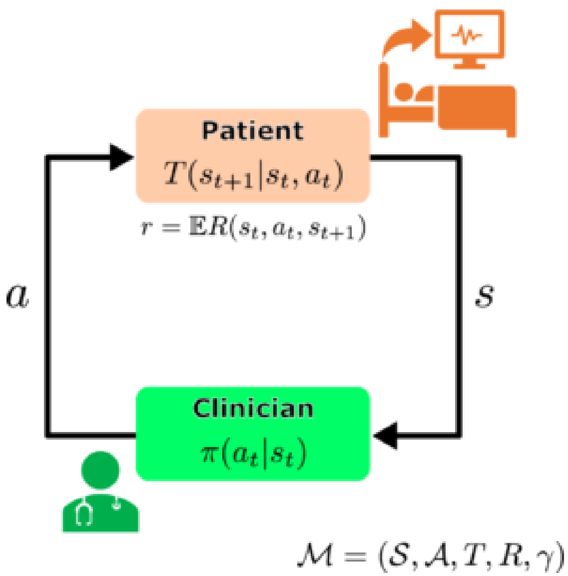
Predicting Professional Players’ Chess Moves



- On every move *s*, a number of *simulations* are run. Think of simulations as mini-games the agent plays against itself to see which moves result in the most favourable outcomes.
- Each simulation entails executing the following algorithm until the first position that has not been visited by any of the previous simulations is encountered:
- Out of all the legal moves in the current position, select the most productive one.



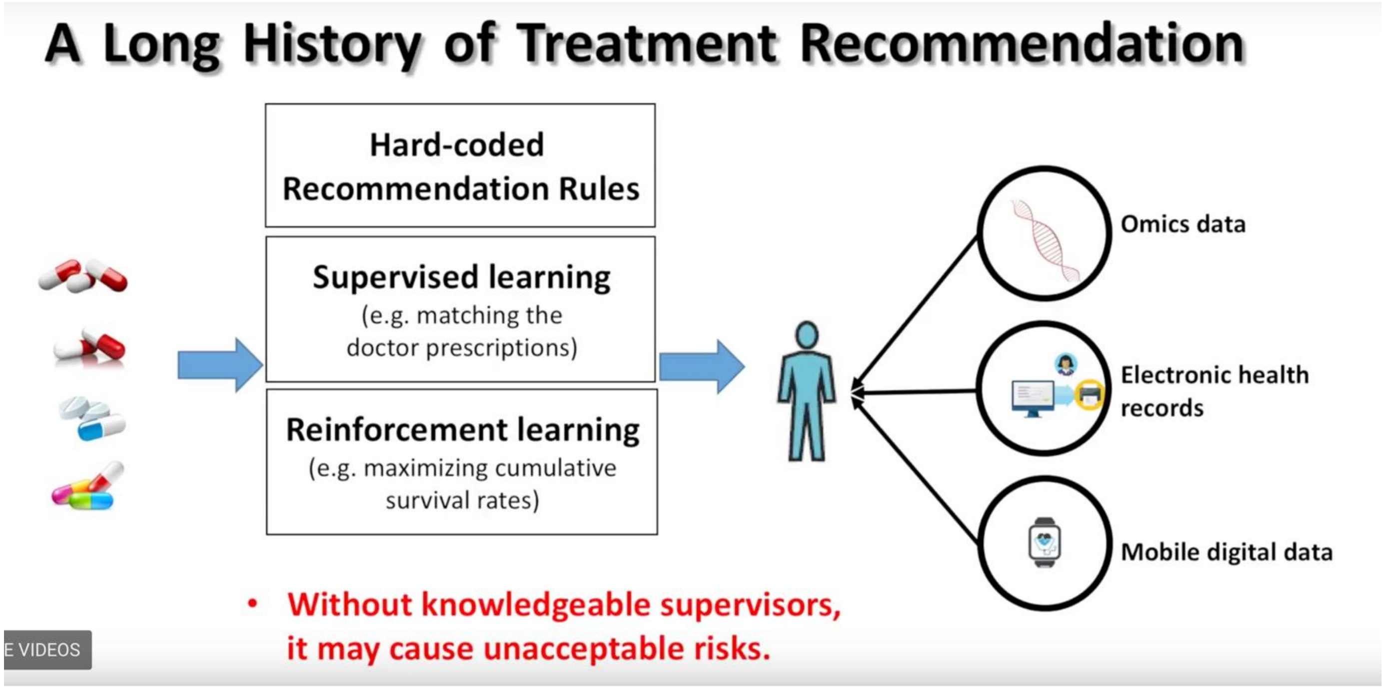
Reinforcement learning in healthcare



Sequential decision-making in healthcare:

- Clinicians or AI agents observe the state of the patient (s),
- select a treatment (a), and monitor the next state.
- The process then repeats.
- As a result of each such transition of the patient's state (whose probability is denoted by T), a reward signal (R) is observed,
- which accounts for the immediate consequence of the applied treatment.

Reinforcement learning in healthcare



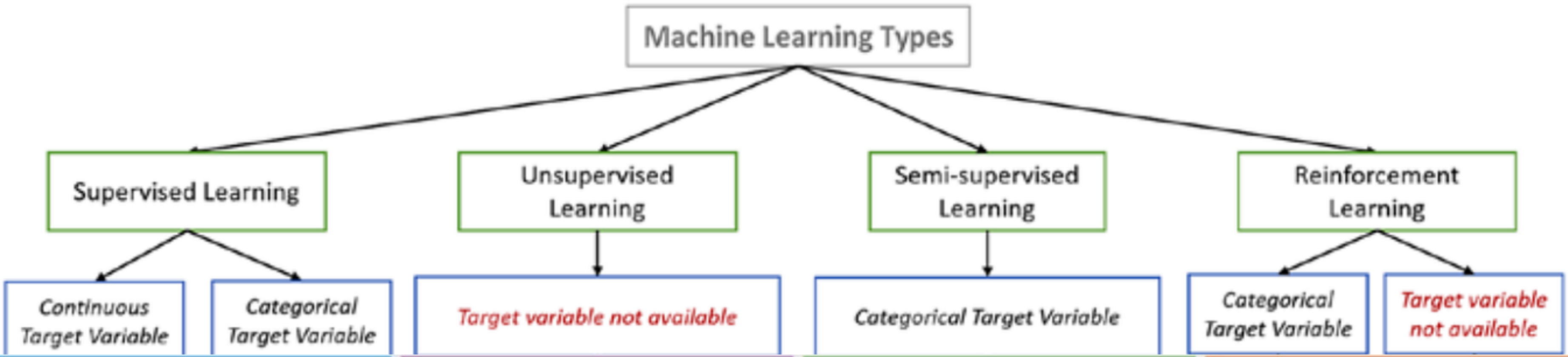
- Finding treatment scenarios made by the physician that match or nearly match the learned policy.
- We then calculate the reward based on the results of these actual treatments.
- A problem with this approach is that, in many cases, the actual number of "non-zero importance weights is very small."
- What this means is essentially, if the learned policy suggests treatments (or lack thereof) that physicians would never do then you will have problems evaluating the policy because there will be no similiar histories where we actually have the outcomes with which to compare.

Challenges in RL

- Importance Critera
  - Selecting good evaluation metrics is important because, in certain scenarios, an agent may learn to associate treatments with negative consequences due to the majority of treated patients having adverse outcomes. This is due to the lack of data on non-treated patients.
- Partial observability
  - Unlike in many games in medicine we are almost never able to observe everything going on in the body. We can take blood pressure, temperature, SO2, and simple measures at almost every interval but these are all signals and not the ground truth about the patient.
- Reward function
  - Finding a good reward function is challenging in many real world problems. Healthcare is no exception to this as it is often hard to find a reward function that balances short-term improvement with overall long-term success.
- RL is data hungry
  - Almost all the major breakthroughs in deep RL have been trained on years worth of simulated data.

Algorithm Type	Purpose	Learning Approach	Common Use Cases	Advantages	Disadvantages
Supervised	Predict outcomes from labeled data	Learns from labeled input-output pairs	Spam detection, stock price prediction, fraud detection	High accuracy, easy to understand and deploy	Requires large labeled datasets, time-consuming labeling
Unsupervised	Find patterns in data without labels	Discovers hidden structures in unlabeled data	Customer segmentation, anomaly detection, recommendation systems	Effective with unstructured data, no labeling required	Results can be less interpretable, difficult to validate
Semi-Supervised	Mix of supervised and unsupervised learning	Partially labeled training data	Speech recognition, text classification, bioinformatics	Less labeled data needed, balances learning complexity	Potential for biased results from insufficient labels
Reinforcement	Optimize decision-making over time	Trial and error with feedback loop	Self-driving cars, robotics, game AI	Adapts to dynamic environments, learns autonomously	Computationally expensive, slow learning process

Sub Algorithms For Each Type



Supervised learning

Data scientists provide input, output and feedback to build model (as the definition).

EXAMPLE ALGORITHMS:

Linear regressions
- Sales forecasting.
- Risk assessment.

Support vector machines
- Image classification.
- Financial performance comparison.

Decision trees
- Predictive analytics.
- Pricing.

Unsupervised learning

Use deep learning to arrive at conclusions and patterns through unlabeled training data.

EXAMPLE ALGORITHMS:

Apriori
- Sales functions.
- Word associations.
- Searcher.

K-means clustering
- Performance monitoring.
- Searcher intent.

Artificial neural networks
- Generate new, synthetic data.
- Data mining and pattern recognition.

Semi-supervised learning

Builds a model through a mix of labeled and unlabeled data, a set of categories, suggestions and exampled labels.

EXAMPLE ALGORITHMS:

Generative adversarial networks
- Audio and video manipulation.
- Data creation.

Self-trained Naïve Bayes classifier
- Natural language processing.

Reinforcement learning

Self-interpreting but based on a system of rewards and punishments learned through trial and error, seeking maximum reward.

EXAMPLE ALGORITHMS:

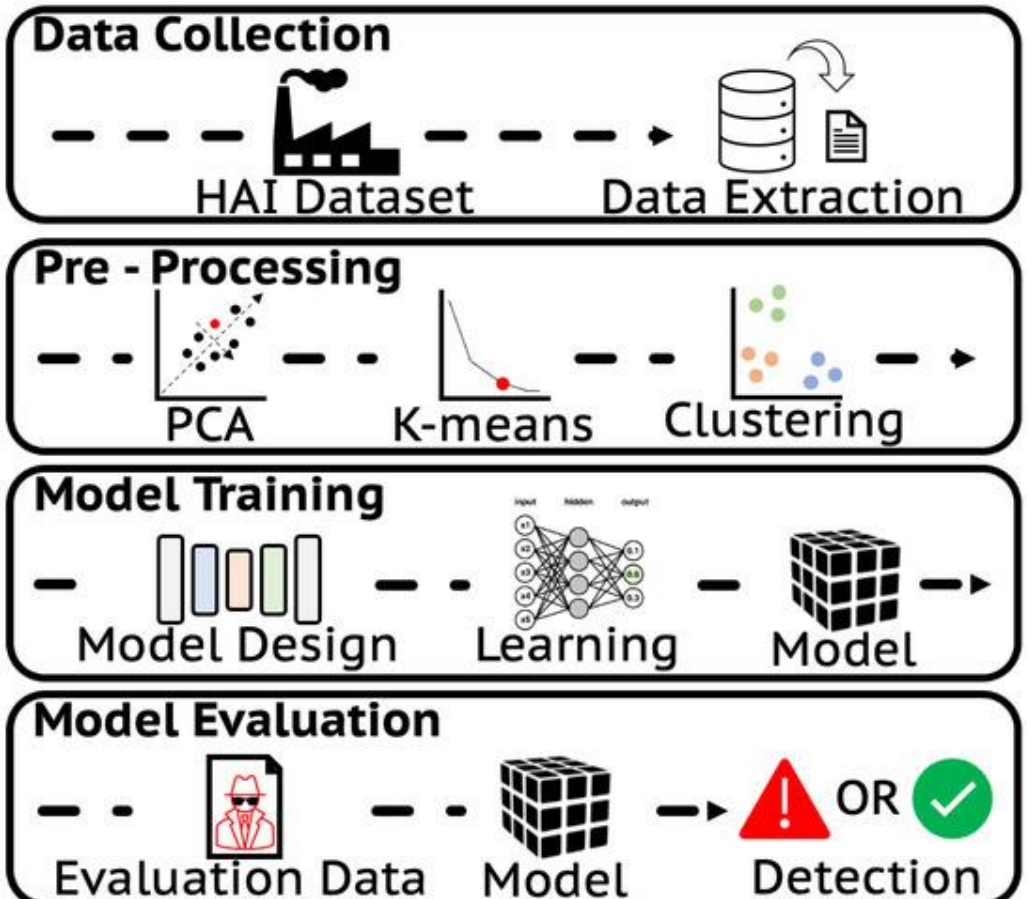
Q-learning
- Policy creation.
- Consumption reduction.

Model-based value estimation
- Linear tasks.
- Estimating parameters.

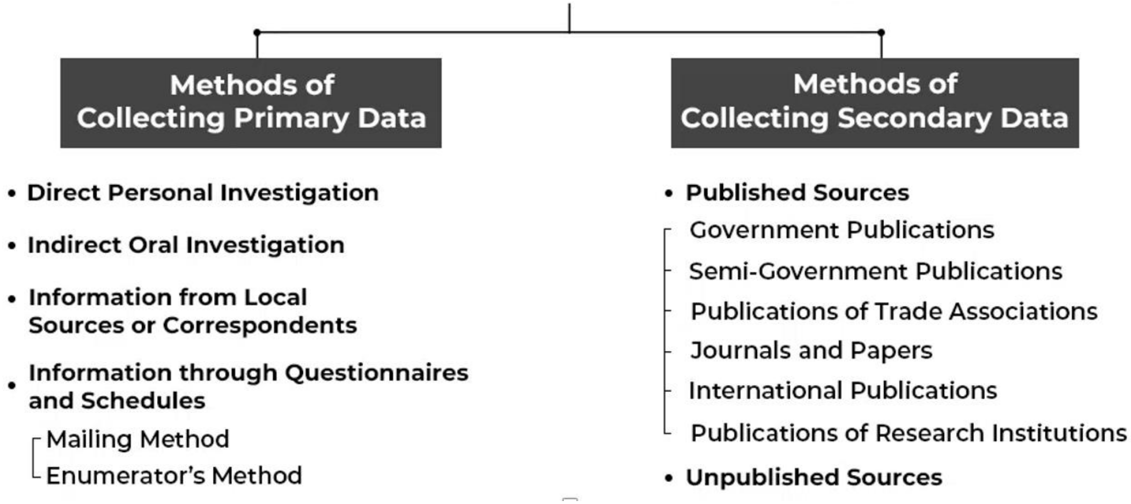
Machine Learning Pipeline

- The structured process of developing ML models.

1. Data Collection,
2. Preprocessing,
3. Feature Engineering,
4. Model Selection,
5. Training, Evaluation, and
6. Deployment.



Step 1: Data Collection



Data collection is a critical step in understanding and utilizing data for various purposes, including research, business intelligence, and machine learning.

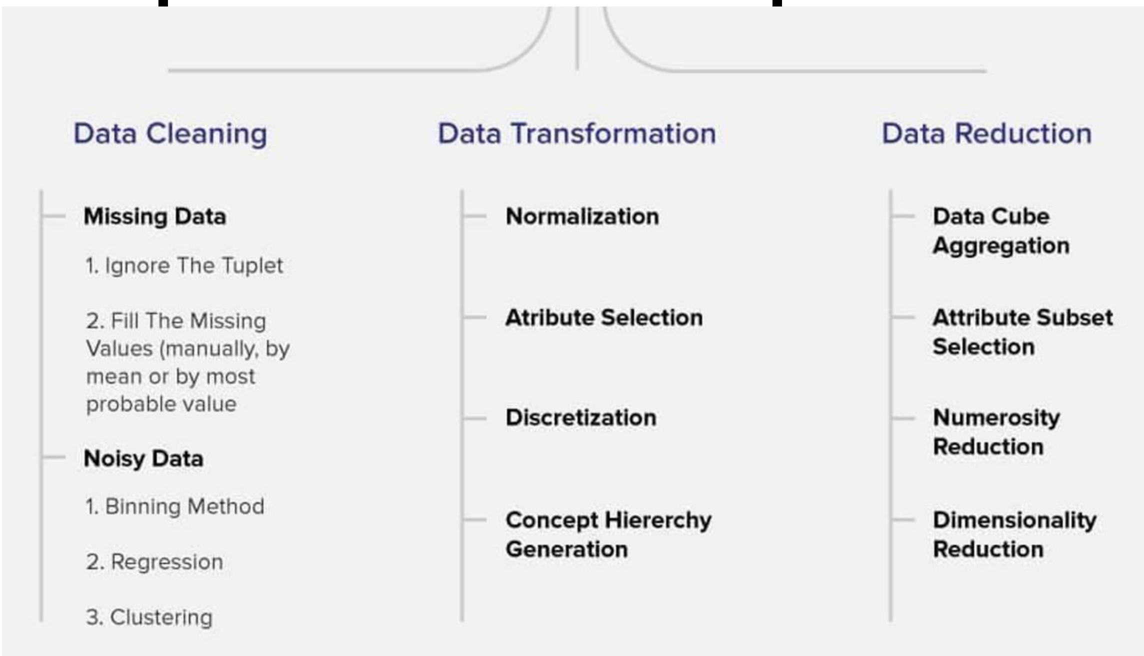
Identifying data sources: Determining where the relevant raw data is located, such as databases, sensors, customer surveys, or external APIs.

Collecting data: Employing various methods like manual entry, online surveys, or data extraction from databases and documents.

Ensuring data quality: Verifying the accuracy, completeness, and relevance of the collected data to avoid biases and ensure meaningful analysis.

Storing and organizing data : Preparing the data for further processing, including cleaning, transformation, and integration into a suitable format.

Step 2: Data Preprocessing



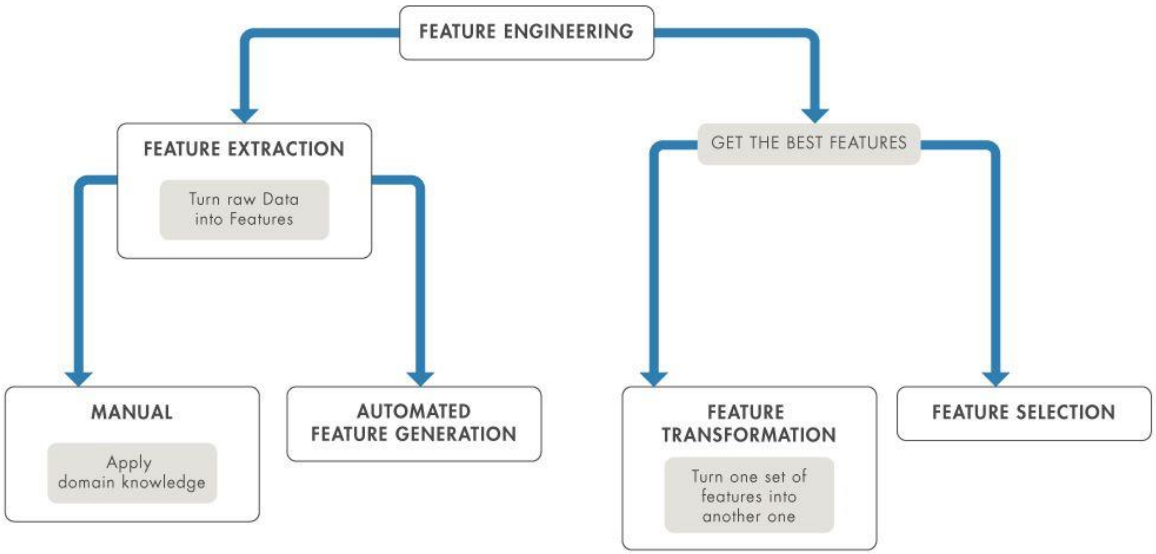
Improved Model Accuracy: Clean and preprocessed data leads to more accurate machine learning models.

Enhanced Model Efficiency : By reducing the amount of data and simplifying its structure, preprocessing can improve model training speed and performance.

Better Data Understanding: Preprocessing helps to identify patterns and trends in the data, making it easier to interpret and analyze.

Avoids Errors and Bias: Addressing data quality issues early on prevents errors and biases that can lead to inaccurate results

Step 3: Feature Engineering



Feature creation: Generating new features from existing ones, such as combining variables or creating interaction terms.

Feature transformation: Modifying existing features to improve their suitability for the model, such as scaling or normalization.

Feature extraction: Using techniques like PCA to reduce dimensionality and identify important features.

Feature selection: Choosing the most relevant features for the model, potentially discarding irrelevant or redundant one.

Step 4: Model Selection

Candidate Models: Identify a range of potential models that could be suitable for the problem.

Performance Evaluation: Assess the performance of each candidate model using appropriate metrics, such as accuracy, precision, recall, or F1-score.

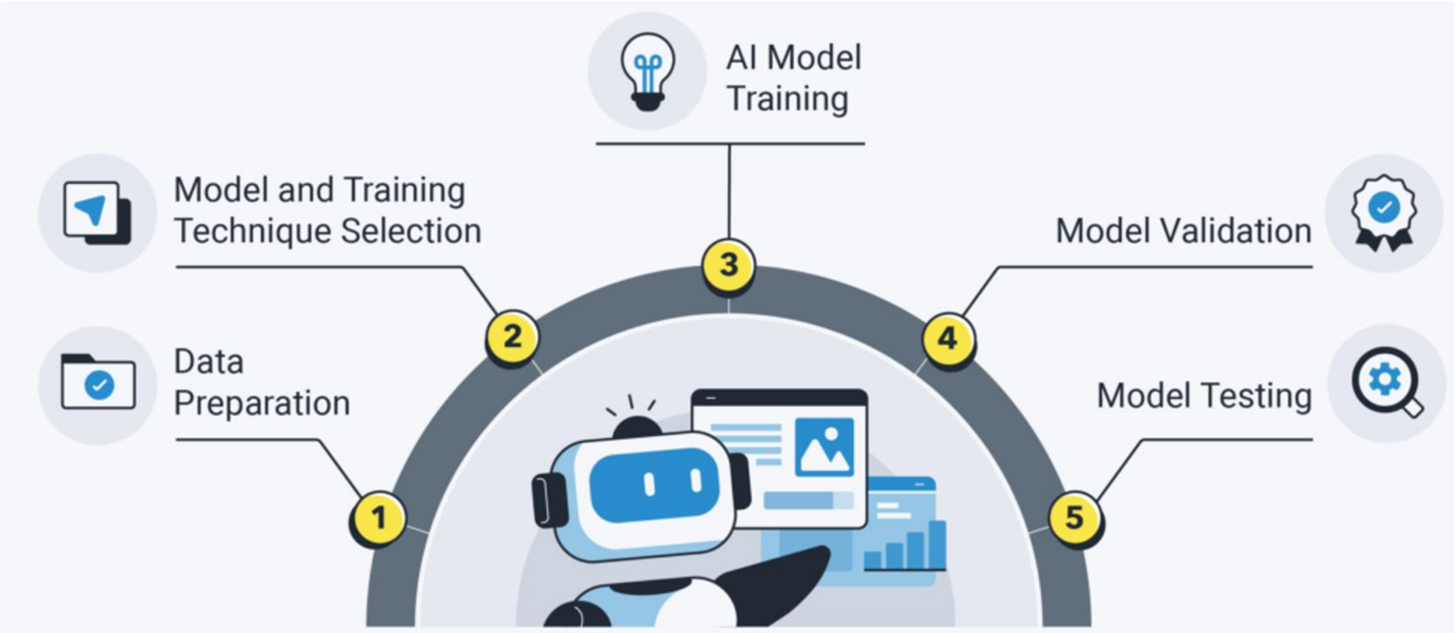
Model Selection: Choose the model that performs best across the evaluation criteria and aligns with the specific needs of the task.

Bias-Variance Tradeoff: Model selection seeks to find a balance between bias (underfitting) and variance (overfitting).

Model Complexity: Simpler models are generally preferred if they achieve comparable performance to more complex models.

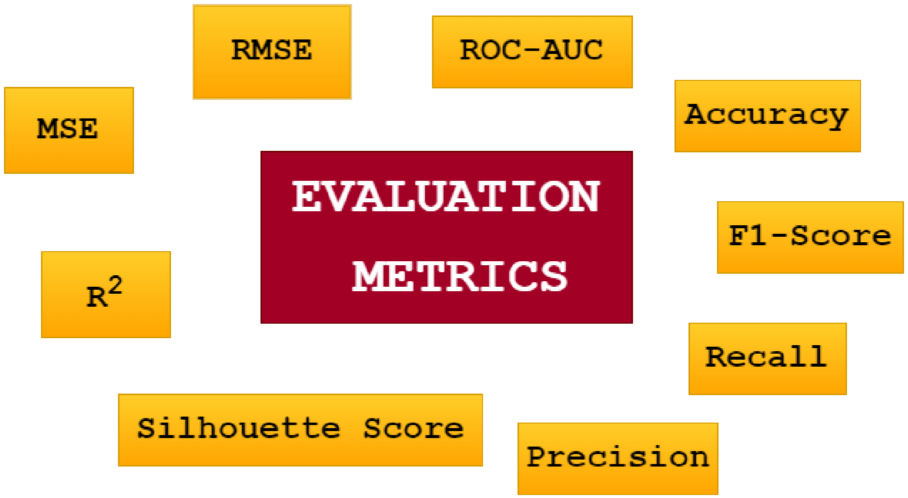
Data Availability: The amount and quality of data available can influence the selection of an appropriate model.

Step 5: Model Training



- Teaching the model to recognize patterns in data.
- The algorithm then adjusts its internal parameters (like weights and biases) to make predictions or perform other tasks.
- The goal is to find the best combination of parameters that minimizes a loss function, which measures how well the model is performing.

Step 6: Model Evaluation



Ensuring Model Performance: It helps determine if the model is accurate and reliable in making predictions.

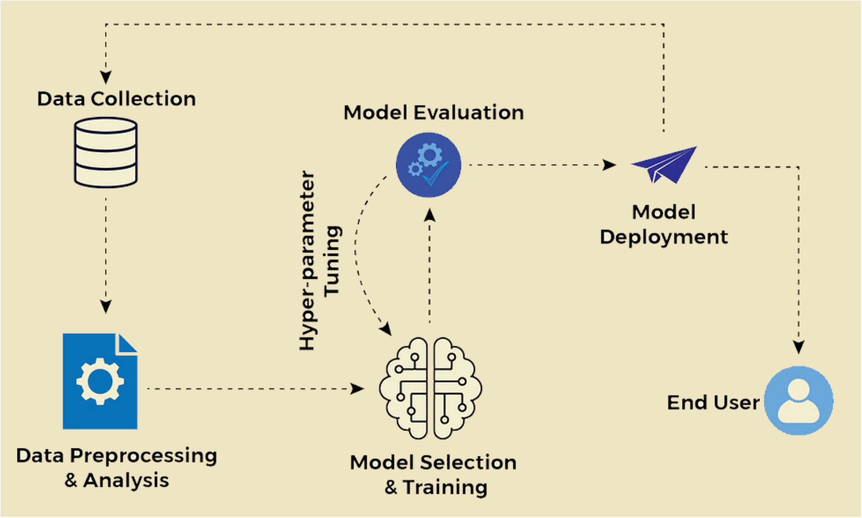
Identifying Weaknesses: It helps pinpoint areas where the model is struggling, allowing for targeted improvements.

Guiding Model Development: The results of evaluation provide valuable insights for refining the model and its parameters.

Generalization Assessment: It assesses how well the model can generalize to unseen data, indicating its ability to perform in real-world situations.

Comparing Models: It allows for comparing different models and selecting the one that performs best for a specific task.

Step 7: Model Deployment



Transition to Production: It's the phase where the model moves from being tested and refined to being used in a live, production environment.

Model Accessibility: It ensures that the model can be accessed and utilized by other systems, applications, or users who need to make predictions or decisions based on its output.

Inference and Predictions: Once deployed, the model can perform inference, which is the process of using the model to make predictions or generate insights based on new input data.

Real-time or Batch Processing: Deployments can be set up for real-time inference (e.g., predicting fraud in real-time transactions) or for batch processing (e.g., running predictions on large datasets overnight).

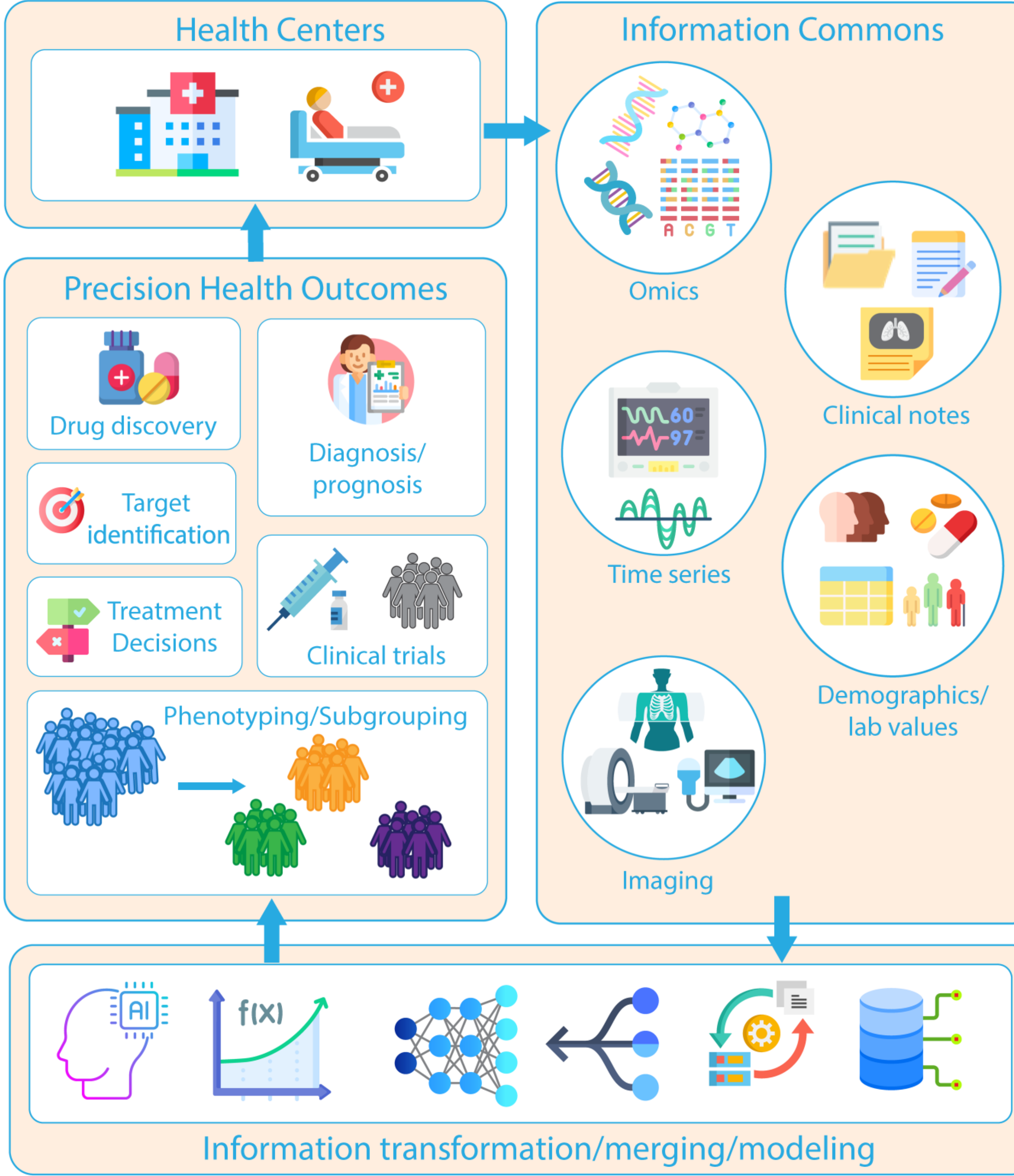
Integration with Applications: Deployments often involve integrating the model into existing applications or services to enable users to interact with it.

Scalability and Reliability: Deployments need to be designed with scalability in mind, allowing the model to handle increasing workloads and ensure its reliability and performance in the production environment.

Monitoring and Maintenance: After deployment, the model needs to be monitored to track its performance, detect any issues, and potentially retrain or update it as needed.

ML in Healthcare

Disease diagnosis, Personalized medicine, and Drug discovery.



ML in Finance

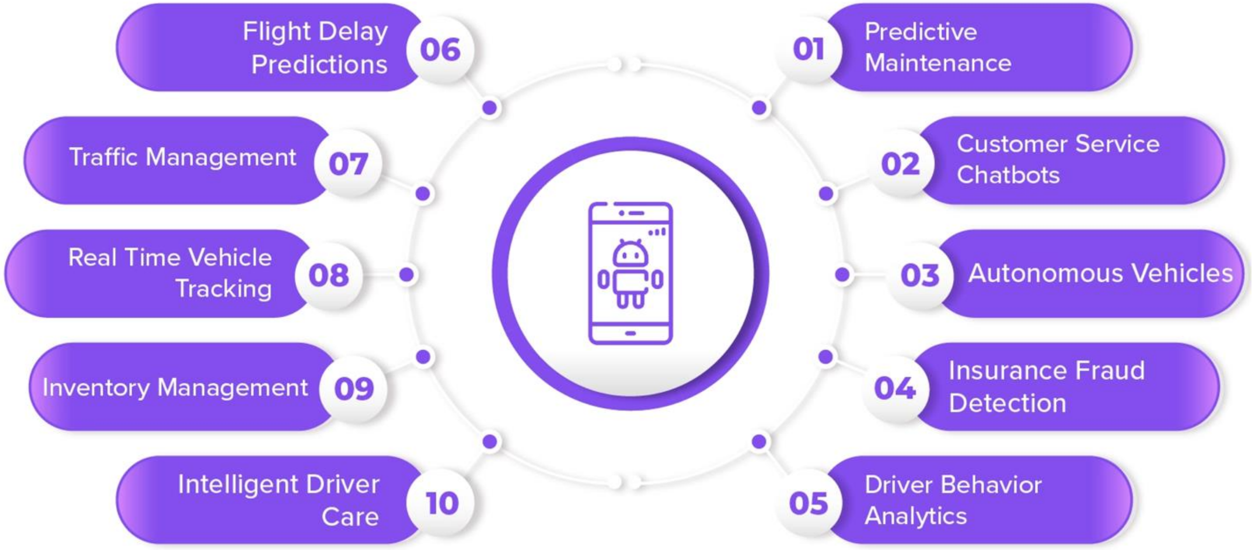
- Fraud detection, Credit scoring, and Algorithmic trading.

ML in Retail

Customer recommendations, Demand forecasting, and Inventory management.

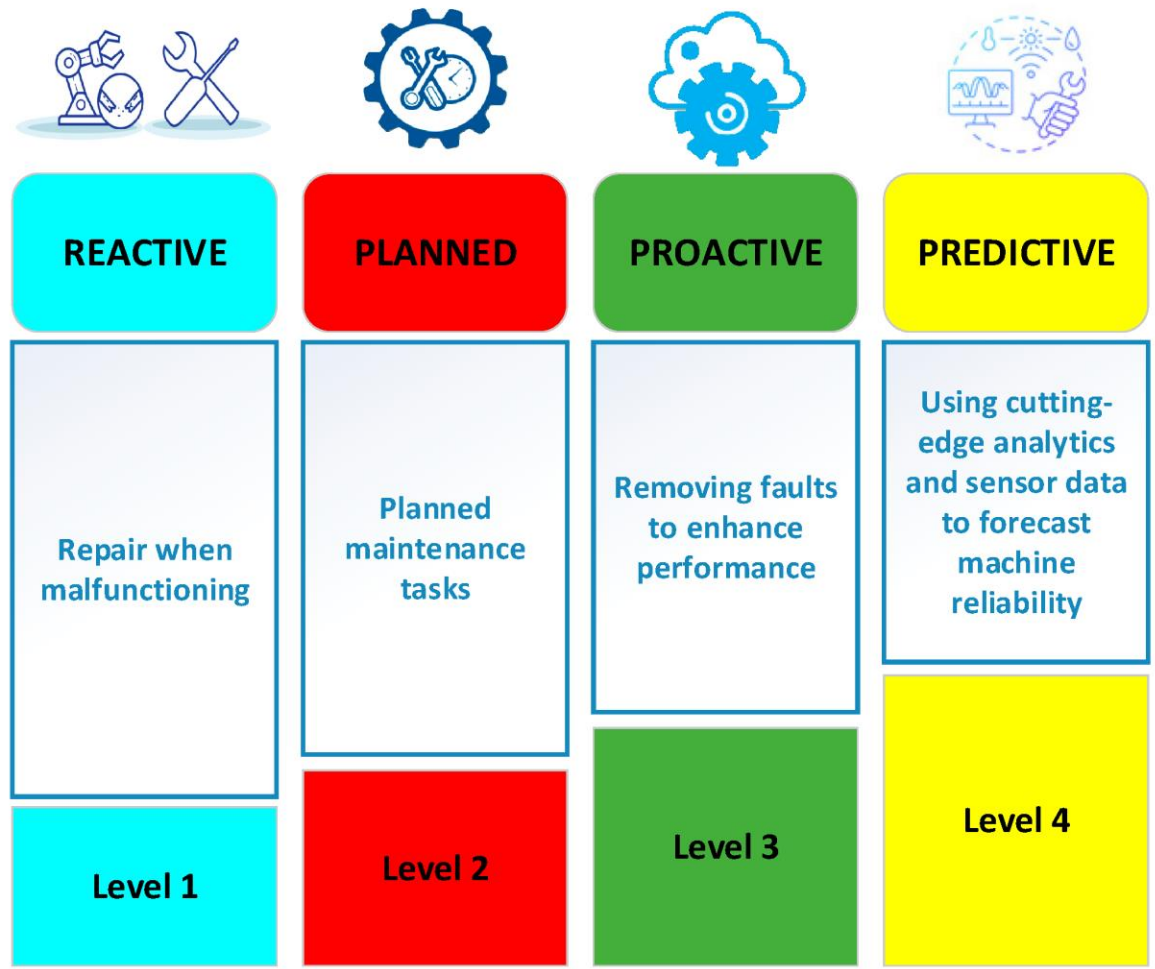
ML in Transportation

- Self-driving cars, Traffic prediction, and Route optimization.



ML in Manufacturing

Predictive maintenance, Quality control, and Automation.



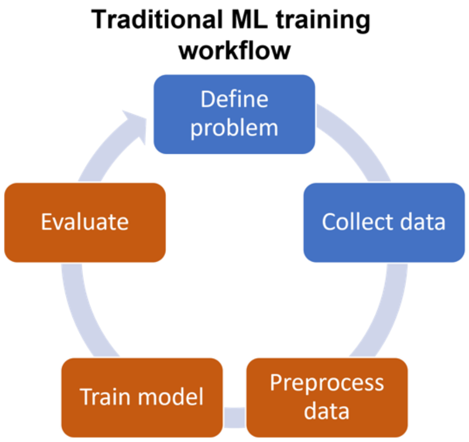
- ML in Cybersecurity : Anomaly detection, Malware detection, and Intrusion prevention.
- ML in Entertainment: Content recommendations, Music generation, and Game AI.
- ML in Social Media: Sentiment analysis, Chatbots, and Fake news detection.

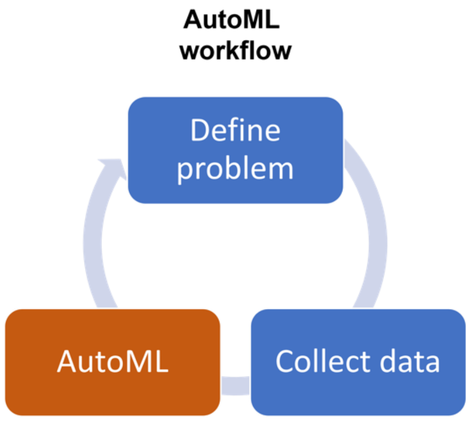
The Future of Machine Learning Algorithms

1. More Efficient and Scalable Algorithms
2. Greater Interpretability and Transparency
3. Federated Learning
4. Autonomous Machine Learning (AutoML)
5. MultiModal Learning
6. TinyML
7. Quantum and Neuromorphic Computing
8. Advanced Model Architectures
9. Personalization & Interaction
10. Creativity & Innovation
11. Tool Use and Agentic Behavior
12. Ethical and Societal Integration /Economic and Social Impact

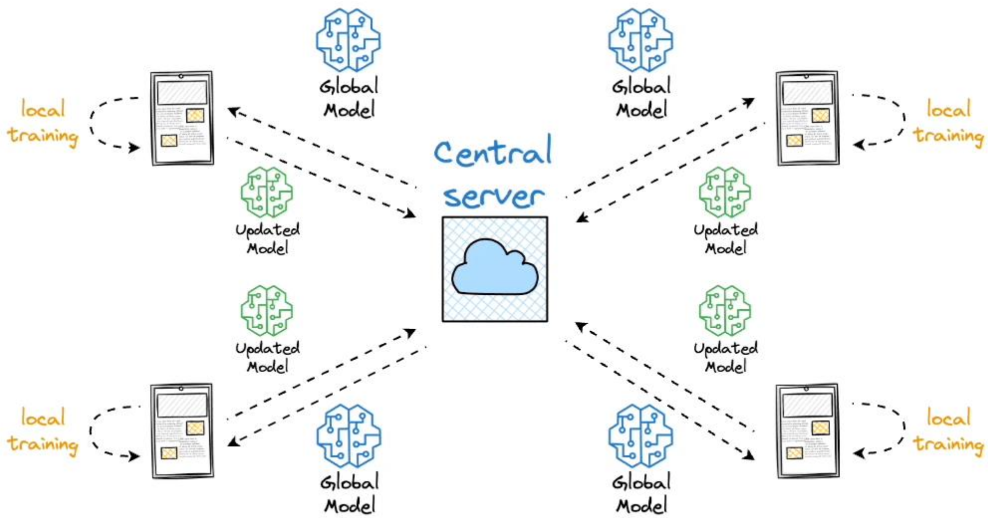
Automated Machine Learning (AutoML)

- AutoML is becoming a big trend, aiming to automate the entire ML process, from data preparation to model selection and tuning. This makes ML more accessible to organizations with less technical expertise and helps experts like Certified Natural Language Processing or Certified Computer Vision professionals work more efficiently.
- Why It Matters:
  - Saves time on repetitive tasks like data cleaning and model tuning.
  - Opens up ML to non-experts, making AI easier to adopt.





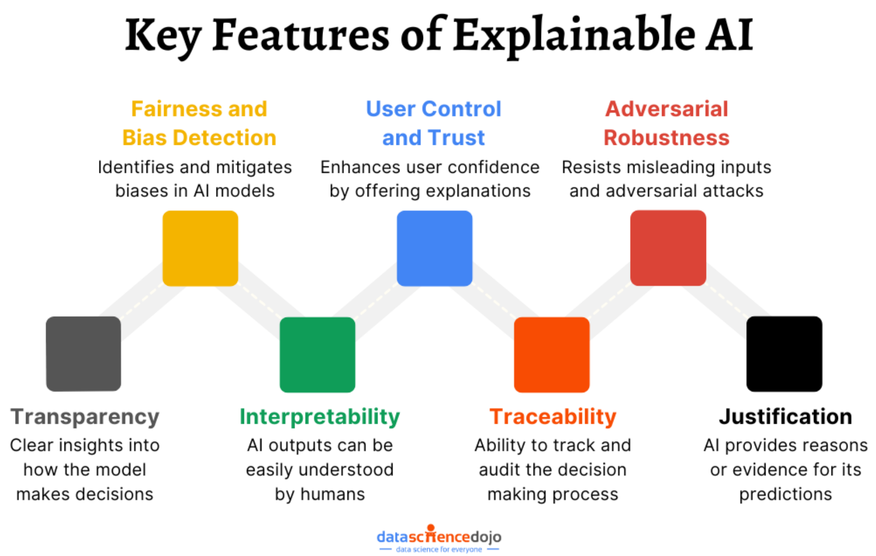
Federated Learning



- **Low-resource models** will become more common, reducing the need for massive datasets and computing power.
- Techniques like **federated learning** and **compressed models** (e.g., quantization, pruning) will allow ML to scale to edge devices and embedded systems
- With growing concerns over data privacy, federated learning is becoming important.
- It allows models to be trained on decentralized devices, keeping data local instead of centralizing it. This is particularly useful in sectors like healthcare and finance.
- Why It Matters:
  - Boosts data privacy and security.
  - Enables collaboration across organizations without sharing sensitive data

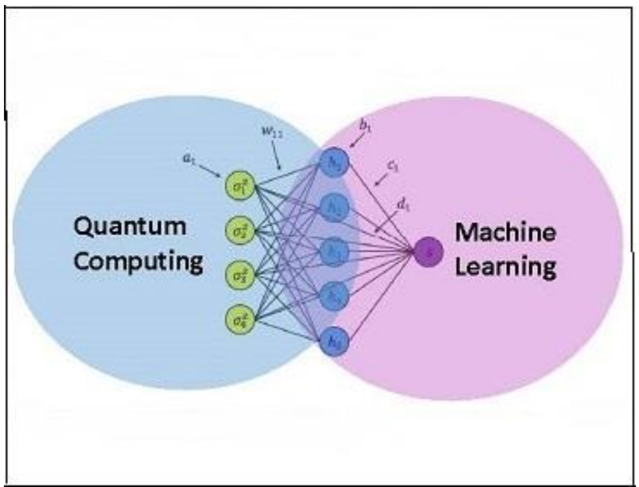
Greater Interpretability and Transparency

- As machine learning models get more complex, explainability becomes crucial.
- As ML is adopted in critical domains (healthcare, law, finance), there will be growing demand for explainable AI (XAI).
- Algorithms that provide human-understandable justifications for their decisions will gain prominence.
- Why It Matters:
  - Builds trust in AI systems by making predictions more understandable.
  - Helps with legal compliance in sectors that require transparency.



Quantum Machine Learning

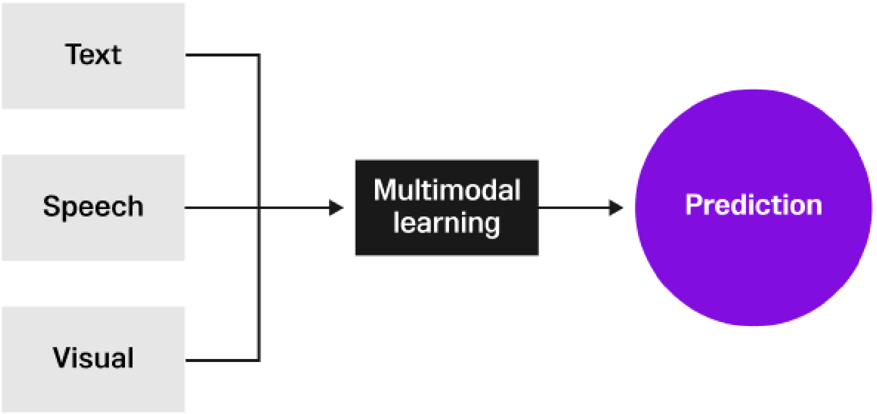
- Quantum computing could change machine learning by speeding up with Quantum Advantage.
- Why It Matters:
  - Quantum computing can dramatically speed up model training.
  - It will help solve complex problems that classical computers struggle with.



Quantum Machine Learning MOOC, created by Peter Wittek from the University of Toronto in Spring 2019
https://www.youtube.com/watch?v=QtWCmO_KIlg&themeRefresh=1

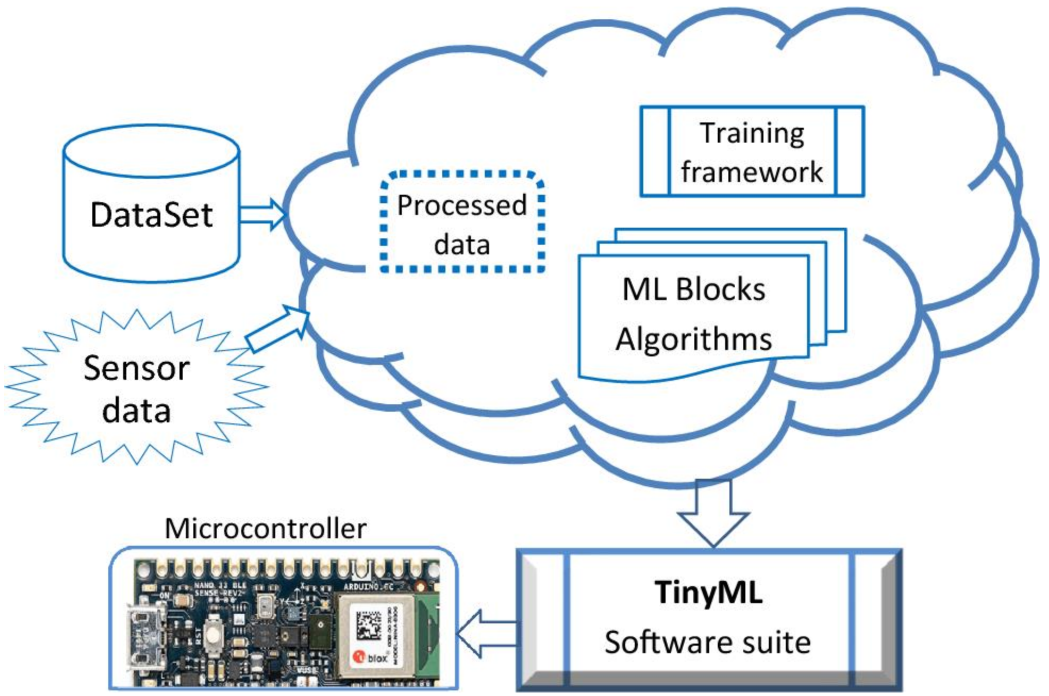
Multimodal Learning

- Multimodal learning involves creating models that process and understand data from multiple sources like text, images, and audio.
- Certified Computer Vision and Certified Natural Language Processing professionals can use this approach to build stronger models in fields like healthcare, entertainment, and customer service.
- Why It Matters:
  - Enables smoother human-machine interactions.
  - Improves AI systems that need multiple data types for better decision-making.



TinyML

- With the rise of edge computing, TinyML is becoming more popular.
- It focuses on running machine learning models on small, low-power devices, such as sensors and smartphones.
- This is crucial for industries that need real-time data processing at the edge, such as manufacturing and smart cities.
- Why It Matters:
  - Allows real-time ML on devices with limited power and processing capability.
  - Important for the future of IoT and edge computing, where quick responses are essential.



Advanced Model Architectures

- GenAI is powered by foundation models (e.g., transformers), which are scalable and adaptable to many domains.
- Expect evolution toward multimodal models that can understand and generate across multiple types of input/output (text + image + audio + video).

Personalization & Interaction

- GenAI enables highly personalized assistants, tutors, creative tools, and more.
- Future ML algorithms will focus on interactive learning — learning from user feedback in real time.

Creativity & Innovation

- Generative models are revolutionizing content creation — from art and music to design and product development.
- They’re enabling entirely new workflows and creative possibilities.

Tool Use and Agentic Behavior

- GenAI is evolving into AI agents that can use tools, browse the web, write code, and automate multi-step tasks.
- This requires algorithms to integrate planning, reasoning, and learning on the fly.

Economic and Social Impact

- Generative models are reshaping industries — media, education, customer service, programming, and beyond.
- ML research is increasingly focused on controllability, alignment, and safety of these powerful models.

Summary

- ML is revolutionizing industries and shaping the future.
- Machine learning is the most rapidly growing technology that can be used to improve and transform our daily lives.
- However, it is important to monitor how we deploy it across different industries to predict possible outcomes and improve efficiency.
- Since it is based on algorithms, even a slight change in data can significantly impact the results.

Book & Code References

- Introduction to Machine Learning with Python by Andreas C. Müller & Sarah Guido
- A Course in Machine Learning by Hal Daumé III

Code:

1. Introduction to ml with python by Andreas
2. Microsoft Data-Science-For-Beginners Public