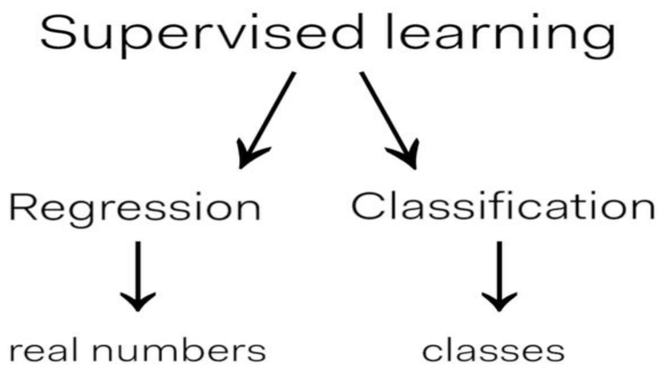
<u>**CLASSIFICATION ALGORITHMS OF MACHINE LEARNING**</u>

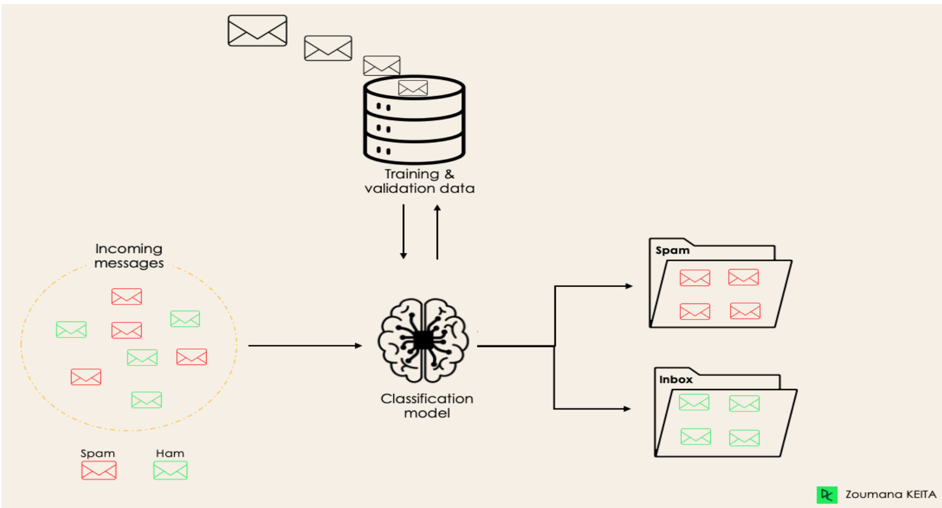
As we know, the Supervised Machine Learning algorithm can be broadly classified into Regression and Classification Algorithms.

In Regression algorithms, we have predicted the output for numerical values, but to predict the categorical values, we need Classification algorithms.



What is the Classification Algorithm?

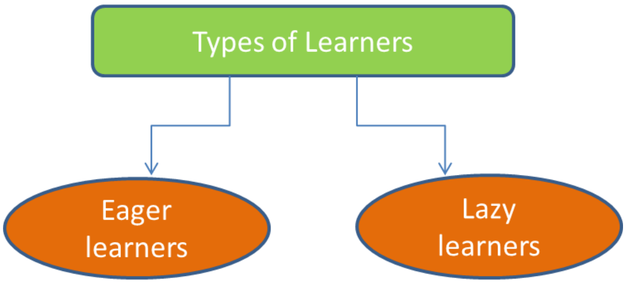
- The Classification algorithm is a Supervised Learning technique that is used to identify the category of new observations on the basis of training data.
- In Classification, a program learns from the given dataset or observations and then classifies new observation into a number of classes or groups.
- Such as, **Yes** or **No, 0** or **1, Spam** or **Not Spam, cat** or **dog, etc.**
- Classes can be called as targets/labels or categories.
- Output variable of Classification is a category, not a value, such as 'Green or Blue', 'fruit or animal', etc. Since the Classification algorithm is a supervised learning technique, hence it takes labelled input data, which means it contains input with the corresponding output.
- The best example of an ML classification algorithm is Email Spam Detector.



- The main goal of the Classification algorithm is to identify the category of a given dataset, and these algorithms are mainly used to predict the output for the categorical data.

Learners in Classification Problems

There are two types of learners in machine learning classification



Eager Learners

- ✓ Eager learners are machine learning algorithms that **first build a model from the training dataset** before making any prediction on future datasets.
- ✓ This spends more time during the training process because of their eagerness to have a better generalization during the training from learning the weights.
- ✓ **This requires less time to make predictions**.

Most machine learning algorithms are eager learners, and below are some examples:

- ➢ Logistic Regression.
- ➢ Support Vector Machine.
- ➢ Decision Trees.
- ➢ Artificial Neural Networks.

Lazy learners

- ✓ Lazy learners or instance-based learners, on the other hand, **do not create any model immediately from the training data**, and this is where the lazy aspect comes from.
- ✓ They just memorize the training data, and each time there is a need to make a prediction, they search for the nearest neighbour from the whole training data
- ✓ **This requires more time to make predictions**

Some examples of this kind are:

- ➢ K-Nearest Neighbour.
- ➢ Case-based reasoning.

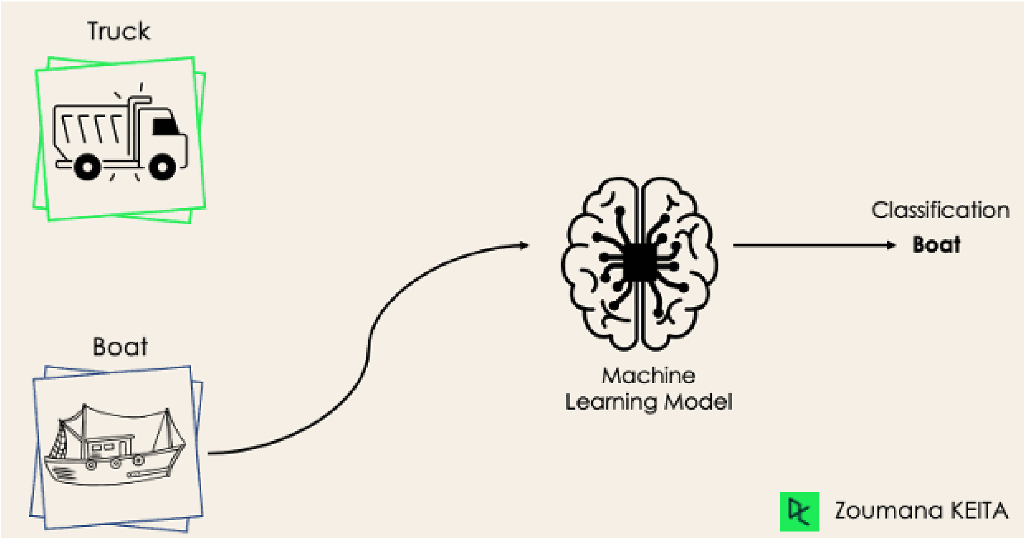
The algorithm which implements the classification on a dataset is known as a classifier.

Different Types of Classification Tasks in Machine Learning

Binary Classifier

If the classification problem has only two possible outcomes, then it is called as Binary Classifier.

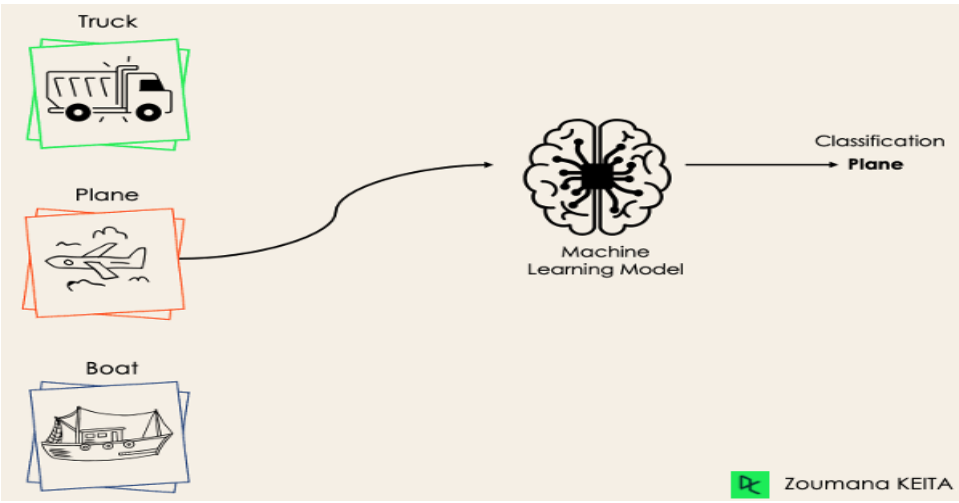
Examples: YES or NO, MALE or FEMALE, SPAM or NOT SPAM, CAT or DOG, Truck or Boat etc.



Multi-class Classifier

If a classification problem has more than two outcomes, then it is called as Multi-class Classifier.

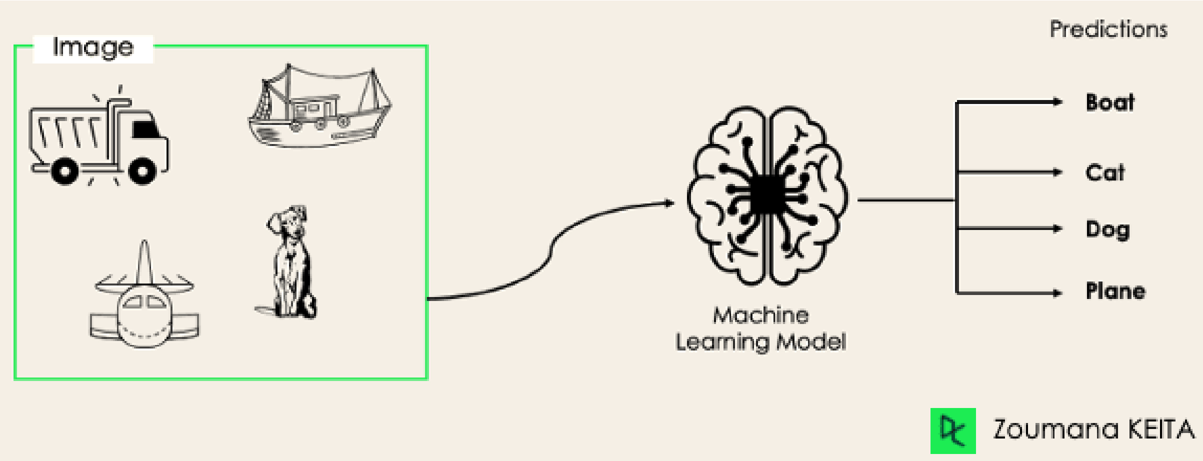
Example: Classifications of types of crops, Classification of types of music, Classification of types of vehicles.



Multi-Label Classification

It is used when there are two or more classes and the data we want to classify may belong to none of the classes or all of them at the same time.

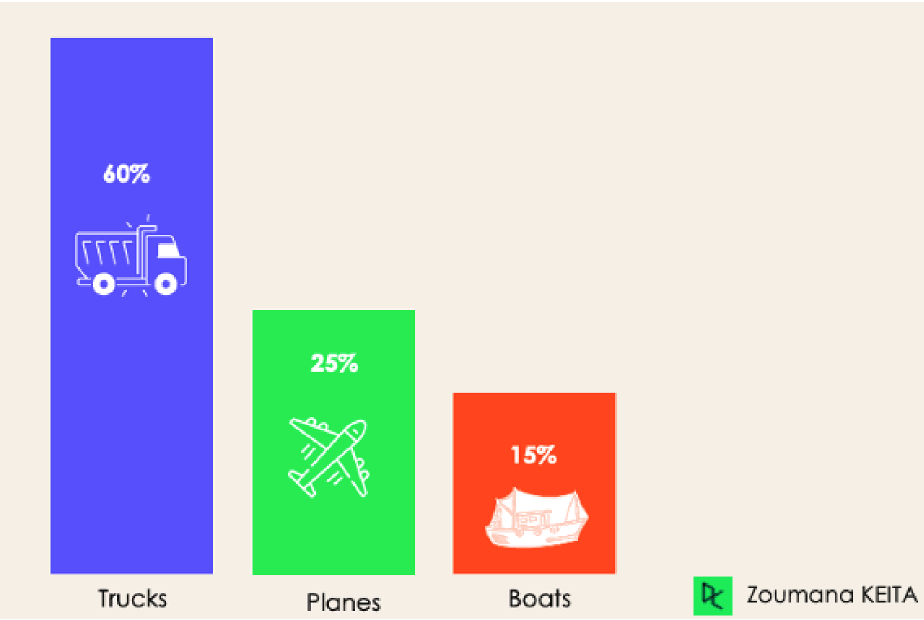
E.g. to classify which traffic signs are contained on an image and an image can contain multiple objects, as illustrated below: the model predicted that the image contains: a plane, a boat, a truck, and a dog



Imbalanced Classification

For the imbalanced classification, the number of examples is unevenly distributed in each class, meaning that we can have more of one class than the others in the training data.

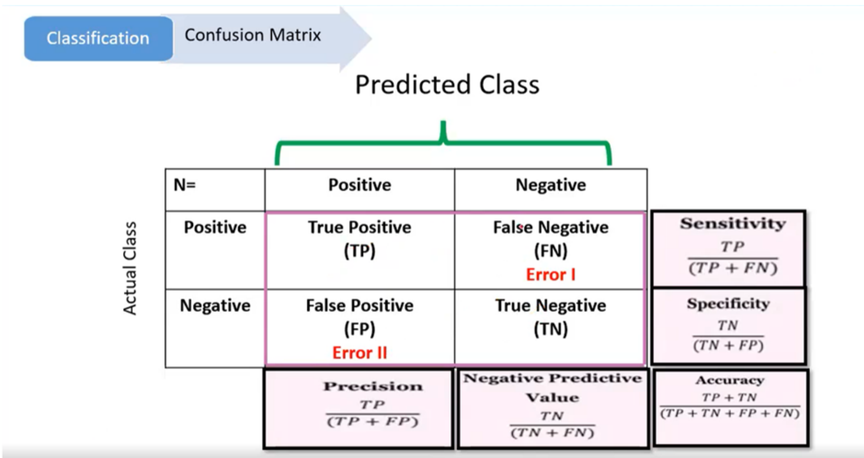
Let's consider the following 3-class classification scenario where the training data contains: 60% of trucks, 25% of planes, and 15% of boats.



Evaluating a Classification model

Confusion Matrix

- ✓ The confusion matrix provides us a matrix/table as output and describes the performance of the model.
- ✓ It is also known as the error matrix.
- ✓ The matrix consists of predictions result in a summarized form, which has a total number of correct predictions and incorrect predictions.
- ✓ The matrix looks like as below table:



Error I and II can be used interchangeably when refer to FN and FP respectively

Accuracy

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

We get accuracy by answering this question

1. Out of the prediction made by the model, what percentage is correct?
2. What is the percentage of correct classification of both(purchased & non-purchased) to the total input of the test set?
3. What is the overall correctness percentage for both 'purchased' and 'non-purchased' categories with respect to the entire test set?
4. What proportion of correct predictions is represented by the accuracy?
5. In the context of the confusion matrix, what percentage indicates the accuracy of predictions?
6. What is the accuracy score derived from the confusion matrix?
7. What is the rate of correct predictions, expressed as a percentage?
8. What is the success rate in percentage for the model's predictions?
9. What proportions of the model's predictions are correct?
10. In the context of prediction accuracy, what is the model's success percentage?

Recall

$$Recall = \frac{TP}{TP + FN}$$

We get recall by answering this question

1. What is the accuracy percentage for correctly classifying 'purchased/non-purchased' items in the total test set?
2. Could you provide the percentage of accurate classifications for 'purchased/non-purchased' items in relation to the entire test set?
3. In terms of the test set, what percentage of ‘purchased/non-purchased’ items is correctly classified?
4. What proportion of the total test set consists of accurately classified 'purchased/non-purchased' items?
5. How is the accuracy percentage calculated for 'purchased/non-purchased' items in the context of the test set?
6. What is the success rate for correctly identifying 'purchased/non-purchased' items as a percentage of the total test set?
7. Could you share the percentage of correct classifications for 'purchased/non-purchased' items relative to the overall test set size?
8. In the test set, what percentage of items classified as 'purchased/non-purchased' are accurate?
9. What portion of the total input in the test set corresponds to the correct classification percentage for 'purchased/non-purchased' items?
10. How often are 'purchased/non-purchased' items correctly classified, expressed as a percentage of the entire test set?

Precision

$$Precision = \frac{TP}{TP + FP}$$

We get precision by answering this question

1. What is the percentage of correctly identified 'purchased/non-purchased' items out of the total instances classified as 'purchased' in the test set?
2. Could you share the precision percentage for the 'purchased/non-purchased' category, considering instances correctly identified as 'purchased' and instances incorrectly identified as 'purchased' in the test set?
3. In terms of precision, what percentages of ‘purchased/non-purchased' items are accurately classified among both correct and incorrect classifications in the test set?

4. What proportion of the total instances classified as 'purchased/non-purchased' is represented by accurate classifications, considering both true positives and false positives?
5. How is the precision percentage calculated for the 'purchased'/non-purchased' category, taking into account both instances correctly identified as 'purchased/non-purchased' and instances incorrectly identified as 'purchased' in the test set?
6. What is the accuracy rate for correctly identifying 'purchased/non-purchased' items among both correct and incorrect classifications, expressed as a percentage in the test set?
7. Could you provide the precision percentage for 'purchased/non-purchased' items, incorporating both true positives and false positives in the test set?
8. In the context of the test set, what percentage of instances classified as 'purchased/non-purchased' is accurately identified among both correct and incorrect classifications?
9. What portion of instances classified as 'purchased/non-purchased' corresponds to the precision percentage, considering both true positives and false positives in the test set?
10. How often are 'purchased/non-purchased' items correctly identified, expressed as a percentage of the sum of correct and incorrect classifications for 'purchased' in the test set?

F1-Measure

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

We get F1-Measure by answering this question

1. Could you provide an overview of the overall performance for both 'purchased' and 'non-purchased' categories?
2. What is the combined performance for 'purchased' and 'non-purchased' categories?
3. In terms of overall performance, how do both 'purchased' and 'non-purchased' categories fare?
4. Can you share insights into the combined performance of 'purchased' and 'non-purchased' categories?
5. What is the holistic performance assessment for both 'purchased' and 'non-purchased' categories?
6. How do the overall metrics reflect the performance of both 'purchased' and 'non-purchased' categories?
7. Could you elaborate on the combined performance metrics for both 'purchased' and 'non-purchased' outcomes?
8. In the context of overall performance, what are the results for both 'purchased' and 'non-purchased' categories?
9. Can you provide an overview of how both 'purchased' and 'non-purchased' categories perform on the metrics?
10. What does the overall performance assessment reveal about the performance of 'purchased' and 'non-purchased' categories?

Macro Average

Precision

$$\frac{\text{Precision(Apple)+Precision(Orange)}}{2}$$

We get macro average precision by answering this question

1. Could you elaborate on the overall precision performance, taking into account both correct and incorrect classifications?
2. What is the combined precision score, considering both accurate and inaccurate classifications?
3. In terms of precision, how is the average performance calculated, considering both correct and incorrect classifications?
4. Can you provide insights into the precision metric, factoring in both instances that were correctly and wrongly classified?
5. What is the overall precision performance, taking into consideration both accurate and inaccurate identifications?
6. How is the average precision calculated, considering both correct and incorrect classifications collectively?
7. Could you shed light on the precision metric's performance, incorporating both instances that were correctly and wrongly classified?
8. In the context of precision, what is the average performance when considering both accurate and inaccurate classifications?
9. Can you explain the average precision, taking into account both correct and incorrect classifications in the assessment?
10. What does the precision metric reveal about the average performance, considering both correctly and wrongly classified instances?

Recall

$$\frac{\text{Recall(Apple)+Recall(Orange)}}{2}$$

We get macro average recall by answering this question

1. Can you provide insights into the overall recall performance, considering instances that were correctly identified?
2. What is the combined recall score, focusing on instances that were correctly classified?

3. In terms of recall, how is the average performance calculated, taking into account instances that were correctly identified?
4. Could you elaborate on the recall metric's performance, specifically with regard to instances that were correctly classified?
5. What is the overall recall performance, concentrating on instances that were correctly identified?
6. How is the average recall calculated, considering instances that were correctly classified exclusively?
7. Can you explain the recall metric's performance, emphasizing instances that were correctly identified?
8. In the context of recall, what is the average performance when considering instances that were correctly classified?
9. Could you shed light on the recall metric's performance, with a focus on instances that were correctly identified?
10. What does the recall metric reveal about the average performance, specifically concentrating on instances that were correctly classified?

F1-Measure

$$\frac{F1(Apple)+f2(Orange)}{2}$$

We get macro average F1-Measure by answering this question

1. Can you provide insights into the overall performance captured by the F1 Measure?
2. What is the combined F1 Measure score, representing the average performance across precision and recall?
3. In terms of the F1 Measure, how is the average performance calculated, considering both precision and recall?
4. Could you elaborate on the F1 Measure's overall performance, which balances precision and recall?
5. What is the overall F1 Measure performance, taking into consideration the balance between precision and recall?
6. How is the average F1 Measure calculated, considering both precision and recall in the assessment?
7. Can you explain the overall performance captured by the F1 Measure, balancing both precision and recall?
8. In the context of the F1 Measure, what is the average performance when considering the balance between precision and recall?
9. Could you shed light on the F1 Measure's overall performance, considering the trade-off between precision and recall?
10. What does the F1 Measure reveal about the average performance, with a focus on balancing precision and recall?

Weighted Average

Precision/Recall/F1-Measure

Weighted Average	Formula
Precision	Precision(Apple)*(85/134)+Precision(Orange)*(49/134)
Recall	Recall(Apple)*(85/134)+Recall(Orange)*(49/134)
F1 Measure	F1(Apple)*(85/134)+F2(Orange)*(49/134)

Where, 85 -> Total count of Apple in test data

49 – Total count of Orange in test data

134 – Total count of Apple & Orange in test data

We get weighted average precision/Recall/F-Measure by answering this question

1. Could you provide the total obtained by multiplying the proportion rates (weights) for each class and summing them?
2. What is the cumulative result of multiplying and summing the proportion rates (weights) assigned to each class?
3. In terms of class proportions, what is the sum of the products of the rates (weights) for each individual class?
4. Can you share the total obtained by summing the products of the proportion rates (weights) assigned to each class?
5. What is the combined value resulting from multiplying and summing the proportion rates (weights) for each respective class?
6. How the sum of the products of the proportion does rates (weights) for each class contribute to the overall calculation?
7. Could you elaborate on the total achieved by multiplying and summing the proportion rates (weights) assigned to each class?
8. In the context of class proportions, what is the aggregate outcome when multiplying and summing the rates (weights) for each class?
9. Can you provide the cumulative result of summing the products of the proportion rates (weights) for each individual class?
10. What does the sum of the products of proportion rates (weights) for each class reveal about the overall calculation?