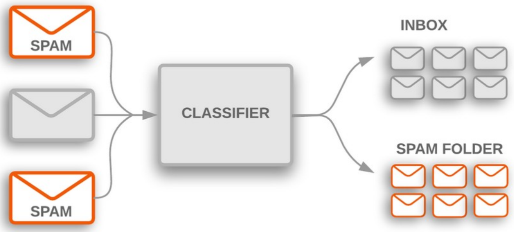
Classification



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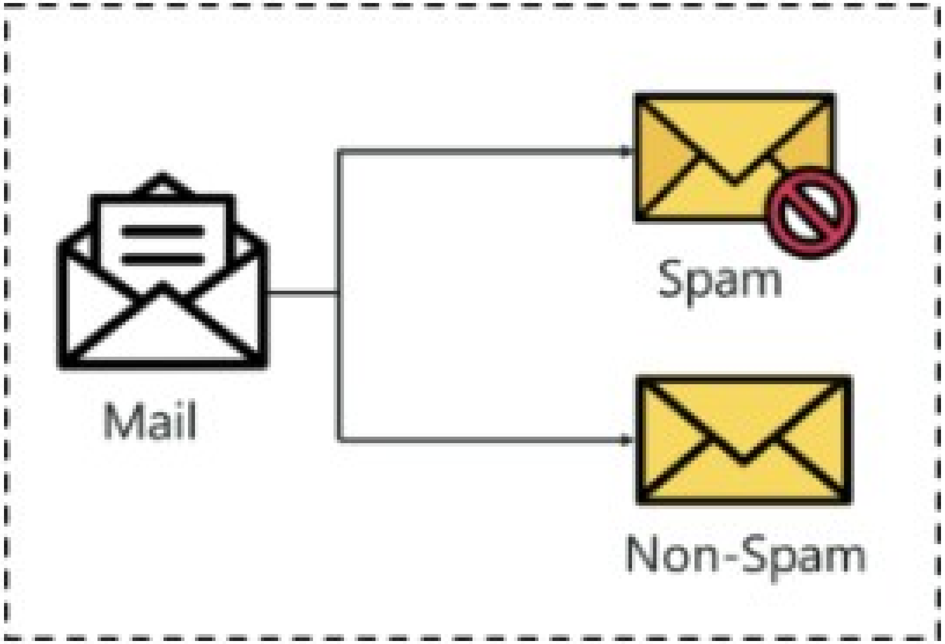
What is Classification?

- Classification is a process of categorizing a given set of data into classes, It can be performed on both structured or unstructured data.
- The process starts with predicting the class of given data points. The classes are often referred to as target, label or categories.
- The classification predictive modeling is the task of approximating the mapping function from input variables to discrete output variables.
- The main goal is to identify which class/category the new data will fall into.

Example:



Example:

- Heart disease detection can be identified as a classification problem, this is a binary classification since there can be only two classes i.e has heart disease or does not have heart disease.
- The classifier, in this case, needs training data to understand how the given input variables are related to the class. And once the classifier is trained accurately, it can be used to detect whether heart disease is there or not for a particular patient.
- Since classification is a type of supervised learning, even the targets are also provided with the input data.

Basic Terminologies used

- Classifier – It is an algorithm that is used to map the input data to a specific category.
- Classification Model – The model predicts or draws a conclusion to the input data given for training, it will predict the class or category for the data.
- Feature – A feature is an individual measurable property of the phenomenon being observed.
- Label- Output variable

Types of Learners

- Lazy Learners –
  - Lazy learners simply store the training data and wait until a testing data appears.
  - The classification is done using the most related data in the stored training data.
  - They have more predicting time compared to eager learners. Eg – k-nearest neighbor, case-based reasoning.

Types of Learners

- Eager Learners –
  - Eager learners construct a classification model based on the given training data before getting data for predictions.
  - It must be able to commit to a single hypothesis that will work for the entire space.
  - Due to this, they take a lot of time in training and less time for a prediction. Eg – Decision Tree, Naive Bayes, Artificial Neural Networks.

Types of Classification

- Binary Classification
- Multi-Class Classification
- Multi-Label Classification
- Imbalanced Classification

Types of Classification

- Linear Models
  - Logistic Regression
  - Support Vector Machines
- Nonlinear models
  - K-nearest Neighbors (KNN)
  - Kernel Support Vector Machines (SVM)
  - Naïve Bayes
  - Decision Tree Classification
  - Random Forest Classification

Binary Classification

- Binary classification refers to those classification tasks that have two class labels.
- Examples include:
  - Email spam detection (spam or not)
  - Churn prediction (churn or not).
  - Conversion prediction (buy or not).
- Typically, binary classification tasks involve one class that is the normal state and another class that is the abnormal state.

Binary Classification – Example

- For example "not spam" is the normal state and "spam" is the abnormal state. Another example is "cancer not detected" is the normal state of a task that involves a medical test and "cancer detected" is the abnormal state.
- The class for the normal state is assigned the class label 0 and the class with the abnormal state is assigned the class label 1.
- It is common to model a binary classification task with a model that predicts a Bernoulli probability distribution for each example.

Binary Classification – Algorithms

- Popular algorithms that can be used for binary classification include:
  - Logistic Regression
  - k-Nearest Neighbors
  - Decision Trees
  - Support Vector Machine
  - Naive Bayes

Evaluation of Binary Classifier

- There are many metrics that can be used to measure the performance of a classifier or predictor; different fields have different preferences for specific metrics due to different goals.
- In medicine sensitivity and specificity are often used, while in information retrieval precision and recall are preferred.
- An important distinction is between metrics that are independent of how often each category occurs in the population (the prevalence), and metrics that depend on the prevalence – both types are useful, but they have very different properties.

Evaluation of Binary Classifier

- Given a classification of a specific data set, there are four basic combinations of actual data category and assigned category: true positives TP (correct positive assignments), true negatives TN (correct negative assignments), false positives FP (incorrect positive assignments), and false negatives FN (incorrect negative assignments).

	Condition positive	**Condition negative**
Test outcome positive	True positive	False positive
Test outcome negative	False negative	True negative

Confusion Matrix

- In the field of machine learning and specifically the problem of statistical classification, a confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix).
- Each row of the matrix represents the instances in a predicted class, while each column represents the instances in an actual class (or vice versa).
- The name stems from the fact that it makes it easy to see whether the system is confusing two classes (i.e. commonly mislabeling one as another).

Confusion Matrix

- Given a sample of 13 pictures, 8 of cats and 5 of dogs, where cats belong to class 1 and dogs belong to class 0,
  - actual = [1,1,1,1,1,1,1,1,0,0,0,0,0],
- assume that a classifier that distinguishes between cats and dogs is trained, and we take the 13 pictures and run them through the classifier, and the classifier makes 8 accurate predictions and misses 5: 3 cats wrongly predicted as dogs (first 3 predictions) and 2 dogs wrongly predicted as cats (last 2 predictions).
  - prediction = [0,0,0,1,1,1,1,1,0,0,0,1,1]

Confusion Matrix

		Actual class	
		Cat	**Dog**
Predicted class	**Cat**	**5**	2
	Dog	3	**3**

		Actual class	
		Cat	**Non-cat**
Predicted class	**Cat**	**5 true positives**	2 false positives
	Non-cat	3 false negatives	**3 true negatives**

F1 Score / Harmonic Mean

$$F_1 = \frac{2}{\mathrm{recall}^{-1} + \mathrm{precision}^{-1}} = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}} = \frac{\mathrm{tp}}{\mathrm{tp} + \frac{1}{2}(\mathrm{fp} + \mathrm{fn})}.$$

Multi Class Classification

- Multi-class classification refers to those classification tasks that have more than two class labels.
- Examples include:
  - Face classification.
  - Plant species classification.
  - Optical character recognition.
- Unlike binary classification, multi-class classification does not have the notion of normal and abnormal outcomes. Instead, examples are classified as belonging to one among a range of known classes.

Multi Class Classification

- The number of class labels may be very large on some problems. For example, a model may predict a photo as belonging to one among thousands or tens of thousands of faces in a face recognition system.
- Problems that involve predicting a sequence of words, such as text translation models, may also be considered a special type of multi-class classification.
- Each word in the sequence of words to be predicted involves a multi-class classification where the size of the vocabulary defines the number of possible classes that may be predicted and could be tens or hundreds of thousands of words in size.

Multi Class Classification - Examples

- Many algorithms used for binary classification can be used for multi-class classification.
- Popular algorithms that can be used for multi-class classification include:
  - k-Nearest Neighbors.
  - Decision Trees.
  - Naive Bayes.
  - Random Forest.
  - Gradient Boosting.

Multi Class Classification

- This involves using a strategy of fitting multiple binary classification models for each class vs. all other classes (called one-vs-rest) or one model for each pair of classes (called one-vs-one).
  – One-vs-Rest: Fit one binary classification model for each class vs. all other classes.
  – One-vs-One: Fit one binary classification model for each pair of classes.
- Binary classification algorithms that can use these strategies for multi-class classification include:
  – Logistic Regression.
  – Support Vector Machine.

Multi-Label Classification?

- Multi-label classification refers to those classification tasks that have two or more class labels, where one or more class labels may be predicted for each example.
- Consider the example of photo classification, where a given photo may have multiple objects in the scene and a model may predict the presence of multiple known objects in the photo, such as “bicycle,” “apple,” “person,” etc.
- This is unlike binary classification and multi-class classification, where a single class label is predicted for each example.

Imbalanced Classification

- Imbalanced classification refers to classification tasks where the number of examples in each class is unequally distributed.
- Typically, imbalanced classification tasks are binary classification tasks where the majority of examples in the training dataset belong to the normal class and a minority of examples belong to the abnormal class.
- Examples include:
  - Fraud detection.
  - Outlier detection.
  - Medical diagnostic tests.

Imbalanced Classification

- These problems are modeled as binary classification tasks, although may require specialized techniques.
- Specialized techniques may be used to change the composition of samples in the training dataset by undersampling the majority class or oversampling the minority class.
- Examples include:
  - Random Undersampling.
  - SMOTE Oversampling.

Imbalanced Classification

- Specialized modeling algorithms may be used that pay more attention to the minority class when fitting the model on the training dataset, such as cost-sensitive machine learning algorithms.
- Examples include:
  - Cost-sensitive Logistic Regression.
  - Cost-sensitive Decision Trees.
  - Cost-sensitive Support Vector Machines.

Useful resources

- https://missinglink.ai
- https://machinelearningmastery.com
- https://www.allaboutcircuits.com
- https://medium.com

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