Supervised Learning I : Regressors, Classifiers and Trees

Gradient descent step

The size of the step that gradient descent takes is called the *learning rate*. Finding an adequate value for the *learning rate* is key to achieve convergence. If this value is too large the algorithm will never reach the optimus, but if is too small it will take too much time to achieve the desired value.

Gradient Descent in Regression

`Gradient Descent` is an iterative algorithm used to tune the parameters in regression models for minimum loss.

Scikit-Learn *Logistic Regression* Implementation

Scikit-Learn has a *Logistic Regression* implementation that fits a model to a set of training data and can classify new or test data points into their respective classes. All important parameters can be specified, as the norm used in penalizations and the solver used in optimization.

Logistic Regression sigmoid function

Logistic Regression models use the *sigmoid function* to link the *log-odds* of a data point to the range [0,1], providing a probability for the classification decision. The *sigmoid function* is widely used in machine learning classification problems because its output can be interpreted as a probability and its derivative is easy to calculate.

Classification Threshold definition

A *Classification Threshold* determines the cutoff where the probabilistic output of a machine learning algorithm classifies data samples as belonging to the positive or negative class. A *Classification Threshold* of 0.5 is well suited to most problems, but particular classification problem could need a fine-tuned threshold in order to improve overall accuracy.

Logistic Regression interpretability

Logistic Regression models have high interpretability compared to most classification algorithms due to optimized feature coefficients. Feature coefficients can be thought as a measure of sensitivity in feature values.

Log-Odds calculation

The product of the feature coefficients and feature values in a *Logistic Regression* model is the *Log-Odds* of a data sample belonging to the positive class. Log odds can take any real value and it's an indirect way to express probabilities.

Logistic Regression Classifier

Logistic Regression is supervised binary classification algorithm used to predict binary response variables that may indicate the presence or absence of some state. It is possible to extend *Logistic Regression* to multi-class classification problems by creating several one-vs-all binary classifiers. In a one-vs-all scheme, n - 1 classes are grouped as one and a classifier learns to discriminate the remaining class from the ensembled group.

Logistic Regression prediction

Logistic Regression models predict the probability of an n-dimensional data point belonging to a specific class by constructing a linear decision boundary. This decision boundary splits the n-dimensional plane in two. In a prediction stage, the point is classified according to which semiplane has the highest probability.

Logistic Regression cost function

The cost function measuring the inaccuracy of a *Logistic Regression* model across all samples is *Log Loss*. The lower this value, the greater the overall classification accuracy. *Log Loss* is also known as *Cross Entropy* loss.

K-Nearest Neighbors Underfitting and Overfitting

The value of k in the KNN algorithm is related to the error rate of the model. A small value of k could lead to overfitting as well as a big value of k can lead to underfitting. Overfitting imply that the model is well on the training data but has poor performance when new data is coming. Underfitting refers to a model that is not good on the training data and also cannot be generalized to predict new data.

KNN Classification Algorithm in Scikit Learn

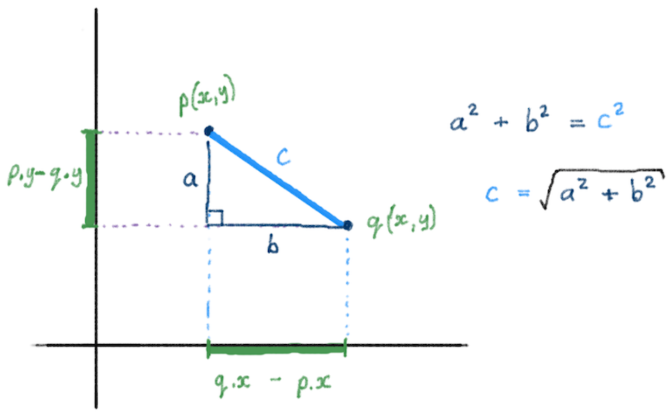
Scikit-learn is a very popular Machine Learning library in Python which provides a `KNeighborsClassifier` object which performs the KNN classification. The `n_neighbors` parameter passed to the `KNeighborsClassifier` object sets the desired `k` value that checks the `k` closest neighbors for each unclassified point.
The object provides a `.fit()` method which takes in training data and a `.predict()` method which returns the classification of a set of data points.

```
from sklearn.neighbors import
KNeighborsClassifier

KNNClassifier =
KNeighborsClassifier(n_neighbors=5)
KNNClassifier.fit(X_train, y_train)
KNNClassifier.predict(X_test)
```

Euclidean Distance

The *Euclidean Distance* between two points can be computed, knowing the coordinates of those points.
On a 2-D plane, the distance between two points **p** and **q** is the square-root of the sum of the squares of the difference between their **x** and **y** components.
Remember the Pythagorean Theorem: **a^2 + b^2 = c^2** ?
We can write a function to compute this distance. Let's assume that points are represented by tuples of the form `(x_coord, y_coord)`. Also remember that computing the square-root of some value **n** can be done in a couple of ways: `math.sqrt(n)`, using the math library, or `n ** 0.5` (**n** raised to the power of 1/2).

```
def distance(p1, p2):
  x_diff_squared = (p1[0] - p2[0]) ** 2
  y_diff_squared = (p1[1] - p2[1]) ** 2
  return (x_diff_squared + y_diff_squared) ** 0.5

distance( (0, 0), (3, 4) )      # => 5.0
```



Elbow Curve Validation Technique in K-Nearest Neighbor Algorithm

Choosing an optimal `k` value in KNN determines the number of neighbors we look at when we assign a value to any new observation.
For a very low value of `k` (suppose k=1), the model overfits on the training data, which leads to a high error rate on the validation set. On the other hand, for a high value of `k`, the model performs poorly on both train and validation set. When `k` increases, validation error decreases and then starts increasing in a "U" shape. An optimal value of `k` can be determined from the elbow curve of the validation error.

K-Nearest Neighbors

The K-Nearest Neighbors algorithm is a supervised machine learning algorithm for labeling an unknown data point given existing labeled data.
The nearness of points is typically determined by using distance algorithms such as the Euclidean distance formula based on parameters of the data. The algorithm will classify a point based on the labels of the K nearest neighbor points, where the value of K can be specified.

KNN of Unknown Data Point

To classify the unknown data point using the KNN (K-Nearest Neighbor) algorithm:

- Normalize the numeric data
- Find the distance between the unknown data point and all training data points
- Sort the distance and find the nearest k data points
- Classify the unknown data point based on the most instances of nearest k points

Normalizing Data

Normalization is a process of converting the numeric columns in the dataset to a common scale while retaining the underlying differences in the range of values.
For example, Min-max normalization converts each value of the numeric column to a value between 0 and 1 using the formula `Normalized value = (NumericValue - MinValue) / (MaxValue - MinValue)` . A downside of Min-max Normalization is that it does not handle outliers very well.

Regression in KNN Algorithm

K-Nearest Neighbor algorithm uses 'feature similarity' to predict values of any new data points. This means that the new point is assigned a value based on how closely it resembles the points in the training set. During regression implementation, the average of the values is taken to be the final prediction, whereas during the classification implementation mode of the values is taken to be the final prediction.

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