Task-7A:

Kernel Density Estimation (KDE) is a linear flattened version of a histogram graph estimated from the dataset. In this algorithm, a continuous curve (kernel / kernel) is drawn for each observation (point). All these curves drawn are added together to make a single uniform density estimation. While doing this addition, it also tries to soften the data (data smoothing).

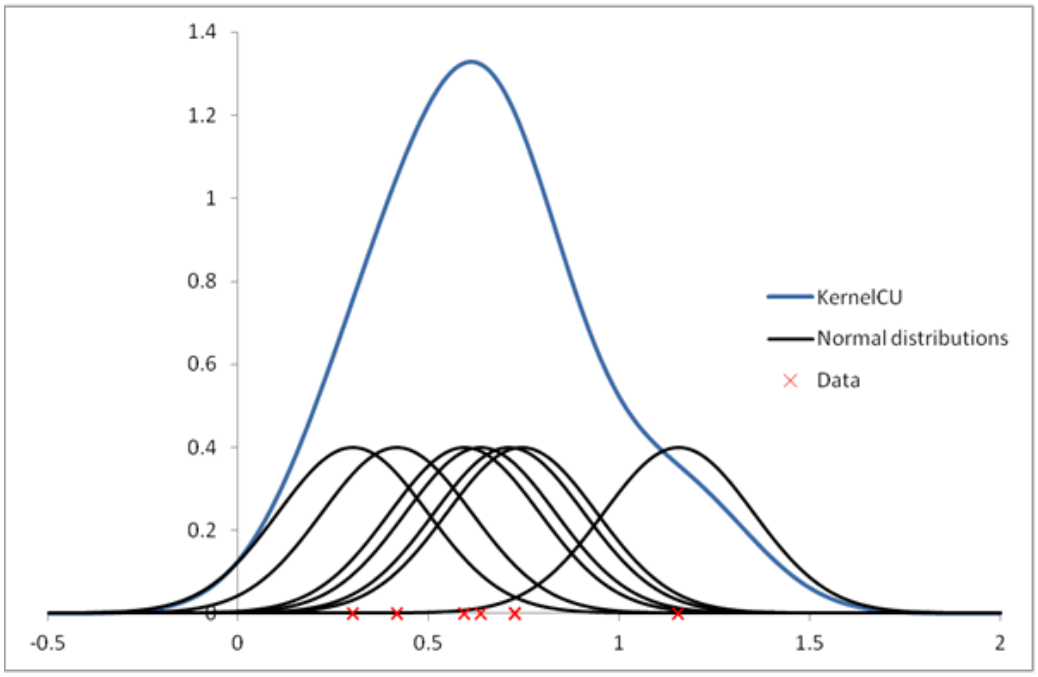
It can actually be defined as a nonparametric method used to estimate the density function of a random variable. This nonparametric algorithm does not take into account any fundamental distribution that is, it does not assume that the data set has a particular pattern. It uses a kernel function whose purpose is to fit the data along a straight line.

The KDE algorithm is:

$$f(x) = \frac{1}{nh} \sum_{i=0}^{n} K\left(\frac{x - x_i}{h}\right)$$

K is the kernel function, n is the number of observations, and x is a particular observation. KDE is essentially the sum of distributions centered around every point in the dataset.

There is also a parameter, h, which is known as bandwith. The bandwith controls the span of the distributions that are places around each part, which in turn affects the smoothening of the distribution.



The value chosen for the bandwith is very important as it controls the overall fit to the data. A poorly chosen bandwith value can cause in either over-smoothening or under-smoothening of the estimate. Therefore, this value should be chosen optimally.

There are some general rules for picking a good bandwith value:

- A small dataset requires a higher bandwidth due to lack of data. In this way, more points can be included.
- For a large dataset, it requires a lower band to be chosen, as there are too many points. It requires less span for a good context.

The kernel used in the KDE algorithm is a positive spacing probability density function with a symmetric function. The area of a kernel must be equal to 1. Commonly used kernels; Gaussian, triangular and Epanechnikov kernel.

Example:

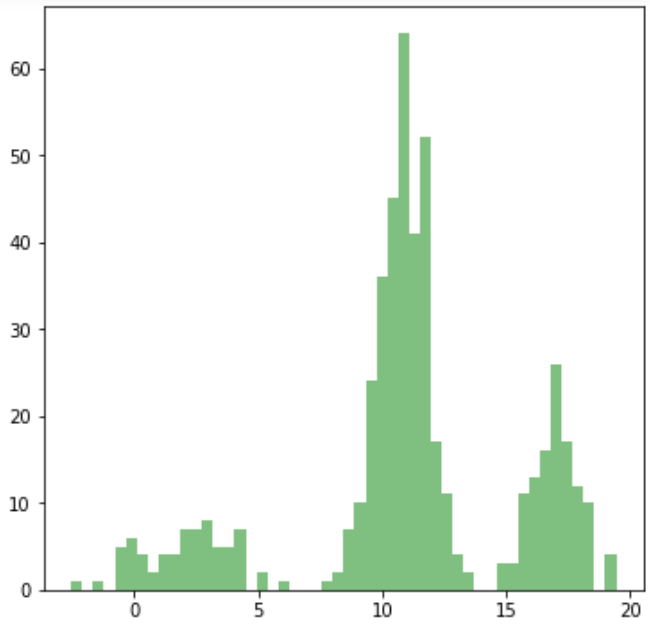
In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
from typing import *
```

In [3]:
```
#generating some random data

def generate_random_data(num_points: int, n_randomization: int=3):
    x = np.random.randn(num_points)

    for _ in range(n_randomization):
        random_slice = int(np.random.rand() * num_points)
        x[random_slice:] += np.random.randint(0, 10)

    return x
```

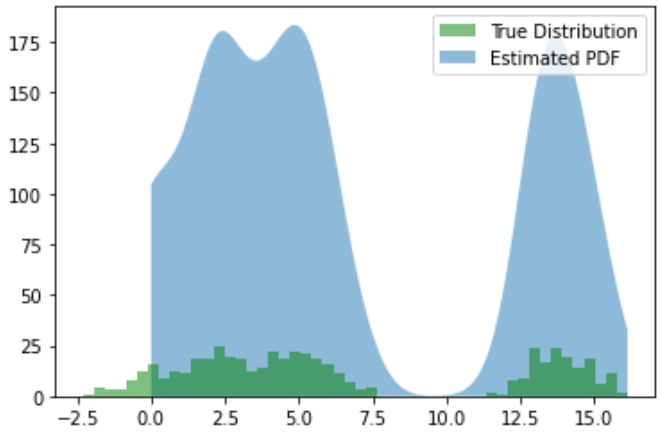
In [4]:
```
def kde(bandwith: float, data: List, kernel: Callable):
    mixture = np.zeros(1000)
    points = np.linspace(0, max(data), 1000)
    for xi in data:
        mixture += kernel(points, xi, bandwith)

    return mixture
```

In [6]:
```
#gaussian kernel function
def gaussian(x: Any, xi: float, bandwith: float):
    exp_section = np.exp(-np.power(x - xi, 2.0))
    return exp_section / (2 * np.power(bandwith, 2.0))
```

In [32]:
```
dist = generate_random_data(500)
hist = np.histogram(dist, bins=50)[1]
plt.figure(
    figsize=(6, 6)
)
plt.hist(dist, bins=50,
         alpha=0.5, color='green', label='True Distribution')
plt.show()
```



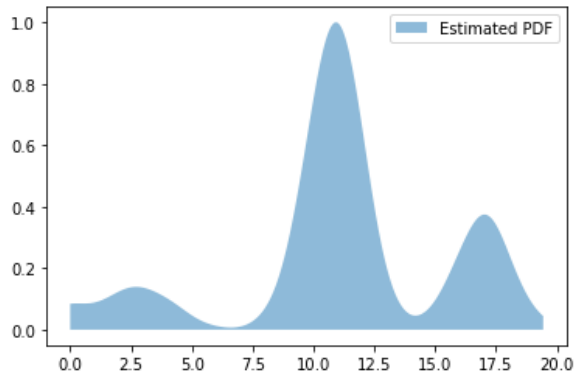
In [31]:
```
##applying kde

plt.hist(dist, bins=50,
         alpha=0.5, color='green', label='True Distribution')
points = kde(0.5, dist, gaussian)
plt.fill_between(np.linspace(0, max(dist), 1000),
                 points, alpha=0.5, label='Estimated PDF')

plt.legend(loc='upper right')
plt.show();
```



Looking at the graphics, it was seen that the KDE model predicted correctly. This is not a probability density function, because it is much higher than the interval 1. It is necessary to normalize the values in order to make them a probability density function.

In [33]:
```
# Normalizing
points = kde(0.5, dist, gaussian)
points /= np.abs(points).max(axis=0)
```

In [34]:
```
plt.fill_between(np.linspace(0, max(dist), 1000),
                 points, alpha=0.5, label='Estimated PDF')

plt.legend(loc='upper right')
plt.show()
```



The graph above has the probability density function.

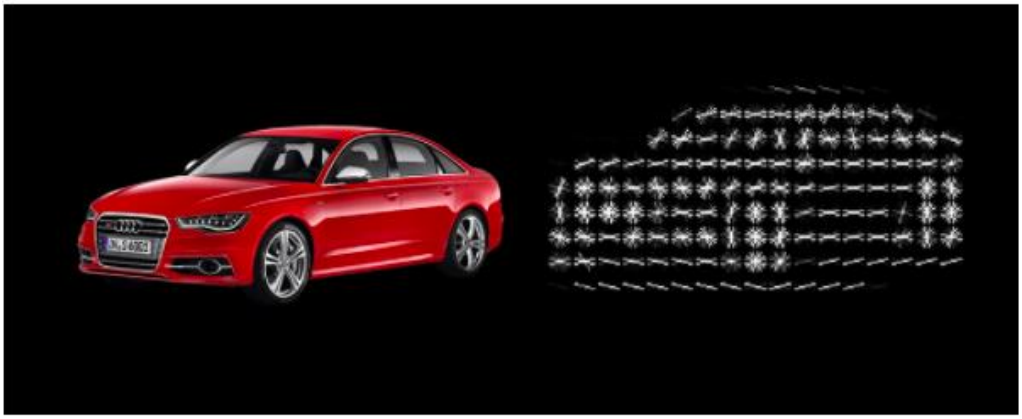
Task-7B:

Histogram of Oriented Gradients (HOG) became widespread in 2005 when Navneet Dalal and Bill Triggs, researchers display their work on HOG, which is a much reliable solution. The algorithm is also a features extractor for the purpose of object detection. Instead of considering the pixel intensities the technique counts the occurrences of gradient vectors represent the light direction to localize image segments. The method uses overlapping local contrast normalization to improve accuracy. One thing that differentiates HOG from others is that it is still heavily used today with fantastic results. The Histogram of Oriented Gradients method is mainly utilized for face and image detection to classify images.

- HOG is mainly used for object detection and image recognition.
- HOG is based on feature descriptors that extract useful information from the Image and discard unnecessary information.
- HOG calculates the size of the gradient and the horizontal and vertical component of the direction of each pixel. He then draws a 9-bin histogram to identify shifts in this data.
- Block normalization can be used to make the model more optimal and less biased.
- HOG algorithms are widely used in the field of autonomous vehicles.
-

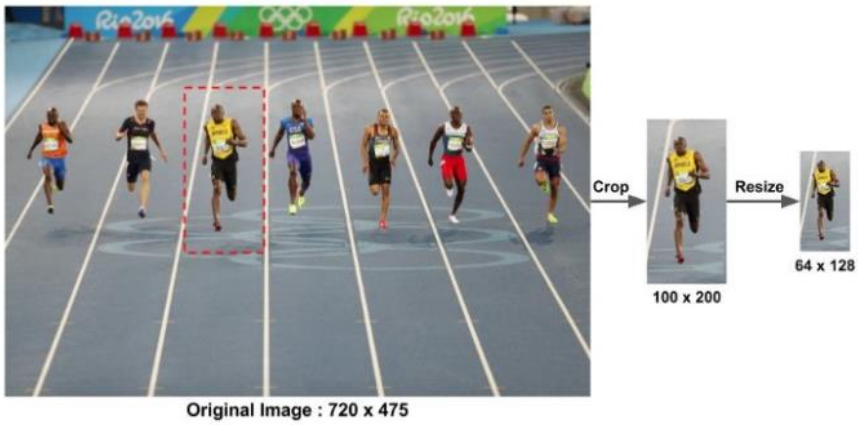
1st step: Feature Descriptors

Feature descriptors represent an image that strives only useful information and ignores unnecessary information in the image. HOG property descriptors convert the display to (width x height x channels) n property vector. These images can also be used in the SVM classification algorithm. It does this using histograms of gradients used as properties of an image while sorting unnecessary information.



2nd step: Preprocessing

A key mistake that individuals often perform when doing HOG object detection is that they forget to preprocess the image so that it has a fixed aspect ratio. When making HOG object detection, the most important thing is to preprocess the image to have a fixed aspect ratio. A common aspect ratio (width: height) is 1: 2.



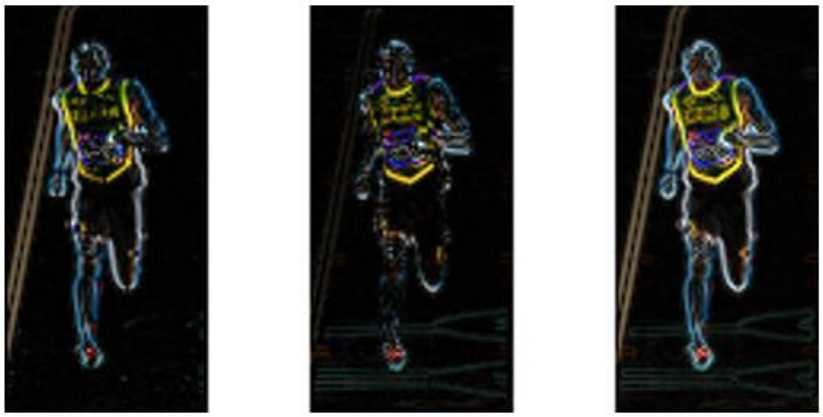
3rd step: Calculating the Gradients

To make the HOG feature descriptor, the horizontal and vertical gradients must be calculated to provide the histogram to be used in the algorithm. Kernels are used to achieve this. Kernels are used to find edges and key points in a particular image.

-1	0	1

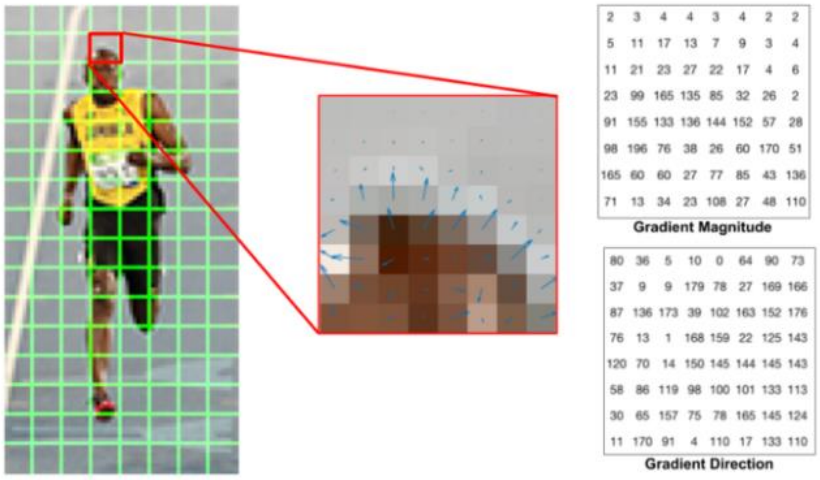
-1
0
1

The main idea in gradient calculation is that where there is a sharp change in density, the magnitude of the gradient increases, the unnecessary information is removed and only the basic parts remain.

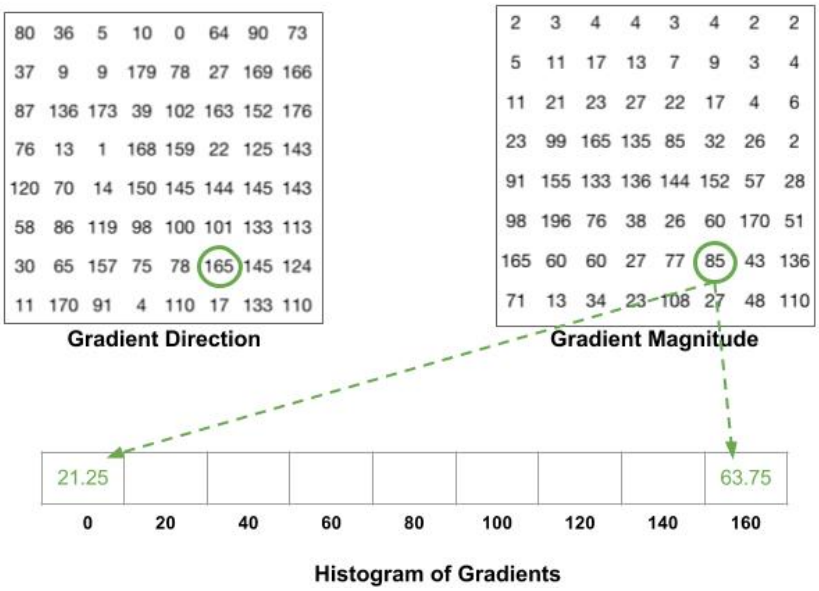


4th Making A Histogram From These Gradients

Feature descriptors allow for a specific concise representation of images, ie a specific size like 8x8. By converting these numbers further to calculate histograms, it is allowed to reflect a more robust image against noise. For the histogram, we should to split it up into nine separate bins, each corresponding to angles from 0–160 in increments of 20.



It is important to decide where each pixel will go within the histogram. A partition is selected depending on the chosen direction, and the value placed in it depends on the size. If a pixel is in the middle of two bins, its size is divided according to their distance from the division. After this process is done, the histogram is created and the boxes with the highest weight can be seen.



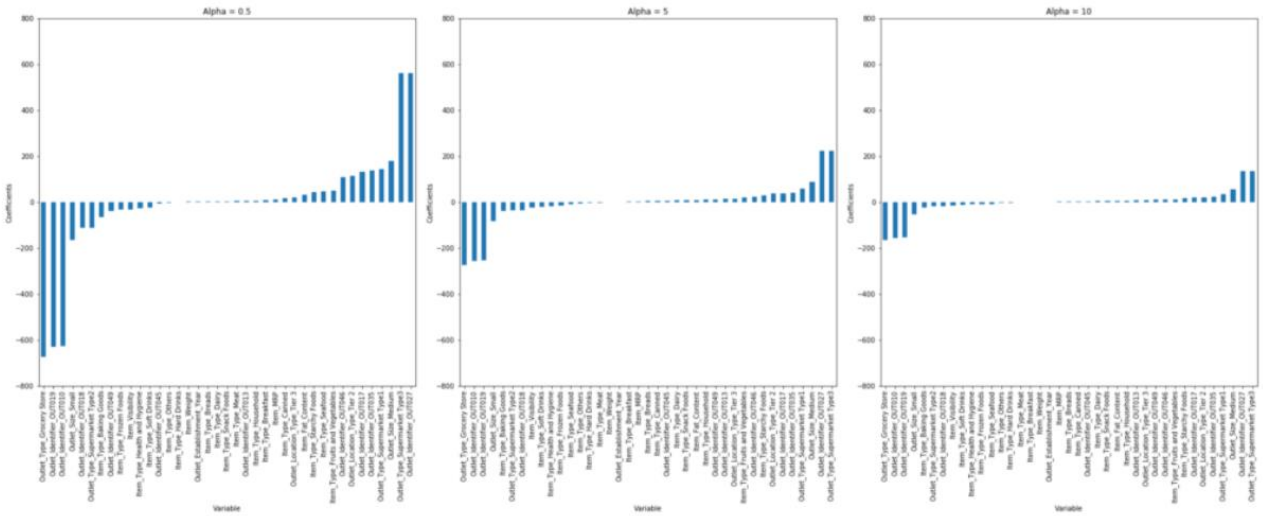
Task-7C:

Regularization is a technique used in regression to reduce the complexity of the model and reduce the coefficients of independent variables. In other words, it is one of the methods used to prevent the model from being overfitted.

Regularization puts a limitation on the coefficients of the variables in the model. The difference between the coefficients tends to be higher in a complex model. A high coefficient means that that variable is much more important to the model. This indicates that the algorithm is trying to model complex relationships to predict. The problem is much greater when the coefficients get bigger. This may cause the variance to increase and the model to be overfit.

There are two main types of regularization: Ridge and LASSO. Both add a penalty term to the model. Both methods include a lambda parameter that decides how important the penalty is based on the squared error term. The higher the penalty, the higher the lambda value and thus the size of the coefficients is reduced.

- **Ridge Regression (L2 Regularization)**
  Ridge regression is a method used to analyze data that suffers from multiple multi-collinearity. Ridge regression adds a penalty (L2 penalty) to the function that is equivalent to the square of the magnitude of the coefficients.
  The model will generate a different coefficient estimate for each lambda value. As the lambda value increases, the model complexity will decrease. Even if, this reduces the model's overfitting, higher values may be insufficient. Choosing the lambda value is important in order to avoid the bias-variance trade-off. The method used for this is cross-validation. Among the values produced by this method, the best lambda value is chosen. Even if the best lambda value is very close to zero, they will never be 0.



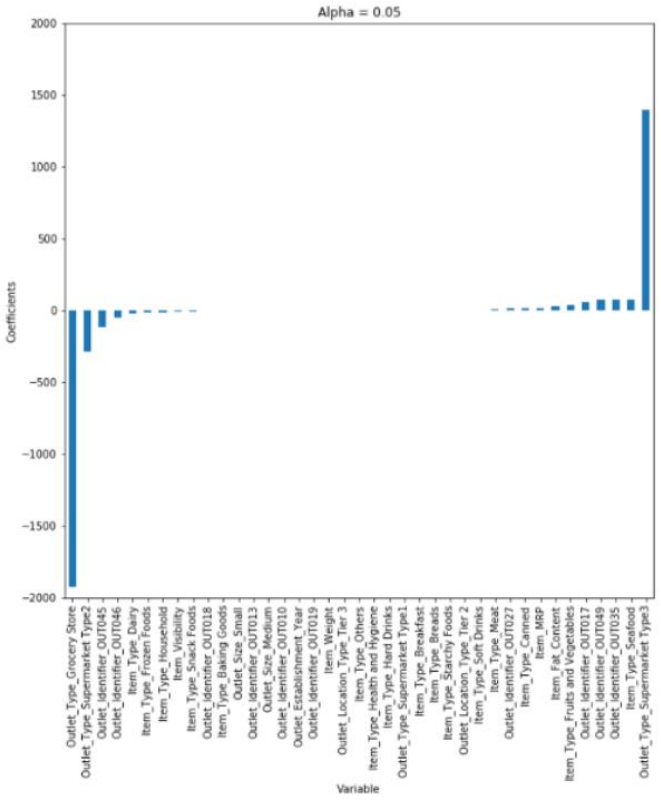
Ridge Regression: Coefficient values if λ = 0.5, 5 and 10 respectively || Source

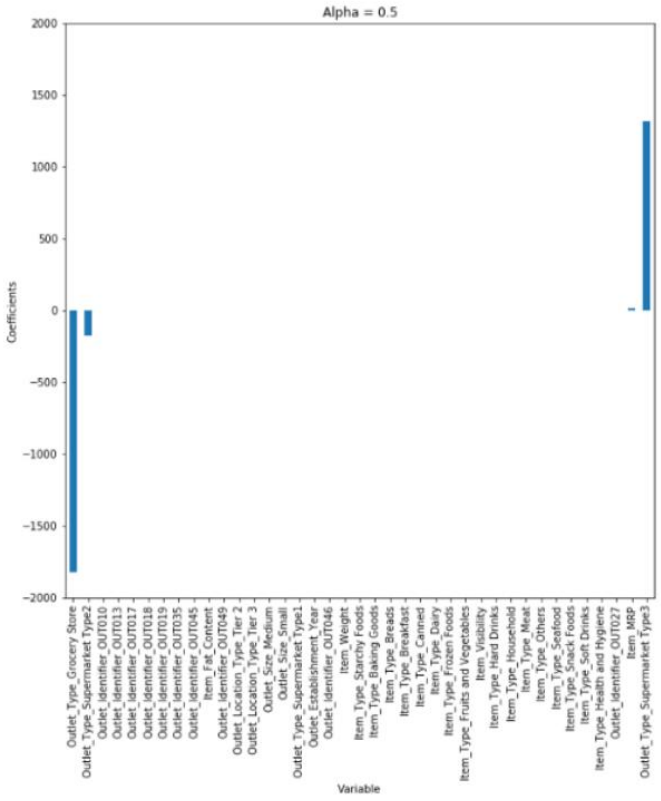
λ = 0. 5 **λ = 5** **λ = 10**

- **LASSO Regression (L1 Regularization)**

The Lasso regression analysis method performs both feature selection and regularization to increase the prediction accuracy of the model. Unlike ridge regression, lasso regression, which means least absolute shrinkage, also allows feature selection by forcing the coefficients of features to zero when the penalty is large enough. This method has the following disadvantage that when the model has correlated variables, it only keeps one variable and sets the other correlated variables to zero. This can result in loss of information and result in lower model accuracy.

In short, it adds an L1 penalty equivalent to the magnitude of the coefficients to the function. This L1 penalty forces some coefficients to be exactly equal to zero when the regularization parameter λ is large enough. This also helps feature selection and shrinks the coefficients of remaining features to reduce model complexity, thus preventing overfitting.

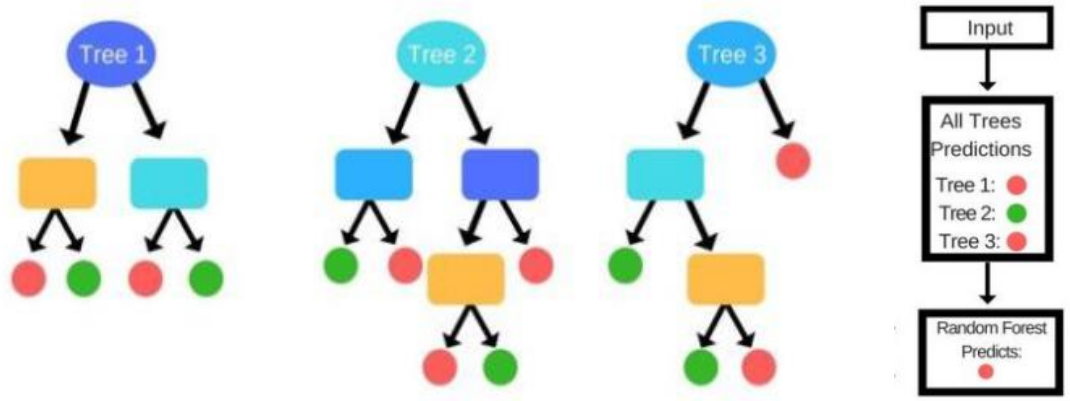




λ = 0. 05 **λ = 0. 5**

Task-7D:

Random Forest algorithm is a supervised classification algorithm. It consists of a large number of individual decision trees. Each working decision tree generates a class estimate. The decision tree with the highest number of votes is chosen as the best for the output of the model. The difference between Random Forest algorithm and the decision tree algorithm is that in Random Forest, the process of finding the root node and splitting the feature nodes will run randomly.

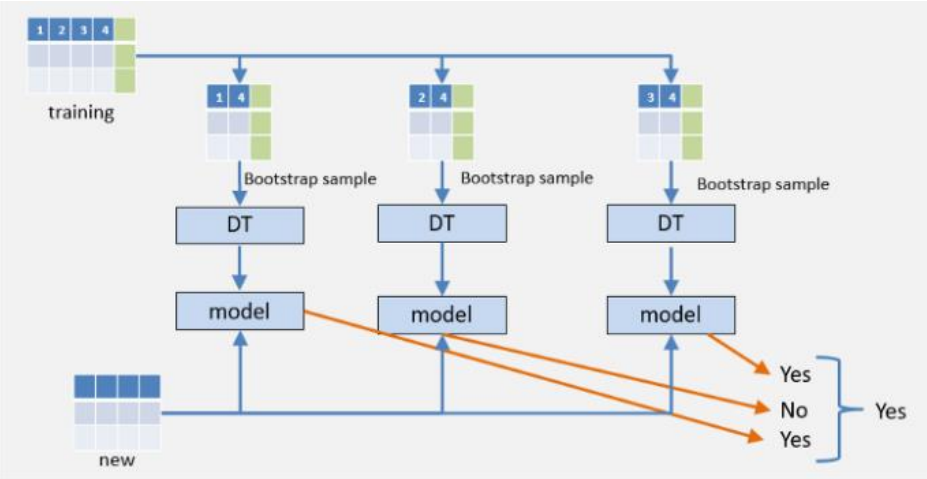


This model of trees is also called an ensemble. The ensemble returns a class prediction based on the votes of the base classifiers.

Random Forest is one of the most popular and most powerful machine learning algorithms which is a type of ensemble machine learning algorithm called Bootstrap Aggregation or Bagging.

Bagging (Bootstrap Aggregation) is a simple ensemble method. It can be used to reduce model's variance. High variance means that the model is overfitted. For example, decision trees usually have high variance. Bagging offers a solution for this high variance problem. It can reduce overfitting by taking an average of several decision trees. Bagging method uses bootstrap sampling and puts together decision trees by averaging them to predict the result.

Bootstrap sampling means sampling rows at random from the training dataset with replacement.



The accuracy of a random forest depends on the strength of the individual decision tree classifiers and a measure of the dependence between them.

Advantages:

Compared with other classification techniques, there are three advantages:

- In classification problems, Random Forest algorithm avoid the overfitting problem.
- The same random forest algorithm can be used for both classification and regression task.
- Random forest algorithm enables selection of features that will contribute to the model from the dataset, feature engineering.
- Because a subset of properties is worked on in the model, it is faster to train data than decision trees. Thus, it can work quickly with hundreds of features.
- Each decision tree included in the model has high variance but low bias. Since all trees are averaged in the random forest algorithm, the variance is also averaged. In this way, the model turns into a low bias and medium variance structure.

Disadvantages:

- Random forest models are not completely interpretable.
- For very large data, the size of the trees is also very large and can take up a lot of memory.
- Since the model has a high tendency to overfit, the most suitable hyperparameters should be selected for the model.

Examples of usage in banking, medical, stock market and e-commerce fields can be given.

- In stock market, Random Forest algorithm can be used to identify a stock's behavior and the expected loss or profit.
- In e-commerce, Random forest algorithm can be used to predict whether the customer will like the recommended products based on the experience of similar customers.
- In medicine, it can be used to identify diseases by analyzing the patient’s medical records.
- In banking, it can be used to predict whether the customer has churn or not.

Example:

```
df=pd.read_csv("bank-additional-full.csv")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 20 columns):
age               41188 non-null int64
job               41188 non-null object
marital           41188 non-null object
education         41188 non-null object
default           41188 non-null object
housing           41188 non-null object
loan              41188 non-null object
contact           41188 non-null object
month             41188 non-null object
day_of_week       41188 non-null object
duration          41188 non-null int64
campaign          41188 non-null int64
pdays             41188 non-null int64
previous          41188 non-null int64
poutcome          41188 non-null object
emp.var.rate      41188 non-null float64
cons.price.idx    41188 non-null float64
cons.conf.idx     41188 non-null float64
euribor3m         41188 non-null float64
y                 41188 non-null object
dtypes: float64(4), int64(5), object(11)
memory usage: 6.3+ MB
```

```
df.head()
```

job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome
housemaid	married	basic.4y	no	no	no	telephone	may	mon	261	1	999	0	nonexistent
services	married	high.school	unknown	no	no	telephone	may	mon	149	1	999	0	nonexistent
services	married	high.school	no	yes	no	telephone	may	mon	226	1	999	0	nonexistent
admin.	married	basic.6y	no	no	no	telephone	may	mon	151	1	999	0	nonexistent
services	married	high.school	no	no	yes	telephone	may	mon	307	1	999	0	nonexistent

```
#Converting string values to dummies
df_final=pd.get_dummies(df,columns=["day_of_week","job",
                                    "marital","education",
                                    "default","housing",
                                    "loan","contact","month",
                                    "poutcome"],drop_first=True)
```

```
#Fitting a Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier

#Sepcifying the random forest-n_estimator specifies the number of trees
rfc=RandomForestClassifier(n_estimators=1000)
rfc.fit(X_train,y_train)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=1000, n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

```
#Getting our Predictions
y_hat=rfc.predict(X_test)


#Printing the Accuarcy, Confusion Matrix and the Classification Report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score


y_actu = pd.Series(y_test, name='Actual')
df_confusion = pd.crosstab(y_actu, y_hat)
acc = accuracy_score(y_test, y_hat, normalize=True)
print('Model Accuracy:%.2f'%acc)
print(df_confusion)
print(classification_report(y_test,y_hat))
```

```
Model Accuracy:0.92
col_0       no  yes
Actual
no       10637  348
yes        690  682
              precision    recall  f1-score   support

          no       0.94      0.97      0.95     10985
         yes       0.66      0.50      0.57      1372

   micro avg       0.92      0.92      0.92     12357
   macro avg       0.80      0.73      0.76     12357
weighted avg       0.91      0.92      0.91     12357
```