Feature Selection With Filtering Method | Constant, Quasi constant and **Duplicate Feature Removal** Machine learning and deep learning is learning from data which consist of diffrent types of features. lets say if we have huge datasets it could have huge featurespace as well.if we have huge feature space then we want some types of algorithms which can select the highest performing features for apping machine learning algorithms otherwise u will endup your machine with overfitting which will deterioate the performace of your model. Training time and Performace of our machine learning depends havily on the features in the datasets. If we having the large datasets then it will definately take long traning time. Its is garanteed that huge feature space will result the better performace. So idealy we have to select the those feature which are actually help in machine learning model learn something usefull. • Unnecessary and redudant features not only slow down the traing time of our algorithms but they are also affect the overall performace of the algorithm. The process of selecting the most suitable feature for training the machine learning model is called a feature selection. • In that we are going to learn about the feature selection with the filtering method. In that we will be do the constant, quasi constant and duplicate feature removal. There is several advantages of performing the feature selection before taring our machine learning model. Models with the less numbers of featutres have higher explainability. • Its very easier to implement the machine lerning models with the reduced features. Fewer feature leads to enhance the generalization which in turns reduces overfitting. • Feature selection reduces data redudancy. Training time for a model with fewer features is significantly lower. Models with the fewer features are less prone to errors. What is Filter Technique? • Filter method is belonging to the feature selection method that select features independently of machine learning models. It doesn't involve any machine learning alorithm while selecting a features. • This is one of the biggest advantage of this method since is doesnt inovolve any machine learning algorithm that's it is a pretty fast. Feature selected by using with the filter method can be use as an input to any machine learning model. And another advantages of the fiter method is they are very fast. Filter method is a generally first step in feature selection pipeline so this kind of best screening method to get subset of the features. There are two kind of feature seection method in filtering method those are the Univariate MultiVariant Univariant • In the univariate we are selecting the feature without taking consideration of other features. Thats it kind of independed. Lets consider we having the 10 features then we can select the some subset of the features without taking the information of nine features for particular feature. In the univariant feature selection we can select the features based on the Fisher score, Mutual Information Gain etc. The univariate filter methods are types of the method where individual features are ranked according to the specific criteria. The top N features are then selected. Diffrent type of the ranking criteria are used for the univariat filter methods. For an example: - Fisher Score, mutual information and variance of the feature. **Multi-Variate** • In in multi-variate feature selection method we take information of feature to feature. Then we will try to find out the best feature out of those subset features and method from which we select known as "pearson correletion". Multivariant filter methods are capable of removing redundant features from the data since they mutual relationship between the features into account. Univariant Filtering Methods. Constant Removal Quasi Constant Removal **Duplicate Feature Removal** Lets Strat With ML. import numpy as np import pandas as pd import seaborn as sns import matplotlib.pyplot as plt import warnings warnings.filterwarnings('ignore') from sklearn.preprocessing import StandardScaler from sklearn.feature selection import VarianceThreshold from sklearn.ensemble import RandomForestClassifier from sklearn.metrics import classification report, accuracy score, mean squared error data = pd.read csv('Churn Modelling.csv') data.head() RowNumber **CustomerId Surname** CreditScore **Geography Gender** Age Tenure Balance NumOfProducts HasCrCard IsActiveMember 15634602 Hargrave 0 619 2 0.00 1 1 1 1 France Female 42 15647311 Hill 608 Spain 83807.86 0 41 Female 2 3 15619304 Onio 502 Female 42 159660.80 3 1 0 France 0 3 15701354 699 0.00 0 Boni Female 39 France 4 15737888 Mitchell 850 2 125510.82 1 1 1 Spain Female 43 data.tail() CreditScore Geography Gender RowNumber CustomerId Surname Tenure Balance NumOfProducts HasCrCard **IsActiveMen** Age 9995 9996 5 0.00 2 15606229 Obijiaku 771 France Male 39 1 9996 9997 15569892 516 35 10 57369.61 Johnstone France Male 0 9997 9998 15584532 Liu 709 Female 36 7 0.00 1 France 9999 75075.31 9998 15682355 Sabbatini 772 42 Germany Male 9999 10000 1 1 15628319 Walker 792 28 4 130142.79 France Female data.shape (10000, 14)In [24]: data.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 10000 entries, 0 to 9999 Data columns (total 14 columns): RowNumber 10000 non-null int64 10000 non-null int64 CustomerId Surname 10000 non-null object 10000 non-null int64 CreditScore Geography 10000 non-null object 10000 non-null object Gender 10000 non-null int64 Age 10000 non-null int64 Tenure Balance 10000 non-null float64 NumOfProducts 10000 non-null int64 10000 non-null int64 HasCrCard 10000 non-null int64 IsActiveMember EstimatedSalary 10000 non-null float64 10000 non-null int64 dtypes: float64(2), int64(9), object(3) memory usage: 976.6+ KB data.describe() CreditScore NumOfProducts HasCrCard IsActiveMember RowNumber CustomerId Age **Tenure** Balance 10000.00000 1.000000e+04 10000.000000 10000.000000 10000.000000 10000.000000 10000.000000 10000.00000 10000.000000 count 76485.889288 0.70550 mean 5000.50000 1.569094e+07 650.528800 38.921800 5.012800 1.530200 0.515100 7.193619e+04 2886.89568 10.487806 2.892174 62397.405202 0.581654 0.45584 0.499797 96.653299 std 1.00000 1.556570e+07 350.000000 18.000000 0.000000 0.000000 1.000000 0.00000 0.000000 min 32.000000 0.00000 25% 584.000000 3.000000 0.000000 1.000000 0.000000 2500.75000 1.562853e+07 50% 37.000000 1.000000 1.00000 5000.50000 1.569074e+07 652.000000 5.000000 97198.540000 1.000000 44.000000 75% 2.000000 7500.25000 1.575323e+07 718.000000 7.000000 127644.240000 1.00000 1.000000 4.000000 1.00000 1.000000 10000.00000 1.581569e+07 850.000000 92.000000 10.000000 250898.090000 max data.columns Out[26]: Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary', 'Exited'], dtype='object') data.nunique() Out[27]: RowNumber 10000 10000 CustomerId 2932 Surname CreditScore 460 3 Geography 2 Gender 70 Age Tenure 11 6382 Balance NumOfProducts 4 2 HasCrCard IsActiveMember 2 9999 EstimatedSalary Exited dtype: int64 from sklearn.preprocessing import LabelEncoder lable = LabelEncoder() data['Geography'] = lable.fit_transform(data['Geography']) data['Gender']=lable.fit_transform(data['Gender']) data.head() **RowNumber CustomerId Surname** CreditScore Age Tenure Balance NumOfProducts HasCrCard IsActiveMember Geography Gender 0 15634602 Hargrave 619 0 0 42 2 0.00 1 1 15647311 Hill 608 0 41 83807.86 0 2 0 1 0 3 15619304 Onio 502 0 42 159660.80 3 0 3 15701354 Boni 699 0 39 0.00 4 2 15737888 Mitchell 850 0 43 2 125510.82 1 data.drop(columns=['Surname'],inplace=True) data.head() RowNumber CustomerId CreditScore Geography Gender Age Tenure Balance NumOfProducts HasCrCard IsActiveMember Estimate 0 1 15634602 619 0 0 42 2 0.00 10 2 15647311 608 41 83807.86 11 2 3 15619304 502 0 0 42 8 159660.80 3 1 0 11 3 15701354 699 39 0.00 4 2 5 15737888 850 43 125510.82 1 data.drop(columns=['CustomerId'],inplace=True) data.drop(columns=['RowNumber'],inplace=True) In [34]: data.head() Out[34]: CreditScore Geography Gender Age Tenure Balance NumOfProducts HasCrCard IsActiveMember EstimatedSalary Exited 0 619 0 0 42 0.00 1 101348.88 608 0 41 83807.86 112542.58 2 502 0 0 42 159660.80 3 0 113931.57 3 699 39 0.00 0 93826.63 0 4 850 2 0 43 125510.82 1 1 1 79084.10 0 x= data.drop(columns=['Exited']) y = data['Exited']

x.shape, y.shape

((10000, 10), (10000,))

x train.shape, x test.shape

((8000, 10), (2000, 10))

((8000, 7), (2000, 7))

duplicated

2

4 5

6

False False

False False

False

Out[73]: ((8000, 7), (2000, 7))

Accuarcy :- 0.855

False dtype: bool

from sklearn.model_selection import train_test_split

Help us to remove the duplicate features inside the data.

var = VarianceThreshold(threshold=0.25) x_train_unique = var.fit_transform(x_train)

x_train_unique.shape,x_test_unique.shape

x test unique = var.transform(x test)

#to remove the duplicated features

x_train_T = pd.DataFrame(x train T) x_test_T =pd.DataFrame(x_test_T)

duplicated = x train T.duplicated()

keep them = [not i for i in duplicated]

x_train_unique = x_train_T[keep_them].T x_test_unique = x_test_T[keep_them].T

x_train_unique.shape,x_test_unique.shape

clf.fit(x_train,y_train) y pred = clf.predict(x test)

def RanndomForest(x_train, x_test, y_train, y_test):

print('Accuarcy :-',accuracy score(y test,y pred))

RanndomForest(x_train_unique,x_test_unique,y_train,y_test)

clf = RandomForestClassifier(random_state=42,n_estimators=100)

 $x_{train_T} = x_{train_unique_T}$ $x_{test_T} = x_{test_unique.T}$

x_train,x_test,y_train,y_test = train_test_split(x,y,train_size=0.80,random_state=42,stratify=y)