Import Library In [387... import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns from glob import glob from sklearn.metrics import mean\_absolute\_error from sklearn.linear\_model import LinearRegression from sklearn.linear\_model import LogisticRegression  $\textbf{from} \ \text{sklearn.neighbors} \ \textbf{import} \ \text{KNeighborsClassifier}$  $\begin{tabular}{ll} from & sklearn.tree & import & DecisionTreeClassifier \\ \end{tabular}$  $\label{from:constraint} \textbf{from} \ \ \text{sklearn.ensemble} \ \ \textbf{import} \ \ \text{RandomForestClassifier}$ from sklearn.naive\_bayes import GaussianNB from sklearn.pipeline import make\_pipeline from sklearn.model\_selection import train\_test\_split from sklearn.preprocessing import OneHotEncoder from sklearn.metrics import accuracy\_score , classification\_report import pandas\_profiling from category\_encoders import OneHotEncoder from sklearn.metrics import mean\_squared\_error from sklearn.model\_selection import cross\_validate t=pd.read\_csv("test.csv") In [388... t.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 418 entries, 0 to 417 Data columns (total 11 columns): # Column Non-Null Count Dtype -----0 PassengerId 418 non-null int64 418 non-null int64 1 Pclass 418 non-null 2 Name object 3 Sex 418 non-null object 332 non-null float64 Age 418 non-null SibSp int64 418 non-null 6 Parch int64 418 non-null 7 Ticket object 8 Fare 417 non-null float64 Cabin 91 non-null object 10 Embarked 418 non-null object dtypes: float64(2), int64(4), object(5) memory usage: 36.0+ KB Import Data In [389... def wrangel(path): # read data df=pd.read\_csv(path) #extract the social name df["title"]=df["Name"].str.extract("([A-Za-z]+)\.", expand=False) #convert title categorcal data df.loc[df["title"]=="Mr" , "title"] = 0
df.loc[df["title"]=="Miss" , "title"] = 1
df.loc[df["title"]=="Mrs" , "title"] = 2
df.loc[df["title"]=="Master" , "title"] = 3  $conditions = (df["title"] == 'Ms') \mid (df["title"] == 'Col') \mid (df["title"] == 'Rev') \mid (df["title"] == 'Dr') \mid (df["title"] == 'Dona')$ df.loc[conditions, "title"] = 4 #fill NAN Value of Fare Accorging to Social Name df["Fare"].fillna(df.groupby("Pclass")["Fare"].transform("median"),inplace=True) #fill NAN Value of Age Accorging to Social Name df["Age"].fillna(df.groupby("title")["Age"].transform("median"),inplace=True) #fill NAN Value of Embarked Accorging to Median df["Embarked"]=df["Embarked"].fillna("S") #remove nan columns drop=[] drop.append("Cabin") drop.append("Name") drop.append("Ticket") drop.append("title") df.drop(columns=drop,inplace=True) #convert Sex categorcal data , "Sex"] = 0 df.loc[df["Sex"]=="male" # Male ---> 0 df.loc[df["Sex"]=="female" , "Sex"] = 1 # Female ---> 1 #convert Embarked categorcal data , "Embarked"] = 0df.loc[df["Embarked"]=="S" # S ---> 1 , "Embarked"] df.loc[df["Embarked"]=="C" = 1 # C ---> 2 , "Embarked"] = 2 df.loc[df["Embarked"]=="Q" return df test = wrangel("test.csv") In [390... df = wrangel("train.csv") df.head() In [340... Out[340]: Passengerld Survived Pclass Sex Age SibSp Parch Fare Embarked 0 1 0 22.0 7.2500 0 1 1 38.0 0 71.2833 1 2 3 1 26.0 0 7.9250 0 3 1 35.0 0 53.1000 0 1 4 5 0 35.0 0 8.0500 0 df.info() In [341... <class 'pandas.core.frame.DataFrame'> RangeIndex: 891 entries, 0 to 890 Data columns (total 9 columns): Column Non-Null Count Dtype 0 PassengerId 891 non-null int64 Survived 891 non-null int64 1 2 Pclass 891 non-null int64 3 Sex 891 non-null object 4 Age 891 non-null float64 5 SibSp 891 non-null int64 6 Parch 891 non-null int64 7 Fare 891 non-null float64 8 Embarked 891 non-null object dtypes: float64(2), int64(5), object(2) memory usage: 62.8+ KB In [391... pandas\_profiling.ProfileReport(df) | 0/5 [00:00<?, ?it/s] Summarize dataset: 0%| | 0/1 [00:00<?, ?it/s] Generate report structure: 0%| | 0/1 [00:00<?, ?it/s] Render HTML: 0%| Pandas Profiling Report Overview Variables Interactions Correlations Missing values Sample Overview Overview Alerts 7 Reproduction **Dataset statistics** Variable types Numeric **Number of variables** 9 5 4 **Number of observations** 891 Categorical Missing cells 0 Missing cells (%) 0.0% **Duplicate rows** 0 **Duplicate rows (%)** 0.0% Total size in memory 62.8 KiB Average record size in memory 72.1 B **Variables** Select Columns ∨ PassengerId n - - I --- - - - /m\ Out[391]: df["Embarked"].value\_counts() 646 Out[343]: 168 77 Name: Embarked, dtype: int64 test.info() In [344... <class 'pandas.core.frame.DataFrame'> RangeIndex: 418 entries, 0 to 417 Data columns (total 8 columns): # Column Non-Null Count Dtype O PassengerId 418 non-null int64 418 non-null 1 Pclass int64 2 Sex 418 non-null object 3 418 non-null float64 Age 418 non-null int64 SibSp 5 418 non-null Parch int64 6 Fare 418 non-null float64 418 non-null Embarked object dtypes: float64(2), int64(4), object(2)memory usage: 26.2+ KB In [352... test.isnull().sum() PassengerId Out[352]: Pclass 0 Sex Age SibSp Parch 0 Fare Embarked 0 dtype: int64 **Exploer Data** In [353... print("Survive :",(df["Survived"]==1).sum()) print("Deceased :",(df["Survived"]==0).sum()) Survive : 342 Deceased: 549 df.describe() In [354... Out[354]: PassengerId Survived **Pclass** Age SibSp Parch Fare 891.000000 891.000000 891.000000 891.000000 891.000000 891.000000 891.000000 mean 446.000000 0.383838 2.308642 29.393008 0.523008 0.381594 32.204208 257.353842 49.693429 0.486592 0.836071 13.269209 1.102743 0.806057 1.000000 0.000000 1.000000 min 0.420000 0.000000 0.000000 0.000000 223.500000 0.000000 2.000000 21.000000 0.000000 0.000000 7.910400 25% 446.000000 **50**% 0.000000 3.000000 30.000000 0.000000 0.000000 14.454200 75% 668.500000 1.000000 3.000000 35.000000 1.000000 0.000000 31.000000 891.000000 1.000000 3.000000 80.000000 8.000000 6.000000 512.329200 In [355... # Create the pie chart values=df["Survived"].value\_counts() label=["Deceased ","Survive "] plt.pie(values, labels=label, autopct='%1.1f%%') # Add a title plt.title('Distribution of Survived') # Display the chart plt.show() Distribution of Survived Deceased 61.6% 38.4% Survive plt.hist(df["Parch"], bins=5, edgecolor='black'); plt.xlabel('Values') plt.ylabel('Frequancy') plt.title("Values of Parch") plt.show(); Values of Parch 800 700 600 500 Frequancy 400 300 200 100 0 2 3 Values survive=df[df["Survived"]==1]["SibSp"].value\_counts() death=df[df["Survived"]==0]["SibSp"].value\_counts() dx=pd.DataFrame([survive, death], index=["survive", "death"]) dx.plot(kind="bar"); plt.title("Survive of SibSp "); Survive of SibSp 400 350 300 8 5 250 200 150 100 50 death survive=df[df["Survived"]==1]["Pclass"].value\_counts() death=df[df["Survived"]==0]["Pclass"].value\_counts() dx=pd.DataFrame([survive, death], index=["survive", "death"]) dx.plot(kind="bar"); plt.title("Survive of Pclass "); Survive of Pclass 350 3 300 250 200 -150 100 50 0 class1=df[df["Pclass"]==1]["Embarked"].value\_counts()
class2=df[df["Pclass"]==2]["Embarked"].value\_counts()
class3=df[df["Pclass"]==3]["Embarked"].value\_counts() dx=pd.DataFrame([class1,class2,class3],index=["class 1","class 2","class 3"]) dx.plot(kind="bar", stacked=True); plt.title("Survive of Pclass "); Survive of Pclass 500 1 400 300 200 100 class We Found that Embarked from S in 1st & 2nd & 3rd Class # Create the pie chart In [360... values=df["Sex"].value\_counts() label=["male", "female"] plt.pie(values, labels=label, autopct='%1.1f%%') # Add a title plt.title('Distribution of Survived') # Display the chart plt.show() Distribution of Survived male 35.2% female survive = df[df["Survived"]==1]["Sex"].value\_counts() = df[df["Survived"]==0]["Sex"].value\_counts() = pd.DataFrame([survive, death], index=["survive", "death"]) dx=dx.rename(columns={0:"male",1:"female"}) dx.plot(kind="bar") plt.legend() plt.title("Survive of Sex"); Survive of Sex female male 400 300 200 100 In [ ]: corrleation = df.drop(columns="Survived").corr() In [362... sns.heatmap(corrleation) <AxesSubplot:> Out[362]: - 1.0 PassengerId -- 0.8 Pclass - 0.6 Age 0.2 SibSp 0.0 Parch --0.2-0.4Fare -PassengerId Pclass SibSp Parch Fare Age Split Data In [ ]: In [363... Out[363]: Passengerld Survived Pclass Sex Age SibSp Parch Fare Embarked 1 3 0 22.0 0 7.2500 0 1 1 38.0 0 71.2833 1 1 3 0 7.9250 2 1 3 1 26.0 0 0 1 35.0 0 53.1000 5 0 0 0 8.0500 4 3 0 35.0 0 887 0 0 13.0000 0 886 0 0 27.0 887 888 1 19.0 0 30.0000 888 0 2 23.4500 889 1 21.0 0 889 890 0 26.0 0 30.0000 890 891 0 32.0 0 0 7.7500 2 891 rows × 9 columns In [364... target="Survived" y = df[target] X = df.drop(columns=target) x\_train , x\_test , y\_train , y\_test = train\_test\_split(X,y,test\_size=0.2,random\_state=42) print("X\_train shape:", x\_train.shape) print("y\_train shape:", y\_train.shape) print("X\_test shape:", x\_test.shape) print("y\_test shape:", y\_test.shape) X\_train shape: (712, 8) y\_train shape: (712,) X\_test shape: (179, 8) y\_test shape: (179,) Baseline In [365... y\_train\_mean = y\_train.mean() print ("Baseline :", round(y\_train\_mean, 2)) Baseline : 0.38 Logestic Regression **Itrate** log\_model = LogisticRegression(max\_iter=10000) In [366... log\_model.fit(x\_train,y\_train) In [367... Out[367]: LogisticRegression LogisticRegression(max\_iter=10000) **Evaluate** accuracy=classification\_report(y\_test, log\_model.predict(x\_test)) print(accuracy) precision recall f1-score support 0.82 0.85 0.83 1 0.77 0.73 0.75 74 accuracy 0.80 179 0.79 0.79 0.79 179 macro avg weighted avg 0.80 0.80 179 In [369... acc\_test = accuracy\_score(y\_test,log\_model.predict(x\_test)) acc\_test = accuracy\_score(y\_test,log\_model.predict(x\_test)) acc\_train= accuracy\_score(y\_train, log\_model.predict(x\_train)) print("Accuracy test:", round(acc\_test, 2)) print("Accuracy train:", round(acc\_train, 2)) Accuracy test: 0.8 Accuracy train: 0.8 **KNN Classfier** knn= KNeighborsClassifier(n\_neighbors=13) knn.fit(x\_train,y\_train) Out[370]: KNeighborsClassifier KNeighborsClassifier(n\_neighbors=13) accuracy=classification\_report(y\_test,knn.predict(x\_test)) print(accuracy) precision recall f1-score support 0 0.63 0.90 0.75 105 1 0.66 0.26 0.37 74 0.64 179 accuracy 0.56 179 0.64 0.58 macro avg weighted avg 0.64 0.64 0.59 179 scoring="accuracy" score = cross\_validate(knn , x\_train.drop(columns=["PassengerId"], axis=1), y\_train, cv=k\_fold, n\_jobs=1, scoring=scoring) print(score['test\_score'])  $[0.72222222\ 0.69444444\ 0.71830986\ 0.63380282\ 0.70422535\ 0.78873239$ 0.71830986 0.69014085 0.74647887 0.66197183] print("Accuracy :",round(np.mean(score['test\_score']),2)) Accuracy : 0.71 **Descion Tree** In [374... # Create a decision tree classifier dec\_tree= DecisionTreeClassifier() # Train the classifier dec\_tree.fit(x\_train, y\_train) Out[374]: ▼ DecisionTreeClassifier DecisionTreeClassifier() accuracy=classification\_report(y\_test, dec\_tree.predict(x\_test)) print(accuracy) recall f1-score precision support 0 0.79 0.76 0.78 105 0.68 0.72 0.70 74 accuracy 0.74 179 macro avg 0.74 0.74 0.74 179 weighted avg 0.75 0.74 0.74 179 In [376... acc\_test = accuracy\_score(y\_test, dec\_tree.predict(x\_test)) print("Accuracy test:", round(acc\_test, 2)) Accuracy test: 0.74 In [377... scoring="accuracy" score = cross\_validate(dec\_tree , x\_train.drop(columns=["PassengerId"],axis=1),y\_train,cv=k\_fold, n\_jobs=1,scoring=scoring) print("Accuracy :", round(np.mean(score['test\_score']), 2)) Accuracy: 0.78 Random Forest In [378... # Create a Random Forest classifier rf\_classifier = RandomForestClassifier() # Train the classifier rf\_classifier.fit(x\_train, y\_train) Out[378]: ▼ RandomForestClassifier RandomForestClassifier() In [379... # Calculate the accuracy accuracy = accuracy\_score(y\_test, rf\_classifier.predict(x\_test)) print("Accuracy:", round(accuracy, 2)) Accuracy: 0.84 scoring="accuracy" In [380... score = cross\_validate(rf\_classifier , x\_train.drop(columns=["PassengerId"],axis=1),y\_train, n\_jobs=1,scoring=scoring) print("Accuracy :", round(np.mean(score['test\_score']),1)) Accuracy : 0.8 Naive Bayes nav= GaussianNB() In [381... # Train the classifier nav.fit(x\_train, y\_train) Out[381]: ▼ GaussianNB GaussianNB() In [382... # Calculate the accuracy accuracy = accuracy\_score(y\_test, nav.predict(x\_test)) print("Accuracy:", round(accuracy,2)) Accuracy: 0.78 scoring="accuracy" In [383... score = cross\_validate(nav , x\_train.drop(columns=["PassengerId"],axis=1),y\_train, n\_jobs=1,scoring=scoring) print("Accuracy :", round(np.mean(score['test\_score']), 2)) Accuracy : 0.8 Communicat The best model is Random Forest with Accuracy: 82 pred\_test=rf\_classifier.predict(test) In [384... data = pd.DataFrame({'PassengerId': test["PassengerId"], 'Survived': pred\_test}) data.head() In [385... Out[385]: PassengerId Survived 0 892 0 893 0 2 894 0 0 895 4 0 896 data.to\_csv(r'D:\projects\gender\_submission.csv', index=False)