0 892 0 3 Kelly, Mr. James male 0 0 330911 7.8292 NaN Q 34.5 1 893 1 Wilkes, Mrs. James (Ellen Needs) female 363272 7.0000 NaN S 2 894 0 2 Myles, Mr. Thomas Francis 240276 9.6875 Q 62.0 0 0 NaN male 3 895 0 Wirz, Mr. Albert male 27.0 315154 8.6625 NaN 4 896 1 3 Hirvonen, Mrs. Alexander (Helga E Lindqvist) female 22.0 1 1 3101298 12.2875 NaN S ... 0 0 413 1305 3 Spector, Mr. Woolf 0 A.5. 3236 8.0500 NaN S male NaN 1306 1 PC 17758 108.9000 C105 С 414 Oliva y Ocana, Dona. Fermina female 39.0 0 3 415 1307 0 SOTON/O.Q. 3101262 S Saether, Mr. Simon Sivertsen male 38.5 0 7.2500 NaN 416 1308 0 Ware, Mr. Frederick male NaN 359309 8.0500 NaN S 417 1309 0 3 Peter, Master. Michael J С male NaN 1 1 2668 22.3583 NaN 418 rows × 12 columns df.head() In [3]: Out[3]: Passengerld Survived Pclass Name Sex Age SibSp Parch Ticket Fare Cabin Embarked 0 892 0 3 Kelly, Mr. James 330911 7.8292 NaN Q male 34.5 0 0 Wilkes, Mrs. James (Ellen Needs) 1 3 S 893 female 47.0 363272 7.0000 NaN 2 894 0 2 Myles, Mr. Thomas Francis 240276 9.6875 Q male 62.0 0 NaN S 3 895 0 3 Wirz, Mr. Albert 315154 8.6625 NaN male 27.0 896 1 3 Hirvonen, Mrs. Alexander (Helga E Lindqvist) female 22.0 1 3101298 12.2875 S 1 NaN df.tail() In [4]: Passengerld Survived Pclass Sex Age SibSp Parch Ticket Fare Cabin Embarked Out[4]: Name A.5. 3236 413 1305 0 3 Spector, Mr. Woolf 0 0 8.0500 NaN S male NaN С 414 1306 1 1 Oliva y Ocana, Dona. Fermina female 0 PC 17758 108.9000 C105 415 1307 0 Saether, Mr. Simon Sivertsen 0 0 SOTON/O.Q. 3101262 S 3 male 38.5 7.2500 NaN 416 1308 0 Ware, Mr. Frederick male NaN 0 359309 8.0500 NaN S С 417 1309 0 3 Peter, Master. Michael J 2668 22.3583 NaN male NaN 1 1 df.shape In [5]: (418, 12)Out[5]: df.describe() Out[7]: Passengerld Survived **Pclass** Age SibSp Parch Fare 418.000000 418.000000 332.000000 418.000000 418.000000 417.000000 count 418.000000 mean 1100.500000 0.447368 0.392344 0.363636 2.265550 30.272590 35.627188 0.481622 0.841838 0.896760 55.907576 std 120.810458 14.181209 0.981429 1.000000 892.000000 0.000000 0.170000 0.000000 0.000000 0.000000 min **25**% 996.250000 0.000000 1.000000 21.000000 0.000000 0.000000 7.895800 **50**% 1100.500000 0.000000 3.000000 27.000000 0.000000 0.000000 14.454200 3.000000 39.000000 1.000000 **75**% 1204.750000 1.000000 0.000000 31.500000 max 1309.000000 1.000000 3.000000 76.000000 8.000000 9.000000 512.329200 df.isnull().sum() In [8]: PassengerId 0 Out[8]: Survived 0 0 **Pclass** 0 Name 0 Sex 86 Age SibSp 0 Parch 0 Ticket 0 Fare 1 Cabin 327 Embarked 0 dtype: int64 df.dtypes In [12]: int64 PassengerId Out[12]: Survived int64 **Pclass** int64 Name object object Sex float64 Age SibSp int64 Parch int64 Ticket object Fare float64 Cabin object Embarked object dtype: object df['Age'] = df['Age'].fillna(df['Age'].mean()) In [13]: df['Fare'] = df['Fare'].fillna(df['Fare'].mean()) Embarked = df['Embarked'].unique() for Embarkeds in Embarked: print("->", Embarkeds) -> Q -> S -> C df['Embarked'] = df['Embarked'].map( {'Q': 0, 'S':1, 'C':2}).astype(int) In [15]: df['Sex'] = df['Sex'].map( {'female': 1, 'male':0}).astype(int) df.dtypes In [16]: PassengerId int64 Out[16]: Survived int64 Pclass int64 Name object Sex int32 float64 Age SibSp int64 Parch int64 Ticket object Fare float64 Cabin object Embarked int32 dtype: object In [17]: | df['Age'] = df['Age'].astype(int) df['Fare'] = df['Fare'].astype(int) data = df.drop(['PassengerId','Name','Cabin','Ticket'], axis =1, inplace=True) In [18]: df.head() Out[18]: Survived Pclass Sex Age SibSp Parch Fare Embarked 0 7 34 0 0 0 47 0 9 0 62 0 0 27 1 3 22 12 1 1 1 1 In [19]: import matplotlib.pyplot as plt fig = plt.figure(figsize =(10, 7)) plt.hist(x = [df[df['Survived']==1]['Age'], df[df['Survived']==0]['Age']], stacked=True, color = ['g', 'r'], label = ['Survived', 'Not survived'])plt.title('Age Histogram with Survival') plt.xlabel('Age') plt.ylabel('No of passengers') plt.legend() <matplotlib.legend.Legend at 0x2af49e1e410> Out[19]: Age Histogram with Survival Survived Not survived 175 150 125 No of passengers 100 75 50 25

Age SibSp Parch

Name

Sex

Ticket

Fare

Cabin Embarked

In [1]: **import** numpy **as** np

In [2]:

Out[2]:

import pandas as pd
import seaborn as sns

from sklearn.svm import SVC

Passengerld Survived Pclass

from sklearn.linear\_model import LogisticRegression
from sklearn.model\_selection import train\_test\_split
from sklearn.metrics import classification\_report

from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier

df=pd.read\_csv("C:/Users/Admin/Desktop/tested.csv")

from sklearn.metrics import accuracy\_score
from sklearn.tree import DecisionTreeClassifier



In [21]: column = 'Survived'

# Create a bar chart

survival\_counts = df[column].value\_counts()

survival\_counts.plot(kind='bar', rot=0)

# Adding labels and title

plr.xlabel('Survived')

plt.title('Survival Count (0 = No, 1 = Yes)')

# Show the plot

plt.show()

Survival Count (0 = No, 1 = Yes)

250

200

Survival Count (0 = No, 1 = Yes)

To [22]: Train = df.drop(['Survived'], axis=1)

Test = df.iloc[:,1]

x\_train, x\_lest, y\_train, y\_test = train\_test\_split(Train, Test, test\_size = 0.2, random\_state = 1)

In [23]: LR = LogisticRegression(solver='liblinear', max\_iter=200)

print('Logistic regression accuracy: {:.2f}%'.format(LRAcc\*100))

LR.fit(x\_train, y\_train)
y\_pred = LR.predict(x\_test)

In [ ]

LRAcc = accuracy\_score(y\_pred,y\_test)

Logistic regression accuracy: 92.86%