The sinking of the Titanic is one of the most tragic tragedies in history. The tragedy took place on April 15th, 1912. The Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers. The numbers of survivors were low due to lack of lifeboats for all passengers. Some passengers were more likely to survive than others, such as women, children, and upperclass. This case study analyzes what sorts of people were likely to survive this tragedy. The dataset includes the following:

- Pclass: Ticket class (1 = 1st, 2 = 2nd, 3 = 3rd)
- Sex: Sex
- Age: Age in years
- Sibsp: # of siblings / spouses aboard the Titanic
- Parch: # of parents / children aboard the Titanic
- Ticket:Ticket number
- Fare: Passenger fare
- · Cabin: Cabin number
- Embarked: Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton
- Target class: Survived: (0 = No, 1 = Yes)



import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

Read the data using pandas dataframe
titanic_df = pd.read_csv('/content/titanic.csv')

Show the data head!
titanic_df.head()

_		PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
	0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
	1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2833	C85	С
	2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/02. 3101282	7.9250	NaN	S

TITANIC II

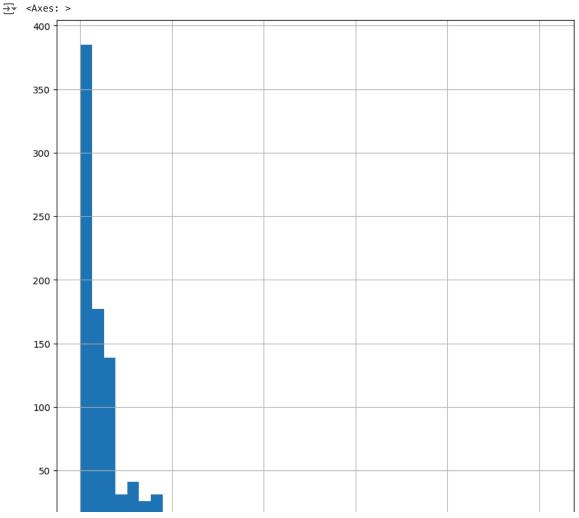
[#] Let's count the number of survivors and non-survivors survived_df = titanic_df[titanic_df['Survived'] == 1] no_survived_df = titanic_df[titanic_df['Survived'] == 0]

```
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                                               Logistic_Regression_and_Naive_Bayes_Titanic_Survival_Prediction.ipynb - Colab
   # Count the survived and deceased
   print("Total =", len(titanic_df))
   print("Number of passengers who survived =", len(survived_df))
   print("Percentage Survived =", 1. * len(survived_df) / len(titanic_df) * 100.0, "%")
   print("Number of passengers who did not Survive =", len(no_survived_df))
   print("Percentage who did not survive =", 1. * len(no_survived_df) / len(titanic_df) * 100.0, "%")
    → Total = 891
        Number of passengers who survived = 342
        Percentage Survived = 38.38383838383838 %
        Number of passengers who did not Survive = 549
        Percentage who did not survive = 61.61616161616161 %
   # Bar Chart to indicate the number of people who survived based on their class
   # If you are a first class, you have a higher chance of survival
   plt.figure(figsize = [10, 10])
   plt.subplot(211)
   sns.countplot(x = 'Pclass', data = titanic_df)
   plt.subplot(212)
   sns.countplot(x = 'Pclass', hue = 'Survived', data = titanic_df)
    <Axes: xlabel='Pclass', ylabel='count'>
            500
            400
            300
         count
            200
            100
              0
                                                                                              3
                                                               2
                                                             Pclass
                                                                                                      Survived
            350
                                                                                                           0
                                                                                                           1
            300
            250
         count
           200
            150
            100
             50
   # Bar Chart to indicate the number of people survived based on their siblings status
   # If you have 1 siblings (SibSp = 1), you have a higher chance of survival compared to being alone (SibSp = 0)
   plt.figure(figsize = [10, 10])
   plt.subplot(211)
   sns.countplot(x = 'SibSp', data = titanic_df)
   plt.subplot(212)
```

sns.countplot(x = 'SibSp', hue = 'Survived', data = titanic_df)

<Axes: xlabel='SibSp', ylabel='count'> 300 SibSp Survived # Bar Chart to indicate the number of people survived based on their Parch status (how many parents onboard) # If you have 1, 2, or 3 family members (Parch = 1,2), you have a higher chance of survival compared to being alone (Parch = 0) plt.figure(figsize = [15, 10]) plt.subplot(211) sns.countplot(x = 'Parch', data = titanic_df) plt.subplot(212) sns.countplot(x = 'Parch', hue = 'Survived', data = titanic_df); \overline{z} Parch Survived

```
# Bar Chart to indicate the number of people survived based on their sex
# If you are a female, you have a higher chance of survival compared to other ports!
plt.figure(figsize = [15, 10])
plt.subplot(211)
sns.countplot(x = 'Sex', data = titanic_df)
plt.subplot(212)
sns.countplot(x = 'Sex', hue = 'Survived', data = titanic_df)
<Axes: xlabel='Sex', ylabel='count'>
       500
       400
     300
       200
       100
         0
                                                                                                  female
                                       male
                                                                     Sex
                                                                                                                          Survived
                                                                                                                             1
       400
       300
     unt
# Age Histogram
plt.figure(figsize=[15, 10])
titanic_df['Age'].hist(bins = 40)
→ <Axes: >
     50
     40
     30
     20
# Fare Histogram
plt.figure(figsize=[10, 10])
titanic_df['Fare'].hist(bins = 40)
```



Let's explore which dataset is missing
sns.heatmap(titanic_df.isnull(), yticklabels = False, cbar = False, cmap="Blues")



Let's drop the cabin coloumn and test with inplace = true and false titanic_df.drop('Cabin', axis = 1, inplace = True)

Let's drop the embarked, Ticket, passengerID, and Name as well titanic_df.drop(['Name', 'Ticket', 'Embarked', 'PassengerId'], axis = 1, inplace = True)

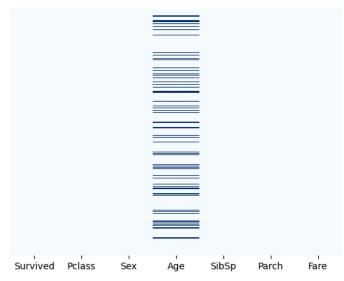
titanic_df

₹		Survived	Pclass	Sex	Age	SibSp	Parch	Fare
	0	0	3	male	22.0	1	0	7.2500
	1	1	1	female	38.0	1	0	71.2833
	2	1	3	female	26.0	0	0	7.9250
	3	1	1	female	35.0	1	0	53.1000
	4	0	3	male	35.0	0	0	8.0500
	886	0	2	male	27.0	0	0	13.0000
	887	1	1	female	19.0	0	0	30.0000
	888	0	3	female	NaN	1	2	23.4500
	889	1	1	male	26.0	0	0	30.0000
	890	0	3	male	32.0	0	0	7.7500

891 rows × 7 columns

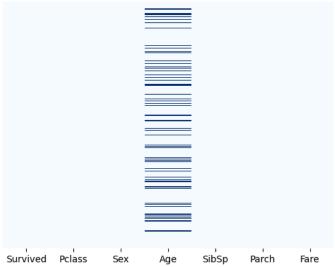
Let's view the data one more time!
sns.heatmap(titanic_df.isnull(), yticklabels = False, cbar = False, cmap="Blues")





Let's get the average age for male (\sim 29) and female (\sim 25) plt.figure(figsize=(15, 10)) plt.subplot(211) sns.boxplot(x = 'Sex', y = 'Age', data = titanic_df)

```
<Axes: xlabel='Sex', ylabel='Age'>
       80
                                       0
       70
       60
       50
     96 40
       30
       20
       10
def fill_age(data):
   """Fills missing age values based on sex, Male=29, Female=25.
       data: A pandas Series containing 'Age' and 'Sex' columns.
   Returns:
       A pandas Series with filled age values.
   age = data['Age']
   sex = data['Sex']
   # Use loc to fill NaN values based on sex
   data.loc[pd.isnull(age) & (sex == 'male'), 'Age'] = 29
   data.loc[pd.isnull(age) & (sex == 'female'), 'Age'] = 25
    return data
# Let's view the data one more time!
sns.heatmap(titanic_df.isnull(), yticklabels = False, cbar = False, cmap="Blues")
→ <Axes: >
```



You just need one column only to represent male or female
pd.get_dummies(titanic_df['Sex'])

_		female	male
	0	False	True
	1	True	False
	2	True	False
	3	True	False
	4	False	True
	886	False	True
	887	True	False
	888	True	False
	889	False	True
	890	False	True

891 rows × 2 columns

male = pd.get_dummies(titanic_df['Sex'], drop_first = True)

first let's drop the embarked and sex
titanic_df.drop(['Sex'], axis = 1, inplace = True)

titanic_df

→		Survived	Pclass	Age	SibSp	Parch	Fare
	0	0	3	22.0	1	0	7.2500
	1	1	1	38.0	1	0	71.2833
	2	1	3	26.0	0	0	7.9250
	3	1	1	35.0	1	0	53.1000
	4	0	3	35.0	0	0	8.0500
	886	0	2	27.0	0	0	13.0000
	887	1	1	19.0	0	0	30.0000
	888	0	3	NaN	1	2	23.4500
	889	1	1	26.0	0	0	30.0000
	890	0	3	32.0	0	0	7.7500

891 rows × 6 columns

Now let's add the encoded column male again
titanic_df = pd.concat([titanic_df, male], axis = 1)

titanic_df

→

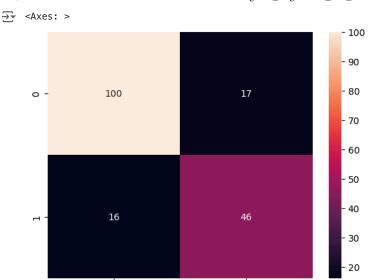
	Survived	Pclass	Age	SibSp	Parch	Fare	male
0	0	3	22.0	1	0	7.2500	True
1	1	1	38.0	1	0	71.2833	False
2	1	3	26.0	0	0	7.9250	False
3	1	1	35.0	1	0	53.1000	False
4	0	3	35.0	0	0	8.0500	True
886	0	2	27.0	0	0	13.0000	True
887	1	1	19.0	0	0	30.0000	False
888	0	3	NaN	1	2	23.4500	False
889	1	1	26.0	0	0	30.0000	True
890	0	3	32.0	0	0	7.7500	True

891 rows × 7 columns

Train Logistic Regression Classifier Model

```
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
# 1. Create an imputer object with a strategy (e.g., mean, median)
imputer = SimpleImputer(strategy='mean') # or strategy='median'
#Let's drop the target coloumn before we do train test split
X = titanic_df.drop('Survived', axis = 1).values
y = titanic_df['Survived'].values
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=10)
# 3. Fit the imputer on the training data and transform both train and test sets
X_train = imputer.fit_transform(X_train) # Fit on training data and transform
X_test = imputer.transform(X_test)
                                       # Transform the test data
# 4. Now, fit your Logistic Regression model
classifier = LogisticRegression(random_state=0)
classifier.fit(X_train, y_train)
\overline{z}
           LogisticRegression
    LogisticRegression(random_state=0)
Assess Trained Model Performance
#Assess Trained Model Performance
y_predict_test = classifier.predict(X_test)
y_predict_test
1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
           0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0,
           0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1,
           0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0,
           1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0,
           0,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 0,\ 1,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,
           0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0,
           0, 0, 1])
from sklearn.metrics import confusion_matrix
```

cm = confusion_matrix(y_test, y_predict_test)
sns.heatmap(cm, annot = True, fmt = "d")



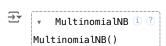
1

from sklearn.metrics import classification_report
print(classification_report(y_test, y_predict_test))

_	precision	recall	f1-score	support
0 1	0.86 0.73	0.85 0.74	0.86 0.74	117 62
accuracy macro avg weighted avg	0.80 0.82	0.80 0.82	0.82 0.80 0.82	179 179 179

Fitting Naive Bayes Classifier Model

Fitting Naive Bayes Classifier Model
from sklearn.naive_bayes import MultinomialNB
classifier = MultinomialNB()
classifier.fit(X_train, y_train)



y_predict_test = classifier.predict(X_test)
y_predict_test

cm = confusion_matrix(y_test, y_predict_test)
sns.heatmap(cm, annot = True, fmt = "d")

print(classification_report(y_test, y_predict_test))

→	precision		recall	f1-score	support	
	0	0.79	0.89	0.84	117	
	1	0.72	0.55	0.62	62	