

In [327]:

```
from IPython.display import Image, display

display(Image(filename="headerImage.png"))
```

In [ ]:

# PYTHON ML PROJECT ON TITANIC DATASET:

In [ ]:

## Data Dictionary:

In [328]:

111

#### *Variable Definition*

Key

survival Survival 0 = No, 1 = Yes  
 pclass Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd  
 sex Sex  
 Age Age in years  
 sibsp no. of siblings / spouses aboard the Titanic  
 parch no. of parents / children aboard the Titanic  
 ticket Ticket number  
 fare Passenger fare (in British pounds (£))  
 cabin Cabin number  
 embarked Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton

111

Out[328]:

## Import the dataset:

In [329]:

```
import pandas as pd  
  
df = pd.read_csv("train.csv")
```

## Ignore warnings:

In [330]:

```
import warnings  
warnings.filterwarnings('ignore')
```

## Do some basic inspections:

### Check how many rows and columns exist:

In [331]:

```
print("No. of rows in the dataset = ", df.shape[0])  
print("No. of columns in the dataset = ", df.shape[1])
```

No. of rows in the dataset = 891  
No. of columns in the dataset = 12

In [332]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 891 entries, 0 to 890  
Data columns (total 12 columns):  
 #   Column      Non-Null Count  Dtype     
---  --    
 0   PassengerId 891 non-null    int64    
 1   Survived     891 non-null    int64    
 2   Pclass       891 non-null    int64    
 3   Name         891 non-null    object    
 4   Sex          891 non-null    object    
 5   Age          714 non-null    float64   
 6   SibSp        891 non-null    int64    
 7   Parch        891 non-null    int64    
 8   Ticket       891 non-null    object    
 9   Fare          891 non-null    float64   
 10  Cabin         204 non-null    object    
 11  Embarked     889 non-null    object    
dtypes: float64(2), int64(5), object(5)  
memory usage: 83.7+ KB
```

In [333]:

```
df.dtypes
```

Out[333]:

```
PassengerId      int64  
Survived        int64  
Pclass          int64  
Name            object  
Sex             object  
Age             float64  
SibSp           int64  
Parch           int64
```

```
      -- -- -- -- -- -- --  
Ticket          object  
Fare           float64  
Cabin          object  
Embarked       object  
dtype: object
```

In [334]:

```
df.isnull().sum()
```

Out [334]:

```
PassengerId      C
Survived         C
Pclass           C
Name             C
Sex              C
Age              177
SibSp            C
Parch            C
Ticket          C
Fare             C
Cabin          687
Embarked        2
dtype: int64
```

## Handle missing-values:

In [335]:

```
df['Age'].fillna(df['Age'].median(), inplace=True)
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
df.drop('Cabin', axis=1, inplace=True)
```

In [336]:

```
df.isnull().sum()
```

Out [336]:

```
PassengerId  
Survived  
Pclass  
Name  
Sex  
Age  
SibSp  
Parch  
Ticket  
Fare  
Embarked  
dtype: int64
```

## **View the first few rows of the dataset:**

In [337]:

```
df.head(5)
```

Out[337]:

PassengerId	Survived	Pclass	Name		Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S

PassengerId	Survived	Pclass	Futrelle, Mrs. Jacques Heath (Lily May Peel)	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
3	4	1									
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

**Create a new dataframe based on this original dataframe upon which we will do Machine-Learning:**

In [338]:

```
df_copy = df.copy()
```

In [339]:

```
df_copy['Number of Family Members'] = df_copy['SibSp'] + df_copy['Parch'] + 1
```

**Do some further data-cleaning (going to be useful for ML):**

In [340]:

```
df_copy.drop(['PassengerId', 'Name', 'Ticket'], axis=1, inplace=True)
df_copy['Sex'] = df_copy['Sex'].map({'male': 0, 'female': 1})
df_copy["Age"] = df_copy["Age"].astype(int)
df_copy["Fare"] = df_copy["Fare"].astype(int)
df_copy["Pclass"] = df_copy["Pclass"].astype(int)

from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df_copy['Embarkation Point Encoded'] = label_encoder.fit_transform(df_copy['Embarked'])
```

In [341]:

```
df.head(3)
```

Out[341]:

PassengerId	Survived	Pclass	Name		Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S

In [342]:

```
df_copy.head(3)
```

Out[342]:

Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	2	2
1	1	1	1	38	1	0	71	2	0
2	1	3	1	26	0	0	7	1	2

In [ ]:

**EDA (Exploratory Data Analysis Questions):**

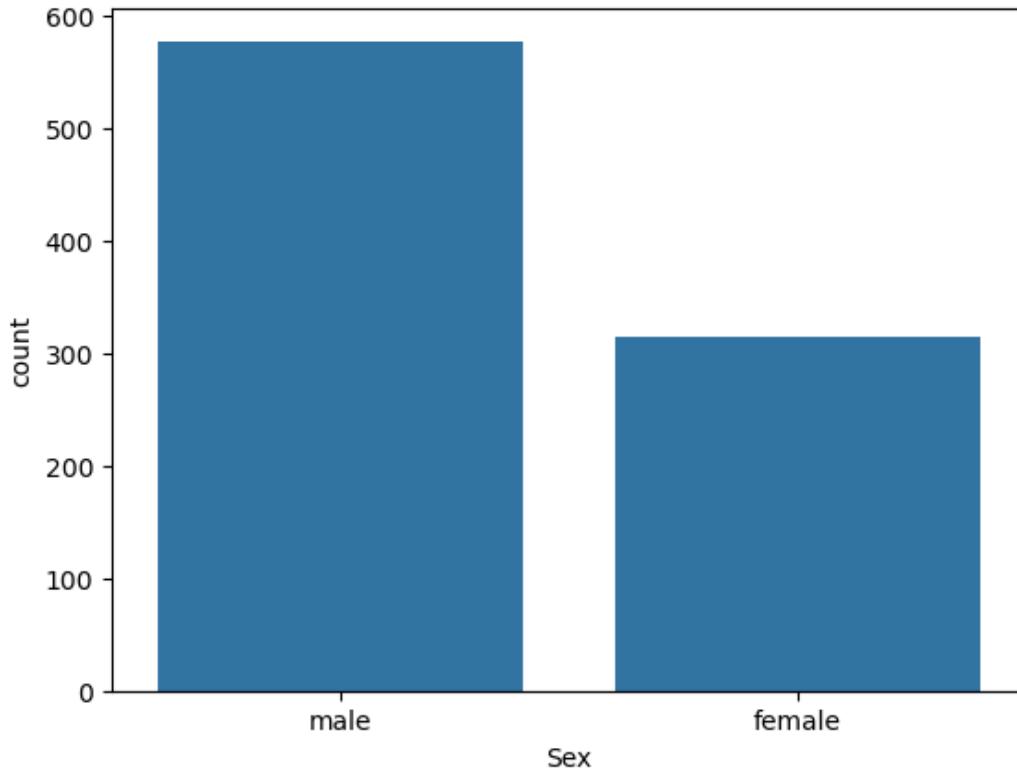
## Q1] HOW MANY males AND females boarded the ship:

In [343]:

```
import seaborn as sns
sns.countplot(x="Sex", data=df)
```

Out [343]:

```
<Axes: xlabel='Sex', ylabel='count'>
```



In [344]:

```
survivors_by_gender = df.groupby("Sex") ["Survived"].count().reset_index(name="No. of survivors")
survivors_by_gender
```

Out [344]:

Sex	No. of survivors
0 female	314
1 male	577

In [345]:

```
survivors_by_gender = df[df["Survived"]==0].groupby("Sex") ["Survived"].count().reset_index(name="No. of passengers who died")
survivors_by_gender
```

Out [345]:

Sex	No. of passengers who died
0 female	81
1 male	468

## CONCLUSIONS AT THIS POINT:

- Around 80% of females survived the disaster.
- 55% of males survived the disaster.

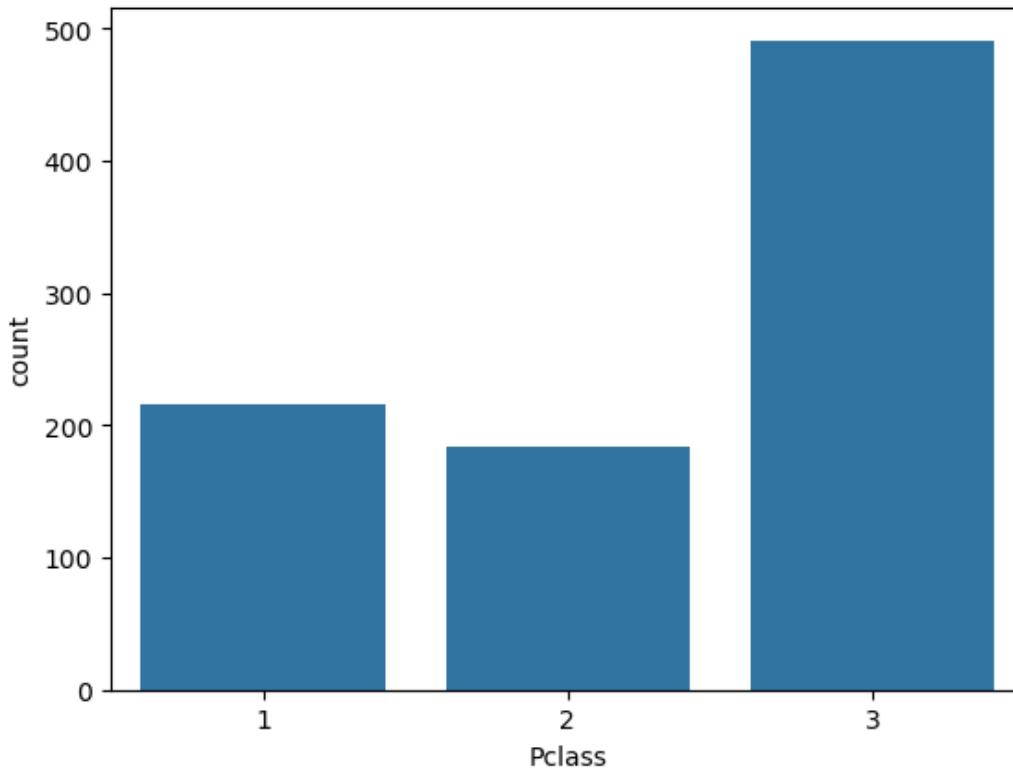
## Q2] HOW MANY PEOPLE WERE THERE IN EACH Passenger-class:

In [346]:

```
import seaborn as sns
sns.countplot(x="Pclass", data=df)
```

Out[346]:

```
<Axes: xlabel='Pclass', ylabel='count'>
```



## Q3] AVERAGE TICKET-PRICES PAID BY EACH Passenger-class:

In [347]:

```
result = df.groupby("Pclass") ["Fare"].mean().reset_index()
result
```

Out[347]:

Pclass	Fare
0	1 84.154687
1	2 20.662183
2	3 13.675550

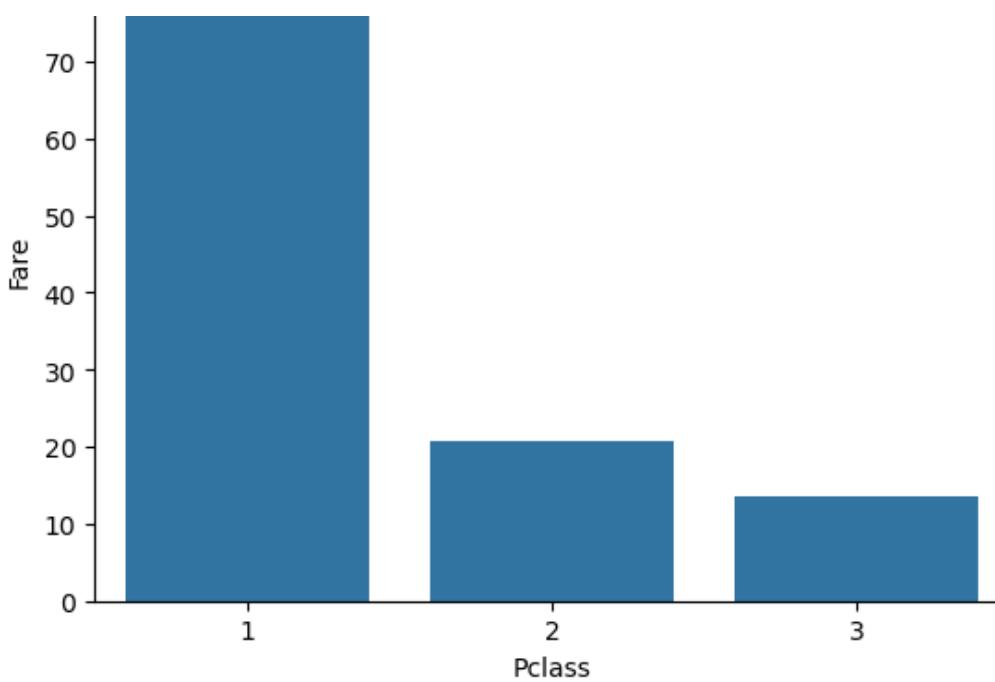
In [348]:

```
import seaborn as sns
sns.barplot(x="Pclass", y="Fare", data=result)
```

Out[348]:

```
<Axes: xlabel='Pclass', ylabel='Fare'>
```





## Q4] HOW MANY PEOPLE SURVIVED IN EACH Passenger-class AND HOW MANY DID NOT SURVIVE:

In [349]:

```
result = df["Pclass"].value_counts().reset_index(name="Total no. of Passengers in the class")
result
```

Out [349]:

Pclass	Total no. of Passengers in the class
0	3
1	1
2	2

In [350]:

```
result = result.sort_values(by="Pclass")
result
```

Out [350]:

Pclass	Total no. of Passengers in the class
1	1
2	2
0	3

In [351]:

```
result = result.sort_values(by="Pclass").reset_index(drop=True)
result = df[df["Survived"]==1].groupby("Pclass")["Survived"].count().reset_index(name="Total no. of survivors")
result
```

Out [351]:

Pclass	Total no. of survivors
0	1
1	131
2	143

Pclass	Total no. of survivors
1	87
2	119

In [ ]:

In [352]:

```
result = df[df["Survived"]==0].groupby("Pclass") ["Survived"].count().reset_index(name="Did not survive")
result
```

Out [352]:

Pclass	Did not survive
0	80
1	97
2	372

## CONCLUSION TILL HERE:

- Most people on the ship were from 3rd passenger-class.
- People belonging to the 1st passenger-class paid the most fare.
- More than 50% of people in 1st passenger-class survived the disaster.
- Only 47% passengers in 2nd passenger-class survived the disaster.
- Only 24% passengers in 3rd passenger-class survived the disaster.

In [ ]:

In [ ]:

In [ ]:

## ML QUESTIONS:

### Q1] PREDICTING FARE-AMOUNT BASED ON:

- Passenger Class
- Family Members
- Embarkation Point

In [353]:

```
from sklearn import linear_model
reg = linear_model.LinearRegression()
independent_variables = ["Pclass", "Number of Family Members", "Embarkation Point Encoded"]
reg.fit(df_copy[independent_variables], df["Fare"])
reg.predict([[3, 2, 2]])
```

Out [353]:

```
array([6.21894201])
```

In [ ]:

## Q2] PREDICTING PASSENGER-AGE BASED ON:

- Passenger Class
- Number of Family Members
- Gender

In [354]:

```
from sklearn import linear_model
reg = linear_model.LinearRegression()
independent_variables = ["Pclass", "Number of Family Members", "Sex"]
reg.fit(df_copy[independent_variables], df["Age"])
reg.predict([[3,2,0]])
```

Out[354]:

```
array([26.37839535])
```

In [ ]:

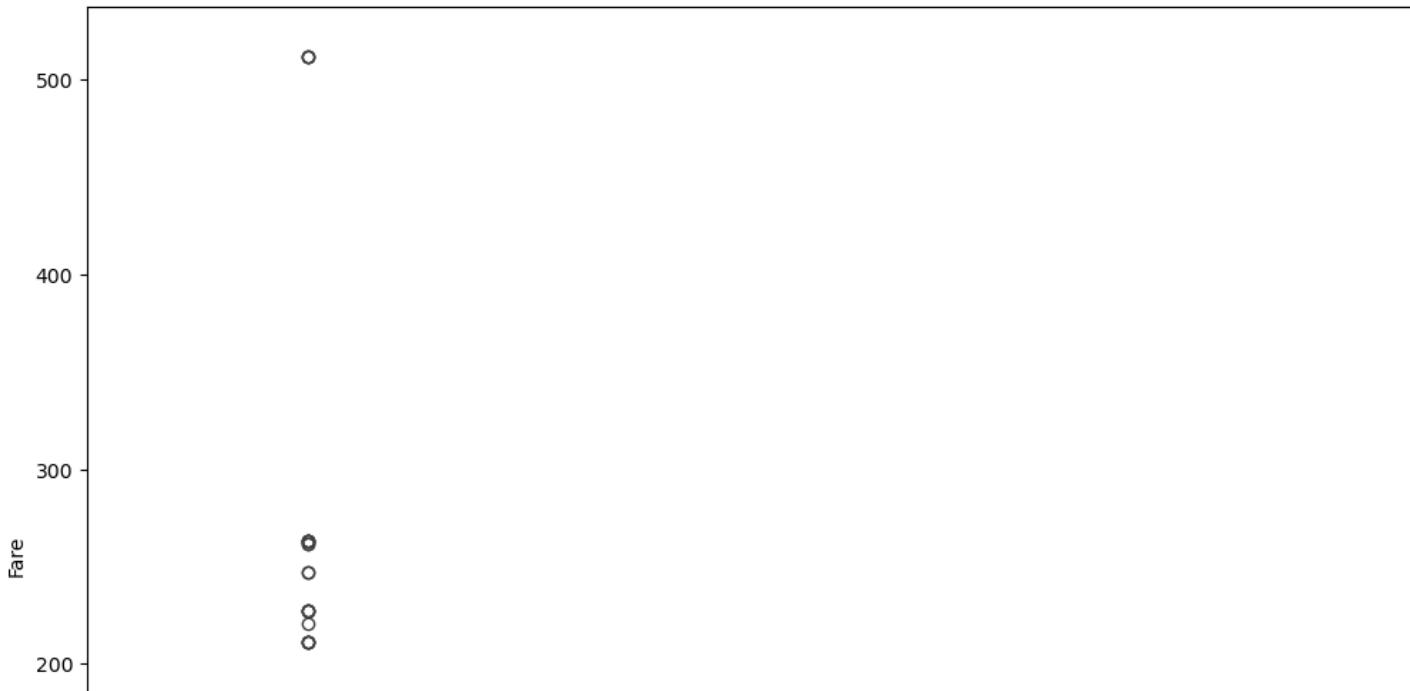
## Q3] RELATIONSHIP BETWEEN FARE AND PASSENGER-CLASS:

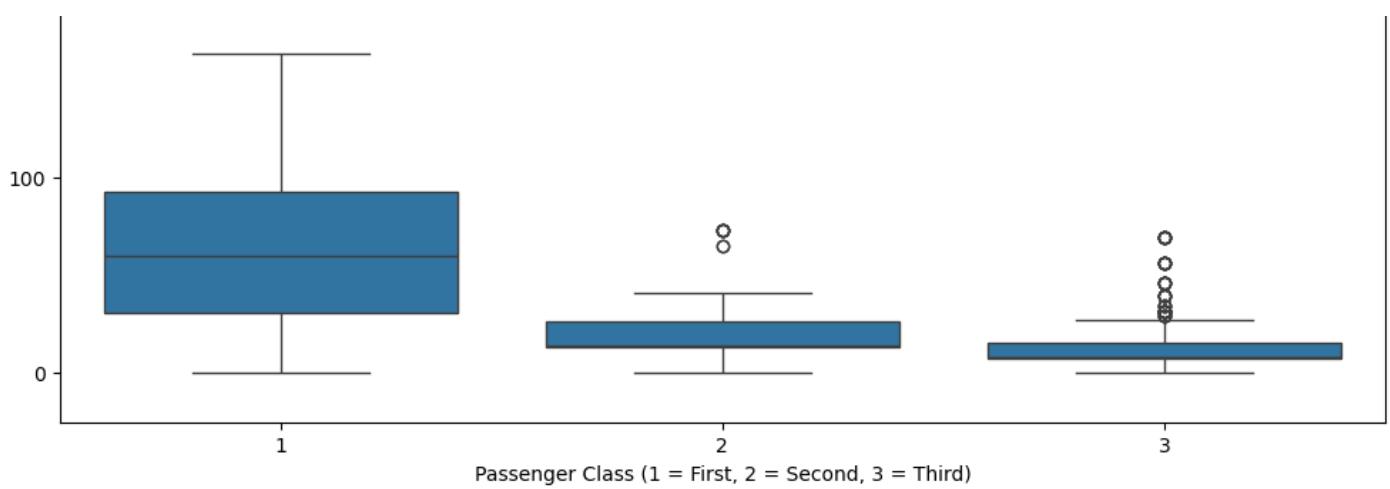
In [355]:

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12,10))
sns.boxplot(x='Pclass', y='Fare', data=df_copy)
plt.title("Fare Distribution by Passenger Class")
plt.xlabel("Passenger Class (1 = First, 2 = Second, 3 = Third)")
plt.ylabel("Fare")
plt.show()
```

Fare Distribution by Passenger Class





### CONCLUSION AT THIS POINT:

- Passengers belonging to class 1 paid highest fair and in the range of 50 to 100 pounds (approx.)
- Passengers belonging to class 2 paid moderate fair and in the range of 20 to 40 pounds (approx.)
- Passengers belonging to class 3 paid least fair and in the range of 20 to 30 pounds (approx.)

In [356]:

```
df_copy.head(10)
```

Out [356]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2	2
1	1	1	1	38	1	0	71	C	2	0
2	1	3	1	26	0	0	7	S	1	2
3	1	1	1	35	1	0	53	S	2	2
4	0	3	0	35	0	0	8	S	1	2
5	0	3	0	28	0	0	8	Q	1	1
6	0	1	0	54	0	0	51	S	1	2
7	0	3	0	2	3	1	21	S	5	2
8	1	3	1	27	0	2	11	S	3	2
9	1	2	1	14	1	0	30	C	2	0

In [ ]:

### Q4] Effect of Family Size on Fare

In [357]:

```
from sklearn import linear_model
reg = linear_model.LinearRegression()

reg.fit(df_copy[['Number of Family Members']], df['Fare'])
reg.predict([[1]])
```

Out [357]:

```
array([26.15448989])
```

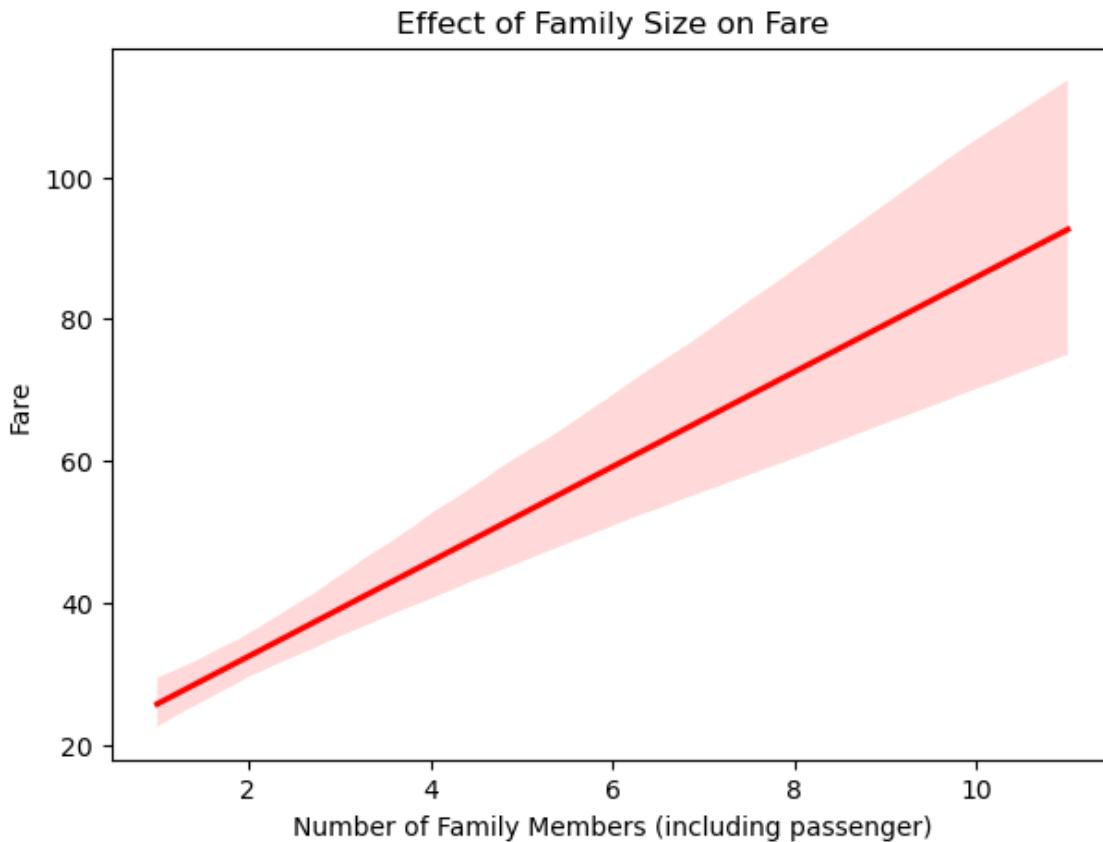
In [358]:

```

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(7, 5))
sns.regplot(x='Number of Family Members', y='Fare', data=df_copy, scatter=False, color='red')
plt.title("Effect of Family Size on Fare")
plt.xlabel("Number of Family Members (including passenger)")
plt.ylabel("Fare")
plt.show()

```



**CONCLUSION AT THIS POINT:** Ticket Prices increases as the no. of family members increases (for all passenger classes 1 , 2 and 3)

## Q5] PREDICTING SURVIVAL BASED ON:

- Age
- Fare

In [359] :

```
df_copy.head(10)
```

Out[359] :

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2	2
1	1	1	1	38	1	0	71	C	2	0
2	1	3	1	26	0	0	7	S	1	2
3	1	1	1	35	1	0	53	S	2	2
4	0	3	0	35	0	0	8	S	1	2
5	0	3	0	28	0	0	8	Q	1	1
6	0	1	0	54	0	0	51	S	1	2
7	0	3	0	2	3	1	21	S	5	2

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
8	1	3	1	27	0	2	11	S	3	2
9	1	2	1	14	1	0	30	C	2	0

In [360]:

```
from sklearn.linear_model import LogisticRegression
reg = linear_model.LogisticRegression()

reg.fit(df_copy[["Age", "Fare"]], df["Survived"])
reg.predict([[20, 7.25]])
```

Out[360]:

```
array([0])
```

In [361]:

```
from sklearn.linear_model import LogisticRegression
reg = linear_model.LogisticRegression()

reg.fit(df_copy[["Age", "Fare"]], df["Survived"])
reg.predict([[54, 1030.07]])
```

Out[361]:

```
array([1])
```

In [362]:

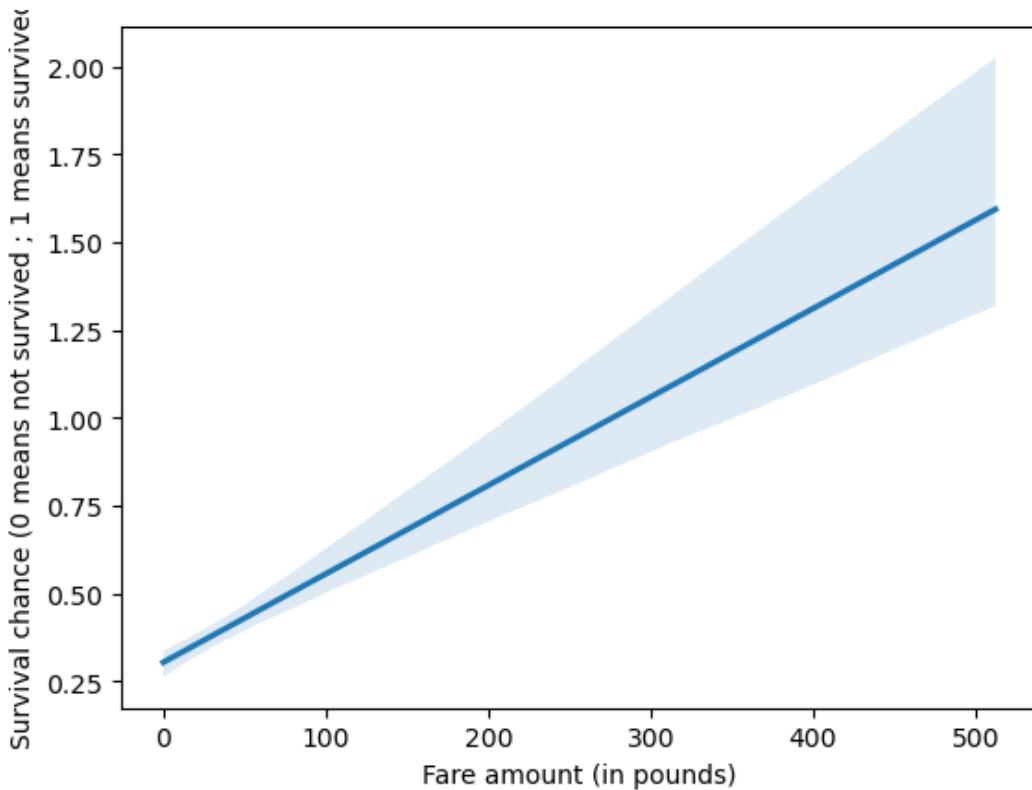
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.regplot(x="Fare", y="Survived", data=df_copy, scatter=False)

plt.xlabel("Fare amount (in pounds)")
plt.ylabel("Survival chance (0 means not survived ; 1 means survived)")
```

Out[362]:

```
Text(0, 0.5, 'Survival chance (0 means not survived ; 1 means survived)')
```



In [363]:

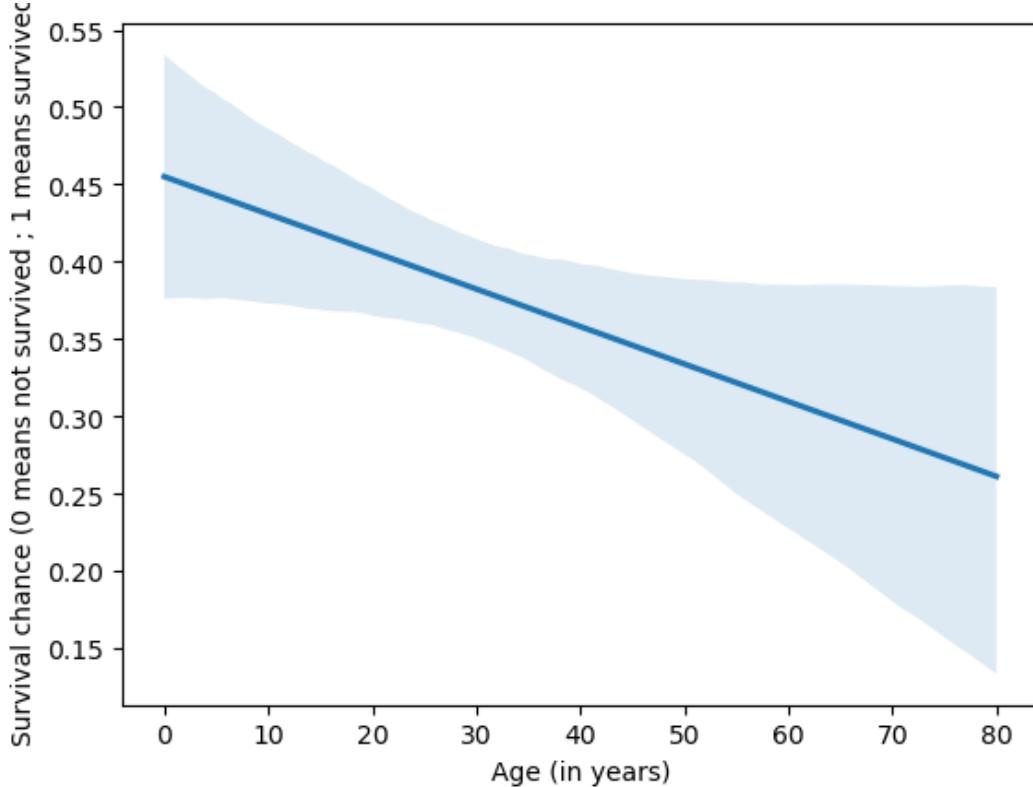
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.regplot(x="Age", y="Survived", data=df_copy, scatter=False)

plt.xlabel("Age (in years)")
plt.ylabel("Survival chance (0 means not survived ; 1 means survived)")
```

Out[363]:

Text(0, 0.5, 'Survival chance (0 means not survived ; 1 means survived)')



### CONCLUSION AT THIS POINT:

- A 20 year old (male/female) who paid nearly 7 pounds was likely not to survive.
- A 50 year old (male/female) who paid nearly 1000 pounds was likely to survive.
- People who spent more money on the trip; were more likely to survive.
- People who were elderly were more likely to not survive.

In [ ]:

### CONCLUSION DRAWN FROM THE ENTIRE ANALYSIS (TILL HERE):

- Passengers in higher classes (1st class) paid substantially higher fares than those in lower classes.
- Males in higher classes tended to be older, while females and lower-class passengers were generally younger.
- Customers in higher passenger-class pay higher fares
- Larger families tended to pay slightly higher total fares, possibly because they booked together or purchased multiple tickets.
- Younger passengers and those who paid higher fares (likely first-class passengers) had a higher chance of survival.

In [ ]:

```
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```
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```

## USE DECISION-TREE TO PREDICT Passenger-Survival based on :

- Pclass
- Sex
- Age
- Sibsp (No. of Siblings if any)
- Parch (No. of parents / children aboard on Titanic)
- Fare

```
In [364]:
```

```
df_copy.head(5)
```

```
Out[364]:
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2	2
1	1	1	1	38	1	0	71	C	2	0
2	1	3	1	26	0	0	7	S	1	2
3	1	1	1	35	1	0	53	S	2	2
4	0	3	0	35	0	0	8	S	1	2

```
In [365]:
```

```
from sklearn import tree
model = tree.DecisionTreeClassifier()
```

```
independent_variables = ["Pclass", "Sex", "Age", "SibSp", "Parch", "Fare"]
model.fit(df_copy[independent_variables], df_copy["Survived"])
```

```
Out[365]:
```

```
▼
DecisionTreeClassifier
    i ?
```

► Parameters

```
In [366]:
```

```
#Check the model's accuracy:
model.score(df_copy[independent_variables], df_copy["Survived"])
```

```
Out[366]:
```

```
0.9528619528619529
```

```
In [367]:
```

```
df.head(5)
```

```
Out[367]:
```

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
-------------	----------	--------	------	-----	-----	-------	-------	--------	------	----------

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
1	2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	5	0	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

In [368]:

```
df_copy.head(5)
```

Out [368]:

Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2
1	1	1	1	38	1	0	71	C	0
2	1	3	1	26	0	0	7	S	2
3	1	1	1	35	1	0	53	S	2
4	0	3	0	35	0	0	8	S	2

**Now make a prediction for a person with these details:**

- Passenger-class : 3
- Gender : Male
- Age: 22
- No. of siblings: 1
- No. of parents and children: 0
- Trip Fare: 7 pounds (approx.)

In [369]:

```
model.predict([[3,0,22.0,1,0,7.25]])
```

Out [369]:

```
array([0])
```

**CONCLUSION OF THIS POINT: PASSENGER WITH THESE DETAILS WAS LIKELY TO SURVIVE**

- Passenger-class : 3
- Gender : Male
- Age: 22
- No. of siblings: 1
- No. of parents and children: 0
- Trip Fare: 7 pounds (approx.)

In [ ]:

In [370]:

```
df_copy.head(5)
```

Out [370]:

Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	1	0	PC 17599
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450

0	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
1	1	1	1	38	1	0	71	C	2	0
2	1	3	1	26	0	0	7	S	1	2
3	1	1	1	35	1	0	53	S	2	2
4	0	3	0	35	0	0	8	S	1	2

In [371]:

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, plot_tree
import matplotlib.pyplot as plt

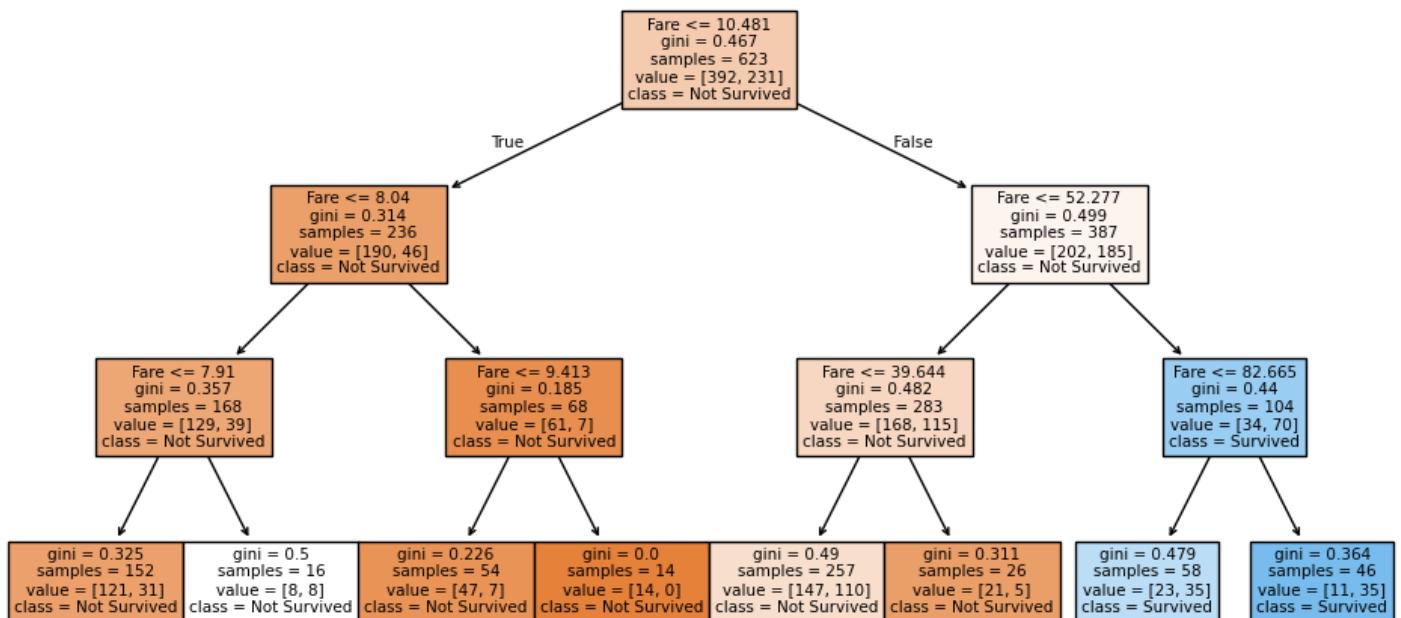
X = df[['Fare']]
y = df['Survived']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

model = DecisionTreeClassifier(max_depth=3, random_state=42)
model.fit(X_train, y_train)

plt.figure(figsize=(12, 6))
plot_tree(model, feature_names=['Fare'], class_names=['Not Survived', 'Survived'], filled=True)
plt.show()

print("Accuracy:", model.score(X_test, y_test))
```



Accuracy: 0.6716417910447762

**CONCLUSION OF THIS POINT:** Passengers who paid higher prices (i.e. more than 83 pounds) had a much greater chance of survival.)

In [ ]:

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```
In [372]:
```

```
df.head(5)
```

```
Out[372]:
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

```
In [373]:
```

```
df_copy.head(5)
```

```
Out[373]:
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2	2
1	1	1	1	38	1	0	71	C	2	0
2	1	3	1	26	0	0	7	S	1	2
3	1	1	1	35	1	0	53	S	2	2
4	0	3	0	35	0	0	8	S	1	2

```
In [ ]:
```

**KNN QUESTION ]** Using the Titanic dataset, build a K-Nearest Neighbors (KNN) model to predict whether a passenger (male / female) survived or not based on their Age , Gender and Fare. After training, predict the survival status of a female passenger aged 30 years who paid a fare of \$100. Finally, find out how well your model performs using the accuracy score.

```
In [374]:
```

```
df.head()
```

```
Out[374]:
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S

PassengerId	Survived	Pclass	Futrelle, Mrs. Jacques Heath (Lily May Peel)	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
3	4	1	1						113803	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

In [375]:

```
df_copy.head()
```

Out [375]:

Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2
1	1	1	1	38	1	0	71	C	2
2	1	3	1	26	0	0	7	S	1
3	1	1	1	35	1	0	53	S	2
4	0	3	0	35	0	0	8	S	1

In [376]:

```
df.isnull().sum()
```

Out [376]:

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Embarked         0
dtype: int64
```

In [377]:

```
df_copy.isnull().sum()
```

Out [377]:

```
Survived          0
Pclass            0
Sex               0
Age               0
SibSp             0
Parch             0
Fare              0
Embarked          0
Number of Family Members  0
Embarkation Point Encoded  0
dtype: int64
```

In [378]:

```
df_copy.head()
```

Out [378]:

Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2
1	1	1	1	38	1	0	71	C	2
2	1	3	1	26	0	0	7	S	1

3	Survived	1	Pclass	1	Sex	1	Age	35	SibSp	1	Parch	0	Fare	53	Embarked	S	Number of Family Members	2	Embarcation Point Encoded	2
4	0	0	3	0	0	35	0	0	0	0	0	8	0	53	S	1	1	2		

In [379]:

```
inputs = df_copy.drop(["Survived", "Pclass", "SibSp", "Parch", "Embarked", "Number of Family Members", "Embarcation Point Encoded"], axis="columns")
```

In [380]:

```
outputs = df_copy.drop(["Age", "Fare", "Pclass", "Sex", "SibSp", "Parch", "Embarked", "Number of Family Members", "Embarcation Point Encoded"], axis="columns")
```

In [381]:

```
inputs
```

Out[381]:

	Sex	Age	Fare
0	0	22	7
1	1	38	71
2	1	26	7
3	1	35	53
4	0	35	8
...	...	...	...
886	0	27	13
887	1	19	30
888	1	28	23
889	0	26	30
890	0	32	7

891 rows × 3 columns

In [382]:

```
outputs
```

Out[382]:

	Survived
0	0
1	1
2	1
3	1
4	0
...	...
886	0
887	1
888	0
889	1
890	0

891 rows × 1 columns

In [383]:

```
from sklearn.model_selection import train_test_split
X = inputs
y = outputs
```

In [384]:

```
X
```

Out[384]:

Sex	Age	Fare
0	0	22
1	1	38
2	1	26
3	1	35
4	0	35
...	...	...
<b>886</b>	0	27
<b>887</b>	1	19
<b>888</b>	1	28
<b>889</b>	0	26
<b>890</b>	0	32

891 rows × 3 columns

In [385]:

```
y
```

Out[385]:

Survived
0
1
2
3
4
...
<b>886</b>
<b>887</b>
<b>888</b>
<b>889</b>
<b>890</b>

891 rows × 1 columns

In [386]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
```

In [387]:

```
len(X_train)
```

Out[387]:

712

In [388]:

```
len(X_test)
```

Out[388]:

179

## Create KNN (K Nearest Neighbour Classifier)

In [389]:

```
from sklearn.neighbors import KNeighborsClassifier  
knn = KNeighborsClassifier(n_neighbors=5)
```

In [390]:

```
knn.fit(X_train, y_train)
```

Out[390]:

▼  
KNeighborsClassifier  
  i ?

► Parameters

In [391]:

```
knn.score(X_test, y_test)
```

Out[391]:

0.7318435754189944

In [392]:

```
knn.predict([[1, 38, 71]])
```

Out[392]:

array([1])

In [393]:

```
df.head()
```

Out[393]:

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	Cumings, Mrs. John Bradley (Florence Briggs Th... e)	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	5	0	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

In [394]:

```
df_copy.head()
```

Out[394]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarcation Point Encoded
Survived	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarcation Point Encoded
0	0	3	0	22	1	0	7	S	2	2
1	1	1	1	38	1	0	71	C	2	0
2	1	3	1	26	0	0	7	S	1	2
3	1	1	1	35	1	0	53	S	2	2
4	0	3	0	35	0	0	8	S	1	2

**CONCLUSION OF THIS KNN MODEL: A Female Person of 38 years of age and with an income of 71 pounds (British pounds) is likely to survive**

## Plot Confusion Matrix

In [395]:

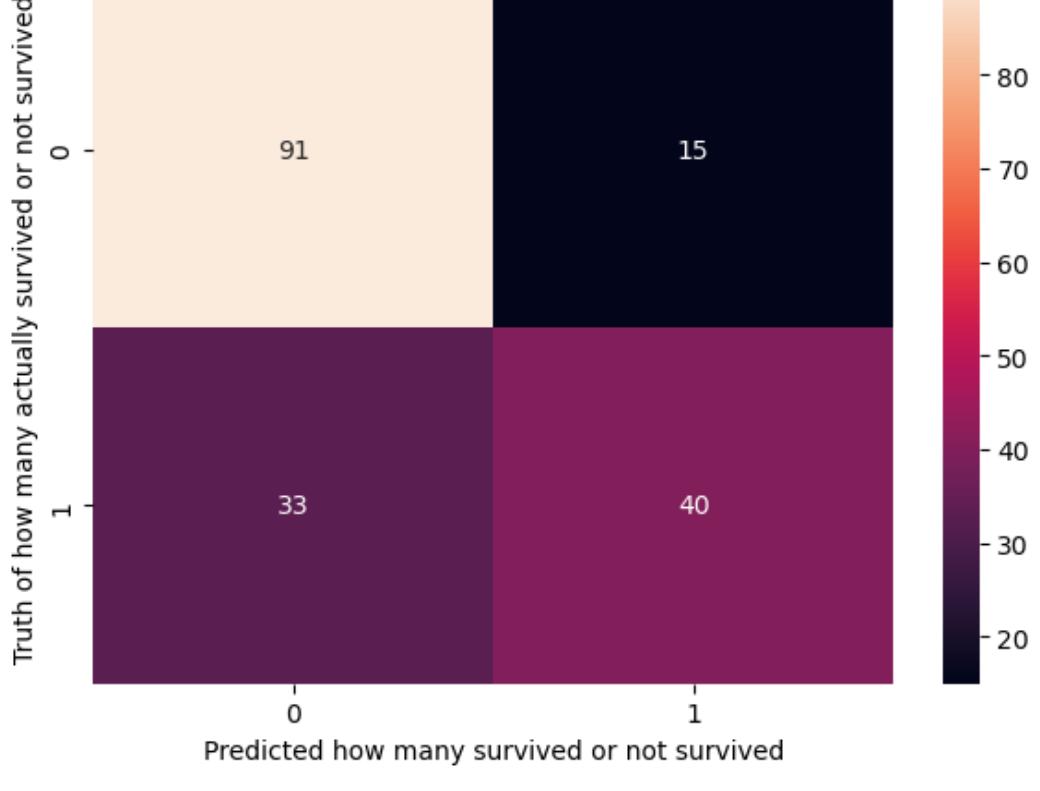
```
from sklearn.metrics import confusion_matrix
y_pred = knn.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm
```

Out [395]:

```
array([[91, 15],
       [33, 40]])
```

In [396]:

```
import matplotlib.pyplot as plt
import seaborn as sn
plt.figure(figsize=(7,5))
sn.heatmap(cm, annot=True)
plt.xlabel('Predicted how many survived or not survived')
plt.ylabel('Truth of how many actually survived or not survived')
plt.show()
```



## Prepare a classification report:

In [397]:

```
from sklearn.metrics import classification_report
```

```
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
0	0.73	0.86	0.79	106
1	0.73	0.55	0.62	73
accuracy			0.73	179
macro avg	0.73	0.70	0.71	179
weighted avg	0.73	0.73	0.72	179

**Meaning of the heatmap created : 0s and 1s on the heatmap means :**

- 0 means passenger did not survived
  - 1 means passenger survived

## **CONCLUSIONS DRAWN FROM THE ABOVE HEATMAP CREATED :**

- We accurately predicted that 91 passengers didn't survive and 40 passengers survived
  - 33 passengers actually survived but we falsely predicted that they didn't survive
  - We falsely predicted that 15 passengers survived but actually they didn't.

In [ ]:

In [ ]:

**RANDOM FOREST QUESTION]** Using a Random Forest Classifier, find out which features — Sex, Age, or Fare — are most important for predicting survival.

In [398]:

```
df.head()
```

Out[398]:

PassengerId	Survived	Pclass	Name		Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	S

In [399]:

```
df copy.head()
```

Out [399] :

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2	2
1	1	1	1	38	1	0	71	C	2	0
2	1	3	1	26	0	0	7	S	1	2

3	Survived	Pclass <sup>1</sup>	Sex	Age <sup>35</sup>	SibSp	Parch	Fare <sup>53</sup>	Embarked <sup>8</sup>	Number of Family Members <sup>2</sup>	Embarkation Point Encoded <sup>2</sup>
4	0	3	0	35	0	0	8	S	1	2

In [400]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import numpy as np

X = df_copy[["Sex", "Age", "Fare"]]
y = df_copy["Survived"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state=42) # Split dataset into 75% train and 25% test

randomForest_Model = RandomForestClassifier(n_estimators=100, random_state=42)
randomForest_Model.fit(X_train, y_train)

#Check model score:
randomForest_Model.score(X_test,y_test)
```

Out[400]:

0.7668161434977578

In [401]:

```
#Make Predictions:
y_predicted = randomForest_Model.predict(X_test)
```

In [402]:

y\_predicted

Out[402]:

```
array([0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0,
       1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0,
       1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0,
       0, 1, 0])
```

In [403]:

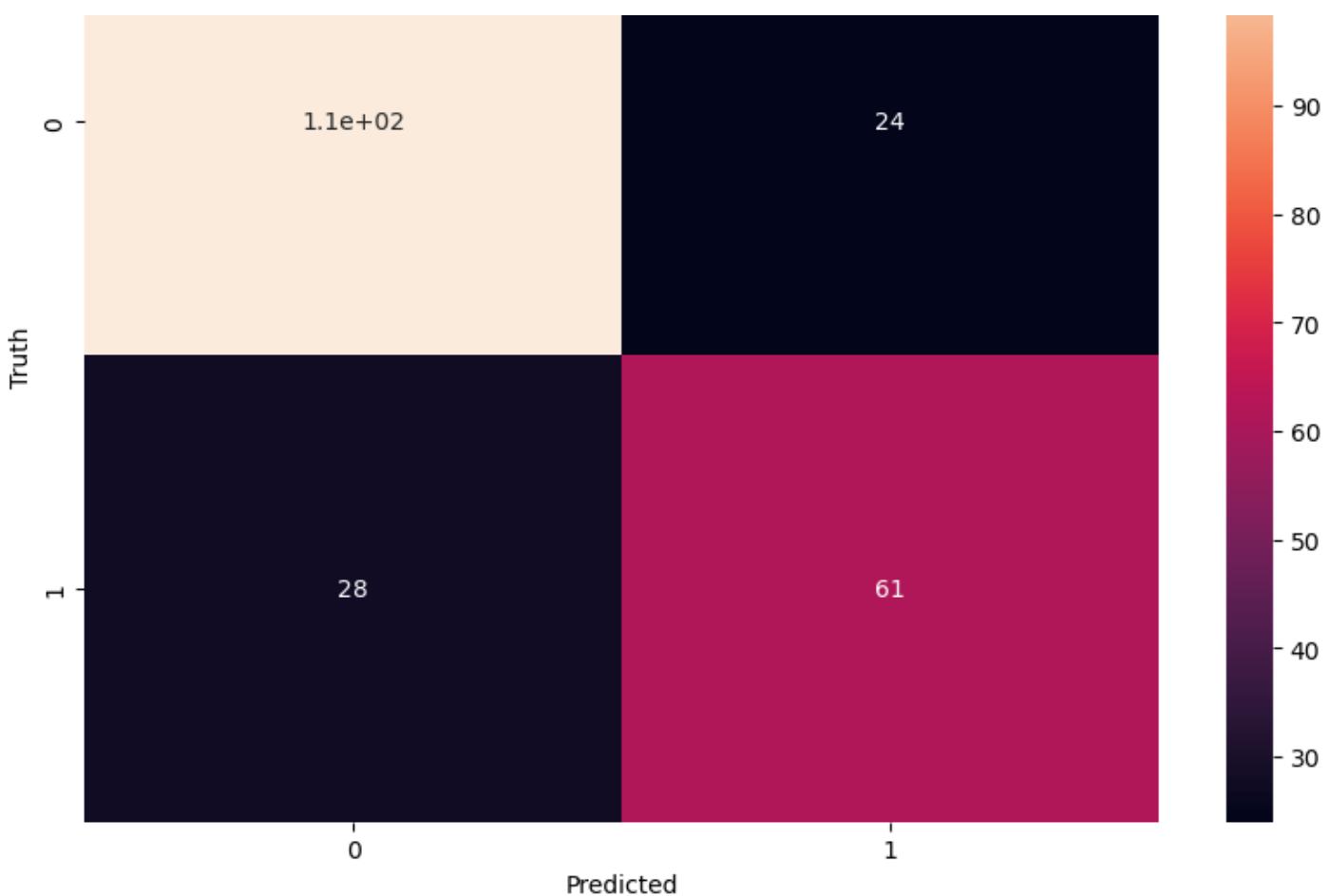
```
# Confusion Matrix:
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_predicted)
```

```
import matplotlib.pyplot as plt
import seaborn as sn
plt.figure(figsize=(10,7))
sn.heatmap(cm, annot=True)
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

Out[403]:

Text(95.7222222222221, 0.5, 'Truth')





#### **CONCLUSION FROM THE ABOVE HEATMAP]**

- The model correctly predicted that :
  - 110 passengers did not survived
  - 61 passengers survived
- The model incorrectly predicted that :
  - 28 passengers didnt survive ; but actually they did survive
  - 24 passengers survived ; but actually they didnt

In [ ]:

```
[ ]
```

In [ ]:

```
[ ]
```

In [ ]:

```
[ ]
```

#### **NAIVE BAYES QUESTION] Predict a passenger's survival chances based on his'/her's passenger-class and family-size ; using naive bayes**

In [404]:

```
df_copy.head(5)
```

Out[404]:

Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
0	0	3	0	22	1	0	7	S	2
1	1	1	1	38	1	0	71	C	0
2	1	3	1	26	0	0	7	S	2

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Number of Family Members	Embarkation Point Encoded
3	1	1	1	35	1	0	53	S	2	2
4	0	3	0	35	0	0	8	S	1	2

In [405]:

```
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score

X = df_copy[["Pclass", "Number of Family Members"]]
y = df_copy["Survived"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42
)

naive_bayes_model = MultinomialNB()
naive_bayes_model.fit(X_train, y_train)

# Make predictions for the testing-data:
y_pred = naive_bayes_model.predict(X_test)

# Check the accuracy of the model:
print("Predicted:", y_pred)
print("Accuracy:", accuracy_score(y_test, y_pred))
```

Accuracy: 0.5783582089552238

In [406]:

```
new_passengers = pd.DataFrame([
    [1, 3],      # Example 1: 1st class, 3 family members
    [3, 1],      # Example 2: 3rd class, 1 family member
    [2, 0],      # Example 3: 2nd class, traveling alone
    [3, 5],      # Example 4: 3rd class, 5 family members
    [2,10],     # Example 5: 2nd class, 10 family members
    [1,4],       # Example 6: 1st class, 4 family members
    [3,30]       # Example 7: 3rd class, 30 family members
], columns=["Pclass", "Number of Family Members"])

predictions = naive_bayes_model.predict(new_passengers)

# Show results
result_df = new_passengers.copy()
result_df["Predicted Survival (1=Survived, 0=Not Survived)"] = predictions
result_df
```

Out[406]:

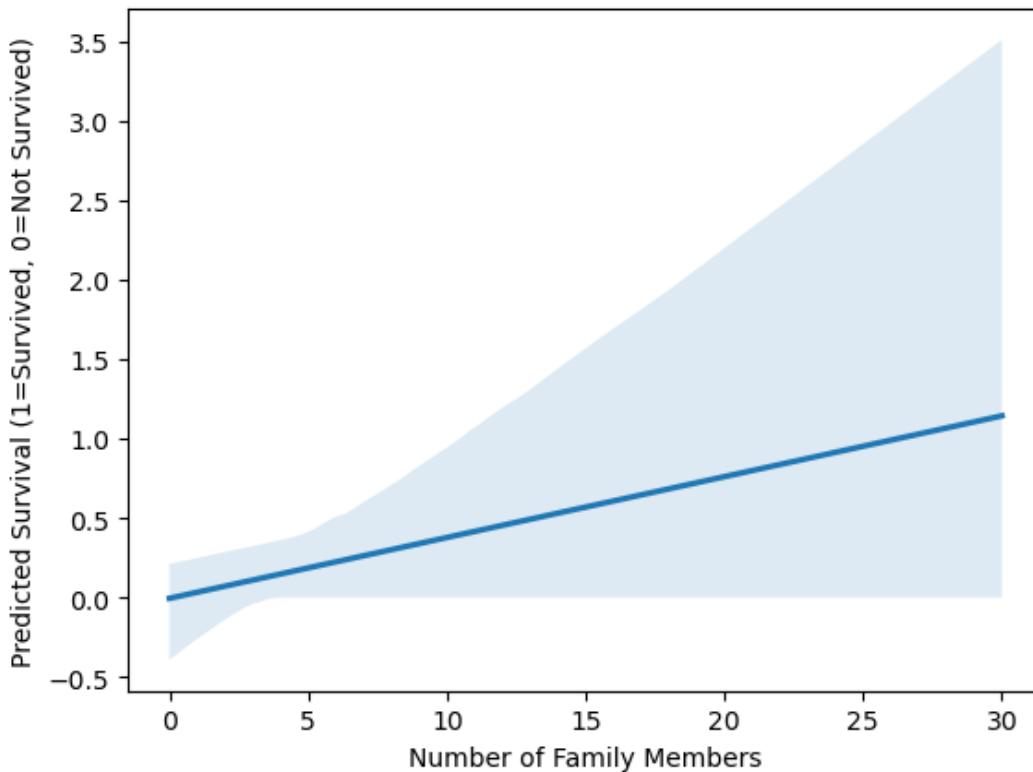
Pclass	Number of Family Members	Predicted Survival (1=Survived, 0=Not Survived)
0	1	3
1	3	1
2	2	0
3	3	5
4	2	10
5	1	4
6	3	30

In [407]:

```
import seaborn as sns
sns.regplot(scatter=False, data=result_df, x="Number of Family Members", y="Predicted Survival (1=Survived, 0=Not Survived)")
```

Out[407]:

```
<Axes: xlabel='Number of Family Members', ylabel='Predicted Survival (1=Survived, 0=Not Survived)'>
```



**CONCLUSION OF THE ABOVE VISUALIZATION: Larger families had the highest chance of survival.**

In [ ]:

In [ ]:

In [ ]:

In [408]:

```
from IPython.display import Image, display
display(Image(filename="ending_image.jpg", width=700, height=300))
```





In [ ]:

## END OF THE NOTEBOOK

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In [ ]: