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Part 1:

Part 1: Import the Libraries and Data

```
# Import libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load datasets
titanic_train_data = pd.read_csv("/content/titanic_train.csv")
testing_resultsitanic_test_data =
pd.read_csv("/content/titanic_test.csv")
```

Part 2: Plot the Data

```
# Display the first few rows of the dataset
titanic_train_data.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	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

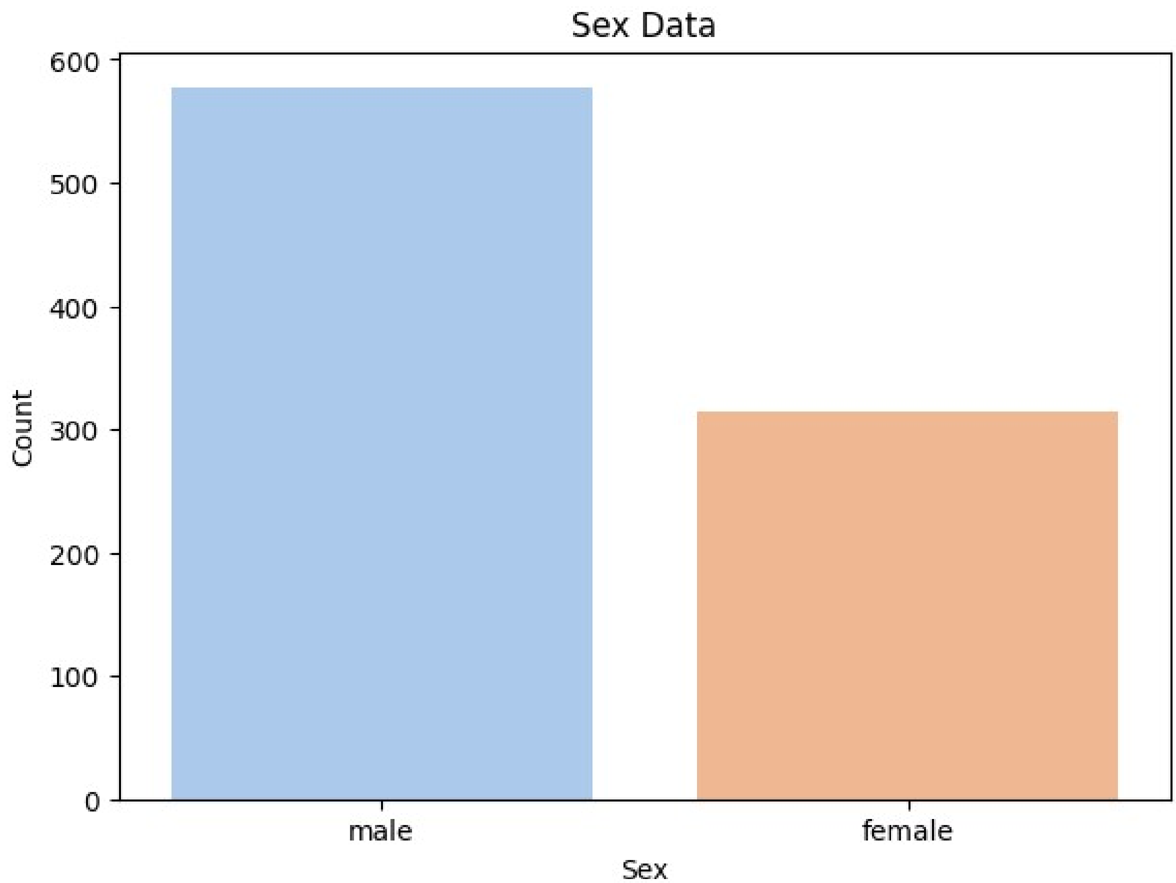
Next steps: View recommended plots

```
# Plot the data for Sex
plt.figure(figsize=(7, 5))
sns.countplot(data=titanic_train_data, x='Sex', palette='pastel')
plt.title('Sex Data')
plt.xlabel('Sex')
plt.ylabel('Count')
plt.show()

<ipython-input-168-489d2095a7a8>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=titanic_train_data, x='Sex', palette='pastel')
```

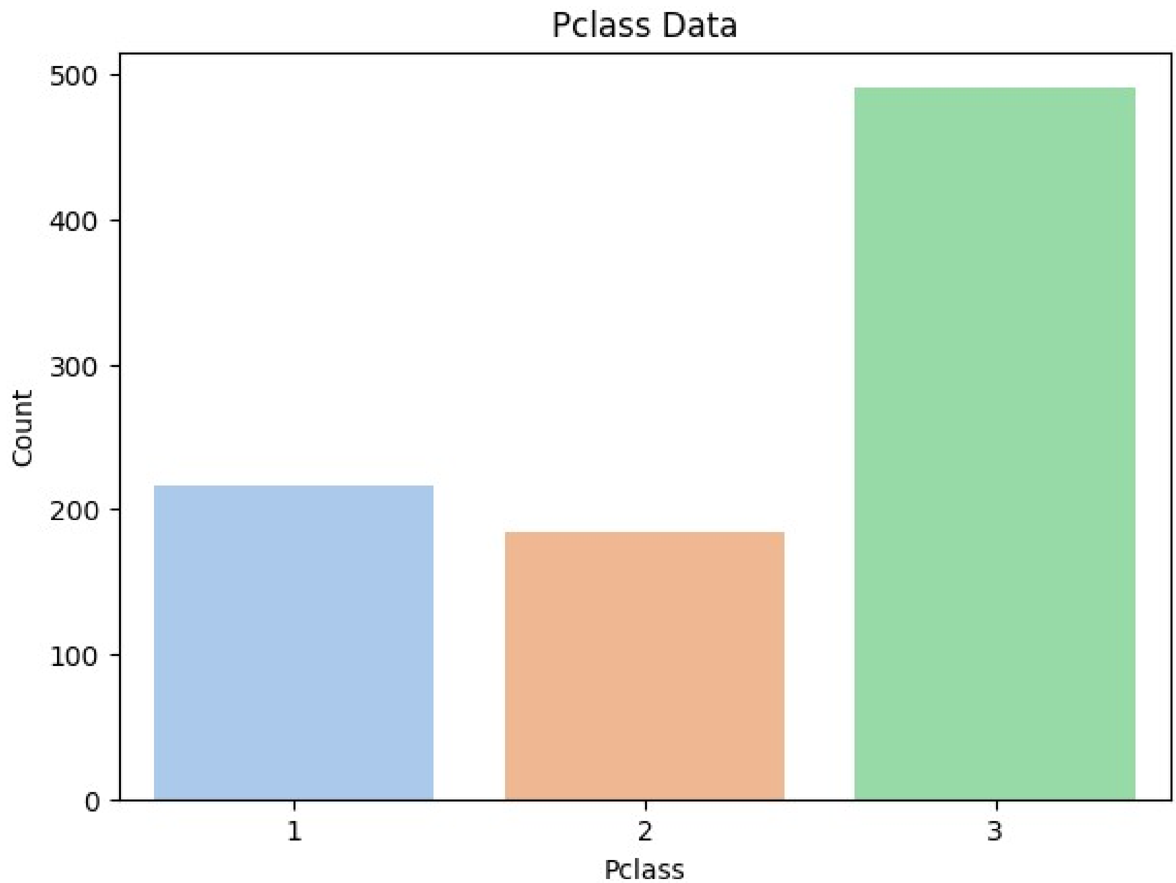



```python
# Plot the data for Pclass
plt.figure(figsize=(7, 5))
sns.countplot(data=titanic_train_data, x='Pclass', palette='pastel')
plt.title('Pclass Data')
plt.xlabel('Pclass')
plt.ylabel('Count')
plt.show()
```

```
<ipython-input-169-fc59cf76b336>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=titanic_train_data, x='Pclass', palette='pastel')
```

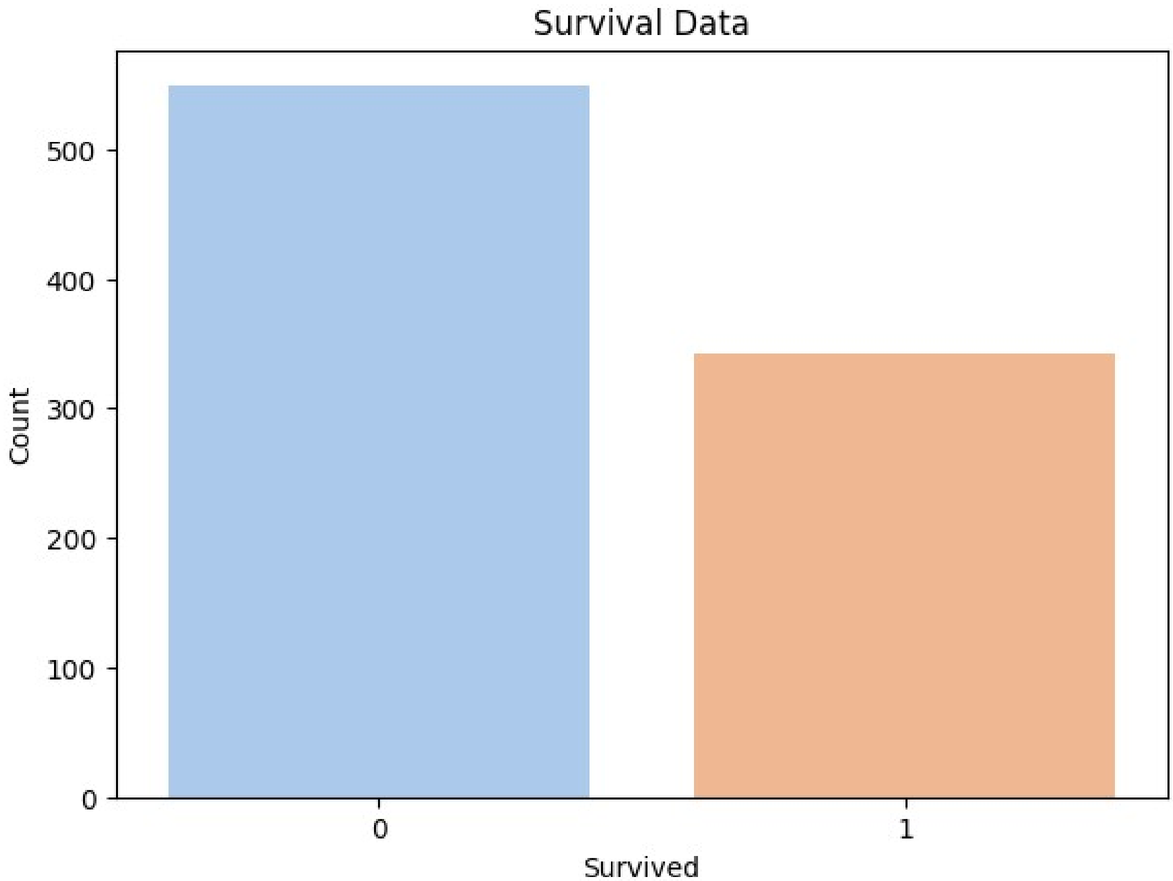



```
# Plot the data for Survival
plt.figure(figsize=(7, 5))
sns.countplot(data=titanic_train_data, x='Survived', palette='pastel')
plt.title('Survival Data')
plt.xlabel('Survived')
plt.ylabel('Count')
plt.show()
```

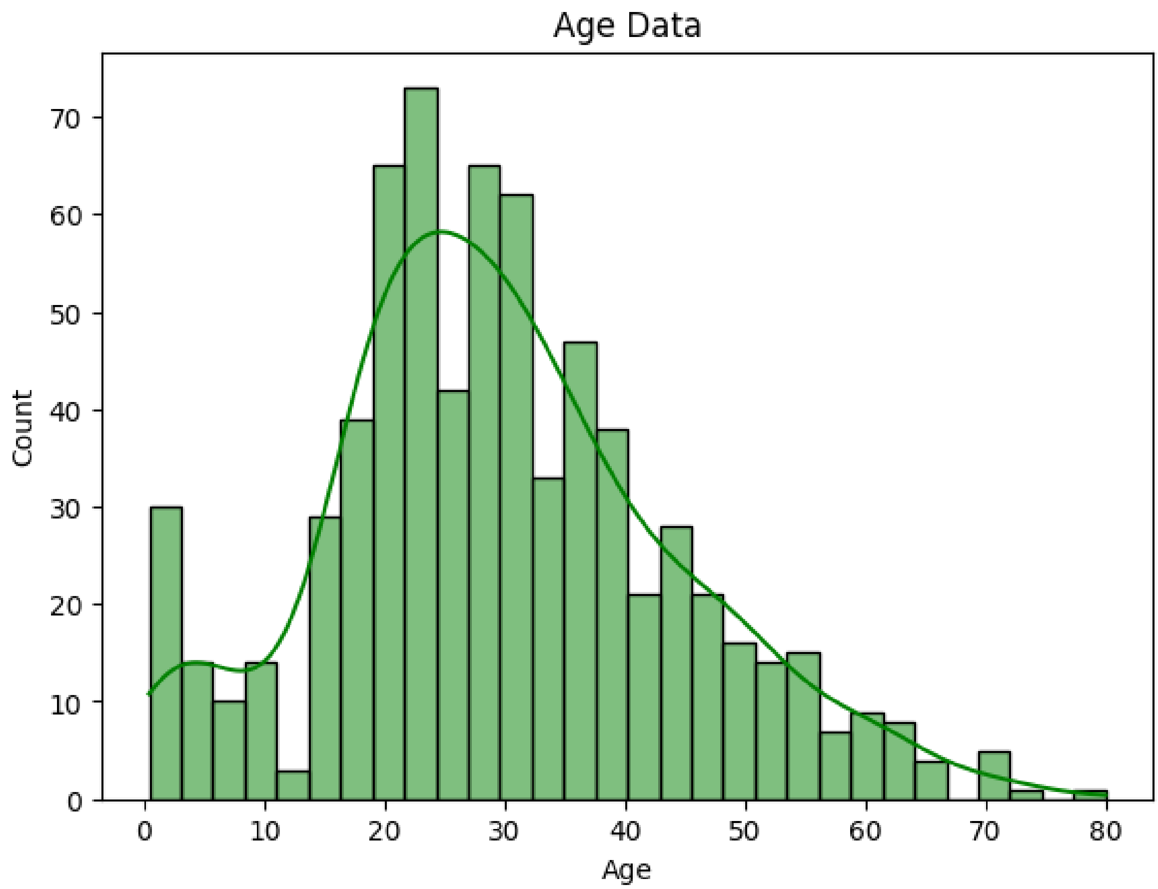
```
<ipython-input-170-b705cd8dfc8d>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=titanic_train_data, x='Survived',
palette='pastel')
```




```
# Plot the data for Age
plt.figure(figsize=(7, 5))
sns.histplot(titanic_train_data['Age'].dropna(), kde=True, bins=30,
color='green')
plt.title('Age Data')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



Part 3: Perform Simple Linear Regression on the SURVIVAL feature column (you can check the internet on how you can perform simple linear regression)

```
# Import necessary libraries
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

# Remove rows containing missing values in the 'Age' and 'Fare'
columns from the dataset and store the resulting dataframe in
'titanic_train_data'.
titanic_train_data = titanic_train_data[['Age', 'Fare']].dropna()

# Split the data into features (X) and target (y)
X = titanic_train_data[['Age']]
y = titanic_train_data['Fare']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

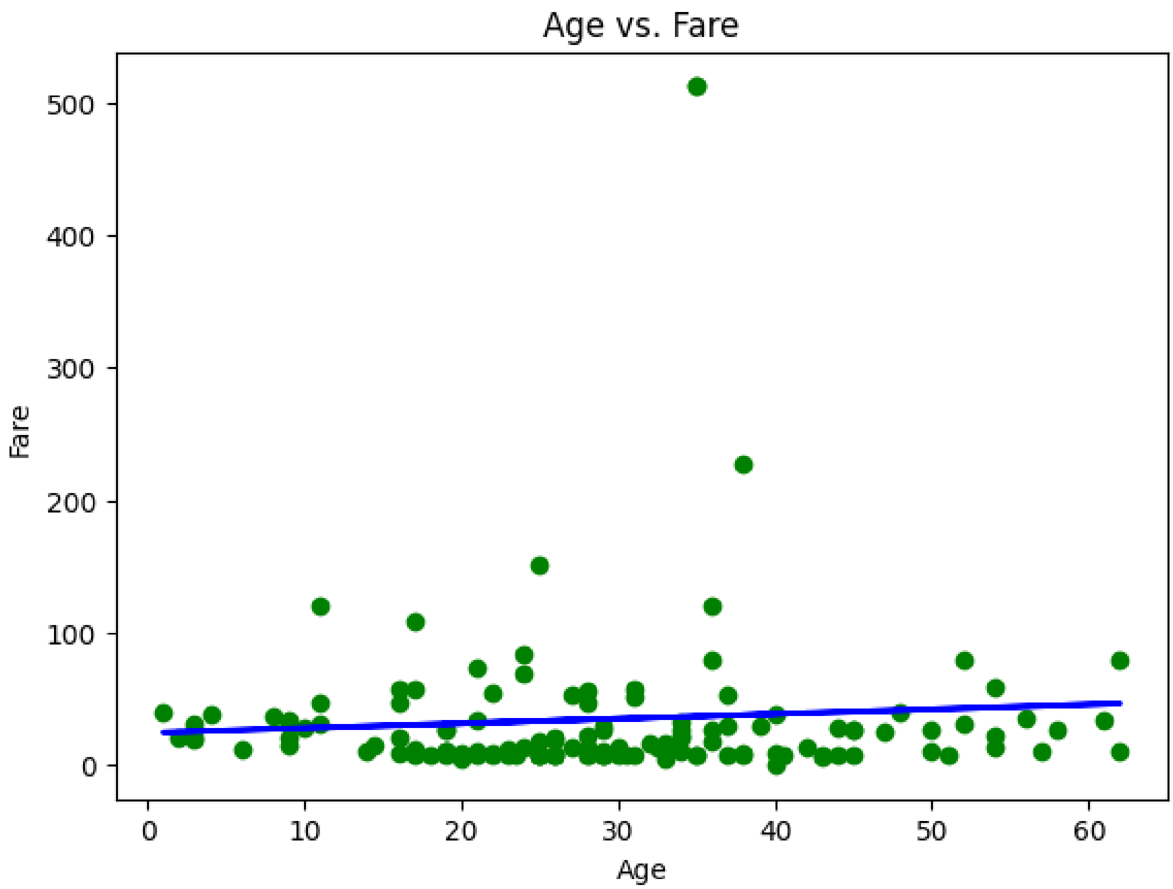
```python
# Initialize and fit the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Print the calculated mean squared error and R-squared.
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse:.2f}")
print(f"R-squared: {r2:.2f}")

# Plot a visualization showing the relationship between 'Age' and
'Fare', with actual test data points in green and the linear
regression line in blue.
plt.figure(figsize=(7, 5))
plt.scatter(X_test, y_test, color='green')
plt.plot(X_test, y_pred, color='blue', linewidth=2)
plt.title('Age vs. Fare')
plt.xlabel('Age')
plt.ylabel('Fare')
plt.show()
```

```
Mean Squared Error: 4147.43
R-squared: 0.00
```



Decision Tree Classification

Objectives: In this lab, you will use a decision tree classifier model to determine who survived the Titanic cruise ship disaster. Part 1: Create a Decision Tree Classifier Part 2: Apply the Decison Tree Mode Part 3: Evaluate the Decison Tree Model

##Scenario/Background In this lab you will create a decision tree classifier that will work with a data set which contains the details about the more than 1300 hundred passengers who were onboard the passenger liner Titanic on its infamous maiden voyage.

##Required Resources

- 1 PC with Internet access
- Python libraries: pandas, sklearn, and IPython.display
- Additonal application: Graphviz
- Datafiles: titanic-train.csv, titanic-test.csv, titanic_all.csv

Part 2: Create a Decision Tree Classifier

In this part of the lab, you will create a decision tree classifier that will learn from a labelled dataset.

The dataset contains the names and demographic details for each passenger. In addition, details of the passengers' trip are included. From this data, we can be build a decision tree that illustrates the factors that contributed to survivability, or lack of it, for the voyage.

The datasets contain the following variables:

Variable	Description
1. PassengerID	Unique identifier for each passenger
2. Survival	Did the passenger survive? (0 = No; 1 = Yes)
3. Pclass	Passenger ticket class. (1 = 1st; 2 = 2nd; 3 = 3rd)
4. Name	Name of the passenger. (last name, first name)
5. Gender	Male or female
6. Age	Age in years. Mostly integers with float values for children under one year.
7. SibSp	Number of siblings or spouse onboard.
8. Parch	Number of parents or children onboard.
9. Ticket	Ticket number
10. Fare	Amount paid for fare in pre-1970 British Pounds
11. Cabin	Cabin number
12. Embarked	Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

With the data above, what kinds of questions can we ask about the factors that contributed to passengers surviving or perishing in the Titanic disaster?

- Is the age matter in surviving in titanic disaster?
- Is the gender have advantages in surviving is such disaster?
- Is the number of siblings or spouse on board matter in terms of surviving a disaster?
- Is the number of parents or children on board matter in terms of surviving a disaster?

Step 1: Create the dataframe a) Import pandas and the csv file

First, import pandas and create a dataframe from the Titanic training data set, which is stored in the titanictrain.csv file. Use the pd.read_csv() method.

```
# Import the pandas library
import pandas as pd

#create a pandas dataframe called "training" from the titanic-
train.csv file
training = pd.read_csv("/content/titanic_train.csv")
```

b) Verify the import and take a look at the data.

```
#Code cell 2
#verify the contents of the training dataframe using the pandas info() method.
training.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
```

Are there missing values in the data set?

- Yes, from the given table above the variable Age and Cabin was missed some values.

```
#Code cell 3
#view the first few rows of the data
training.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	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

Next steps: View recommended plots

Step 2: Prepare the Data for the Decision Tree Model. a) Replace string data with numeric labels

We will use scikit-learn to create the decision trees. The decision tree model we will be using can only handle numeric data. The values for the Gender variable must be transformed into numeric representations. 0 will be used to represent "male" and 1 will represent "female."

In this code, a lambda expression is used with the apply() dataframe method. This lambda expression represents a function that uses a conditional statement to replace the text values in the columns with the appropriate numeric value. The lambda statement can be interpreted as "if the parameter toLabel equals 'male', return 0, if the value is something else, return 1." The apply() method will execute this function on the values in every row of the "Gender" column of the dataframe.

```
training.rename(columns = {'Sex': 'Gender'}, inplace = True)

#code cell 4
training["Gender"] = training["Gender"].apply(lambda toLabel: 0 if
toLabel ==
'male' else 1)
```

b) Verify that the Gender variable has been changed. The output should show values of 0 or 1 for the Gender variable in the dataset.

```
#code cell 5
training.head()
```

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	NaN	S

Next steps: View recommended plots

c) Address Missing Values in the Dataset The output of the info() method above indicated that about 180 observations are missing the age value. The age value is important to our analysis. We must address these missing values in some way. While not ideal, we can replace these missing age values with the mean of the ages for the entire dataset.

This is done by using the fillna() method on the "Age" column in the dataset. The fillna() method will change the original dataframe by using the inplace = True argument

```
#code cell 6
training["Age"].fillna(training["Age"].mean(), inplace=True)
```

d) Verify that the values have been replaced.

```
#code cell 7
#verify that the missing values for the age variable have been
eliminated.
training.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   Gender       891 non-null    int64
 5   Age          891 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(6), object(4)
memory usage: 83.7+ KB
```

What is the value that was used to replace the missing ages?

```
#use code to answer the question above
print(training["Age"].mean)

<bound method NDFrame._add_numeric_operations.<locals>.mean of 0
22.000000
1      38.000000
2      26.000000
3      35.000000
4      35.000000
         ...
886    27.000000
887    19.000000
888    29.699118
889    26.000000
890    32.000000
Name: Age, Length: 891, dtype: float64>
```

Step 3: Train and Score the Decision Tree Model. a) Create an array object with the variable that will be the target for the model. The purpose of the model is to classify passengers as survivors or victims. The dataset identifies survivors and victims. The model will learn which input variable values are most likely to belong to victims and survivors, and then use that information to classify passengers from a unique test data set.

```
#code cell 8
#create the array for the target values
y_target = training["Survived"].values
```

b) Create an array of the values that will be the input for the model. Only some of the features of the data are useful for creating the classifier tree. We create a list of the columns from the data that we want the classifier to use as the input variables and then create an array using the column name from that variable. The variable X_input holds the values for all the features that the model will use to learn how to make the classifications. After the model is trained, we will use this variable to assign these labels to the test data set.

```
#code cell 9
columns = ["Fare", "Pclass", "Gender", "Age", "SibSp"]

#create the variable to hold the features that the classifier will use
X_input = training[list(columns)].values
```

c) Create the learned model. Import the decision tree module from the sklearn machine learning library. Create the classifier object clf_train. Then, use the fit() method of the classifier object, with the X_input and y_target variables as parameters, to train the model.

```
#code cell 10
#import the tree module from the sklearn library
from sklearn import tree

#create clf_train as a decision tree classifier object
clf_train = tree.DecisionTreeClassifier(criterion="entropy",
max_depth=3)

#train the model using the fit() method of the decision tree object.
#Supply the method with the input variable X_input and the target
variable y_target
clf_train = clf_train.fit(X_input, y_target)
```

d) Evaluate the model Use the score() method of the decision tree object to display the percentage accuracy of the assignments made by the classifier. It takes the input and target variables as arguments.

```
#code cell 11
clf_train.score(X_input,y_target)

0.8226711560044894
```

This score value indicates that classifications made by the model should be correct approximately 82% of the time.

Step 6: Visualize the Tree a) Create the intermediate file output Import the sklearn.externals.six StringIO module which is used to output the characteristics of the decision tree to a file. We will create a Graphviz dot file which will allow us to export the results of the classifier into a format that can be converted into a graphic.

```
#code cell 12
from six import StringIO
with open("titanic.dot", 'w') as f:
  f = tree.export_graphviz(clf_train, out_file=f,
feature_names=columns)
```

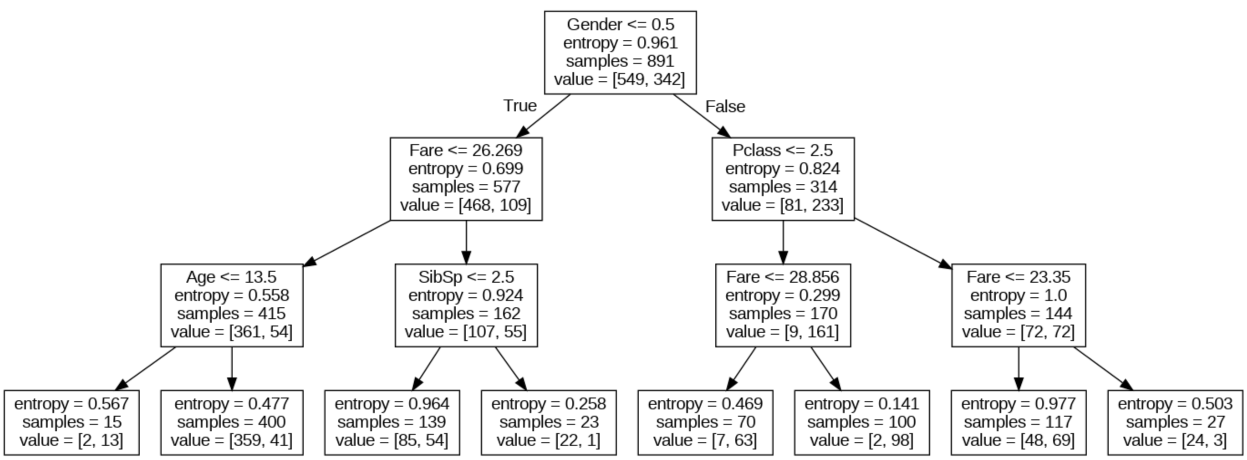
b) Install Graphviz To visualize the decision tree, Graphviz needs to be installed from a terminal. The installation requires that a prompt be answered, which can't be done from a notebook code cell. Use the apt-get install graphviz command from the terminal command line to install this software. **c) Convert the intermediate file to a graphic** The dot file that was created above can be converted to a .png file with the graphiz dot renderer. This is a shell command, so use ! before it to run it from this noteblook. The new titanic.png graphic file should appear in the directory that contains this notebook.

```
#code cell 13
#run the Graphviz dot command to convert the .dot file to .png
!dot -Tpng titanic.dot -o titanic.png
```

d) Display the image Now we will import the Image module from the IPython.display library. This will allow us to open and display an external graphics file on the notebook page. The Image function is used to display the file, with the .png file name as argument.

```
#code cell 14
#import the Image module from the Ipython.display libary
from IPython.display import Image

#display the decison tree graphic
Image("/content/titanic.png")
```



e) Interpret the tree From the tree, we can see several things. First, at the root of the tree is the Gender variable, indicating that it is the single most important factor in making the classification. The branches to the left are for Gender = 0 or male. Each root and intermediate node contains the decision factor, the entropy, and the number of passengers who fit the critierion at that point in the tree. For example, the root node indicates that there are 891 observations that make up the learning data set. At the next level, we can see that 577 people were male, and 314 were female. In the third level, at the far right, we can see that 415 people were male and paid a fare of less than 26.2686. Finally, the leaf nodes for that intermediate node indicate that 15 of these passengers were below the age of 13.5, and the other 400 were older than that age. Finally, the elements in the value array indicate survival. The first value is the number of people who died, and the second is the number of survivors for each criterion. The root node tells us that out of our sample, 549 people died and 342 survived. Entropy is a measure of noise in the decision. Noise can be viewed as uncertainty. For example, in nodes in which the decision results in equal values in the survival value array, the entropy is at its highest possible value, which is 1.0. This means that the model was unable to definitively make the classification decision based on the input variables. For values of very low entropy, the decision was much more clear cut, and the difference in the number of survivors and victims is much higher.

What describes the group that had the most deaths by number? Which group had the most survivors?

- The group that had the most death is the gender which 549 deaths in numbers and 342 survived in numbers.

Part 2: Apply the Decision Tree Model

Step 1: The pandas describe() method.

In this part of the lab, we will use the results of the learned decision tree model to label an unlabelled dataset of Titanic passengers. The decision tree will evaluate the features of each observation and label the observation as survived (label = 1) or died (label = 0).

Step 1: Import and Prepare the Data In this step, you will import and prepare the data for analysis.

a) Import the data. Name the dataframe "testing" and import the file titanic-test.csv

```
#code cell 15
#import the file into the 'testing' dataframe.
testing = pd.read_csv("/content/titanic_test.csv")

testing.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
 1   Pclass       418 non-null    int64
 2   Name         418 non-null    object
 3   Sex          418 non-null    object
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64
 6   Parch        418 non-null    int64
 7   Ticket       418 non-null    object
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object
 10  Embarked     418 non-null    object
```

```
dtypes: float64(2), int64(4), object(5)
memory usage: 36.0+ KB

testing.rename(columns = {'Sex': 'Gender'}, inplace = True)
```

How many records are in the data set?

- 418 records

Which important variables(s) are missing values and how many are missing?

- The Age with the missing values of 86. The Fare with the missing values of 1.

b) Use a lambda expression to replace the "male" and "female" values with 0 for male and 1 for female.

```
#code cell 16
#replace the Gender labels in the testing dataframe
# Hint: look at code cell 4
#code cell 4
testing["Gender"] = testing["Gender"].apply(lambda toLabel: 0 if
toLabel ==
'male' else 1)
```

c) Replace the missing age values with the mean of the ages.

```
#code cell 17
#Use the fillna method of the testing dataframe column "Age"
#to replace missing values with the mean of the age values.
testing["Age"].fillna(testing["Age"].mean(), inplace=True)
testing["Fare"].fillna(testing["Fare"].mean(), inplace=True)

testing.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
 1   Pclass       418 non-null    int64
 2   Name         418 non-null    object
 3   Gender       418 non-null    int64
 4   Age          418 non-null    float64
 5   SibSp        418 non-null    int64
 6   Parch        418 non-null    int64
 7   Ticket       418 non-null    object
```

```
 8   Fare          418 non-null    float64
 9   Cabin         91 non-null     object
 10  Embarked      418 non-null    object
dtypes: float64(2), int64(5), object(4)
memory usage: 36.0+ KB
```

Step 2: Label the testing dataset In this step, you will apply the learned model to the testing dataset. Check that the missing values have been filled and that the Gender labels are 0 and 1.

```
#code cell 19
#create the variable X_input to hold the features that the classifier
will use
X_input = testing[list(columns)].values
```

b) Apply the model to the testing data set. Use the predict() method of the clf_train object that was trained to label the observations in the testing data set with the most likely survival classification. Provide the array of input variables from the testing data set as the parameter for this method.

```
#code cell 20
#apply the model to the testing data and store the result in a pandas
dataframe.
#Use X_input as the argurment for the predict() method of the
clf_train classifier object
target_labels = clf_train.predict(X_input)

#convert the target array into a pandas dataframe using the
pd.DataFrame() method and target as argument
target_labels = pd.DataFrame({'Est_Survival':target_labels,
'Name':testing['Name']})

#display the first few rows of the data set
target_labels.head()
```

	Est_Survival	Name
0	0	Kelly, Mr. James
1	1	Wilkes, Mrs. James (Ellen Needs)
2	0	Myles, Mr. Thomas Francis
3	0	Wirz, Mr. Albert
4	1	Hirvonen, Mrs. Alexander (Helga E Lindqvist)

Next steps: View recommended plots

c) Evaluate the accuracy of the estimated labels The ground truth for the survival of each passenger can be found in another file called all_data.csv. To select only the passengers contained in the testing dataset, we merge the target_labels dataframe and the all_data dataframe on the field Name. We then compare the estimated label with the ground truth dataframe and compute the accuracy of the learned model.

```
testing.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
 1   Pclass       418 non-null    int64
 2   Name         418 non-null    object
 3   Gender       418 non-null    int64
 4   Age          418 non-null    float64
 5   SibSp        418 non-null    int64
 6   Parch        418 non-null    int64
 7   Ticket       418 non-null    object
 8   Fare         418 non-null    float64
 9   Cabin        91 non-null     object
 10  Embarked     418 non-null    object
dtypes: float64(2), int64(5), object(4)
memory usage: 36.0+ KB

#code cell 21
#import the numpy library as np
import numpy as np

# Load data for all passengers in the variable all_data
```

```
all_data = pd.read_csv("/content/titanic_all.csv")

# Merging using the field Name as key, selects only the rows of the two datasets that refer to the same passenger
testing_results = pd.merge(target_labels, all_data[['Name','Survived']], on=['Name'])

# Compute the accuracy as a ratio of matching observations to total osbervations. Store this in in the variable acc.
acc = np.sum(testing_results['Survived'] == testing_results['Survived']) / float(len(testing_results))

# Print the result
all_data.head()
```

	Passenger	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	1	1	Allen, Miss. Elisabeth Walton	female	29.0000	0	0	24160	211.3375	B5	S
1	2	1	1	Allison, Master. Hudson Trevor	male	0.9167	1	2	113781	151.5500	C22 C26	S
2	3	0	1	Allison, Miss. Helen Loraine	female	2.0000	1	2	113781	151.5500	C22 C26	S
3	4	0	1	Allison, Mr. Hudson Joshua Creighton	male	30.0000	1	2	113781	151.5500	C22 C26	S
4	5	0	1	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	female	25.0000	1	2	113781	151.5500	C22 C26	S

Next steps: View recommended plots

Part 3: Evaluate the Decision Tree Model

The sklearn library includes a module that can be used to evaluate the accurracy of the decision tree model. The train_test_split() method will divide the observations in whole data set into two randomly selected arrays of observations that makeup the testing and training datasets. After fitting the model to the training data, the trained model can be scored and the prediction accurracy compared for both the training and test datasets. It is desirable for the two scores to be close, but the accuracy for the test dataset is normally lower that for the training data set.

Step 1: The pandas describe() method.

This time we will import the data from a csv file, but we will specify the columns that we want to have appear in the dataframe. We will do this by passing an array-like list of column names to the read_csv() method usecols parameter. Use the following columns: 'Survived', 'Fare', 'Pclass', 'Gender', 'Age', and 'SibSP'. Each should be in quotes and the list should be square brackets. Name this dataframe all_data.

```
#code cell 22
#import the titanic_all.csv file into a dataframe called all_data. Specify thelist of columns to import.
all_data = pd.read_csv("/content/titanic_all.csv", usecols=['Survived','Pclass', 'Gender','Age','SibSp','Fare'])

#View info for the new dataframe
all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1308 entries, 0 to 1307
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  1308 non-null   int64
 1   Pclass    1308 non-null   int64
 2   Gender    1308 non-null   object
 3   Age       1045 non-null   float64
 4   SibSp     1308 non-null   int64
 5   Fare      1308 non-null   float64
dtypes: float64(2), int64(3), object(1)
memory usage: 61.4+ KB
```

How many records are in the data set?

- 1308 records

Which important variables(s) are missing values and how many are missing?

- Age with the missing values of 263

Step 2: Prepare the data. a) Remove the "male" and "female" strings and replace them with 0 and 1 respectively.

```
#code cell 23
#Label the gender variable with 0 and 1
all_data["Gender"] = all_data["Gender"].apply(lambda toLabel: 0 if
toLabel ==
'male' else 1)
```

c) Replace the missing age values with the mean of the age of all members of the data set.

```
#code cell 24
#replace missing Age values with the mean age
all_data["Age"].fillna(testing["Age"].mean(), inplace=True)

#display the first few rows of the data set
all_data.head()
```

	Survived	Pclass	Gender	Age	SibSp	Fare
0	1	1	1	29.0000	0	211.3375
1	1	1	0	0.9167	1	151.5500
2	0	1	1	2.0000	1	151.5500
3	0	1	0	30.0000	1	151.5500
4	0	1	1	25.0000	1	151.5500

Next steps: View recommended plots

```
all_data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1308 entries, 0 to 1307
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  1308 non-null   int64  
 1   Pclass    1308 non-null   int64  
 2   Gender    1308 non-null   int64  
 3   Age       1308 non-null   float64
 4   SibSp     1308 non-null   int64  
 5   Fare      1308 non-null   float64
dtypes: float64(2), int64(4)
memory usage: 61.4 KB
```

Step 2: Create the input and output variables for the training and testing data. The sklearn library includes modules that help with model selection. We will import from sklearn.model_selection the train_test_split() method. This method will automatically split the entire dataset, returning in total four numpy arrays, two for the features (test and validation) and two for the labels (test and validation). One parameter of the method specifies the proportion of observations to use for testing and training. Another parameter specifies a seed value that will be used to randomize assignment of the observation to testing or training. This is used so that another user can replicate your work by receiving the same assignments of observations to datasets. The syntax of the method is: `train_test_split(input_X, target_y, test_size=0.4, random_state=0)` 40% of the data will be used for testing. The random seed is set to 0. The method returns four values. These values are the input varibles for training and testing data and the target variables for the training and testing data in that order.

a) Designate the input variables and output variables and generate the arrays

```
#code cell 25
#Import train_test_split() from the sklearn.model_selection libary
from sklearn.model_selection import train_test_split

#create the input and target variables as uppercase X and lowercase y.
Reuse the columns variable.
X = all_data[list(columns)].values
y = all_data["Survived"].values

#generate the four testing and training data arrays with the
train_test_split() method
X_train,X_test,y_train,y_test=train_test_split(X, y, test_size=0.40,
random_state=0)
```

b) Train the model and fit it to the testing data. Now the model can be fit again. The model will be trained using only the training datat, as selected by the train_test_split function

```
#code cell 26
#create the training decision tree object
clf_train = tree.DecisionTreeClassifier(criterion="entropy",
max_depth=3)

#fit the training model using the input and target variables
clf_train = clf_train.fit(X_train, y_train)
```

c) Compare models by scoring each. Use the score() method of each decision tree object to generate scores.

```
#code cell 27
#score the model on the two datasets and store the scores in
variables. Convert the scores to strings using str()
train_score = str(clf_train.score(X_train,y_train))
test_score = str(clf_train.score(X_test,y_test))

#output the values in a test string
print('Training score = '+ train_score+' Testing score = '+test_score)

Training score = 0.8201530612244898 Testing score = 0.8053435114503816
```

We have now compared the scores for the trained model on both test and validation data. As expected, the test accuracy score is close, but lower than the score for the training data. This is because normally, the model tends to overfit the training data, therefore the test score is a better evaluation of how the model is able to generalize outside of the training data.

Part 4: For Further Study (optional)

If you have the time and are interested, you could try the following and see how the decision tree is affected. **1. Remove observations with missing Age values.** Using a mean to replace missing age values may affect the accuracy of the model. One approach to this might be to remove all observations with missing age values. Although this will decrease the size of the training dataset, it could improve accuracy. **2. Remove the input variables.** Another issue with this type of analysis is the identification of which input variables, or features, are essential to the accuracy of the classifier. One way to do this is to try running the classifier with different sets of input variables by editing the list of variables that is used to fit the model.

###**Conclusion**

As I observed while after doing the activity, we explored the creation of decision tree classifier that will work with a data set. In the beginning I clean the data first and also I tend to handle the missing records in the data set. Also, we evaluated the performance of the decision tree classifier. As seen in the code cell #14 the hierarchical positioning of variables that shows the prediction of survival it revealed that the critical factor for survival was the gender and it shows that the higher chances that can survived is the females according to the tree hierchy.

In conclusion, this hands-on activity helps me to experience the use decision tree classifier where it taught me how to create decision tree classifier, how to apply it, and also how to evaluate it. Also, machine learning play vital role in the Titanic dataset analysis, enabling the prediction of survival probabilities based on key factors, contributing to understanding historical events and informing future disaster management strategies.
