Before you turn this problem in, make sure everything runs as expected. First, **restart the kernel** (in the menu bar, select Kernel\$\rightarrow\$Restart) and then **run all cells** (in the menu bar, select Cell\$\rightarrow\$Run All).

Make sure that in addition to the code, you provide written answers for all questions of the assignment.

Below, please fill in your name and collaborators:

```
In [1]: NAME = "Jordan Vercillo"
COLLABORATORS = "Jordan Vercillo"
```

### **Assignment 2 - Data Analysis using Pandas**

### (15 points total)

For this assignment, we will analyze the open dataset with data on the passengers aboard the Titanic.

The data file for this assignment can be downloaded from Kaggle website: https://www.kaggle.com/c/titanic/data, file train.csv. It is also attached to the assignment page. The definition of all variables can be found on the same Kaggle page, in the Data Dictionary section.

Read the data from the file into pandas DataFrame. Analyze, clean and transform the data to answer the following question:

#### What categories of passengers were most likely to survive the Titanic disaster?

### **Question 1.** (4 points)

- The answer to the main question What categories of passengers were most likely to survive the Titanic disaster? (2 points)
- The detailed explanation of the logic of the analysis (2 points)

#### **Question 2.** (3 points)

- What other attributes did you use for the analysis? Explain how you used them and why
  you decided to use them.
- Provide a complete list of all attributes used.

### **Question 3.** (3 points)

• Did you engineer any attributes (created new attributes)? If yes, explain the rationale and how the new attributes were used in the analysis?

• If you have excluded any attributes from the analysis, provide an explanation why you believe they can be excluded.

### **Question 4.** (5 points)

• How did you treat missing values for those attributes that you included in the analysis (for example, age attribute)? Provide a detailed explanation in the comments.

### Question1.\_\_\_My\_Analysis

RESULT: The category that had the highest chance of survival (with a number of passengers greater than 10, below 10 is too much of an outlier), is wealthy females with or without kids

I tested a bunch of variables including Age, Gender, Port of Embarkation, Ticket Class, Age, Traveling alone or with Family, Traveling with children and Family size.

I came to a few meaniful realizations like females were most likely to survive (74% survival rate), Children (51% survival rate),1st class (62% survival rate), Traveling with Kids (51% survival rate)

Adult (18-60) Females in first class traveling without kids (98%)

Adult (18-60) Females in first class traveling with kids (95%)

Female Children with kids, young moms, also had a 100% chance of survival but there wasn't too many, about 11

First I analyzed the data, .info(), Describe(), I checked out what it looked like with .head(), experimented with making passenger ID the index but decided I didn't need it. I also renamed the columns to make it easier to read. I then had to impute or remove all the missing values then find the survival rate and test certain values against the survival rate. I made sure to format the data as a data frame (for better readabliity) include a count (To see how many vlaues are there and if it's statisically significant), and sort it by decending based on my key variable "survived"

After I tested all the variables individually I started to group them by common variables like ['AgeGroup', 'TicketClass', 'TravelersWithKids', 'Gender']. I tried looking at it in a few different ways to see if I could find anything meaniful about the analysis. I made sure to pay more attention to results that had enough of a sample size to be accurate, ie. males without kids in 3rd class had 273 data points and a 12% chance of survival while females without kids had 57 data points and a 98% chance of survival. Something like Senior 60+ in 3rd class female with 100% chance of survival I counted as an outlier because I didn't feel that there was a statistically significant size of samples.

That reasoning led to me modify my analysis when needed like when I initally created the age variables to include infants, toddlers, teens, but then realized that there wasn't enough there to make any meaniful inferences. (It did look like most infants survived 85% chance which was nice to see :) )

Question2.

- 0 Passengerld 889 non-null int64
- 1 Survived 889 non-null int64
- 2 TicketClass 889 non-null int64
- 3 Name 889 non-null object
- 4 Gender 889 non-null object
- 5 Age 889 non-null float64
- 6 SiblingsSpousesAboard 889 non-null int64
- 7 ParentsChildrenAboard 889 non-null int64
- 8 TicketNumber 889 non-null object

9 PassengerFare 889 non-null float64

- 10 PortOfEmbarkation 889 non-null object
- 11 Title 889 non-null object
- 12 LastName 889 non-null object
- 13 TravelersWithKids 889 non-null int32
- 14 Traveling Alone 889 non-null int32
- 15 FamilySize 889 non-null int64

**USED IN ANALYSIS** 

I used Survived as the main indicator of whether the Passenger Survived

I used ticketClass to see what class there were seated in to see if that impacted survival, I also used this as one of the most important indicators for my final analysis

Name was mainly to extract data for last name and title to be used in cleaning the analysis

I used Gender to see who had a higher chance of survival Male or Female, I also

used this as one of the most important indicators for my final analysis

I used Age to see if children, senior or adults had the highest chance of survival, I also used this as one of the most important indicators for my final analysis

SiblingsSpousesAboard was used to see if the passenger was traveling by themselves along with ParentsChildrenAboard

ParentsChildrenAboard was primarily used to see if the passenger was traveling with Kids or not

TravelersWithKids was used to see if families or parents had a higher chance of survival

**NOT USED IN ANALYSIS** 

Passenger ID was not used in the analysis because we we're looking at specific passengers but grouping them into categories

Ticket Number was used to see family size however this was not used in the final analysis

Passenger fare could be used to indicate how wealthy a person but TicketClass also provided that information and was better organized for analysis

Port of Embarkation I took a look at but didn't show anything that stood out too much.

Question3.

- 11 Title 889 non-null object
- 12 LastName 889 non-null object
- 13 TravelersWithKids 889 non-null int32
- 14 Traveling Alone 889 non-null int32
- 15 FamilySize 889 non-null int64

I created a couple of attributes, however I did not use too many of them for the analysis aside from Traveling with Kids.

11 Title (Created to help impute the value of age more accurately, I removed the last name from the name attribute, lambda x: x.split(','), then I was able to isloate the title as each title ended with a "." apply(lambda x: x[1].split('.')[0].strip(). I felt that using

title more accurately imputed the age as title is more tied to your age, ie. DR. older, Master is another name for a younger person.)

12 LastName (To try and find family size but this would introduce potential errors if someone had the same last name but wasn't traveling together)

13 TravelersWithKids (The parents column I tested to see if this column was greater than 0 which would indicate that they were traveling with kids, I didn't need to know the family size just if they were parents with kids or not)

14 Traveling Alone (I used a calc to see if SibSp and Parch == 0 because this would indicate if they are traveling alone or with someone, family, kids, parents)

15 FamilySize (I tried to see if family size had an impact on survivalbility, I used the same ticket number to check as I noticed each family last name had a common ticket number. I found that families 2-4 were the sweet spot for suvivability but any less or more would reduce your survivability.)

Question4.

First I dropped the 2 missing values from PortOfEmbarkation, this wouldn't impact the results of my analysis

## Dropping the 2 missing values from PortOfEmbarkation

Titanic.dropna(subset=['PortOfEmbarkation'], inplace=True)

I then created a variable Name\_Split to split the "Name" attribute into 2 sections, 1 with the Last name before the "," and another section after. I then noticed that the title ended with a "." so I created my second attribute "Title which would select the 2nd section ie. Braund, / Mr. Owen Haris, then split it again but kept the first second ie. Braund, / Mr. / Owen Haris. Finally I droped the new attribute and kept Title.

Titanic['Name\_Split'] = Titanic['Name'].apply(lambda x: x.split(',')) Titanic['Title'] = Titanic['Name\_Split'].apply(lambda x: x[1].split('.')[0].strip()) Titanic.drop('Name\_Split', axis=1, inplace=True)

I then created a median\_ages variable that would provide the medium value of all things I felt were important like my newly created title attribute, Ticket Class and Gender. This would be better than something like the mean as mean could include outliers like 80+ or below 5 which could skew the accurate guess of age we

## were looking for. median seemed like a more accurate calcuation

median\_ages = Titanic.groupby(['Title', 'TicketClass', 'Gender'])['Age'].median() median\_ages

I then had to create an impute\_age function which would look for missing values in the "Age" column and return the medium age using the medium\_age variable created previously using the pd.isnull function.

Finally I applied this function to the age column and effected the entire row by including axis = 1

## Imputing Age based on the medium value of groupby, title, gender, and ticketclass

def impute\_age(row): if pd.isnull(row['Age']): return median\_ages[row['Title'], row['TicketClass'], row['Gender']] else: return row['Age']

Titanic['Age'] = Titanic.apply(impute\_age, axis=1)

#### \*\*MAIN ANALYSIS BELOW\*\*

```
In [2]: import numpy as np
import pandas as pd

In [3]: Titanic = pd.read_csv("train.csv")
    Titanic
```

Out[3]:		Passengerld	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	F
	0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2!
	1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17599	71.2{
	2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.97
	3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.10
	4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0!
	•••						•••				
	886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00
	887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00
	888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4!
	889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00
	890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7!
	891 rc	ows × 12 colur	nns								
	4										<b>•</b>
In [4]:	Titar	nic.head()									
		,,									

localhost:8891/lab/tree/OneDrive/Python/Data Science/Foundations of Data Science/Asssignemnts/assignment2.ipynb

0         1         0         3 Mr. Owen Harris         male 22.0         1         0 A/5 21171         7.250C           1         2         1         1 Email Mrs. John Bradley (Florence Briggs Th         6 Female 38.0         1         0 PC 17599         71.2833           2         3         1         3 Miss. Laina Miss. Laina         6 Female 26.0         0         0 STON/O2. 3101282         7.925C           3         4         1         1 Heikkinen, Mrs. Jacques Heath (Lily May Peel)         6 Female Heath (Lily May Peel)         35.0         1         0 113803         53.100C           4         5         0         3 William Henry         male 35.0         0         0 373450         8.050C	Out[4]:		PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
1       2       1       1       Mrs. John Bradley (Florence Briggs Th       female       38.0       1       0       PC 17599       71.2833         2       3       1       3       Heikkinen, Miss. Laina       female       26.0       0       0       STON/O2. 3101282       7.925C         3       4       1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)       female       35.0       1       0       113803       53.100C         4       5       0       3       Allen, Mr. William Henry       male       35.0       0       0       373450       8.050C		0	1	0	3	Mr. Owen	male	22.0	1	0		7.2500
2 3 1 3 Miss. female 26.0 0 0 3101/02. 7.9250  Futrelle, Mrs. Jacques Heath (Lily May Peel)  Allen, Mr. Male 35.0 0 0 373450 8.0500 Henry		1	2	1	1	Mrs. John Bradley (Florence Briggs	female	38.0	1	0	PC 17599	71.2833
Mrs. Jacques Heath (Lily May Peel)  Allen, Mr. Henry  Allen, Mr. Henry  Mrs. Jacques Hemale 35.0 1 0 113803 53.1000  1 35.0 0 0 373450 8.0500		2	3	1	3	Miss.	female	26.0	0	0		7.9250
<b>4</b> 5 0 3 William male 35.0 0 0 373450 8.0500 Henry		3	4	1	1	Mrs. Jacques Heath (Lily May	female	35.0	1	0	113803	53.1000
←		4	5	0	3	William	male	35.0	0	0	373450	8.050C
		4										•

### In [5]: Titanic.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 [6]: Titanic.describe()

```
Out[6]:
                 PassengerId
                                Survived
                                               Pclass
                                                            Age
                                                                       SibSp
                                                                                   Parch
                                                                                                Far€
                  891.000000
                              891.000000
                                          891.000000
                                                      714.000000
                                                                  891.000000
                                                                             891.000000
                                                                                          891.000000
          count
                  446.000000
                                0.383838
                                            2.308642
                                                       29.699118
                                                                    0.523008
                                                                                0.381594
                                                                                           32.204208
          mean
            std
                  257.353842
                                0.486592
                                            0.836071
                                                       14.526497
                                                                    1.102743
                                                                                0.806057
                                                                                           49.693429
            min
                    1.000000
                                0.000000
                                            1.000000
                                                        0.420000
                                                                    0.000000
                                                                                0.000000
                                                                                            0.000000
           25%
                                0.000000
                                            2.000000
                                                       20.125000
                                                                    0.000000
                                                                                0.000000
                  223.500000
                                                                                            7.910400
           50%
                  446.000000
                                 0.000000
                                            3.000000
                                                       28.000000
                                                                    0.000000
                                                                                0.000000
                                                                                           14.454200
           75%
                  668.500000
                                1.000000
                                            3.000000
                                                       38.000000
                                                                    1.000000
                                                                                0.000000
                                                                                           31.000000
           max
                  891.000000
                                 1.000000
                                            3.000000
                                                       80.000000
                                                                    8.000000
                                                                                6.000000 512.329200
          Titanic["Survived"].describe()
 In [7]:
 Out[7]:
          count
                    891.000000
                      0.383838
          mean
                      0.486592
          std
          min
                      0.000000
          25%
                      0.000000
          50%
                      0.000000
          75%
                      1.000000
                      1.000000
          max
          Name: Survived, dtype: float64
 In [8]: S_Rate = (Titanic["Survived"].mean())*100
          f_s_rate = "{:.2f}%".format(S_Rate)
          print("The average survival rate is :", f_s_rate)
        The average survival rate is: 38.38%
 In [9]: Titanic.rename(columns={
              'survival': 'Survived',
              'Pclass': 'TicketClass',
              'Sex': 'Gender',
              'SibSp': 'SiblingsSpousesAboard',
              'Parch': 'ParentsChildrenAboard',
              'Ticket': 'TicketNumber',
              'Fare': 'PassengerFare',
              'Cabin': 'CabinNumber',
              'Embarked': 'PortOfEmbarkation'
          }, inplace=True)
         Titanic.set_index('PassengerId', inplace=True)
In [10]:
In [11]: Titanic.head()
```

Out[11]:		Survived	TicketClass	Name	Gender	Age	SiblingsSpousesAboard	Paren
	Passengerld							
	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	
	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	
	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	
	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	
	5	0	3	Allen, Mr. William Henry	male	35.0	0	
	4							•
In [12]:	Titanic.res	et_index(i	inplace= <b>True</b>	)				
In [13]:	Titanic.head	d()						

Out[13]:		PassengerId	Survived	TicketClass	Name	Gender	Age	SiblingsSpousesAboard	Pa
	0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	
	1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	
	2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	
	3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	
	4	5	0	3	Allen, Mr. William Henry	male	35.0	0	
	4								•
In [14]:	Tit	anic.info()							
F C -	Range	ss 'pandas.ceIndex: 891 columns (to Column PassengerIce Survived TicketClass Name Gender Age SiblingsSpot ParentsChil TicketNumbe	entries, otal 12 co d d s ousesAboar drenAboar	0 to 890 lumns): Non-Null 891 non- 891 non- 891 non- 891 non- 714 non- d 891 non-	Count Dt null ir null ir null ir null ob null ob null fl null ir	ype  t64 t64 ject ject oat64 t64 t64			
c	9 10 11 Ityp	PassengerFa CabinNumber PortOfEmbar es: float64( ry usage: 83	are rkation (2), int64	891 non- 204 non- 889 non-	null fl null ob null ob	oat64 ject ject			

# This is cleaning of the dataset and imputing of NaN values

```
In [15]: #Dropping the 2 missing values from PortOfEmbarkation
         Titanic.dropna(subset=['PortOfEmbarkation'], inplace=True)
In [16]: #Splitting Name to find the title to get a more accurate imputation of age
         Titanic['Name_Split'] = Titanic['Name'].apply(lambda x: x.split(','))
         Titanic['Title'] = Titanic['Name_Split'].apply(lambda x: x[1].split('.')[0].strip()
         Titanic.drop('Name_Split', axis=1, inplace=True)
         print(Titanic['Title'].value_counts())
        Title
                        517
        Mr
        Miss
                        181
        Mrs
                        124
        Master
                         40
        Dr
                          7
        Rev
                          6
                          2
        Mlle
                          2
        Major
                          2
        Col
        the Countess
                          1
        Capt
                          1
       Ms
        Sir
                          1
                          1
        Lady
                          1
        Mme
        Don
                          1
        Jonkheer
                          1
        Name: count, dtype: int64
In [17]: Titanic.head()
```

Out[17]:		PassengerId	Survived	TicketClass	Name	Gender	Age	SiblingsSpousesAboard	Pa
	0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	
	1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	
	2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	
	3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	
	4	5	0	3	Allen, Mr. William Henry	male	35.0	0	
	4								•
In [18]:		dian_ages = dian_ages	Titanic.gr	roupby([' <mark>Tit</mark>	:le', 'Tick	etClass'	, 'Ge	nder'])['Age'].median	()

```
TicketClass Gender
Out[18]: Title
         Capt
                       1
                                    male
                                               70.0
         Col
                                    male
                                               58.0
                       1
         Don
                       1
                                    male
                                               40.0
         Dr
                                    female
                                               49.0
                        1
                                    male
                                               44.0
                        2
                                    male
                                               38.5
         Jonkheer
                        1
                                    male
                                               38.0
                        1
                                    female
                                               48.0
         Lady
         Major
                        1
                                    male
                                               48.5
         Master
                        1
                                    male
                                               4.0
                        2
                                    male
                                              1.0
                        3
                                    male
                                               4.0
         Miss
                        1
                                    female
                                              30.0
                        2
                                    female
                                              24.0
                        3
                                    female
                                              18.0
         Mlle
                        1
                                    female
                                              24.0
         Mme
                        1
                                    female
                                               24.0
         Mr
                        1
                                    male
                                              40.0
                        2
                                    male
                                              31.0
                        3
                                    male
                                              26.0
                                              40.0
         Mrs
                        1
                                    female
                        2
                                    female
                                              32.0
                        3
                                    female
                                              31.0
                        2
                                    female
                                              28.0
         Ms
                       2
         Rev
                                    male
                                              46.5
         Sir
                        1
                                    male
                                              49.0
                                     female
         the Countess 1
                                              33.0
         Name: Age, dtype: float64
In [19]: #Imputing Age based on the medium value of groupby, title, gender, and ticketclass
         def impute_age(row):
             if pd.isnull(row['Age']):
                 return median_ages[row['Title'], row['TicketClass'], row['Gender']]
             else:
                 return row['Age']
         Titanic['Age'] = Titanic.apply(impute_age, axis=1)
In [20]: #Dropping CabinNumber as there's too many missing values and TicketClass can provid
         Titanic.drop('CabinNumber', axis=1, inplace=True)
In [21]: #Creating Last name column
         Titanic['LastName'] = Titanic['Name'].apply(lambda x: x.split(',')[0])
In [22]: #Traveling with Kids
         Titanic['TravelersWithKids'] = (Titanic['ParentsChildrenAboard']>0).astype(bool)
In [23]: #Traveling Alone?
         Titanic['Traveling Alone'] = ((Titanic['ParentsChildrenAboard']+Titanic['SiblingsSp
In [24]: #Family Size based on same ticket number, this could be inaccurate due to sharing t
         Titanic['FamilySize'] = Titanic.groupby('TicketNumber')['TicketNumber'].transform('
```

### In [25]: Titanic.info()

<class 'pandas.core.frame.DataFrame'>

Index: 889 entries, 0 to 890 Data columns (total 16 columns):

#	Column	Non-Null Count	Dtype
0	PassengerId	889 non-null	int64
1	Survived	889 non-null	int64
2	TicketClass	889 non-null	int64
3	Name	889 non-null	object
4	Gender	889 non-null	object
5	Age	889 non-null	float64
6	SiblingsSpousesAboard	889 non-null	int64
7	ParentsChildrenAboard	889 non-null	int64
8	TicketNumber	889 non-null	object
9	PassengerFare	889 non-null	float64
10	PortOfEmbarkation	889 non-null	object
11	Title	889 non-null	object
12	LastName	889 non-null	object
13	TravelersWithKids	889 non-null	bool
14	Traveling Alone	889 non-null	int32
15	FamilySize	889 non-null	int64
dtyp	es: bool(1), float64(2)	, int32(1), int6	4(6), object(6)

memory usage: 108.5+ KB

In [26]: Titanic

Out[26]:

	PassengerId	Survived	TicketClass	Name	Gender	Age	SiblingsSpousesAboard
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0
•••							
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	18.0	1
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0
889 rd	ows × 16 colur	nns					
4							<b>&gt;</b>

### Creating groupings of categories

GenderGroup: (Male/Female)

Port of Embarkation: (C/Q/S)

AgeGroup: ('Child' 0-12, 'Teen'12-18, 'Adult' 18-60, 'Senior' 60+)

TicketClassGroup: Wealth Status (1,2,3)

Traveling Alone: Single or Family (is parentsaboard and siblingsaboard is equal to 0)

ParentswithChildren: Parents column = 1

## FamilySizegroup: value counts based on Last Name and Ticket Number

```
In [27]: print("The average survival rate is :", f_s_rate)
    The average survival rate is : 38.38%
In [28]: #Gender Group
    gender_survival = Titanic.groupby('Gender')['Survived'].mean().sort_values(ascendin gender_survival)

Out[28]: Gender
    female    0.740385
    male    0.188908
    Name: Survived, dtype: float64

In [29]: print("Females are most likely to survive")
    Females are most likely to survive

In [30]: port_survival = Titanic.groupby('PortOfEmbarkation')['Survived'].mean().sort_values
```

```
port survival
Out[30]: PortOfEmbarkation
              0.553571
         C
         Q
              0.389610
         S
              0.336957
         Name: Survived, dtype: float64
In [31]: print("Port C Most likely to survive")
        Port C Most likely to survive
In [32]: bins = [0,1,3,12,18,60,120]
         labels = ['Infant','Toddlers','Child', 'Teen', 'Adult', 'Senior']
         Titanic['AgeGroup'] = pd.cut(Titanic['Age'], bins=bins, labels=labels)
         Titanic.groupby('AgeGroup')['Survived'].mean().sort_values(ascending=False)
        C:\Users\jverc\AppData\Local\Temp\ipykernel_7632\2220056522.py:4: FutureWarning: The
        default of observed=False is deprecated and will be changed to True in a future vers
        ion of pandas. Pass observed=False to retain current behavior or observed=True to ad
        opt the future default and silence this warning.
         Titanic.groupby('AgeGroup')['Survived'].mean().sort_values(ascending=False)
Out[32]: AgeGroup
         Infant
                     0.857143
         Child
                     0.511628
         Toddlers
                     0.500000
         Teen
                     0.475728
         Adult
                     0.354046
          Senior
                     0.190476
         Name: Survived, dtype: float64
In [33]: bins = [0, 18, 60, 120]
         labels = ['Children 0-18','Adult 12-60', 'Senior 60+']
         Titanic['AgeGroup'] = pd.cut(Titanic['Age'], bins=bins, labels=labels)
         Titanic.groupby('AgeGroup')['Survived'].mean().sort_values(ascending=False)
        C:\Users\jverc\AppData\Local\Temp\ipykernel_7632\2072681962.py:4: FutureWarning: The
        default of observed=False is deprecated and will be changed to True in a future vers
        ion of pandas. Pass observed=False to retain current behavior or observed=True to ad
        opt the future default and silence this warning.
          Titanic.groupby('AgeGroup')['Survived'].mean().sort_values(ascending=False)
Out[33]: AgeGroup
         Children 0-18
                          0.517045
         Adult 12-60
                          0.354046
         Senior 60+
                          0.190476
         Name: Survived, dtype: float64
In [34]: | age_group_survival = Titanic.groupby('AgeGroup')['Survived'].mean()
         sorted_survival_rates = age_group_survival.sort_values(ascending=False)
         age_group_counts = Titanic.groupby('AgeGroup')['Survived'].count()
         age_group_stats = pd.DataFrame({
              'Survival Rate': sorted_survival_rates,
             'Count': age_group_counts
         }).sort_values(by='Survival Rate', ascending=False)
         age_group_stats
```

```
default of observed=False is deprecated and will be changed to True in a future vers
        ion of pandas. Pass observed=False to retain current behavior or observed=True to ad
        opt the future default and silence this warning.
          age_group_survival = Titanic.groupby('AgeGroup')['Survived'].mean()
        C:\Users\jverc\AppData\Local\Temp\ipykernel_7632\2796588955.py:3: FutureWarning: The
        default of observed=False is deprecated and will be changed to True in a future vers
        ion of pandas. Pass observed=False to retain current behavior or observed=True to ad
        opt the future default and silence this warning.
          age group counts = Titanic.groupby('AgeGroup')['Survived'].count()
Out[34]:
                       Survival Rate Count
            AgeGroup
          Children 0-18
                           0.517045
                                       176
           Adult 12-60
                           0.354046
                                       692
            Senior 60+
                           0.190476
                                       21
In [35]: print("under 18 are most likely to survive")
        under 18 are most likely to survive
In [36]: ticket_class_survival = Titanic.groupby('TicketClass')['Survived'].mean().sort_valu
         ticket_class_survival
Out[36]: TicketClass
              0.626168
          2
              0.472826
              0.242363
         Name: Survived, dtype: float64
In [37]: print("1st Class are most likely to survive")
        1st Class are most likely to survive
In [38]: Titanic.groupby('Traveling Alone')['Survived'].mean().sort_values(ascending=False)
Out[38]: Traveling Alone
              0.505650
         0
               0.300935
         Name: Survived, dtype: float64
In [39]: print("Traveling with Family most likely to survive")
        Traveling with Family most likely to survive
In [40]: parents_survival = Titanic.groupby('TravelersWithKids')['Survived'].mean().sort_val
         parents_survival
Out[40]: TravelersWithKids
         True
                   0.511737
          False
                   0.341716
         Name: Survived, dtype: float64
```

C:\Users\jverc\AppData\Local\Temp\ipykernel\_7632\2796588955.py:1: FutureWarning: The

```
print("Traveling with Children most likely to survive")
        Traveling with Children most likely to survive
In [42]: Titanic.groupby('FamilySize')['Survived'].mean().sort_values(ascending=False)
Out[42]: FamilySize
              0.698413
         3
          2
              0.569892
         4
              0.500000
              0.297989
         1
         7
              0.238095
              0.000000
              0.000000
         Name: Survived, dtype: float64
In [43]: print("Family size of 2-4 are most likely to survive, while traveling alone or with
        Family size of 2-4 are most likely to survive, while traveling alone or with too big
        of a family reduced your survivability
In [44]: | Titanic.groupby('Title')['Survived'].mean().sort_values(ascending=False)
Out[44]: Title
         the Countess
                          1.000000
         Mlle
                          1.000000
         Sir
                          1.000000
         Ms
                          1.000000
         Lady
                          1.000000
                          1.000000
         Mme
         Mrs
                          0.790323
         Miss
                          0.696133
                          0.575000
         Master
         Col
                          0.500000
         Major
                          0.500000
         Dr
                          0.428571
                          0.156673
         Mr
                          0.000000
          Jonkheer
         Rev
                          0.000000
         Don
                          0.000000
                          0.000000
         Capt
         Name: Survived, dtype: float64
In [45]: survival_rate = Titanic.groupby('Title')['Survived'].mean()
         title_counts = Titanic.groupby('Title')['Survived'].count()
         survival rate df = survival rate.reset index(name='Survival Rate')
         title counts df = title counts.reset index(name='Count')
         title_stats = pd.merge(survival_rate_df, title_counts_df, on='Title')
         title stats_sorted = title_stats.sort_values(by='Survival Rate', ascending=False)
         title_stats_sorted
```

t[45]:		Title	Survival Rate	Count
	16	the Countess	1.000000	1
t[45]:	9	Mlle	1.000000	2
	15	Sir	1.000000	1
	13	Ms	1.000000	1
	5	Lady	1.000000	1
	10	Mme	1.000000	1
	12	Mrs	0.790323	124
	8	Miss	0.696133	181
	7	Master	0.575000	40
	1	Col	0.500000	2
	6	Major	0.500000	2
	3	Dr	0.428571	7
	11	Mr	0.156673	517
	4	Jonkheer	0.000000	1
	14	Rev	0.000000	6
	2	Don	0.000000	1
	0	Capt	0.000000	1

In [46]: print("Mrs, Miss, and Master most likely to survive while Mr had a 15% survival rat

Mrs, Miss, and Master most likely to survive while Mr had a 15% survival rate

In [47]: multi\_grouped = Titanic.groupby(['AgeGroup', 'TicketClass','TravelersWithKids','Gen
multi\_grouped

C:\Users\jverc\AppData\Local\Temp\ipykernel\_7632\258836269.py:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future vers ion of pandas. Pass observed=False to retain current behavior or observed=True to ad opt the future default and silence this warning.

multi\_grouped = Titanic.groupby(['AgeGroup', 'TicketClass','TravelersWithKids','Ge
nder'])['Survived'].mean().unstack().sort\_index(ascending=False)

Out[47]:

		Gender	remaie	maie
AgeGroup	TicketClass	TravelersWithKids		
Senior 60+	3	True	NaN	NaN
		False	1.000000	0.000000
	2	True	NaN	NaN
		False	NaN	0.333333
	1	True	NaN	0.000000
		False	1.000000	0.111111
Adult 12-60	3	True	0.375000	0.066667
		False	0.488372	0.120879
	2	True	0.950000	0.000000
		False	0.880952	0.087500
	1	True	0.956522	0.312500
		False	0.982456	0.393258
Children 0-18	3	True	0.371429	0.277778
		False	0.682927	0.157895
	2	True	1.000000	1.000000
		False	1.000000	0.000000
	1	True	0.857143	1.000000
		False	1.000000	0.000000

Gender

female

male

C:\Users\jverc\AppData\Local\Temp\ipykernel\_7632\1131773453.py:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future vers ion of pandas. Pass observed=False to retain current behavior or observed=True to ad opt the future default and silence this warning.

grouped = Titanic.groupby(['AgeGroup', 'TicketClass', 'TravelersWithKids', 'Gende
r']).agg(

Out[48]:		AgeGroup	TicketClass	TravelersWithKids	Gender	SurvivalRate	Count
	0	Children 0-18	1	False	female	1.000000	4
	3	Children 0-18	1	True	male	1.000000	4
	4	Children 0-18	2	False	female	1.000000	3
	32	Senior 60+	3	False	female	1.000000	1
	6	Children 0-18	2	True	female	1.000000	11
	7	Children 0-18	2	True	male	1.000000	9
	24	Senior 60+	1	False	female	1.000000	1
	12	Adult 12-60	1	False	female	0.982456	57
	14	Adult 12-60	1	True	female	0.956522	23
	18	Adult 12-60	2	True	female	0.950000	20
	16	Adult 12-60	2	False	female	0.880952	42
	2	Children 0-18	1	True	female	0.857143	7
	8	Children 0-18	3	False	female	0.682927	41
	20	Adult 12-60	3	False	female	0.488372	43
	13	Adult 12-60	1	False	male	0.393258	89
	22	Adult 12-60	3	True	female	0.375000	24
	10	Children 0-18	3	True	female	0.371429	35
	29	Senior 60+	2	False	male	0.333333	3
	15	Adult 12-60	1	True	male	0.312500	16
	11	Children 0-18	3	True	male	0.277778	36
	9	Children 0-18	3	False	male	0.157895	19
	21	Adult 12-60	3	False	male	0.120879	273
	25	Senior 60+	1	False	male	0.111111	9
	17	Adult 12-60	2	False	male	0.087500	80
	23	Adult 12-60	3	True	male	0.066667	15
	19	Adult 12-60	2	True	male	0.000000	10
	1	Children 0-18	1	False	male	0.000000	1
	27	Senior 60+	1	True	male	0.000000	3
	5	Children 0-18	2	False	male	0.000000	6
	33	Senior 60+	3	False	male	0.000000	4

C:\Users\jverc\AppData\Local\Temp\ipykernel\_7632\2320419055.py:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future vers ion of pandas. Pass observed=False to retain current behavior or observed=True to ad opt the future default and silence this warning.

grouped = Titanic.groupby(['AgeGroup', 'TicketClass', 'TravelersWithKids', 'Gende
r']).agg(

Out[49]:		AgeGroup	TicketClass	TravelersWithKids	Gender	SurvivalRate	Count
	6	Children 0-18	2	True	female	1.000000	11
	12	Adult 12-60	1	False	female	0.982456	57
	14	Adult 12-60	1	True	female	0.956522	23
	18	Adult 12-60	2	True	female	0.950000	20
	16	Adult 12-60	2	False	female	0.880952	42
	8	Children 0-18	3	False	female	0.682927	41
	20	Adult 12-60	3	False	female	0.488372	43
	13	Adult 12-60	1	False	male	0.393258	89
	22	Adult 12-60	3	True	female	0.375000	24
	10	Children 0-18	3	True	female	0.371429	35
	15	Adult 12-60	1	True	male	0.312500	16
	11	Children 0-18	3	True	male	0.277778	36
	9	Children 0-18	3	False	male	0.157895	19
	21	Adult 12-60	3	False	male	0.120879	273
	17	Adult 12-60	2	False	male	0.087500	80
	23	Adult 12-60	3	True	male	0.066667	15

```
sorted_groups = filtered_groups.sort_values(by='SurvivalRate', ascending=False)
sorted_groups
```

C:\Users\jverc\AppData\Local\Temp\ipykernel\_7632\2606926184.py:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future vers ion of pandas. Pass observed=False to retain current behavior or observed=True to ad opt the future default and silence this warning.

grouped = Titanic.groupby(['AgeGroup','TravelersWithKids', 'Gender']).agg(

_		-	_	_	-	
$\cap$	14-			a	- 1	

	AgeGroup	TravelersWithKids	Gender	SurvivalRate	Count
8	Senior 60+	False	female	1.000000	2
4	4 Adult 12-60	False	female	0.802817	142
(	6 Adult 12-60	True	female	0.746269	67
(	Children 0-18	False	female	0.729167	48
2	2 Children 0-18	True	female	0.566038	53
3	Children 0-18	True	male	0.469388	49
į	Adult 12-60	False	male	0.169683	442
7	7 Adult 12-60	True	male	0.146341	41
9	Senior 60+	False	male	0.125000	16
	Children 0-18	False	male	0.115385	26
1	Senior 60+	True	male	0.000000	3

C:\Users\jverc\AppData\Local\Temp\ipykernel\_7632\1257758034.py:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future vers ion of pandas. Pass observed=False to retain current behavior or observed=True to ad opt the future default and silence this warning.

grouped = Titanic.groupby(['AgeGroup','TicketClass', 'Gender']).agg(

	AgeGroup	TicketClass	Gender	SurvivalRate	Count
2	Children 0-18	2	female	1.000000	14
16	Senior 60+	3	female	1.000000	1
12	Senior 60+	1	female	1.000000	1
6	Adult 12-60	1	female	0.975000	80
0	Children 0-18	1	female	0.909091	11
8	Adult 12-60	2	female	0.903226	62
1	Children 0-18	1	male	0.800000	5
3	Children 0-18	2	male	0.600000	15
4	Children 0-18	3	female	0.539474	76
10	Adult 12-60	3	female	0.447761	67
7	Adult 12-60	1	male	0.380952	105
15	Senior 60+	2	male	0.333333	3
5	Children 0-18	3	male	0.236364	55
11	Adult 12-60	3	male	0.118056	288
13	Senior 60+	1	male	0.083333	12
9	Adult 12-60	2	male	0.077778	90
17	Senior 60+	3	male	0.000000	4

In [ ]: