# newbook-fromscratch

February 29, 2024

So, here's the story of the people who are travelling to a destination from various HomePlanets. But sadly they met with a unexpected accident and some people got transported from the ship. So our job is to find if a person with some details can be transported or stayed in ship.

Let's not wait any minute,

We need some packages to be imported and they are imported here, some may be imported later in the notebook.

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Our data is brought into the book by these statements.

[3]:
```
og_train_data = pd.read_csv('train.csv')
og_test_data  = pd.read_csv('test.csv')

data = og_train_data
```

Let's take a peek at the data.

[4]:
```
data.head()
```

[4]:
```
  PassengerId HomePlanet CryoSleep  Cabin  Destination   Age    VIP  \
0     0001_01     Europa     False  B/0/P  TRAPPIST-1e  39.0  False
1     0002_01      Earth     False  F/0/S  TRAPPIST-1e  24.0  False
2     0003_01     Europa     False  A/0/S  TRAPPIST-1e  58.0   True
3     0003_02     Europa     False  A/0/S  TRAPPIST-1e  33.0  False
4     0004_01      Earth     False  F/1/S  TRAPPIST-1e  16.0  False

   RoomService  FoodCourt  ShoppingMall     Spa  VRDeck               Name  \
0          0.0        0.0           0.0     0.0     0.0    Maham Ofracculy
1        109.0        9.0          25.0   549.0    44.0       Juanna Vines
2         43.0     3576.0           0.0  6715.0    49.0      Altark Susent
3          0.0     1283.0         371.0  3329.0   193.0       Solam Susent
4        303.0       70.0         151.0   565.0     2.0  Willy Santantines

   Transported
```

```
0        False
1         True
2        False
3        False
4         True
```

[5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8693 entries, 0 to 8692
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   PassengerId   8693 non-null   object
 1   HomePlanet    8492 non-null   object
 2   CryoSleep     8476 non-null   object
 3   Cabin         8494 non-null   object
 4   Destination   8511 non-null   object
 5   Age           8514 non-null   float64
 6   VIP           8490 non-null   object
 7   RoomService   8512 non-null   float64
 8   FoodCourt     8510 non-null   float64
 9   ShoppingMall  8485 non-null   float64
 10  Spa           8510 non-null   float64
 11  VRDeck        8505 non-null   float64
 12  Name          8493 non-null   object
 13  Transported   8693 non-null   bool
dtypes: bool(1), float64(6), object(7)
memory usage: 891.5+ KB
```

The data types of the attributes are as follows.

[6]:

```
data.dtypes
```

[6]:

```
PassengerId      object
HomePlanet       object
CryoSleep        object
Cabin            object
Destination      object
Age             float64
VIP              object
RoomService     float64
FoodCourt       float64
ShoppingMall    float64
Spa             float64
VRDeck          float64
Name             object
Transported        bool
```

```
dtype: object
```

**Are there any duplicated rows in the data?**

```
[7]: data[data.duplicated()]
```

```
[7]: Empty DataFrame
     Columns: [PassengerId, HomePlanet, CryoSleep, Cabin, Destination, Age, VIP,
     RoomService, FoodCourt, ShoppingMall, Spa, VRDeck, Name, Transported]
     Index: []
```

- There are no duplicated rows in the data

**How does the data can be described?**

```
[8]: data.describe()
```

```
[8]:                Age   RoomService     FoodCourt  ShoppingMall           Spa  \
     count  8514.000000   8512.000000   8510.000000   8485.000000   8510.000000
     mean     28.827930    224.687617    458.077203    173.729169    311.138778
     std      14.489021    666.717663   1611.489240    604.696458   1136.705535
     min       0.000000      0.000000      0.000000      0.000000      0.000000
     25%      19.000000      0.000000      0.000000      0.000000      0.000000
     50%      27.000000      0.000000      0.000000      0.000000      0.000000
     75%      38.000000     47.000000     76.000000     27.000000     59.000000
     max      79.000000  14327.000000  29813.000000  23492.000000  22408.000000

                  VRDeck
     count   8505.000000
     mean     304.854791
     std     1145.717189
     min        0.000000
     25%        0.000000
     50%        0.000000
     75%       46.000000
     max    24133.000000
```

**Are there any missing values in the data? If so, then how many?**

```
[9]: data.isnull().sum()
```

```
[9]: PassengerId       0
     HomePlanet      201
     CryoSleep       217
     Cabin           199
     Destination     182
     Age             179
     VIP             203
     RoomService     181
```

```
FoodCourt       183
ShoppingMall    208
Spa             183
VRDeck          188
Name            200
Transported       0
dtype: int64
```

### What is the shape of the data?

```
[10]: data.shape
```

```
[10]: (8693, 14)
```

### columns are:

```
[11]: data.columns
```

```
[11]: Index(['PassengerId', 'HomePlanet', 'CryoSleep', 'Cabin', 'Destination', 'Age',
              'VIP', 'RoomService', 'FoodCourt', 'ShoppingMall', 'Spa', 'VRDeck',
              'Name', 'Transported'],
             dtype='object')
```

### How many unique values are there for the features?

```
[12]: data.nunique()
```

```
[12]: PassengerId     8693
      HomePlanet         3
      CryoSleep          2
      Cabin           6560
      Destination        3
      Age               80
      VIP                2
      RoomService     1273
      FoodCourt       1507
      ShoppingMall    1115
      Spa             1327
      VRDeck          1306
      Name            8473
      Transported        2
      dtype: int64
```

- I think we can say that the transportation doesn't depend on the 'PassengerId' and 'Name' of the people.
- So, I am going to remove them from the data and store it in a new DataFrame.

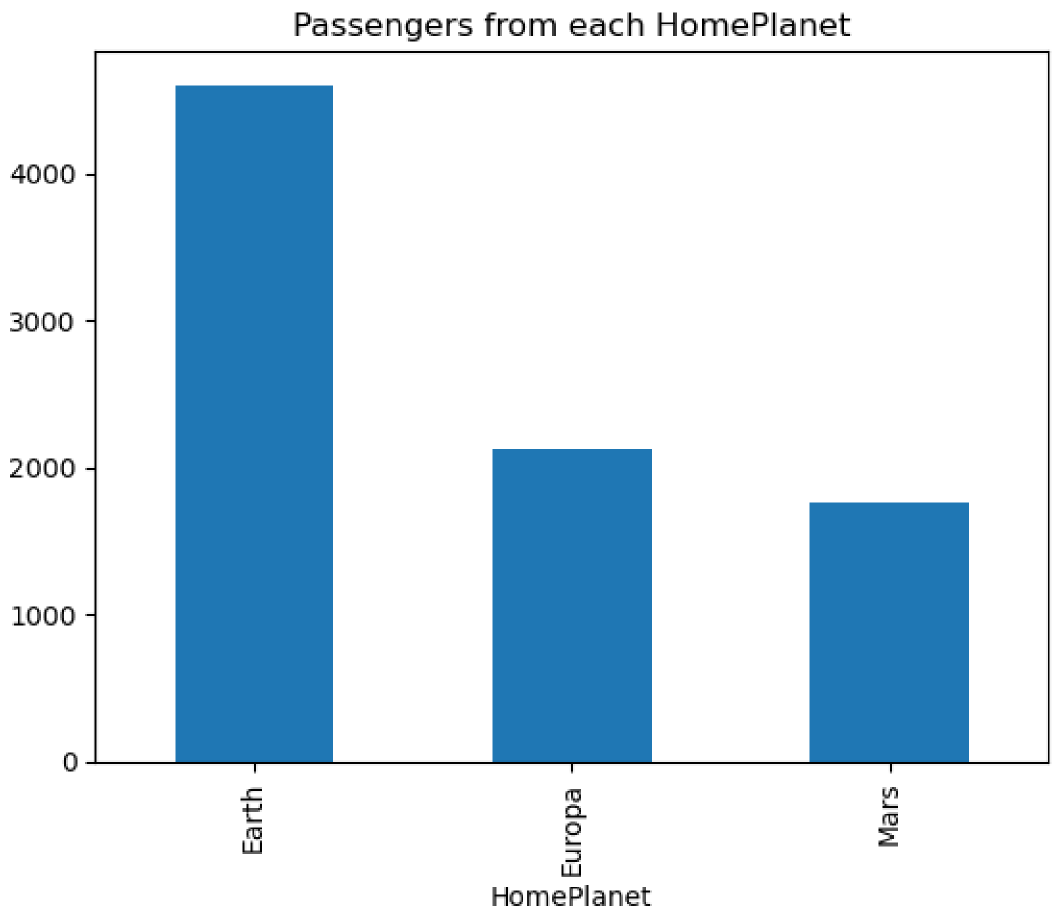
```
[13]: lowDim_data = data.drop(columns = ['PassengerId', 'Name'])
```

```
[14]: lowDim_data.head()
```

```
[14]:   HomePlanet CryoSleep  Cabin  Destination   Age    VIP  RoomService  \
     0      Europa     False  B/0/P  TRAPPIST-1e  39.0  False          0.0
     1       Earth     False  F/0/S  TRAPPIST-1e  24.0  False        109.0
     2      Europa     False  A/0/S  TRAPPIST-1e  58.0   True         43.0
     3      Europa     False  A/0/S  TRAPPIST-1e  33.0  False          0.0
     4       Earth     False  F/1/S  TRAPPIST-1e  16.0  False        303.0

        FoodCourt  ShoppingMall     Spa  VRDeck  Transported
     0        0.0           0.0     0.0     0.0        False
     1        9.0          25.0   549.0    44.0         True
     2     3576.0           0.0  6715.0    49.0        False
     3     1283.0         371.0  3329.0   193.0        False
     4       70.0         151.0   565.0     2.0         True
```

Let’s see that how many are from each HomePlanet

```
[15]: # def addlabels(x,y):
      #     for i in range(len(x)):
      #         plt.text(i, y[i], y[i], ha = 'center')
      ax = data['HomePlanet'].value_counts() \
                        .plot(kind = 'bar', title = 'Passengers from each HomePlanet')
      # ax.addlabels()
      plt.show()
```



[16]:
```
data['HomePlanet'].value_counts()
```

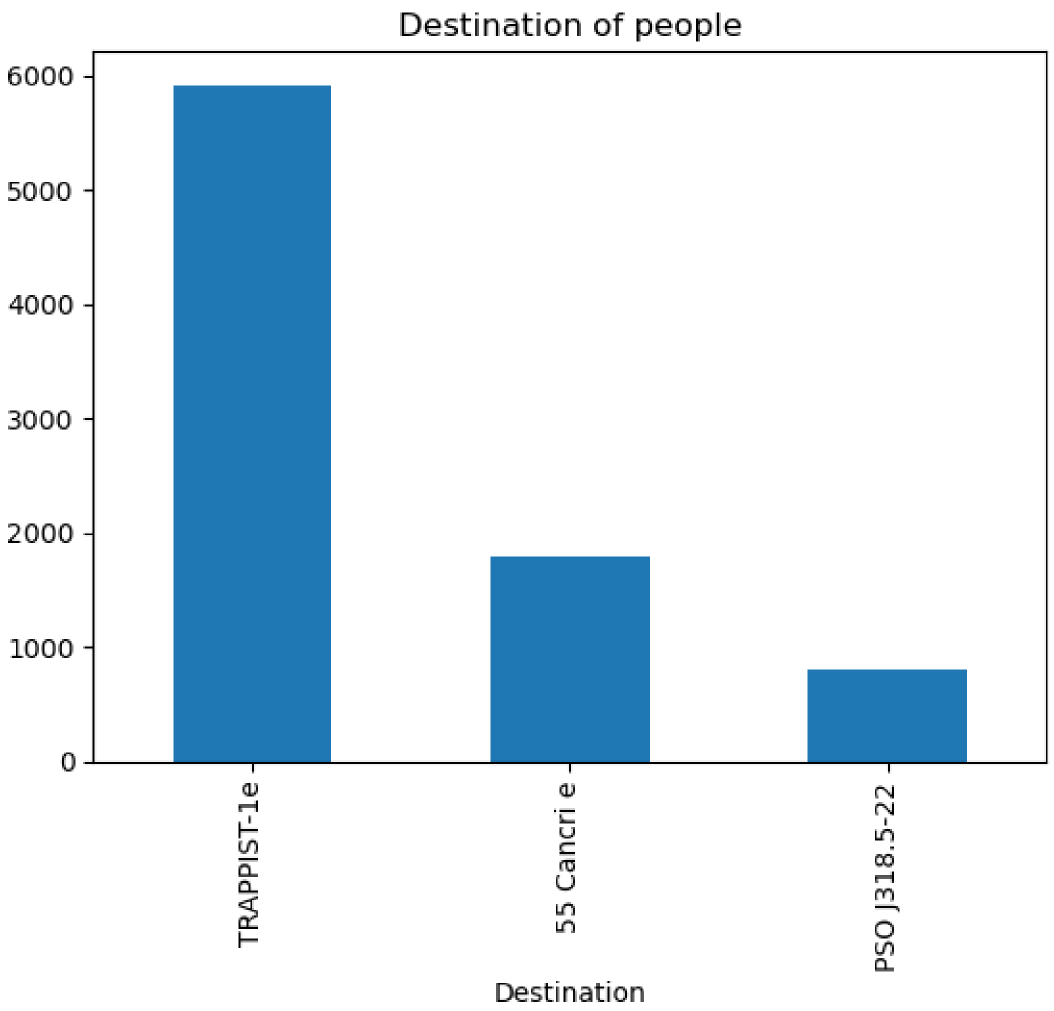
[16]:
```
HomePlanet
Earth     4602
Europa    2131
Mars      1759
Name: count, dtype: int64
```

**Maximum people are from Earth. Europa and Mars passengers are close in numbers but far less than the number from earth.**

**Where do the passengers want to go?**

[17]:
```
data['Destination'].value_counts().plot(kind = 'bar', title = 'Destination of␣
 ↪people')
```

[17]:
```
<Axes: title={'center': 'Destination of people'}, xlabel='Destination'>
```



I'm going to fill the Null values of HomePlanet and Destination with Mode of the Cols

```
[18]: data['Destination'].value_counts()
```

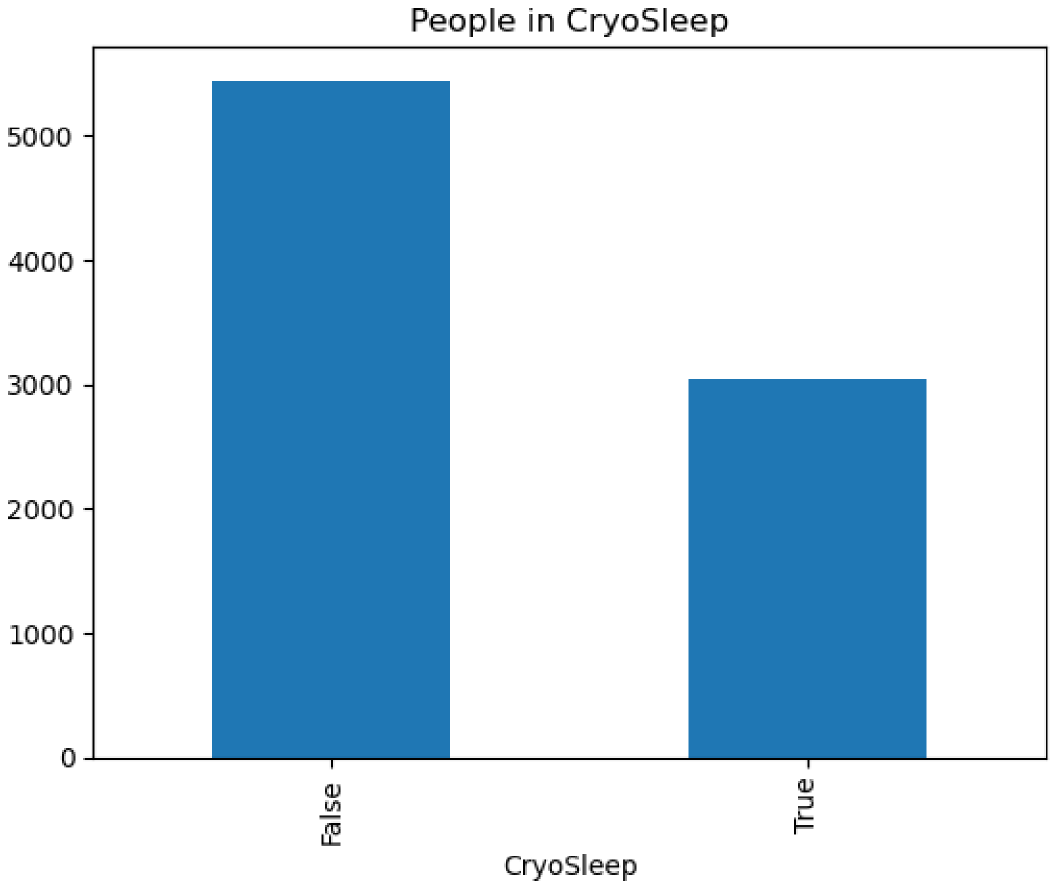
```
[18]: Destination
      TRAPPIST-1e      5915
      55 Cancri e      1800
      PSO J318.5-22     796
      Name: count, dtype: int64
```

- Maximum people are going to the `TRAPPIST-1e`

```
[19]: lowDim_data['HomePlanet'].fillna('Earth', inplace=True)
      lowDim_data['Destination'].fillna('TRAPPIST-1e', inplace=True)
```

**So, how many people are in CryoSleep?**

[20]:
```
data['CryoSleep'].value_counts().plot(kind = 'bar', title = 'People in CryoSleep')
plt.figure(figsize = (10, 10))
plt.show()
```



```
<Figure size 1000x1000 with 0 Axes>
```

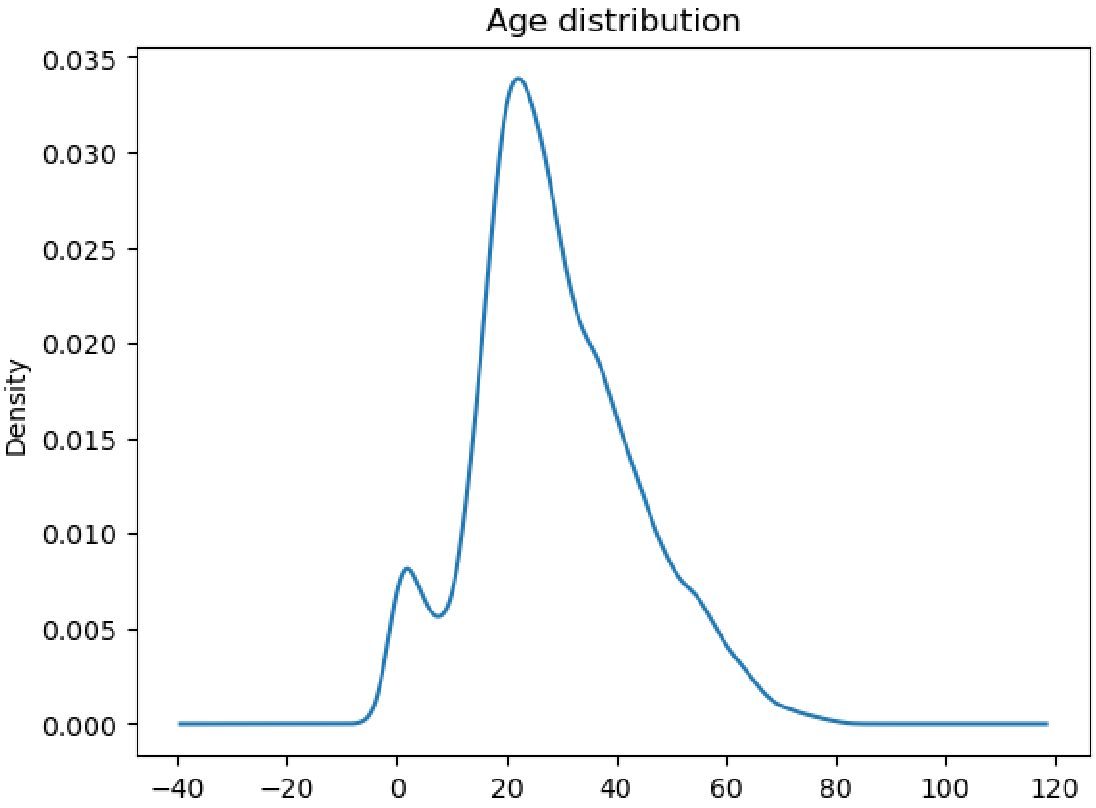
[21]:
```
data['CryoSleep'].value_counts()
```

[21]:
```
CryoSleep
False    5439
True     3037
Name: count, dtype: int64
```

More people are `not` in CryoSleep

**What is the age distribution in passengers?**

[22]:
```
data['Age'].plot(kind = 'kde', title = 'Age distribution', x = 'Age')
plt.show()
```



```
[23]: data['Age'].value_counts().head(20)
```

```
[23]: Age
      24.0    324
      18.0    320
      21.0    311
      19.0    293
      23.0    292
      22.0    291
      20.0    277
      26.0    268
      28.0    267
      27.0    259
      25.0    243
      29.0    230
      31.0    202
      32.0    199
      30.0    183
      33.0    178
      36.0    178
      0.0     178
```

```
37.0    177
35.0    171
Name: count, dtype: int64
```

We can observe that most people are of from range (15 - 40) approximately.

**How many got transported?**

```
[24]: data['Transported'].value_counts()
```

```
[24]: Transported
      True     4378
      False    4315
      Name: count, dtype: int64
```

- Nearly `Half` of the people got transported.

I'm converting some columns data types to the appropriate types. Because `CryoSleep` and `VIP` are actually boolean but in the dataset they are observed as object datatype.

```
[25]: lowDim_data['CryoSleep'] = lowDim_data['CryoSleep'].astype('bool')
      lowDim_data['VIP'] = lowDim_data['VIP'].astype('bool')
```

And also converting `HomePlane, Cabin, Destination` to string datatype which are in object datatype.

```
[26]: for i in ['HomePlanet', 'Cabin', 'Destination']:
              lowDim_data[i] = lowDim_data[i].astype('str')
```

- Checking that how many `null` values are there

```
[27]: lowDim_data.isna().sum()
```

```
[27]: HomePlanet        0
      CryoSleep         0
      Cabin             0
      Destination       0
      Age             179
      VIP               0
      RoomService     181
      FoodCourt       183
      ShoppingMall    208
      Spa             183
      VRDeck          188
      Transported       0
      dtype: int64
```

Now i'm going to fill these null values with their median, cause median gives us the middle value of data which is not effected by the outliers.

Note that i didn't removed the outliers.

[28]:

```
for i in ['Age','RoomService', 'FoodCourt', 'ShoppingMall', 'Spa', 'VRDeck']:
    lowDim_data[i] = lowDim_data[i].fillna(float(lowDim_data[i].median()))
```

Again checking the data for the Null values.

[29]:

```
lowDim_data.isnull().sum()
```

[29]:

```
HomePlanet      0
CryoSleep       0
Cabin           0
Destination     0
Age             0
VIP             0
RoomService     0
FoodCourt       0
ShoppingMall    0
Spa             0
VRDeck          0
Transported     0
dtype: int64
```

Now there are no Null values in the data.

**Encoding the columns of the dataframe** That is i'm converting the string type values to numerical values for the implementation of the model.

[30]:

```
from sklearn import preprocessing
# label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

# df['species'].unique()
for i in ['HomePlanet', 'CryoSleep', 'Cabin', 'Destination',␣
 ↪'VIP','Transported']:
    lowDim_data[i] = label_encoder.fit_transform(lowDim_data[i])
```

checking the datatypes of the data before model fitting.

[31]:

```
lowDim_data.dtypes
```

[31]:

```
HomePlanet        int32
CryoSleep         int64
Cabin             int32
Destination       int32
Age             float64
VIP               int64
RoomService     float64
```

```
FoodCourt       float64
ShoppingMall    float64
Spa             float64
VRDeck          float64
Transported       int64
dtype: object
```

### This is how our data looks after the encoding

```
[32]: lowDim_data.head()
```

```
[32]:    HomePlanet  CryoSleep  Cabin  Destination   Age  VIP  RoomService  \
      0           1          0    149            2  39.0    0          0.0
      1           0          0   2184            2  24.0    0        109.0
      2           1          0      1            2  58.0    1         43.0
      3           1          0      1            2  33.0    0          0.0
      4           0          0   2186            2  16.0    0        303.0

         FoodCourt  ShoppingMall     Spa  VRDeck  Transported
      0        0.0           0.0     0.0     0.0            0
      1        9.0          25.0   549.0    44.0            1
      2     3576.0           0.0  6715.0    49.0            0
      3     1283.0         371.0  3329.0   193.0            0
      4       70.0         151.0   565.0     2.0            1
```

### How the variables are correlated?

```
[33]: lowDim_data.corr()
```

```
[33]:               HomePlanet  CryoSleep     Cabin  Destination       Age  \
      HomePlanet      1.000000   0.083239 -0.470328     0.034737  0.133577
      CryoSleep       0.083239   1.000000  0.112433    -0.094061 -0.073406
      Cabin          -0.470328   0.112433  1.000000     0.117281 -0.236994
      Destination     0.034737  -0.094061  0.117281     1.000000 -0.006771
      Age             0.133577  -0.073406 -0.236994    -0.006771  1.000000
      VIP             0.085260  -0.050342 -0.094719    -0.035430  0.058490
      RoomService     0.211751  -0.240750 -0.073802     0.045733  0.068629
      FoodCourt       0.071454  -0.202675 -0.260056    -0.111057  0.127390
      ShoppingMall    0.101383  -0.207213 -0.067709     0.024721  0.033148
      Spa             0.055047  -0.196893 -0.180768    -0.055815  0.120946
      VRDeck          0.039824  -0.190437 -0.210865    -0.073293  0.099590
      Transported     0.115461   0.451744 -0.052604    -0.108152 -0.074233

                         VIP  RoomService  FoodCourt  ShoppingMall       Spa  \
      HomePlanet    0.085260     0.211751   0.071454      0.101383  0.055047
      CryoSleep    -0.050342    -0.240750  -0.202675     -0.207213 -0.196893
      Cabin        -0.094719    -0.073802  -0.260056     -0.067709 -0.180768
      Destination  -0.035430     0.045733  -0.111057      0.024721 -0.055815
```

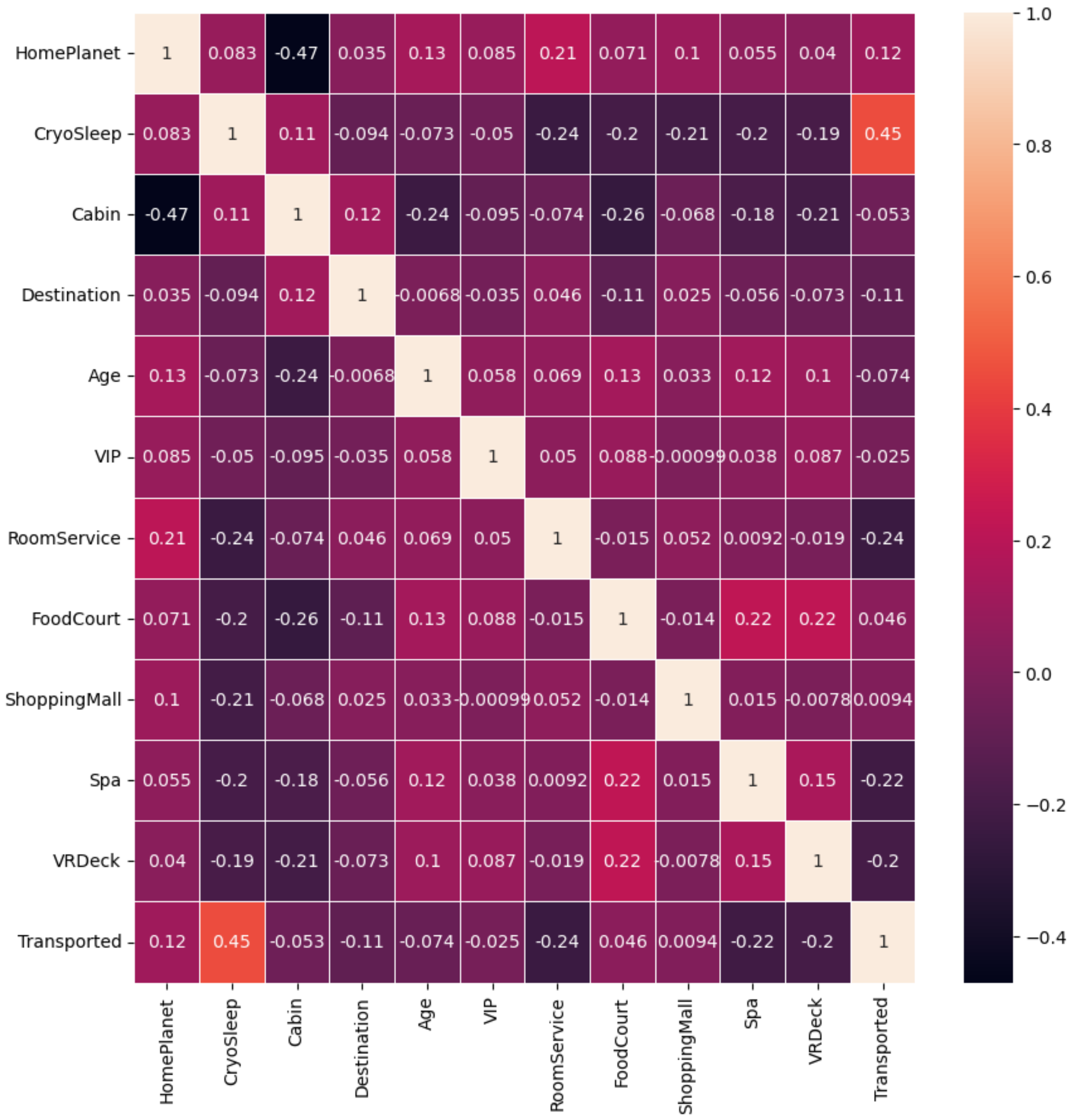
```
Age           0.058490     0.068629    0.127390       0.033148  0.120946
VIP           1.000000     0.050354    0.088208      -0.000992  0.037896
RoomService   0.050354     1.000000   -0.015126       0.052337  0.009244
FoodCourt     0.088208    -0.015126    1.000000      -0.013717  0.221468
ShoppingMall -0.000992     0.052337   -0.013717       1.000000  0.014542
Spa           0.037896     0.009244    0.221468       0.014542  1.000000
VRDeck        0.087235    -0.018624    0.224572      -0.007849  0.147658
Transported  -0.024602    -0.241124    0.045583       0.009391 -0.218545

                VRDeck  Transported
HomePlanet    0.039824     0.115461
CryoSleep    -0.190437     0.451744
Cabin        -0.210865    -0.052604
Destination  -0.073293    -0.108152
Age           0.099590    -0.074233
VIP           0.087235    -0.024602
RoomService  -0.018624    -0.241124
FoodCourt     0.224572     0.045583
ShoppingMall -0.007849     0.009391
Spa           0.147658    -0.218545
VRDeck        1.000000    -0.204874
Transported  -0.204874     1.000000
```

[34]:

```
fig, ax = plt.subplots(figsize = (10, 10))
sns.heatmap(lowDim_data.corr(), annot = True, linewidths=.5, ax=ax)
```

[34]:

```
<Axes: >
```



From the correlation plot we can see that there are no seriously correlated variables in the data. The highest value is between `Cryosleep` and `Transported` with `0.45`

Splitting training data into train and validate datasets

[35]:
```
x = lowDim_data.iloc[:, :-1]
y = lowDim_data.iloc[:, -1]
```

[36]:
```
from sklearn.model_selection import train_test_split
x_train, x_validate, y_train, y_validate = train_test_split(x, y, test_size=0.2)
```

[37]:
```
y_validate.head()
```

[37]:

```
6885    1
925     1
3861    0
4631    1
1558    0
Name: Transported, dtype: int64
```

We are using KNN classifier for our data, ofcourse there are other models but KNN is also a powerful model.

[38]:

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(x_train, y_train)
```

[38]:

```
KNeighborsClassifier(n_neighbors=3)
```

Importing the test data

[39]:

```
test_data = pd.read_csv('test.csv')
```

[40]:

```
test_data.head()
```

[40]:

```
  PassengerId HomePlanet CryoSleep  Cabin  Destination   Age    VIP  \
0     0013_01      Earth      True  G/3/S  TRAPPIST-1e  27.0  False
1     0018_01      Earth     False  F/4/S  TRAPPIST-1e  19.0  False
2     0019_01     Europa      True  C/0/S  55 Cancri e  31.0  False
3     0021_01     Europa     False  C/1/S  TRAPPIST-1e  38.0  False
4     0023_01      Earth     False  F/5/S  TRAPPIST-1e  20.0  False

   RoomService  FoodCourt  ShoppingMall     Spa  VRDeck              Name
0          0.0        0.0           0.0     0.0     0.0   Nelly Carsoning
1          0.0        9.0           0.0  2823.0     0.0    Lerome Peckers
2          0.0        0.0           0.0     0.0     0.0   Sabih Unhearfus
3          0.0     6652.0           0.0   181.0   585.0  Meratz Caltilter
4         10.0        0.0         635.0     0.0     0.0   Brence Harperez
```

Now we'll do all the steps that are done on the train data for the test data to get the test data to the same state as the train data before fitting the model.

[41]:

```
test_data.drop(columns=['PassengerId', 'Name'], inplace = True)
```

[42]:

```
test_data.isnull().sum()
```

[42]:

```
HomePlanet       87
CryoSleep        93
Cabin           100
Destination      92
Age              91
```

```
VIP              93
RoomService      82
FoodCourt       106
ShoppingMall     98
Spa             101
VRDeck           80
dtype: int64
```

[43]:

```
test_data.dtypes
```

[43]:

```
HomePlanet       object
CryoSleep        object
Cabin            object
Destination      object
Age             float64
VIP              object
RoomService     float64
FoodCourt       float64
ShoppingMall    float64
Spa             float64
VRDeck          float64
dtype: object
```

[44]:

```
test_data['CryoSleep'] = test_data['CryoSleep'].astype('bool')
test_data['VIP'] = test_data['VIP'].astype('bool')
```

[45]:

```
for i in ['HomePlanet', 'Cabin', 'Destination']:
        test_data[i] = test_data[i].astype('str')
```

[46]:

```
test_data.isnull().sum()
```

[46]:

```
HomePlanet        0
CryoSleep         0
Cabin             0
Destination       0
Age              91
VIP               0
RoomService      82
FoodCourt       106
ShoppingMall     98
Spa             101
VRDeck           80
dtype: int64
```

[47]:

```
for i in ['Age','RoomService', 'FoodCourt', 'ShoppingMall', 'Spa', 'VRDeck']:
    test_data[i] = test_data[i].fillna(float(test_data[i].mode()))
```

```
C:\Users\91970\AppData\Local\Temp\ipykernel_27200\3196287623.py:2:
FutureWarning: Calling float on a single element Series is deprecated and will
raise a TypeError in the future. Use float(ser.iloc[0]) instead
  test_data[i] = test_data[i].fillna(float(test_data[i].mode()))
```

[48]:

```
test_data.isnull().sum()
```

[48]:

```
HomePlanet      0
CryoSleep       0
Cabin           0
Destination     0
Age             0
VIP             0
RoomService     0
FoodCourt       0
ShoppingMall    0
Spa             0
VRDeck          0
dtype: int64
```

[49]:

```
# from sklearn import preprocessing
# # label_encoder object knows how to understand word labels.
# label_encoder = preprocessing.LabelEncoder()


for i in ['HomePlanet', 'CryoSleep', 'Cabin', 'Destination', 'VIP']:
    test_data[i] = label_encoder.fit_transform(test_data[i])
```

[50]:

```
test_data.dtypes
```

[50]:

```
HomePlanet        int32
CryoSleep         int64
Cabin             int32
Destination       int32
Age             float64
VIP               int64
RoomService     float64
FoodCourt       float64
ShoppingMall    float64
Spa             float64
VRDeck          float64
dtype: object
```

[51]:

```
test_data.head()
```

[51]:

```
   HomePlanet  CryoSleep  Cabin  Destination   Age  VIP  RoomService  \
0           0          1   2784            2  27.0    0          0.0
```

```
1           0          0   1867            2  19.0     0          0.0
2           1          1    257            0  31.0     0          0.0
3           1          0    259            2  38.0     0          0.0
4           0          0   1940            2  20.0     0         10.0

   FoodCourt  ShoppingMall     Spa  VRDeck
0        0.0           0.0     0.0     0.0
1        9.0           0.0  2823.0     0.0
2        0.0           0.0     0.0     0.0
3     6652.0           0.0   181.0   585.0
4        0.0         635.0     0.0     0.0
```

This is how our test data looks after the process

### Predicting the `Transported` values for the test data

```
[52]: knn.predict(test_data)
```

```
[52]: array([1, 0, 1, …, 1, 1, 1], dtype=int64)
```

Since i dont have the transported values for the test data(actual) i'm taking the validation data from the above splitting and calculate the acuracy score from it.

```
[53]: validate_y = knn.predict(x_validate)
```

This is how the values are predicted by our model

```
[54]: validate_y
```

```
[54]: array([1, 1, 0, …, 1, 1, 1], dtype=int64)
```

Total how many are Transported and not

```
[55]: validate_y = pd.DataFrame(validate_y) #converting the numpy array structure to␣
       ↪pandas dataframe
```

```
[56]: validate_y.value_counts() # 1 means transported, 0 means not transported
```

```
[56]: 1    872
      0    867
      Name: count, dtype: int64
```

This is how the actual validation data `Transported` values are:

```
[57]: y_validate.value_counts()  # 1 means transported, 0 means not transported
```

```
[57]: Transported
      0    882
      1    857
```

```
Name: count, dtype: int64
```

Formula for accuracy `accuracy = (number of correct predictions) / (total number of predictions)`

[58]:

```
y_validate = np.array(y_validate)
validate_y = np.array(validate_y)
```

[59]:

```
from sklearn.metrics import accuracy_score
```

[60]:

```
print(f"Our model Accuracy is : {accuracy_score(y_validate, validate_y)} which␣
 ↪is not so bad, because we didn't removed the outliers and didn't tuned our  ␣
 ↪ hyperparameters")
```

```
Our model Accuracy is : 0.7429557216791259 which is not so bad, because we
didn't removed the outliers and didn't tuned our    hyperparameters
```