space-titanic-12.10.23

October 12, 2023

[1]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

```
/kaggle/input/spaceship-titanic/sample_submission.csv
/kaggle/input/spaceship-titanic/train.csv
/kaggle/input/spaceship-titanic/test.csv
```

[2]:
```
train_data = pd.read_csv("/kaggle/input/spaceship-titanic/train.csv")
test_data = pd.read_csv("/kaggle/input/spaceship-titanic/test.csv")

train_data
```

[2]:
```
     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
```

```
...          ...       ...      ...       ...          ...    ...    ...
8688     9276_01    Europa    False     A/98/P     55 Cancri e  41.0   True
8689     9278_01     Earth     True  G/1499/S  PSO J318.5-22  18.0  False
8690     9279_01     Earth    False  G/1500/S    TRAPPIST-1e  26.0  False
8691     9280_01    Europa    False    E/608/S   55 Cancri e  32.0  False
8692     9280_02    Europa    False    E/608/S    TRAPPIST-1e  44.0  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
...           ...        ...           ...     ...     ...                ...
8688          0.0     6819.0           0.0  1643.0    74.0  Gravior Noxnuther
8689          0.0        0.0           0.0     0.0     0.0    Kurta Mondalley
8690          0.0        0.0        1872.0     1.0     0.0       Fayey Connon
8691          0.0     1049.0           0.0   353.0  3235.0  Celeon Hontichre
8692        126.0     4688.0           0.0     0.0    12.0  Propsh Hontichre

      Transported
0           False
1            True
2           False
3           False
4            True
...           ...
8688        False
8689        False
8690         True
8691        False
8692         True

[8693 rows x 14 columns]
```

[3]:

```
train_data.nunique()
```

[3]:

```
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
```

0.0.1 Breaking down the Cabin feature

Cabin - The cabin number where the passenger is staying. Takes the form deck/num/side, where side can be either P for Port or S for Starboard.

[4]:
```
cabin_train_data = train_data["Cabin"].str.split(pat = "/", expand=True)
split_cabin_train = cabin_train_data.rename(columns={0: "deck", 1: "num", 2:␣
↪"side"})

split_cabin_train.head(6)
```

[4]:
```
  deck num side
0    B   0    P
1    F   0    S
2    A   0    S
3    A   0    S
4    F   1    S
5    F   0    P
```

[5]:
```
split_cabin_train.nunique()
```

[5]:
```
deck        8
num      1817
side        2
dtype: int64
```

We can see “num” has too many values while “deck” and “size” don’t. We’ll ignore it as it is probably not important. We can also see the 2 sides can have decks named the same, so we cant use just the deck feature.

[6]:
```
cabin_test_data = test_data["Cabin"].str.split(pat = "/", expand=True)
split_cabin_test = cabin_test_data.rename(columns={0: "deck", 1: "num", 2:␣
↪"side"})
```

[7]:
```
train_data = train_data.drop("Cabin", axis = 1).join(split_cabin_train[["deck",␣
↪"side"]])
test_data = test_data.drop("Cabin", axis = 1).join(split_cabin_test[["deck",␣
↪"side"]])

train_data
```

[7]:
```
     PassengerId HomePlanet CryoSleep    Destination   Age    VIP  \
0        0001_01     Europa     False    TRAPPIST-1e  39.0  False
1        0002_01      Earth     False    TRAPPIST-1e  24.0  False
2        0003_01     Europa     False    TRAPPIST-1e  58.0   True
3        0003_02     Europa     False    TRAPPIST-1e  33.0  False
4        0004_01      Earth     False    TRAPPIST-1e  16.0  False
…            …        …      …             …     …     …
8688     9276_01     Europa     False    55 Cancri e  41.0   True
8689     9278_01      Earth      True  PSO J318.5-22  18.0  False
8690     9279_01      Earth     False    TRAPPIST-1e  26.0  False
8691     9280_01     Europa     False    55 Cancri e  32.0  False
8692     9280_02     Europa     False    TRAPPIST-1e  44.0  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
…             …          …            …       …       …                 …
8688          0.0     6819.0           0.0  1643.0    74.0   Gravior Noxnuther
8689          0.0        0.0           0.0     0.0     0.0     Kurta Mondalley
8690          0.0        0.0        1872.0     1.0     0.0        Fayey Connon
8691          0.0     1049.0           0.0   353.0  3235.0    Celeon Hontichre
8692        126.0     4688.0           0.0     0.0    12.0    Propsh Hontichre

      Transported deck side
0           False    B    P
1            True    F    S
2           False    A    S
3           False    A    S
4            True    F    S
…             …   …   …
8688        False    A    P
8689        False    G    S
8690         True    G    S
8691        False    E    S
8692         True    E    S

[8693 rows x 15 columns]
```

1 Encoding the categorical data

Note that in the precess we drop the columns: “PassengerId” ans “Name”, as they are not needed.

1.0.1 It was wrong to Encode the HomePlanet, Destination, deck and side features with Ordinal Encoding as there is no meaningful order between them

Is planer Earth better then Europa? Is deck G higher than C and F? We don't know and can't tell.

This will be fixed on the next version annd it's interesting to see how much of a difference it will make.

[8]:
```
from sklearn.preprocessing import OrdinalEncoder

categorical_data = ["HomePlanet", "CryoSleep", "Destination", "VIP", "deck",␣
 ↪"side"]
other_data = ["Age", "RoomService", "FoodCourt", "ShoppingMall", "Spa",␣
 ↪"VRDeck"]

encoder = OrdinalEncoder()

temp_np_array = encoder.fit_transform(train_data[categorical_data])
encoded_train_df = pd.DataFrame(data = temp_np_array, columns =␣
 ↪categorical_data)
train_data = encoded_train_df.join(train_data[other_data]).
 ↪join(train_data["Transported"])

temp_np_array = encoder.transform(test_data[categorical_data])
encoded_test_df = pd.DataFrame(data = temp_np_array, columns = categorical_data)
test_data = encoded_test_df.join(test_data[other_data])

test_data.head()
```

[8]:
```
   HomePlanet  CryoSleep  Destination  VIP  deck  side   Age  RoomService  \
0         0.0        1.0          2.0  0.0   6.0   1.0  27.0          0.0
1         0.0        0.0          2.0  0.0   5.0   1.0  19.0          0.0
2         1.0        1.0          0.0  0.0   2.0   1.0  31.0          0.0
3         1.0        0.0          2.0  0.0   2.0   1.0  38.0          0.0
4         0.0        0.0          2.0  0.0   5.0   1.0  20.0         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
```

2 Encoding the label

[9]:
```
train_data["Transported"] = train_data["Transported"].transform(lambda x: 1.0␣
↪if x == True else 0.0)

train_data.head(15)
```

[9]:

	HomePlanet	CryoSleep	Destination	VIP	deck	side	Age	RoomService
0	1.0	0.0	2.0	0.0	1.0	0.0	39.0	0.0
1	0.0	0.0	2.0	0.0	5.0	1.0	24.0	109.0
2	1.0	0.0	2.0	1.0	0.0	1.0	58.0	43.0
3	1.0	0.0	2.0	0.0	0.0	1.0	33.0	0.0
4	0.0	0.0	2.0	0.0	5.0	1.0	16.0	303.0
5	0.0	0.0	1.0	0.0	5.0	0.0	44.0	0.0
6	0.0	0.0	2.0	0.0	5.0	1.0	26.0	42.0
7	0.0	1.0	2.0	0.0	6.0	1.0	28.0	0.0
8	0.0	0.0	2.0	0.0	5.0	1.0	35.0	0.0
9	1.0	1.0	0.0	0.0	1.0	0.0	14.0	0.0
10	1.0	1.0	2.0	0.0	1.0	0.0	34.0	0.0
11	1.0	0.0	0.0	0.0	1.0	0.0	45.0	39.0
12	2.0	0.0	2.0	0.0	5.0	0.0	32.0	73.0
13	0.0	0.0	2.0	0.0	6.0	1.0	48.0	719.0
14	0.0	0.0	2.0	0.0	5.0	0.0	28.0	8.0

\

	FoodCourt	ShoppingMall	Spa	VRDeck	Transported
0	0.0	0.0	0.0	0.0	0.0
1	9.0	25.0	549.0	44.0	1.0
2	3576.0	0.0	6715.0	49.0	0.0
3	1283.0	371.0	3329.0	193.0	0.0
4	70.0	151.0	565.0	2.0	1.0
5	483.0	0.0	291.0	0.0	1.0
6	1539.0	3.0	0.0	0.0	1.0
7	0.0	0.0	0.0	NaN	1.0
8	785.0	17.0	216.0	0.0	1.0
9	0.0	0.0	0.0	0.0	1.0
10	0.0	NaN	0.0	0.0	1.0
11	7295.0	589.0	110.0	124.0	1.0
12	0.0	1123.0	0.0	113.0	1.0
13	1.0	65.0	0.0	24.0	0.0
14	974.0	12.0	2.0	7.0	1.0

3 Checking for NaN values

[10]:
```
train_data.isna().sum()
```

[10]:
```
HomePlanet      201
CryoSleep       217
Destination     182
VIP             203
deck            199
side            199
Age             179
RoomService     181
FoodCourt       183
ShoppingMall    208
Spa             183
VRDeck          188
Transported       0
dtype: int64
```

[11]:
```python
201 + 217 + 182 + 203 + 199 + 199 + 179 + 181 + 183 + 208 + 183 + 188
#number of missing values
```

[11]:
```
2323
```

[12]:
```python
train_data[train_data.isnull().any(axis=1)].shape[0]
#rows which have at least one missing value
```

[12]:
```
1929
```

[13]:
```python
2323 - 1929
```

[13]:
```
394
```

We can see that there are only 2323 - 1929 = 394 rows which have more than one missing values.

If this numer were larger, it would have meant most of the missing data appeared on those rows - and we'd remove them since they were useless (filled with mostly missng data).

Since this is not the case, and each feature has a relatively small number of missing data, we'll impute them instead.

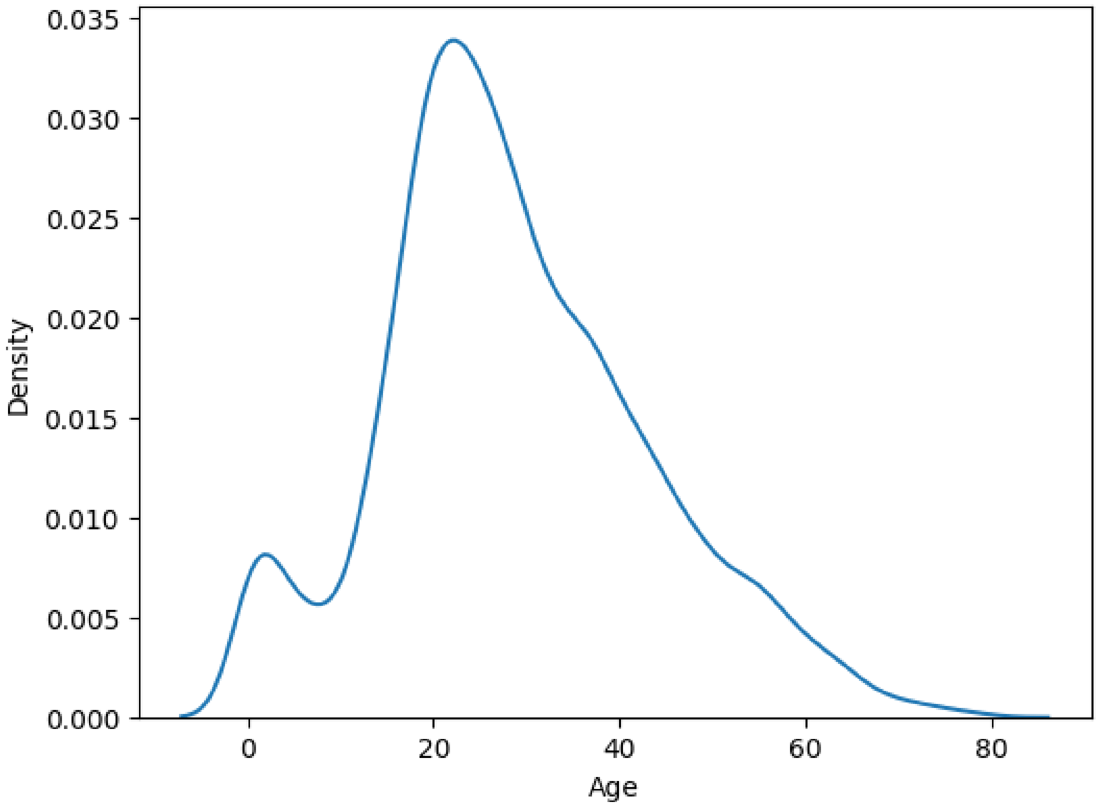
3.1 Imputing the continous features first

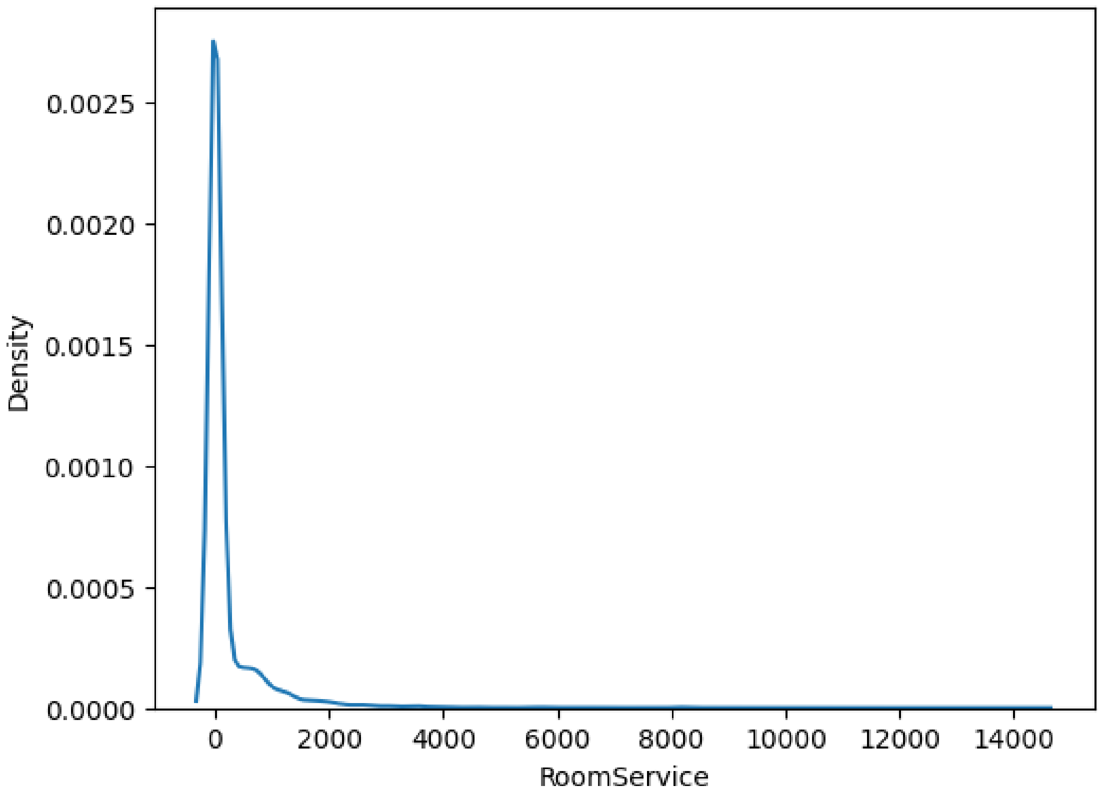
Which are Age, RoomService, FoodCourt, ShoppingMall, Spa, VRDeck

we'll check first if they need to be normalized

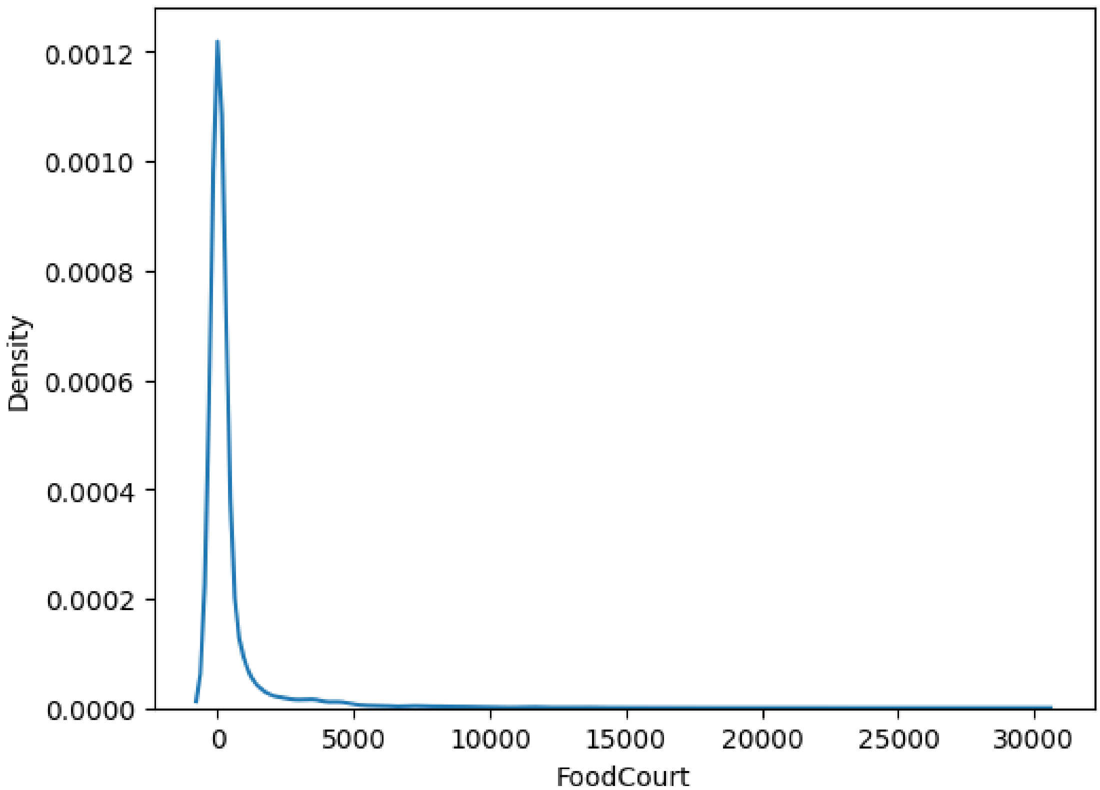
[14]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

continous = ["Age", "RoomService", "FoodCourt", "ShoppingMall", "Spa", "VRDeck"]

for feature in continous:
    plt.figure() #this creates a new figure on which each plot will appear
```

```
sns.kdeplot (train_data[feature])
#sns.boxplot (train_data[feature])
```

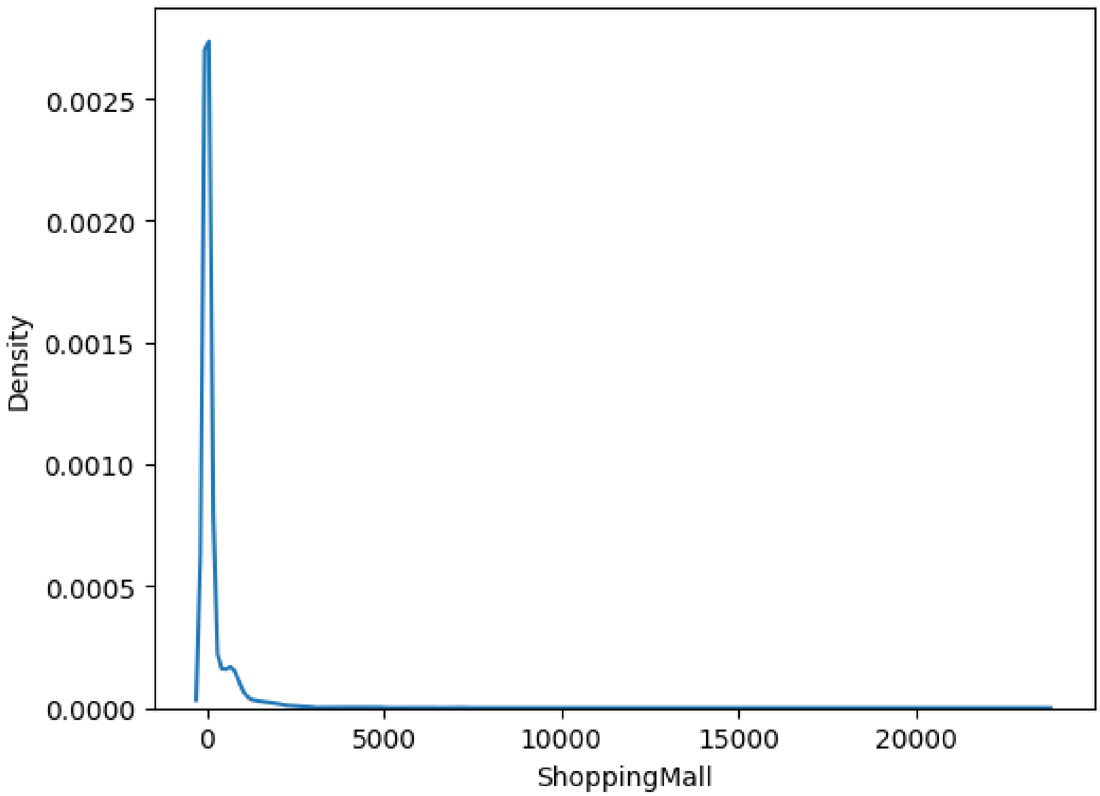




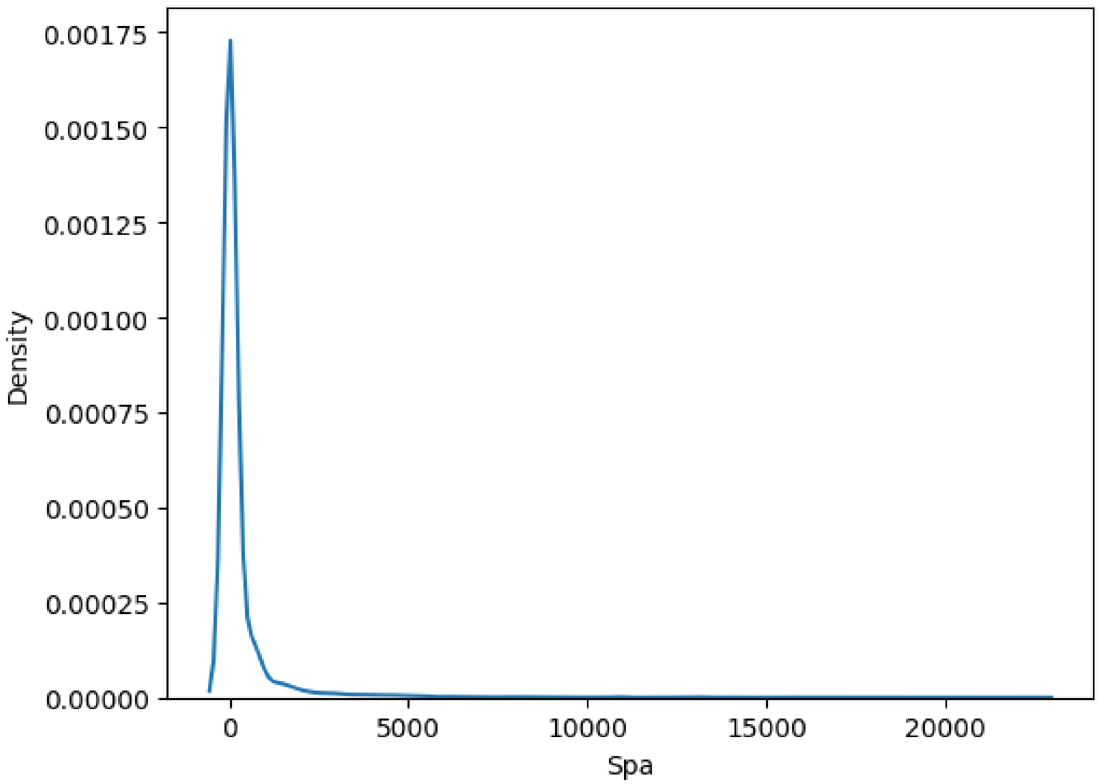
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
Density
0
2000
4000
6000
8000
10000
12000
14000
RoomService

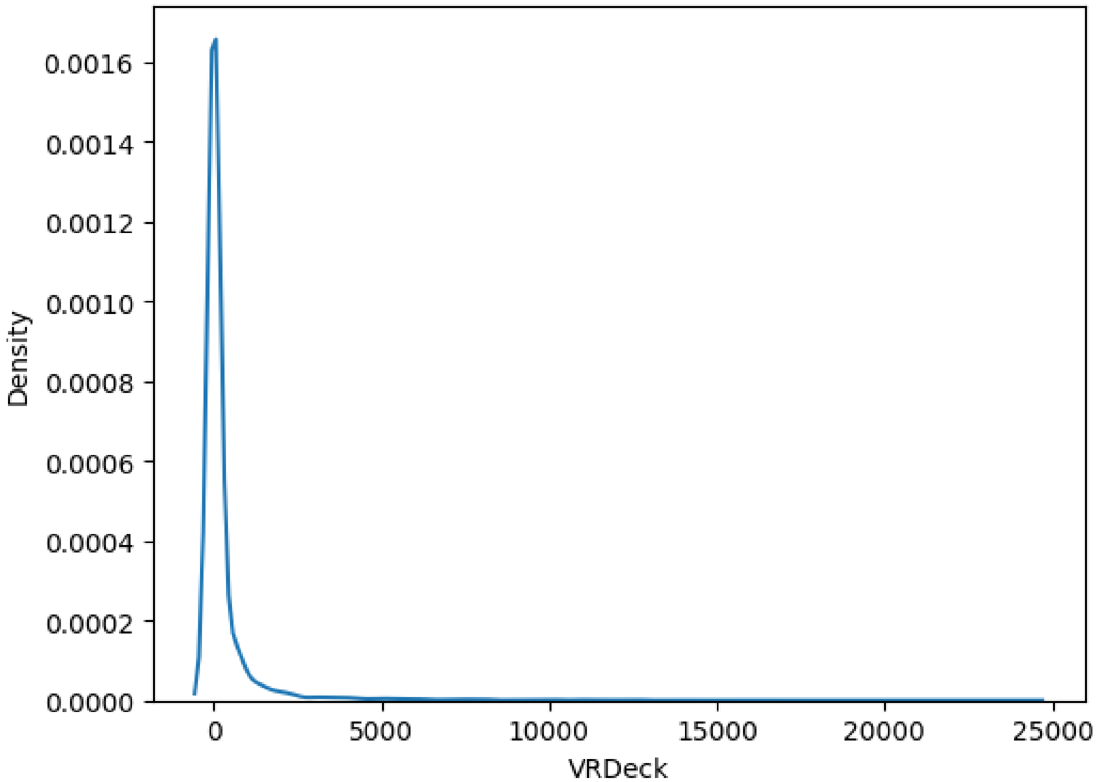


0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
Density
0
5000
10000
15000
20000
25000
30000
FoodCourt



0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
Density
0
5000
10000
15000
20000
ShoppingMall


0.00175
0.00150
0.00125
0.00100
0.00075
0.00050
0.00025
0.00000
Density
0
5000
10000
15000
20000
Spa



3.1.1 We can see the each feature is distributed fairly normally (with positive values), but Age and the other featrues are on completely different scale,

3.1.2 and that might not sit well with some models. So we'll scale the continous data.

As for outliers we can see a single anomily only in "ShoppingMall",

but it does make sense that it could be a real observation of someone who spent a lot more than the rest.

4 Scaling

[15]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

train_data[continous] = scaler.fit_transform(train_data[continous])
test_data[continous] = scaler.transform(test_data[continous])

train_data.describe()
```

[15]:

```
         HomePlanet     CryoSleep  Destination          VIP         deck  \
count  8492.000000  8476.000000  8511.000000  8490.000000  8494.000000
mean      0.665214     0.358306     1.483492     0.023439     4.305392
std       0.798155     0.479531     0.820237     0.151303     1.778233
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     1.000000     0.000000     3.000000
50%       0.000000     0.000000     2.000000     0.000000     5.000000
75%       1.000000     1.000000     2.000000     0.000000     6.000000
max       2.000000     1.000000     2.000000     1.000000     7.000000

              side          Age  RoomService    FoodCourt  ShoppingMall  \
count  8494.000000  8514.000000  8512.000000  8510.000000   8485.000000
mean      0.504827     0.364911     0.015683     0.015365      0.007395
std       0.500006     0.183405     0.046536     0.054053      0.025741
min       0.000000     0.000000     0.000000     0.000000      0.000000
25%       0.000000     0.240506     0.000000     0.000000      0.000000
50%       1.000000     0.341772     0.000000     0.000000      0.000000
75%       1.000000     0.481013     0.003281     0.002549      0.001149
max       1.000000     1.000000     1.000000     1.000000      1.000000

               Spa       VRDeck  Transported
count  8510.000000  8505.000000  8693.000000
mean      0.013885     0.012632     0.503624
std       0.050728     0.047475     0.500016
min       0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000
50%       0.000000     0.000000     1.000000
75%       0.002633     0.001906     1.000000
max       1.000000     1.000000     1.000000
```

4.0.1 Now heaving the data scaled, we can fill in the missing values

[16]:

```python
from sklearn.impute import SimpleImputer

continous_imp = SimpleImputer (strategy='mean') #this is also the standard␣
↪option
discrete_imp = SimpleImputer (strategy='most_frequent')

discrete = ["HomePlanet", "CryoSleep", "Destination", "VIP", "deck", "side"]

train_data[continous] = continous_imp.fit_transform(train_data[continous])
train_data[discrete] = discrete_imp.fit_transform(train_data[discrete])

test_data[continous] = continous_imp.transform(test_data[continous])
test_data[discrete] = discrete_imp.transform(test_data[discrete])

test_data.isna().sum()
```

```
# There is no more missind data on bothe the train and test sets.
```

[16]:
```
HomePlanet      0
CryoSleep       0
Destination     0
VIP             0
deck            0
side            0
Age             0
RoomService     0
FoodCourt       0
ShoppingMall    0
Spa             0
VRDeck          0
dtype: int64
```

4.0.2 Now we can probably start training model and see which is the best with cross validation before choosing one and running it on the test set

First well create the models and test them with their default parameters.

5 Model Training

[17]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
import xgboost

logistic_regression = LogisticRegression(max_iter=1000, random_state = 0)
svc = SVC(random_state = 0)
naive_bayes = GaussianNB()
random_forest = RandomForestClassifier(random_state = 0)
xgb = xgboost.XGBClassifier(random_state = 0)
```

[18]:
```
from sklearn.model_selection import cross_val_score

X = train_data.copy()
y = X.pop ("Transported") #pop extracts the desired column and drops it from␣
↪the dataset if came from.
```

[19]:
```
# The model is tested on "accuracy" so this scorer will make sure our model are␣
↪also tested on accuracy (and not their default scoring matric) in the cross␣
↪validation.
from sklearn.metrics import make_scorer, accuracy_score

accuracy_scorer = make_scorer(accuracy_score)
```

```
logistic_regression_scores = cross_val_score(logistic_regression, X, y, scoring = accuracy_scorer, cv = 5)
svc_scores = cross_val_score(svc, X, y, scoring = accuracy_scorer, cv = 5)
naive_bayes_scores = cross_val_score(naive_bayes, X, y, scoring = accuracy_scorer, cv = 5)
random_forest_scores = cross_val_score(random_forest, X, y, scoring = accuracy_scorer, cv = 5)
xgb_scores = cross_val_score(xgb, X, y, scoring = accuracy_scorer, cv = 5)
```

[20]:

```
models = {"logistic regression" : logistic_regression_scores,
          "svc" : svc_scores,
          "naive_bayes" : naive_bayes_scores,
          "random forest" : random_forest_scores,
          "XGBoost" : xgb_scores,}

for key, value in models.items():
    print (f"The average accuracy score of model: {key} is: {value.mean()} ")
```

```
The average accuracy score of model: logistic regression is: 0.7647544883472704
The average accuracy score of model: svc is: 0.7248384221451822
The average accuracy score of model: naive_bayes is: 0.7028662161169568
The average accuracy score of model: random forest is: 0.7862658657972421
The average accuracy score of model: XGBoost is: 0.7919032736431066
```

5.0.1 We can see a very tight competition with the best models being:

1. XGBoost
2. Random Forest
3. Logistic regression

Perhaps the logistic regression would have fared better if the encoding was One Hot

6 Without optimizing any of the models, let's create the first submission of results from the test set from these 3 models

[21]:

```
original_test_data = pd.read_csv("/kaggle/input/spaceship-titanic/test.csv")
```

6.0.1 Predicting using the XGBoost model and formating its predictions to be sent off

[22]:

```
xgb.fit(X,y)
xgb_pred = pd.Series(xgb.predict(test_data))

# returning the predictions to a format of True-False instead of 1/0
xgb_pred = xgb_pred.transform(lambda x: True if x == 1.0 else False)
```

```
#joining the list of passender ID's with the list of their predictions
xgb_to_submit = pd.concat([original_test_data["PassengerId"], xgb_pred], axis=1)

#renaming the predicions column
xgb_to_submit.rename(columns={0: "Transported"}, inplace = True)
xgb_to_submit.set_index('PassengerId', inplace = True)

xgb_to_submit.to_csv("/kaggle/working/XGBoost_submission")
```

6.0.2 Predicting using the Random Rorest model and formating its predictions to be sent off

[23]:
```
random_forest.fit(X,y)
rf_pred = pd.Series(random_forest.predict(test_data))

# returning the predictions to a format of True-False instead of 1/0
rf_pred = rf_pred.transform(lambda x: True if x == 1.0 else False)

#joining the list of passender ID's with the list of their predictions
rf_to_submit = pd.concat([original_test_data["PassengerId"], rf_pred], axis=1)

#renaming the predicions column
rf_to_submit.rename(columns={0: "Transported"}, inplace = True)
rf_to_submit.set_index('PassengerId', inplace = True)

rf_to_submit.to_csv("/kaggle/working/Random_Forest_submission")
```

6.0.3 Predicting using the Logistic Regression model and formating its predictions to be sent off

[24]:
```
logistic_regression.fit(X,y)
lr_pred = pd.Series(logistic_regression.predict(test_data))

# returning the predictions to a format of True-False instead of 1/0
lr_pred = lr_pred.transform(lambda x: True if x == 1.0 else False)

#joining the list of passender ID's with the list of their predictions
lr_to_submit = pd.concat([original_test_data["PassengerId"], lr_pred], axis=1)

#renaming the predicions column
lr_to_submit.rename(columns={0: "Transported"}, inplace = True)
lr_to_submit.set_index('PassengerId', inplace = True)

lr_to_submit.to_csv("/kaggle/working/Logistic_Regression_submission")
```

7 END