Supermarket_notebook

July 11, 2023

1 Final Project

Welcome to the final practical project for our course on Data Science Bootcamp. Throughout this project, you will go through the entire data science process, starting from data loading and cleaning, all the way to running a model and making predictions. This hands-on project will provide you with valuable experience and allow you to apply the concepts and techniques you've learned in the course. Get ready to dive into real-world data analysis and build your skills as a data scientist!

1.1 Important Remarks:

- The ultimate goal of this project is to conduct comprehensive data analysis and build 2 models using the provided datasets.
- Code is not the only thing graded here. Well-written and understandable documentation of your code is to be expected
- Clear reasoning behind your choices in every step of the notebook is important. Be it the choice of a data cleaning technique or selecting certain features in your analysis or the choice of your 2 models.

2 Importing packages

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import math
```

[2]:
```
from sklearn import linear_model
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.tree import DecisionTreeRegressor
from sklearn import metrics
```

3 Load the dataset into data

[3]:
```
data = pd.read_csv("supermarket_survey.csv", delimiter=';')
```

4 Dataset overview and statistical summary

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 353 entries, 0 to 352
Data columns (total 46 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   randomInt               353 non-null    int64
 1   age                     345 non-null    object
 2   gender                  347 non-null    object
 3   district                334 non-null    object
 4   modeOfTransportation    341 non-null    object
 5   distance                338 non-null    object
 6   G03Q13amountOfPeople    345 non-null    object
 7   income                  331 non-null    float64
 8   frequency               339 non-null    object
 9   days[1]                 353 non-null    object
 10  days[2]                 353 non-null    object
 11  days[3]                 353 non-null    object
 12  days[4]                 353 non-null    object
 13  days[5]                 353 non-null    object
 14  days[6]                 353 non-null    object
 15  days[7]                 353 non-null    object
 16  time[1]                 353 non-null    object
 17  time[2]                 353 non-null    object
 18  time[3]                 353 non-null    object
 19  time[4]                 353 non-null    object
 20  time[5]                 353 non-null    object
 21  moneySpent              338 non-null    object
 22  orderingItems           334 non-null    object
 23  deliveringItems         333 non-null    object
 24  willingPayDelivery      166 non-null    object
 25  findProducts            334 non-null    object
 26  usingDiscounts          326 non-null    object
 27  preferCash              331 non-null    object
 28  preferCashless          329 non-null    object
 29  isRelaxing              327 non-null    object
 30  satisGeneralStore       332 non-null    float64
 31  satisMusic              288 non-null    float64
 32  satisQualityProducts    329 non-null    float64
 33  satisGeneralAssortment  330 non-null    float64
```

```
 34  satisVeganProducts       274 non-null    float64
 35  satisOrganicProducts     301 non-null    float64
 36  satisGlutenfreeProducts  209 non-null    float64
 37  satisAnimalProducts      307 non-null    float64
 38  ideasExtendedBusiness    324 non-null    float64
 39  ideasHelpCarry           322 non-null    float64
 40  ideasCustomerCouncil     318 non-null    float64
 41  ideasFreeWifi            324 non-null    float64
 42  ideasTouchDisplay        320 non-null    float64
 43  ideasSelfCheckout        323 non-null    float64
 44  ideasBikeParking         312 non-null    float64
 45  ideasUndergroundParking  300 non-null    float64
dtypes: float64(17), int64(1), object(28)
memory usage: 127.0+ KB
```

[5]:

```
data.describe()
```

[5]:

```
        randomInt         income  satisGeneralStore  satisMusic  \
count  353.000000     331.000000         332.000000  288.000000
mean     2.609065   66275.568882           7.424699    5.236111
std      1.105322  132542.950482           1.705790    2.507094
min      1.000000  -99932.000000           1.000000    1.000000
25%      2.000000    2290.000000           7.000000    3.000000
50%      3.000000   21000.000000           8.000000    5.000000
75%      4.000000   80284.000000           8.000000    7.000000
max      4.000000  999999.000000          10.000000   10.000000

       satisQualityProducts  satisGeneralAssortment  satisVeganProducts  \
count            329.000000              330.000000          274.000000
mean               7.498480                7.278788            6.350365
std                1.479792                1.674366            2.177444
min                1.000000                1.000000            1.000000
25%                7.000000                7.000000            5.000000
50%                8.000000                8.000000            7.000000
75%                8.000000                8.000000            8.000000
max               10.000000               10.000000           10.000000

       satisOrganicProducts  satisGlutenfreeProducts  satisAnimalProducts  \
count            301.000000               209.000000           307.000000
mean               6.767442                 6.315789             7.348534
std                1.981347                 2.269317             1.902618
min                1.000000                 1.000000             1.000000
25%                6.000000                 5.000000             6.500000
50%                7.000000                 6.000000             8.000000
75%                8.000000                 8.000000             9.000000
max               10.000000                10.000000            10.000000
```

```
       ideasExtendedBusiness  ideasHelpCarry  ideasCustomerCouncil  \
count             324.000000      322.000000            318.000000
mean                6.919753        3.711180              3.232704
std                 3.129760        3.027465              2.668179
min                 1.000000        1.000000              1.000000
25%                 5.000000        1.000000              1.000000
50%                 8.000000        2.000000              2.000000
75%                10.000000        6.000000              5.000000
max                10.000000       10.000000             10.000000

       ideasFreeWifi  ideasTouchDisplay  ideasSelfCheckout  ideasBikeParking  \
count     324.000000         320.000000         323.000000        312.000000
mean        6.410494           5.571875           7.857585          7.602564
std         3.147757           3.197936           2.668804          2.752793
min         1.000000           1.000000           1.000000          1.000000
25%         4.000000           3.000000           7.000000          6.000000
50%         7.000000           6.000000           9.000000          8.000000
75%         9.000000           9.000000          10.000000         10.000000
max        10.000000          10.000000          10.000000         10.000000

       ideasUndergroundParking
count               300.000000
mean                  5.396667
std                   3.321057
min                   1.000000
25%                   2.000000
50%                   6.000000
75%                   8.000000
max                  10.000000
```

[6]:
```
data.head()
```

[6]:
```
   randomInt    age  gender    district modeOfTransportation distance  \
0          4    NaN    Male      Godham              Own Car    1-2km
1          4    NaN     NaN         NaN                  NaN      NaN
2          3  20-25  Female  Springtown              Own Car     >7km
3          4    NaN     NaN         NaN                  NaN      NaN
4          3  15-20    Male   Piltunder              Own Car    1-2km

  G03Q13amountOfPeople    income    frequency days[1]  …  \
0                    3  120000.0        Twice      No  …
1                  NaN       NaN          NaN      No  …
2                    2      15.0  Three times      No  …
3                  NaN    1337.0          NaN      No  …
4                    4  250000.0        Twice      No  …

  satisGlutenfreeProducts satisAnimalProducts ideasExtendedBusiness  \
```

```
0                     8.0                  7.0                   2.0
1                     NaN                  NaN                   NaN
2                     7.0                  NaN                   7.0
3                     NaN                  NaN                   NaN
4                     8.0                  1.0                   9.0

  ideasHelpCarry ideasCustomerCouncil ideasFreeWifi ideasTouchDisplay  \
0            4.0                  3.0           4.0               NaN
1            NaN                  NaN           NaN               NaN
2            7.0                  7.0           7.0               NaN
3            NaN                  NaN           NaN               NaN
4            2.0                  1.0          10.0              10.0

  ideasSelfCheckout ideasBikeParking ideasUndergroundParking
0               4.0              NaN                     NaN
1               NaN              NaN                     NaN
2               7.0              7.0                     7.0
3               NaN              NaN                     NaN
4              10.0              8.0                     NaN

[5 rows x 46 columns]
```

5 Data cleaning

[7]:
```
data.isnull().sum()
```

[7]:
```
randomInt                      0
age                            8
gender                         6
district                      19
modeOfTransportation          12
distance                      15
G03Q13amountOfPeople           8
income                        22
frequency                     14
days[1]                        0
days[2]                        0
days[3]                        0
days[4]                        0
days[5]                        0
days[6]                        0
days[7]                        0
time[1]                        0
time[2]                        0
time[3]                        0
time[4]                        0
```

```
time[5]                       0
moneySpent                   15
orderingItems                19
deliveringItems              20
willingPayDelivery          187
findProducts                 19
usingDiscounts               27
preferCash                   22
preferCashless               24
isRelaxing                   26
satisGeneralStore            21
satisMusic                   65
satisQualityProducts         24
satisGeneralAssortment       23
satisVeganProducts           79
satisOrganicProducts         52
satisGlutenfreeProducts     144
satisAnimalProducts          46
ideasExtendedBusiness        29
ideasHelpCarry               31
ideasCustomerCouncil         35
ideasFreeWifi                29
ideasTouchDisplay            33
ideasSelfCheckout            30
ideasBikeParking             41
ideasUndergroundParking      53
dtype: int64
```

[8]:

```
# There are 45 columns -- but do we really need that much ?
# Here is the data that we will need for our analysis

# age
# gender
# district
# modeOfTransportation
# distance
# income
# frequency
# moneySpent -- y
# orderingItems -- y
# deliveringItems
# usingDiscounts
# preferCash -- y
# preferCashless -- y
# satisGeneralStore -- y
# satisQualityProducts
# satisVeganProducts
```

```
# satisOrganicProducts
# satisGlutenfreeProducts
# satisAnimalProducts

# notice the sign "-- y", we will discuss about that in later phrase
```

[9]:
```
# getting all the required data
data = data[['age', 'gender', 'district', 'modeOfTransportation', 'distance',␣
↪'income', 'frequency', 'moneySpent', 'orderingItems', 'deliveringItems',␣
↪'usingDiscounts', 'preferCash', 'preferCashless', 'satisGeneralStore',␣
↪'satisQualityProducts', 'satisVeganProducts', 'satisOrganicProducts',␣
↪'satisGlutenfreeProducts','satisAnimalProducts']]
```

[10]:
```
data.isnull().sum()
```

[10]:
```
age                          8
gender                       6
district                    19
modeOfTransportation        12
distance                    15
income                      22
frequency                   14
moneySpent                  15
orderingItems               19
deliveringItems             20
usingDiscounts              27
preferCash                  22
preferCashless              24
satisGeneralStore           21
satisQualityProducts        24
satisVeganProducts          79
satisOrganicProducts        52
satisGlutenfreeProducts    144
satisAnimalProducts         46
dtype: int64
```

[11]:
```
# lets get the unique list in string form
# finding unique's in columns
def unique_cols():
    print('\nGender: ', data['gender'].unique())
    print('\nDistrict: ', data['district'].unique())
    print('\nDistance: ', data['distance'].unique())
    print('\nMode of Transportation: ',data['modeOfTransportation'].unique())
    print('\nFrequency: ', data['frequency'].unique())
    print('\nMoney spent: ', data['moneySpent'].unique())
    print('\nOrdering Items: ', data['orderingItems'].unique())
    print('\nDelievering Items: ', data['deliveringItems'].unique())
```

```
unique_cols()
```

```
Gender:  ['Male' nan 'Female' 'Prefer not to say' 'Diverse']

District:  ['Godham' nan 'Springtown' 'Piltunder' 'Metrapalis' 'Duckborg']

Distance:  ['1-2km' nan '>7km' '500 meters to 1km' '3-5km' '5-7km'
 'Less than few hundred meters']

Mode of Transportation:  ['Own Car' nan 'Walking' 'Bicycle' 'Taxi' 'Rented car
("car sharing")'
 'Public transportation']

Frequency:  ['Twice' nan 'Three times' 'Once' 'Four times' 'More than four
times']

Money spent:  ['Between 75 and 100 USD' nan 'Between 50 and 75' 'Less than 25
USD'
 '100 to 125 USD' 'Between 25 and 50 USD' 'More than 125 USD']

Ordering Items:  ['… ordering online.' nan '…selecting them myself in the
store.']

Delievering Items:  ['… get them directly delivered to my address.' nan
 '…get them myself in and from the store.'
 '… get them delivered to the store for me to pick-up.']
```

[12]:
```
# we suppose that, we only need to fill null values only in District, Ordering␣
↪Items, Delievering Items
```

[13]:
```
# doing manual cleaning

# age
def calculate_average_age(row):
    if isinstance(row, str):
        if row.startswith('>'):
            return int(row[1:])
        lower, upper = map(int, row.split('-'))
        average = (lower + upper) / 2
        return math.ceil(average)
    else:
        return row

data['age'] = data['age'].apply(calculate_average_age)
```

[14]:
```
# gender

# considering gender outputs like Prefer not to say and Diverse in Others␣
↪category -- no offense or hate to anyone

data['gender'] = data['gender'].replace(['Prefer not to say',␣
↪'Diverse'],'Others')
```

[15]:
```
# distance
data['distance'] = data['distance'].replace(['1-2km','2.0', '>7km', '500 meters␣
↪to 1km', '3-5km', '5-7km', 'Less than few hundred meters'], [2,2,7,1,5,7,0.
↪5])
```

[16]:
```
# mode of transportation
data['modeOfTransportation'] = data['modeOfTransportation'].replace(['Rented␣
↪car ("car sharing")'], ['Rented Car'])
```

[17]:
```
# frequency
data['frequency'] = data['frequency'].replace(['Twice', 'Three times', 'Once',␣
↪'Four times','More than four times'], [2,3,1,4,5])
```

[18]:
```
# money spent
data['moneySpent'] = data['moneySpent'].replace(['Between 75 and 100 USD',␣
↪'Between 50 and 75', 'Less than 25 USD', '100 to 125 USD', 'Between 25 and␣
↪50 USD','More than 125 USD'], [100,75,25,125,50,125])
```

[19]:
```
# string data type -- doing mode function
def valChange(colName):
    data[colName] = data[colName].fillna(data[colName].mode().iloc[0])

valChange('gender')
valChange('district')
valChange('modeOfTransportation')
valChange('orderingItems')
valChange('deliveringItems')
valChange('usingDiscounts')
valChange('preferCash')
valChange('preferCashless')
```

[20]:
```
# numeric data type -- doing median function
def numChange(colName):
    data[colName] = data[colName].fillna(data[colName].median())

numChange('age')
numChange('distance')
numChange('income')
numChange('frequency')
```

```
numChange('moneySpent')
numChange('satisGeneralStore')
numChange('satisQualityProducts')
numChange('satisOrganicProducts')
numChange('satisVeganProducts')
numChange('satisGlutenfreeProducts')
numChange('satisAnimalProducts')
```

[21]:
```
# now checking changes
# finding unique's in columns
unique_cols()
```

```
Gender:  ['Male' 'Female' 'Others']

District:  ['Godham' 'Springtown' 'Piltunder' 'Metrapalis' 'Duckborg']

Distance:  [2.  7.  1.  5.  0.5]

Mode of Transportation:  ['Own Car' 'Bicycle' 'Walking' 'Taxi' 'Rented Car'
'Public transportation']

Frequency:  [2. 3. 1. 4. 5.]

Money spent:  [100.  75.  25. 125.  50.]

Ordering Items:  ['… ordering online.' '…selecting them myself in the store.']

Delievering Items:  ['… get them directly delivered to my address.'
 '…get them myself in and from the store.'
 '… get them delivered to the store for me to pick-up.']
```

[22]:
```
data.head()
```

[22]:
```
    age  gender    district modeOfTransportation  distance    income  \
0  38.0    Male      Godham              Own Car       2.0  120000.0
1  38.0    Male  Springtown              Bicycle       2.0   21000.0
2  23.0  Female  Springtown              Own Car       7.0      15.0
3  38.0    Male  Springtown              Bicycle       2.0    1337.0
4  18.0    Male   Piltunder              Own Car       2.0  250000.0

   frequency  moneySpent                         orderingItems  \
0        2.0       100.0                    … ordering online.
1        2.0        75.0  …selecting them myself in the store.
2        3.0        75.0  …selecting them myself in the store.
3        2.0        75.0  …selecting them myself in the store.
4        2.0        75.0  …selecting them myself in the store.
```

```
                             deliveringItems   usingDiscounts  \
0  … get them directly delivered to my address.  Rather disagree
1       …get them myself in and from the store.     Rather agree
2       …get them myself in and from the store.     Rather agree
3       …get them myself in and from the store.     Rather agree
4       …get them myself in and from the store.     Rather agree

          preferCash  preferCashless  satisGeneralStore  satisQualityProducts  \
0  Strongly disagree    Rather agree                4.0                   4.0
1  Strongly disagree  Strongly agree                8.0                   8.0
2  Strongly disagree  Strongly agree                8.0                   7.0
3  Strongly disagree  Strongly agree                8.0                   8.0
4    Rather disagree  Strongly agree                8.0                   7.0

   satisVeganProducts  satisOrganicProducts  satisGlutenfreeProducts  \
0                 2.0                   8.0                      8.0
1                 7.0                   7.0                      6.0
2                 7.0                   7.0                      7.0
3                 7.0                   7.0                      6.0
4                 8.0                   8.0                      8.0

   satisAnimalProducts
0                  7.0
1                  8.0
2                  8.0
3                  8.0
4                  1.0
```

[23]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 353 entries, 0 to 352
Data columns (total 19 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   age                      353 non-null    float64
 1   gender                   353 non-null    object
 2   district                 353 non-null    object
 3   modeOfTransportation     353 non-null    object
 4   distance                 353 non-null    float64
 5   income                   353 non-null    float64
 6   frequency                353 non-null    float64
 7   moneySpent               353 non-null    float64
 8   orderingItems            353 non-null    object
 9   deliveringItems          353 non-null    object
 10  usingDiscounts           353 non-null    object
```

```
 11  preferCash              353 non-null    object
 12  preferCashless          353 non-null    object
 13  satisGeneralStore       353 non-null    float64
 14  satisQualityProducts    353 non-null    float64
 15  satisVeganProducts      353 non-null    float64
 16  satisOrganicProducts    353 non-null    float64
 17  satisGlutenfreeProducts 353 non-null    float64
 18  satisAnimalProducts     353 non-null    float64
dtypes: float64(11), object(8)
memory usage: 52.5+ KB
```

6 EDA

[24]:
```
sns.pairplot(data[['age', 'distance', 'income','frequency', 'moneySpent']])
```

[24]:
```
<seaborn.axisgrid.PairGrid at 0x7f828f33c460>
```

[25]:
```
data.corr()
```

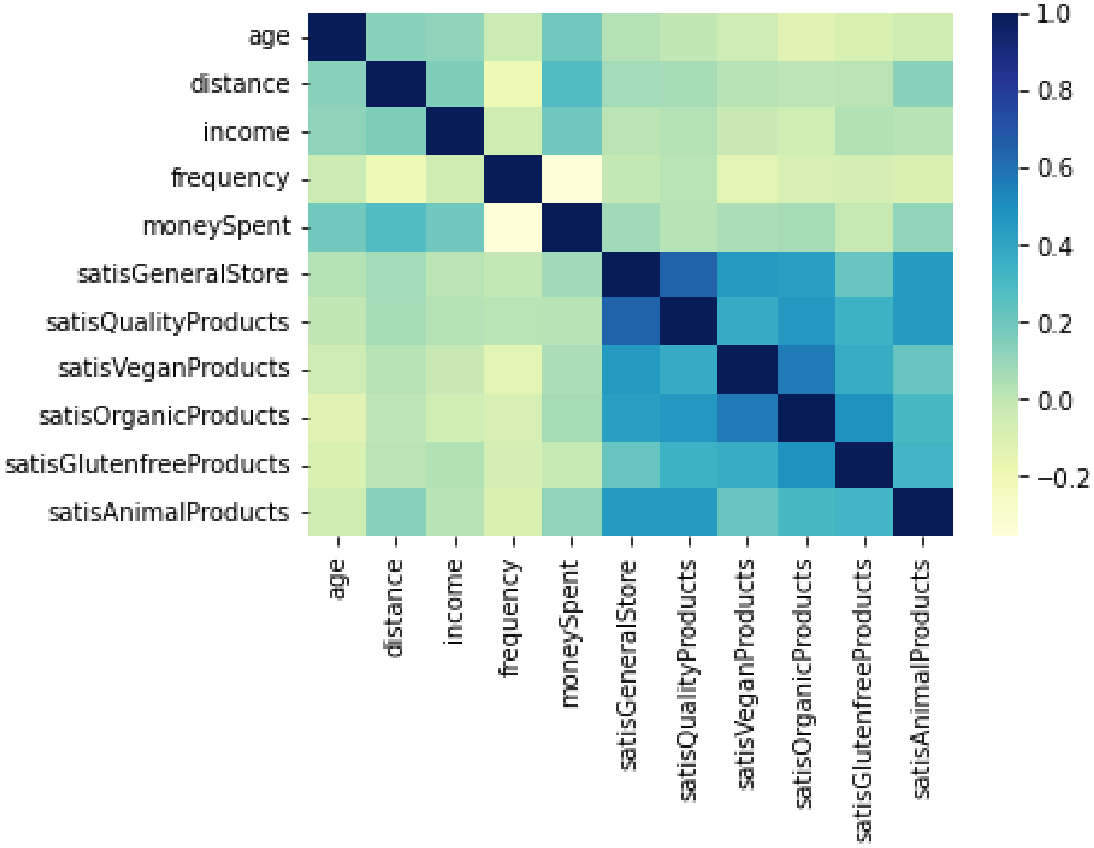
[25]:

	age	distance	income	frequency	moneySpent \
age	1.000000	0.132301	0.119989	-0.036081	0.191339
distance	0.132301	1.000000	0.159086	-0.201215	0.279534
income	0.119989	0.159086	1.000000	-0.051165	0.198282
frequency	-0.036081	-0.201215	-0.051165	1.000000	-0.353857
moneySpent	0.191339	0.279534	0.198282	-0.353857	1.000000
satisGeneralStore	0.028356	0.071000	0.012640	-0.004845	0.076840
satisQualityProducts	-0.002794	0.065509	0.029034	0.020179	0.023101
satisVeganProducts	-0.044946	0.026608	-0.019691	-0.133064	0.048848
satisOrganicProducts	-0.131003	0.009380	-0.053751	-0.086931	0.068409
satisGlutenfreeProducts	-0.089568	0.015791	0.036320	-0.070098	-0.014784

```
satisAnimalProducts     -0.049384  0.129122  0.023667  -0.096666    0.115160

                         satisGeneralStore  satisQualityProducts  \
age                               0.028356             -0.002794
distance                          0.071000              0.065509
income                            0.012640              0.029034
frequency                        -0.004845              0.020179
moneySpent                        0.076840              0.023101
satisGeneralStore                 1.000000              0.644214
satisQualityProducts              0.644214              1.000000
satisVeganProducts                0.454009              0.375205
satisOrganicProducts              0.428265              0.456884
satisGlutenfreeProducts           0.221575              0.340310
satisAnimalProducts               0.445069              0.446103

                         satisVeganProducts  satisOrganicProducts  \
age                               -0.044946             -0.131003
distance                           0.026608              0.009380
income                            -0.019691             -0.053751
frequency                         -0.133064             -0.086931
moneySpent                         0.048848              0.068409
satisGeneralStore                  0.454009              0.428265
satisQualityProducts               0.375205              0.456884
satisVeganProducts                 1.000000              0.567772
satisOrganicProducts               0.567772              1.000000
satisGlutenfreeProducts            0.365422              0.486447
satisAnimalProducts                0.220878              0.306700

                         satisGlutenfreeProducts  satisAnimalProducts
age                                    -0.089568            -0.049384
distance                                0.015791             0.129122
income                                  0.036320             0.023667
frequency                              -0.070098            -0.096666
moneySpent                             -0.014784             0.115160
satisGeneralStore                       0.221575             0.445069
satisQualityProducts                    0.340310             0.446103
satisVeganProducts                      0.365422             0.220878
satisOrganicProducts                    0.486447             0.306700
satisGlutenfreeProducts                 1.000000             0.319793
satisAnimalProducts                     0.319793             1.000000
```

[26]:
```
import matplotlib.pyplot as plt
sns.heatmap(data.corr(), cmap="YlGnBu")
```

[26]: <AxesSubplot:>



[27]:
```
# Relation between age and moneySpent
data[['age', 'moneySpent']].groupby(['age'], as_index = False).mean()
```

[27]:

	age	moneySpent
0	18.0	65.000000
1	23.0	55.660377
2	28.0	61.224490
3	33.0	79.729730
4	38.0	77.049180
5	43.0	86.764706
6	48.0	87.500000
7	53.0	81.250000
8	58.0	72.058824
9	63.0	76.785714
10	68.0	85.000000
11	73.0	50.000000
12	75.0	75.000000

[28]:
```
# Relation between age, income, moneySpent
data[['age', 'income', 'moneySpent']].groupby(['age', 'moneySpent']).count()
```

[28]:

```
                  income
age  moneySpent
18.0 25.0              1
     50.0              4
     75.0              3
     100.0             2
23.0 25.0             20
     50.0             17
     75.0              7
     100.0             2
     125.0             7
28.0 25.0             13
     50.0             17
     75.0              8
     100.0             6
     125.0             5
33.0 25.0              4
     50.0             10
     75.0              8
     100.0             5
     125.0            10
38.0 25.0              6
     50.0             17
     75.0             19
     100.0             4
     125.0            15
43.0 25.0              3
     50.0              7
     75.0              7
     100.0             5
     125.0            12
48.0 25.0              3
     50.0              5
     75.0              1
     100.0             4
     125.0             9
53.0 25.0              3
     50.0              7
     75.0              7
     100.0             2
     125.0             9
58.0 25.0              2
     50.0              7
     75.0              1
     100.0             5
     125.0             2
63.0 50.0              6
```

```
           75.0                4
           100.0               1
           125.0               3
     68.0  25.0                1
           50.0                3
           75.0                7
           100.0               5
           125.0               4
     73.0  25.0                1
           50.0                2
           75.0                1
     75.0  25.0                1
           50.0                1
           100.0               1
           125.0               1
```

[29]:
```python
# correlation values between pclass, survival, age
print('age w/t income:',data['age'].corr(data['income']))
print('age w/t moneySpent:',data['age'].corr(data['moneySpent']))
print('income w/t moneySpent:',data['income'].corr(data['moneySpent']))
```

```
age w/t income: 0.11998934244358012
age w/t moneySpent: 0.1913387598763577
income w/t moneySpent: 0.1982822005500373
```

7 Data Processing and normalization

Applying Label Encoding to the categorical data – gender,district,modeOfTransportation,orderingItems,deliveringItems,usingDiscounts,preferCash,preferCashless

[30]:
```python
le = LabelEncoder()

def applyLE(colName):
    data[colName] = le.fit_transform(data[colName])

applyLE('gender')
applyLE('district')
applyLE('modeOfTransportation')
applyLE('orderingItems')
applyLE('deliveringItems')
applyLE('usingDiscounts')
applyLE('preferCash')
applyLE('preferCashless')
```

[31]:
```python
data.head(10)
```

```
[31]:    age  gender  district  modeOfTransportation  distance    income  \
      0  38.0       1         1                     1       2.0  120000.0
      1  38.0       1         4                     0       2.0   21000.0
      2  23.0       0         4                     1       7.0      15.0
      3  38.0       1         4                     0       2.0    1337.0
      4  18.0       1         3                     1       2.0  250000.0
      5  23.0       2         2                     5       1.0     500.0
      6  63.0       1         1                     1       2.0    5000.0
      7  43.0       0         1                     0       1.0   21000.0
      8  28.0       1         2                     5       1.0     600.0
      9  23.0       0         4                     0       1.0    1200.0

         frequency  moneySpent  orderingItems  deliveringItems  usingDiscounts  \
      0        2.0       100.0              0                1               2
      1        2.0        75.0              1                2               1
      2        3.0        75.0              1                2               1
      3        2.0        75.0              1                2               1
      4        2.0        75.0              1                2               1
      5        2.0        25.0              1                2               3
      6        1.0       125.0              1                2               0
      7        2.0        50.0              1                2               4
      8        4.0        25.0              1                2               2
      9        4.0        25.0              1                2               3

         preferCash  preferCashless  satisGeneralStore  satisQualityProducts  \
      0           4               1                4.0                   4.0
      1           4               3                8.0                   8.0
      2           4               3                8.0                   7.0
      3           4               3                8.0                   8.0
      4           2               3                8.0                   7.0
      5           4               3                7.0                   9.0
      6           0               0                8.0                   8.0
      7           0               0                8.0                   9.0
      8           4               3                8.0                   7.0
      9           2               3                8.0                   7.0

         satisVeganProducts  satisOrganicProducts  satisGlutenfreeProducts  \
      0                 2.0                   8.0                      8.0
      1                 7.0                   7.0                      6.0
      2                 7.0                   7.0                      7.0
      3                 7.0                   7.0                      6.0
      4                 8.0                   8.0                      8.0
      5                 6.0                   7.0                     10.0
      6                 5.0                   6.0                      6.0
      7                 7.0                   7.0                      6.0
      8                 6.0                   6.0                      6.0
      9                 8.0                   6.0                      3.0
```

```
   satisAnimalProducts
0                  7.0
1                  8.0
2                  8.0
3                  8.0
4                  1.0
5                 10.0
6                  7.0
7                  7.0
8                  8.0
9                  7.0
```

[32]:
```
# remember those "--y" signs , I remarked earlier, they can be the value of y
```

[33]:
```
X = data[['age','district','modeOfTransportation','distance','income','frequency']].values
y = data['moneySpent'].values
```

Test size can be different in scenarios - but here I've taken 0.3

[34]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=20)
```

Scaling the values, the scaling is used for making data points generalized so that the distance between them will be lower, this will help the machine.

[35]:
```
scale = StandardScaler()

X_train_scaled = scale.fit_transform(X_train)
X_test_scaled = scale.transform(X_test)
```

8 Creating ML model 1

[36]:
```
regr = linear_model.LinearRegression()
regr.fit(X_train_scaled,y_train)
```

[36]:
```
LinearRegression()
```

[37]:
```
print(regr.coef_)
```

```
[  3.95148216  -1.31398446  -2.51895413   6.76845651   4.31928503
 -12.03906325]
```

8.1 Prediction on Test data

[38]:
```
y_pred_1 = regr.predict(X_test)
```

8.2 Model 1 Performance

[39]:
```
accuracy_score = round(regr.score(X_train_scaled, y_train) * 100, 2)
print("Model accuracy for training:", accuracy_score, "%")
```

```
Model accuracy for training: 26.59 %
```

[40]:
```
accuracy_score = round(regr.score(X_test_scaled, y_test) * 100, 2)
print("Model accuracy for testing:", accuracy_score, "%")
```

```
Model accuracy for testing: 6.18 %
```

9 Creating ML model 2

[41]:
```
regr = linear_model.LogisticRegression()
regr.fit(X_train_scaled,y_train)
```

[41]:
```
LogisticRegression()
```

[42]:
```
print(regr.coef_)
```

```
[[-0.41769757 -0.00763657  0.28580581 -0.29563659 -0.36924122  0.68841193]
 [-0.05477075 -0.13850925  0.11476936 -0.14579297 -0.41256936  0.37039811]
 [ 0.06246955  0.35459052 -0.3102762  -0.05507704  0.24020486  0.09260001]
 [ 0.39942692 -0.01180072 -0.0895435   0.07269962  0.28385299 -0.46431066]
 [ 0.01057186 -0.19664398 -0.00075547  0.42380698  0.25775272 -0.68709939]]
```

9.1 Prediction on Test data

[43]:
```
y_pred_2 = regr.predict(X_test_scaled)
```

9.2 ## Model 2 Performance

[44]:
```
accuracy_score = round(regr.score(X_train_scaled, y_train) * 100, 2)
print("Model accuracy for training:", accuracy_score, "%")
```

```
Model accuracy for training: 42.91 %
```

[45]:
```
accuracy_score = round(regr.score(X_test_scaled, y_test) * 100, 2)
print("Model accuracy for testing:", accuracy_score, "%")
```

```
Model accuracy for testing: 38.68 %
```

10 Report and insight from your analysis

10.1 Model and Dataset Analysis

- This is Regression Problem, based on the given data multivariate analysis would be applicable here.
- Dataset is not clean at the first insight. Cleaning dataset took up much time.
- We got too much unnecessary data which will not be useful for prediction.

10.2 Dataset overview and statistical summary Analysis

- Using 19 columns for our EDA and further model prediction

10.3 EDA Analysis

- Using Label Encoding for categorical values
- Correlation age w/t income: 0.11998934244358012
- Correlation age w/t moneySpent: 0.1913387598763577
- Correlation income w/t moneySpent: 0.1982822005500373

10.4 Data Processing Analysis

- Linear Regression Accuracy: [Training: 26.59%, Testing: 6.18%]
- Logistic Regression Accuracy: [Training: 42.91%, Testing: 38.68%]