DATA 119 Final Project

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Project A

```
import numpy as np
import pandas as pd
import plotnine as p9
import statsmodels.api as sm
import sklearn.metrics as metrics
```

```
df = pd.read_csv("marketing_campaign.csv", sep="\t")
pd.set_option('display.max_rows', None)
df.head(5)
```

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Rec
0	5524	1957	Graduation	Single	58138.0	0	0	04-09-2012	58
1	2174	1954	Graduation	Single	46344.0	1	1	08-03-2014	38
2	4141	1965	Graduation	Together	71613.0	0	0	21-08-2013	26
3	6182	1984	Graduation	Together	26646.0	1	0	10-02-2014	26
4	5324	1981	PhD	Married	58293.0	1	0	19-01-2014	94

```
df.columns
```

```
Index(['ID', 'Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Dt_Customer', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
```

```
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Z_CostContact', 'Z_Revenue', 'Response'],
      dtype='object')
```

```
#These variables are meaningless
#so we decide to delete them

df = df.drop(columns=['ID', 'Z_CostContact','Z_Revenue'])
df.columns
```

```
Index(['Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Dt_Customer', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Response'],
      dtype='object')
```

```
# Name the variables in a more meaning way

df = df.rename(columns={"Response": "AcceptedLastCmp"})
df.columns
```

```
Index(['Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Dt_Customer', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'AcceptedLastCmp'],
      dtype='object')
```

```
df['Income'].isna().sum() / df.shape[0]
#only 1% missing data, so let's drop it
df = df.dropna()
```

```
#Summary statistics for variables
print(df['Year_Birth'].describe())
```

```
count    2216.000000
mean     1968.820397
std        11.985554
min      1893.000000
25%      1959.000000
50%      1970.000000
75%      1977.000000
max      1996.000000
Name: Year_Birth, dtype: float64
```

```
print(df[df['Year_Birth'] < 1920]['Dt_Customer'])
print("It looks like some data entry error")
print("because it is quite impossible to be born that early \nand become a customer for th
print("So we can delete the data")

index = df[df['Year_Birth'] < 1920].index
df = df.drop(index)
```

```
192    26-09-2013
239    17-05-2014
339    26-09-2013
Name: Dt_Customer, dtype: object
It looks like some data entry error
because it is quite impossible to be born that early
and become a customer for the first time in 2010s.
So we can delete the data
```

```
#Summary statistics for variables
print(df['Year_Birth'].describe())
```

```
count    2213.000000
mean     1968.917307
std        11.700216
min      1940.000000
25%      1959.000000
50%      1970.000000
75%      1977.000000
max      1996.000000
Name: Year_Birth, dtype: float64
```

```
# Visualize the distirbution of variables
(p9.ggplot(df) +
 p9.aes (x = 'Year_Birth') +
 p9.geom_histogram(bins=16)+
 p9.labs(x = "Birth Year of Cutsomers \n", y = "Count",title= "Distribution of Birth Year
         caption = "This histogram shows the distribution of Birth Year of Cutsomers.\n" +
          "The distribution is centered at approximately 1970, and roughly ranges from 194
          "It is an unimodal, left skewed distribution. There are no obvious unusual value
```


```
<Figure Size: (640 x 480)>
```

```
print(df['Income'].describe())
```

```
count      2213.000000
```

```
mean      52236.581563
std       25178.603047
min        1730.000000
25%       35246.000000
50%       51373.000000
75%       68487.000000
max      666666.000000
Name: Income, dtype: float64
```

```python
print(df['Income'].describe())
```

```
count      2213.000000
mean      52236.581563
std       25178.603047
min        1730.000000
25%       35246.000000
50%       51373.000000
75%       68487.000000
max      666666.000000
Name: Income, dtype: float64
```

```python
# Visualize the distirbution of variables
(p9.ggplot(df) +
 p9.aes (x = 'Income') +
 p9.geom_histogram(bins=16)+
 p9.labs(x = "Yearly Household Income of Cutsomers\n(Log Transformed)", y = "Count",title=
         caption = "This histogram shows the distribution of yearly household income of cu
          "The distribution is centered at approximately 50,000, and roughly ranges from 1
          "It is an unimodal, left skewed distribution. There are unusually high values.")
```

This histogram shows the distribution of yearly household income of cutsomers.
The distribution is centered at approximately 50,000, and roughly ranges from 1000 to 700,000.
It is an unimodal, left skewed distribution. There are unusually high values.

```
<Figure Size: (640 x 480)>
```

```
print(df['Dt_Customer'].describe())
```

```
count          2213
unique          662
top      31-08-2012
freq             12
Name: Dt_Customer, dtype: object
```

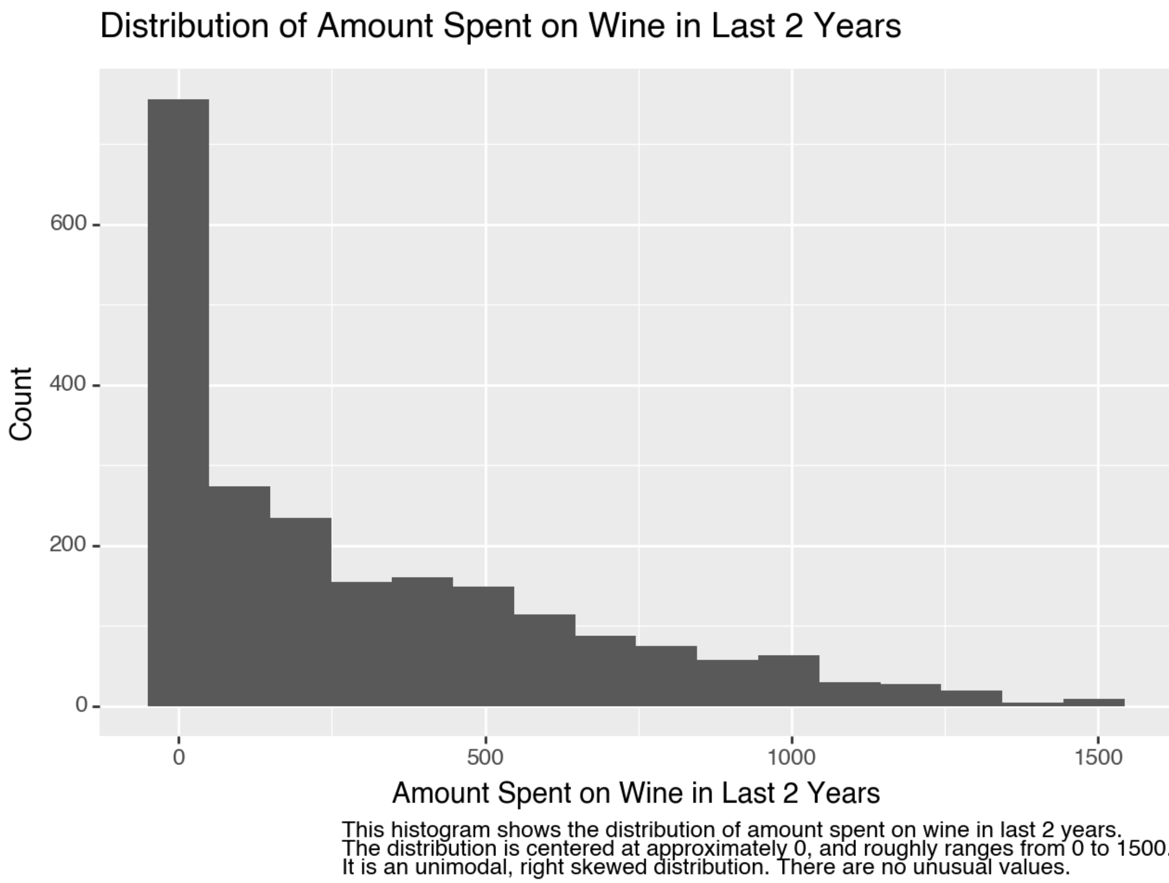
```
print(df['Recency'].describe())
```

```
count    2213.000000
mean       49.007682
std        28.941864
min         0.000000
25%        24.000000
50%        49.000000
75%        74.000000
max        99.000000
Name: Recency, dtype: float64
```

```
print(df['MntWines'].describe())
```

```
count    2213.000000
mean      305.153638
std       337.305490
min         0.000000
25%        24.000000
50%       175.000000
75%       505.000000
max      1493.000000
Name: MntWines, dtype: float64
```

```
# Visualize the distirbution of variables
(p9.ggplot(df) +
 p9.aes (x = 'MntWines') +
 p9.geom_histogram(bins=16)+
 p9.labs(x = "Amount Spent on Wine in Last 2 Years", y = "Count",title= "Distribution of A
         caption = "This histogram shows the distribution of amount spent on wine in last
          "The distribution is centered at approximately 0, and roughly ranges from 0 to 1
          "It is an unimodal, right skewed distribution. There are no unusual values."))
```




```
<Figure Size: (640 x 480)>
```

```
print(df['MntFruits'].describe())
```

```
count    2213.000000
mean       26.323995
std        39.735932
min         0.000000
25%         2.000000
50%         8.000000
75%        33.000000
max       199.000000
Name: MntFruits, dtype: float64
```

```python
print(df['MntMeatProducts'].describe())
```

```
count    2213.000000
mean      166.962494
std       224.226178
min         0.000000
25%        16.000000
50%        68.000000
75%       232.000000
max      1725.000000
Name: MntMeatProducts, dtype: float64
```

```python
print(df['MntFishProducts'].describe())
```

```
count    2213.000000
mean       37.635337
std        54.763278
min         0.000000
25%         3.000000
50%        12.000000
75%        50.000000
max       259.000000
Name: MntFishProducts, dtype: float64
```

```python
print(df['MntSweetProducts'].describe())
```

```
count    2213.000000
mean       27.034794
std        41.085433
min         0.000000
25%         1.000000
50%         8.000000
75%        33.000000
max       262.000000
Name: MntSweetProducts, dtype: float64
```

```python
print(df['MntGoldProds'].describe())
```

```
count    2213.000000
mean       43.911432
std        51.699746
min         0.000000
25%         9.000000
50%        24.000000
75%        56.000000
max       321.000000
Name: MntGoldProds, dtype: float64
```

```
print(df['NumDealsPurchases'].describe())
```

```
count    2213.000000
mean        2.325350
std         1.924402
min         0.000000
25%         1.000000
50%         2.000000
75%         3.000000
max        15.000000
Name: NumDealsPurchases, dtype: float64
```

```
print(df['NumWebPurchases'].describe())
```

```
count    2213.000000
mean        4.087664
std         2.741664
min         0.000000
25%         2.000000
50%         4.000000
75%         6.000000
max        27.000000
Name: NumWebPurchases, dtype: float64
```

```
print(df['NumCatalogPurchases'].describe())
```

```
count    2213.000000
mean        2.671487
```

```
std          2.927096
min          0.000000
25%          0.000000
50%          2.000000
75%          4.000000
max         28.000000
Name: NumCatalogPurchases, dtype: float64
```

```
print(df['NumStorePurchases'].describe())
```

```
count    2213.000000
mean        5.805242
std         3.250752
min         0.000000
25%         3.000000
50%         5.000000
75%         8.000000
max        13.000000
Name: NumStorePurchases, dtype: float64
```

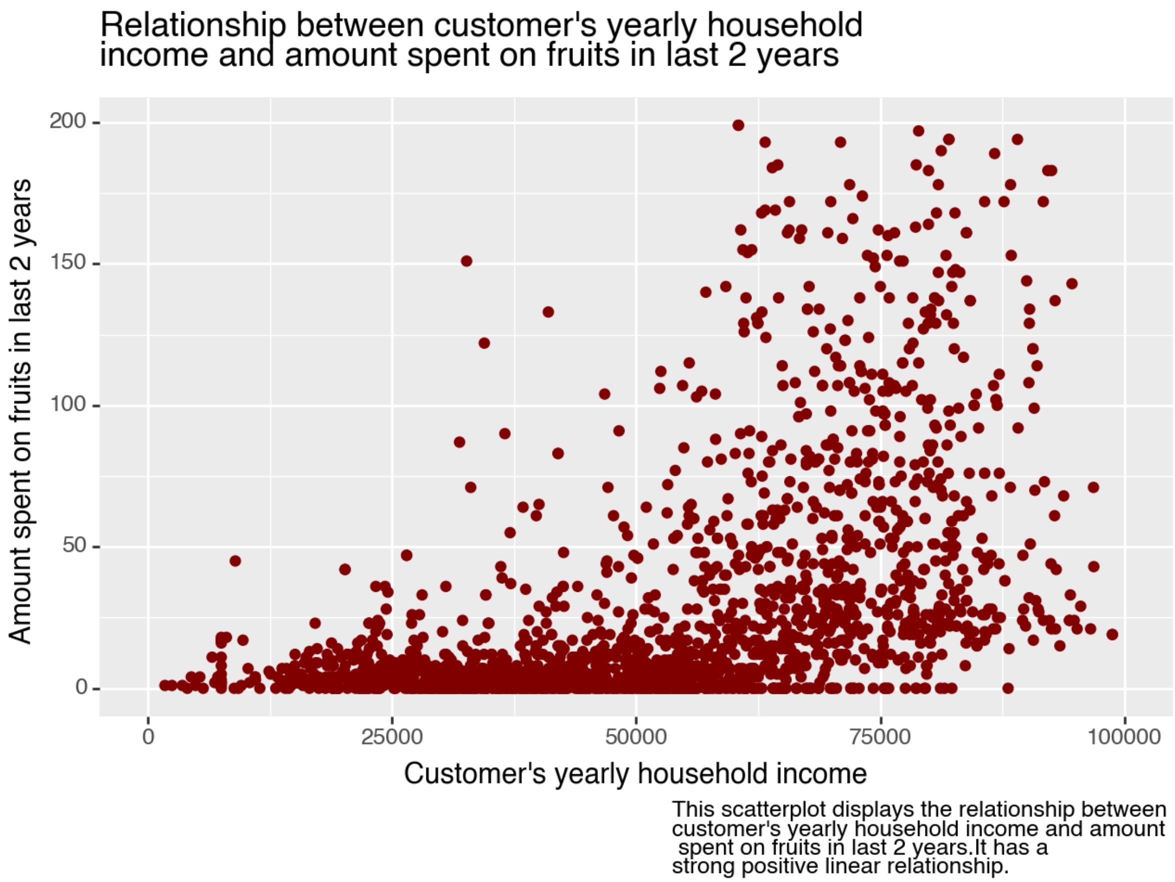
```
print(df['NumWebVisitsMonth'].describe())
```

```
count    2213.000000
mean        5.321735
std         2.425092
min         0.000000
25%         3.000000
50%         6.000000
75%         7.000000
max        20.000000
Name: NumWebVisitsMonth, dtype: float64
```

```
# create scatterplots
(p9.ggplot(df, p9.aes(x = 'Income', y = 'MntFruits'))  +
 p9.geom_point(color = 'maroon') +
 p9.xlim(0,100000) +
 p9.labs(x = "Customer's yearly household income", y = "Amount spent on fruits in last 2 y
        title= "Relationship between customer's yearly household \nincome and amount spent
          caption = "This scatterplot displays the relationship between \ncustomer's yearl
```

```
+ "It has a \nstrong positive linear relationship."))
```

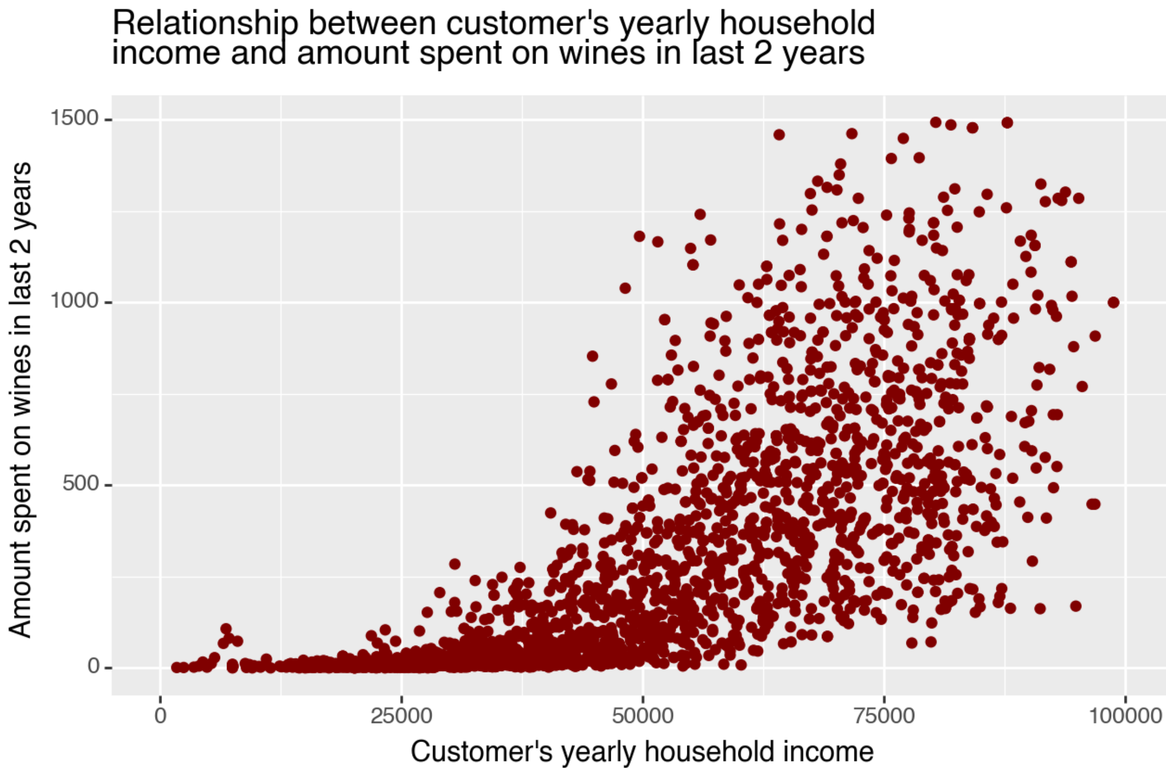
```
/opt/homebrew/lib/python3.9/site-packages/plotnine/layer.py:364: PlotnineWarning: geom_point
```




```
<Figure Size: (640 x 480)>
```

```
# create scatterplots
(p9.ggplot(df, p9.aes(x = 'Income', y = 'MntWines'))  +
 p9.geom_point(color = 'maroon') +
 p9.xlim(0,100000) +
 p9.labs(x = "Customer's yearly household income", y = "Amount spent on wines in last 2 ye
        title= "Relationship between customer's yearly household \nincome and amount spent
          caption = "This scatterplot displays the relationship between \ncustomer's yearl
          + "It has a \nstrong positive relationship but looks \nlike quadratic relationsh
```

```
/opt/homebrew/lib/python3.9/site-packages/plotnine/layer.py:364: PlotnineWarning: geom_point
```

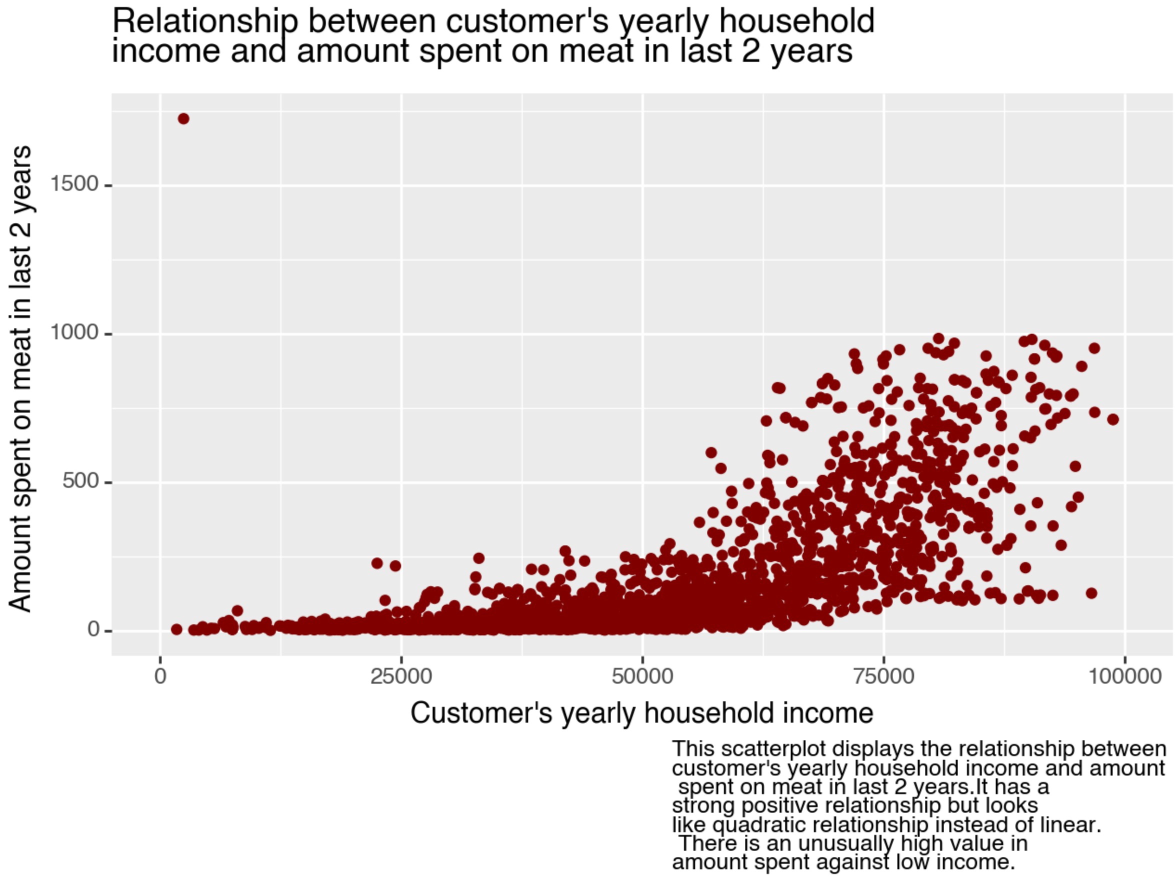


This scatterplot displays the relationship between customer's yearly household income and amount spent on wines in last 2 years.It has a strong positive relationship but looks like quadratic relationship instead of linear.

```
<Figure Size: (640 x 480)>
```

```
# create scatterplots
(p9.ggplot(df, p9.aes(x = 'Income', y = 'MntMeatProducts'))  +
 p9.geom_point(color = 'maroon') +
 p9.xlim(0,100000) +
 p9.labs(x = "Customer's yearly household income", y = "Amount spent on meat in last 2 yea
        title= "Relationship between customer's yearly household \nincome and amount spent
          caption = "This scatterplot displays the relationship between \ncustomer's yearl
          + "It has a \nstrong positive relationship but looks \nlike quadratic relationsh
```

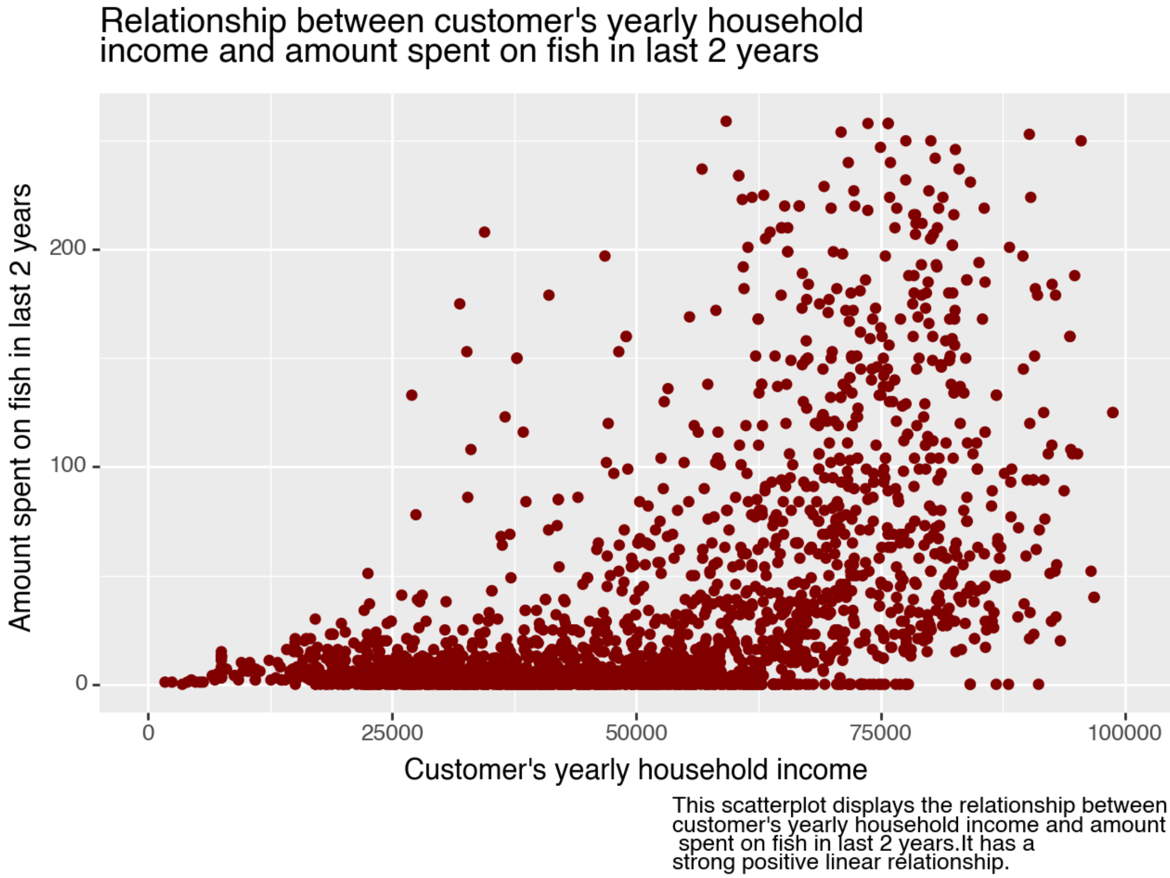
```
/opt/homebrew/lib/python3.9/site-packages/plotnine/layer.py:364: PlotnineWarning: geom_point
```




```
<Figure Size: (640 x 480)>
```

```
# create scatterplots
(p9.ggplot(df, p9.aes(x = 'Income', y = 'MntFishProducts'))  +
 p9.geom_point(color = 'maroon') +
 p9.xlim(0,100000) +
 p9.labs(x = "Customer's yearly household income", y = "Amount spent on fish in last 2 yea
         title= "Relationship between customer's yearly household \nincome and amount spent
           caption = "This scatterplot displays the relationship between \ncustomer's yearl
           + "It has a \nstrong positive linear relationship."))
```

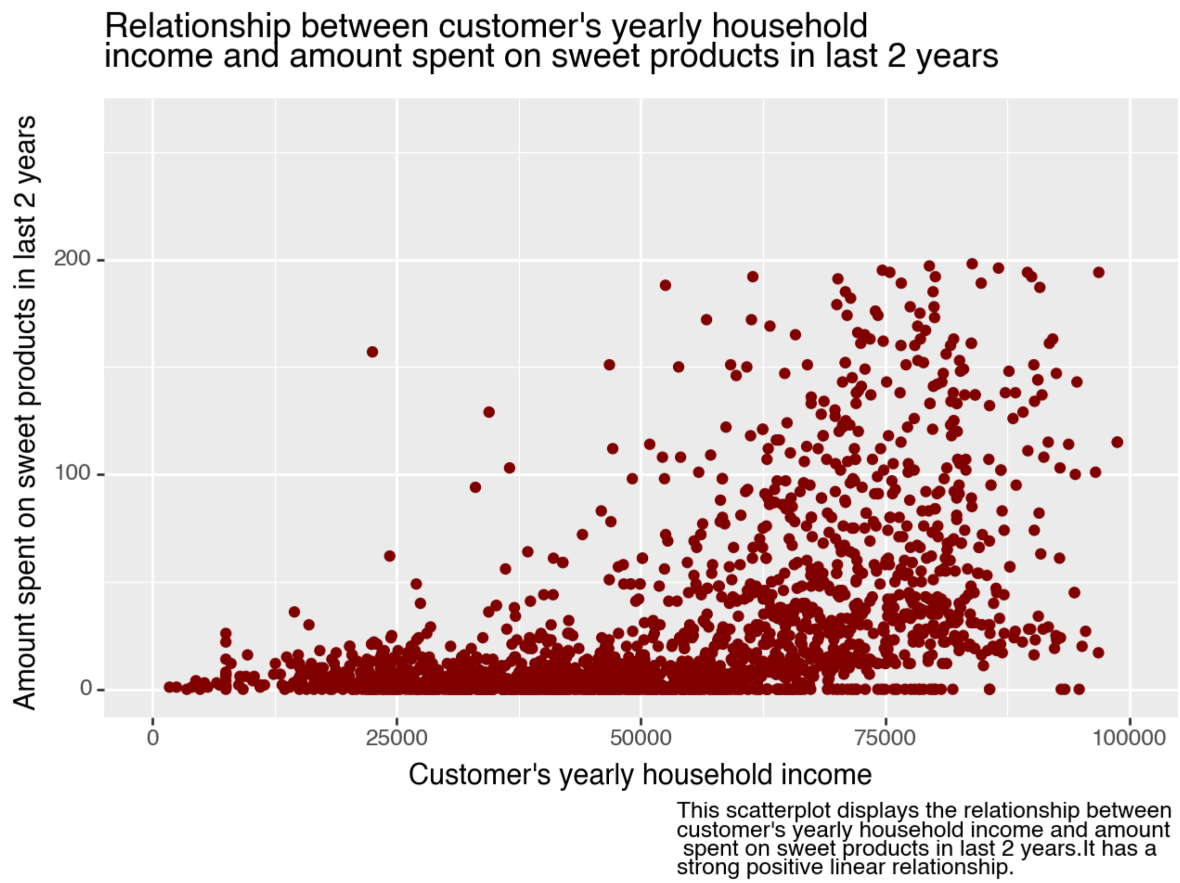
```
/opt/homebrew/lib/python3.9/site-packages/plotnine/layer.py:364: PlotnineWarning: geom_point
```




```
<Figure Size: (640 x 480)>
```

```
# create scatterplots
(p9.ggplot(df, p9.aes(x = 'Income', y = 'MntSweetProducts'))  +
 p9.geom_point(color = 'maroon') +
 p9.xlim(0,100000) +
 p9.labs(x = "Customer's yearly household income", y = "Amount spent on sweet products in
        title= "Relationship between customer's yearly household \nincome and amount spent
          caption = "This scatterplot displays the relationship between \ncustomer's yearl
          + "It has a \nstrong positive linear relationship."))
```

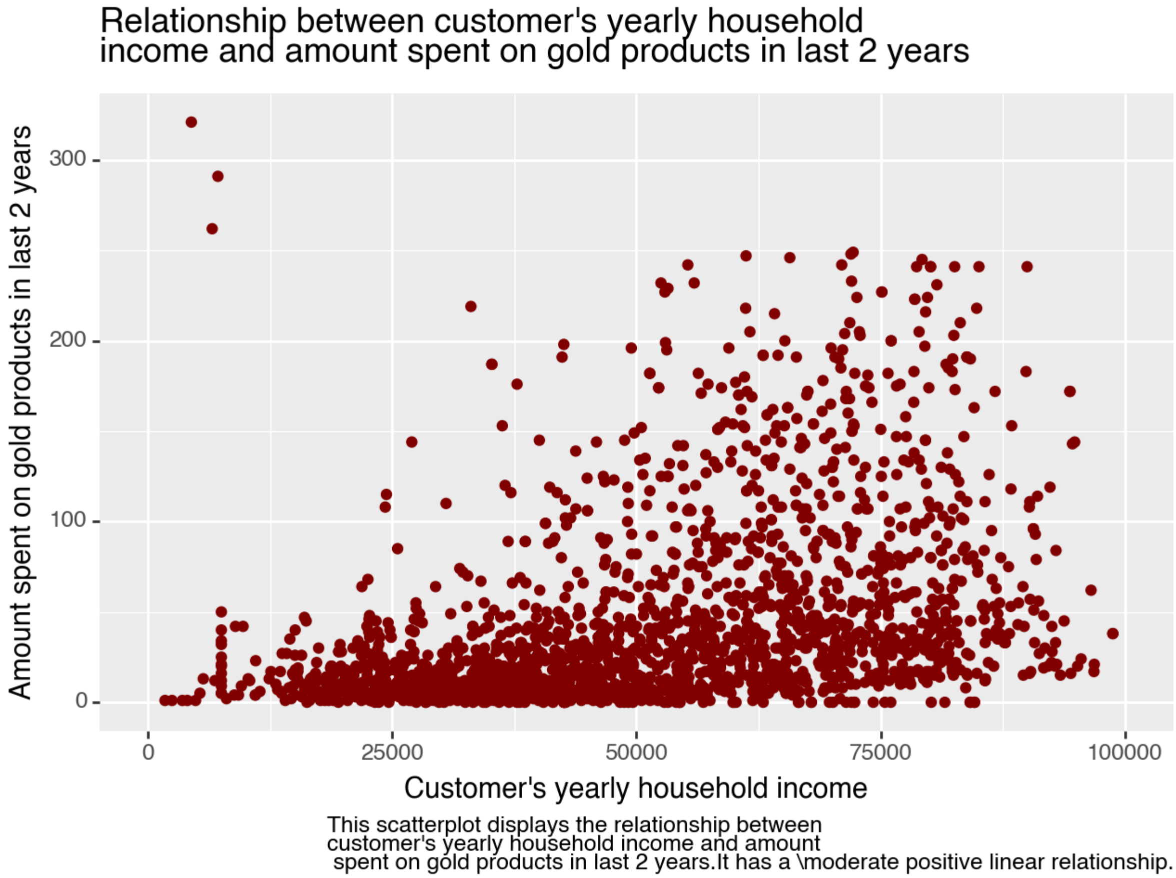
```
/opt/homebrew/lib/python3.9/site-packages/plotnine/layer.py:364: PlotnineWarning: geom_point
```




```
<Figure Size: (640 x 480)>
```

```
# create scatterplots
(p9.ggplot(df, p9.aes(x = 'Income', y = 'MntGoldProds'))  +
 p9.geom_point(color = 'maroon') +
 p9.xlim(0,100000) +
 p9.labs(x = "Customer's yearly household income", y = "Amount spent on gold products in l
        title= "Relationship between customer's yearly household \nincome and amount spent
          caption = "This scatterplot displays the relationship between \ncustomer's yearl
          + "It has a \moderate positive linear relationship."))
```

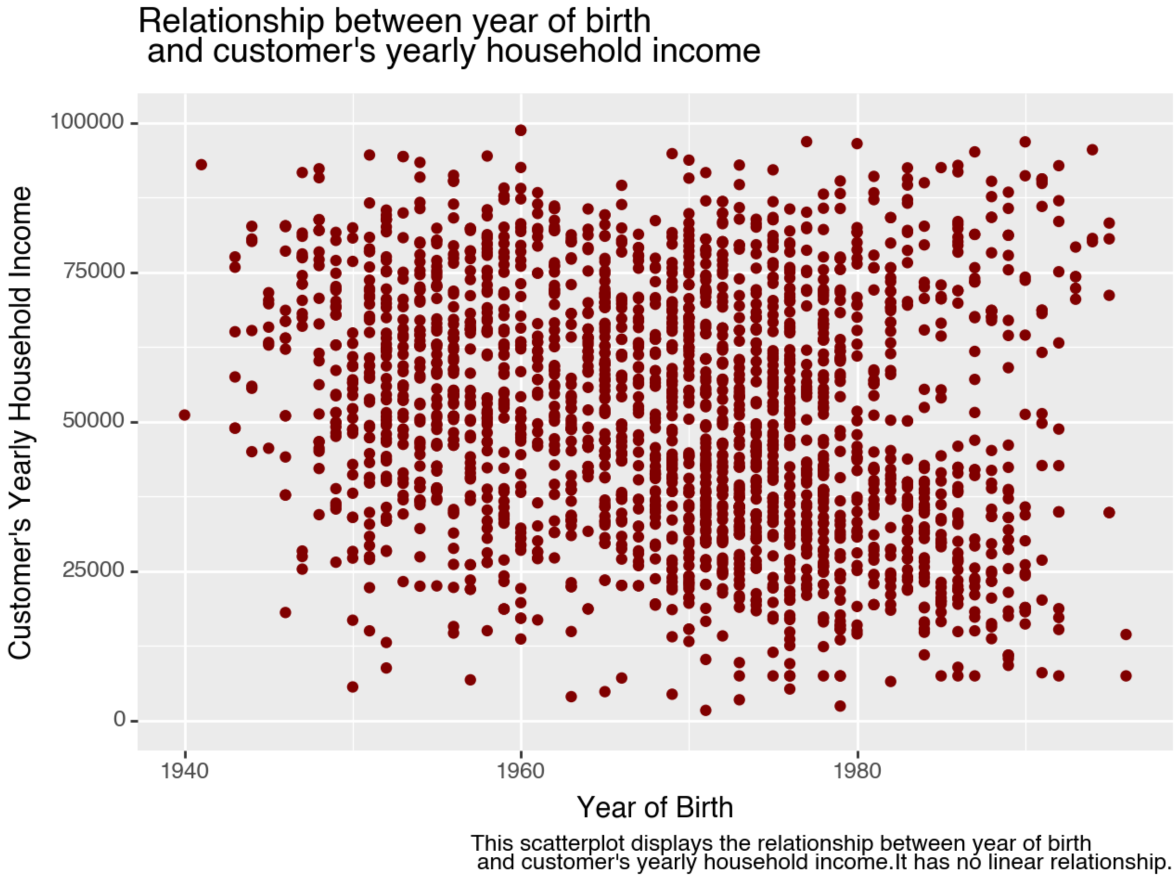
```
/opt/homebrew/lib/python3.9/site-packages/plotnine/layer.py:364: PlotnineWarning: geom_point
```




```
<Figure Size: (640 x 480)>
```

```
# create scatterplots
(p9.ggplot(df, p9.aes(x = 'Year_Birth', y = 'Income'))  +
 p9.geom_point(color = 'maroon') +
 p9.ylim(0,100000) +
 p9.labs(x = "Year of Birth", y = "Customer's Yearly Household Income",
        title= "Relationship between year of birth\n and customer's yearly household incom
          caption = "This scatterplot displays the relationship between year of birth\n an
          + "It has no linear relationship."))
```

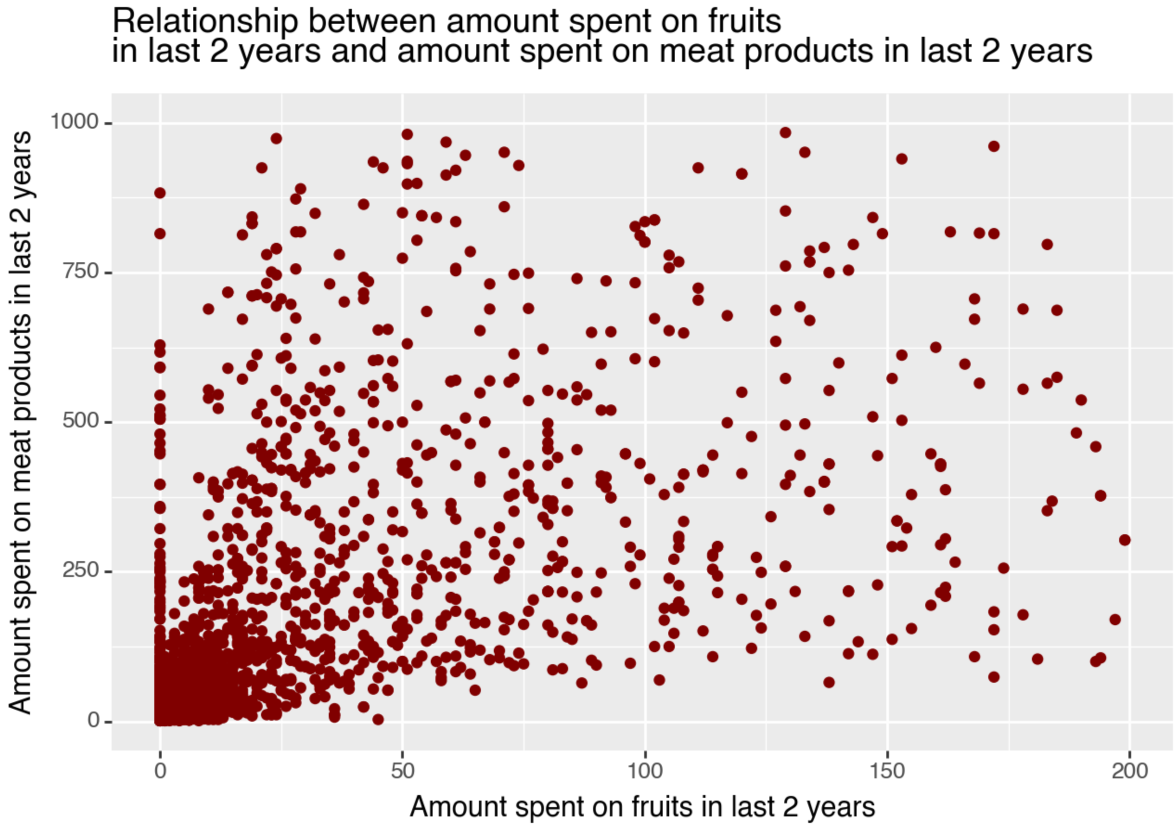
```
/opt/homebrew/lib/python3.9/site-packages/plotnine/layer.py:364: PlotnineWarning: geom_point
```




```
<Figure Size: (640 x 480)>
```

```
# create scatterplots
(p9.ggplot(df, p9.aes(x = 'MntFruits', y = 'MntMeatProducts'))  +
 p9.geom_point(color = 'maroon') +
 p9.ylim(1,1000) +
 p9.labs(x = "Amount spent on fruits in last 2 years", y = "Amount spent on meat products 
        title= "Relationship between amount spent on fruits \nin last 2 years and amount s
          caption = "This scatterplot displays the relationship between amount spent on fr
          + "It has no linear relationship."))
```

```
/opt/homebrew/lib/python3.9/site-packages/plotnine/layer.py:364: PlotnineWarning: geom_point
```



This scatterplot displays the relationship between amount spent on fruits
in last 2 years and amount spent on meat products in last 2 years.It has no linear relationship.

```
<Figure Size: (640 x 480)>
```

```
data = pd.get_dummies(df, columns=['Education','Marital_Status'],drop_first = True)
data.head(5)

#remove date because it is string
# Acceted Last Campaign is our response
df = data.drop(['Dt_Customer'], axis = 1)
df.corr()
```

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFru
Year_Birth	1.000000	-0.163295	0.237738	-0.362112	-0.015971	-0.164843	-0.0135
Income	-0.163295	1.000000	-0.428231	0.019285	-0.003111	0.578481	0.43024
Kidhome	0.237738	-0.428231	1.000000	-0.039485	0.010196	-0.497407	-0.3733
Teenhome	-0.362112	0.019285	-0.039485	1.000000	0.014764	0.004312	-0.1757

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFru
Recency	-0.015971	-0.003111	0.010196	0.014764	1.000000	0.016332	-0.0051
MntWines	-0.164843	0.578481	-0.497407	0.004312	0.016332	1.000000	0.38589
MntFruits	-0.013542	0.430248	-0.373305	-0.175736	-0.005129	0.385892	1.00000
MntMeatProducts	-0.033823	0.584361	-0.439192	-0.260778	0.023177	0.568189	0.54676
MntFishProducts	-0.041316	0.438523	-0.388777	-0.204954	0.001007	0.397035	0.59306
MntSweetProducts	-0.021710	0.440532	-0.378014	-0.162794	0.025495	0.389731	0.57149
MntGoldProds	-0.059960	0.325073	-0.355095	-0.018315	0.018394	0.391604	0.39350
NumDealsPurchases	-0.065866	-0.082874	0.216913	0.386298	0.002236	0.008769	-0.1342
NumWebPurchases	-0.162366	0.388183	-0.372410	0.162368	-0.005518	0.553704	0.30234
NumCatalogPurchases	-0.126012	0.589090	-0.504706	-0.112207	0.024423	0.634306	0.48564
NumStorePurchases	-0.139229	0.530120	-0.502062	0.049556	-0.000109	0.640343	0.45990
NumWebVisitsMonth	0.120355	-0.552736	0.447273	0.130839	-0.019075	-0.321666	-0.4177
AcceptedCmp3	0.061001	-0.016063	0.015999	-0.042669	-0.032240	0.061460	0.01468
AcceptedCmp4	-0.070114	0.184615	-0.162201	0.038279	0.017631	0.373389	0.00663
AcceptedCmp5	0.018936	0.335032	-0.204660	-0.189961	0.000347	0.472909	0.20902
AcceptedCmp1	-0.012021	0.277071	-0.174339	-0.145058	-0.021036	0.351647	0.19244
AcceptedCmp2	-0.007857	0.087635	-0.081946	-0.015580	-0.001382	0.206319	-0.0099
Complain	-0.004631	-0.024902	0.037013	0.007784	0.005750	-0.036376	-0.0029
AcceptedLastCmp	0.020803	0.133302	-0.078076	-0.154189	-0.199899	0.246434	0.12305
Education_Basic	0.115537	-0.200604	0.055294	-0.120058	-0.003078	-0.139712	-0.0605
Education_Graduation	0.061987	0.019384	-0.002017	-0.025420	0.030405	-0.060141	0.11519
Education_Master	-0.074821	0.012022	0.012915	0.023358	-0.025955	0.036672	-0.0553
Education_PhD	-0.123004	0.080526	-0.043152	0.093275	-0.007680	0.158160	-0.0852
Marital_Status_Alone	0.012859	-0.012364	0.038300	0.010903	-0.023778	-0.013164	-0.0207
Marital_Status_Divorced	-0.068717	0.009056	-0.019509	0.054853	0.003127	0.021292	0.01027
Marital_Status_Married	0.044240	-0.016157	0.017733	0.007943	-0.019158	-0.012490	-0.0135
Marital_Status_Single	0.125229	-0.026008	0.015005	-0.100826	0.004444	-0.020356	0.01300
Marital_Status_Together	-0.053004	0.022422	0.010024	0.026119	0.020533	0.004322	-0.0153
Marital_Status_Widow	-0.163701	0.031801	-0.072045	0.048207	-0.001336	0.034659	0.02631
Marital_Status_YOLO	0.010497	-0.004546	-0.024759	0.027325	-0.047821	0.001502	-0.0176

Project D

LASSO Classification

```
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
import sklearn
from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.model_selection import train_test_split

#standardize data
X = df.drop(['AcceptedLastCmp'], axis = 1)
y = data['AcceptedLastCmp']


scaler = StandardScaler()
scaler.fit(X)
X_pp = pd.DataFrame(scaler.transform(X), columns =['Year_Birth', 'Income', 'Kidhome', 'Tee
       'MntFruits', 'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Education_Basic', 'Education_Graduation',
       'Education_Master', 'Education_PhD', 'Marital_Status_Alone',
       'Marital_Status_Divorced', 'Marital_Status_Married',
       'Marital_Status_Single', 'Marital_Status_Together',
       'Marital_Status_Widow', 'Marital_Status_YOLO'])
```

```python
from sklearn.linear_model import RidgeClassifierCV

#fit ridge classification
coefs_ridge = pd.DataFrame(data = None, columns = ['Year_Birth', 'Income', 'Kidhome', 'Tee
       'MntFruits', 'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Education_Basic', 'Education_Graduation',
       'Education_Master', 'Education_PhD', 'Marital_Status_Alone',
       'Marital_Status_Divorced', 'Marital_Status_Married',
       'Marital_Status_Single', 'Marital_Status_Together',
       'Marital_Status_Widow', 'Marital_Status_YOLO'])

alphas = np.arange(-2, 8, 0.1)
alphas = np.power(10, alphas)


model_ridge = RidgeClassifierCV(alphas = alphas).fit(X_pp, y)
print("alpha: ", model_ridge.alpha_)
```

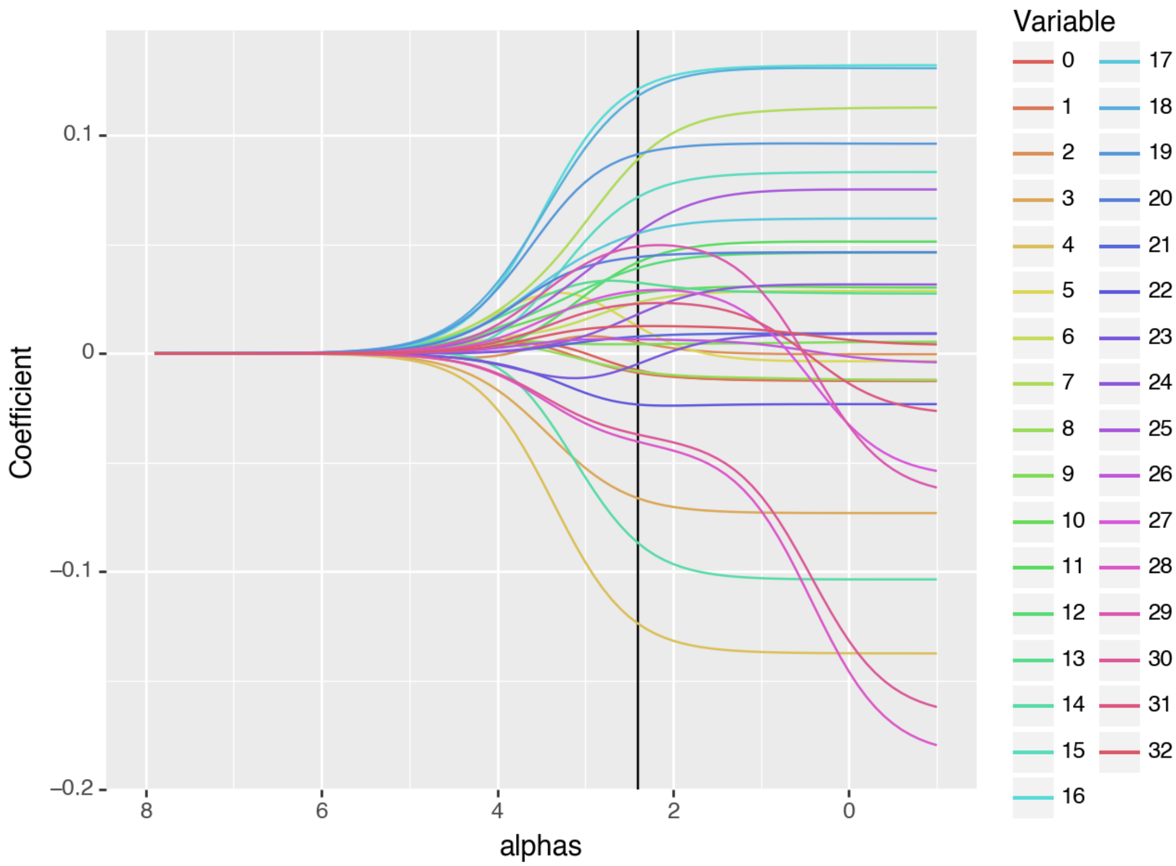
```
print("Coefficents: ", model_ridge.coef_)
print("Based on cross-validation, alpha=", model_ridge.alpha_, "is the best")
```

```
alpha:  251.18864315096027
Coefficents:  [[-0.00766182 -0.00891105  0.00506828 -0.0664298  -0.12389496  0.01231712
   0.02337978  0.08906701 -0.00817197  0.00423442  0.02747556  0.04179369
   0.03916608  0.03244353 -0.08691125  0.07172633  0.12124407  0.055037
   0.11811865  0.09137715  0.04421128  0.00775704 -0.02346739 -0.00482688
   0.01795495  0.05553376  0.00649319  0.02868643 -0.04048278  0.04903153
  -0.03719046  0.02278394  0.01250525]]
Based on cross-validation, alpha= 251.18864315096027 is the best
```

```
from sklearn.linear_model import RidgeClassifier

#fit ridge at best alpha
bestRidge = RidgeClassifier(alpha = model_ridge.alpha_).fit(X_pp, y)
```

```
#graph ridge classification
import math

coefs_ridge = pd.DataFrame()

for i in range(0, len(alphas)):
    temp_model = RidgeClassifierCV(alphas = alphas[i]).fit(X_pp, y)
    coefs_ridge = pd.concat([coefs_ridge, pd.Series(temp_model.coef_[0]).to_frame().T], ig


coefs_ridge['alphas'] = np.log10(alphas)
coefs_ridge_melt = pd.melt(coefs_ridge, id_vars = 'alphas',var_name = 'Variable', value_na

(p9.ggplot(coefs_ridge_melt, p9.aes(x = 'alphas', y = 'Coefficient', color = 'Variable'))
  p9.geom_line() + p9.xlim(8, -1))
```

```
/opt/homebrew/lib/python3.9/site-packages/plotnine/geoms/geom_path.py:98: PlotnineWarning: g
```



<Figure Size: (640 x 480)>

```
from sklearn.linear_model import LogisticRegressionCV
from sklearn.linear_model import LogisticRegression



#fit LASSO

coefs_lasso = pd.DataFrame(data = None, columns = ['Year_Birth', 'Income', 'Kidhome', 'Tee
        'MntFruits', 'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
        'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
        'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
        'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
        'AcceptedCmp2', 'Complain', 'Education_Basic', 'Education_Graduation',
        'Education_Master', 'Education_PhD', 'Marital_Status_Alone',
```

```
        'Marital_Status_Divorced', 'Marital_Status_Married',
        'Marital_Status_Single', 'Marital_Status_Together',
        'Marital_Status_Widow', 'Marital_Status_YOLO'])

alphas = np.arange(-3, 0.3, 0.1)
alphas = np.power(10, alphas)

Lassocvmodel = LogisticRegressionCV(penalty = 'l1', solver = 'liblinear', Cs=alphas)
Lassocvmodel = Lassocvmodel.fit(X_pp, y)
print("Based on cross validation,")
print("The best alpha is")
print(Lassocvmodel.C_)
print("The coefficients are")
```

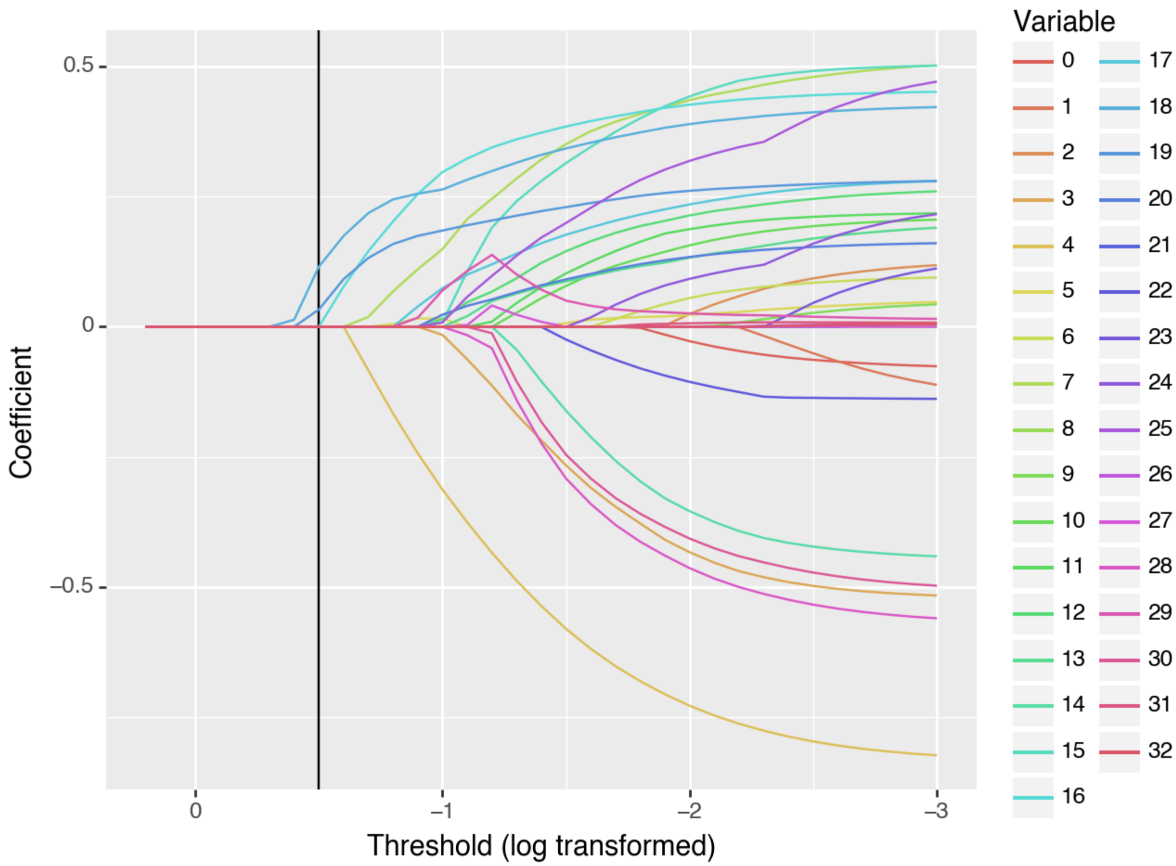
```
Based on cross validation,
The best alpha is
[0.31622777]
The coefficients are
```

```
#fit best lasso
bestLasso = LogisticRegression(penalty = 'l1', solver = 'liblinear', C=Lassocvmodel.C_[0])
bestLasso = bestLasso.fit(X_pp, y)
bestLasso.coef_
```

```
array([[-0.0537513 , -0.01757567,  0.07293286, -0.48108146, -0.77587533,
         0.03248612,  0.07678184,  0.46495109,  0.        ,  0.01461655,
         0.18309188,  0.20533359,  0.23521451,  0.15547739, -0.40569267,
         0.48058019,  0.43951778,  0.25667642,  0.40485997,  0.2696717 ,
         0.14775686,  0.        , -0.13433533,  0.        ,  0.11921204,
         0.35529035,  0.00197923,  0.        , -0.51313461,  0.02207345,
        -0.45261997,  0.0086923 ,  0.00093212]])
```

```
#create LASSO coefficient plots
from sklearn.linear_model import Lasso

coefs_lasso = pd.DataFrame()


for threshold in alphas:
  model = LogisticRegression(penalty = 'l1', solver = 'liblinear', C=threshold)
```

```
  tempmodel = model.fit(X_pp, y)
  coefs_lasso = pd.concat([coefs_lasso, pd.Series(tempmodel.coef_[0]).to_frame().T], ignor



low_lasso_plt = coefs_lasso

#create LASSO coefficient plotslow_lasso_plt = coefs_lasso
#low_lasso_plt.rename(columns={0:'Year_Birth', 1:'Income', 2:'Kidhome', 3:'Teenhome', 4:'R
#       6:'MntFruits', 7:'MntMeatProducts', 8:'MntFishProducts', 9:'MntSweetProducts',
#       10:'MntGoldProds', 11:'NumDealsPurchases', 12:'NumWebPurchases',
#       13:'NumCatalogPurchases', 14:'NumStorePurchases', 15:'NumWebVisitsMonth',
#       16:'AcceptedCmp3', 17:'AcceptedCmp4', 18:'AcceptedCmp5', 19:'AcceptedCmp1',
#       20:'AcceptedCmp2', 21:'Complain', 22:'Education_Basic', 23:'Education_Graduation',
#       24:'Education_Master', 25:'Education_PhD', 26:'Marital_Status_Alone',
#       27:'Marital_Status_Divorced', 28:'Marital_Status_Married',
#       29:'Marital_Status_Single', 30:'Marital_Status_Together',
#       31:'Marital_Status_Widow', 32:'Marital_Status_YOLO'}, inplace = True)


#low_lasso_plt['Threshold'] = alphas[::-1]
low_lasso_plt['Threshold'] = np.log10(alphas[::-1])

low_lasso_plt_melt = pd.melt(low_lasso_plt, id_vars = 'Threshold', var_name = 'Variable',

(p9.ggplot(low_lasso_plt_melt, p9.aes(x = 'Threshold', y = 'Coefficient', color = 'Variabl
  p9.labs(x = "Threshold (log transformed)") + p9.geom_line() + p9.scale_x_reverse())
```



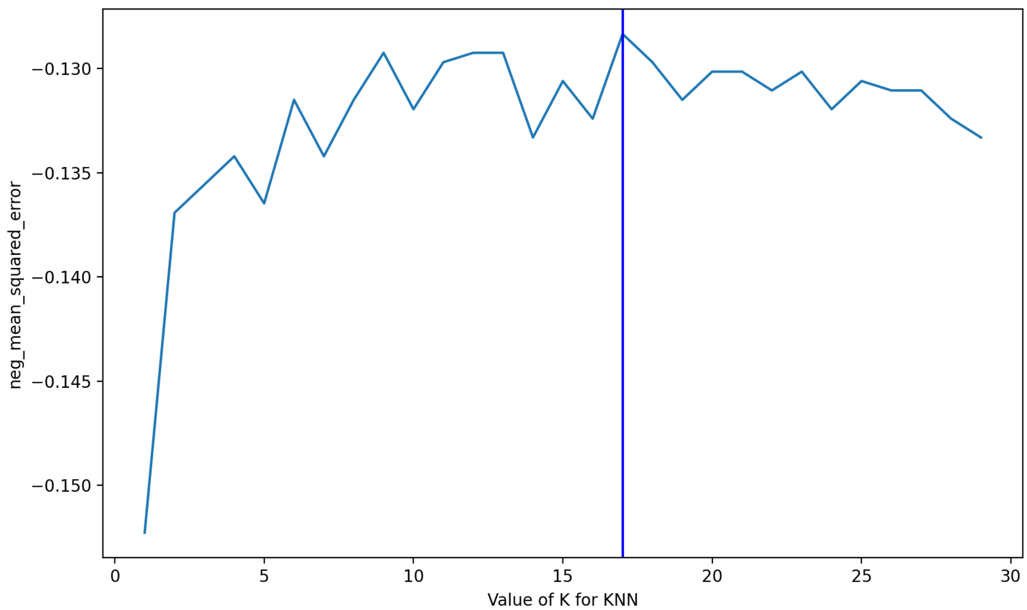
<Figure Size: (640 x 480)>

In LASSO model, whether consumers accepted the offer in the last campaign is depended on most factors in the dataset. There are four variables LASSO believes that are not important: MntFishProducts, Complain, Education_Graduation, and Marital_Status_Divorced.

The most significant variable in LASSO is recency (Number of days since customer's last purchase)

KNN Classification

```python
#perform KNN Classification

from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import LeaveOneOut

cv = LeaveOneOut()

k_range = range(1, 30)
k_scores = []

for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_pp, y, cv=cv, scoring='neg_mean_squared_error')
    k_scores.append(scores.mean())

plt.figure(figsize=(10,6))

plt.plot(k_range, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('neg_mean_squared_error')
plt.axvline(x = 17, color = 'b')
plt.show()
print("Using LeaveOneOut, k=17 is the best")
```




```
Using LeaveOneOut, k=17 is the best
```

```
#fit knn at best alpha
knnModel = KNeighborsClassifier(n_neighbors=17)
```

```
from sklearn.linear_model import LinearRegression

#modelLinear = LinearRegression().fit(X[['CRBI', 'Walks', 'Division_W', 'Hits', 'CRuns', '
#linearScores = cross_val_score(modelLinear, df1[['CRBI', 'Walks', 'Division_W', 'Hits', '
#meanLinear = np.mean(linearScores)
#print("For linear regression, the neg mean absolute error is")
#print(meanLinear)

ridgeScores = cross_val_score(bestRidge, X_pp, y, scoring='neg_mean_absolute_error',cv=cv)
meanRidge = np.mean(ridgeScores)
print("For ridge regression, the neg absolute error is")
print(meanRidge)


lassoScores = cross_val_score(bestLasso, X_pp, y, scoring='neg_mean_absolute_error',cv=cv)
```

```
meanLASSO = np.mean(lassoScores)
print("For LASSO, the neg mean absolute error is")
print(meanLASSO)


knnScore = cross_val_score(knnModel, X_pp, y, scoring='neg_mean_absolute_error',cv=cv)
meanKNN = np.mean(knnScore)
print("For kNN, the neg mean absolute error is")
print(meanKNN)
```

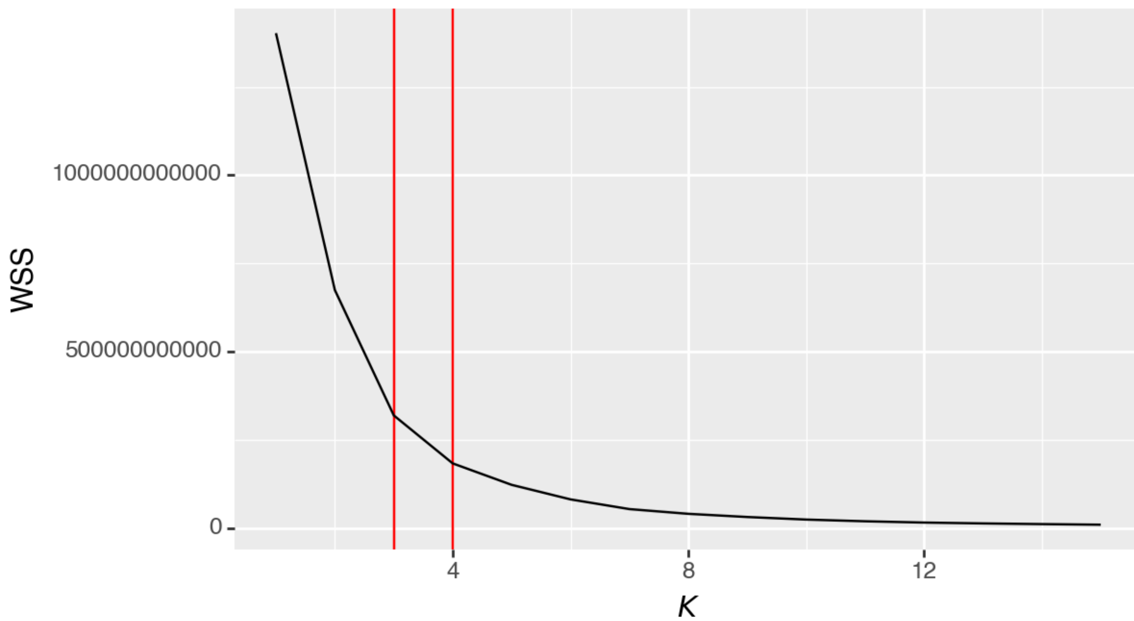
```
For ridge regression, the neg absolute error is
-0.12065070040668775
For LASSO, the neg mean absolute error is
-0.11296882060551287
For kNN, the neg mean absolute error is
-0.12833258020786262
```

The mean_absolute_error function computes mean absolute error, a risk metric corresponding to the expected value of the absolute error loss or l1-norm loss. Among ridge, LASSO, and KNN models, the the neg mean absolute error is actually pretty similar. However, LASSO model is a little bit better because its mean neg mean absolute error is closest to 0 compared to others. Thus, I would recommend the LASSO model

Clustering

```
#perform k-means clustering
from sklearn.cluster import KMeans

inertias = []

for i in range(1,16):
    kmeans = KMeans(n_clusters=i, n_init = 20)
    kmeans.fit(df)
    inertias.append(kmeans.inertia_)


chooseK = {'K': range(1, 16), 'Inertia': inertias}
chooseK_df = pd.DataFrame(data = chooseK)
```

```
#create elbow plot
print(p9.ggplot(chooseK_df, p9.aes(x = 'K', y = 'Inertia')) +
        p9.geom_vline(xintercept = 3, color = "red") +
       p9.geom_vline(xintercept = 4, color = "red") +
       p9.geom_line() +
       p9.scale_x_continuous(name = "$K$") +
       p9.scale_y_continuous(name = "WSS") +
       p9.theme(legend_position = "none", figure_size = [6, 3.5]))
```




```
#select best k
print("Using the elbow method, the k = 4 is \nwhere WSS is small and first starts to dimin
n_cluster = 4

kmeans2 = KMeans(n_clusters= n_cluster, n_init = 20,random_state= 923)
clust_2 = kmeans2.fit(df)
```

```
Using the elbow method, the k = 4 is
where WSS is small and first starts to diminish.
```

```
cluster_1 = df[clust_2.labels_== 0.0]
cluster_1.describe()
```

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntM
count	742.000000	742.000000	742.000000	742.000000	742.000000	742.000000	742.000000	742.0
mean	1973.200809	28369.243935	0.808625	0.314016	48.521563	30.625337	5.985175	25.58
std	10.705547	8440.305747	0.477319	0.481555	28.687745	44.807458	11.808003	69.74
min	1946.000000	1730.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000
25%	1967.000000	22686.750000	1.000000	0.000000	24.000000	6.000000	1.000000	7.000
50%	1974.000000	30019.000000	1.000000	0.000000	49.000000	14.000000	3.000000	13.00
75%	1981.000000	35376.000000	1.000000	1.000000	74.750000	33.750000	6.000000	24.00
max	1996.000000	40344.000000	2.000000	2.000000	99.000000	284.000000	151.000000	1725.

```
cluster_2 = df[clust_2.labels_== 1.0]
cluster_2.describe()
```

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProduct
count	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
mean	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
min	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
25%	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
50%	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
75%	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
max	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0

```
cluster_3 = df[clust_2.labels_== 2.0]
cluster_3.describe()
```

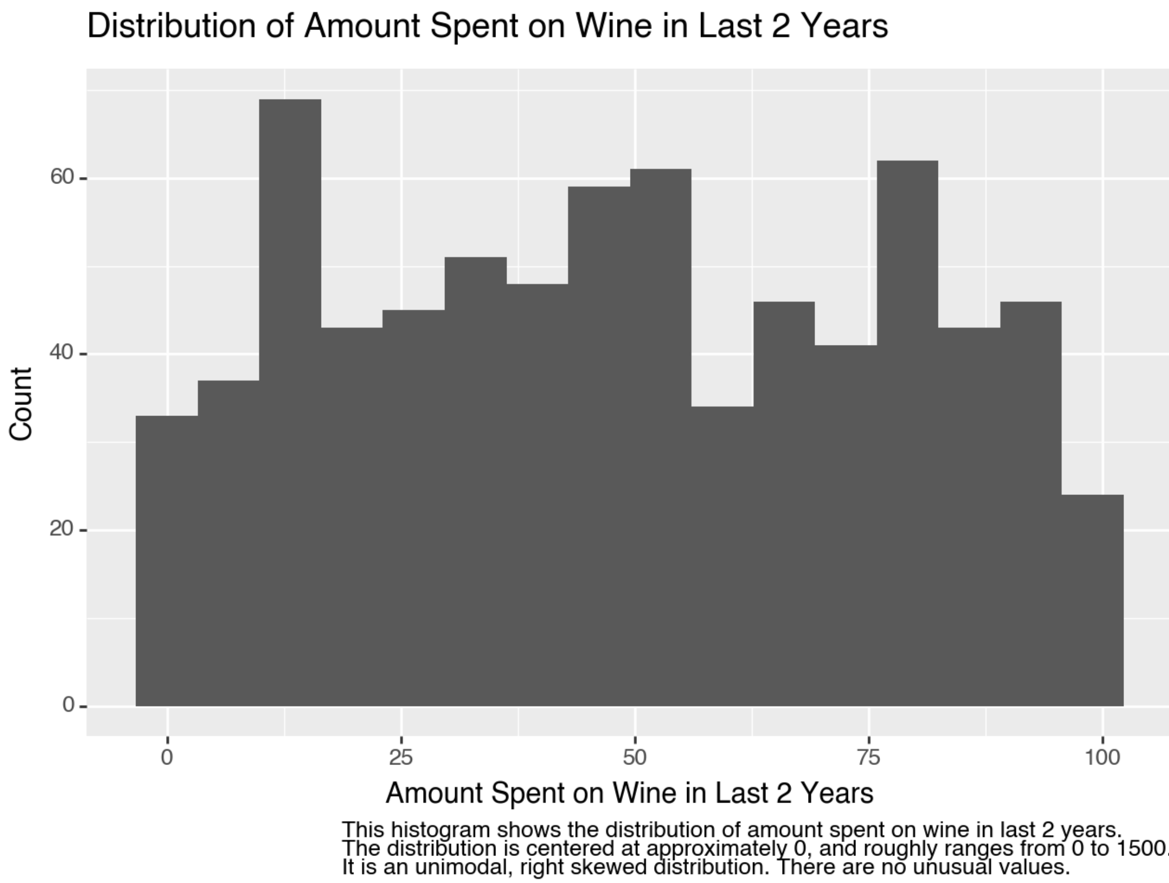
	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	Mn
count	686.000000	686.000000	686.000000	686.000000	686.000000	686.000000	686.000000	686
mean	1967.533528	76958.275510	0.086006	0.351312	49.036443	615.760933	56.724490	397
std	12.582152	11493.315693	0.285733	0.507367	29.600456	323.822784	48.220947	251
min	1941.000000	64713.000000	0.000000	0.000000	0.000000	1.000000	0.000000	1.0
25%	1957.000000	69756.000000	0.000000	0.000000	23.000000	372.000000	21.000000	196
50%	1968.000000	75299.000000	0.000000	0.000000	50.000000	562.500000	40.000000	363
75%	1976.000000	81375.250000	0.000000	1.000000	74.000000	829.000000	84.000000	549

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	Mn
max	1995.000000	162397.000000	2.000000	2.000000	99.000000	1493.000000	197.000000	172

```
cluster_4 = df[clust_2.labels_== 3.0]
cluster_4.describe()
```

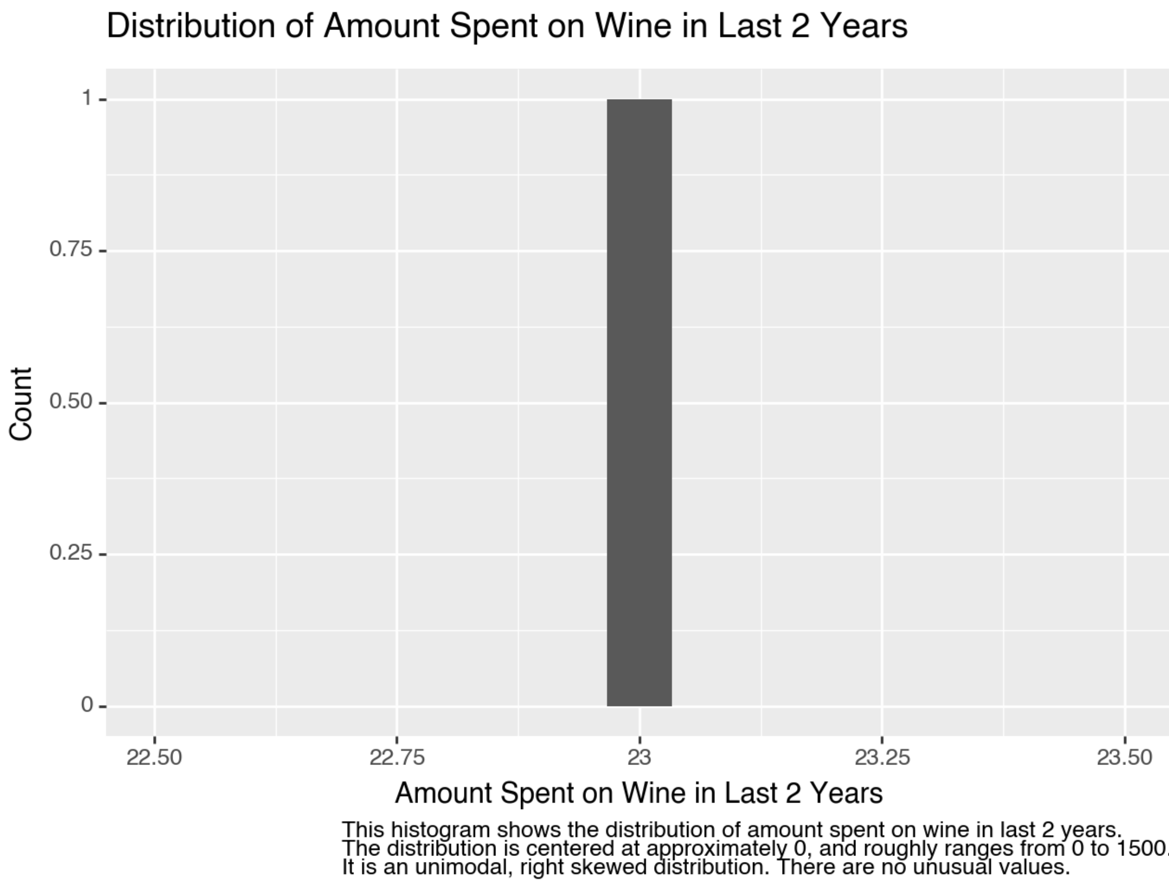
	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	Mnt
count	784.000000	784.000000	784.000000	784.000000	784.000000	784.000000	784.000000	784.
mean	1966.063776	52410.118622	0.405612	0.822704	49.475765	293.571429	18.988520	99.3
std	10.605356	7108.505354	0.536075	0.485230	28.629744	267.563659	32.227458	108.
min	1940.000000	40442.000000	0.000000	0.000000	0.000000	4.000000	0.000000	1.00
25%	1957.000000	46101.000000	0.000000	1.000000	25.000000	81.000000	1.000000	27.0
50%	1966.000000	52372.500000	0.000000	1.000000	51.000000	215.500000	6.500000	68.0
75%	1974.000000	58498.500000	1.000000	1.000000	73.250000	425.500000	20.000000	133.
max	1992.000000	64590.000000	2.000000	2.000000	99.000000	1459.000000	199.000000	818.

```
(p9.ggplot(df[clust_2.labels_== 0]) +
        p9.aes (x = 'Recency') +
        p9.geom_histogram(bins=16)+
        p9.labs(x = "Amount Spent on Wine in Last 2 Years", y = "Count",title= "Distributi
         caption = "This histogram shows the distribution of amount spent on wine in last
          "The distribution is centered at approximately 0, and roughly ranges from 0 to 1
          "It is an unimodal, right skewed distribution. There are no unusual values."))
```



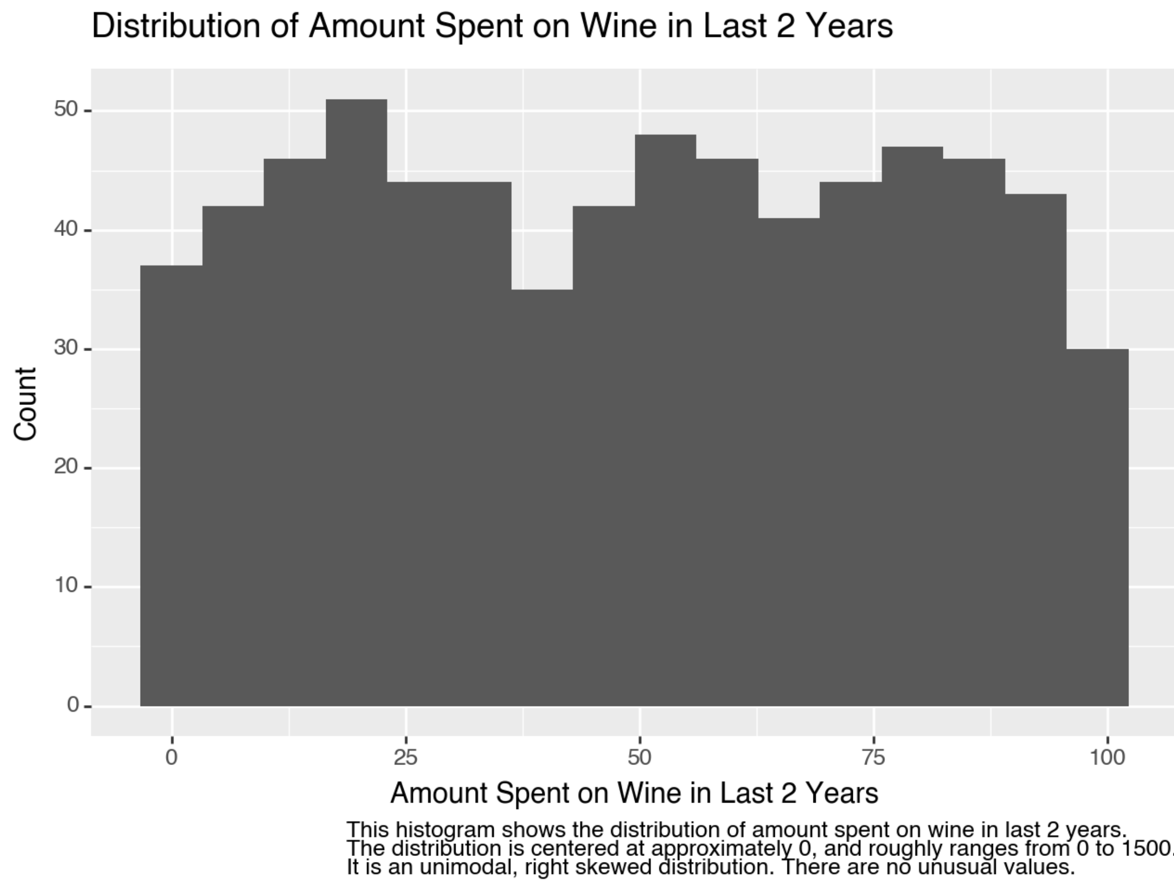
<Figure Size: (640 x 480)>

```
(p9.ggplot(df[clust_2.labels_== 1]) +
        p9.aes (x = 'Recency') +
        p9.geom_histogram(bins=16)+
        p9.labs(x = "Amount Spent on Wine in Last 2 Years", y = "Count",title= "Distributi
         caption = "This histogram shows the distribution of amount spent on wine in last
          "The distribution is centered at approximately 0, and roughly ranges from 0 to 1
          "It is an unimodal, right skewed distribution. There are no unusual values."))
```



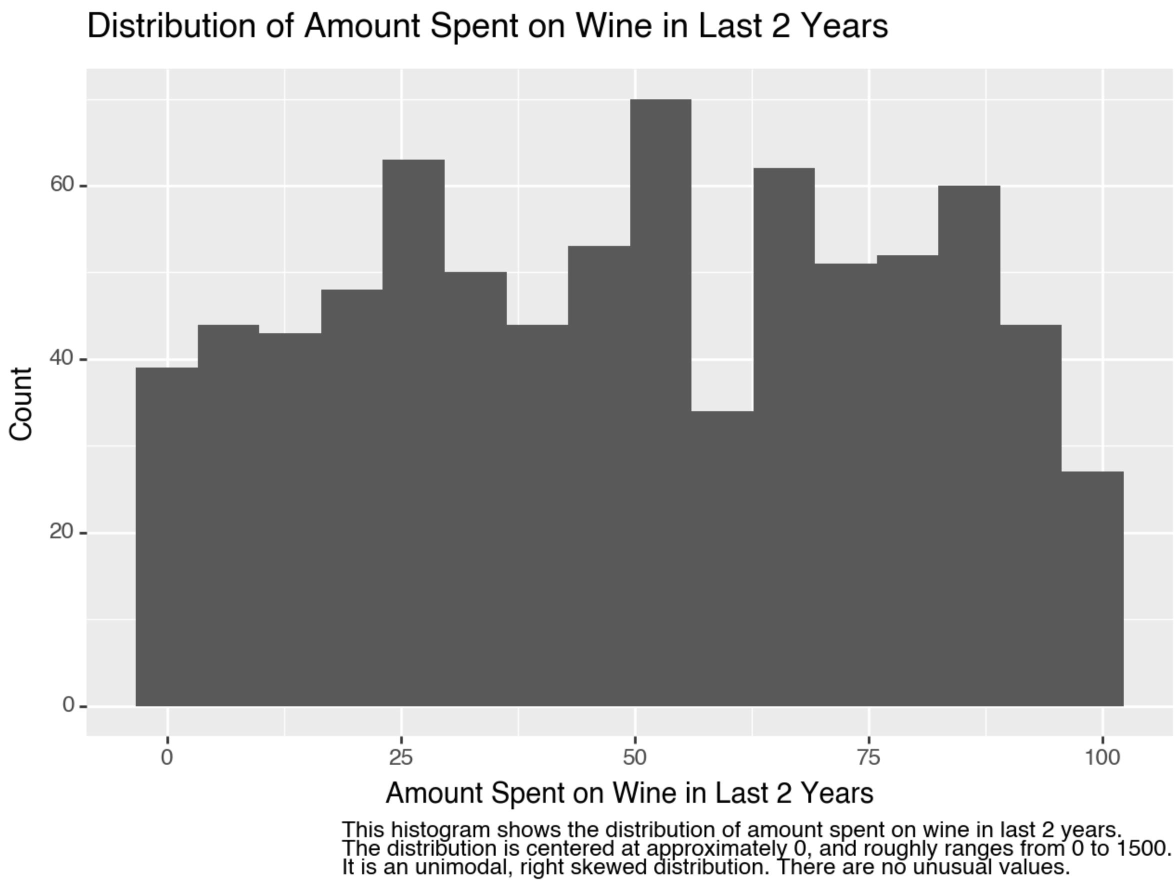

```
<Figure Size: (640 x 480)>
```

```
(p9.ggplot(df[clust_2.labels_== 2]) +
        p9.aes (x = 'Recency') +
        p9.geom_histogram(bins=16)+
        p9.labs(x = "Amount Spent on Wine in Last 2 Years", y = "Count",title= "Distributi
         caption = "This histogram shows the distribution of amount spent on wine in last
          "The distribution is centered at approximately 0, and roughly ranges from 0 to 1
          "It is an unimodal, right skewed distribution. There are no unusual values."))
```




```
<Figure Size: (640 x 480)>
```

```
(p9.ggplot(df[clust_2.labels_== 3]) +
        p9.aes (x = 'Recency') +
        p9.geom_histogram(bins=16)+
        p9.labs(x = "Amount Spent on Wine in Last 2 Years", y = "Count",title= "Distributi
         caption = "This histogram shows the distribution of amount spent on wine in last
          "The distribution is centered at approximately 0, and roughly ranges from 0 to 1
          "It is an unimodal, right skewed distribution. There are no unusual values."))
```




```
<Figure Size: (640 x 480)>
```

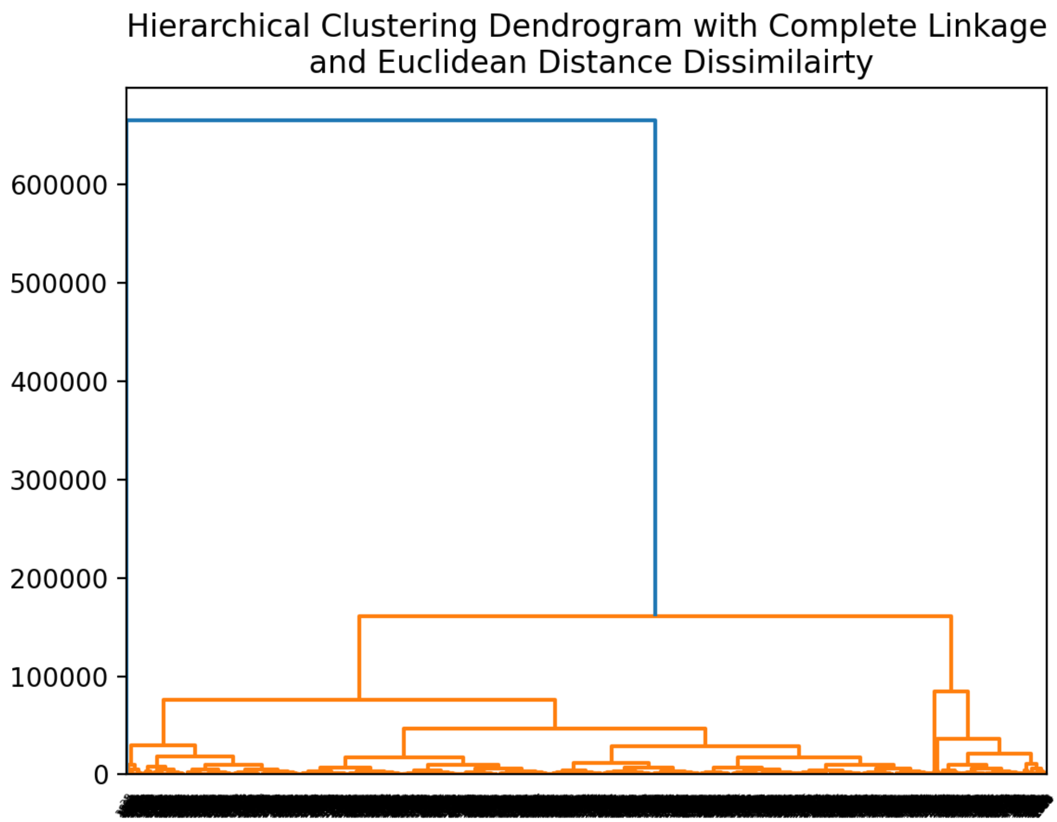
Hierarchical Clustering

```
#perform hierarchical clustering analysis
from sklearn.cluster import AgglomerativeClustering
from matplotlib import pyplot as plt
from scipy.cluster.hierarchy import dendrogram

#first hierarchical clustering analysis,
#Euclidean distance with complete linkage
clust_3 = AgglomerativeClustering(distance_threshold = 0, n_clusters = None, linkage = 'co
```

```
def plot_dendrogram(model, **kwargs):
    # Create linkage matrix and then plot the dendrogram
```

```
    # create the counts of samples under each node
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack(
        [model.children_, model.distances_, counts]
    ).astype(float)
    # Plot the corresponding dendrogram
    dendrogram(linkage_matrix, **kwargs,leaf_rotation=50, leaf_font_size = 4)
```

```
# PLOT for first dendrogram
plot_dendrogram(clust_3, truncate_mode = "level", p = 53,
                labels = df.index)
plt.title("Hierarchical Clustering Dendrogram with Complete Linkage\n and Euclidean Distan
plt.xlabel("")

plt.show()
```




```
print("I will use the value of K from k-means clustering to cut the dendrograms.")
print()
clust_3a = AgglomerativeClustering(n_clusters = 4, linkage = 'complete').fit(df)
```

```
I will use the value of K from k-means clustering to cut the dendrograms.
```

```
hcluster_1 = df[clust_3a.labels_== 0]
hcluster_1.describe()
```

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits
count	1940.000000	1940.000000	1940.000000	1940.000000	1940.000000	1940.000000	1940.000000
mean	1968.996907	47148.914433	0.495361	0.556186	48.978351	255.289175	20.872680
std	11.462070	17798.797025	0.545486	0.544500	28.874246	303.185788	34.194387

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits
min	1940.000000	1730.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1960.000000	33451.500000	0.000000	0.000000	24.000000	19.000000	1.000000
50%	1970.000000	46927.000000	0.000000	1.000000	49.000000	123.000000	6.000000
75%	1977.000000	62585.250000	1.000000	1.000000	74.000000	407.000000	23.000000
max	1996.000000	77870.000000	2.000000	2.000000	99.000000	1462.000000	199.000000

```
hcluster_2 = df[clust_3a.labels_== 1]
hcluster_2.describe()
```

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeat
count	7.000000	7.000000	7.000000	7.000000	7.000000	7.000000	7.000000	7.000000
mean	1971.857143	158024.285714	0.285714	0.285714	52.285714	29.000000	3.142857	708.14285
std	10.652520	2778.833551	0.487950	0.487950	34.625204	32.377976	5.698789	875.52944
min	1949.000000	153924.000000	0.000000	0.000000	13.000000	1.000000	0.000000	1.000000
25%	1972.000000	157035.000000	0.000000	0.000000	26.000000	1.500000	1.000000	5.500000
50%	1975.000000	157243.000000	0.000000	0.000000	37.000000	20.000000	1.000000	16.000000
75%	1976.500000	159268.000000	0.500000	0.500000	83.000000	47.000000	1.500000	1602.0000
max	1982.000000	162397.000000	1.000000	1.000000	98.000000	85.000000	16.000000	1725.0000

```
hcluster_3 = df[clust_3a.labels_== 2]
hcluster_3.describe()
```

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	Mn
count	265.000000	265.000000	265.000000	265.000000	265.000000	265.000000	265.000000	265
mean	1968.226415	84369.150943	0.052830	0.143396	49.233962	678.611321	66.890566	504
std	13.360165	5613.342458	0.224118	0.382134	29.406599	342.799178	52.497541	244
min	1941.000000	77882.000000	0.000000	0.000000	0.000000	6.000000	0.000000	3.0
25%	1958.000000	80184.000000	0.000000	0.000000	23.000000	416.000000	24.000000	324
50%	1969.000000	82582.000000	0.000000	0.000000	51.000000	650.000000	50.000000	482
75%	1978.000000	86857.000000	0.000000	0.000000	73.000000	938.000000	102.000000	706
max	1995.000000	113734.000000	1.000000	2.000000	99.000000	1493.000000	197.000000	984

```
hcluster_4 = df[clust_3a.labels_== 3]
hcluster_4.describe()
```

	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProduct
count	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
mean	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
min	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
25%	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
50%	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
75%	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0
max	1977.0	666666.0	1.0	0.0	23.0	9.0	14.0	18.0