Data Wrangling – Predicting Catalog Demand

by Travis Gillespie

Table of Contents

Introduction

This file contains the code used to gather, assess, clean, analyze, and visualize the data used to write up my report.

Gathering Data

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
# %matplotlib inline
# import requests
# import tweepy
# import json
# import time
# import sys
# import re
# from datetime import datetime, timedelta
```

In [2]:
```
# p1-customers.xlsx - This dataset includes the following information on abo
df_customers_original = pd.read_excel("./assets/data/p1-customers.xlsx")

# p1-mailinglist.xlsx - This dataset is the 250 customers that you need to p
    # Score_No: The probability that the customer WILL NOT respond to the ca
    # Score_Yes: The probability that the customer WILL respond to the catal
df_mailingList_original = pd.read_excel("./assets/data/p1-mailinglist.xlsx")
```

In [3]:
```
df_customers = df_customers_original.copy()
df_mailingList = df_mailingList_original.copy()
```

Assessing Data

Quality

As noted in the project details, the data provided is clean and does not require preparation. Therefore there are not any records that need to be reomved or data types that need to be modified; as shown using the *.info()* function.

In [4]:
```
df_customers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2375 entries, 0 to 2374
Data columns (total 12 columns):
Name                         2375 non-null object
Customer_Segment             2375 non-null object
Customer_ID                  2375 non-null int64
Address                      2375 non-null object
City                         2375 non-null object
State                        2375 non-null object
ZIP                          2375 non-null int64
Avg_Sale_Amount              2375 non-null float64
Store_Number                 2375 non-null int64
Responded_to_Last_Catalog    2375 non-null object
Avg_Num_Products_Purchased   2375 non-null int64
#_Years_as_Customer          2375 non-null int64
dtypes: float64(1), int64(5), object(6)
memory usage: 222.7+ KB
```

In [5]:
```
df_mailingList.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 12 columns):
Name                            250 non-null object
Customer_Segment                250 non-null object
Customer_ID                     250 non-null int64
Address                         250 non-null object
City                            250 non-null object
State                           250 non-null object
ZIP                             250 non-null int64
Store_Number                    250 non-null int64
Avg_Num_Products_Purchased      250 non-null int64
#_Years_as_Customer             250 non-null float64
Score_No                        250 non-null float64
Score_Yes                       250 non-null float64
dtypes: float64(3), int64(4), object(5)
memory usage: 23.5+ KB
```

In [6]:
```
df_customers.head(3)
```

Out[6]:

	Name	Customer_Segment	Customer_ID	Address	City	State	ZIP	Avg_Sale_Amount
0	Pamela Wright	Store Mailing List	2	376 S Jasmine St	Denver	CO	80224	227.90
1	Danell Valdez	Store Mailing List	7	12066 E Lake Cir	Greenwood Village	CO	80111	55.00
2	Jessica Rinehart	Store Mailing List	8	7225 S Gaylord St	Centennial	CO	80122	212.57

In [7]:
```
df_mailingList.head(3)
```

Out[7]:

	Name	Customer_Segment	Customer_ID	Address	City	State	ZIP	Store_Number	A
0	A Giametti	Loyalty Club Only	2213	5326 S Lisbon Way	Centennial	CO	80015	105	
1	Abby Pierson	Loyalty Club and Credit Card	2785	4344 W Roanoke Pl	Denver	CO	80236	101	
2	Adele Hallman	Loyalty Club Only	2931	5219 S Delaware St	Englewood	CO	80110	101	

In [8]:
```
list(df_customers.columns.values)

# Customer_Segment
# Customer_ID
# Responded_to_Last_Catalog
# Avg_Sale_Amount
# Avg_Num_Products_Purchased
# _Years_as_Customer
# Store_Number
```

Out[8]:
```
['Name',
 'Customer_Segment',
 'Customer_ID',
 'Address',
 'City',
 'State',
 'ZIP',
 'Avg_Sale_Amount',
 'Store_Number',
 'Responded_to_Last_Catalog',
 'Avg_Num_Products_Purchased',
 '#_Years_as_Customer']
```

In [9]:
```
list(df_mailingList.columns.values)
```

Out[9]:
```
['Name',
 'Customer_Segment',
 'Customer_ID',
 'Address',
 'City',
 'State',
 'ZIP',
 'Store_Number',
 'Avg_Num_Products_Purchased',
 '#_Years_as_Customer',
 'Score_No',
 'Score_Yes']
```

In [10]:
```
# df_joined = df_customers.merge(df_mailingList, suffixes=['_Customers', '_
# scorecard_joined = scorecard_joined.merge(df_gainsight_activity_pivoted,
# df_joined.head()
```

Tidiness

Create dummy variables for Customer_Segment column

In [11]:
```
# dropping first column "Credit Card Only"... define that category will be
# customerSegment_dummies = pd.get_dummies(df_customers.Customer_Segment, p
# customerSegment_dummies.head(3)

df_customers_dummies = pd.get_dummies(df_customers, columns = ["Customer_Se

df_customers_dummies.rename(index=str, columns={"Customer_Segment_Loyalty C
                                                "Customer_Segment_Loyalty Club and Credit Car
                                                "Customer_Segment_Store Mailing List": "Custo

df_customers_dummies.head(3)
```

Out[11]:

	Name	Customer_ID	Address	City	State	ZIP	Avg_Sale_Amount	Store_Number	Res
0	Pamela Wright	2	376 S Jasmine St	Denver	CO	80224	227.90	100	
1	Danell Valdez	7	12066 E Lake Cir	Greenwood Village	CO	80111	55.00	105	
2	Jessica Rinehart	8	7225 S Gaylord St	Centennial	CO	80122	212.57	101	

In [12]:
```
_mailingList

ailingList_dummies = pd.get_dummies(df_mailingList, columns = ["Customer_Seg

ailingList_dummies.rename(index=str, columns={"Customer_Segment_Loyalty Club
                                        "Customer_Segment_Loyalty Club and Credit Card": "
                                        "Customer_Segment_Store Mailing List": "Customer_S
```

Cleaning Data

The datasets provided for this project were already clean. No further cleanup was required.

Analyzing, and Visualizing Data

Insight One: Correlation

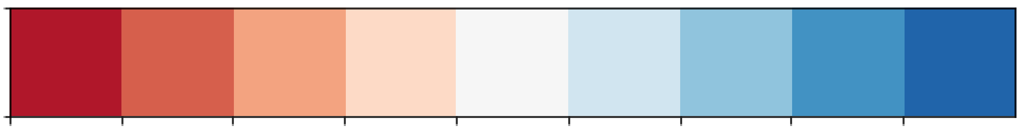
In [13]:
```
# COLORMAPS

# use cmap to set the chart colors
cmap = sns.choose_colorbrewer_palette(data_type = "d") # set data_type to d
```

name RdBu

n 9

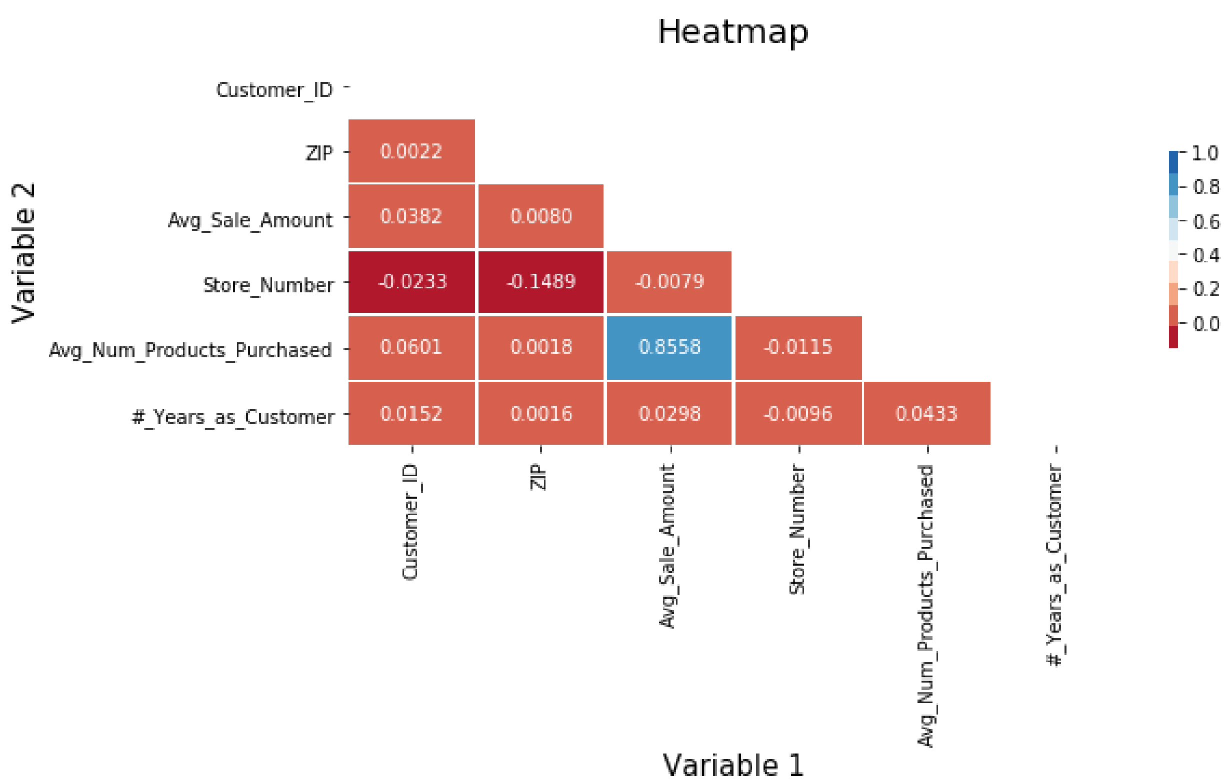
desat 1.00

variant regular



In [14]:
```
# sns.regplot(x="Avg_Num_Products_Purchased", y="Avg_Sale_Amount", data=df_

# deleteletes = df_customers["Avg_Sale_Amount"].unique()

# for i in deleteletes:
#     print(i)

sns.pairplot(df_customers)
plt.savefig('./assets/images/pairplot_df_Customers', dpi = 300)
```

In [15]:
```
# CORRELATION MATRIX


corr = df_customers.corr(method='pearson')

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
fig, ax = plt.subplots(figsize=(10, 6))

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, annot=True, fmt='.4f',
            cmap=cmap, cbar=True, ax=ax, mask = mask,
            square=False, linewidths=.5,cbar_kws={"shrink": .5})
ax.set_title('Heatmap', fontsize = 18)
ax.set_xlabel('Variable 1', fontsize = 15)
ax.set_ylabel('Variable 2', fontsize = 15)
ax.set_yticklabels(ax.get_yticklabels(), rotation="horizontal", fontsize =
ax.set_xticklabels(ax.get_xticklabels(), fontsize = 10)
plt.tight_layout()
plt.savefig('./assets/images/pearsonCorrelation', dpi = 300, bbox_inches='t
plt.show()


# MARKDOWN RESPONSE
# I needed help masking the parallel values within this heatmap 9 . Notice
```



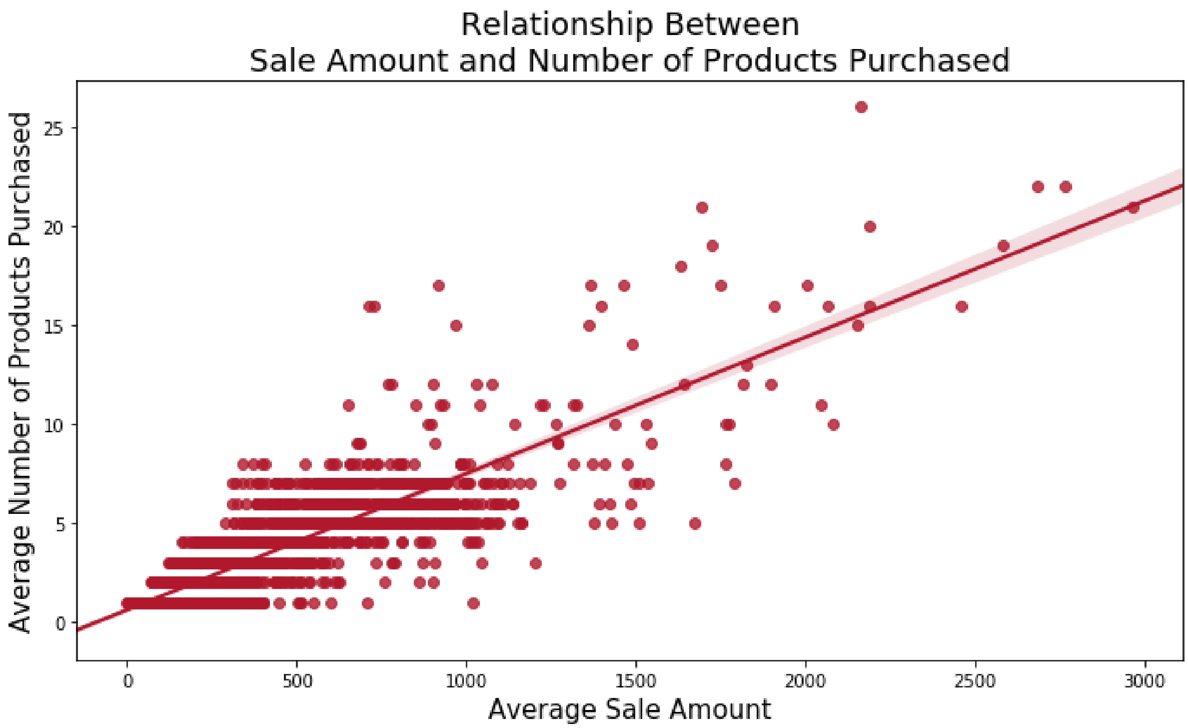
In [16]:
```
# https://code.i-harness.com/en/q/186322a
from scipy.stats import pearsonr
pearsonr(df_customers["Avg_Sale_Amount"], df_customers["Avg_Num_Products_Pu
```

Out[16]:
```
(0.8557542170755578, 0.0)
```

The pair plot and Pearson Correlation matrix suggests *Avg_Sale_Amount* and *Avg_Num_Products_Purchased* have a strong positive correlation of approximately 0.8558.

In [17]:
```
# SCATTER PLOT

plt.figure(figsize=(10, 6))
sns.regplot(data = df_customers, x = "Avg_Sale_Amount", y = "Avg_Num_Produc
            ci = 95, color = cmap[0])
plt.title('Relationship Between\nSale Amount and Number of Products Purchas
plt.xlabel('Average Sale Amount', fontsize = 15)
plt.ylabel('\nAverage Number of Products Purchased', fontsize = 15)
plt.xticks(fontsize = 10)
plt.yticks(fontsize = 10)
plt.tight_layout()
plt.savefig('./assets/images/scatterPlot.png', dpi = 300)
plt.show()
# help(sns.regplot)

#  MARKDOWN RESPONSE
# This graph displays a positive correlation between retweet count and favo
```

```
/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is depre
cated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this wi
ll be interpreted as an array index, `arr[np.array(seq)]`, which will res
ult either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



The scatter plot clearly displays the relationship between *Avg_Sale_Amount* and *Avg_Num_Products_Purchased* as a positive correlation.

Note: I'm not sure why this scatter plot has a *Future Warning*. It looks like it is in regards a tuples issue. I have not encoutered this issue in the past and will need to conduct further investigation to understand why this is occuring, and how to avoid it in the future.

Now to code dummies for the categorical variables.

In [18]:
```
# analysis w/ dummies
df_customers_dummies.head(3)
```

Out[18]:

	Name	Customer_ID	Address	City	State	ZIP	Avg_Sale_Amount	Store_Number	Res
0	Pamela Wright	2	376 S Jasmine St	Denver	CO	80224	227.90	100	
1	Danell Valdez	7	12066 E Lake Cir	Greenwood Village	CO	80111	55.00	105	
2	Jessica Rinehart	8	7225 S Gaylord St	Centennial	CO	80122	212.57	101	

In [19]:
```
# df_customers_dummies.columns
```

Insight Two: Linear Regression with Dummies

In [20]:
```
# # https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.linreg


# from scipy import stats


# x = df_customers_dummies["Avg_Sale_Amount"]
# y = df_customers_dummies["Avg_Num_Products_Purchased"]

# slope, intercept, r_value, p_value, std_err = stats.linregress(x, y)

# print("slope: %f    intercept: %f" % (slope, intercept))
```

Now to run linear regression for categorical predictors.

In [21]:

```
regFormulaDummies = """Avg_Sale_Amount ~ Avg_Num_Products_Purchased +
                       Customer_Segment_Loyalty_Club_Only +
                       Customer_Segment_Loyalty_Club_and_Credit_Card +
                       Customer_Segment_Store_Mailing_List"""

reg = smf.ols(formula = regFormulaDummies,
              data = df_customers_dummies).fit()
reg.summary()
```

Out[21]:

OLS Regression Results

Dep. Variable:	Avg_Sale_Amount	**R-squared:**	0.837
Model:	OLS	**Adj. R-squared:**	0.837
Method:	Least Squares	**F-statistic:**	3040.
Date:	Fri, 04 Jan 2019	**Prob (F-statistic):**	0.00
Time:	01:22:00	**Log-Likelihood:**	-15061.
No. Observations:	2375	**AIC:**	3.013e+04
Df Residuals:	2370	**BIC:**	3.016e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.97
Intercept	303.4635	10.576	28.694	0.000	282.725	324.2
Avg_Num_Products_Purchased	66.9762	1.515	44.208	0.000	64.005	69.9
Customer_Segment_Loyalty_Club_Only	-149.3557	8.973	-16.645	0.000	-166.951	-131.7
Customer_Segment_Loyalty_Club_and_Credit_Card	281.8388	11.910	23.664	0.000	258.484	305.1
Customer_Segment_Store_Mailing_List	-245.4177	9.768	-25.125	0.000	-264.572	-226.2

Omnibus:	359.638	**Durbin-Watson:**	2.045
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	4770.580
Skew:	0.232	**Prob(JB):**	0.00
Kurtosis:	9.928	**Cond. No.**	25.0

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [22]:
```
# rounding coefficients to two decimal places

coef_Intercept = round(303.4635, 2) # Intercept
coef_Avg_Products_Purchased = round(66.9762,2) # Avg_Num_Products_Purchased
coef_Club_Only = round(-149.3557,2) # Customer_Segment_Loyalty_Club_Only
coef_Customer_Club_and_Card = round(281.8388,2) # Customer_Segment_Loyalty_
coef_Mail_List = round(-245.4177,2) # Customer_Segment_Store_Mailing_List
```

Now let's calculate the best linear regression equation based on the available data.

In [23]:
```
# Multiple Linear Regression equation
# y = b0 + b1x1 + b2x2 + b3x3
```

$PredictedAverageSaleAmount = 303.46 +$
$(66.98 \times AvgNumProductsPurchased) +$
$(-149.36 \times CustomerSegmentLoyaltyClubOnly) +$
$(281.84 \times CustomerSegmentLoyaltyClubAndCreditCard) +$
$(-245.42 \times CustomerSegmentStoreMailingList$

Insight Three: Calculations

Predicted_Average_Sale_Amount is calculated by following the *PredictedAverageSaleAmount* formula above. Substitute the formula's variables with corresponding column values for each of the 250 customers in the mailing list dataset. Finally sum the *Predicted_Average_Sale_Amount* values.

Example Formula

```
PredictedAverageSaleAmount = 303.46 +
                             (66.98 × AvgNumProductsPurchased) +
                             (- 149.36 × CustomerSegmentLoyaltyClubO
nly) +
                             (281.84 × CustomerSegmentLoyaltyClubAnd
CreditCard) +
                             (- 245.42 × CustomerSegmentStoreMailing
List)
```

In [24]:
```
df_mailingList_dummies["Predicted_Average_Sale_Amount"] = coef_Intercept +
```

In [25]:
```
predictedAverageSaleAmount_Overall = sum(df_mailingList_dummies["Predicted_
predictedAverageSaleAmount_Overall = round(predictedAverageSaleAmount_Overa
predictedAverageSaleAmount_Overall
```

Out[25]:
```
138295.16
```

Predicted_Revenue is calculated by finding the product of *PredictedAverageSaleAmount* and

Score_Yes (the probability a customer will respond and make a purchase), then taking the sum of all those values.

Example Formula

```
Predicted_Revenue = Predicted_Average_Sale_Amount * Score_Yes
```

In [26]:
```
df_mailingList_dummies["Predicted_Revenue"] = df_mailingList_dummies["Predi
```

In [27]:
```
predictedRevenue_Overall = sum(df_mailingList_dummies["Predicted_Revenue"])
predictedRevenue_Overall = round(predictedRevenue_Overall, 2)
predictedRevenue_Overall
```

Out[27]: 47225.91

Predicted_Profit is calculated by subtracting the catalog cost (given $6.50) from the product of *Predicted_Revenue* and average gross margin (which is a given value of 50%).

Example Formula

```
Predicted_Profit = (0.5 * Predicted_Revenue) - 6.5
```

In [28]:
```
df_mailingList_dummies["Predicted_Profit"] = (0.5 * df_mailingList_dummies[
```

In [29]:
```
predictedProfit_Overall = sum(df_mailingList_dummies["Predicted_Profit"])
predictedProfit_Overall = round(predictedProfit_Overall, 2)
predictedProfit_Overall
```

Out[29]: 21987.96

Overall *Predicted_Profit* can also be calculated by taking half of the overall *Predicted_Revenue* and subtracting the product of 250 customers and $6.50 catalog cost.

In [30]:
```
(0.5 * predictedRevenue_Overall) - (6.5*250)
```

Out[30]: 21987.955

In [31]:
```
df_mailingList_dummies.head(3)
```

Out[31]:

	Name	Customer_ID	Address	City	State	ZIP	Store_Number	Avg_Num_Products_Pu
0	A Giametti	2213	5326 S Lisbon Way	Centennial	CO	80015	105	
1	Abby Pierson	2785	4344 W Roanoke Pl	Denver	CO	80236	101	
2	Adele Hallman	2931	5219 S Delaware St	Englewood	CO	80110	101	

In [32]:
```
def formay(x):
    return "${:,.2f}".format((x))


d = {'Variable Name':['Overall Predicted Average Sale Amount', 'Overall Pre
     'Values':[predictedAverageSaleAmount_Overall,predictedRevenue_Overall,
    }

df_overallValues = pd.DataFrame(data = d)

df_overallValues['Values'] = df_overallValues['Values'].apply(formay)

df_overallValues
```

Out[32]:

	Variable Name	Values
0	Overall Predicted Average Sale Amount	$138,295.16
1	Overall Predicted Revenue	$47,225.91
2	Overall Predicted Profit	$21,987.96

Store Data

In [33]:
```
df_mailingList_dummies.to_csv("./assets/data/df_mailingList_dummies.csv", i
df_customers_dummies.to_csv("./assets/data/df_customers_dummies.csv", index
df_overallValues.to_csv("./assets/data/df_overallValues.csv", index = False
```

Initial Discovery

The following items were used during my initial discovery. Although I did not reference these items in my report. I enjoyed playing around with these different models and decided to keep them in my submission for future reference.

In [34]:
```
df_customers.groupby('Store_Number')["Customer_Segment"].describe()
```

Out[34]:

Store_Number	count	unique	top	freq
100	326	4	Store Mailing List	151
101	276	4	Store Mailing List	133
102	85	4	Store Mailing List	42
103	225	4	Store Mailing List	102
104	270	4	Store Mailing List	128
105	305	4	Store Mailing List	142
106	283	4	Store Mailing List	129
107	226	4	Store Mailing List	96
108	210	4	Store Mailing List	109
109	169	4	Store Mailing List	76

In [35]:
```
round(df_customers_dummies.describe(),1)
```

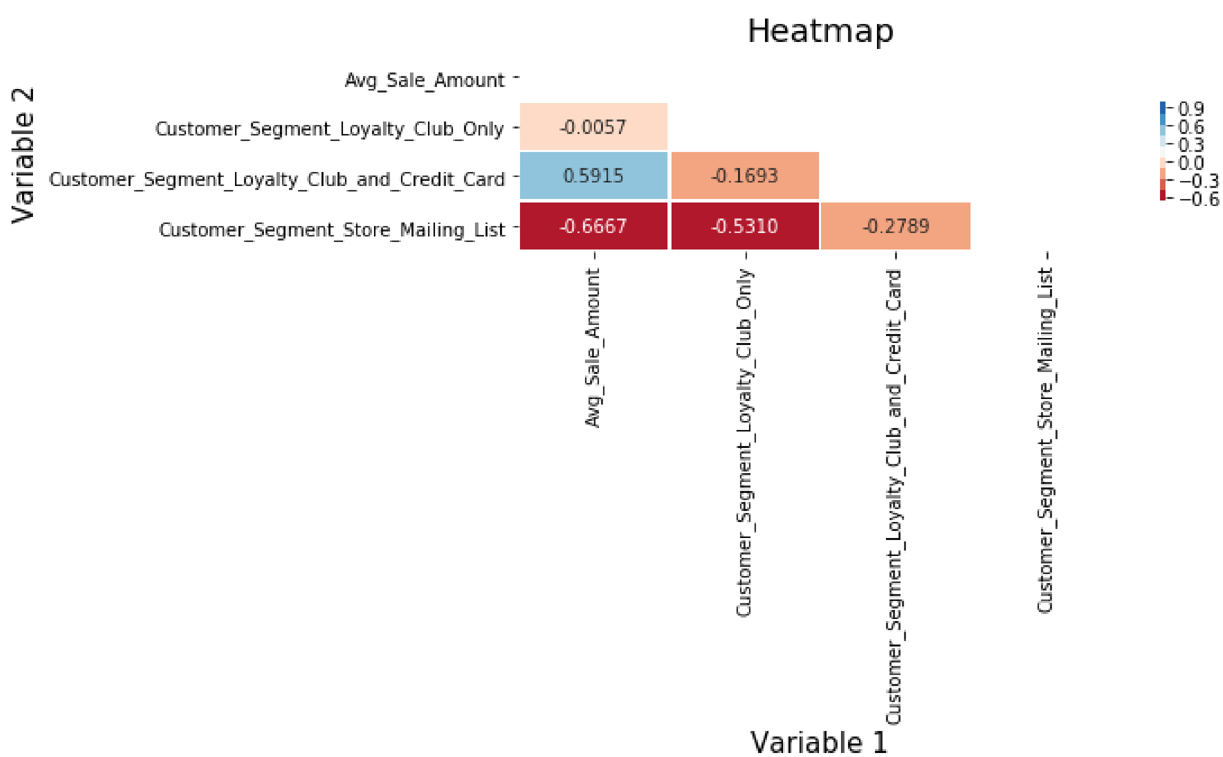
Out[35]:

	Customer_ID	ZIP	Avg_Sale_Amount	Store_Number	Avg_Num_Products_Purchased	#_Ye
count	2375.0	2375.0	2375.0	2375.0	2375.0	
mean	1647.8	80123.3	399.8	104.3	3.3	
std	962.7	107.3	340.1	2.8	2.7	
min	2.0	80002.0	1.2	100.0	1.0	
25%	820.5	80014.0	168.9	101.0	1.0	
50%	1629.0	80123.0	281.3	105.0	3.0	
75%	2492.5	80221.0	572.4	107.0	5.0	
max	3335.0	80640.0	2963.5	109.0	26.0	

In [36]:
```
calcPears_A = df_customers.corr(method = 'pearson')
print("Corr Method A:")
print(calcPears_A)
print()
print("Corr Method B:")
```

```
Corr Method A:
                           Customer_ID       ZIP  Avg_Sale_Amount  \
Customer_ID                   1.000000  0.002159         0.038235   
ZIP                           0.002159  1.000000         0.007973   
Avg_Sale_Amount               0.038235  0.007973         1.000000   
Store_Number                 -0.023323 -0.148906        -0.007946   
Avg_Num_Products_Purchased    0.060136  0.001790         0.855754   
#_Years_as_Customer           0.015164  0.001643         0.029782   

                           Store_Number  Avg_Num_Products_Purchased  \
Customer_ID                   -0.023323                    0.060136   
ZIP                           -0.148906                    0.001790   
Avg_Sale_Amount               -0.007946                    0.855754   
Store_Number                   1.000000                   -0.011525   
Avg_Num_Products_Purchased    -0.011525                    1.000000   
#_Years_as_Customer           -0.009573                    0.043346   

                           #_Years_as_Customer  
Customer_ID                           0.015164  
```

In [37]:
```
# CORRELATION MATRIX


corr = df_customers_dummies[["Avg_Sale_Amount",
                             "Customer_Segment_Loyalty_Club_Only",
                             "Customer_Segment_Loyalty_Club_and_Credit_Card
                             "Customer_Segment_Store_Mailing_List"
                            ]].corr(method='pearson')

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
fig, ax = plt.subplots(figsize=(10, 6))

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, annot=True, fmt='.4f',
            cmap=cmap, cbar=True, ax=ax, mask = mask,
            square=False, linewidths=.5,cbar_kws={"shrink": .5})
ax.set_title('Heatmap', fontsize = 18)
ax.set_xlabel('Variable 1', fontsize = 15)
ax.set_ylabel('Variable 2', fontsize = 15)
ax.set_yticklabels(ax.get_yticklabels(), rotation="horizontal", fontsize =
ax.set_xticklabels(ax.get_xticklabels(), fontsize = 10)
plt.tight_layout()
# plt.savefig('./assets/images/pearsonCorrelation', dpi = 300, bbox_inches=
plt.show()
```



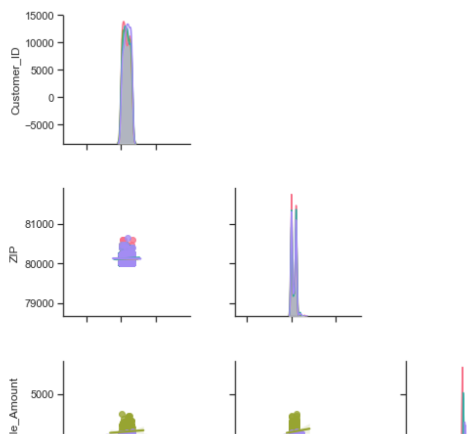
In [38]:
```
sns.set(style="ticks")
sns.pairplot(df_customers, kind="reg")
```

```
/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is depre
cated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this wi
ll be interpreted as an array index, `arr[np.array(seq)]`, which will res
ult either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[38]: <seaborn.axisgrid.PairGrid at 0x1a2c9c3f28>

In [39]:
```
sns.set(style="ticks")
g = sns.pairplot(df_customers, hue="Customer_Segment",kind="reg", palette="

for i, j in zip(*np.triu_indices_from(g.axes, 1)):
    g.axes[i, j].set_visible(False)
```

```
/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is depre
cated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this wi
ll be interpreted as an array index, `arr[np.array(seq)]`, which will res
ult either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [40]:
```
sns.set(style="ticks")
g = sns.pairplot(df_mailingList, hue="Customer_Segment", palette="husl")

for i, j in zip(*np.triu_indices_from(g.axes, 1)):
    g.axes[i, j].set_visible(False)
```

```
/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureW
arning: Using a non-tuple sequence for multidimensional indexing is depre
cated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this wi
ll be interpreted as an array index, `arr[np.array(seq)]`, which will res
ult either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Resources

1. Dummy Variables in Pandas (https://youtu.be/0s_1IsROgDc)
2. SciPy Docs (https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.linregress.html)
3. Regression in Python (http://songhuiming.github.io/pages/2017/01/21/linear-regression-in-python-chapter-3-regression-with-categorical-predictors/)
4. Multiple Linear Regression (https://towardsdatascience.com/simple-and-multiple-linear-regression-in-python-c928425168f9)

In [ ]: