Step 1: Business and Data Understanding

Key Decisions:

1. What decisions needs to be made?

Ans: Whether to send out $6.50 catalog to the 250 new customers which are the potential buyers.

Reviewer: Awesome—The main business decision is about whether catalogs should be sent to new customers, based on expected profit.

2. What data is needed to inform those decisions?

Ans: Whether the total profit from these 250 new customers will meet expected value of 10,000. To break it down, we will need to predict ave_sale_amount for each customer.

Reviewer: Suggestion—A more complete response can be given here. Predicting sales amount is required, but is not sufficient. In order to calculate net profit per customer, the cost of printing and shipping the catalogs is also part of the data required. It was mentioned in the answer above, but should be mentioned here as well.

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
% matplotlib inline
customer = pd.read_excel("p1-customers.xlsx")
mail = pd.read_excel("p1-mailinglist.xlsx")
```

In [2]:
```
customer.head()
```

Out[2]:

	Name	Customer_Segment	Customer_ID	Address	City	State	ZIP	Avg_Sa
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
3	Nancy Clark	Store Mailing List	9	4497 Cornish Way	Denver	CO	80239	195.31
4	Andrea Brun	Store Mailing List	10	2316 E 5th Ave	Denver	CO	80206	110.55

In [3]:
```
#mail.head()
```

In [4]:
```
customer.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]:
```
mail.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
```

Step 2: Analysis, Modeling, and Validation

1 How and why did you select the predictor variables in your model?

Ans: The first thing is the target variable. My origional thought is `Responded_to_Last_Catalog`, but it turns out the majority of customers doesn't response (2204 vs 171), these customers actually has a higher `Avg_Sale_Amount` (308 vs 162). Another confusing thing is in `p1-mailinglist.xlsx` : `Score_Yes`. How is this probability calculated? This is important but however beyond this question.

With some commom sense and some data exploration, the predictor variables are Customer_Segment (multi-class) and Avg_Num_Products_Purchased (continuous).

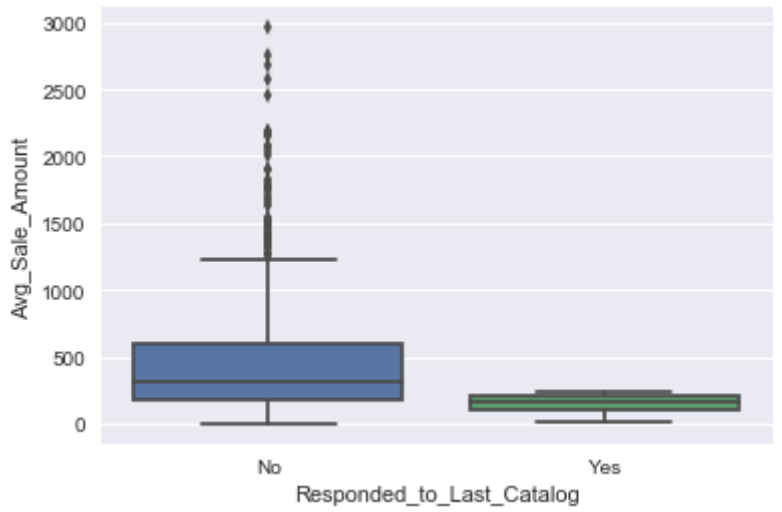
Reviewer: Awesome—Correct, these are the predictor variables that should be selected.

In [6]:
```
customer['Responded_to_Last_Catalog'].value_counts()
```

Out[6]:
```
No     2204
Yes     171
Name: Responded_to_Last_Catalog, dtype: int64
```

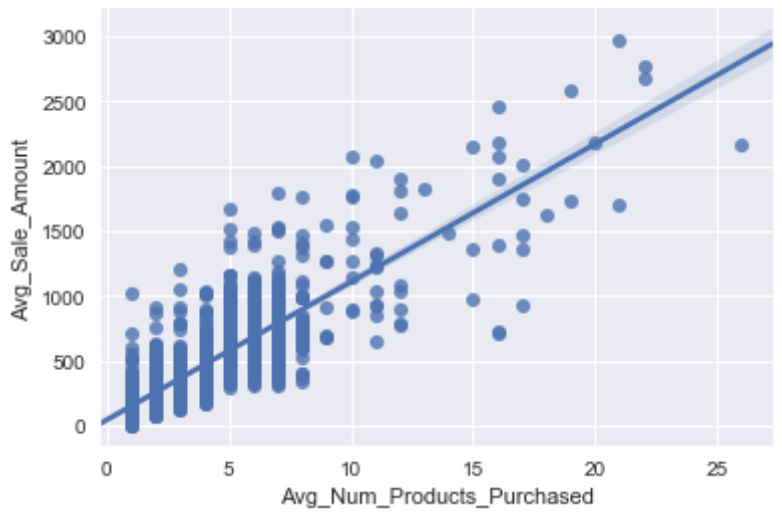
In [7]:
```
sns.boxplot(x='Responded_to_Last_Catalog', y = "Avg_Sale_Amount",data =
customer)
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x10d1ca6d8>



In [8]:
```
sns.regplot(x='Avg_Num_Products_Purchased', y = "Avg_Sale_Amount",data =
customer)
```

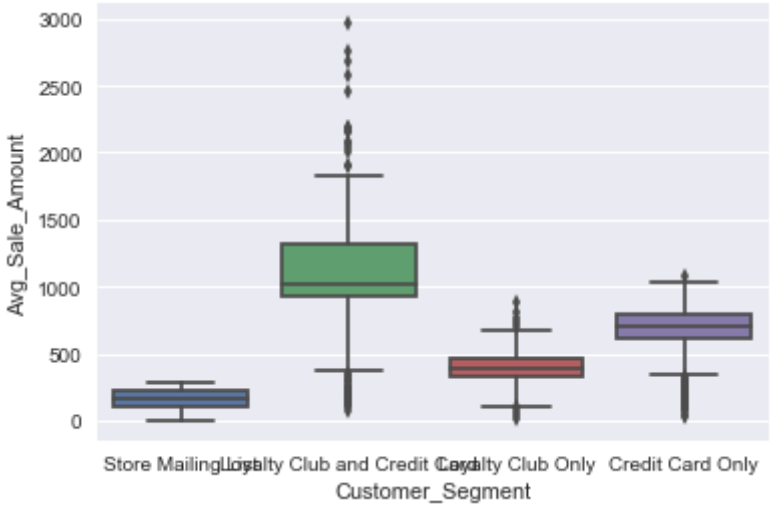
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x10d3edc88>



Reviewer: Suggestion—These plots would be more clear to the reader if a title and description were included.

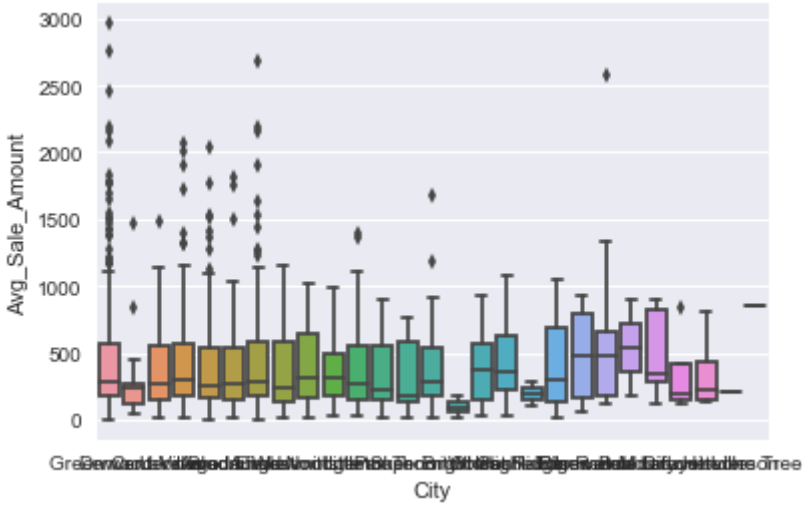
In [9]:
```
sns.boxplot(x="Customer_Segment", y = "Avg_Sale_Amount",data = customer)
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x10fa18ef0>



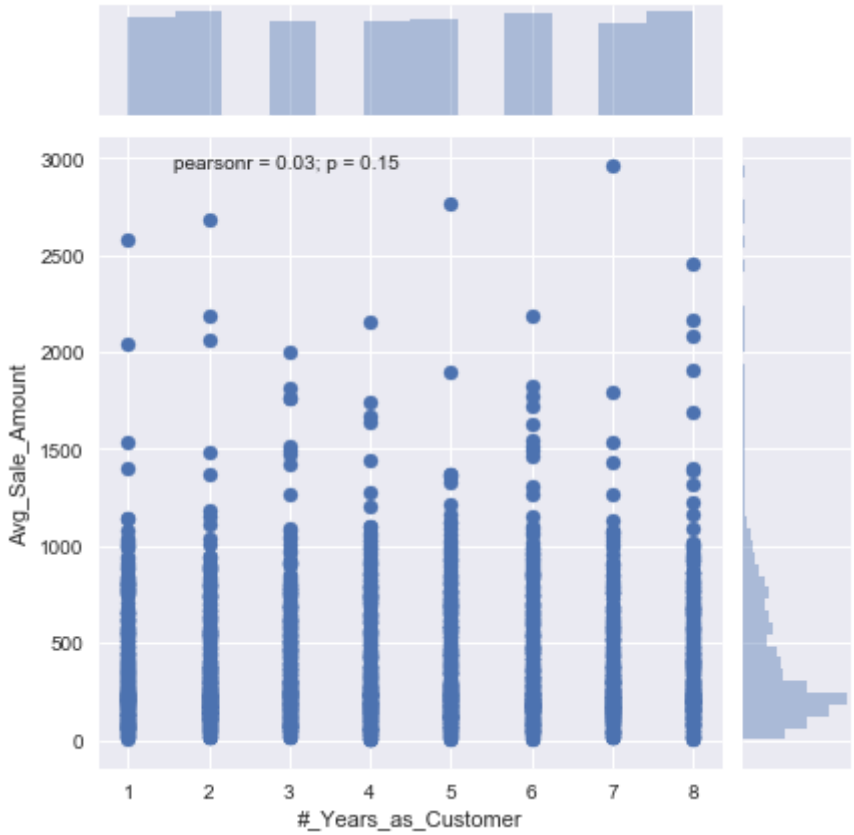
In [10]:
```
sns.boxplot(x="City", y = "Avg_Sale_Amount",data = customer)
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x10fed0240>



In [11]:
```
sns.jointplot(x='#_Years_as_Customer', y ='Avg_Sale_Amount', data = cust
omer)
```

Out[11]: <seaborn.axisgrid.JointGrid at 0x1102c5748>



In [20]:
```
dummies = pd.get_dummies(customer['Customer_Segment'])
X = pd.concat([customer['Avg_Num_Products_Purchased'], dummies], axis=1)
X = X.drop("Credit Card Only",axis=1)  # use "Credit Card Only" as defau
lt
y = customer["Avg_Sale_Amount"]
X.head()
```

Out[20]:

	Avg_Num_Products_Purchased	Loyalty Club Only	Loyalty Club and Credit Card	Store Mailing List
0	1	0	0	1
1	1	0	0	1
2	1	0	0	1
3	1	0	0	1
4	1	0	0	1

In [21]:
```
import statsmodels.api as sm
#from scipy import stats
X2 = sm.add_constant(X)
est = sm.OLS(y, X2)
est2 = est.fit()
print(est2.summary())
```

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:	Sun, 30 Apr 2017	Prob (F-statistic):	0.00
Time:	09:35:34	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	0.975]
const	303.4635	10.576	28.694	0.000	282.725	324.202
Avg_Num_Products_Purchased	66.9762	1.515	44.208	0.000	64.005	69.947
Loyalty Club Only	-149.3557	8.973	-16.645	0.000	-166.951	-131.760
Loyalty Club and Credit Card	281.8388	11.910	23.664	0.000	258.484	305.194
Store Mailing List	-245.4177	9.768	-25.125	0.000	-264.572	-226.263

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.

2. Explain why you believe your linear model is a good model.

Ans: The R value is 0.837, indicating a good fit. The p value is almost zero for each variable, indicating good choices of variables.

Reviewer: Awesome—The selected model has high R-Squared and significant p-value.

3.What is the best linear regression equation based on the available data?

Ans: y = 303.46 + 66.98 x Avg_Num_Products_Purchased - 149.36 x Loyalty Club Only + 281.84 x Loyalty Club and Credit Card - 245.42 x Store Mailing List

Reviewer: Suggestion—For completeness, the term 0 * Credit Card Only can be included.

Step 3: Presentation/Visualization

1. What is your recommendation? Should the company send the catalog to these 250 customers?

Ans: Yes

2. How did you come up with your recommendation?

Ans: I used the linear model to predict how much individual cusotemer will pay, times its chance to buy, times gross margin rate, minus cost and compare with expected profit. If it exceeds expectation, it is a buy.

3. What is the expected profit from the new catalog

Ans: According to the following analysis, the average customer will pay $ 504 with 26% chance. And the total profit after 50% gross margin and 6.50 cost will be $ 21,986. This exceeds the threshold profit of $10,000. So I would recommend to do this catalog ad campaign.

Reviewer: Awesome—The final profit calculation is correct.

In addition, in the `p1-customers.xlsx`, the customers who don't respond may also contribute to "Avg_Sale_Amount". I don't have a clear explanation at this moment.

In [22]:
```
from sklearn.linear_model import LinearRegression, Ridge
#model = LinearRegression() # ridicularly larege intercept
model = Ridge()
model.fit(X, y)
model.coef_, model.intercept_
```

Out[22]:
```
(array([  67.18451485, -148.44601123,  280.28027038, -244.0996339 ]),
 302.0567744490408)
```

In [23]:
```
model.score(X,y)
```

Out[23]:
```
0.83687450635195815
```

In [25]:
```
dummies = pd.get_dummies(mail['Customer_Segment'])
X_test = pd.concat([mail['Avg_Num_Products_Purchased'], dummies],
axis=1)
X_test = X_test.drop("Credit Card Only", axis = 1)
X_test.head()
```

Out[25]:

	Avg_Num_Products_Purchased	Loyalty Club Only	Loyalty Club and Credit Card	Store Mailing List
0	3	1	0	0
1	6	0	1	0
2	7	1	0	0
3	2	1	0	0
4	4	1	0	0

In [26]:
```
y_test = model.predict(X_test)
```

In [27]:
```
import numpy as np
print(np.median(y_test))
print(mail["Score_Yes"].median())
```

```
503.610319012
0.257990433
```

In [28]:
```
sum(mail["Score_Yes"]*y_test*0.5) - 6.5 *250
```

Out[28]:
```
21985.880836152253
```

In [29]:
```
(mail["Score_Yes"]*y_test)[0]  # first record of revenue
```

Out[29]:
```
108.33783124317979
```