asg2

July 7, 2020

0.1 Data Mining Assignment 2

Members

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0.2 What we are mining

-which barbershop type makes more money(traditional or online based) and why

We were approached by a client that wants to start a barbershop, he wants us to recommend to him which type of barbershop he should start, online or traditional. An online barbershop is mobile and clients call him to go to them while a traditional barbershop is located in building where clients come to get their hair done. We've collected a sample of 50 barbers that operate in town, windhoek. Barbers filled out forms that were sent to them.

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from apyori import apriori
import numpy as np
import sklearn
from sklearn import cluster
from sklearn.cluster import KMeans
import networkx as nx
import statsmodels.api as sm
from statsmodels.formula.api import ols
from IPython.display import Image
from IPython.core.display import HTML


%matplotlib inline
```

[4]:
```
df = pd.read_csv("./barbershop.csv")
df.head()
```

[4]:
```
    cellphone     hairstyle  cost  monthly_rent  transport_cost  \
0   819107859          Trim    80        2500.0             800
1   818659596  Temple Fade    70        2800.0             760
2   817122486      Low Fade    70        3500.0             730
3   813777117        Mohawk    70        3800.0             410
4   817028800      Low Fade    60        2200.0             580

    clients_per_month  monthly_income form_of_transport working_hours  \
0                 380           13000              taxi       6am-5pm
1                 540           14000       private_car       6am-5pm
2                 520           14000              taxi      6am-12pm
3                 360           14000              taxi       6am-5pm
4                 550           15000              taxi      6am-12pm

    clients_cut per trip shop_type promotion_platform_1 promotion_platform_2
0                    NaN  building                 none                 none
1                    NaN  building            instagram                 none
2                    NaN  building            instagram             whatsapp
3                    NaN  building                 none                 none
4                    NaN  building                 none                 none
```

Data preprossing

-cleaning

check if there are any null values, helps understand the structure of our current data

[96]:
```
df.isnull().any()
```

[96]:
```
cellphone               False
hairstyle               False
cost                    False
monthly_rent             True
transport_cost          False
clients_per_month       False
monthly_income          False
form_of_transport       False
working_hours           False
clients_cut per trip     True
shop_type               False
promotion_platform_1    False
promotion_platform_2    False
dtype: bool
```

Replace missing values depending on the data type,

[97]:
```
median = df['transport_cost'].median()
df.fillna({'monthly_rent':0, 'clients_per_trip': 0, 'transport_cost':median},␣
 ↪inplace=True)
```

```
# res = df.apply(lambda x: x.fillna(0) if x.dtype.kind in 'biufc' else x.
↪fillna('.'))
```

[98]:
```
#drop redundant working_hours column
df.drop(columns=['working_hours', 'cellphone'], inplace=True)
#check data types of our column,
#this guides as what type operations we can perform on them
#and the graphs that will be suitable to represent them
df.dtypes
```

[98]:
```
hairstyle                 object
cost                       int64
monthly_rent             float64
transport_cost             int64
clients_per_month          int64
monthly_income             int64
form_of_transport         object
clients_cut per trip     float64
shop_type                 object
promotion_platform_1      object
promotion_platform_2      object
dtype: object
```

Calculate the avarage null values in the dataset This tells us that: overrall most of the columns are filled 50% of the records in the monthly rent column are null while only 49% in clients cut per trip are null

[99]:
```
df.isnull().sum() / len(df)
```

[99]:
```
hairstyle               0.00
cost                    0.00
monthly_rent            0.00
transport_cost          0.00
clients_per_month       0.00
monthly_income          0.00
form_of_transport       0.00
clients_cut per trip    0.48
shop_type               0.00
promotion_platform_1    0.00
promotion_platform_2    0.00
dtype: float64
```

Format all string types to lower case

[100]:
```
df['hairstyle'].str.lower()
```

[100]:
```
0              trim
1       temple fade
```

2	low fade
3	mohawk
4	low fade
5	temple fade
6	waves + fade
7	mohawk
8	mohawk
9	low fade
10	temple fade
11	temple fade
12	low fade
13	temple fade
14	temple fade
15	temple fade
16	low fade
17	low fade
18	mohawk
19	low fade
20	low fade
21	waves + fade
22	mohawk
23	low fade
24	temple fade
25	low fade
26	temple fade
27	trim
28	mohawk
29	low fade
30	mohawk
31	mohawk
32	waves + fade
33	trim
34	low fade
35	low fade
36	low fade
37	low fade
38	mohawk
39	mohawk
40	mohawk
41	fade
42	low fade
43	temple fade
44	temple fade
45	mohawk
46	low fade
47	low fade
48	temple fade

```
49    waves + fade
Name: hairstyle, dtype: object
```

Fix column names that might cause issues down the road

[101]:
```python
df.rename(columns={'clients_cut per trip':'clients_per_trip'}, inplace=True)
```

[102]:
```python
profit = df['monthly_income']-df['monthly_rent']-df['transport_cost']
df['profit'] = profit

#split data set into online and building
online_df = df[df['shop_type'] == 'online']
traditional_df = df[df['shop_type'] == 'building']
```

1 1.Data Modeling

Data modeling refers to a group of processes in which multiple sets of data are combined and analyzed to uncover relationships or patterns. The goal of data modeling is to use past data to inform future efforts.

[103]:
```python
df.describe()
```

[103]:
```
             cost  monthly_rent  transport_cost  clients_per_month  \
count  50.000000      50.00000       50.000000          50.000000
mean   70.600000    1484.00000      590.600000         460.800000
std    13.910795    1548.45018      120.516067          69.188887
min    50.000000       0.00000      400.000000         340.000000
25%    60.000000       0.00000      485.000000         382.500000
50%    70.000000    1000.00000      615.000000         470.000000
75%    80.000000    3100.00000      697.500000         520.000000
max    90.000000    3800.00000      800.000000         550.000000

       monthly_income  clients_per_trip        profit
count        50.00000         26.000000     50.000000
mean      21460.00000          2.423077  19385.400000
std        5639.54695          1.701131   6153.853019
min       12000.00000          1.000000   9700.000000
25%       16250.00000          1.000000  14160.000000
50%       22000.00000          2.000000  19055.000000
75%       26000.00000          3.000000  24400.000000
max       34000.00000          7.000000  33300.000000
```

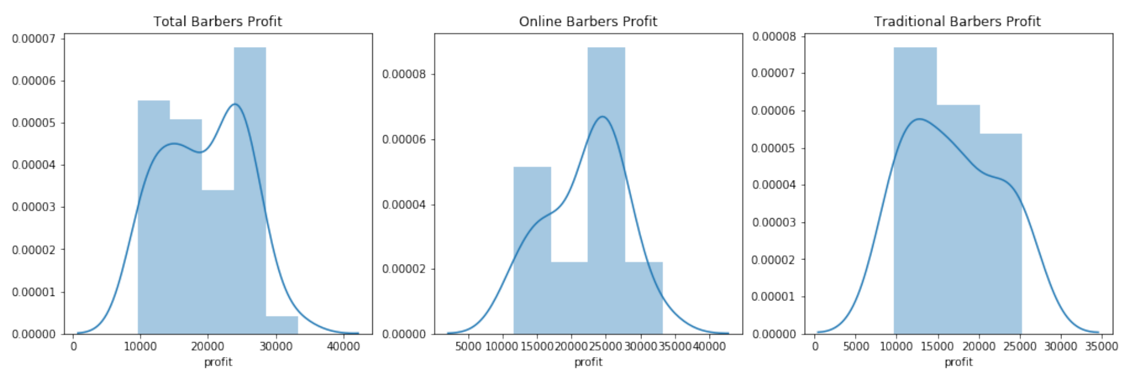
From the describe funtion gives us overall descriptive analysis, from this we see that: We took a sample of 50 barbers of which the avarage price of a hair cut is N\$ 70, with one standard deviation from the mean price bieng N\$ 13. The minimum price for a hair cut is N\$50 while the highest amounts to N\$90. 50% of the hair cut price fall below N\$70, and the monthly income bieng N\$22 000.

On average a barber makes N\19300$profitpermonthwithasinglestandarddeviationofN$
6 000

Data Distribution

[154]:
```
f, axes = plt.subplots(1, 3)
f.set_size_inches(17, 5)

axes[0].set_title("Total Barbers Profit")
axes[1].set_title("Online Barbers Profit")
axes[2].set_title("Traditional Barbers Profit")

filter_data = df.dropna(subset=['profit'])
sns.distplot(filter_data['profit'], ax=axes[0])

filter_data = online_df.dropna(subset=['profit'])
sns.distplot(filter_data['profit'], ax=axes[1])

filter_data = traditional_df.dropna(subset=['profit'])
sns.distplot(filter_data['profit'], ax=axes[2])
```

[154]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fce9dd95c90>`



Distribution analysis plot shows us the general pattern that our data follow, first thing to notice from the above graph is that our data is not symmetrical and does not follow a normal distribution. This graph shows that most online barbers make around N\$ 25 000 while Traditional are at around N\$ 14 000 profit

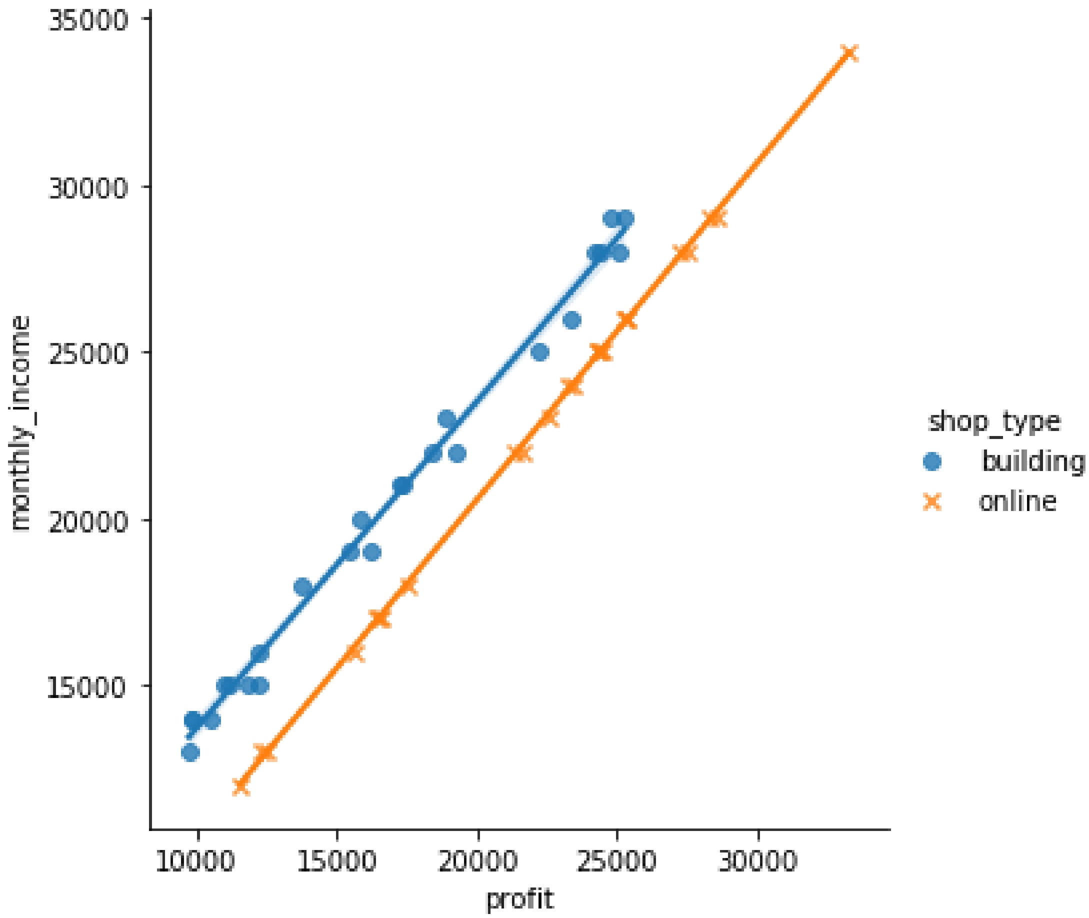
Statistical Regression

[105]:
```
#linear regression
```

[106]:
```
m = ols('profit ~ monthly_income - transport_cost - transport_cost', df).fit()
print(m.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 profit   R-squared:                       0.938
Model:                            OLS   Adj. R-squared:                  0.937
Method:                 Least Squares   F-statistic:                     725.1
Date:                Wed, 01 Jul 2020   Prob (F-statistic):           1.27e-30
Time:                        18:19:32   Log-Likelihood:                -437.20
No. Observations:                  50   AIC:                             878.4
Df Residuals:                      48   BIC:                             882.2
Df Model:                           1
Covariance Type:            nonrobust
================================================================================
==
                     coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
--
Intercept      -3293.0811    870.225     -3.784      0.000   -5042.786
-1543.376
monthly_income     1.0568      0.039     26.928      0.000       0.978
1.136
==============================================================================
Omnibus:                       87.670   Durbin-Watson:                   0.304
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                5.638
Skew:                          -0.108   Prob(JB):                       0.0597
Kurtosis:                       1.369   Cond. No.                     8.81e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 8.81e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[107]:
```
sns.lmplot(x="profit", y="monthly_income", hue="shop_type", data=df,␣
 ↪markers=["o", "x"])
plt.show()
```



Regression analysis aims to plot out data points in our data set and draw division between those points to differentiate them. Regression draws the best fit line shows how far other data points are from that line.

2 2.Identifying Patterns

[123]:
```
df2 = df[['hairstyle','shop_type']]

records = []
for i in range(0, df2.shape[0]):
    records.append([str(df2.values[i,j]) for j in range(0, len(df2.columns))])

association_rules = apriori(records,use_colnames = True, min_length=2)
association_results = list(association_rules)
```

[109]:
```python
for item in association_results:

    # first index of the inner list
    # Contains base item and add item
    pair = item[0]
    items = [x for x in pair]
    if(len(items) < 2):
        continue

    print("Rule: " + items[0] + " -> " + items[1])

    #second index of the inner list
    print("Support: " + str(item[1]))

    #third index of the list located at 0th
    #of the third index of the inner list

    print("Confidence: " + str(item[2][0][2]))
    print("Lift: " + str(item[2][0][3]))
    print("=====================================")
```

```
Rule: building -> Low Fade
Support: 0.18
Confidence: 0.18
Lift: 1.0
=====================================
Rule: online -> Low Fade
Support: 0.18
Confidence: 0.18
Lift: 1.0
=====================================
Rule: building -> Mohawk
Support: 0.1
Confidence: 0.1
Lift: 1.0
=====================================
Rule: online -> Mohawk
Support: 0.14
Confidence: 0.14
Lift: 1.0
=====================================
Rule: building -> Temple Fade
Support: 0.16
Confidence: 0.16
Lift: 1.0
=====================================
```

We use apryori algorithm to find the association between haircut types and shop types, this will help us understand which haircut the is favoured by online and traditional community. To increase his profit the barber will to master the type of hair cut that his customers like.

First of all lets define some terms: Support - overrall popularity of a hairstyle, number of transactions containing a particular hairstyle over total transactions

Confidence - likely of hairstyle A if shop type B is chosen, vice versa.

Lift - lift(A->B) is the increase in ratio of haircut B when shop type A is used, vice versa.

From our analysis we found that all our associations have a lift of 1, so there's no association between the shop type and hairstyle favoured. There difference in support and confidence is negligible.

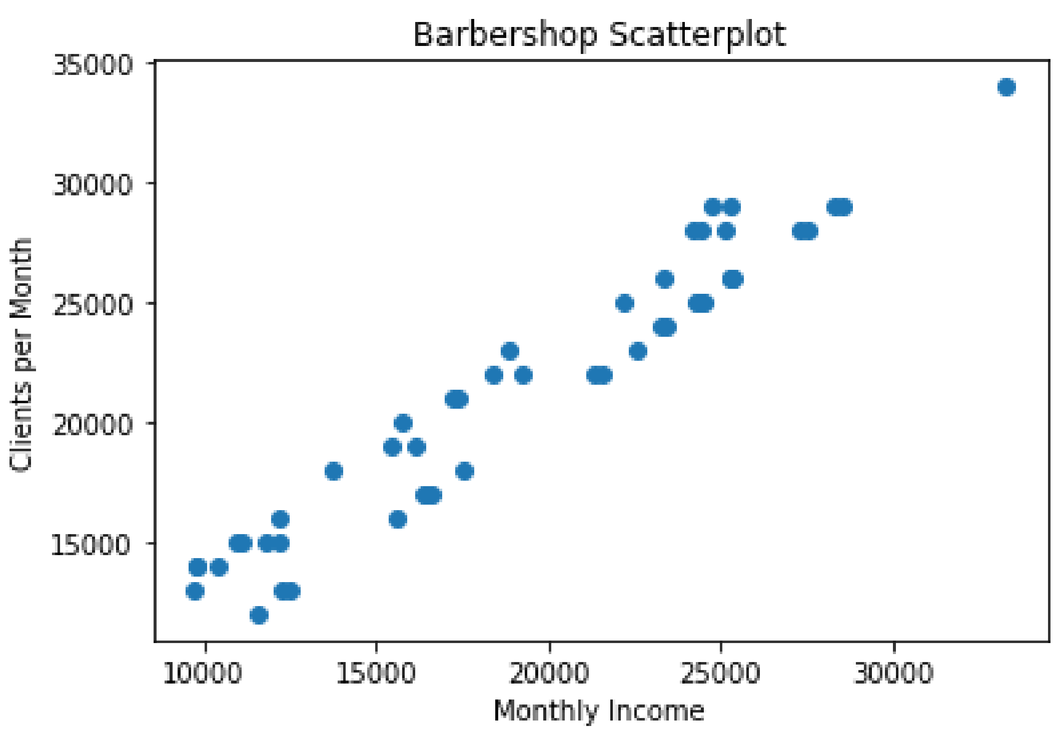
3 3.Data Visualization

Scatter Plot

Scatter plots are used to plot data points on horizontal and vertical axis in the attempt to show how much one variable is affected by another.

[110]:
```
plt.scatter(df.profit, df.monthly_income)
plt.title('Barbershop Scatterplot')
plt.xlabel('Monthly Income')
plt.ylabel('Clients per Month')
```

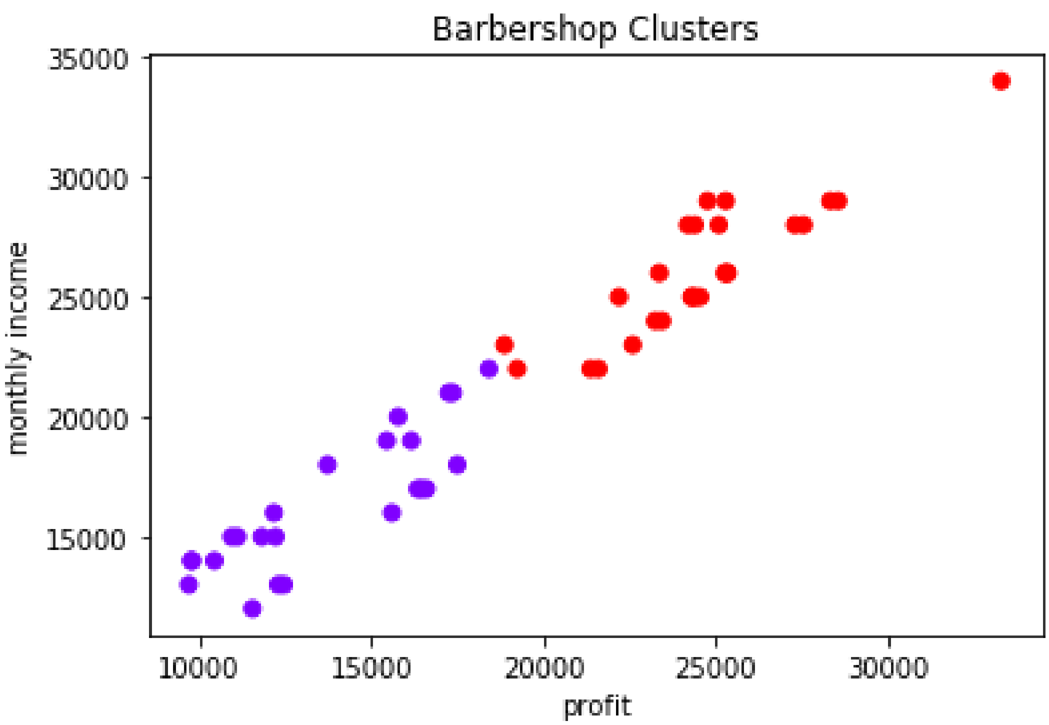
[110]:
```
Text(0, 0.5, 'Clients per Month')
```



Data Cluster

The KMeans algorithm clusters data by trying to separate samples in n groups of equal variance, minimizing a criterion known as the inertia or within-cluster sum-of-squares.

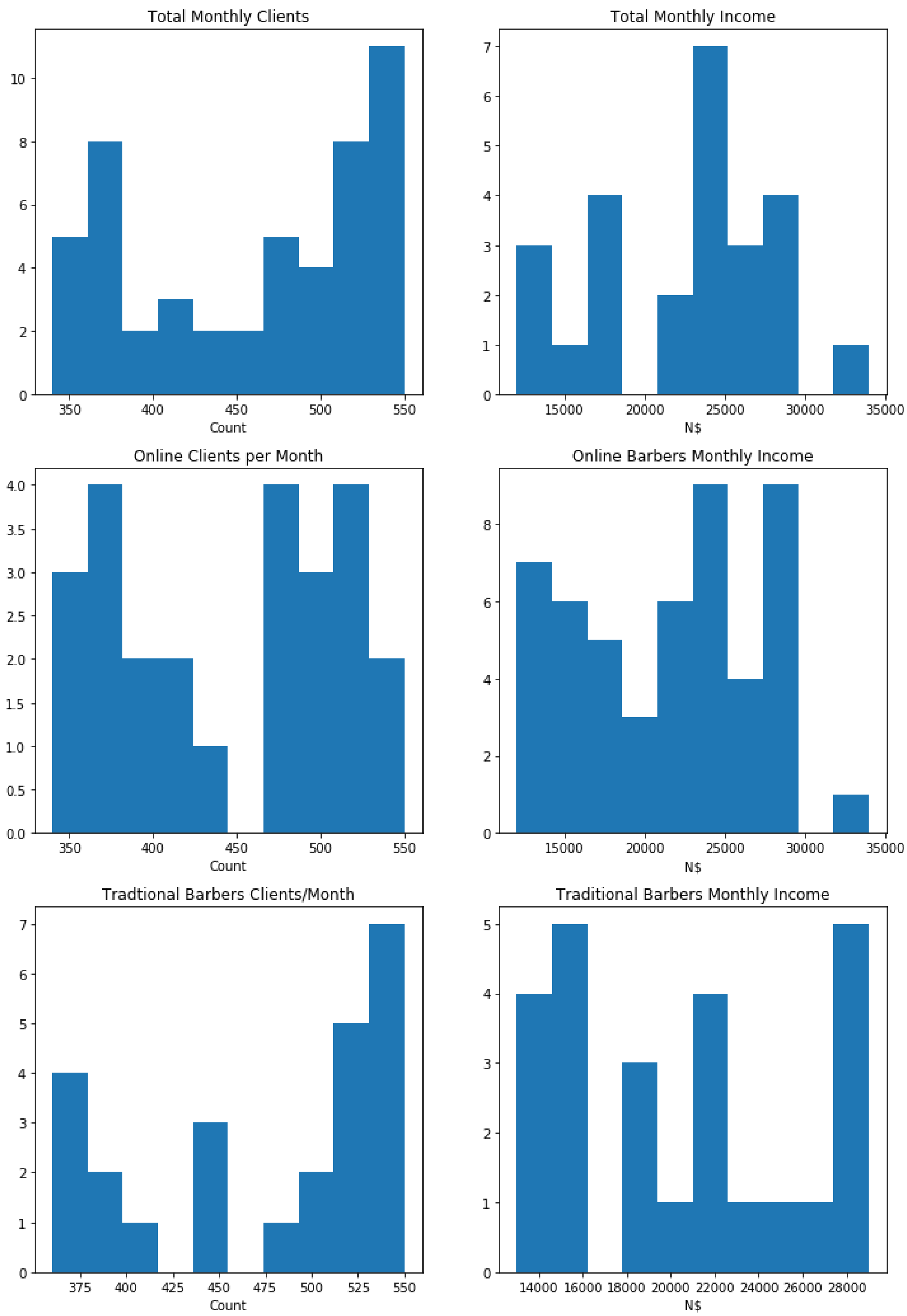
[125]:
```
df2 = df.dropna(axis='columns')
kmeans = KMeans(n_clusters=2).fit(df2._get_numeric_data())
centroids = kmeans.cluster_centers_

plt.scatter(df['profit'], df['monthly_income'], c=kmeans.labels_,␣
 ↪cmap='rainbow')
plt.title('Barbershop Clusters')
plt.xlabel('profit')
plt.ylabel('monthly income')
plt.show()
```



Histogram

[130]:
```
fig = plt.figure(figsize=(12, 18))
total_clients = fig.add_subplot(321)
total_income = fig.add_subplot(322)
```

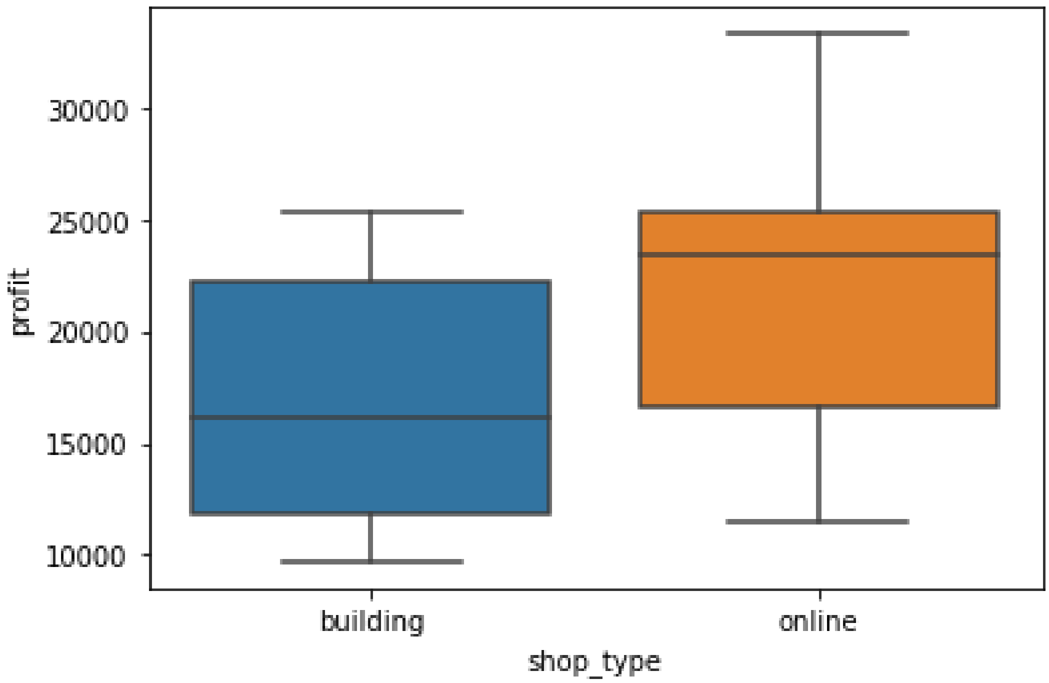
```
online_clients = fig.add_subplot(323)
online_income = fig.add_subplot(324)

traditional_clients = fig.add_subplot(325)
traditional_income = fig.add_subplot(326)

total_clients.hist(df.clients_per_month)
total_clients.set_xlabel('Count')
total_clients.set_title("Total Monthly Clients")

total_income.hist(online_df.monthly_income)
total_income.set_xlabel('N$')
total_income.set_title("Total Monthly Income")

online_clients.hist(online_df.clients_per_month)
online_clients.set_xlabel('Count')
online_clients.set_title("Online Clients per Month")

online_income.hist(df.monthly_income)
online_income.set_xlabel('N$')
online_income.set_title("Online Barbers Monthly Income")

traditional_clients.hist(traditional_df.clients_per_month)
traditional_clients.set_xlabel('Count')
traditional_clients.set_title("Tradtional Barbers Clients/Month")

traditional_income.hist(traditional_df.monthly_income)
traditional_income.set_xlabel('N$')
traditional_income.set_title("Traditional Barbers Monthly Income")

plt.show()
```


Total Monthly Clients
0
2
4
6
8
10
350
400
450
500
550
Count
Total Monthly Income
0
1
2
3
4
5
6
7
15000
20000
25000
30000
35000
N$
Online Clients per Month
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
350
400
450
500
550
Count
Online Barbers Monthly Income
0
2
4
6
8
15000
20000
25000
30000
35000
N$
Tradtional Barbers Clients/Month
0
1
2
3
4
5
6
7
375
400
425
450
475
500
525
550
Count
Traditional Barbers Monthly Income
0
1
2
3
4
5
14000
16000
18000
20000
22000
24000
26000
28000
N$

The histogram show the frequeceny of monthly customers and the the total income for that month.

Box Plot

[137]:
```
ax = sns.boxplot(x='shop_type', y='profit', data=df, orient="v")
```

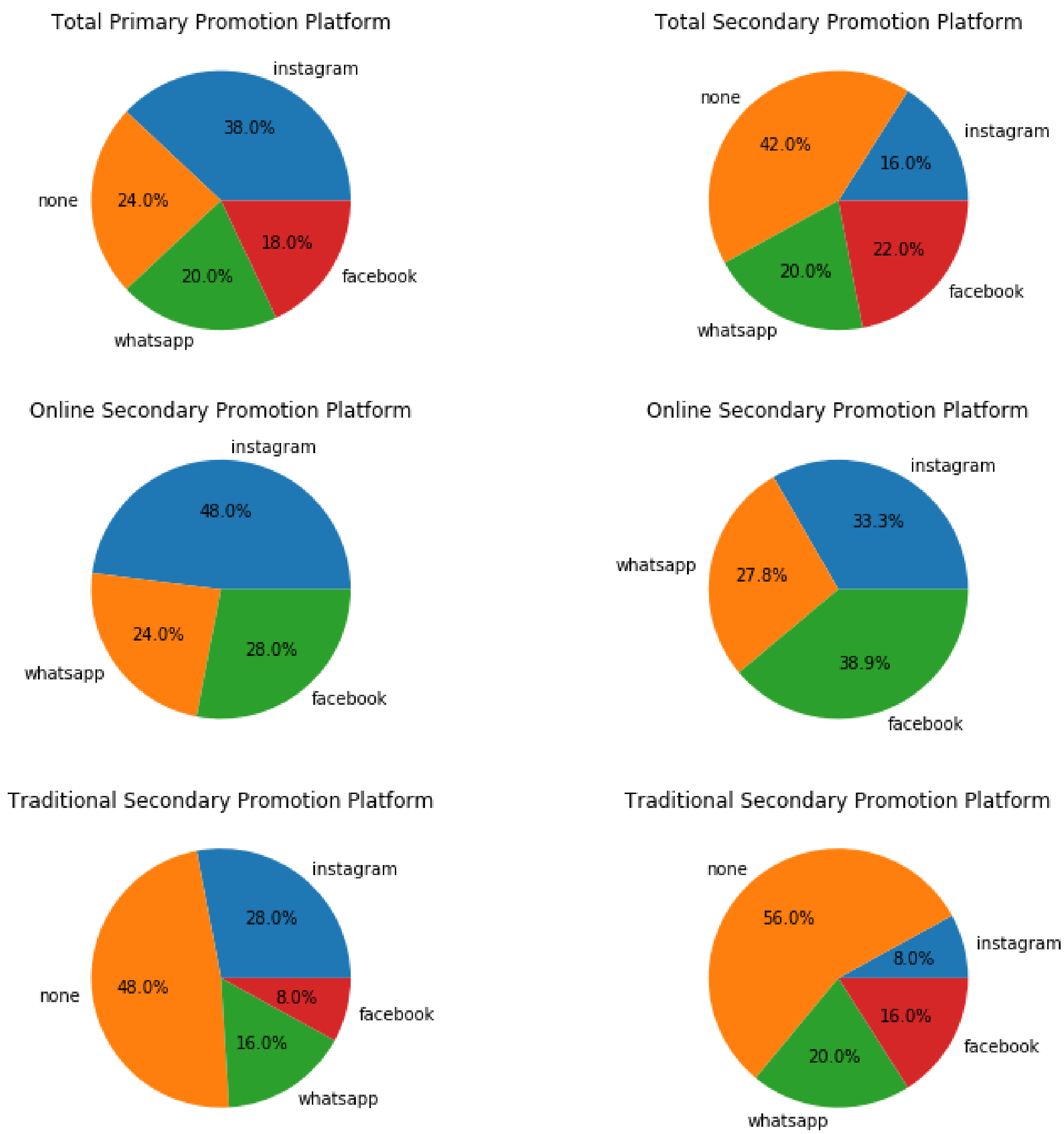


Pie Chart

[122]:
```
fig = plt.figure()
fig.set_figheight(12)
fig.set_figwidth(12)

one = fig.add_subplot(321)
two = fig.add_subplot(322)
three = fig.add_subplot(323)
four = fig.add_subplot(324)
five = fig.add_subplot(325)
six = fig.add_subplot(326)

one.set_title("Total Primary Promotion Platform")
two.set_title("Total Secondary Promotion Platform")
three.set_title("Online Secondary Promotion Platform")
four.set_title("Online Secondary Promotion Platform")
five.set_title("Traditional Secondary Promotion Platform")
six.set_title("Traditional Secondary Promotion Platform")
```

```
type_counts_1 = df['promotion_platform_1'].value_counts()
type_counts_2 = df['promotion_platform_2'].value_counts()

type_counts_online_1 = online_df['promotion_platform_1'].value_counts()
type_counts_online_2 = online_df['promotion_platform_2'].value_counts()

type_counts_traditional_1 = traditional_df['promotion_platform_1'].
 ↪value_counts()
type_counts_traditional_2 = traditional_df['promotion_platform_2'].
 ↪value_counts()


df1 = pd.DataFrame({'prtype': type_counts_1},
                  index = ['instagram', 'none', 'whatsapp', 'facebook'])
df2 = pd.DataFrame({'prtype': type_counts_2},
                  index = ['instagram', 'none', 'whatsapp', 'facebook'])
df3 = pd.DataFrame({'prtype': type_counts_online_1},
                  index = ['instagram', 'whatsapp', 'facebook'])
df4 = pd.DataFrame({'prtype': type_counts_online_2},
                  index = ['instagram', 'whatsapp', 'facebook'])
df5 = pd.DataFrame({'prtype': type_counts_traditional_1},
                  index = ['instagram', 'none', 'whatsapp', 'facebook'])
df6 = pd.DataFrame({'prtype': type_counts_traditional_2},
                  index = ['instagram', 'none', 'whatsapp', 'facebook'])

one.pie(df1['prtype'],labels=['instagram', 'none', 'whatsapp', 'facebook'],␣
 ↪autopct='%1.1f%%')
two.pie(df2['prtype'],labels=['instagram', 'none', 'whatsapp', 'facebook'],␣
 ↪autopct='%1.1f%%')
three.pie(df3['prtype'],labels=['instagram', 'whatsapp', 'facebook'],␣
 ↪autopct='%1.1f%%')
four.pie(df4['prtype'],labels=['instagram', 'whatsapp', 'facebook'],␣
 ↪autopct='%1.1f%%')
five.pie(df5['prtype'],labels=['instagram', 'none', 'whatsapp', 'facebook'],␣
 ↪autopct='%1.1f%%')
six.pie(df6['prtype'],labels=['instagram', 'none', 'whatsapp', 'facebook'],␣
 ↪autopct='%1.1f%%')

plt.show(block=False)
```

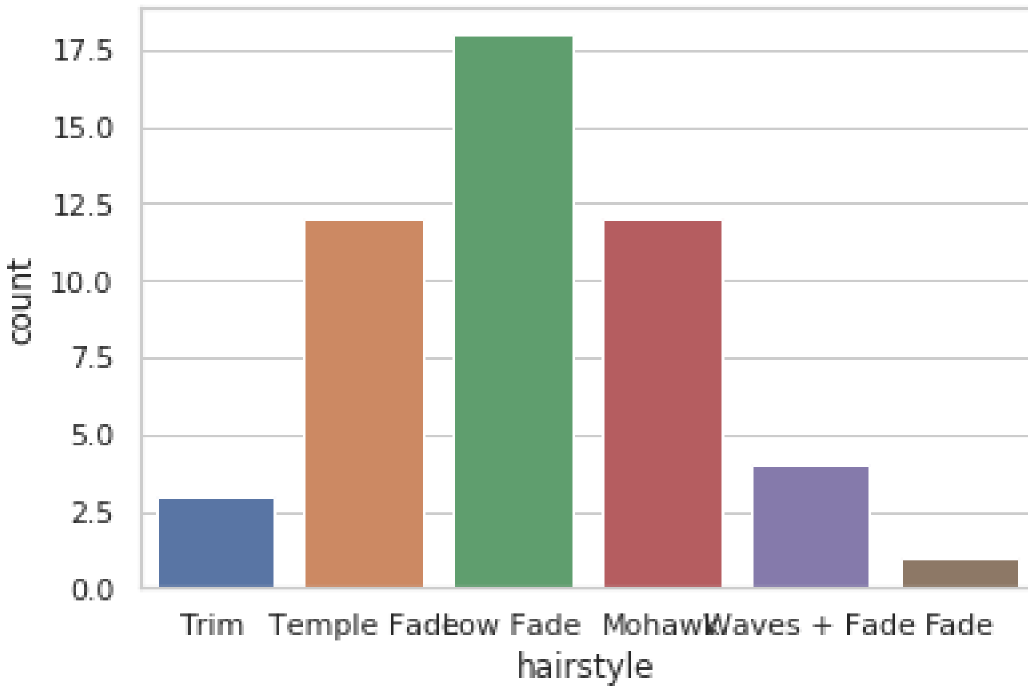
```
           prtype
instagram      12
whatsapp        6
facebook        7
```



A pie graphs proportions of classes in a population, here observe the proportion of barbers that use social media to promote their business. We found that majority (38%) of barbers use only instagram for promotion. The least used primary platform is facebook scoring at 18%. 48% of online barber choose instagram as their primary platform while only 28% of traditional barber use instagram. Majority(48%) of traditional barbers do not use any social media platform to promote their barbershops.

Bar Graph

[40]:
```
ax = sns.countplot(x='hairstyle', data=df)
```



We use a bar graph to find the most liked hair style, in our findings the low fade seems to be most like, second best is the temple fade while the normal fade is the least cut.

4 4.Prototype

Visit our github repo to download the prototype, these are only screenshots of how it looks like

https://github.com/Pelema/dwm

This is the page that allows a user to enter data, either an existing CSV file or each single user's data

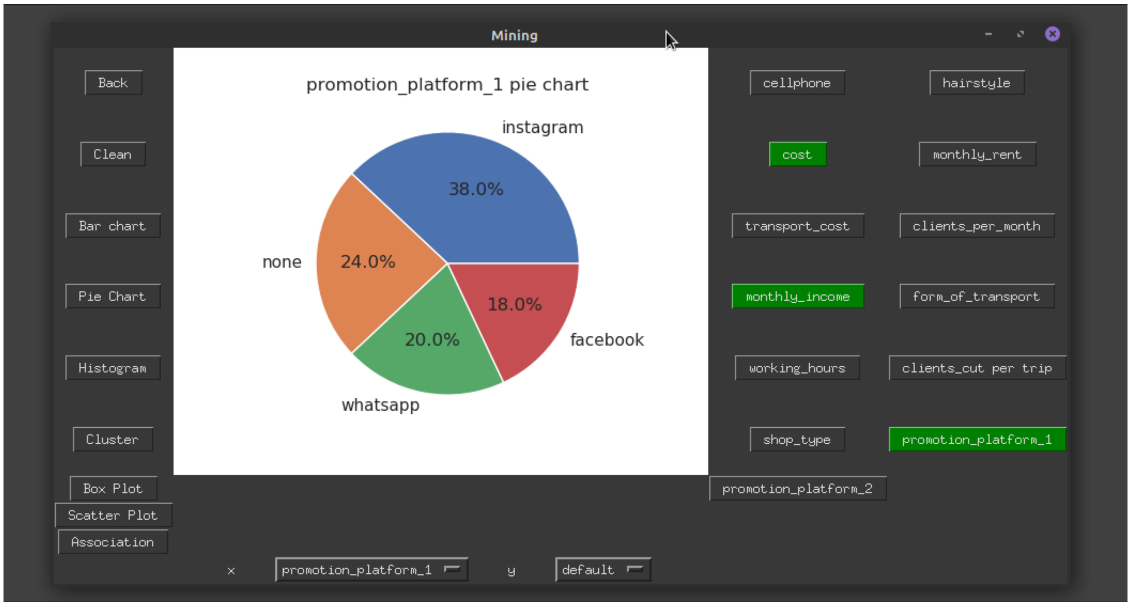
[9]:
```
Image(filename= "./start_up.png")
```

[9]:

This is page where we do our data mining

[10]:
```
Image(filename= "./mining.png")
```

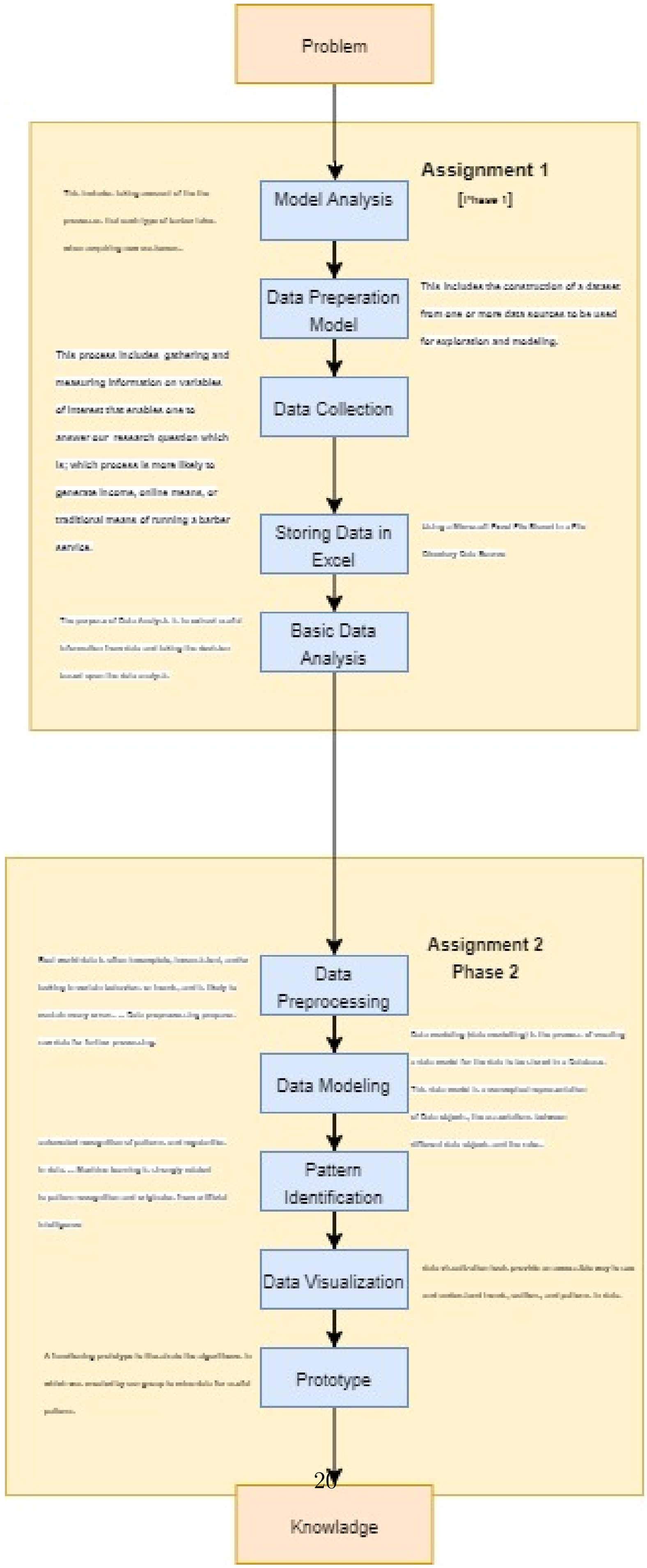
[10]:



4.1 Transition modelling

[13]:
```
Image(filename= "./Transition Modeling (1).jpg", width=600)
```

[13]:


Problem
Assignment 1
[Phase 1]
Model Analysis
Data Preperation Model
This includes the construction of a dataset from one or more data sources to be used for exploration and modeling.
This process includes gathering and measuring information on variables of interest that enables one to answer our research question which is; which process is more likely to generate income, online means, or traditional means of running a barber service.
Data Collection
Storing Data in Excel
Basic Data Analysis
Assignment 2
Phase 2
Data Preprocessing
Data Modeling
Pattern Identification
Data Visualization
Prototype
Knowladge

4.2 Conlusion

We've found that on average althoug both traditional and online barbers bring in around the same monthly income, traditional barbers profits are often lower due to higher fixed costs such as monthly rent.

```
[ ]:
```

```
[ ]:
```