STAT 576: Data Informatics

Poshmark Sales Report Analysis

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Contents

1 Introduction

1.1 What is Poshmark?

Poshmark is a social platform established in 2011 where people from United States can buy and sell women's, men's and kids fashion items. The appeal of Poshmark is that you can create your own boutique and shop great deals without leaving the comfort of your own couch!

1.2 Motivation

Poshmark sales data was made available as of last winter of 2018 to each individual seller. Data such as merchandise category, subcategory, location of purchase by state, and much more are readily available in the sales report. It is left to each Poshmark seller to analyze their data independently. However, the average seller would be overwhelmed with the amount of information the data provides. As a result, most sellers do not take advantage of the data set.

The seller is self-aware than fashion merchandise go through trends, hence it becomes difficult to justify whether a merchandise is worth purchasing. For example, a merchandise with a high profit margin may take months to sell which can be an issue for sellers who use Poshmark as main source of income.

The seller in this analysis had two main propositions: 1) find which items have the highest profit in the shortest amount of waiting time (i.e. the difference between listing date and order date) and 2) Compare top selling brands per day/month.

2 Data

The sales report was provided by a Poshmark boutique seller (closet handle @stylesforu). Sellers can easily attain their sales report via their profile page on the Poshmark website or mobile application. The sales report is downloaded as a CSV file.

The seller's sale report contains 1552 entries and twenty-six columns. However, only a subset of columns are analyzed in this report. Target variables include number of days it took to sell an item, top selling brand, and net earnings. Predictor variables include the merchandise category, the listing title, the listing and order dates, and the state which the merchandise was purchased.

2.1 Variable Transformations

The CSV file contained a column of dates which an item was listed and a column of dates which an item was sold. The difference between the two dates determined the amount of time a merchandise spent in inventory before being sold.

Additionally, a variable that contained net earnings per day spent in inventory was created as a metric to measure the performance of a merchandise.

Data cleaning included stripping away the dollar sign ($) from columns that involved cost to allow arithmetic manipulation and removing of Emoji plain text from listing titles for proper text mining.

2.2 Descriptive Analysis

2.2.1 Text Mining

Figure 1 shows that listing titles that contain more than thirty characters typically spend less time in inventory than shorter listing titles.

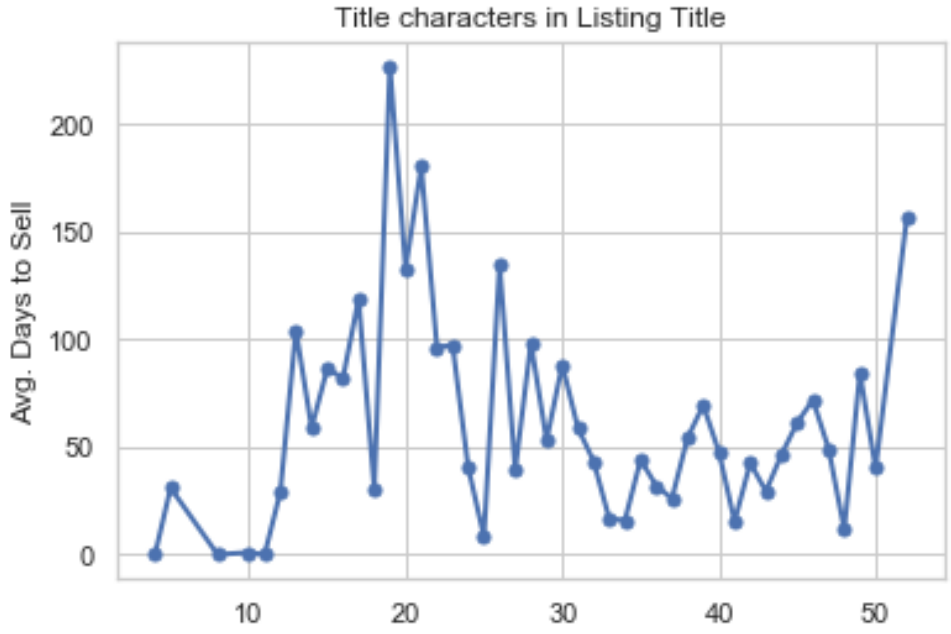


Figure 1: Longer title characters perform fairly well

This is not surprising given that online buyers tend to look for merchandise with specific attributes (e.g. New small adidas black track pants).

Figure 2 shows a very similar story such that listing titles that contain more than nine words typically spend less time in inventory than shorter listing titles.

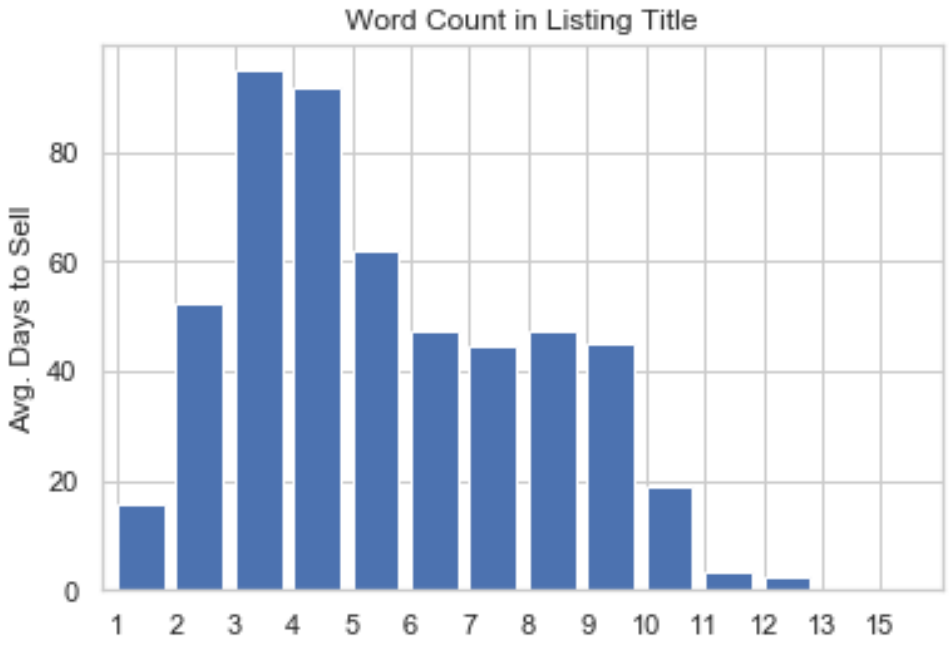


Figure 2: More words mean better sales

One possible explanation can be the key words that most sellers use to capture the buyers interest. The most popular words in each listing title where keywords such as NWT (New with Tags), JUST, !, IN, HP, LEFT. In fact, about 85.70% of listing titles contained key tags.

2.2.2 Top performing brands

Figure 3 shows the top selling brands that sold the quickest. Note that an average day to sell of zero means that the merchandise sold that same day.

Brand	Avg Days to Sell	Avg Net Earnings per day
BCBGeneration	0.0	27.38
Sole (Sense)ability	0.0	25.60
Catherine Malandrino	0.0	24.00
Dexflex Comfort	0.0	14.80
American Apparel	0.0	14.40
Liberty	0.0	8.00
Calvin Klein	0.0	5.05

Figure 3: Top brands with the quickest sells

Figure 4 shows the top selling brands that have the highest average net earnings. It is interesting to see that the brand "Sam Edelman" has a high average net earning yet on average takes forty days to sell.

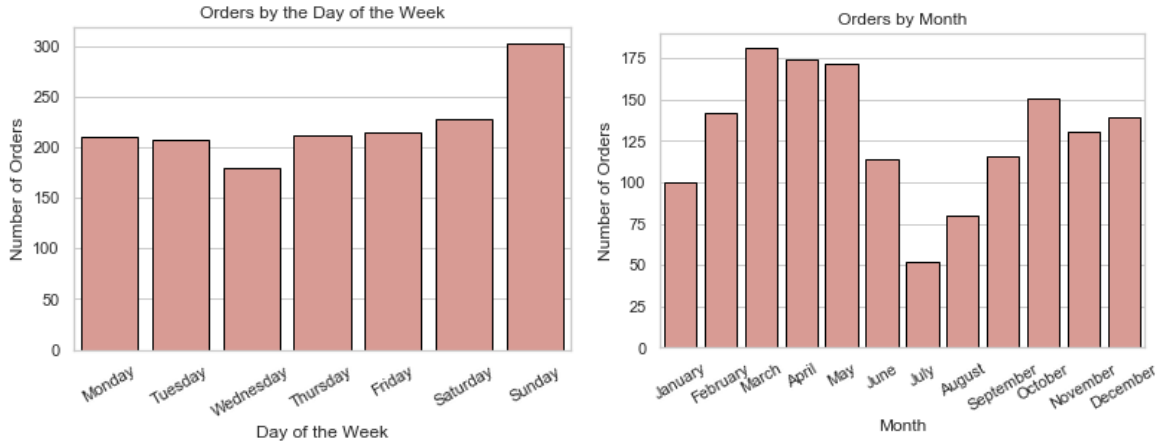
Brand	Avg Days to Sell	Avg Net Earnings per day
Gucci	7.0	45.71
UGG	2.0	28.00
BCBGeneration	0.0	27.38
Sole (Sense)ability	0.0	25.60
Catherine Malandrino	0.0	24.00
Ted Baker	2.0	24.00
Sam Edelman	40.0	22.65

Figure 4: Top brands with the best (avg) net earnings

This is a perfect example that shows a brand that is more of an investment purchase for the seller.

2.2.3 Best selling times

Figure 5(a) shows the volume of orders by the day of the week. It makes sense to why the best days would be Saturday and Sunday.



(a) Weekends are best for selling

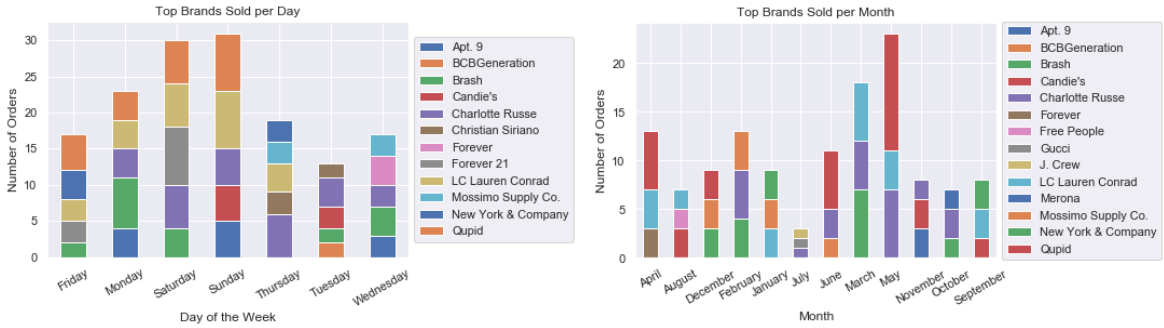
(b) Spring and winter are the best months

Figure 5: Comparison between sales by week and month

Figure 5(b) shows the volume of orders by month. The pattern is not quite obvious to the viewer. The best selling months are most likely dependent on the seller's merchandise preferences.

2.2.4 Top selling brands

Figure 6(a) shows the top five brands by the day of the week. It makes sense to why the best days would be Saturday and Sunday.



(a) Qupid performs best on weekends

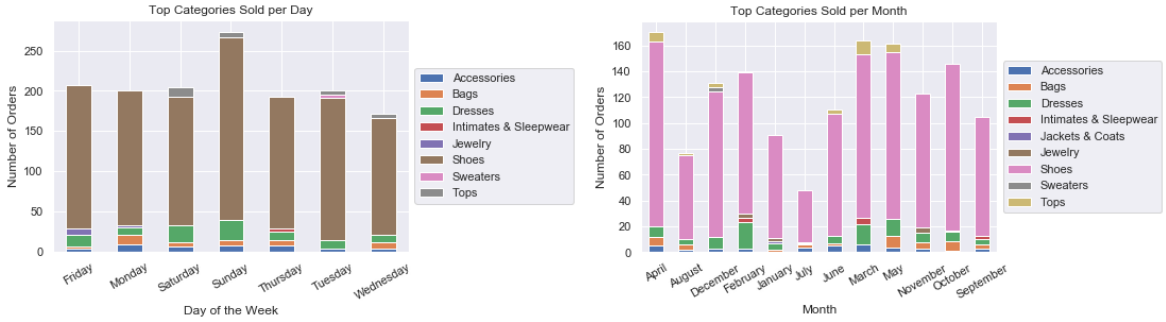
(b) Qupid is consistent throughout the year

Figure 6: Comparison between top brands by week and month

Figure 6(b) shows the volume of orders by month. Both plots show that Qupid, LC Lauren Conrad, and Brash are the seller's highest selling brands.

2.2.5 Top selling categories

Figure 7(a) shows the top five categories by the day of the week. It should be reminded that this particular client is a boutique seller. Hence, the analysis is shifted to the other high-selling categories. It can seen that bags and dresses are the seller's backup merchandise to sell.



(a) Bags and dresses are runner-ups

(b) Dresses and bags sell throughout the year

Figure 7: Comparison between top categories by week and month

Figure 7(b) shows the top five categories by month. The results are similar to Figure 7(a).

3 Methods

Poshmark sellers tend to post their merchandise with a given asking price that best suits the market. Additionally, online buyers are allowed to view these merchandise and purchase on the spot. However, buyers are also allowed to offer a price on the merchandise which the seller can either accept, decline, or counteroffer.

Knowing whether a particular merchandise will receive an offer will give the seller insight on how stock up future inventory.

A logistic regression is used to classify whether a merchandise will receive an offer based key features such as the item's brand, order price, and purchasing location based on the seller's domestic state.

4 Results

The data was split into testing and training set which contained was 40% and 60% of the original data, respectively.

4.1 Confusion matrix

Figure 8 shows the confusion matrix of the model, where "1" = Offer and "0" = No offer (i.e. purchased at seller's listed price)

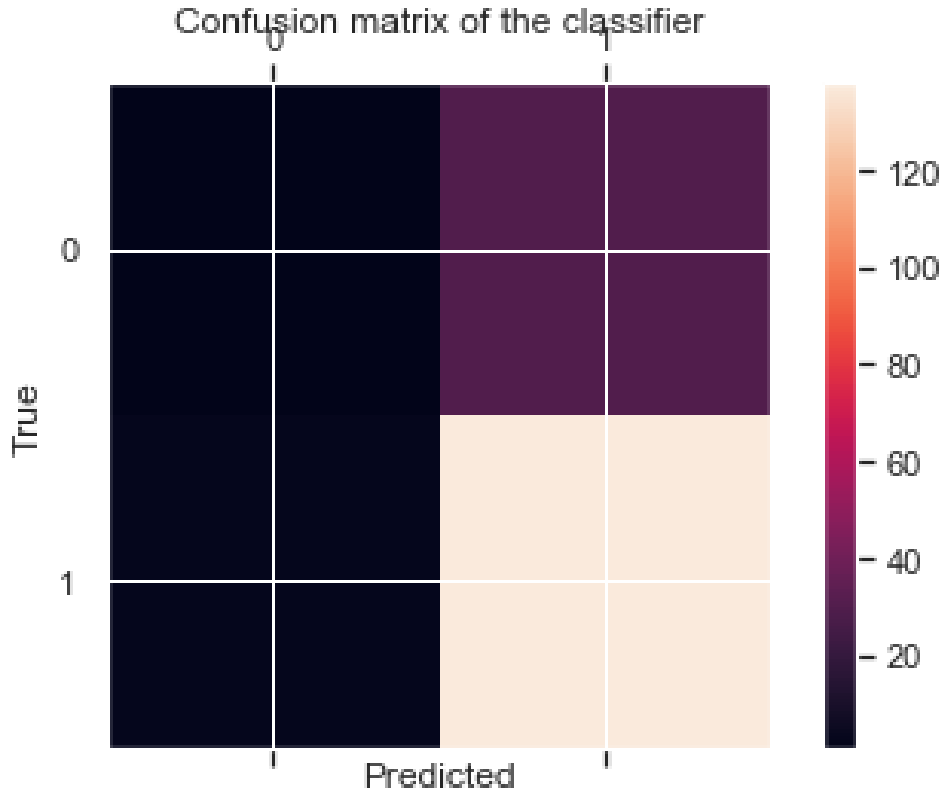


Figure 8: Confusion matrix of the model. Performance is sub-par

The model is good at detecting true negatives, or correctly identifying items that will sell at the seller's listed price.

4.2 Classification report

Figure 9 shows the classification report of the model. The model is strongly accuracy at 81%.

	precision	recall	f1-score	support
0	0.25	0.03	0.06	31
1	0.82	0.98	0.89	141
accuracy			0.81	172
macro avg	0.54	0.51	0.48	172
weighted avg	0.72	0.81	0.74	172

Figure 9: Classification of the model

Also to note is the high precision and recall on "1", but very low recall for "0". This is an issue if the seller has a preference to sell merchandise at a firm-holding price.

4.3 ROC curve

Figure 10 shows the ROC curve of the model.

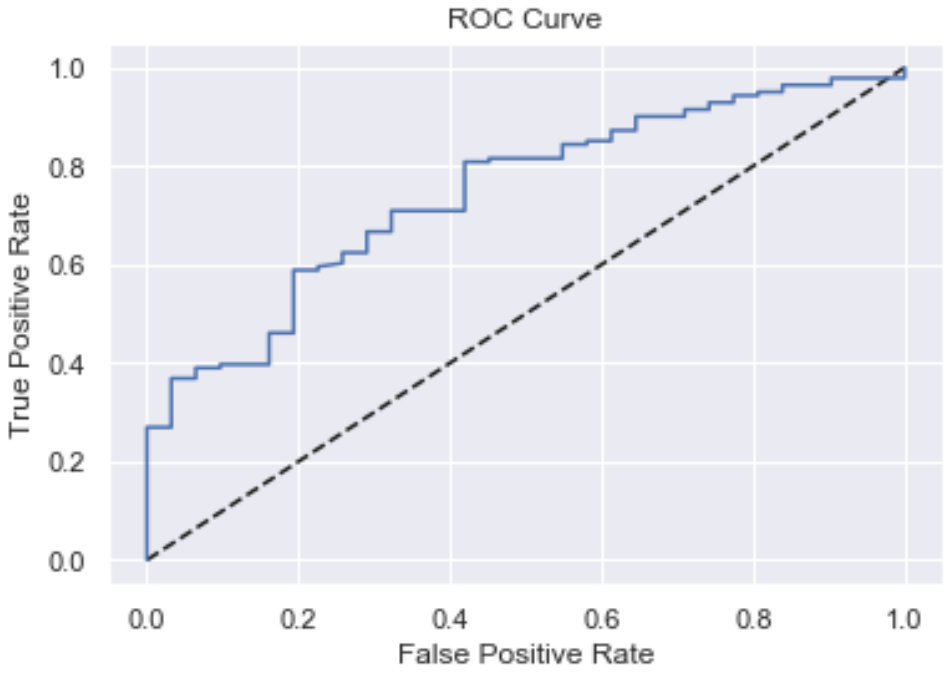


Figure 10: ROC Curve

5 Conclusion

The brand that contains the highest profits in the shortest amount of waiting time include BCBGeneration, while Qupid is the seller's most reliable brand to sell weekly and monthly.

As for classification, a proper logistic model can accurately predict whether a merchandise will receive an offer based on the item's brand, order price, and purchasing location based on the seller's domestic state.

6 Future Research

Poshmark has newly released an inventory report that includes merchandise that have not sold yet. The seller can gage how well their items will sell based on the items sold from their sales report.

Moreover, the average days spent in inventory before being sold can be modeled using queuing and waiting time analysis.

6.1 Limitation

The analysis only used a subset of columns provided. Also, only one user has provided their sales report. Hence, this analysis is not representative to all Poshmark sellers.

7 Appendix: Code

```
# Importing necessary library
from messytables import CSVTableSet, type_guess, \
types_processor, headers_guess, headers_processor, \
offset_processor

import pandas as pd
import numpy as np
from IPython.display import display
import nltk
from nltk.tokenize import word_tokenize
from nltk.probability import FreqDist
import re
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import roc_curve
from sklearn.metrics import accuracy_score
# Open the Sales Activity Report into Python
fh = open('sales_activity_report.csv', 'rb')

# Load a file object:
table_set = CSVTableSet(fh)

# If you aren't sure what kind of file it is, you can use
# any_tableset.
#table_set = any_tableset(fh)

# A table set is a collection of tables:
row_set = table_set.tables[0]

# guess header names and the offset of the header:
offset, headers = headers_guess(row_set.sample)
row_set.register_processor(headers_processor(headers))

# add one to begin with content, not the header:
row_set.register_processor(offset_processor(offset + 1))

# guess column types:
types = type_guess(row_set.sample, strict=True)

# and tell the row set to apply these types to
# each row when traversing the iterator:
row_set.register_processor(types_processor(types))
# import the table of values from the summary report
df = pd.read_csv('sales_activity_report.csv', header = offset-1, skipfooter=2, engine='
                                        python')
em = pd.read_csv('emojis.csv')

# Remove the dollar sign from Order Price, Seller Shipping Discount,
# Upgraded Shipping Label Fee, Net Earnings, Sales Tax (Paid by Buyer)
df['Order Price']=[x.strip('$') for x in df['Order Price']]
df['Order Price']=df['Order Price'].astype(float)

df['Seller Shipping Discount']=[x.strip('$') for x in df['Seller Shipping Discount']]
df['Seller Shipping Discount']=df['Seller Shipping Discount'].astype(float)

df['Upgraded Shipping Label Fee']=[x.strip('$') for x in df['Upgraded Shipping Label Fee']
                                        ]
df['Upgraded Shipping Label Fee']=df['Upgraded Shipping Label Fee'].astype(float)

df['Net Earnings']=[x.strip('$') for x in df['Net Earnings']]
df['Net Earnings']=df['Net Earnings'].astype(float)
```

```
#df['Sales Tax (Paid by Buyer)']=[x.strip('$') for x in df['Sales Tax (Paid by Buyer)']]
df['Sales Tax (Paid by Buyer)']=df['Sales Tax (Paid by Buyer)'].astype(str).str.replace('$
                                                    ', '')
df['Sales Tax (Paid by Buyer)']=df['Sales Tax (Paid by Buyer)'].replace(
[r'--$', 'nan'], value=np.nan, regex=True)
df['Sales Tax (Paid by Buyer)']=df['Sales Tax (Paid by Buyer)'].astype(float)

# Convert Listing Date and Order Date into datetime format
df['Listing Date'] = pd.to_datetime(df['Listing Date'])
df['Order Date'] = pd.to_datetime(df['Order Date'])
# Remove emoji from listing title
char_list = em['emoji'].values.tolist()
def remove_emoji(listing_title):
return re.sub("|".join(char_list), "", listing_title)

Listing_titles = pd.Series(df['Listing Title'].apply(remove_emoji))
# Appling word tokenize in the listing titles for breaking the titles
token_titles = Listing_titles.apply(word_tokenize)

# Finding the frequency distinct throughout all the titles
token_titles_combined = [st for row in token_titles for st in row]
fdist = FreqDist(token_titles_combined)

# To find the frequency of top 26 words
fdist10 = fdist.most_common(26) # Key tags include NWT, JUST, !, IN, HP, LEFT

# Proportion of listing titles that contain key tags
Listing_titles_key_tags = Listing_titles.str.contains('NWT|JUST|!|IN|HP|LEFT', case = True
                                                    )
prop = np.sum(Listing_titles_key_tags) / Listing_titles.shape[0]
print('Proportion of Listing titles that contain key tags: %.2f' % (prop*100)); del(prop)
# Create variable that represents the number of days it took to sell
time_to_sell = df['Order Date'] - df['Listing Date']
time_to_sell.rename('Time to Sell', inplace=True)

# Create variable that represents the net earnings per day
net_earnings_per_day = df['Net Earnings'] / time_to_sell.replace(pd.Timedelta('0 days'),
                                                    pd.Timedelta('1 days')).astype('timedelta64[D]'
                                                    )
net_earnings_per_day = round(net_earnings_per_day, 2)
net_earnings_per_day = net_earnings_per_day.rename('Net Earnings per day', inplace=True)
# Word count versus the time it took to sell
foo = pd.concat([token_titles.apply(len), time_to_sell.astype('timedelta64[D]')], axis=1)
foo.rename(columns={'Listing Title':'Word count'}, inplace=True)
# Average time to sell based on word count
sns.set(style="whitegrid")
chart = foo.groupby('Word count').mean().plot(
kind='bar', align='edge', width=0.8)
plt.title('Word Count in Listing Title')
plt.ylabel('Avg. Days to Sell', fontsize=12)
plt.xlabel('', fontsize=12)
plt.legend().remove()
chart.set_xticklabels(chart.get_xticklabels(), rotation=0)
plt.show(); del(chart, foo)
# Title characters versus the time it took to sell
foo = pd.concat([Listing_titles.apply(len), time_to_sell.astype('timedelta64[D]')], axis=1
                                                    )
foo.rename(columns={'Listing Title':'Title characters'}, inplace=True)
# Average time to sell based on title characters
foo = foo.groupby('Title characters').mean()
sns.set(style="whitegrid")
chart = plt.plot(foo.index, foo.values, 'b-o', linewidth=2, markersize=5)
plt.title('Title characters in Listing Title')
plt.ylabel('Avg. Days to Sell', fontsize=12)
plt.xlabel('', fontsize=12)
plt.show(); del(chart, foo)
# Find the top brands that sell the quickest

# Create data frame that contains the time it took to sell and brands
```

```
df1 = pd.concat([df['Brand'], time_to_sell.astype('timedelta64[D]'), net_earnings_per_day]
                                                    , axis=1)
# Average the net earnings
df1 = df1.groupby('Brand').mean()
df1.rename(columns={'Net Earnings per day':'Avg Net Earnings per day',
  'Time to Sell':'Avg Days to Sell'}, inplace=True)
# Top brands with the best (avg) net earnings
q = df1.sort_values(by=['Avg Days to Sell', 'Avg Net Earnings per day'], ascending=[True,
                                                    False])
top_avg_net_earnings = q.nlargest(7, 'Avg Net Earnings per day')
display(round(top_avg_net_earnings, 2))
# Top brands with the quickest sells
quickest_sells = q.nsmallest(7, 'Avg Days to Sell')
display(round(quickest_sells, 2))
del(df1, q)
# Find the best selling day of the week

# Group number of items sold and day of week
cats = [ 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
orders_by_weekday = pd.Categorical(df['Order Date'].dt.day_name(), categories=cats,
                                                    ordered=True)
orders_by_weekday_count = orders_by_weekday.value_counts()
sns.set(style="whitegrid")
chart = sns.barplot(orders_by_weekday_count.index, orders_by_weekday_count.values,
color="salmon", saturation=.5,
edgecolor='black')
plt.title('Orders by the Day of the Week')
plt.ylabel('Number of Orders', fontsize=12)
plt.xlabel('Day of the Week', fontsize=12)
chart.set_xticklabels(chart.get_xticklabels(), rotation=30)
plt.show(); del(chart, cats)
# Find the best selling day of the month

# Group number of items sold and month

cats = ['January', 'February', 'March', 'April', 'May', 'June',
'July', 'August', 'September', 'October', 'November', 'December']
orders_by_month = pd.Categorical(df['Order Date'].dt.month_name(), categories=cats,
                                                    ordered=True)
orders_by_month_count = orders_by_month.value_counts()
sns.set(style="whitegrid")
chart = sns.barplot(orders_by_month_count.index, orders_by_month_count.values,
color="salmon", saturation=.5,
edgecolor='black')
plt.title('Orders by Month')
plt.ylabel('Number of Orders', fontsize=12)
plt.xlabel('Month', fontsize=12)
chart.set_xticklabels(chart.get_xticklabels(), rotation=30)
plt.show(); del(chart, cats)
# Compare top selling brands per week

df2 = pd.concat([df['Brand'], df['Order Date'].dt.day_name()], axis=1)
brands_by_week = pd.DataFrame(df2.groupby(['Order Date', 'Brand']).size())
brands_by_week.rename(columns={0:'count'}, inplace=True)
g = brands_by_week['count'].groupby(level=0, group_keys=False)
brands_by_week = pd.DataFrame(g.nlargest(5)); del(df2, g)

sns.set(style="darkgrid", palette="deep")
chart = brands_by_week.unstack().plot(kind='bar', stacked=True)
plt.title('Top Brands Sold per Day')
plt.ylabel('Number of Orders', fontsize=12)
plt.xlabel('Day of the Week', fontsize=12)
handles, labels = chart.get_legend_handles_labels()
plt.gca().legend(loc='center left', bbox_to_anchor=(1, 0.5), labels=[i.strip("()").replace
                                                    ("count, ", "") for i in labels])
chart.set_xticklabels(chart.get_xticklabels(), rotation=30)
plt.show(); del(chart, handles, labels)
# Compare top selling brands per week
```

```
df3 = pd.concat([df['Brand'], df['Order Date'].dt.month_name()], axis=1)
brands_by_month = pd.DataFrame(df3.groupby(['Order Date', 'Brand']).size())
brands_by_month.rename(columns={0:'count'}, inplace=True)
g = brands_by_month['count'].groupby(level=0, group_keys=False)
brands_by_month = pd.DataFrame(g.nlargest(3)); del(df3, g)

sns.set(style="darkgrid")
chart = brands_by_month.unstack().plot(kind='bar', stacked=True)
plt.title('Top Brands Sold per Month')
plt.ylabel('Number of Orders', fontsize=12)
plt.xlabel('Month', fontsize=12)
handles, labels = chart.get_legend_handles_labels()
plt.gca().legend(loc='center left', bbox_to_anchor=(1, 0.5), labels=[i.strip("()").replace
                                        ("count, ", "") for i in labels])
chart.set_xticklabels(chart.get_xticklabels(), rotation=30)
plt.show(); del(chart, handles, labels)
# Compare top categories per week

df2 = pd.concat([df['Category'], df['Order Date'].dt.day_name()], axis=1)
categories_by_week = pd.DataFrame(df2.groupby(['Order Date', 'Category']).size())
categories_by_week.rename(columns={0:'count'}, inplace=True)
g = categories_by_week['count'].groupby(level=0, group_keys=False)
categories_by_week = pd.DataFrame(g.nlargest(5)); del(g, df2)

sns.set(style="darkgrid", palette="deep")
chart = categories_by_week.unstack().plot(kind='bar', stacked=True)
plt.title('Top Categories Sold per Day')
plt.ylabel('Number of Orders', fontsize=12)
plt.xlabel('Day of the Week', fontsize=12)
handles, labels = chart.get_legend_handles_labels()
plt.gca().legend(loc='center left', bbox_to_anchor=(1, 0.5), labels=[i.strip("()").replace
                                        ("count, ", "") for i in labels])
chart.set_xticklabels(chart.get_xticklabels(), rotation=30)
plt.show(); del(chart, handles, labels)
# Compare top categories per month

df3 = pd.concat([df['Category'], df['Order Date'].dt.month_name()], axis=1)
categories_by_month = pd.DataFrame(df3.groupby(['Order Date', 'Category']).size())
categories_by_month.rename(columns={0:'count'}, inplace=True)
g = categories_by_month['count'].groupby(level=0, group_keys=False)
categories_by_month = pd.DataFrame(g.nlargest(5)); del(df3, g)

sns.set(style="darkgrid")
chart = categories_by_month.unstack().plot(kind='bar', stacked=True)
plt.title('Top Categories Sold per Month')
plt.ylabel('Number of Orders', fontsize=12)
plt.xlabel('Month', fontsize=12)
handles, labels = chart.get_legend_handles_labels()
plt.gca().legend(loc='center left', bbox_to_anchor=(1, 0.5), labels=[i.strip("()").replace
                                        ("count, ", "") for i in labels])
chart.set_xticklabels(chart.get_xticklabels(), rotation=30)
plt.show(); del(chart, handles, labels)
# Building a logistic regression model

# Create training and test sets
X = df[['Brand','Order Price', 'Buyer State', 'Offer Order']].dropna()
y = X[['Offer Order']]
X = X[['Brand','Order Price', 'Buyer State']]
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size = 0.4,
random_state=42)
# prepare input data
def prepare_inputs(X_train, X_test):
oe = OneHotEncoder(handle_unknown='ignore')
oe.fit(X_train)
X_train_enc = oe.transform(X_train)
X_test_enc = oe.transform(X_test)
return X_train_enc, X_test_enc
```

```
# prepare target
def prepare_targets(y_train, y_test):
le = LabelEncoder()
le.fit(y_train.values.ravel())
y_train_enc = le.transform(y_train.values.ravel())
y_test_enc = le.transform(y_test.values.ravel())
return y_train_enc, y_test_enc

# prepare input data
X_train_enc, X_test_enc = prepare_inputs(X_train, X_test)
# prepare output data
y_train_enc, y_test_enc = prepare_targets(y_train, y_test)
# summarize
display('Train', X_train.shape, y_train.shape)
display('Test', X_test.shape, y_test.shape)
# Create the classifier: logreg
logreg = LogisticRegression(solver='lbfgs')

# Fit the classifier to the training data
logreg.fit(X_train_enc, y_train_enc)

# Predict the labels of the test set: y_pred
y_pred = logreg.predict(X_test_enc)
# Compute and print the confusion matrix
print(confusion_matrix(y_test_enc, y_pred))
[[  1  28]
[  2 138]]
# Compute and print the classification report
print(classification_report(y_test_enc, y_pred))
# Compute predicted probabilities: y_pred_prob
y_pred_prob = logreg.predict_proba(X_test_enc)[:,1]

# Generate ROC curve values: fpr, tpr, thresholds
fpr, tpr, thresholds = roc_curve(y_test_enc, y_pred_prob)

# Plot ROC curve
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.show()
# Evaluate predictions
accuracy = accuracy_score(y_test_enc, y_pred)
print('Accuracy: %.2f' % (accuracy*100))
```