Project 2¶ ()

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Introduction to Dataset and Relevance¶ ()

This document will examine and interpret what conclusions can be made using the "larger_sales_dataset.csv" obtained from Hassane Skikri through kaggle.com. For convenience sake, we will be referring to the business this dataset comes from as BusA Sales. The set consists of 10000 observations of 10 variables. Though the data in this set is fictional, it represents a realistic example of data that a business may collect during standard operation. Being able to clean, sort, and make sense of such a dataset is a skill that would be beneficial for the vast majority of businesses to employ.

In [112]:
```
import numpy as npimport pandas as pdimport matplotlib.pyplot as plt
```

Import the File¶ ()

In [113]:
```
df = pd.read_csv('larger_sales_dataset.csv')df_sort_date =
df.sort_values(by = 'Order Date')
```

Summary of BusA Sales Data¶ ()

In [114]:
```
df.describe(include = 'all')
```

Out[114]:

	Order ID	Product ID	Product Category	Quantity	Unit Price	Total Price	Order Date	Cu
count	10000	10000	10000	10000.000000	10000.000000	10000.000000	10000	
unique	10000	10000	6	NaN	NaN	NaN	365	
top	921fafe7-640c-42aa-9609-21269106a202	beb24319-053d-4096-b225-867214413960	Sports & Outdoors	NaN	NaN	NaN	2023-12-16	c93
freq	1	1	1719	NaN	NaN	NaN	47	
mean	NaN	NaN	NaN	3.009700	253.278078	762.724197	NaN	
std	NaN	NaN	NaN	1.399286	142.523046	593.515659	NaN	
min	NaN	NaN	NaN	1.000000	10.071462	10.092483	NaN	
25%	NaN	NaN	NaN	2.000000	129.205590	284.388946	NaN	
50%	NaN	NaN	NaN	3.000000	251.669090	602.823424	NaN	
75%	NaN	NaN	NaN	4.000000	378.259451	1129.878504	NaN	
max	NaN	NaN	NaN	5.000000	499.956975	2499.784873	NaN	

In [115]:
```
# Number of Unique Customersprint("Number of Unique Customers: " +
str(df["Customer ID"].nunique()))
```

```
Number of Unique Customers: 10000
```

In [116]:
```
# Range of Datesprint("The range of dates: " + min(df["Order Date"]) + " t
o "  + max(df["Order Date"]))
```

```
The range of dates: 2023-01-01 to 2023-12-31
```

Questions to answer about this set¶ ()

- In which category is the most money being made?
- What time of year are sales peaking for each category?
- What is the average total for orders?
- What percentage of sales are refunded or cancelled?

Where is the money being made?¶ ()

BusA Sales sells items from 6 categories

- Sports & Outdoors
- Home & Kitchen
- Beauty & Health
- Books
- Electronics
- Clothing

Sales by Category¶ ()

In the list below, we can see the distribution of sales made by each of the categories. The highest performing category was Sports & Outdoors bringing in over 1.31 million in sales. This is in comparison to the lowest performing category of Beauty & Health with a perfomance of 1.2 million.

In [117]:
```
cats = ["Sports & Outdoors", "Clothing", "Electronics", "Home & Kitchen",
"Books", "Beauty & Health"]totalpDict = {}counter = 0for i in cats:    tem
pLine = {i: "${:,.2f}".format(round(sum(df["Total Price"][df["Product Cate
gory"] == i]), 2))}    totalpDict[counter] = tempLine    counter = counter
+ 1totalpDict
```

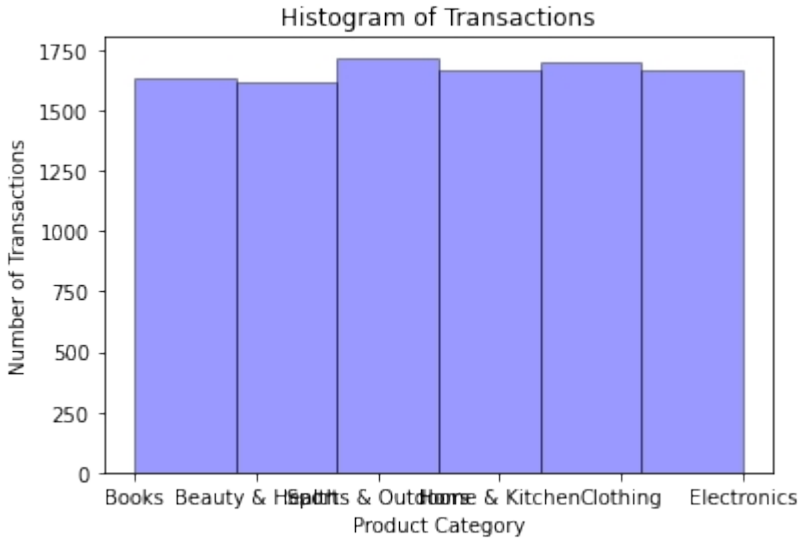
Out[117]:
```
{0: {'Sports & Outdoors': '$1,313,735.43'}, 1: {'Clothing': '$1,303,679.19
'}, 2: {'Electronics': '$1,290,283.08'}, 3: {'Home & Kitchen': '$1,268,471
.95'}, 4: {'Books': '$1,249,307.25'}, 5: {'Beauty & Health': '$1,201,765.0
8'}}
```

Number of Transactions by Category¶ ()

Next, the number of transactions tells us the amount of customers that bought from each category. This is in contrast to the amount they are spending. We can see by plotting a histogram that the 6 categories are remarkably similar to one another.

In [118]:
```
fig = plt.figure()ax1 = fig.add_subplot(1,1,1)ax1.hist(df_sort_date['Produ
ct Category'],          bins = 6,          color = 'b',          alpha
= .4,          edgecolor = 'black')plt.xlabel('Product Category')
plt.ylabel('Number of Transactions')plt.title('Histogram of Transactions')
```

Out[118]:
```
Text(0.5, 1.0, 'Histogram of Transactions')
```



Biggest and Smallest Orders¶ ()

e are also able to see that the top 10 Biggest orders of the 2023 year averaged at Total Price of $2491.64. It is also worth noting that in this top ten, we see the category of Books 3 times, Beauty & Health and Electronics 2 times, and Home & Kitchen, Sports & Outdoors, and Clothing only once.

In [119]:
```
df_sort_price = pd.DataFrame(df, columns=['Total Price', 'Product Category
', 'Order Date']).sort_values(by = 'Total Price')print("10 Smallest Orders
: \n ")print(df_sort_price.head(10))print("\n\n10 Largest Orders: \n")prin
t(df_sort_price.tail(10))
```

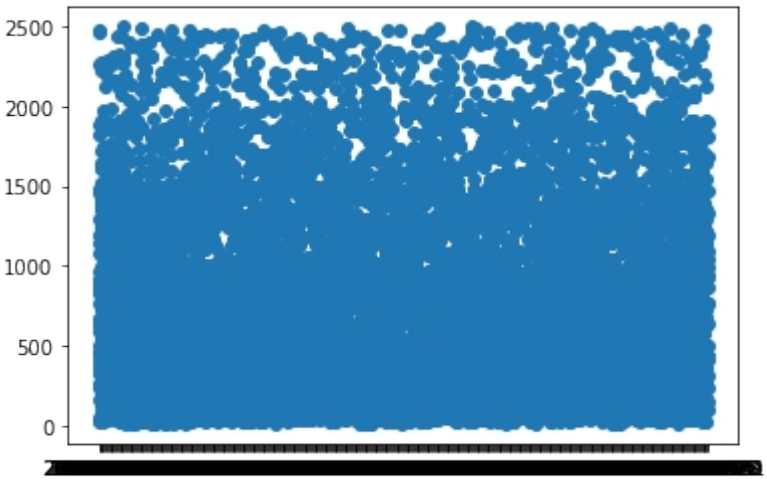
```
10 Smallest Orders:        Total Price   Product Category  Order Date3276
   10.092483           Clothing  2023-01-203159    10.598639     Home & Ki
tchen  2023-02-151921    10.802425     Home & Kitchen  2023-09-198529    1
1.058527  Sports & Outdoors  2023-06-106011    11.112996  Sports & Outdoor
s  2023-11-085262    11.271074    Beauty & Health  2023-02-013914    12.11
1023  Sports & Outdoors  2023-01-17699     12.156129  Sports & Outdoors  2
023-01-234324    12.186533     Home & Kitchen  2023-11-038114    13.001030
     Home & Kitchen  2023-02-1010 Largest Orders:       Total Price   Prod
uct Category  Order Date9731  2485.285955              Books  2023-07-2257
11  2485.948678           Clothing  2023-12-085152  2487.235676        Ele
ctronics  2023-05-301781  2488.128718              Books  2023-09-081280
2490.066090  Sports & Outdoors  2023-01-276786  2492.414897    Beauty & He
alth  2023-10-23154   2494.449821        Electronics  2023-09-144094  2494
.532854              Books  2023-09-299612  2498.581615    Beauty & Health
  2023-01-163240  2499.784873     Home & Kitchen  2023-08-12
```

What Time of the Year are Sales Best?¶ ()

When breaking down the distribution of sales throughout the year, it immediately becomes clear that the data in this file is fictional. With a normal set of data with variables such as ours, it is typical to expect patterns and trends to appear at different times of the year that correlate with seasons, holidays, and other factors. However, when plotting the total price of each observation against the order date, we can see an extraordinarily consistent layout develop through the 10,000 cases.

In [120]:
```
plt.scatter(df_sort_date['Order Date'],                df_sort_date['Total Pr
ice'])
```

Out[120]:
```
<matplotlib.collections.PathCollection at 0x7fbf20337f70>
```



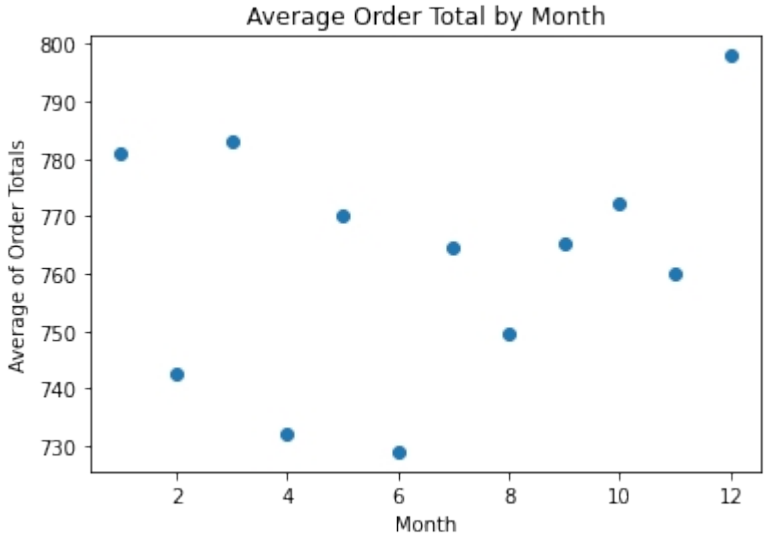
Order Totals Averaged by Month¶ ()

In order to summarize the plot above in a way that is easier understood, I took the average total for orders for each month and plotted them. Doing so, we are able to see that there is a slight deviation in order totals with the smallest amount made per order during the middle of the year before recovering back into the later months. When looking at the graph, it is important that we keep the y-axis in mind. Though the difference in average order totals seems dramatic, looking at the same plot with the bottom limit of our y-axis dropped to 0, we can see that the difference between the months is quite insignificant.

In [121]:
```
#Create Vector of Sorted Order Dates as int(Month)monthLi = []priceLi = []
for i in df_sort_date['Order Date']:    temp = str(i)[5:7]    monthLi.appe
nd(temp)for i in df_sort_date['Total Price']:    priceLi.append(i)    df_m
oney = pd.DataFrame({'Month': monthLi, 'Price': priceLi})#set up scatter p
lot 2 listsmonth = ['01', '02', '03', '04', '05', '06', '07', '08', '09',
'10', '11', '12']monAvgs = []count = 0for j in month:    tempSum = 0    le
ngth = 0    for i in df_money['Month']:        if (i == j):            tem
pSum = tempSum + df_money['Price'][count]            length = length + 1
        count = count + 1    monAvgs.append(tempSum / length)
```

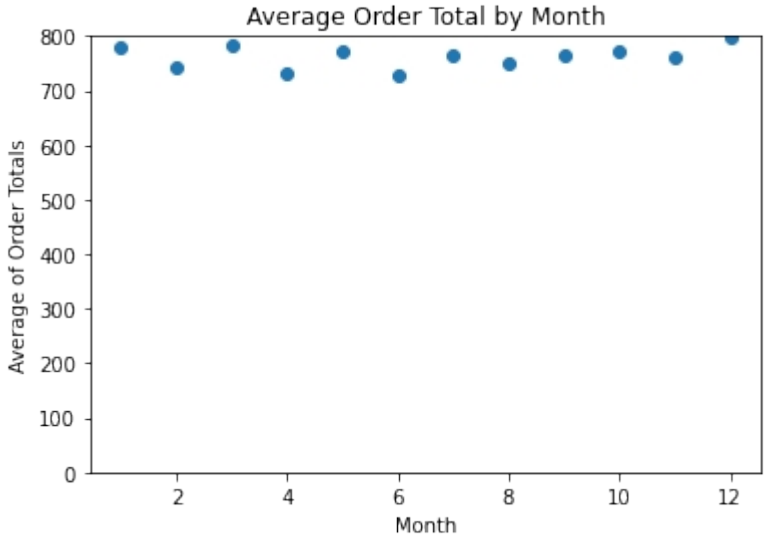
In [122]:
```
fig = plt.figure()ax1 = fig.add_subplot(1,1,1)ax1.scatter(range(1,13), monAvgs)plt.xlabel('Month')plt.ylabel('Average of Order Totals')plt.title('Average Order Total by Month')
```

Out[122]:
```
Text(0.5, 1.0, 'Average Order Total by Month')
```



In [123]:
```
fig = plt.figure()ax1 = fig.add_subplot(1,1,1)ax1.scatter(range(1,13), monAvgs)plt.ylim(0,800)plt.xlabel('Month')plt.ylabel('Average of Order Totals')plt.title('Average Order Total by Month')
```

Out[123]:
```
Text(0.5, 1.0, 'Average Order Total by Month')
```

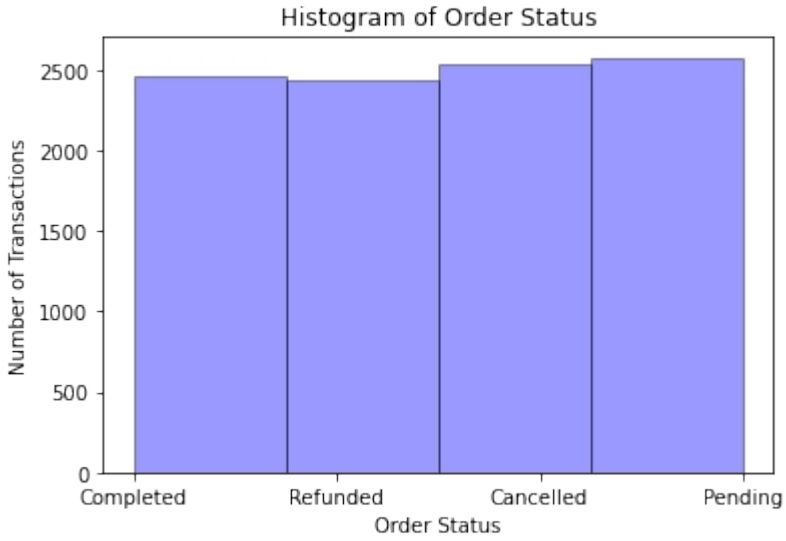


Order Status Distribution¶ ()

An important subject to talk about is the ratio of orders that are either refunded or cancelled. With a combined 49% between the two categories, the amount of orders that are netting a negative return are hard to imagine. This combined with the fact that with a pending order rate of nearly 25% as well, one could expect nearly 2/3 of orders to not be successful.

In [124]:
```
fig = plt.figure()ax1 = fig.add_subplot(1,1,1)ax1.hist(df_sort_date['Order
 Status'],           bins = 4,         color = 'b',          alpha = .4,
      edgecolor = 'black')plt.xlabel('Order Status')plt.ylabel('Number of
Transactions')plt.title('Histogram of Order Status')
```

Out[124]:
```
Text(0.5, 1.0, 'Histogram of Order Status')
```

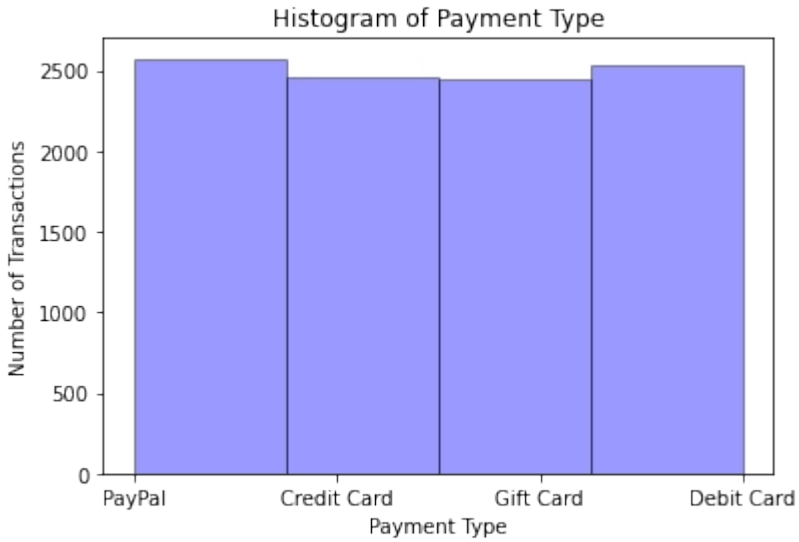


Form of Payment Distribution¶ ()

Finally, below we have the distribution of payment types that customers used during the 2023 fiscal year. Similar to the Order Status plot, we observe a similar amount of transactions between all 4 payment types with the most frequent being Paypal.

In [125]:
```
fig = plt.figure()ax1 = fig.add_subplot(1,1,1)ax1.hist(df_sort_date['Payme
nt Type'],           color = 'b',          bins = 4,          alpha = .4,
      edgecolor = 'black')plt.xlabel('Payment Type')plt.ylabel('Number of
Transactions')plt.title('Histogram of Payment Type')
```

Out[125]:
```
Text(0.5, 1.0, 'Histogram of Payment Type')
```



Conclusion¶ ()

In conclusion, the "larger_sales_dataset" by Hassane Skikri produced some interesting results upon data cleaning and wrangling. We were able to determine that during the fiscal year of 2023, BusA Sales had a total of 10,000 customers. These customers ordered the most from the categories of Sports & Outdoors and Clothing and the least from Beauty & Health. They had the highest order totals in the months of October and November, used Paypal the most, and had an almost 50% rate of either returning or cancelling an order.

While the fields that we observed were realistic, the data seen in this file is highly unlikely to come about during an actual business' operations. In reality, it is likely that you would expect a higher variance in customer preferences (both categorical and chronological), distribution of sales, and a (hopefully) lower margin of refunded/cancelled orders. In addition to what we were given in the set, another field that could prove useful towards BusA's endeavors could be a customer satisfaction survey of some sort.