How can RFM analysis be used to identify customer churn patterns?

In [604]:
```
import pandas as pd
import datetime as dt
import numpy as np
```

In [605]:
```
df = pd.read_csv('/Users/danielyeo/Desktop/Global_Superstore.csv', encoding='ISO-
df.head()
```

Out[605]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	City	State	...	Produ
0	32298	CA-2012-124891	31-07-2012	31-07-2012	Same Day	RH-19495	Rick Hansen	Consumer	New York City	New York	...	TEC-A 100030
1	26341	IN-2013-77878	05-02-2013	07-02-2013	Second Class	JR-16210	Justin Ritter	Corporate	Wollongong	New South Wales	...	FUR-C 100039
2	25330	IN-2013-71249	17-10-2013	18-10-2013	First Class	CR-12730	Craig Reiter	Consumer	Brisbane	Queensland	...	TEC-P 100046
3	13524	ES-2013-1579342	28-01-2013	30-01-2013	First Class	KM-16375	Katherine Murray	Home Office	Berlin	Berlin	...	TEC-P 100045
4	47221	SG-2013-4320	05-11-2013	06-11-2013	Same Day	RH-9495	Rick Hansen	Consumer	Dakar	Dakar	...	TE SH 100005

5 rows × 24 columns

In [606]:
```
df.shape
```

Out[606]:
```
(51290, 24)
```

In [607]:
```
#check for null values
df.isnull().sum()
```

Out[607]:
```
Row ID                0
Order ID              0
Order Date            0
Ship Date             0
Ship Mode             0
Customer ID           0
Customer Name         0
Segment               0
City                  0
State                 0
Country               0
Postal Code       41296
Market                0
Region                0
Product ID            0
Category              0
Sub-Category          0
Product Name          0
Sales                 0
Quantity              0
Discount              0
Profit                0
Shipping Cost         0
Order Priority        0
dtype: int64
```

In [608]:
```
#let's drop Postal Code, missing date, don't need
df = df.drop(columns = ['Postal Code'], inplace = False)
```

In [609]:
```
# cust_freq = df.groupby('Customer Name').size().reset_index(name = 'Order Count'
# cust_freq
```

RFM Analysis

R Recency: How recently a customer made a purchase

F Frequency: How often a customer makes a purchase

M Monetary Value: How much money a customer spends

identify high-value customers, at-risk customers, and churn-prone customers

In [610]:
```
df['Order Date'].value_counts()
```

Out[610]:
```
Order Date
18-06-2014    135
18-11-2014    127
03-09-2014    126
20-11-2014    118
29-12-2014    116
             ...
07-10-2012      1
16-01-2011      1
27-02-2011      1
21-10-2012      1
06-02-2011      1
Name: count, Length: 1430, dtype: int64
```

Our date format is dd-mm-yyyy, so let's tell Pandas to parse dates as day-month-year.

In [611]:
```
df['Order Date'] = pd.to_datetime(df['Order Date'], format='%d-%m-%Y', errors='co
df['Order Date'].value_counts()
```

Out[611]:
```
Order Date
2014-06-18    135
2014-11-18    127
2014-09-03    126
2014-11-20    118
2014-12-29    116
             ...
2012-10-07      1
2011-01-16      1
2011-02-27      1
2012-10-21      1
2011-02-06      1
Name: count, Length: 1430, dtype: int64
```

Recency

In [612]:
```
#lower recency score means customer purchased more recently
recency = df.groupby(by='Customer Name', as_index=False)['Order Date'].max()

recency.columns = ['Customer Name', 'Last Purchase']

recent_date = recency['Last Purchase'].max()

recency['Recency'] = recency['Last Purchase'].apply(lambda x: (recent_date - x).d

recency.head()
```

Out[612]:

	Customer Name	Last Purchase	Recency
0	Aaron Bergman	2014-12-15	16
1	Aaron Hawkins	2014-12-19	12
2	Aaron Smayling	2014-12-08	23
3	Adam Bellavance	2014-11-26	35
4	Adam Hart	2014-12-29	2

Frequency

In [613]:
```
#higher frequency score means customer buys more often
frequency = df.drop_duplicates().groupby(by=['Customer Name'], as_index=False)['O

frequency.columns = ['Customer Name', 'Frequency']

frequency.head()
```

Out[613]:

	Customer Name	Frequency
0	Aaron Bergman	89
1	Aaron Hawkins	56
2	Aaron Smayling	60
3	Adam Bellavance	68
4	Adam Hart	84

Monetary

In [614]:
```
#higher monetary value means more money
monetary = df.groupby(by='Customer Name', as_index=False)['Sales'].sum()

monetary.columns = ['Customer Name', 'Monetary']

monetary.head()
```

Out[614]:

	Customer Name	Monetary
0	Aaron Bergman	24644.62750
1	Aaron Hawkins	20759.51384
2	Aaron Smayling	14212.62840
3	Adam Bellavance	20186.77840
4	Adam Hart	21718.20142

Merge

In [615]:
```
rf = recency.merge(frequency, on = 'Customer Name')

rfm = rf.merge(monetary, on = 'Customer Name').drop(columns='Last Purchase')

rfm.head()
```

Out[615]:

	Customer Name	Recency	Frequency	Monetary
0	Aaron Bergman	16	89	24644.62750
1	Aaron Hawkins	12	56	20759.51384
2	Aaron Smayling	23	60	14212.62840
3	Adam Bellavance	35	68	20186.77840
4	Adam Hart	2	84	21718.20142

In [616]:
```
# Apply quantiles for segmentation
rfm['R_Score'] = pd.qcut(rfm['Recency'], 4, labels=[4, 3, 2, 1]) #4 being most re
rfm['F_Score'] = pd.qcut(rfm['Frequency'], 4, labels=[1, 2, 3, 4])
rfm['M_Score'] = pd.qcut(rfm['Monetary'], 4, labels=[1, 2, 3, 4])
```

In [617]:
```
rfm.head()
```

Out[617]:

	Customer Name	Recency	Frequency	Monetary	R_Score	F_Score	M_Score
0	Aaron Bergman	16	89	24644.62750	3	4	4
1	Aaron Hawkins	12	56	20759.51384	3	2	4
2	Aaron Smayling	23	60	14212.62840	2	2	2
3	Adam Bellavance	35	68	20186.77840	1	3	4
4	Adam Hart	2	84	21718.20142	4	4	4

In [618]:
```
rfm.describe()
```

Out[618]:

	Recency	Frequency	Monetary
count	795.000000	795.000000	795.000000
mean	23.368553	64.515723	15902.518126
std	27.438069	13.432477	5209.813042
min	0.000000	29.000000	3892.227000
25%	6.000000	55.000000	12242.608650
50%	16.000000	64.000000	15257.533900
75%	33.000000	74.000000	18770.796450
max	428.000000	108.000000	40488.070800

In [619]:
```
rfm['RFM_Score'] = rfm['R_Score'].astype(int) + rfm['F_Score'].astype(int) + rfm[

rfm['Churn Status'] = rfm['RFM_Score'].apply(lambda x: 'Non-Churn' if x >= 8 else
```

In [620]:
```
rfm.head()
```

Out[620]:

	Customer Name	Recency	Frequency	Monetary	R_Score	F_Score	M_Score	RFM_Score	Churn Status
0	Aaron Bergman	16	89	24644.62750	3	4	4	11	Non-Churn
1	Aaron Hawkins	12	56	20759.51384	3	2	4	9	Non-Churn
2	Aaron Smayling	23	60	14212.62840	2	2	2	6	Churn
3	Adam Bellavance	35	68	20186.77840	1	3	4	8	Non-Churn
4	Adam Hart	2	84	21718.20142	4	4	4	12	Non-Churn

In [621]:
```
rfm['Churn Status'].value_counts(normalize=True)
```

Out[621]:
```
Churn Status
Churn        0.506918
Non-Churn    0.493082
Name: proportion, dtype: float64
```

In [622]:
```
rfm.shape
```

Out[622]:
```
(795, 9)
```

In [623]:
```
#merge the primary df to our rfm df by Customer Name and Churn Status into cust_a
cust_analysis = df.merge(rfm[['Customer Name', 'RFM_Score', 'Churn Status']], on 



cust_analysis.head()
```

Out[623]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	City	State	...	Cate
0	32298	CA-2012-124891	2012-07-31	31-07-2012	Same Day	RH-19495	Rick Hansen	Consumer	New York City	New York	...	Access
1	26341	IN-2013-77878	2013-02-05	07-02-2013	Second Class	JR-16210	Justin Ritter	Corporate	Wollongong	New South Wales	...	Cl
2	25330	IN-2013-71249	2013-10-17	18-10-2013	First Class	CR-12730	Craig Reiter	Consumer	Brisbane	Queensland	...	Ph
3	13524	ES-2013-1579342	2013-01-28	30-01-2013	First Class	KM-16375	Katherine Murray	Home Office	Berlin	Berlin	...	Ph
4	47221	SG-2013-4320	2013-11-05	06-11-2013	Same Day	RH-9495	Rick Hansen	Consumer	Dakar	Dakar	...	Co

5 rows × 25 columns

In [624]:
```
cust_analysis.shape
```

Out[624]:
```
(51290, 25)
```

Calculate Shipping time

In [625]:
```
cust_analysis['Order Date'].value_counts()
cust_analysis['Ship Date'].value_counts()
```

Out[625]:
```
Ship Date
22-11-2014    130
07-09-2014    115
07-12-2014    101
17-11-2014    101
29-11-2014    100
             ...
25-01-2011      3
07-01-2015      3
03-01-2011      2
06-01-2011      2
05-01-2011      2
Name: count, Length: 1464, dtype: int64
```

Our date format is dd-mm-yyyy, so let's tell Pandas to parse dates as day-month-year.

In [626]:
```
cust_analysis['Order Date'] = pd.to_datetime(cust_analysis['Order Date'], format=
cust_analysis['Ship Date'] = pd.to_datetime(cust_analysis['Ship Date'], format='%
```

In [627]:
```
#Shipping Time converted to days as integers
cust_analysis['Shipping Time'] = (cust_analysis['Ship Date'] - cust_analysis['Ord
```

In [628]:
```
cust_analysis.head()
```

Out[628]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	City	State	...	Proc N
0	32298	CA-2012-124891	2012-07-31	2012-07-31	Same Day	RH-19495	Rick Hansen	Consumer	New York City	New York	...	Plantro CS5 Over- H mona \
1	26341	IN-2013-77878	2013-02-05	2013-02-07	Second Class	JR-16210	Justin Ritter	Corporate	Wollongong	New South Wales	...	Novi Execu Lea Armc B
2	25330	IN-2013-71249	2013-10-17	2013-10-18	First Class	CR-12730	Craig Reiter	Consumer	Brisbane	Queensland	...	N S Ph with C
3	13524	ES-2013-1579342	2013-01-28	2013-01-30	First Class	KM-16375	Katherine Murray	Home Office	Berlin	Berlin	...	Moto S Ph Corc
4	47221	SG-2013-4320	2013-11-05	2013-11-06	Same Day	RH-9495	Rick Hansen	Consumer	Dakar	Dakar	...	S Wire Fax, H Sp

5 rows × 26 columns

EDA Visualization

In [629]:
```
import plotly.express as px
```

RFM Analysis

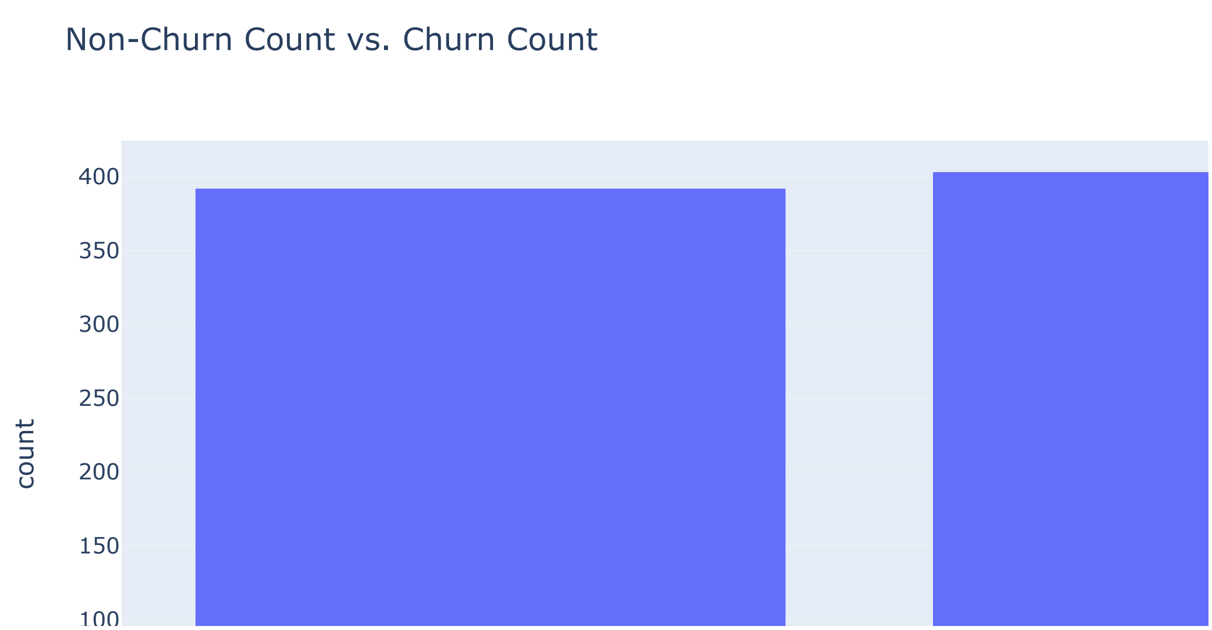
In [630]:
```
rfm.head()
```

Out[630]:

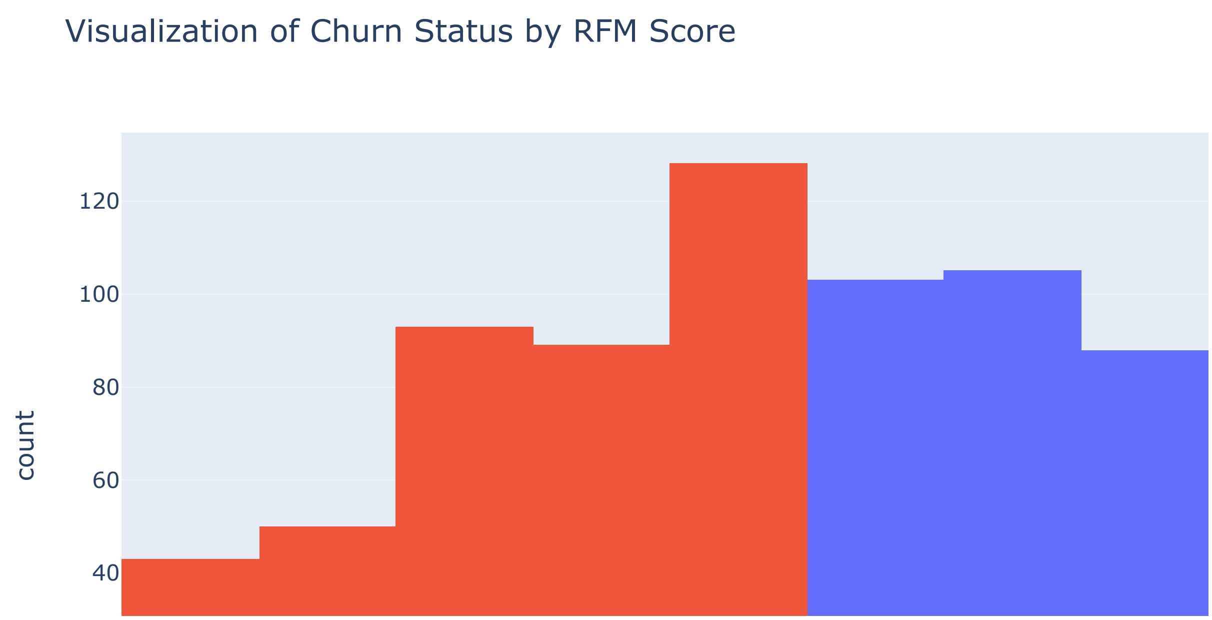
	Customer Name	Recency	Frequency	Monetary	R_Score	F_Score	M_Score	RFM_Score	Churn Status
0	Aaron Bergman	16	89	24644.62750	3	4	4	11	Non-Churn
1	Aaron Hawkins	12	56	20759.51384	3	2	4	9	Non-Churn
2	Aaron Smayling	23	60	14212.62840	2	2	2	6	Churn
3	Adam Bellavance	35	68	20186.77840	1	3	4	8	Non-Churn
4	Adam Hart	2	84	21718.20142	4	4	4	12	Non-Churn

Let's visualize how balanced our dataset is

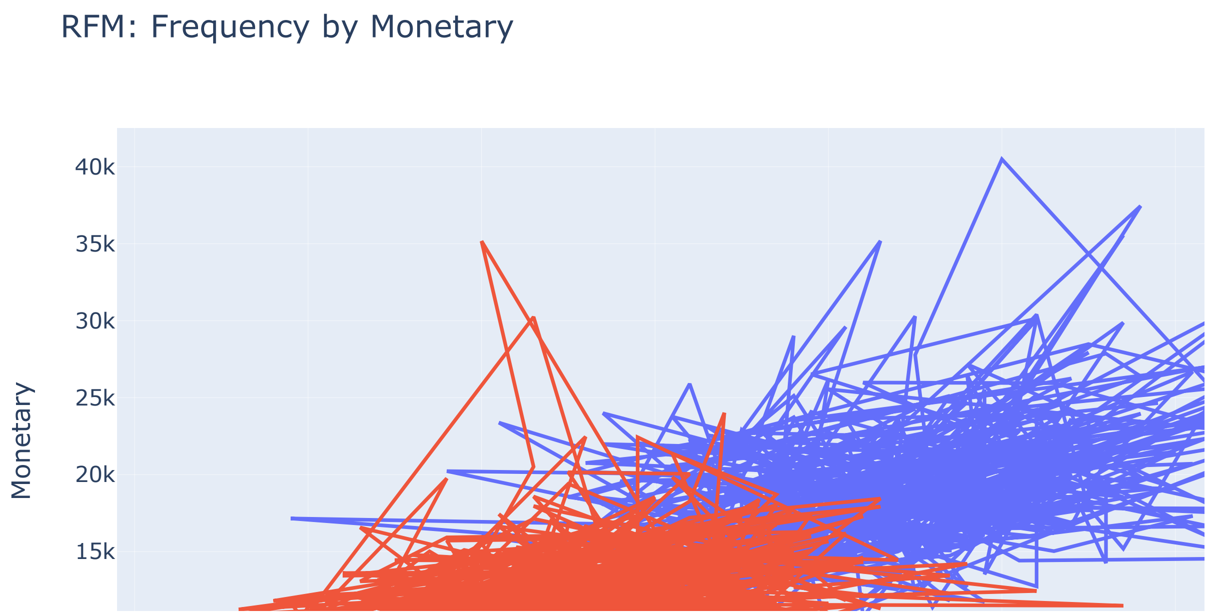
In [631]:
```
fig = px.histogram(rfm, x="Churn Status", title="Non-Churn Count vs. Churn Count"
fig.show()
```



In [632]:
```
fig = px.histogram(rfm, x="RFM_Score", color="Churn Status", title = "Visualizati
fig.show()
```



In [633]:
```
fig = px.line(rfm, x="Frequency", y="Monetary", color="Churn Status", title="RFM:
fig.show()
```



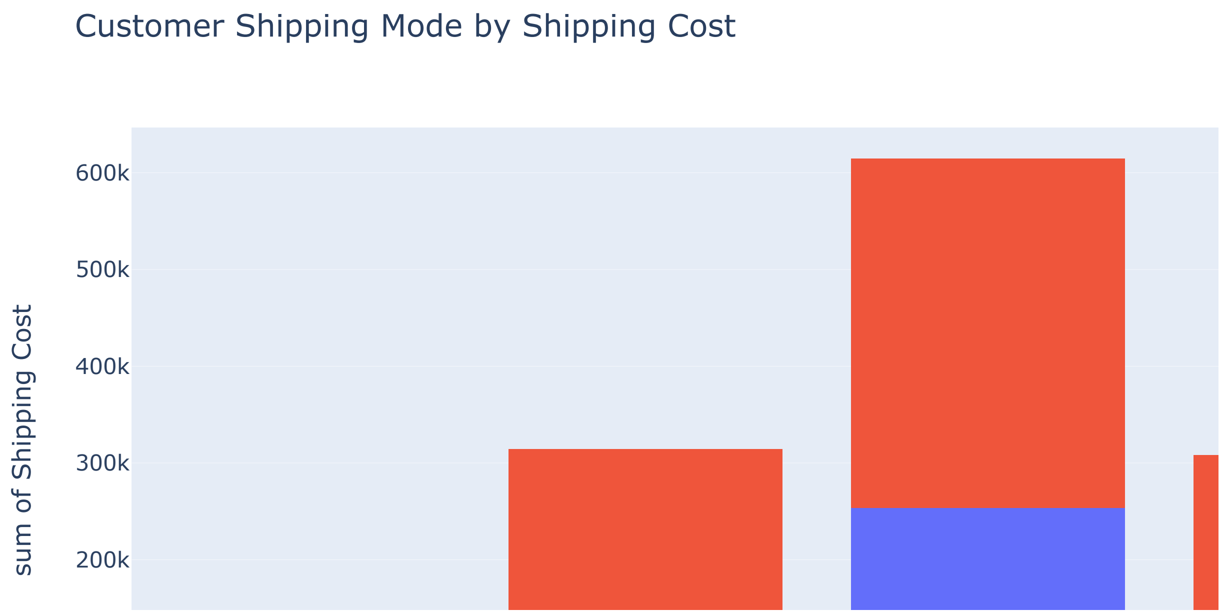
To no surpise, non-churn customers purchase and spend more than churn customers

Shipping

In [635]:
```
fig = px.histogram(cust_analysis, x="Category", y="Shipping Time", color="Churn St
fig.show()

fig = px.histogram(cust_analysis, x="Shipping Time", y="Shipping Cost", color="Ch
fig.show()

fig = px.histogram(cust_analysis, x="Order Priority", color="Churn Status", title
fig.show()

fig = px.histogram(cust_analysis, x="Ship Mode", y="Shipping Cost", color="Churn S
fig.show()
```


Customer Shipping Time by Shipping Cost
sum of Shipping Cost
300k
250k
200k
150k
100k


Churn Status by Order Priority
count
30k
25k
20k
15k
10k

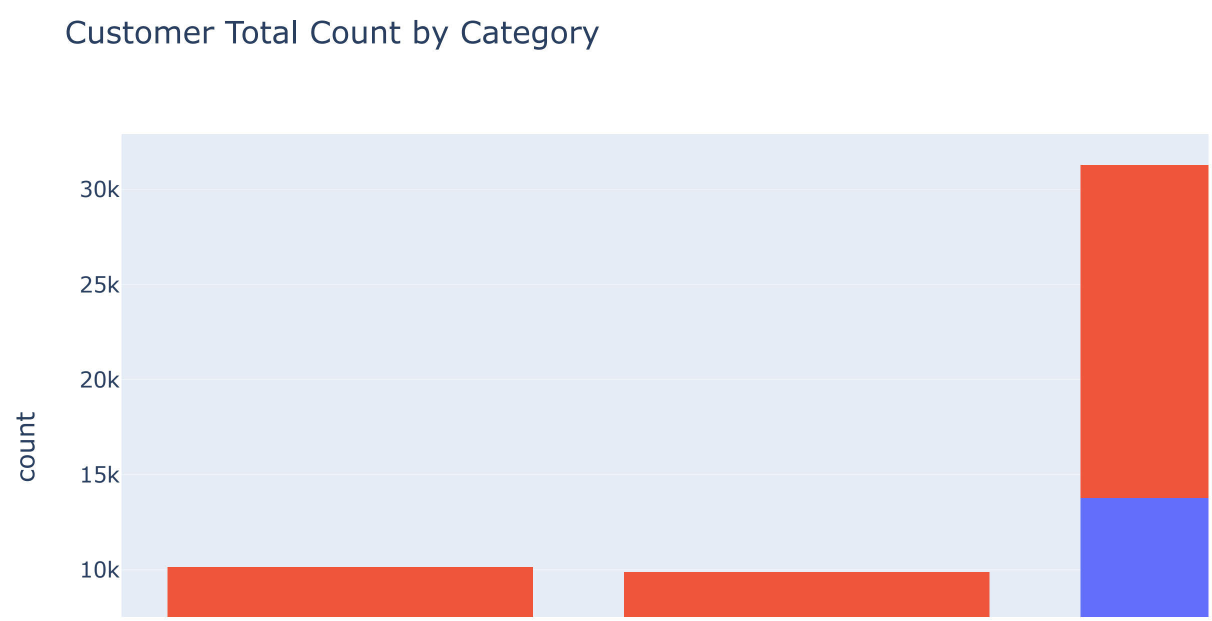


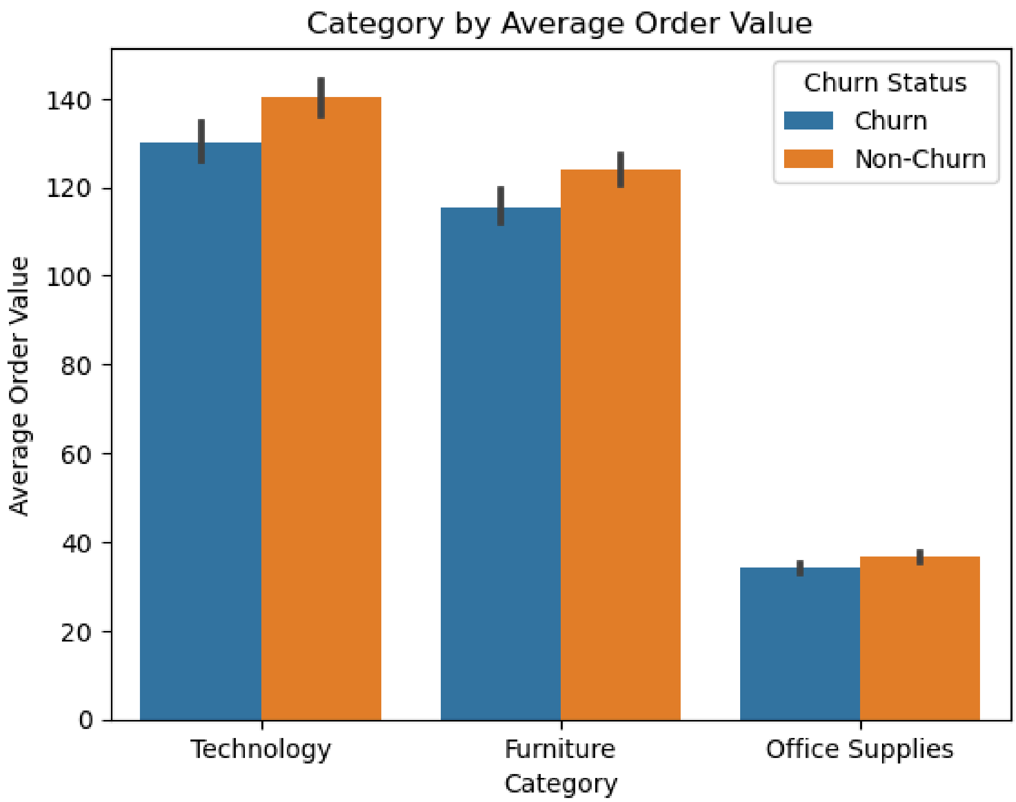
Total shipping costs are higher for non-churn customers, but because they make more purchases and spend more than churn customers, nothing here can give us a clear reason for churn.

None of these visualizations show any explanation in terms of how shipping could correlate with churn.

Feature Engineerging

In [636]:
```
#lets create average order value using Sales/quantity
cust_analysis['Average Order Value'] = cust_analysis['Sales'] / cust_analysis['Qu

import seaborn as sns
import matplotlib.pyplot as plt
#average order value
sns.barplot(data=cust_analysis, x="Category", y="Average Order Value", hue="Churn
plt.title("Category by Average Order Value")

#customer total count by category
fig = px.histogram(cust_analysis, x="Category", color="Churn Status", title="Cust
fig.show()
```





Despite non-churn customers placing more orders, the average order value looks nearly identical between churn and non-churn which soldifies our findings:

churn customers are placing fewer orders than non-churn customers; churn behavior may not be linked to spending behavior.

RFM Risk Tiers Focus over Churn Status Metrics

In [637]:
```
rfm['Risk Tiers'] = rfm['RFM_Score'].apply(lambda x: 'High Risk' if x <= 6 else (
rfm.head()
```

Out[637]:

	Customer Name	Recency	Frequency	Monetary	R_Score	F_Score	M_Score	RFM_Score	Churn Status	Risk Tiers
0	Aaron Bergman	16	89	24644.62750	3	4	4	11	Non-Churn	Low Risk
1	Aaron Hawkins	12	56	20759.51384	3	2	4	9	Non-Churn	Low Risk
2	Aaron Smayling	23	60	14212.62840	2	2	2	6	Churn	High Risk
3	Adam Bellavance	35	68	20186.77840	1	3	4	8	Non-Churn	Moderate Risk
4	Adam Hart	2	84	21718.20142	4	4	4	12	Non-Churn	Low Risk

In [638]:
```
rfm['Risk Tiers'].value_counts(normalize=True)
```

Out[638]:
```
Risk Tiers
Low Risk         0.363522
High Risk        0.345912
Moderate Risk    0.290566
Name: proportion, dtype: float64
```

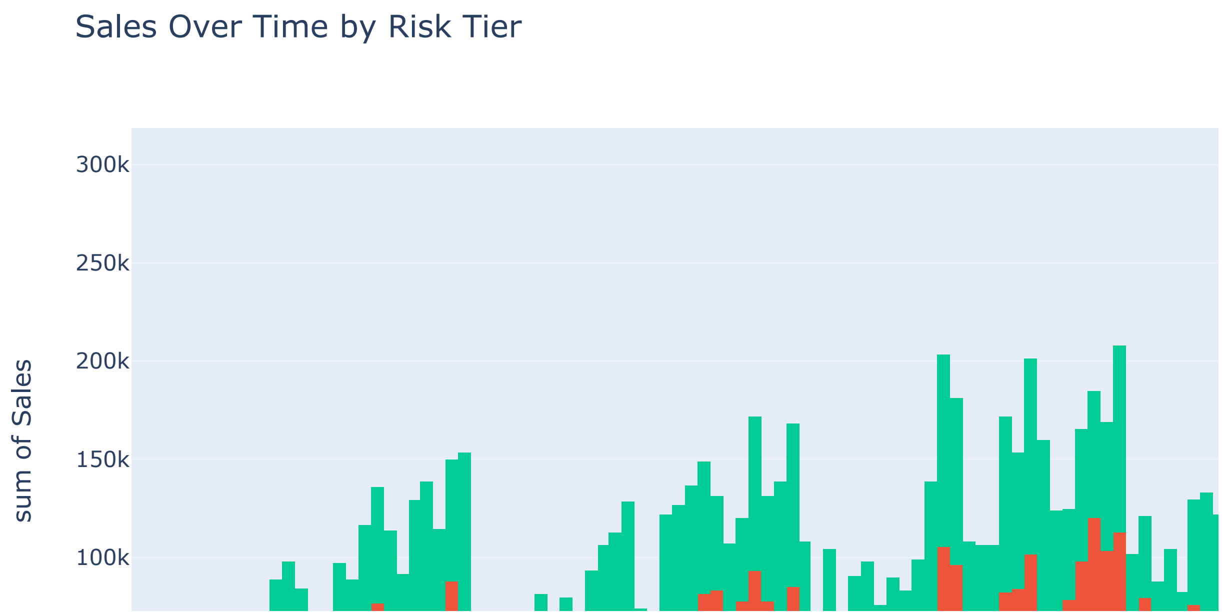
In [639]:
```
cust_analysis = cust_analysis.merge(rfm[['Customer Name', 'Risk Tiers']], on='Cus
cust_analysis.head()
```

Out[639]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	City	State	...	Quanti
0	32298	CA-2012-124891	2012-07-31	2012-07-31	Same Day	RH-19495	Rick Hansen	Consumer	New York City	New York	...	
1	26341	IN-2013-77878	2013-02-05	2013-02-07	Second Class	JR-16210	Justin Ritter	Corporate	Wollongong	New South Wales	...	
2	25330	IN-2013-71249	2013-10-17	2013-10-18	First Class	CR-12730	Craig Reiter	Consumer	Brisbane	Queensland	...	
3	13524	ES-2013-1579342	2013-01-28	2013-01-30	First Class	KM-16375	Katherine Murray	Home Office	Berlin	Berlin	...	
4	47221	SG-2013-4320	2013-11-05	2013-11-06	Same Day	RH-9495	Rick Hansen	Consumer	Dakar	Dakar	...	

5 rows × 28 columns

In [648]:
```
fig = px.histogram(cust_analysis, x="Order Date", y="Sales", color="Risk Tiers", 
fig.show()
```



Analyze high risk customers

In [641]:
```
high_risk = cust_analysis[cust_analysis['Risk Tiers']== 'High Risk']

print(high_risk['Sales'].mean())
print(high_risk['Shipping Cost'].mean())
print(high_risk['Shipping Time'].mean())
```

```
220.9579654908991
24.036218974076117
4.002413127413128
```

Analye moderate risk customers

In [642]:
```
mod_risk = cust_analysis[cust_analysis['Risk Tiers']== 'Moderate Risk']

print(mod_risk['Sales'].mean())
print(mod_risk['Shipping Cost'].mean())
print(mod_risk['Shipping Time'].mean())
```

```
241.5444889887944
25.81428783583097
3.922100715539355
```

Analyze low risk customers

In [643]:
```
low_risk = cust_analysis[cust_analysis['Risk Tiers']== 'Low Risk']

print(low_risk['Sales'].mean())
print(low_risk['Shipping Cost'].mean())
print(low_risk['Shipping Time'].mean())
```

```
266.67975234480247
28.299040141998912
3.979428363371564
```

The average shipping time between high risk and low risk customers are essentially the same and shipping costs don't have a big difference, meaning shipping variables don't seem to correlate with churn.

With spending behavior and shipping variables not telling us much about churn, let's dive into discounts.

Discount by Risk Tiers

In [669]:
```
#proportion of risk tiers
risk_tier_counts = rfm['Risk Tiers'].value_counts(normalize=True).reset_index()
risk_tier_counts.columns = ['Risk Tiers', 'Proportion']

fig = px.histogram(risk_tier_counts, x="Risk Tiers", y="Proportion", color="Risk T
fig.show()

#discount by risk tiers
fig = px.histogram(cust_analysis, x="Discount", y="Risk Tiers", title="Discount by
fig.show()

#discount by risk tiers
fig = px.histogram(cust_analysis, x="Discount", color="Risk Tiers", title="Discou
fig.show()
```


Discount by Risk Tier Customers
Low Risk
High Risk
Risk Tiers


Discount by Risk Tier Customers
30k
25k
20k
15k
10k
count

Low risk customers receive a higher count of discounts compared to high and moderate risk customers, but discounts from 0.004 - 0.005 heavily dominate the graph. Discounts also seem to not be highly correlated with churn prevention.

Key Takeaways:

Churn customers place fewer orders: Churn behavior seems more influenced by engagement freqeuncy rather than spending behavior.

Shipping cost and time show no correlation with churn: reducing churn through shipping incentives are unlikely to yield strong results.

Discount strategies are ineffective at reducing churn: Current discount patterns are not well-targeted toward customers.

Final Key Takeaway:

Churn behavior is not significantly influenced by spending behavior, shipping time, shipping costs, or discounts. Instead, churn appears more closely tied to customer engagement frequency and other behavior factors not captured in the dataset.

In [ ]: