Rosetta Stone Project

- Identifying most valuable subscribers
- Understanding Subscriber segments in each database
- Identifying most likely subscribers that could be sold an additional service
- Outlining any business relevant opportunities that are present

Imports

```
# additional imports
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import numpy as np
from plotnine import *
from sklearn import *
# Linear Regression Model
from sklearn.linear_model import LinearRegression
# Logistic Regression Model
from sklearn.linear_model import LogisticRegression
#Z-score variables
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix, plot_confusion_matrix
# simple TT split cv
from sklearn.model_selection import train_test_split
# k-fold cv
from sklearn.model_selection import KFold
#LOO cv
from sklearn.model_selection import LeaveOneOut
# cross validation metrics
from sklearn.model_selection import cross_val_score
```

```
# cross validation metrics
from sklearn.model_selection import cross_val_predict
# model eval
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.cluster import KMeans
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_score
from sklearn.neighbors import NearestNeighbors
from sklearn.cluster import DBSCAN
from sklearn.cluster import AgglomerativeClustering
import scipy.cluster.hierarchy as sch
from matplotlib import pyplot as plt
%matplotlib inline

import csv

from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error


# reading in data

df = pd.read_csv("https://raw.githubusercontent.com/tmoore-byte/MGSC-410/main/subscriptionData.csv")


df.head()
#num_null3 = df.isnull().sum()
#print(num_null3)
```

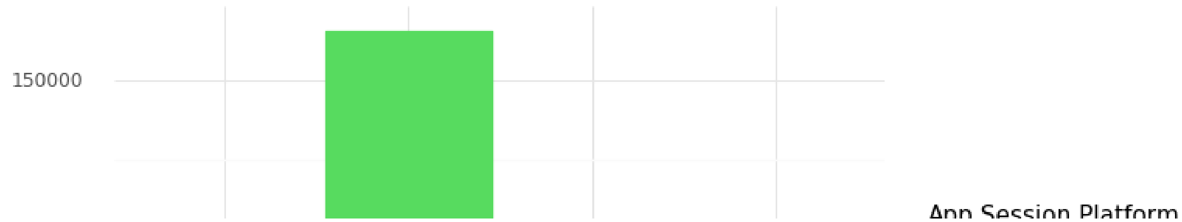
	ID	App.Session.Platform	App.Activity.Type	Language	Subscription.Type	Subsc
0	2	android	App Launch	EBR	Limited	
1	3	ios	App Launch	ESP	Limited	
2	6	android	Completed	ESP	Limited	

```
df.shape
```

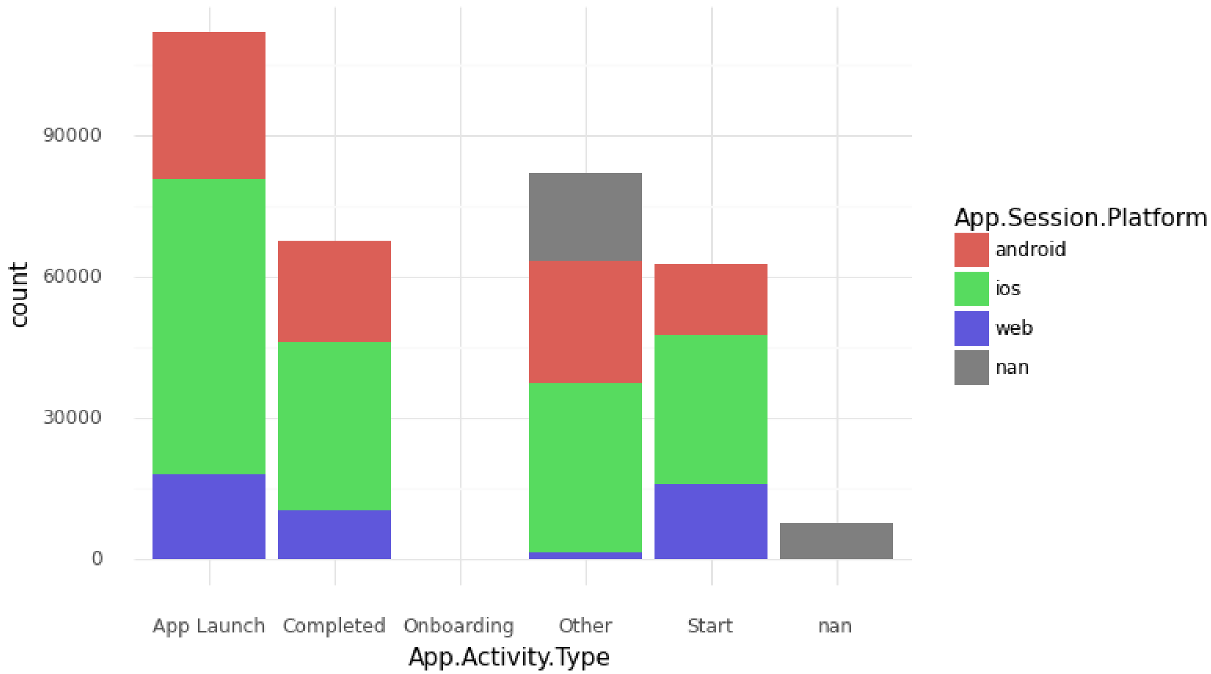
```
(331661, 26)
```

Data Plotting / Visuals

```
(ggplot(df, aes(x = "App.Session.Platform", fill = "App.Session.Platform",
                color = "App.Session.Platform")) +
 geom_bar()+theme_minimal())
```

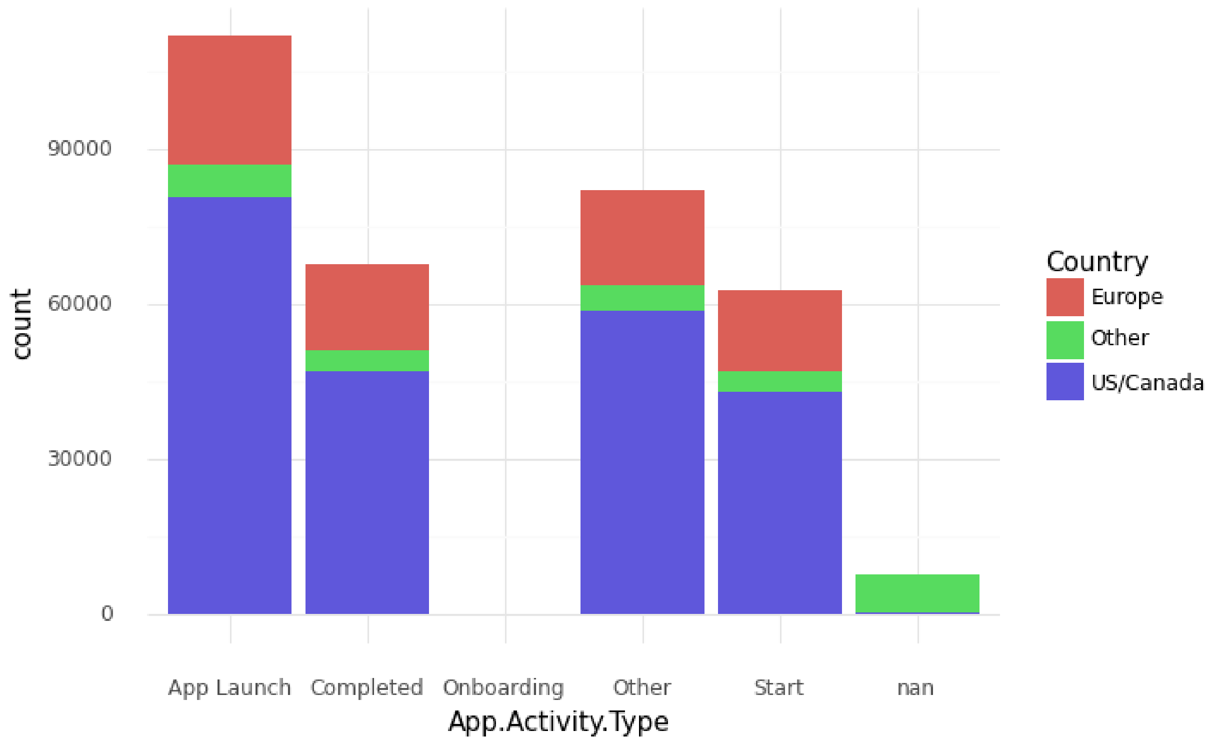



```
(ggplot(df, aes(x = "App.Activity.Type", fill = "App.Session.Platform")) +
 geom_bar()+theme_minimal())
```




```
<ggplot: (8786531088153)>
```

```
(ggplot(df, aes(x = "App.Activity.Type", fill = "Country")) +
 geom_bar()+theme_minimal())
```




```
<ggplot: (8786534727489)>
```

Android and IOS are most used platforms, and also have the highest applaunch count and completion count. Web is lowest in each category. US/Canada have highest app launch and completion, followed by Europe.

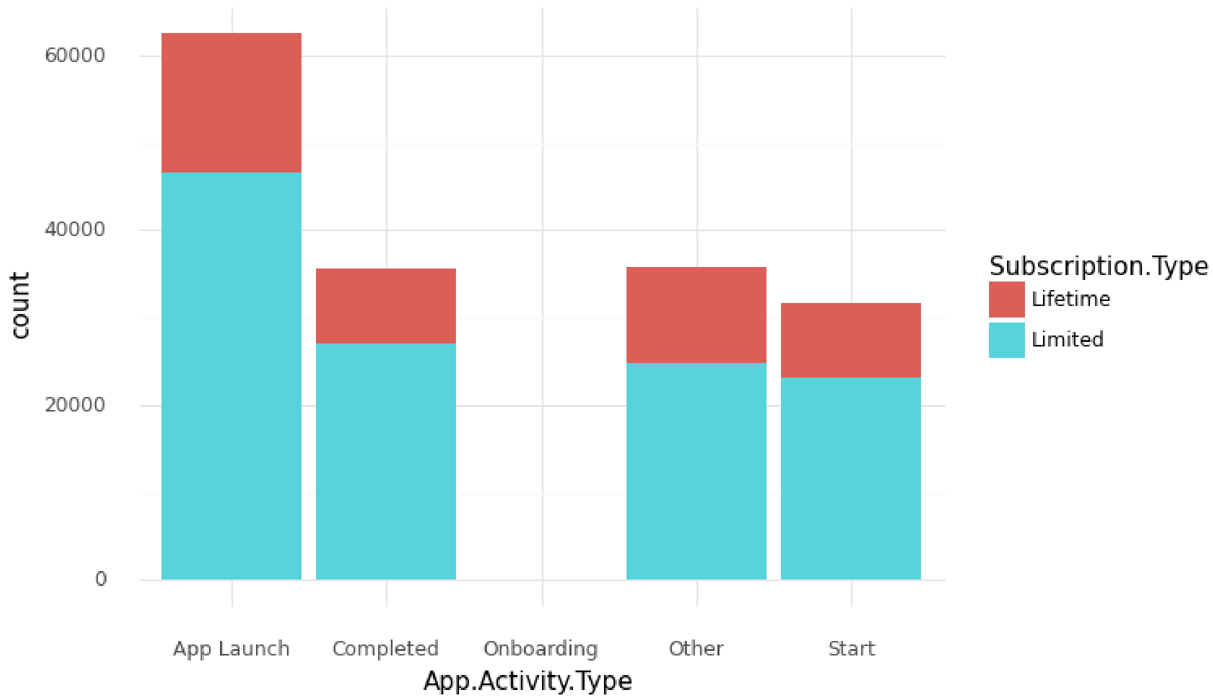
```
# selecting rows w IOS/Android US/canada
platform = "ios"
platform2 = "android"
country = "US/Canada"

# selecting columns
df['App.Session.Platform'] == 'ios'
```

```
0         False
1          True
2         False
3         False
4          True
          ...
331656    False
331657    False
331658    False
331659    False
331660     True
Name: App.Session.Platform, Length: 331661, dtype: bool
```

```
ios = df[df['App.Session.Platform'] == 'ios']
ios
```

ID	App.Session.Platform	App.Activity.Type	Language	Subscription.Typ

```
# ios plot with Subscription type
# p much all CONSUMER USER TYPE
(ggplot(ios, aes(x = "App.Activity.Type", fill = "Subscription.Type")) +
 geom_bar()+theme_minimal())
```




```
<ggplot: (8789891870141)>
```

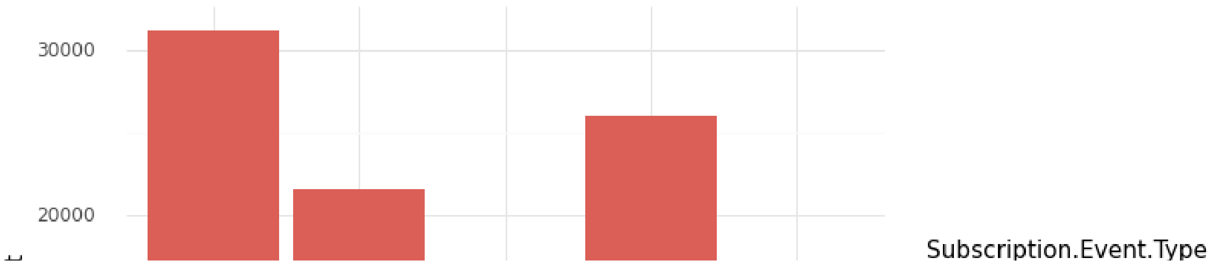
```
(ggplot(ios, aes(x = "App.Activity.Type", fill = "Subscription.Event.Type")) +
 geom_bar()+theme_minimal())
```


```
<ggplot: (8786527858293)>
```

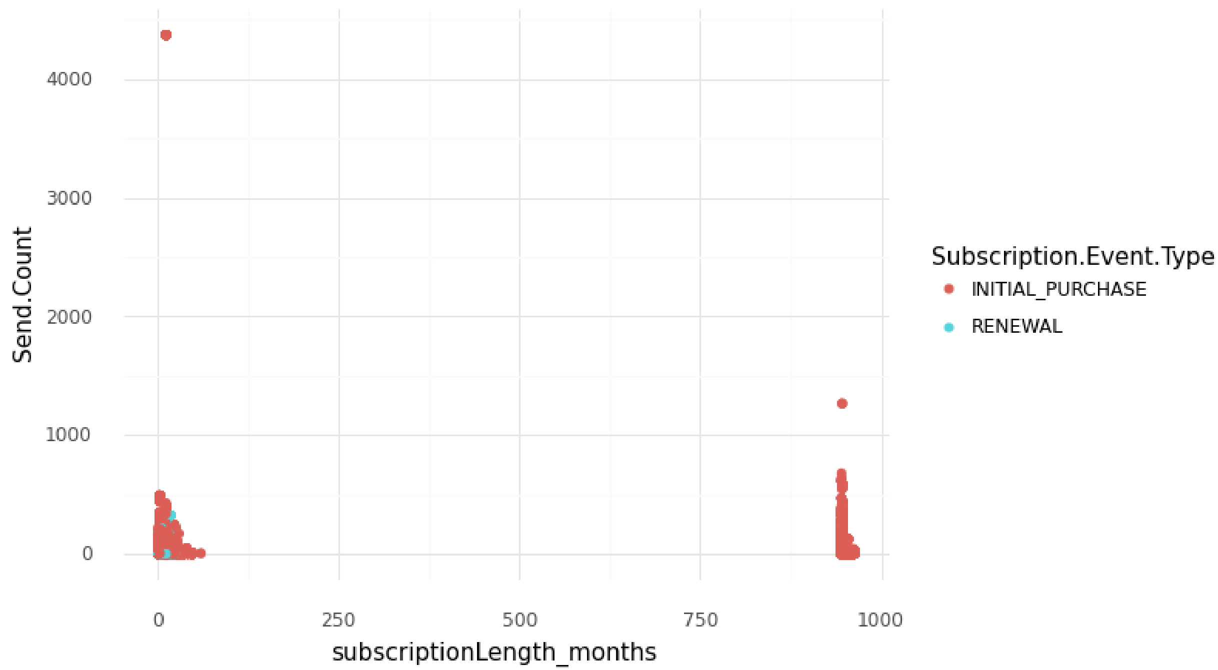
```
android = df[df['App.Session.Platform'] == 'android']
android
```

	ID	App.Session.Platform	App.Activity.Type	Language	Subscription.Typ
0	2	android	App Launch	EBR	Limite
2	6	android	Completed	ESP	Limite
3	7	android	Start	ESP	Limite
10	18	android	App Launch	SVE	Limite
12	23	android	Completed	ESP	Lifetin
...	...	...	...	...	
331640	10902	android	App Launch	ALL	Lifetin
331641	961	android	Completed	EBR	Limite

```
# android plot with renewal type
# p much all CONSUMER USER TYPE
(ggplot(android, aes(x = "App.Activity.Type", fill = "Subscription.Event.Type")) +
 geom_bar()+theme_minimal())
```



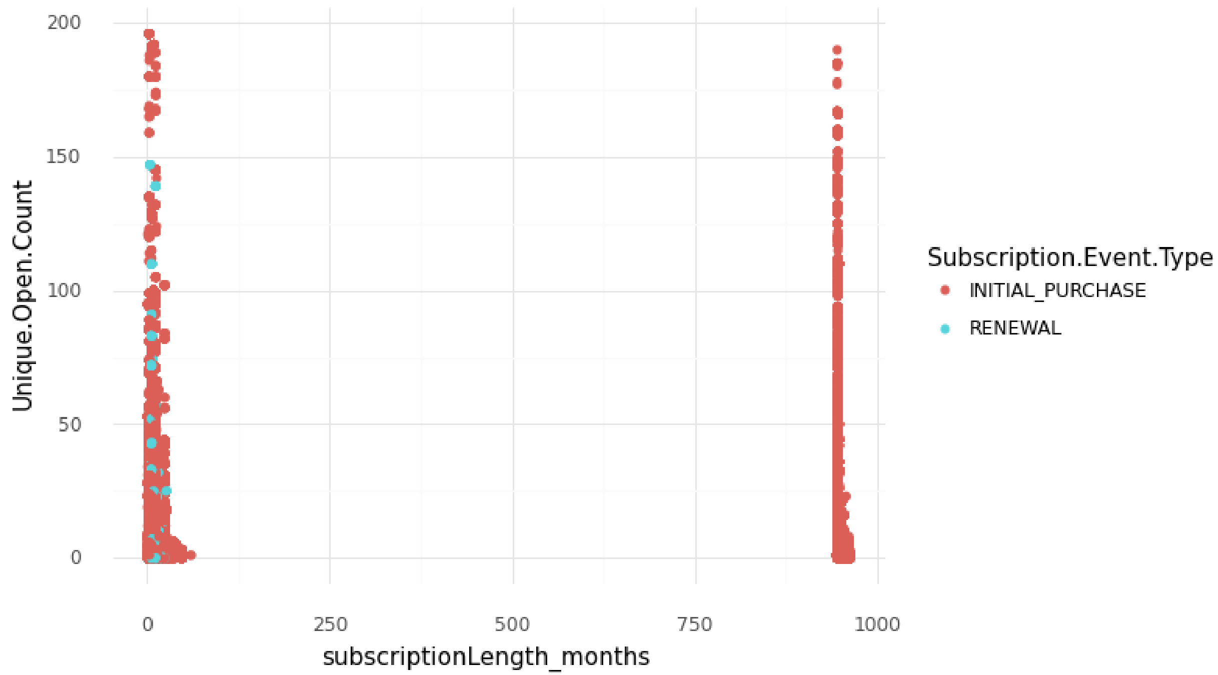

```
(ggplot(df, aes(x = "subscriptionLength_months", y = "Send.Count", color = "Subscription.Event.Type")) +
 geom_point() + theme_minimal())
```




```
<ggplot: (8786527757833)>
```

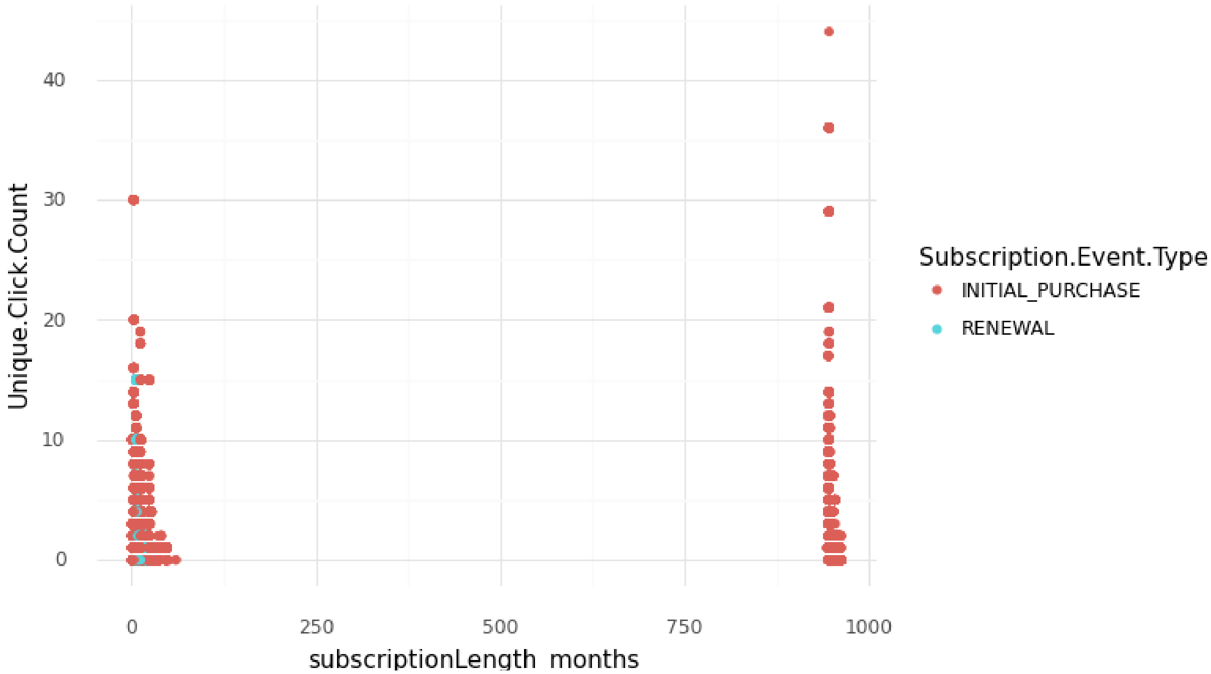
```
(ggplot(df, aes(x = "subscriptionLength_months", y = "Unique.Open.Count",
                color= "Subscription.Event.Type")) +
```

```
geom_point() + theme_minimal())
```



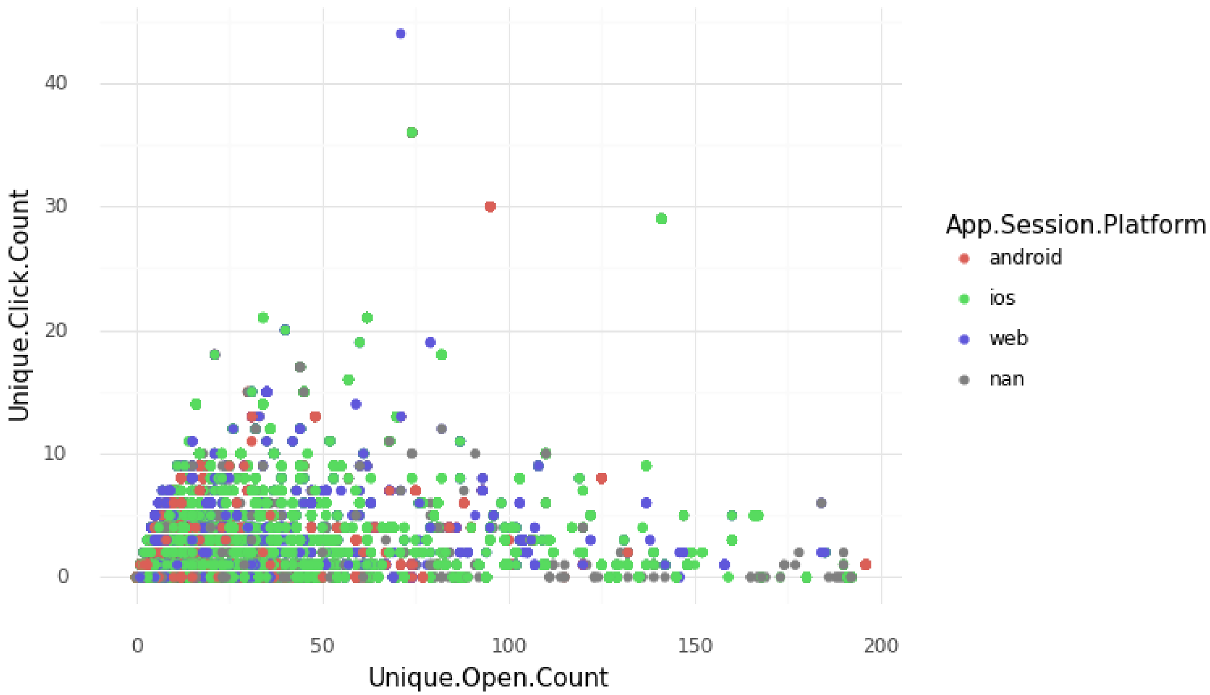

```
<ggplot: (8786511777965)>
```

```
(ggplot(df, aes(x = "subscriptionLength_months", y = "Unique.Click.Count",
                color="Subscription.Event.Type")) +
 geom_point() + theme_minimal())
```



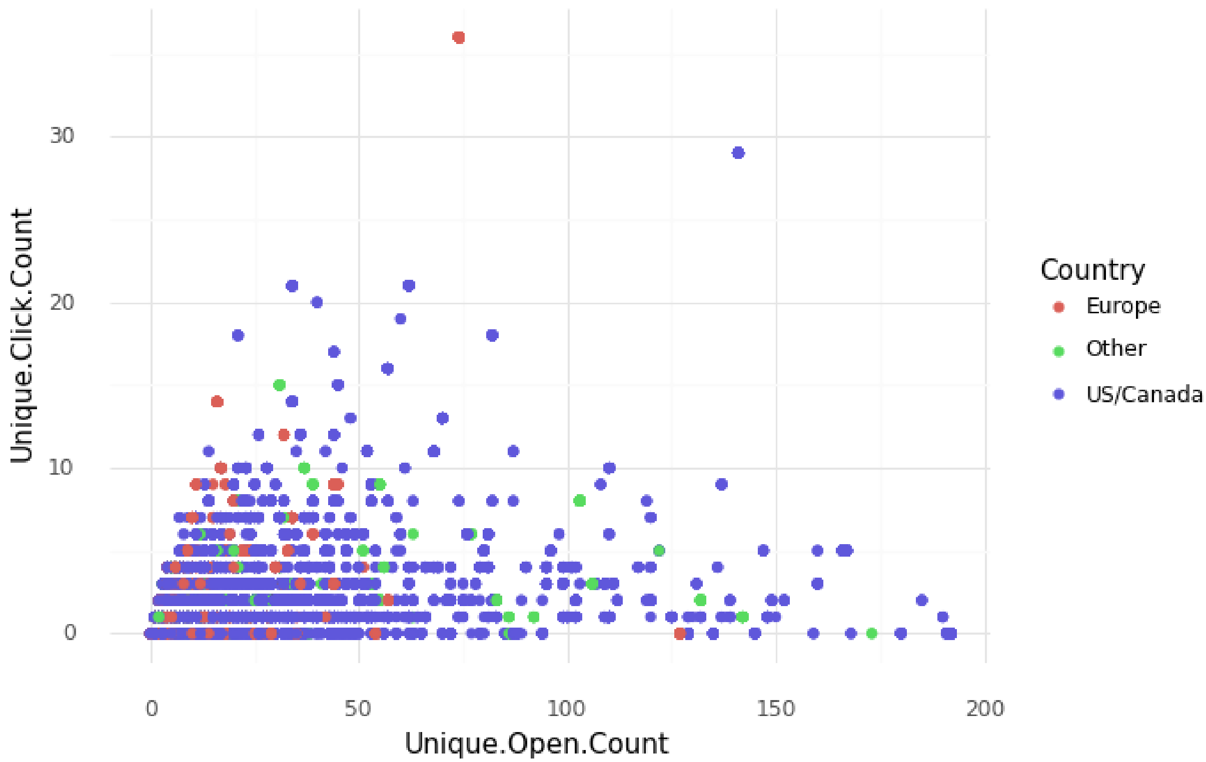

```
(ggplot(df, aes(x = "Subscription.Event.Type", y = "Unique.Click.Count",
                color="Subscription.Event.Type")) +
 geom_point() + theme_minimal())
```


```
(ggplot(df, aes(x = "Unique.Open.Count", y = "Unique.Click.Count",
                 color="App.Session.Platform")) +
 geom_point() + theme_minimal())
```



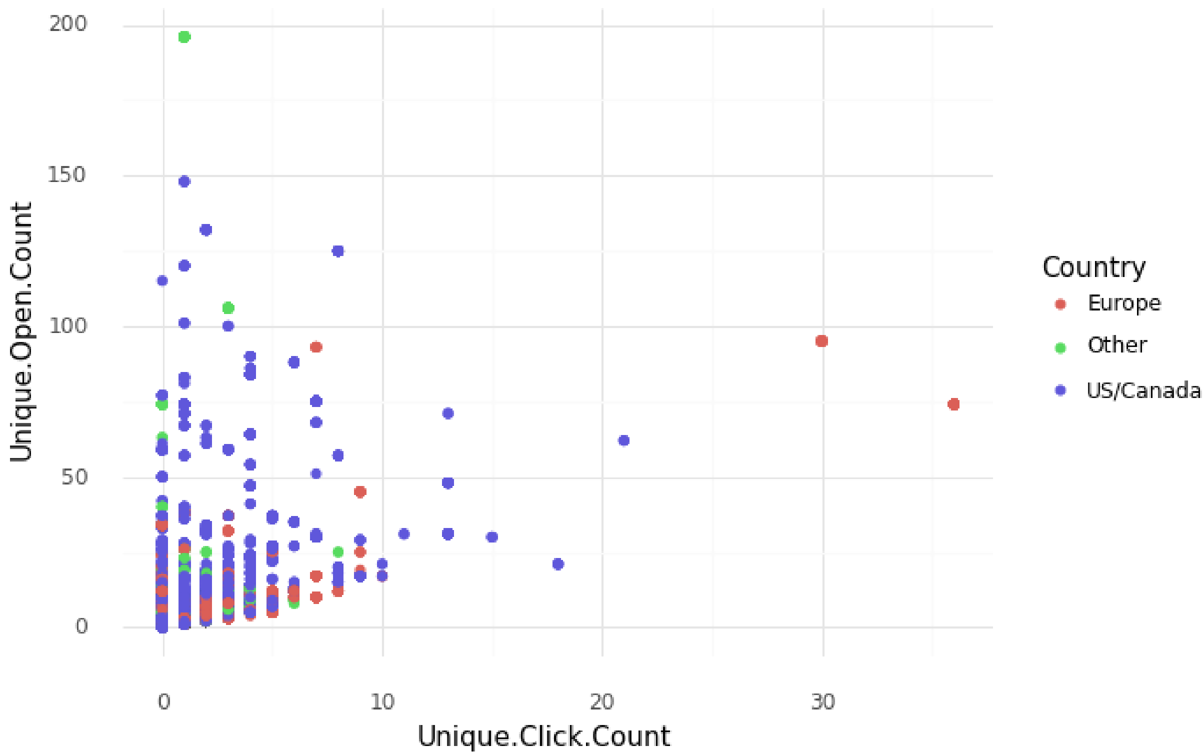

```
<ggplot: (8786510584497)>
```

```
(ggplot(ios, aes(x = "Unique.Open.Count", y = "Unique.Click.Count",
                 color="Country")) +
 geom_point() + theme_minimal())
```



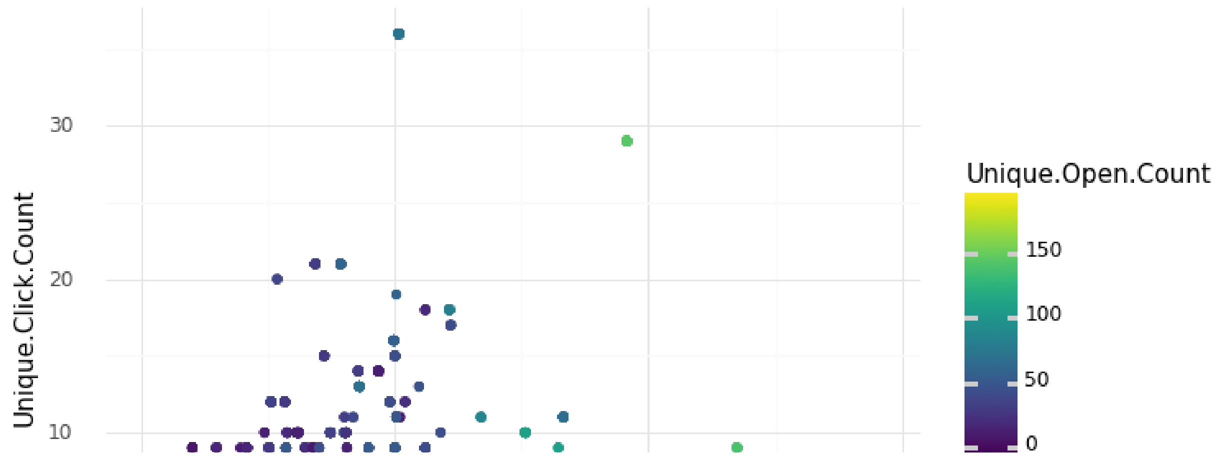

```
<ggplot: (8786498717509)>
```

```
(ggplot(android, aes(x = "Unique.Click.Count", y = "Unique.Open.Count",
                 color="Country")) +
 geom_point() + theme_minimal())
```




```
<ggplot: (8786493125069)>
```

```
(ggplot(ios, aes(x = "Send.Count", y = "Unique.Click.Count",
                 color="Unique.Open.Count")) +
 geom_point() + theme_minimal())
```



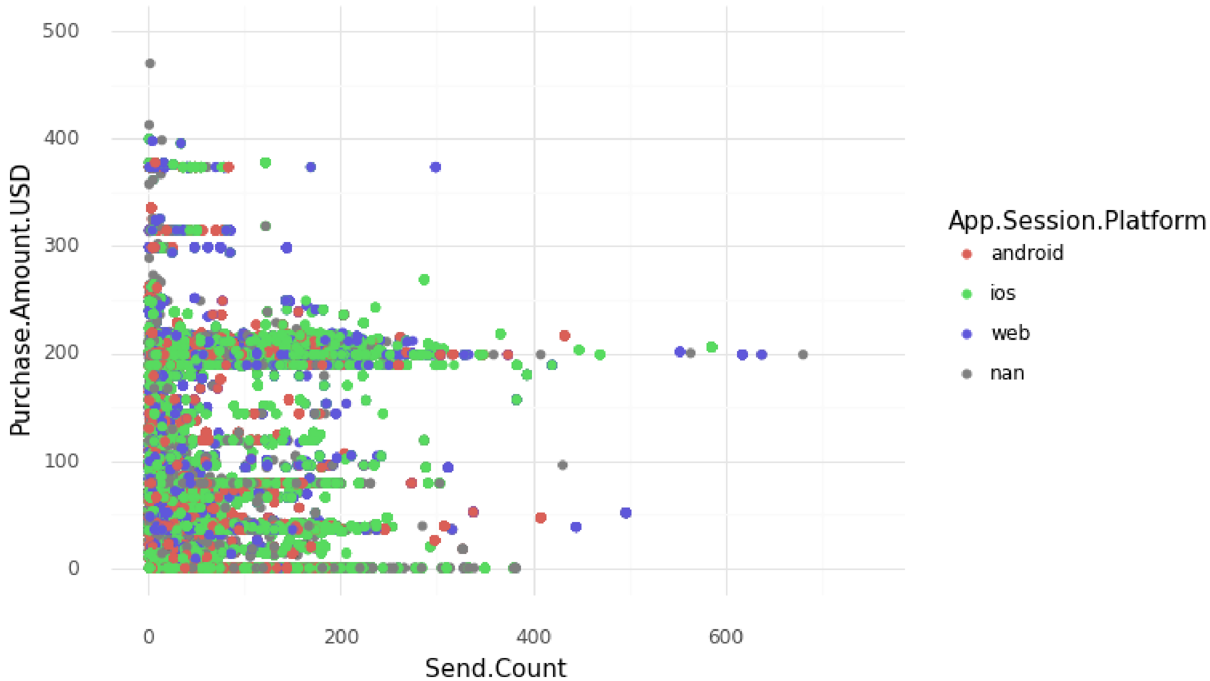

```
# LOOKING AT WEB DATA
web = df[df['Purchase.Store'] == 'Web']
web.head()
```

	ID	App.Session.Platform	App.Activity.Type	Language	Subscription.Type	Subsc
0	2	android	App Launch	EBR	Limited	
1	3	ios	App Launch	ESP	Limited	
2	6	android	Completed	ESP	Limited	
3	7	android	Start	ESP	Limited	
4	8	ios	Completed	DEU	Limited	

5 rows × 26 columns

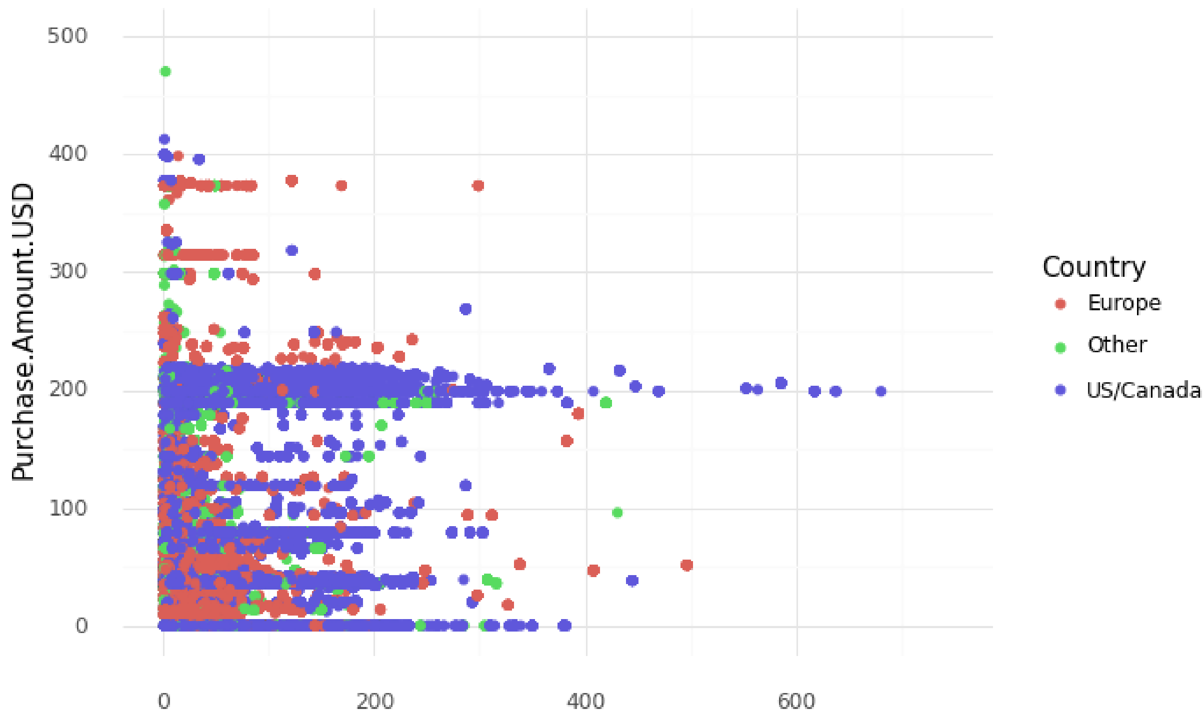
```
# WEB DATA
```

```
(ggplot(web, aes(x = "Send.Count", y = "Purchase.Amount.USD",
                 color="App.Session.Platform")) + xlim(-1,750)+ylim(-1,500)+
 geom_point() + theme_minimal())
```



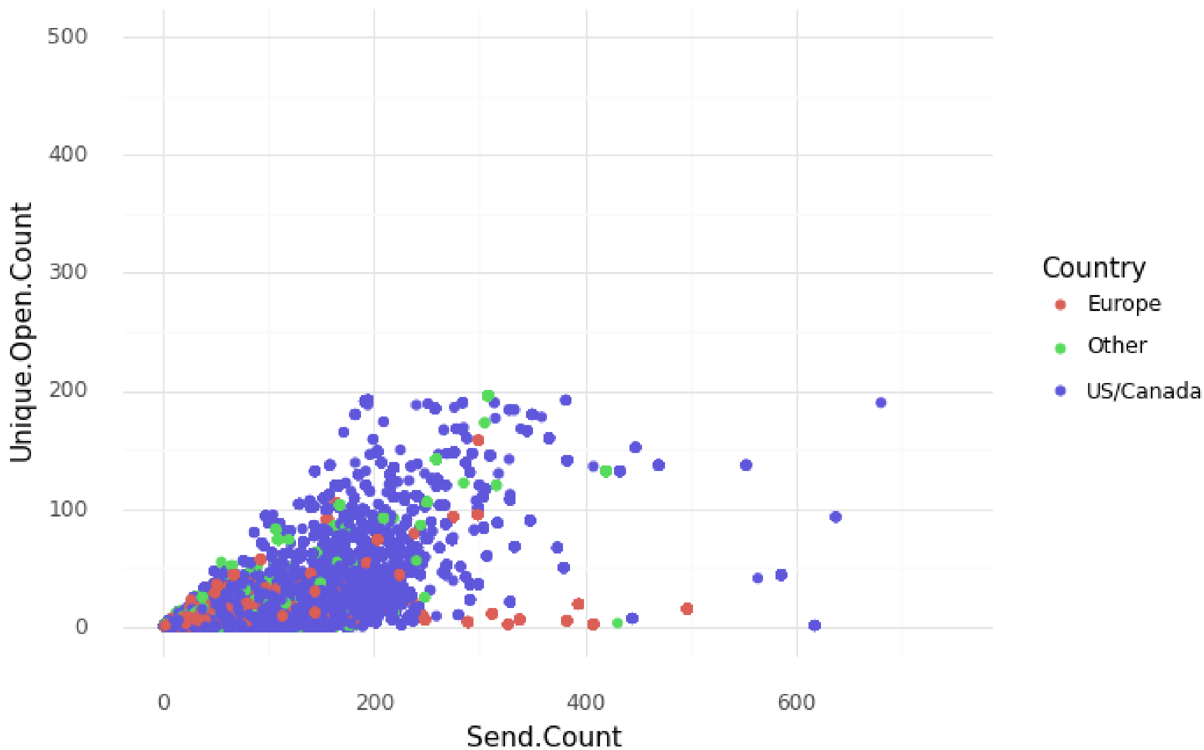

```
<ggplot: (8777552097085)>
```

```
(ggplot(web, aes(x = "Send.Count", y = "Purchase.Amount.USD",
                 color="Country")) + xlim(-1,750)+ylim(-1,500)+
 geom_point() + theme_minimal())
```




```
(ggplot(web, aes(x = "Language", fill = "Purchase.Amount.USD")) +
 geom_bar()+theme_minimal())
```


```
(ggplot(web, aes(x = "Send.Count", y = "Unique.Open.Count",
                  color="Country")) + xlim(-1,750)+ylim(-1,500)+
 geom_point() + theme_minimal())
```




```
<ggplot: (8777550375305)>
```

Modeling

Linear regression

```
# Linear regression model
# ALL DATA
predictors = ["Send.Count", "Unique.Open.Count", "Unique.Click.Count"]
X = df[predictors]
y = df["subscriptionLength_months"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)


# zscoring
z = StandardScaler()
X_train[predictors] = z.fit_transform(X_train[predictors])
X_test[predictors] = z.fit_transform(X_test[predictors])

# building and fitting model
lr = LinearRegression()
lr.fit(X_train, y_train)

print("Train: " , mean_absolute_error(y_train, lr.predict(X_train)))
print("Test: " , mean_absolute_error(y_test, lr.predict(X_test)))
```

```
Train:  313.72575571391656
Test:  313.51250472536367
```

```
# OVER JUST IOS
predictors = ["Send.Count", "Unique.Open.Count", "Unique.Click.Count"]
X2 = ios[predictors]
```

```
y2 = ios["subscriptionLength_months"]
X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y2, test_size=0.25)


# zscoring
z = StandardScaler()
X2_train[predictors] = z.fit_transform(X2_train[predictors])
X2_test[predictors] = z.fit_transform(X2_test[predictors])

# building and fitting model
lr2 = LinearRegression()
lr2.fit(X2_train, y2_train)

print("Train: " , mean_absolute_error(y2_train, lr2.predict(X2_train)))
print("Test: " , mean_absolute_error(y2_test, lr2.predict(X2_test)))
```

```
Train:  347.68212312504903
Test:  347.2410193765053
```

```
# IOS WITH  PREDICTING OPEN COUNT
# SELLING NEW PRODUCTS

# OVER JUST IOS
predictors_new = ["Send.Count", "Unique.Click.Count"]
X2 = ios[predictors_new]
y2 = ios["Unique.Open.Count"]
X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y2, test_size=0.25)


# zscoring
z = StandardScaler()
X2_train[predictors_new] = z.fit_transform(X2_train[predictors_new])
X2_test[predictors_new] = z.fit_transform(X2_test[predictors_new])

# building and fitting model
lr2 = LinearRegression()
lr2.fit(X2_train, y2_train)
```

```
print("Train: " , mean_absolute_error(y2_train, lr2.predict(X2_train)))
print("Test: " , mean_absolute_error(y2_test, lr2.predict(X2_test)))
```

```
Train:  5.698450654672169
Test:  5.70599049361117
```

```
(ggplot(ios, aes(x = "Send.Count", y = "Unique.Click.Count",
                 color="Unique.Open.Count")) +
 geom_point() + theme_minimal()+ stat_smooth(method="lm"))
```

IOS predicting open count was the most accurate linear regression.

```
# OVER JUST android
predictors = ["Send.Count", "Unique.Open.Count", "Unique.Click.Count"]
X3 = android[predictors]
y3 = android["subscriptionLength_months"]
X3_train, X3_test, y3_train, y3_test = train_test_split(X3, y3, test_size=0.25)


# zscoring
z = StandardScaler()
X3_train[predictors] = z.fit_transform(X3_train[predictors])
X3_test[predictors] = z.fit_transform(X3_test[predictors])

# building and fitting model
lr3 = LinearRegression()
lr3.fit(X3_train, y3_train)

print("Train: " , mean_absolute_error(y3_train, lr3.predict(X3_train)))
print("Test: " , mean_absolute_error(y3_test, lr3.predict(X3_test)))
```

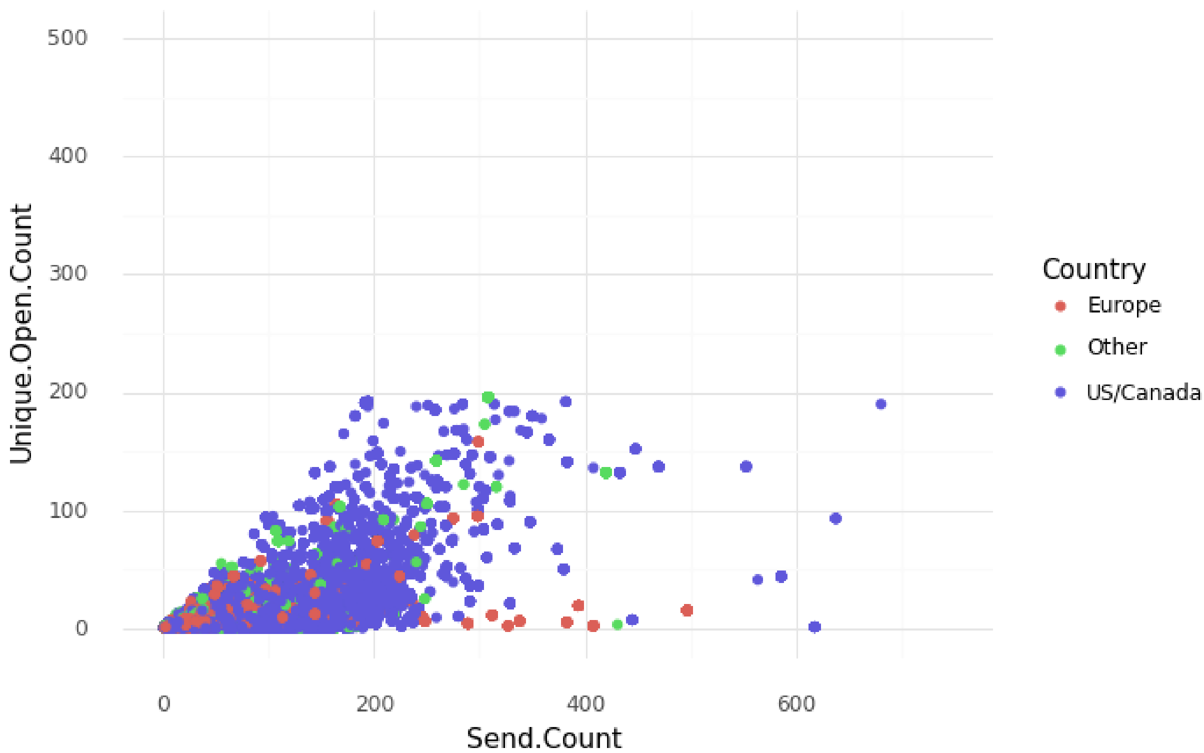
```
Train:  241.59647963442822
Test:  242.6500417353618
```

```
# TRYING TO SEE WHICH VARIABLES MATTER MOST WHEN PURCHASING?
# Purchase store - where it was purchases
  # lead platform - platform used to engage w products (web,app,unknown)
      # App.session.platform - platform used to access content
        # country - which country
```

MODELS OVER WEB DATA

```
(ggplot(web, aes(x = "Send.Count", y = "Unique.Open.Count",
```

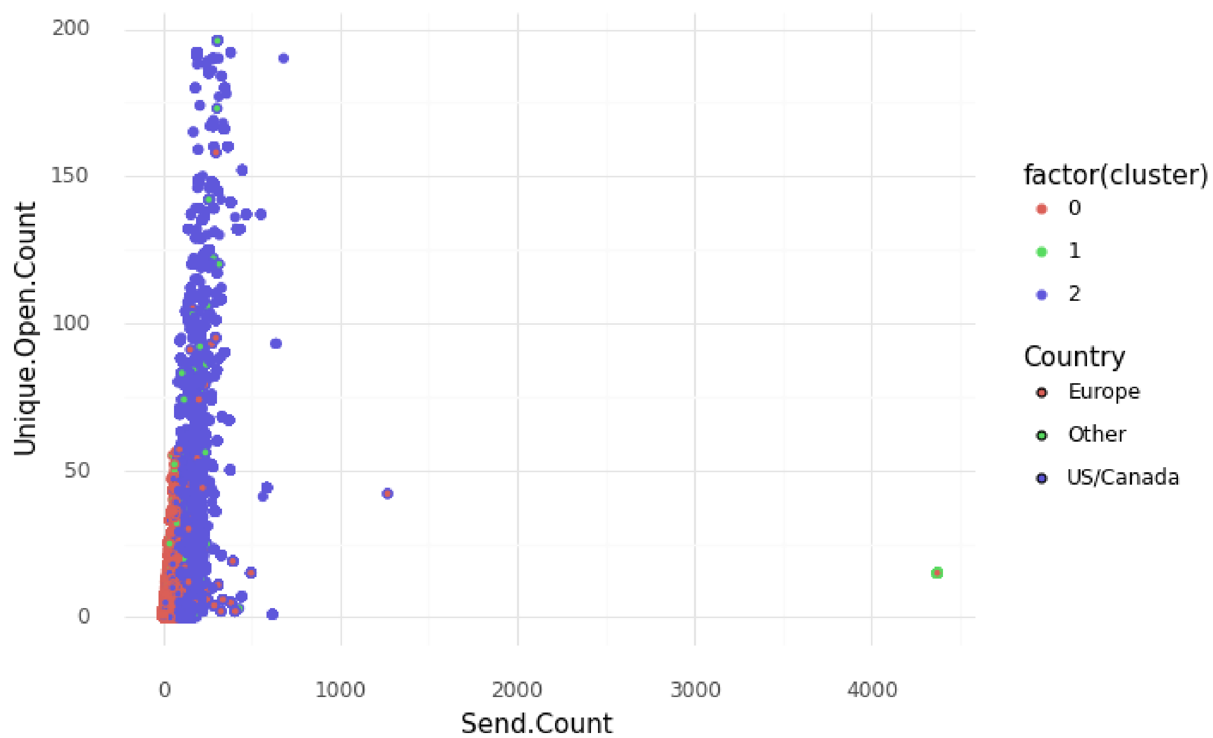
```
                color="Country")) + xlim(-1,750)+ylim(-1,500)+
 geom_point() + theme_minimal())
```




```
<ggplot: (8777544571921)>
```

```
# Linear regression model
# WEB
predictors6 = ["Send.Count", "Unique.Open.Count", "Unique.Click.Count"]
X6 = df[predictors6]
y6 = df["Country"]
X6_train, X6_test, y6_train, y6_test = train_test_split(X6, y6, test_size=0.25)

# zscoring
z = StandardScaler()
```

```
X6_train[predictors6] = z.fit_transform(X6_train[predictors6])
X6_test[predictors6] = z.fit_transform(X6_test[predictors6])

# building and fitting model
lr6 = LinearRegression()
lr6.fit(X6_train, y6_train)

print("Train: " , mean_absolute_error(y6_train, lr6.predict(X6_train)))
print("Test: " , mean_absolute_error(y6_test, lr6.predict(X6_test)))

# clustering web data

# k means model
predictors6 = ["Send.Count", "Unique.Open.Count", "Unique.Click.Count"]
X6 = web[predictors6]
y6 = web["Country"]
X6_train, X6_test, y6_train, y6_test = train_test_split(X6, y6, test_size=0.25)

km6 = KMeans(n_clusters = 3)
km6.fit(X6)

pred = km6.predict(X6)
X6["clusters"] = pred

silhouette_score(X6, pred)

     0.7756717178866481


# graphing clusters on web data
# based on send count, open count, unique click count
# clustering by Country
web["cluster"] = pred
(ggplot(web, aes(x = "Send.Count", y = "Unique.Open.Count",
                  color = "factor(cluster)",fill ="Country")) +
 geom_point() + theme_minimal())
```



<ggplot: (8777549911701)>

```
# tryinh hierarchial clustering using 3 features

features = ["Send.Count", "Unique.Open.Count", "Unique.Click.Count"]
x = web[predictors6]

z = StandardScaler()
x[features] = z.fit_transform(x)

hac = AgglomerativeClustering(affinity = "euclidean", linkage = "ward")
hac.fit(x)

dendrogram = sch.dendrogram(sch.linkage(x, method = 'ward'))
```

Ridge Regression

```
# ridge regression

lr_rr = Ridge()
# over ios
lr_rr.fit(X2_train, y2_train)

print("Train: " , mean_absolute_error(y2_train, lr_rr.predict(X2_train)))
print("Test: " , mean_absolute_error(y2_test, lr_rr.predict(X2_test)))
```

```
Train:  347.68221868453065
Test:  347.2411205064636
```

The ridge regression model over the ios data was not very accurate, resulting in mean absolute error for both training and test set of about 347. This was a major improvement of doing it over all the data with all the different platforms, but it is still not ideal

```
# ridge regression

lr_rr3 = Ridge()
# over android
lr_rr3.fit(X3_train, y3_train)

print("Train: " , mean_absolute_error(y3_train, lr_rr3.predict(X3_train)))
print("Test: " , mean_absolute_error(y3_test, lr_rr3.predict(X3_test)))
```

```
Train:  241.5965808376324
Test:  242.65014663972747
```

Kmeans

```
# k means model
# IOS

km = KMeans(n_clusters = 10)
km.fit(X2)

membership = km.predict(X2)
X2["clusters"] = membership

silhouette_score(X2, membership)
```

```
0.6078239679775439
```

```
# k means model
# android

km = KMeans(n_clusters = 10)
km.fit(X3)

predAndroid = km.predict(X3)
X3["clusters"] = predAndroid

silhouette_score(X3, predAndroid)
```

```
0.6441720340215784
```

Subscribers who can be sold additional products

```
# Volume between platforms WEB/APP and countries
# which variables contribute to the volume (demo user? email Subscriber? push notifications?)
      # for web we can look at Purchase.Amount.USD and model to predict that


# could predict purchase.store


#df = pd.read_csv("https://raw.githubusercontent.com/tmoore-byte/MGSC-410/main/subscriptionData.csv")
#df.dropna(axis=0, how='any', thresh=None, subset=None, inplace=False)


#value = df[].quantile(0.98)
#df = df.replace(np.inf, value)


 # creating random forest to find which segments have low posibilities
 # of renewing their product


 # df.describe()


# df = pd.get_dummies(ios)

 #df.iloc[:,5:].head(5)


# labels are predictions
#labels = np.array(df['Unique.Open.Count'])

# removing labels from df
#df= df.drop('Unique.Open.Count', axis = 1)
```

```
# saving df names
#df_list = list(df.columns)

#array
#df = np.array(df)




#train_features, test_features, train_labels, test_labels = train_test_split(df,
                                                                            #labels,
                                                                            #test_size = 0.25,
                                                                            #random_state = 42)




#print('Training Features Shape:', train_features.shape)
#print('Training Labels Shape:', train_labels.shape)
#print('Testing Features Shape:', test_features.shape)
#print('Testing Labels Shape:', test_labels.shape)




## Import the model we are using
#from sklearn.ensemble import RandomForestRegressor
# Instantiate model with 1000 decision trees
#rf = RandomForestRegressor(n_estimators = 500, random_state = 42)
# Train the model on training data
#rf.fit(train_features, train_labels);


# Use the forest's predict method on the test data
#predictions = rf.predict(test_features)
# Calculate the absolute errors
#errors = abs(predictions - test_labels)
# Print out the mean absolute error (mae)
#print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
```

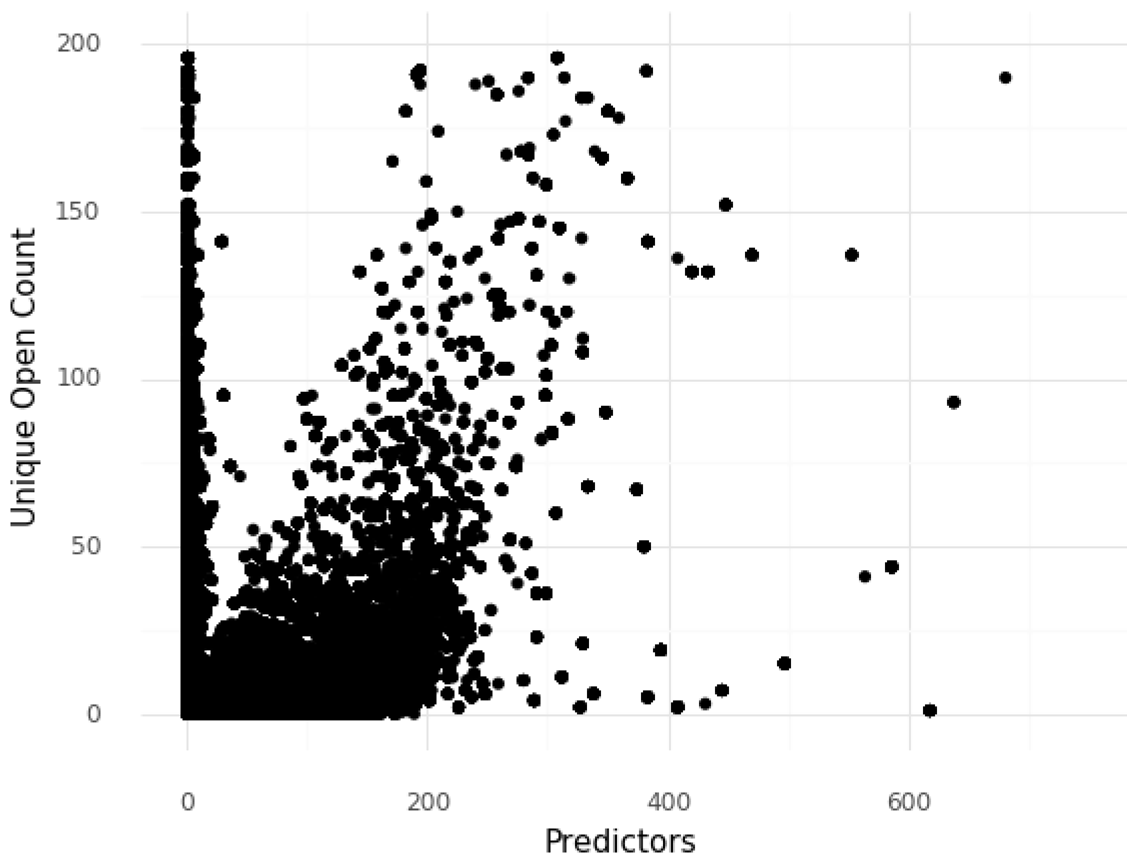
```
# trying linear regression

# ALL DATA
predictors = ["Send.Count", "Unique.Click.Count", "Demo.User",
              "Free.Trial.User", "Auto.Renew", "Push.Notifications"]
X = df[predictors]
y = df["Unique.Open.Count"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25)

# zscoring
z = StandardScaler()
X_train[predictors] = z.fit_transform(X_train[predictors])
X_test[predictors] = z.fit_transform(X_test[predictors])

# building and fitting model
lr = LinearRegression()
model = lr.fit(X_train, y_train)

print("Train: " , mean_absolute_error(y_train, lr.predict(X_train)))
print("Test: " , mean_absolute_error(y_test, lr.predict(X_test)))
```

```
Train:  4.636967817517326
Test:  4.67689617904918
```

MAE of 4.6 for both train and test set, average absolute difference between the true and predicted values. Model was pretty good at predicting Unique.Open.Count (potential new customers) when looking at if the user was a demo user, free trial user, auto renewal user, push notifications, send count total and unique click counts

```
(ggplot(df, aes(x = 'Send.Count', y = "Unique.Open.Count")) +
 geom_point() +
 geom_point(aes(x="Demo.User", y= "Unique.Open.Count"), data=df) +
 geom_point(aes(x="Free.Trial.User",y="Unique.Open.Count"), data=df)+
```

```
geom_point(aes(x="Auto.Renew",y="Unique.Open.Count"), data=df)+
 geom_point(aes(x="Push.Notifications",y="Unique.Open.Count"), data=df)+
 geom_point(aes(x="Unique.Click.Count",y="Unique.Open.Count"), data=df)
+ theme_minimal()+
labs(x = "Predictors", y = "Unique Open Count")+
xlim(-1,750)+ylim(-1,200))
```




```
<ggplot: (8789871919429)>
```