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Final Report:

Telecom Customer Churn Analysis

Problem Statement

Customer Churn is a huge problem for a business. Each time a customer leaves, it represents a significant investment lost. Customer churn prediction is a critical prediction for many businesses because acquiring new clients often costs more than retaining ones.

In this project, I am going to build a customer churn prediction model for a telecom company. Once the company knowing which customer will churn, the marketing team should know exactly what marketing to take for each individual customer to maximize the chances that customer will remain. And successful customer retention can offer huge savings to the company.

The Data

The dataset I am going to use is the “Marketing Series: Customer Churn” from Kaggle.com which is sourced from squarkai.com. It contains 6499 rows (each representing a unique customer) with 21 columns: 19 features, 1 target feature (Churn). The data is composed of both numerical and categorical features.

Target:

- Churn — Whether the customer churned or not (Yes, No)

Numeric Features:

- Tenure — Number of months the customer has been with the company

- MonthlyCharges — The monthly amount charged to the customer
- TotalCharges — The total amount charged to the customer

Categorical Features:

- CustomerID
- Gender — M/F
- SeniorCitizen — Whether the customer is a senior citizen or not (1, 0)
- Partner — Whether customer has a partner or not (Yes, No)
- Dependents — Whether customer has dependents or not (Yes, No)
- PhoneService — Whether the customer has a phone service or not (Yes, No)
- MulitpleLines — Whether the customer has multiple lines or not (Yes, No, No Phone Service)
- InternetService — Customer's internet service type (DSL, Fiber Optic, None)
- OnlineSecurity — Whether the customer has Online Security add-on (Yes, No, No Internet Service)
- OnlineBackup — Whether the customer has Online Backup add-on (Yes, No, No Internet Service)
- DeviceProtection — Whether the customer has Device Protection add-on (Yes, No, No Internet Service)
- TechSupport — Whether the customer has Tech Support add-on (Yes, No, No Internet Service)
- StreamingTV — Whether the customer has streaming TV or not (Yes, No, No Internet Service)
- StreamingMovies — Whether the customer has streaming movies or not (Yes, No, No Internet Service)
- Contract — Term of the customer's contract (Monthly, 1-Year, 2-Year)
- PaperlessBilling — Whether the customer has paperless billing or not (Yes, No)
- PaymentMethod — The customer's payment method (E-Check, Mailed Check, Bank Transfer (Auto), Credit Card (Auto))

Data Wrangling

The dataset is in a csv file. I loaded the data with panda read_csv. Here is the data information:

```
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   CustomerID         6499 non-null   object
 1   Gender             6499 non-null   int64
 2   Senior Citizen     6499 non-null   int64
 3   Partner            6499 non-null   object
 4   Dependents         6499 non-null   object
 5   Tenure             6499 non-null   int64
 6   Phone Service      6499 non-null   object
 7   Multiple Lines     6499 non-null   object
 8   Internet Service   6499 non-null   object
 9   Online Security    6499 non-null   object
 10  Online Backup      6499 non-null   object
 11  Device Protection  6499 non-null   object
 12  Tech Support       6499 non-null   object
```

```
 13   Streaming TV       6499 non-null   object
 14   Streaming Movies   6499 non-null   object
 15   Contract           6499 non-null   object
 16   Paperless Billing  6499 non-null   object
 17   Payment Method     6499 non-null   object
 18   Monthly Charges    6499 non-null   float64
 19   Total Charges      6490 non-null   float64
 20   Churn              6499 non-null   object
dtypes: float64(2), int64(3), object(16)
memory usage: 1.0+ MB
```

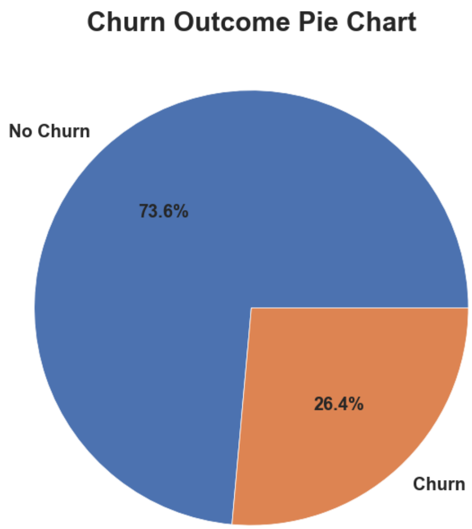
The data look clear, only the Total Charge column has 9 null values. Since it is very little compare the whole dataset. I drop the 9 rows with null values using dropna().

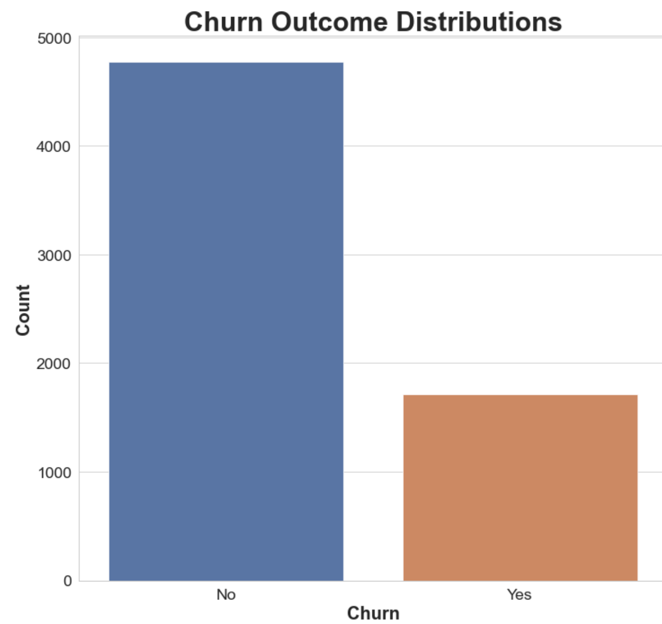
```
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   CustomerID         6490 non-null   object
 1   Gender             6490 non-null   int64
 2   Senior Citizen     6490 non-null   int64
 3   Partner            6490 non-null   object
 4   Dependents         6490 non-null   object
 5   Tenure             6490 non-null   int64
 6   Phone Service      6490 non-null   object
 7   Multiple Lines     6490 non-null   object
 8   Internet Service   6490 non-null   object
 9   Online Security    6490 non-null   object
 10  Online Backup      6490 non-null   object
 11  Device Protection  6490 non-null   object
 12  Tech Support       6490 non-null   object
 13  Streaming TV       6490 non-null   object
 14  Streaming Movies   6490 non-null   object
 15  Contract           6490 non-null   object
 16  Paperless Billing  6490 non-null   object
 17  Payment Method     6490 non-null   object
 18  Monthly Charges    6490 non-null   float64
 19  Total Charges      6490 non-null   float64
 20  Churn              6490 non-null   object
dtypes: float64(2), int64(3), object(16)
memory usage: 1.1+ MB
```

Now, data is clean. We can explore the data.

Data Exploratory Analysis

Target

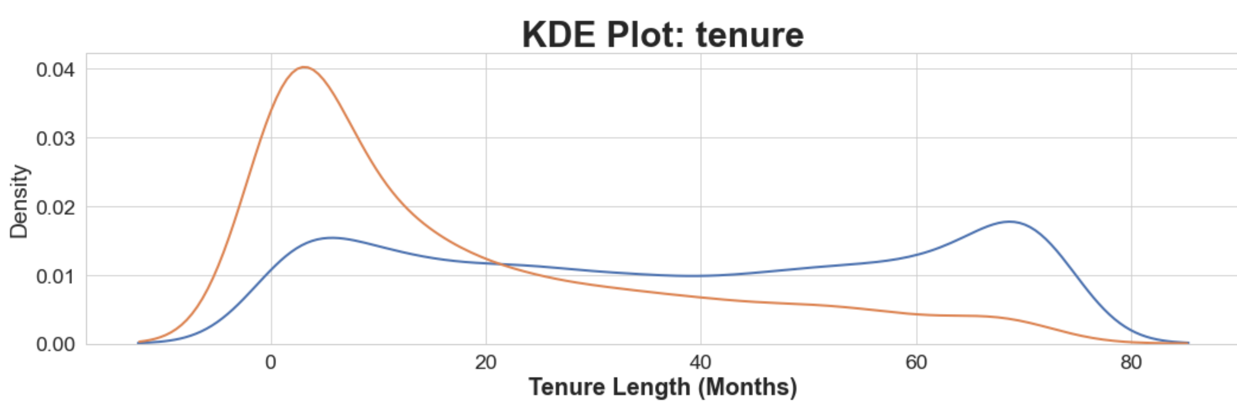


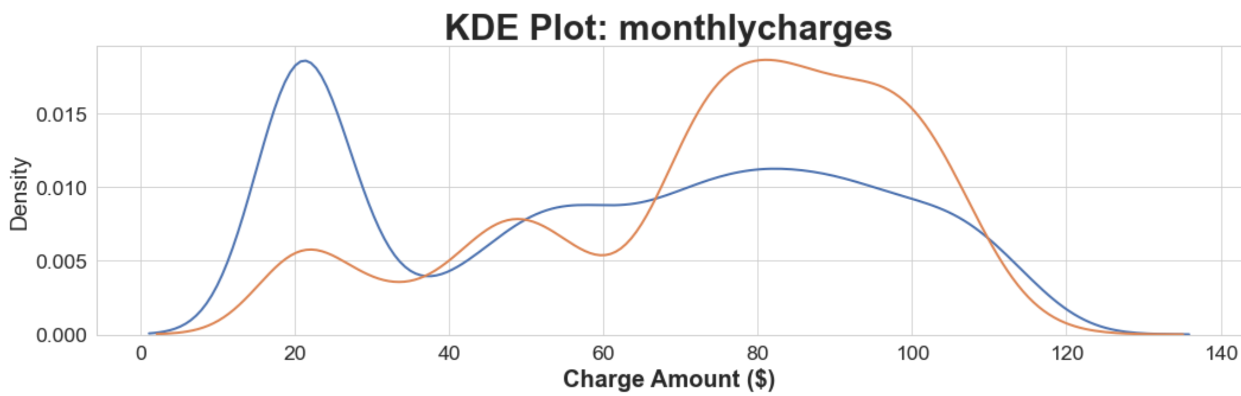


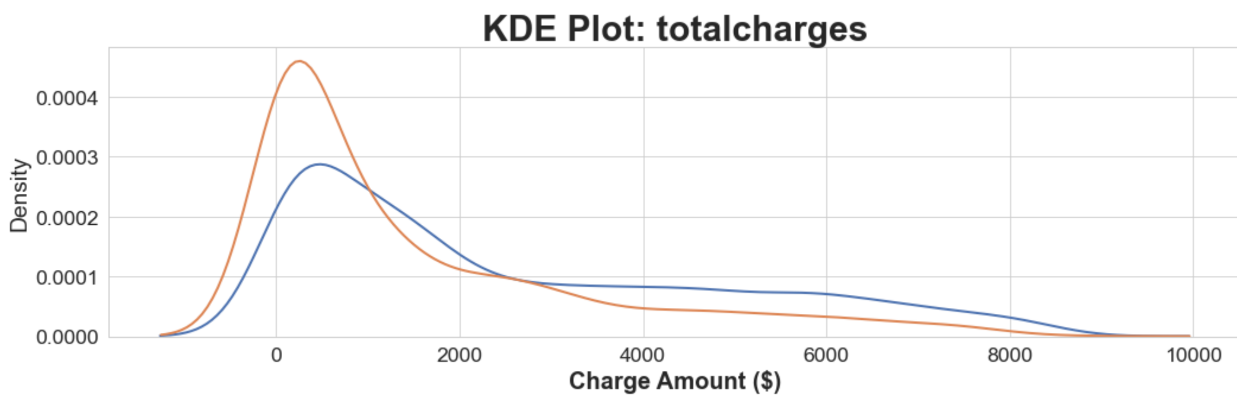
We can see from the pie chart on the left, about 26% of the Telcom customers from our dataset end up churning. This does seem like a rather high amount.

Numerical Features

When working with numerical features, one of the most informative statistics we can look at is the distribution of the data. Here, I used a Kernel-Density-Estimation plot to visualize the probability distributions of the relative variables. In this case, it will the distributions of the numerical features and target value churn.





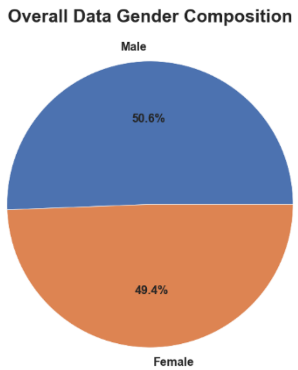


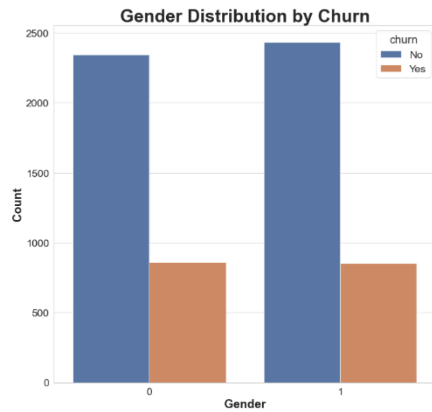
Numeric Variable Conclusions:

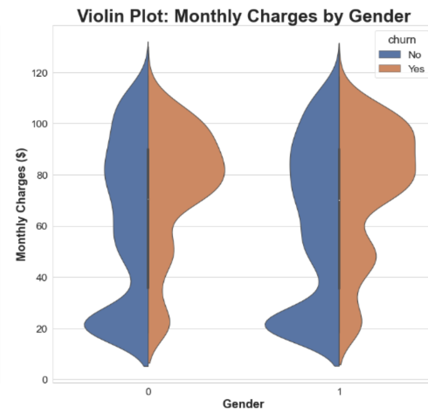
- Tenure: Customers who churn have the highest probability of occurring before 20 months of tenure
- Monthly Charges: Generally speaking, Likelihood of a customer churning increases as charges increase, and customers have the highest probability of churning when their monthly charges exceed 60 dollars. Customers who do not churn are most likely to have bills around 20 dollars, followed by just over 80 dollars.
- Total Charges: Distributions mostly too general for impact of feature (Monthly is most likely more important)

Categorical Features

Gender

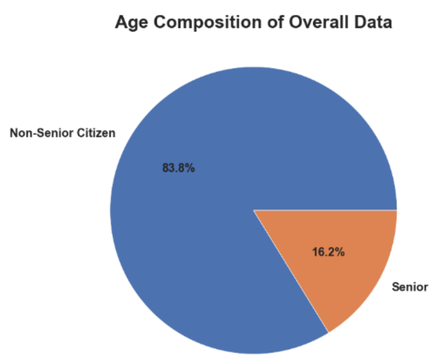


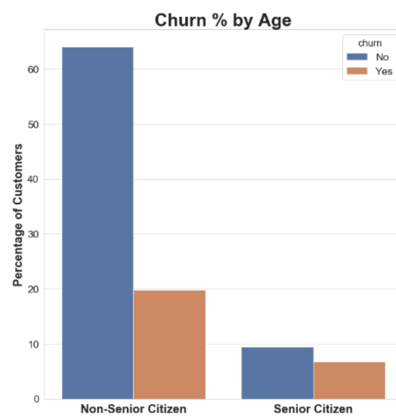


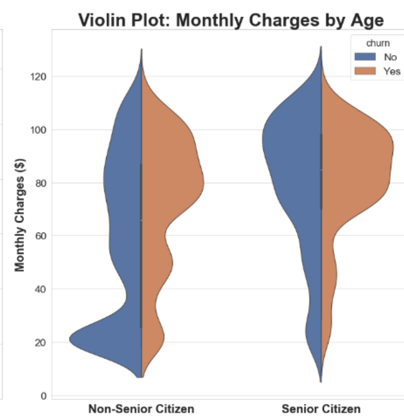


Gender Conclusion: Gender is equivalent in representation in our dataset and dose not appear to be an indicator of Churn

Age



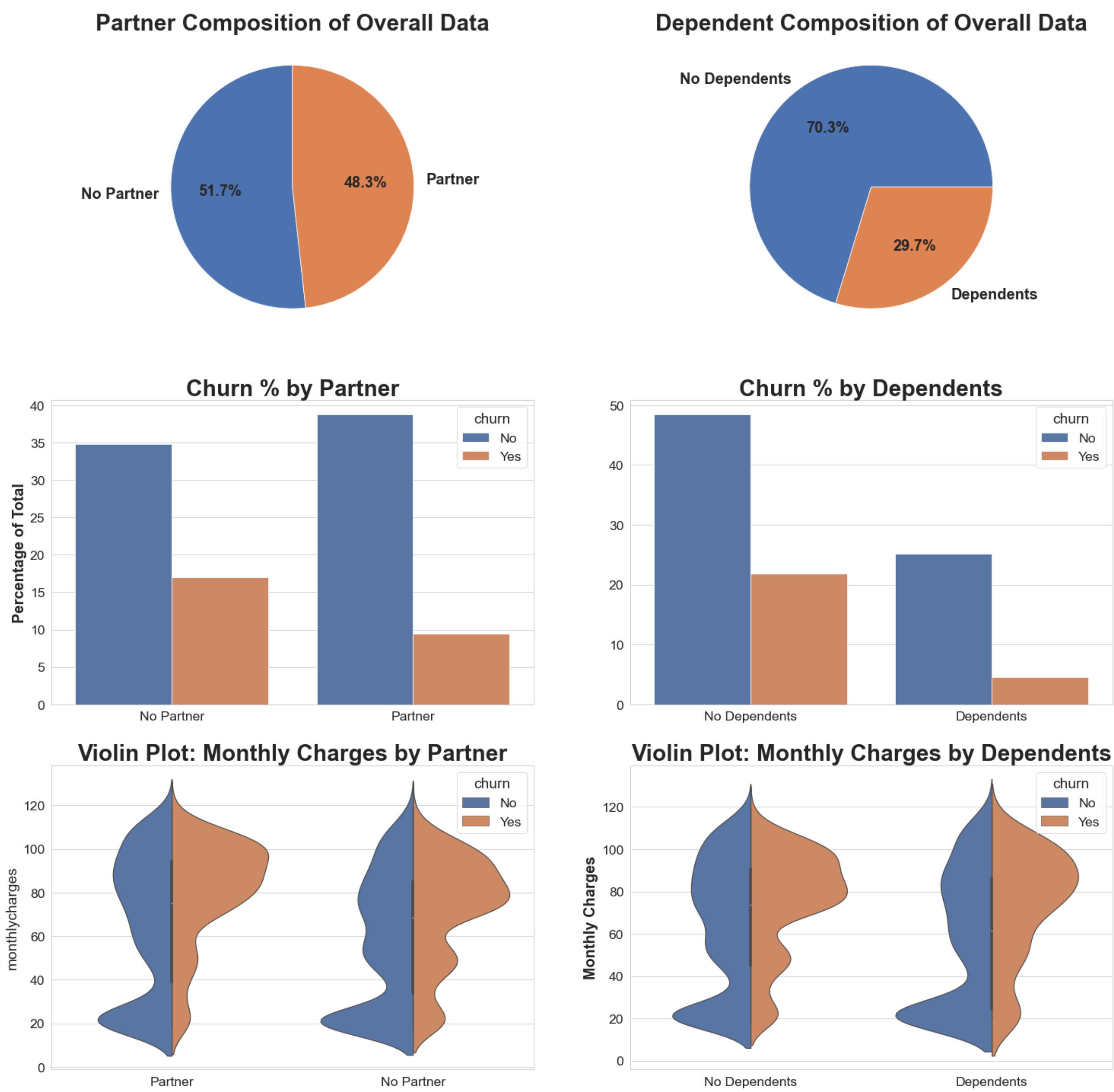




Age Conclusion:

- Our dataset has significantly fewer senior citizens than non-senior citizens
- Overall, more non-senior citizens will churn than senior citizen
- A higher proportion of senior citizens will churn than non-senior citizens
- Senior citizens and non-senior citizens both begin to churn once the monthly charges rise above $60
- Non-senior citizens are most likely to have monthly charges around 20 dollars
- Non-senior citizens will churn are slightly more likely to churn at monthly charges lower than $60 than senior-citizens

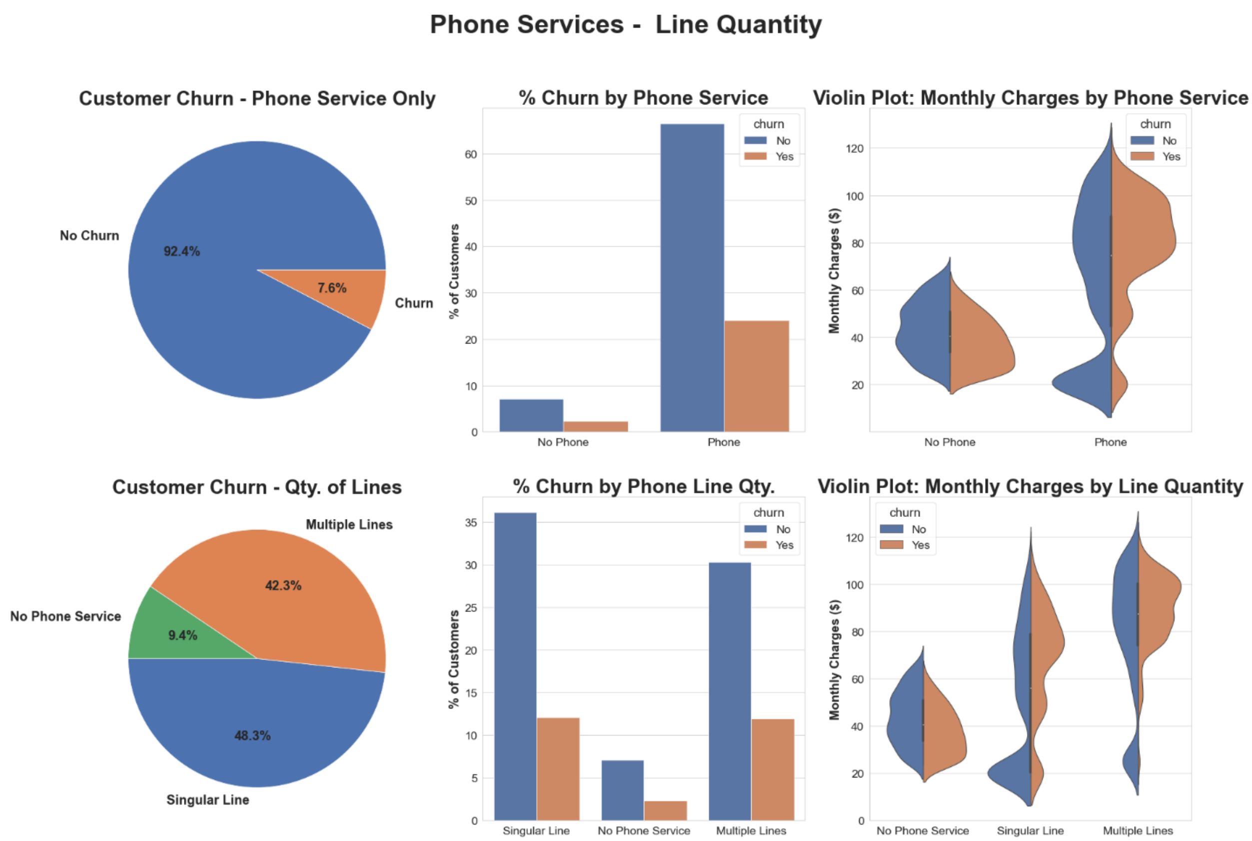
Partner& Dependents



Partner/Dependent Conclusions:

- Overall, those without partners are more likely to churn than those with partners
- Customers without dependents are more likely to churn than those with dependents
- Monthly charges among those who churn and don't churn are pretty similar for both partner values and both dependent values

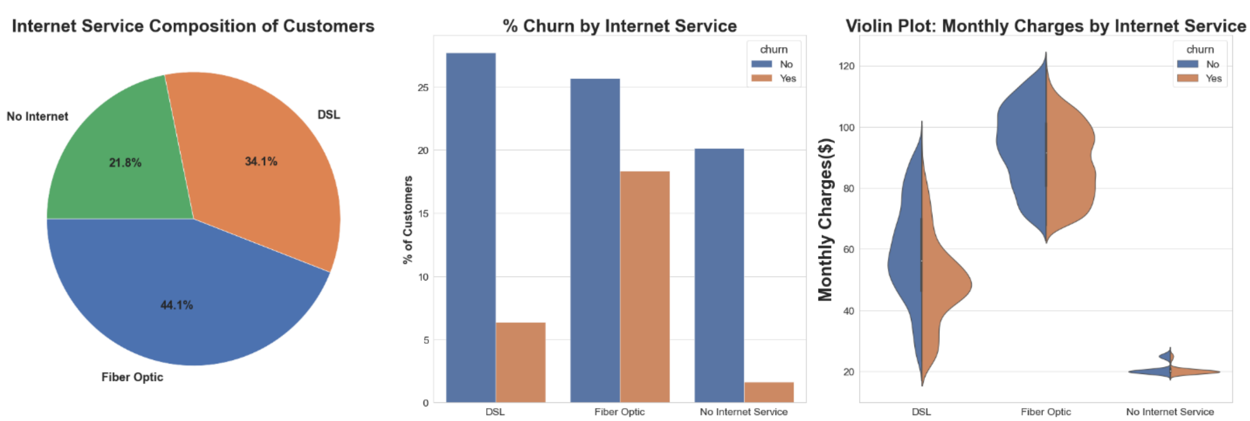
Phone Service & Quantity of Lines



Phone Service Conclusions:

- Significantly more customers with only phone service will not churn than those other customers
- People with only phone service churn about 25% of the time
- Customers with phone services only pay a higher average monthly charge
- Customers with multiple lines churn at approximately the same rate as those with a singular line
- Customers with multiple lines more frequently pay a higher monthly charge than those with singular phone lines

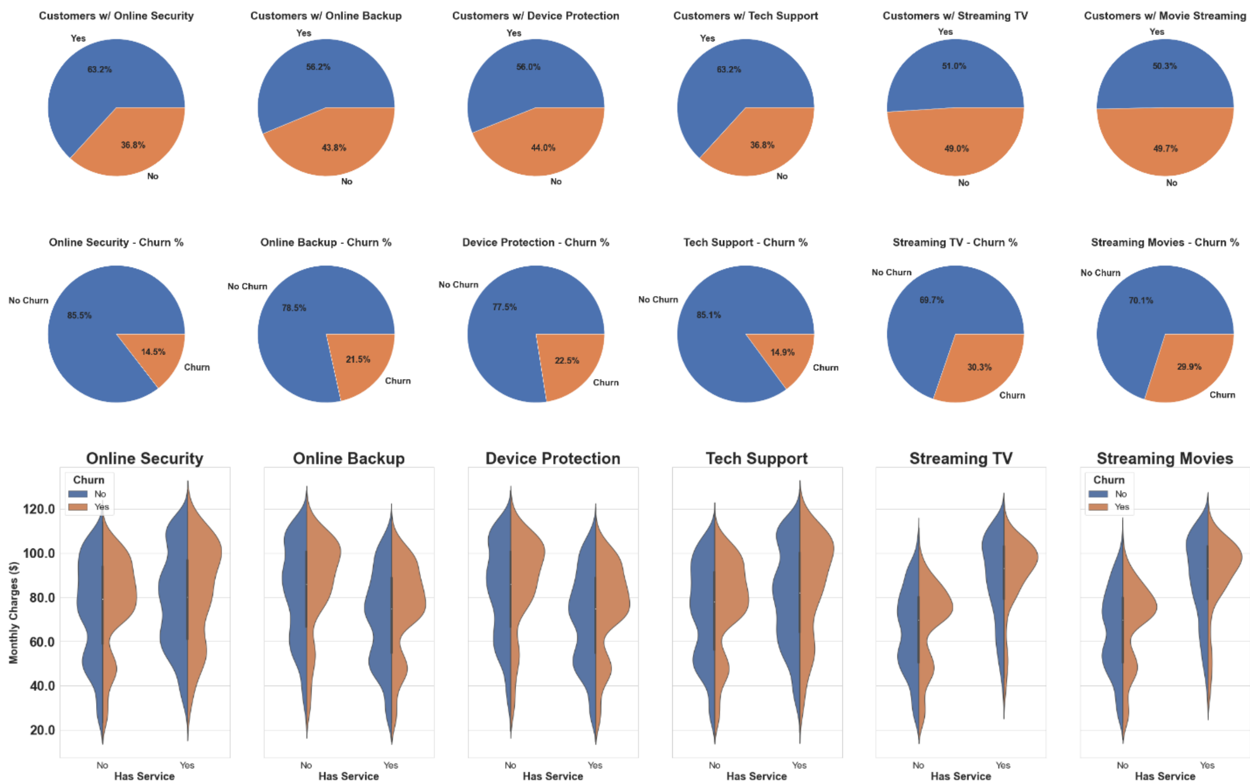
Internet Service



Internet Service Conclusion:

- Fiber Optic is the most popular internet option
- Fiber optic Internet Customers churn at significantly proportions than DSL or No Internet customers
- Fiber Optic is a significantly more expensive service, and customers churn slightly more than not when they have this service
- Customer with DSL are most likely to churn when their monthly charges are between $40 and $60.

Add-On Services



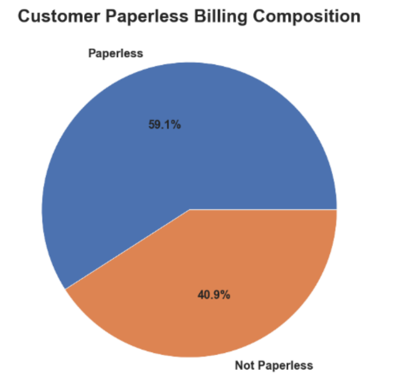
Conclusions:

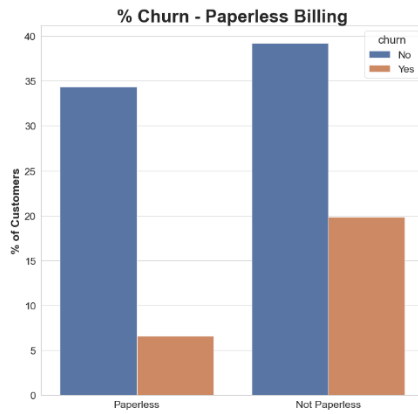
- Customers with TV streaming and/or Movie Streaming services churn more than all other add-on services
- Churn for customer in most categories will peak around a monthly charge of $100

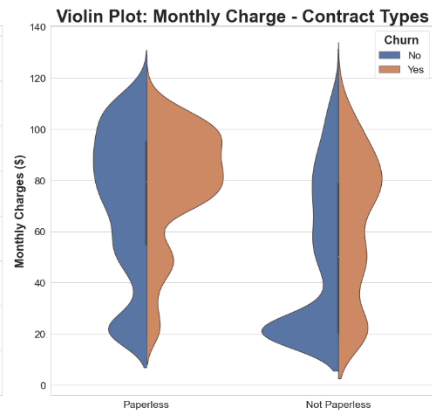
Contracts

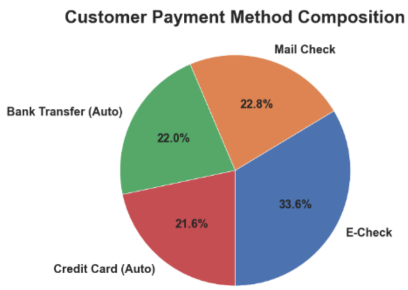
- More than half of customers use a monthly payment option
- Significantly more customers churn on monthly plans
- The longer the plan, the lower the churn rate
- Monthly charges are generally higher the longer the contract is

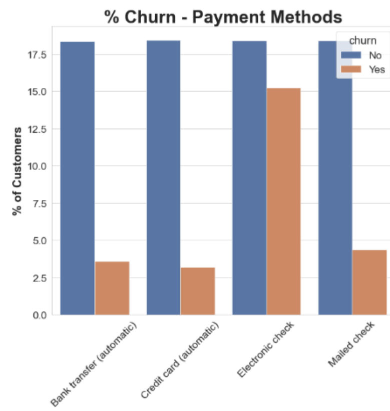
Paperless Billing & Payments

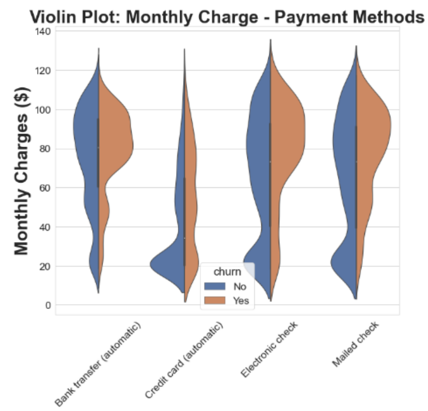










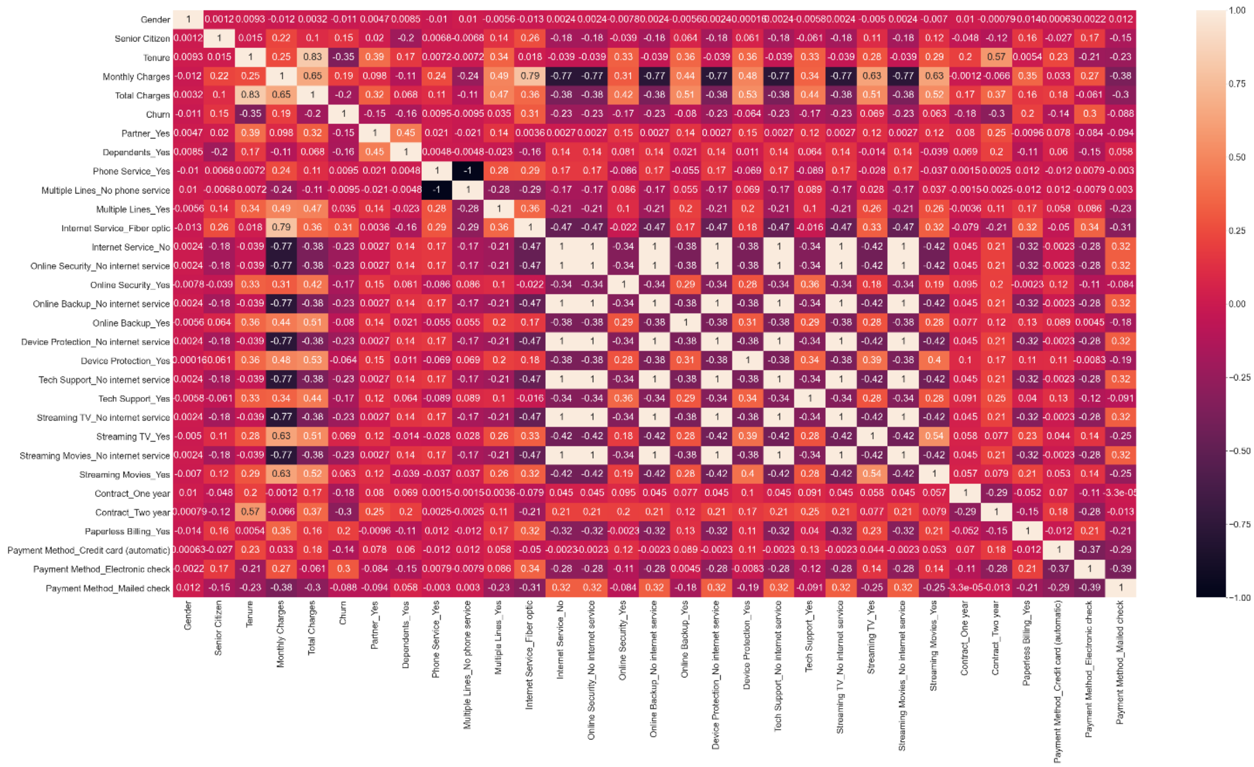


Payments Conclusions:

- Customers with non-paperless billing churn almost 15% more than paperless customers
- Paperless customers churn at similar rates as non-paperless customers when the monthly price is below 60 dollars, once above 60 more paperless customers churn than non-paperless
- Customers who pay with e-check churn more than 10% customers with all other payments methods
- Customers who pay by credit have consistent churn rates regardless of monthly charge, whereas customers paying by bank transfer, e-check, or mailed check all see an up tick in churn once monthly charges rise above 60.

Heat Map

As we can see from the heatmap below, there is no signal features has very strong correlation with customer churn. The features that have the highest correlation are Tenure, -0.35 and payment method, 0.3.



Preprocessing Our Data for Modeling

First, let's look at our data info.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6490 entries, 0 to 6489
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   CustomerID         6490 non-null   object
 1   Gender             6490 non-null   int64
 2   Senior Citizen     6490 non-null   int64
 3   Partner            6490 non-null   object
 4   Dependents         6490 non-null   object
 5   Tenure             6490 non-null   int64
 6   Phone Service      6490 non-null   object
 7   Multiple Lines     6490 non-null   object
 8   Internet Service   6490 non-null   object
 9   Online Security    6490 non-null   object
 10  Online Backup      6490 non-null   object
 11  Device Protection  6490 non-null   object
 12  Tech Support       6490 non-null   object
 13  Streaming TV       6490 non-null   object
 14  Streaming Movies   6490 non-null   object
 15  Contract           6490 non-null   object
 16  Paperless Billing  6490 non-null   object
 17  Payment Method     6490 non-null   object
 18  Monthly Charges    6490 non-null   float64
 19  Total Charges      6490 non-null   float64
```

```
 20  Churn               6490 non-null   object
dtypes: float64(2), int64(3), object(16)
memory usage: 1.0+ MB
```

We do not have any missing data and our datatypes are in order. At the top pf the data, we see the column 'CustomerID'. This column will be irrelevant to our data, as the former does not have any significant values and the latter is a unique identifier of the customer which is something we do not want. I then removed this from our Data Frame via a quick pandas slice:

df2 = df.iloc[:,1:]

The next step is addressing our target variable, Churn. Currently, the values of this feature are 'Yes' and 'No'. This is binary outcome, which is what we want, but our model will not be able to meaningfully interpret this in its current string-form. Instead, I want to replace these variables with numeric binary values:

df2.Churn.replace({"Yes":1, "No":0}, inplace = True)

Up next, we must deal with our remaining categorical variables. A typical solution is to create dummy variable for object type features. A dummy variable is a way of incorporating nominal variable into regression as binary value. I then used the panda function get_dummy to perform this step.

dummy_df = pd.get_dummies(df2)

Now, let's check the data info again.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6490 entries, 0 to 6489
Data columns (total 31 columns):
 #   Column                                   Non-Null Count  Dtype
---  ------                                   --------------  -----
 0   Gender                                   6490 non-null   int64
 1   Senior Citizen                           6490 non-null   int64
 2   Tenure                                   6490 non-null   int64
 3   Monthly Charges                          6490 non-null   float64
 4   Total Charges                            6490 non-null   float64
 5   Churn                                    6490 non-null   int64
 6   Partner_Yes                              6490 non-null   uint8
 7   Dependents_Yes                           6490 non-null   uint8
 8   Phone Service_Yes                        6490 non-null   uint8
 9   Multiple Lines_No phone service          6490 non-null   uint8
 10  Multiple Lines_Yes                       6490 non-null   uint8
 11  Internet Service_Fiber optic             6490 non-null   uint8
 12  Internet Service_No                      6490 non-null   uint8
 13  Online Security_No internet service      6490 non-null   uint8
 14  Online Security_Yes                      6490 non-null   uint8
 15  Online Backup_No internet service        6490 non-null   uint8
 16  Online Backup_Yes                        6490 non-null   uint8
 17  Device Protection_No internet service    6490 non-null   uint8
 18  Device Protection_Yes                    6490 non-null   uint8
 19  Tech Support_No internet service         6490 non-null   uint8
 20  Tech Support_Yes                         6490 non-null   uint8
```

```
 21  Streaming TV_No internet service        6490 non-null   uint8
 22  Streaming TV_Yes                        6490 non-null   uint8
 23  Streaming Movies_No internet service    6490 non-null   uint8
 24  Streaming Movies_Yes                    6490 non-null   uint8
 25  Contract_One year                       6490 non-null   uint8
 26  Contract_Two year                       6490 non-null   uint8
 27  Paperless Billing_Yes                   6490 non-null   uint8
 28  Payment Method_Credit card (automatic)  6490 non-null   uint8
 29  Payment Method_Electronic check         6490 non-null   uint8
 30  Payment Method_Mailed check             6490 non-null   uint8
dtypes: float64(2), int64(4), uint8(25)
memory usage: 462.8 KB
```

All the features are numerical values. And the total increased from 20 to 30.

Lastly, I dropped the outliners from dataset. The data greater 3 z score will consider outliner.

```
dummy_df = dummy_df[(np.abs(stats.zscore(dummy_df)) < 3).all(axis=1)]
```

The final dataset has 5877 rows and 31 columns.

Splitting our Data

We must separate the data into a target feature and predicting features. The target feature is Churn. And the rest are prediction features.

```
# Establish target feature, churn
y = dummy_df.Churn.values

# Drop the target feature from remaining features
X = dummy_df.drop('Churn', axis = 1)

# Save dataframe column titles to list, we will need them in next step
cols = X.columns
```

Feature Scaling

Our data is almost fully pre-processed but there is one more glaring issue to address, scaling. Our data is full of numerical data now, but they are all in the different units. To fix this problem, we will standardize our data values via rescaling an original variable to have equal range & variance as the remaining variable. For our purposes, we will use Min-Max Scaling [0, 1] because the standardize values will lie within the binary range.

```
# Import the necessary sklearn method
from sklearn.preprocessing import MinMaxScaler

# Instantiate a Min-Max scaling object
mm = MinMaxScaler()
```

```
# Fit and transform our feature data into a pandas dataframe
X_transformed = pd.DataFrame(mm.fit_transform(X))
```

Random over-sampling

Our dataset is imbalanced classification. There are 74% not churn and 26% churn. To solve this problem. I used random over-sampling with imblearn.

```
ros = RandomOverSampler(random_state=42)
# fit predictor and target variable
X_ros_transformed, y_ros_transformed = ros.fit_resample(X_transformed, y)
X_ros, y_ros = ros.fit_resample(X, y)
```

Train - Test - Split

We now conduct our standard train test split to sperate our data into a training set and testing set.

```
# Import the necessary sklearn method
from sklearn.preprocessing import MinMaxScaler

# Instantiate a Min-Max scaling object
mm = MinMaxScaler()

# Fit and transform our feature data into a pandas dataframe
X_transformed = pd.DataFrame(mm.fit_transform(X))
```

Building the Models

In this project, I am going to use four different models. Since our project is to predict customer churn, which is a categorical value. The models that I will are logistic Regression, K-Nearest, Random Forest Classifier and XGBoost.

Hyperparameters Tuning for Models

Machine learning algorithms have hyperparameters that allow us to tailor the behavior of the algorithm to our specific dataset. Hyperparameters are the internal coefficients or weights for model found by the learning algorithm. Unlike parameters, hyperparameters are specified by the practitioner when configuring the model. Typically, it is challenging to know what values to use for the hyperparameters of a given algorithm on a given dataset, therefore it is common to use random or grid search strategies for different hyperparameter values.

```
model = LogisticRegression()
solvers = ['newton-cg', 'lbfgs', 'liblinear']
penalty = ['l2']
c_values = [100, 10, 1.0, 0.1, 0.01]
```

```
# define grid search
grid = dict(solver=solvers,penalty=penalty,C=c_values)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
grid_search = GridSearchCV(estimator=model, param_grid=grid, n_jobs=-1, cv=cv,
scoring='accuracy',error_score=0)
grid_result = grid_search.fit(X_ros_transformed,y_ros_transformed)
```

Here are best parameters for each model base on accuracy is the evaluation metric.

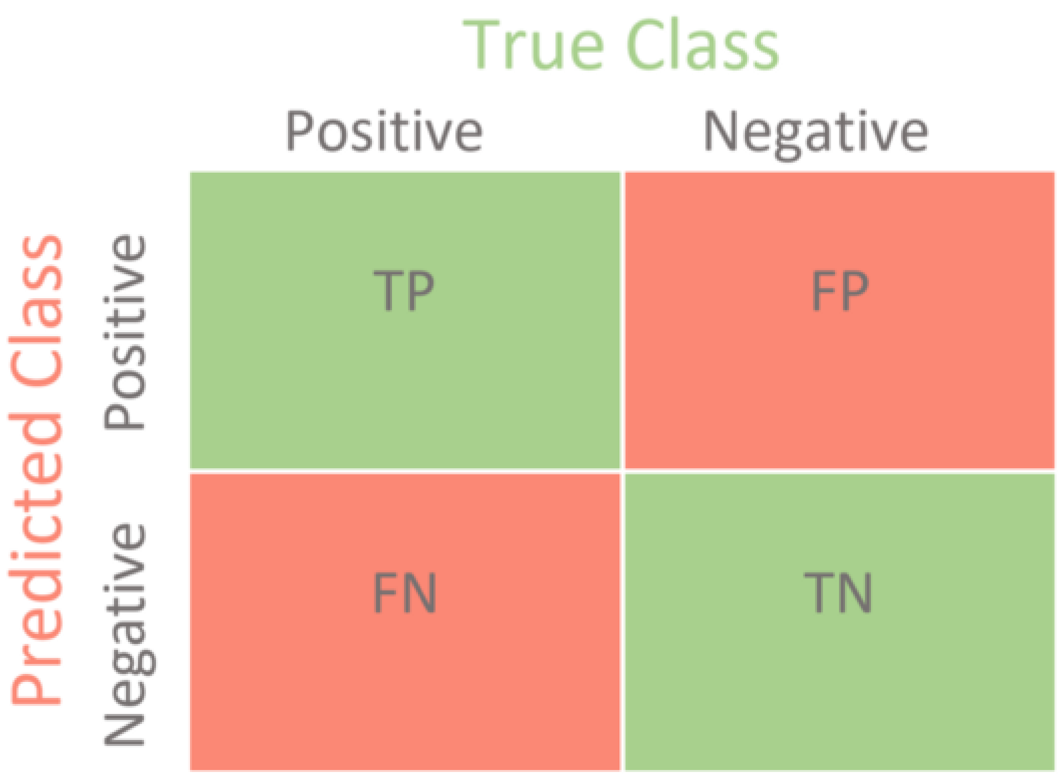
```
logreg_best = LogisticRegression(C=10, penalty='l2', solver = 'liblinear'

knn_best = KNeighborsClassifier(metric='euclidean' , n_neighbors=1, weights='uniform'

rfc_best = RandomForestClassifier(max_features='sqrt', n_estimators= 100)

gbc_best = GradientBoostingClassifier(learning_rate=0.1, max_depth=9, n_estimators=1000,
subsample= 1.0)
```

Confusion Matrix



A confusion Matrix is a visual representation which tells us the degree of four important classification metrics: True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN).

- True Positives (TP): The number of observations where the model predicted the customer would churn (1), and they actually do churn (1)
- True Negatives (TN): The number of observations where the model predicted the customer would not churn (0), and they actually do not churn (0).
- False Positives (FP): The number of observations where the model predicted the customer will churn (1), but in real life they do not churn (0).
- False Negatives (FN): The number of observations where the model predicted the customer will not churn (0), but in real life they do churn (1).

For our purpose of churn, it is worse for us to predict a customer not churning when that customer actually churns in reality, meaning that our False Negatives are more important to pay attention to.

```
Confusion Matrix of the models

 Logistic Regression:
[[768 302]
 [201 887]]

 K-Nearest Neighbors:
[[ 800  270]
 [  70 1018]]

 Random Forest Classifier:
[[ 883  187]
 [  55 1033]]

 XGBoost:
[[ 897  173]
 [  59 1029]]
```

Conclusion:

- Random Forest Classifier has the lower False Negatives, 55.
- And Logistic Regression has highest, 201.
- Random Forest Classifier and XGBoost out performance Logistic Regression and KNN.

Model Reports

In order to derive real meaning from the confusion matrix, we must use these four metrics to produce more descriptive metrics:

1. Precision: How precise the predictions are
    - Precision = TP/PP
    - Out of all the times the model said the customer would churn, how many times did the customer actually churn
2. Recall: Indicates what percentage of the classes we're interested in were actually captured by the model
    - Recall = TP/(TP + FN)

   - Out of all customers we saw that actually churn, what percentage of them did our model correctly identify as 'going to churn'
3. Accuracy: Measures the total number of predictions a model gets right, including both true positives and true negatives
   - Accuracy = (TP + TN) / (TP + FP + TN + FN)
   - Out of all predictions made, what percentage were correct?
4. F1 Score: Harmonic Mean of Precision and Recall --- a strong indicator of precision and recall
   - F1 = 2(Precision*Recall) / (Precision + Recall)
   - Penalizes models heavily if they are skewed towards precision or recall
   - Generally, the most used metric for model performance

```
Classification Report of the models

 Logistic Regression:
              precision    recall  f1-score   support

           0     0.7926    0.7178    0.7533      1070
           1     0.7460    0.8153    0.7791      1088

    accuracy                         0.7669      2158
   macro avg     0.7693    0.7665    0.7662      2158
weighted avg     0.7691    0.7669    0.7663      2158


 K-Nearest Neighbors:
              precision    recall  f1-score   support

           0     0.9195    0.7477    0.8247      1070
           1     0.7904    0.9357    0.8569      1088

    accuracy                         0.8424      2158
   macro avg     0.8550    0.8417    0.8408      2158
weighted avg     0.8544    0.8424    0.8410      2158


 Random Forest Classifier:
              precision    recall  f1-score   support

           0     0.9379    0.8187    0.8743      1070
           1     0.8415    0.9467    0.8910      1088

    accuracy                         0.8832      2158
   macro avg     0.8897    0.8827    0.8826      2158
weighted avg     0.8893    0.8832    0.8827      2158


 XGBoost:
              precision    recall  f1-score   support

           0     0.9387    0.8439    0.8888      1070
           1     0.8604    0.9458    0.9011      1088
```

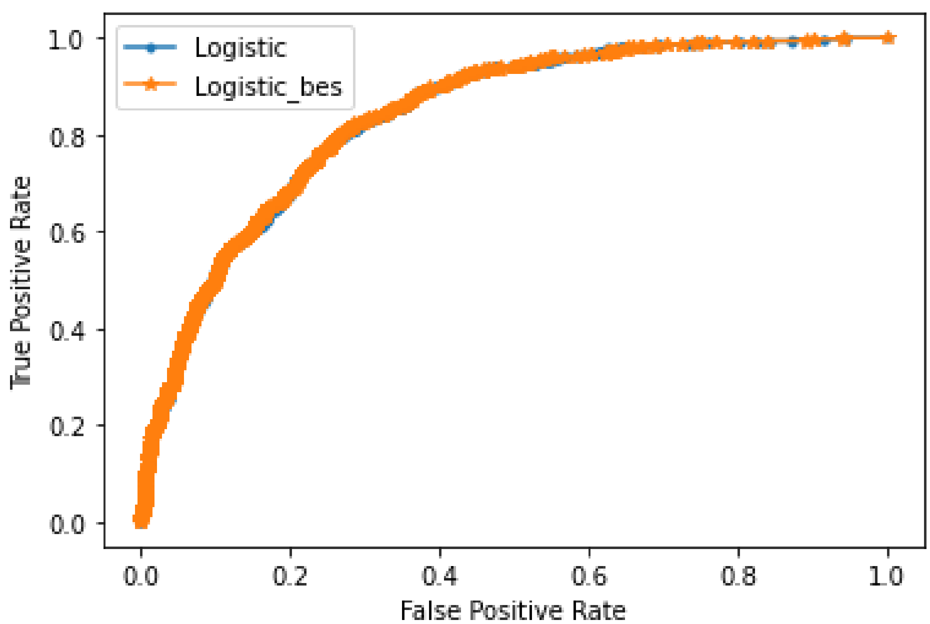
accuracy			0.8953	2158
macro avg	0.8995	0.8948	0.8949	2158
weighted avg	0.8992	0.8953	0.8950	2158

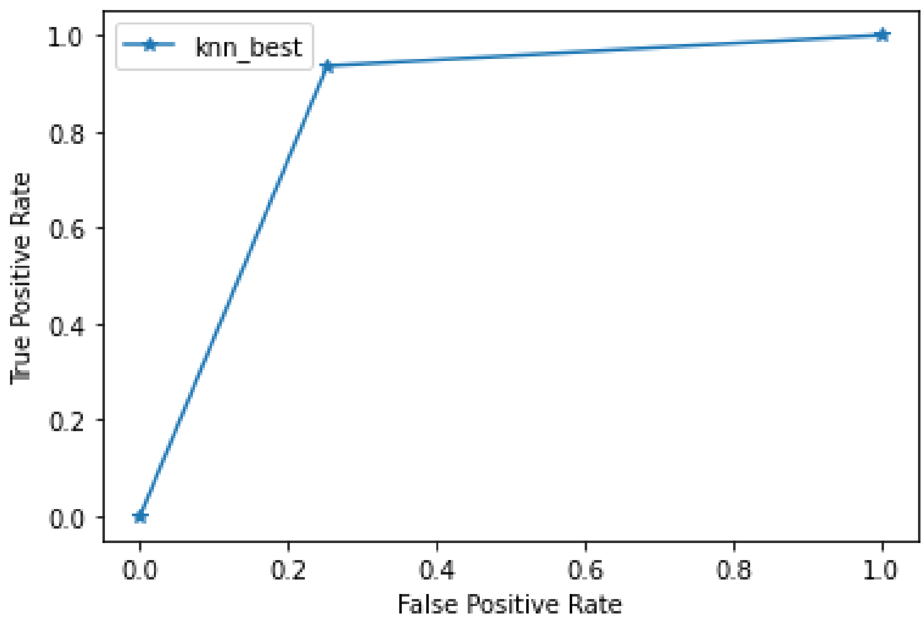
Conclusions:

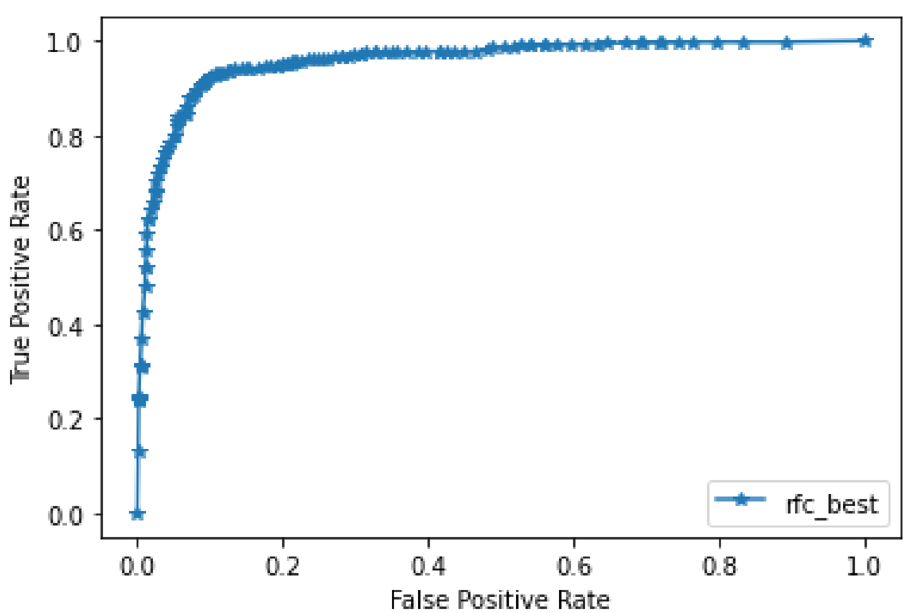
- Overall, XGBoost and Random Forest Classifier are the best models.
- But I will recommend use Random Forest Classifier because it has lower False Negatives and overall performance almost as good as XGBoost.

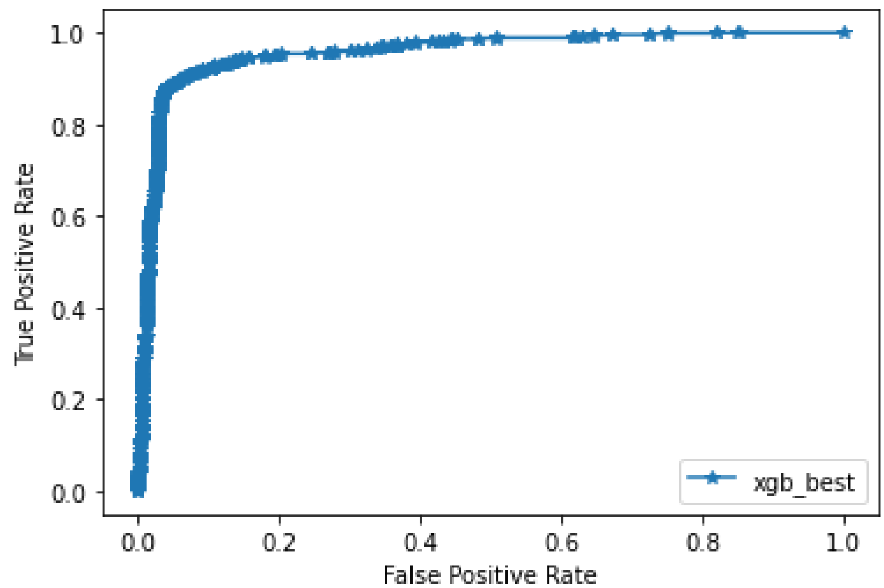
Area Under Curve

The AUC will give us a singular numeric metric to compare instead of a visual representation. An AUC = 1 would represent a perfect classifier, and an AUC = 0.5 represents a classifier which only has 50% precision.




knn_best
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate


rfc_best
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate




```
Area under curve of the models

 Logistic Regression:
0.8397329404892798

 K-Nearest Neighbors:
0.8416626580538757

 Random Forest Classifier:
0.958552089059923

 XGBoost:
0.959980157366685
```

Conclusions:

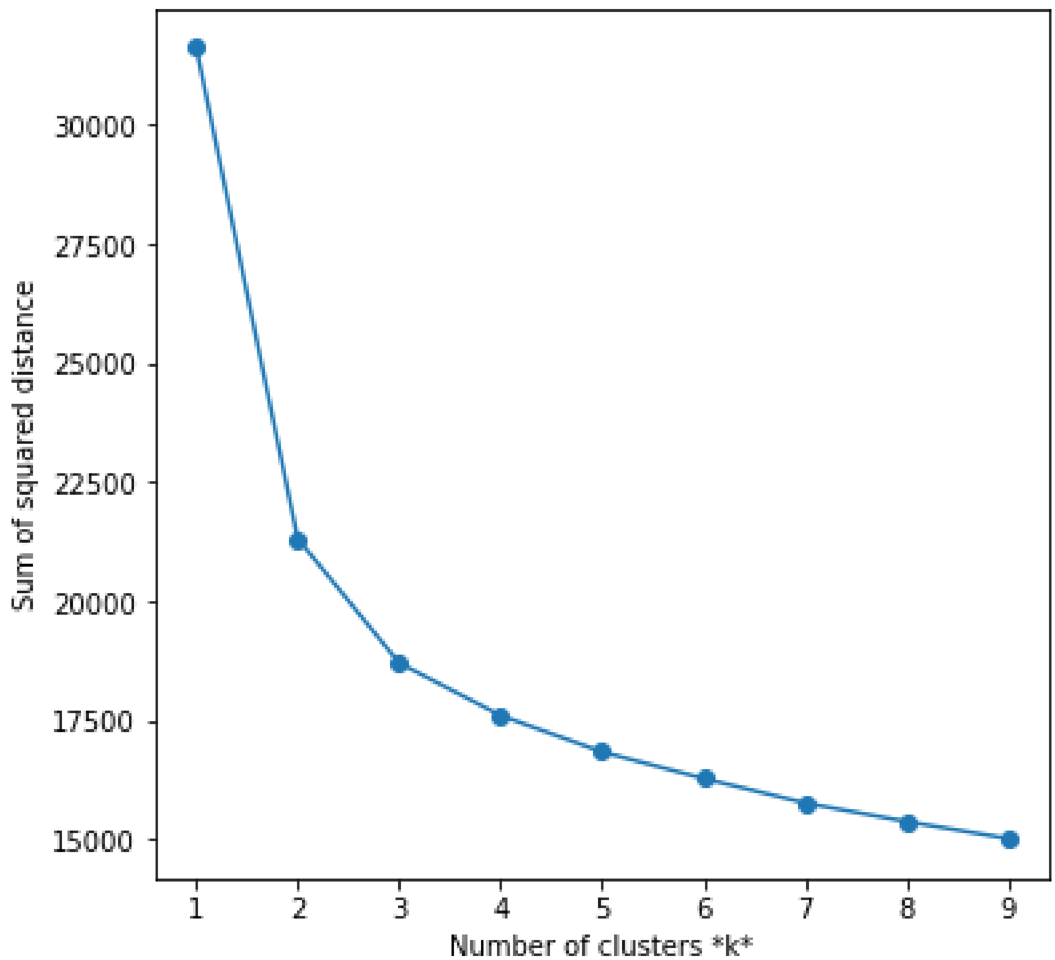
- Again, Random Forest Classifier and XGBoost have much better than the other two
- And Random Forest Classifier will still be the model I recommend using

Extract Step – Add Customer Segmentation

One way we can try to do to improve the model is to create segmentation of customers than use it as one of features in the predicting model. Since our dataset did have label of each customer, we have to use unsupervised clustering algorithm to do customer segmentation. And K-means Clustering is commonly used for customer segmentation.

Elbow Method

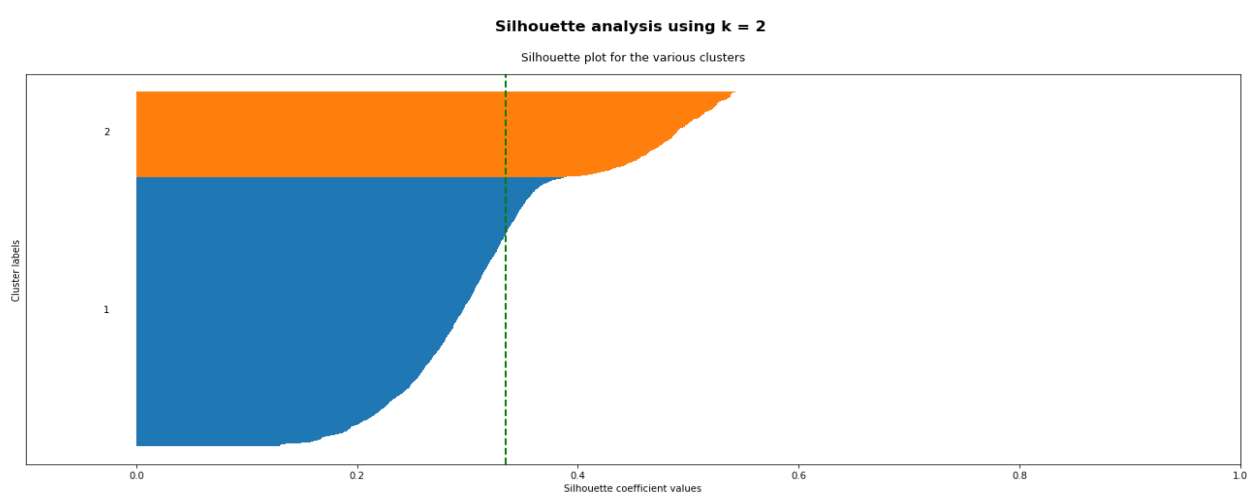
To use K-means clustering, we need to determine how many groups of customers we want to do. To do that, we can use the Elbow Method.

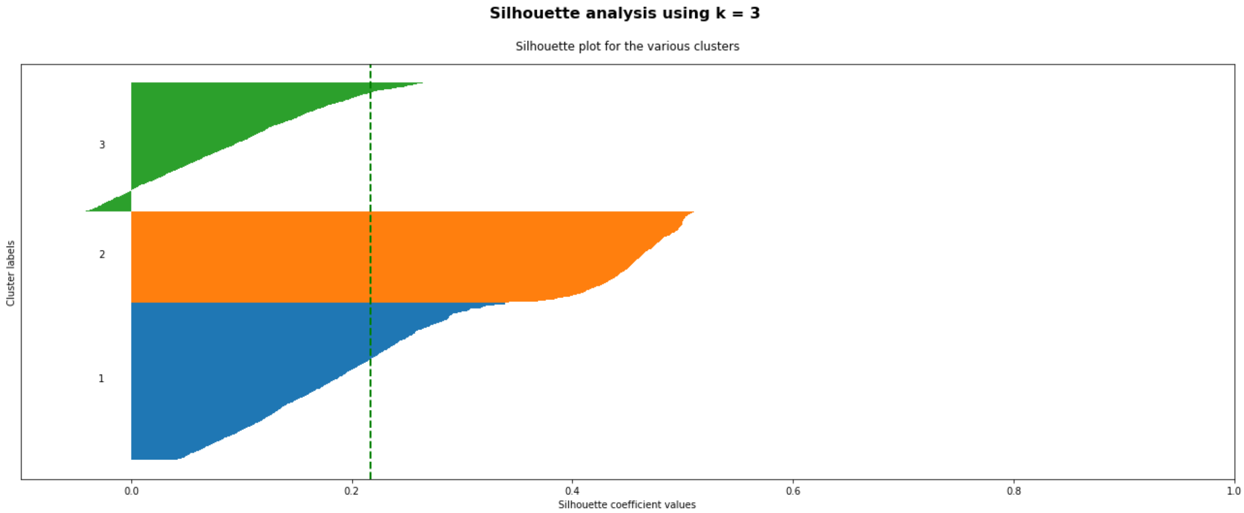


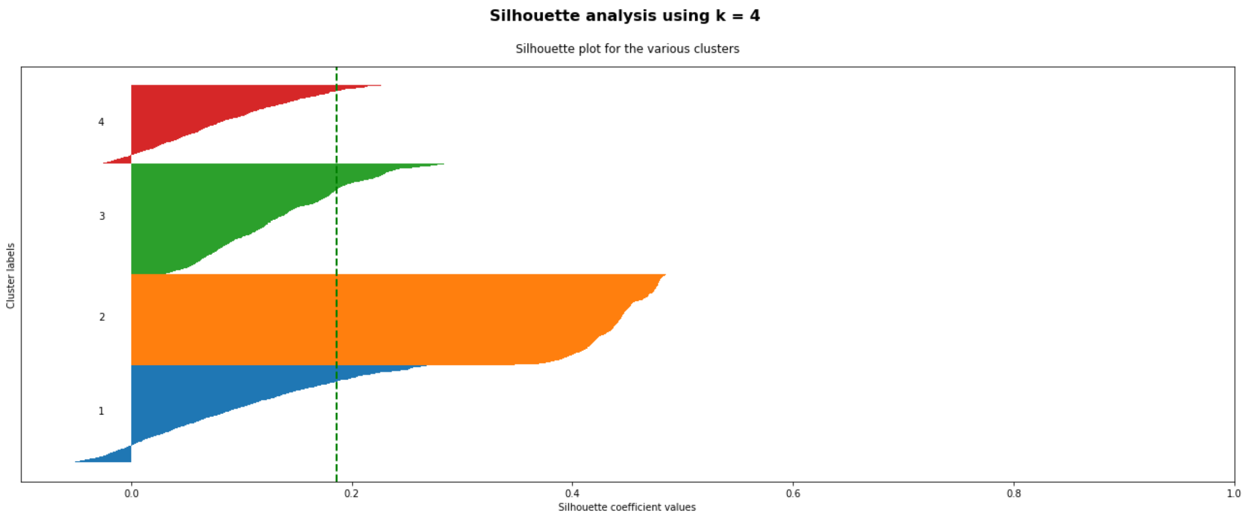
The graph above indicated 2 clusters is the best option.

Silhouette Analysis

Beside the elbow method, silhouette analysis is another method will help us to determine the K.







The graphs above had shown the silhouette analysis for K = 2, 3 and 4.

- As the above plots show, n_clusters=2 has the best average silhouette score of around 0.28 and all clusters being above the average shows that it is actually a good choice.
- Also, the thickness of the silhouette plot gives an indication of how big each cluster is. The plot shows that cluster 1 has almost triple the samples than cluster 2.
- However, as we increased n_clusters to 3 and 4, the average silhouette score decreased to around 0.22 and 0.19 respectively.
- Moreover, the thickness of silhouette plot started showing wide fluctuations.
- The bottom line is: Good n_clusters will have a well above 0.5 silhouette average score as well as all of the clusters have higher than the average score.

K-means clustering

Both methods indicated to use n_clusters = 2. Now, lets apply it to model.

model = sklearn.cluster.KMeans(n_clusters=2)

Call a fit_predict() on X

cluster_assignments = model.fit_predict(X)

Then, we add the result of the model as a new feature to the dataframe.

X['44'] = cluster_assignments.tolist()

Model results (added customer segmentation as a predict feature)

```
       Confusion Matrix of the models

 Logistic Regression:
[[768 302]
 [201 887]]

 K-Nearest Neighbors:
[[ 800  270]
 [  70 1018]]

 Random Forest Classifier:
[[ 881  189]
 [  54 1034]]

 XGBoost:
[[ 896  174]
 [  60 1028]]
```

Same as before, Random Forest Classifier has less False Negatives. Compared to before without adding customer segmentation is a little better has 1 less False Negative than before. Overall, the confusion matric did not change much.

```
Classification Report of the models

 Logistic Regression:
              precision    recall  f1-score   support

           0     0.7926    0.7178    0.7533      1070
           1     0.7460    0.8153    0.7791      1088

    accuracy                         0.7669      2158
   macro avg     0.7693    0.7665    0.7662      2158
weighted avg     0.7691    0.7669    0.7663      2158


 K-Nearest Neighbors:
              precision    recall  f1-score   support

           0     0.9195    0.7477    0.8247      1070
           1     0.7904    0.9357    0.8569      1088
```

```
    accuracy                         0.8424      2158
   macro avg     0.8550    0.8417    0.8408      2158
weighted avg     0.8544    0.8424    0.8410      2158


 Random Forest Classifier:
              precision    recall  f1-score   support

           0     0.9422    0.8234    0.8788      1070
           1     0.8455    0.9504    0.8949      1088

    accuracy                         0.8874      2158
   macro avg     0.8939    0.8869    0.8868      2158
weighted avg     0.8935    0.8874    0.8869      2158


 XGBoost:
              precision    recall  f1-score   support

           0     0.9386    0.8430    0.8882      1070
           1     0.8596    0.9458    0.9007      1088

    accuracy                         0.8948      2158
   macro avg     0.8991    0.8944    0.8944      2158
weighted avg     0.8988    0.8948    0.8945      2158
```

Compared to modeling without customer segmentation, the random forest classifier model performs a little better that before overall. Here our target is churn customer which indicated as '1'

- Precision increased from 84.15% to 84.55%, 0.4% increased
- Recall increased from 94.67% to 95.04%, 0.37% increased
- F1-score increased from 89.1% to 89.49%, 0.39% increased
- Accuracy increased from 88.21% to 88.74%, .53% increased

The increased percentage not much, but it is significant because the original metric scores already high.

Therefore, adding customer segmentation dose improve the model.