Churn Prediction – Milestone Report-2

Objective: Increase customer retention by building predictive model (Churn) to push churn rate down closer to 0%.

Introduction:

Overview: This data set consists of Customer left within last month. Service that each customer has signed up for. Customer account information like payment method, billing type. Demographic info about customers like gender, age and dependents

Url/Link: https://www.kaggle.com/blastchar/telco-customer-churn

Approach:

- Data Wrangling
- EDA
- Inferential Statistics
- Predictive Models (ML)

Data Wrangling & More:

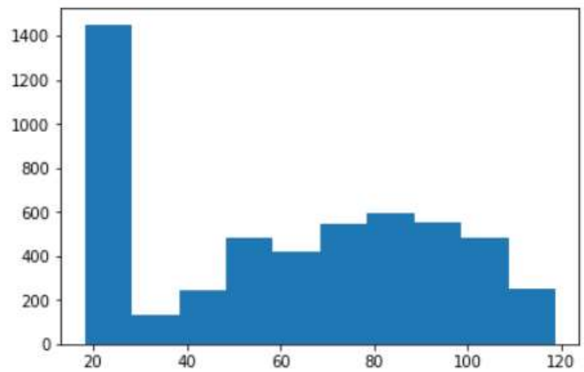
- Fortunately, this is not a 'messy' data set
- The dataset has 11 missing values for total charges column, so replace it with 0 using "df.replace"
- We have more than 7000 rows and 21 attributes (columns)
- Some data that should be categorical are saved as number.
- If there are any missing values then 'df.fillna' can be used to fill the missing data
- Convert Total Charge to numeric
- There are some features that contains ambiguous information's, for example, Online Security contains 3 different labels, but the correct labels are Yes or No using "replace"
- This Data has 16 categorical features:

Data Visualization:

- Histogram for total charges (Churn Customers)

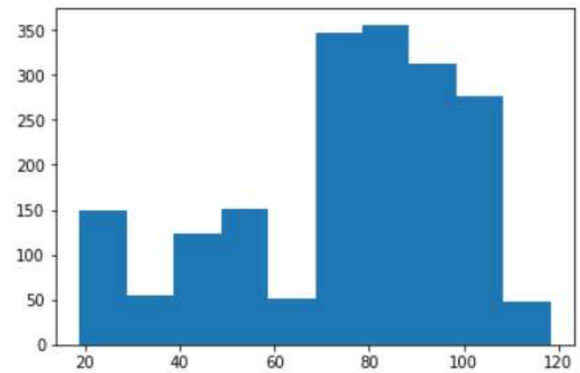
```
# Histogram (Total Charges for Not Churn Customers)

plt.hist(df_not_Churn['MonthlyCharges'],bins= 10)
plt.show()
```




```
# Histogram (Total Charges for Churn Customers)

plt.hist(df_churn['MonthlyCharges'],bins= 10)
plt.show()
```



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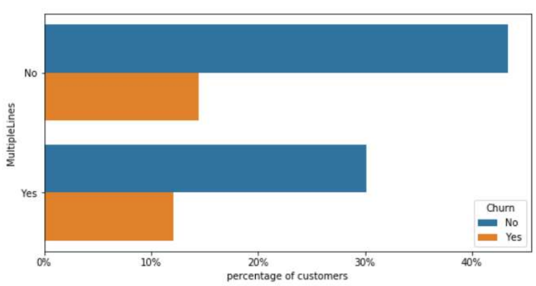
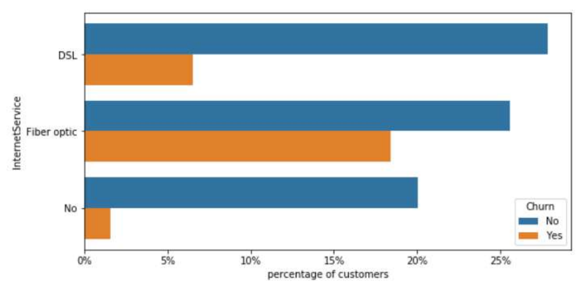
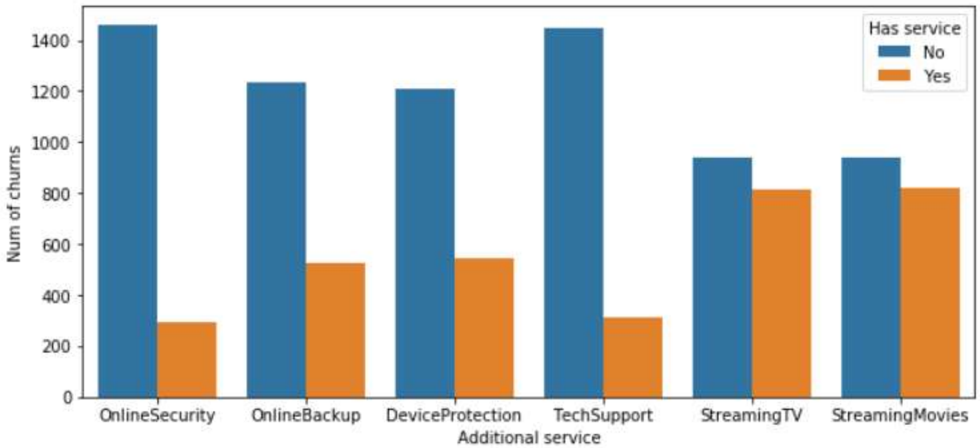
- Bar plot

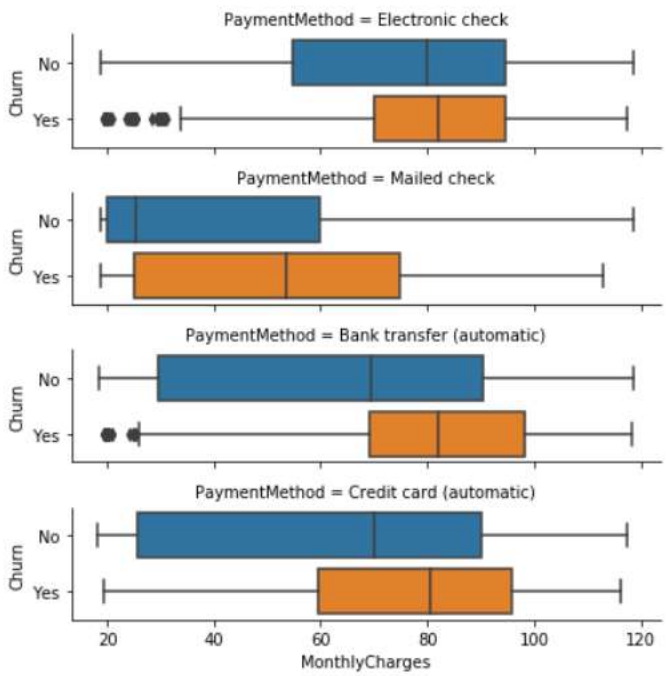




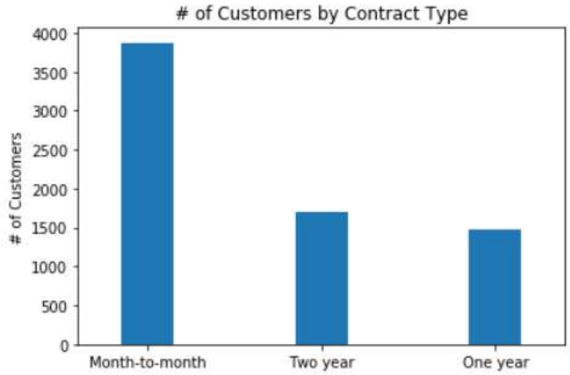
- Customers with multiple lines have a slightly higher churn rate
- Customers without internet have a very low churn rate
- Customers with fiber are more probable to churn than those with DSL connection

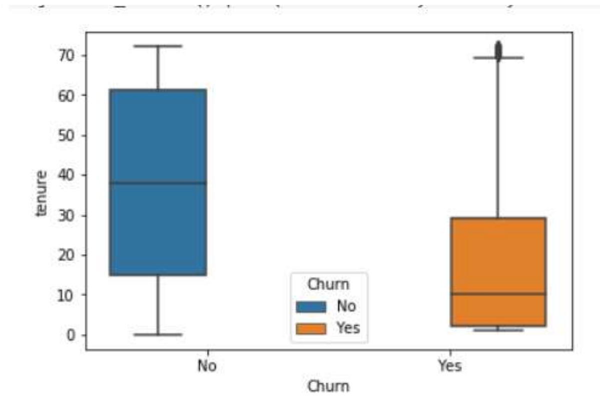


- Customers with online Security and tech support has a very low churn rate
- Customers with Streaming services are more likely to churn



- Customers with automatic payments has high churn rate

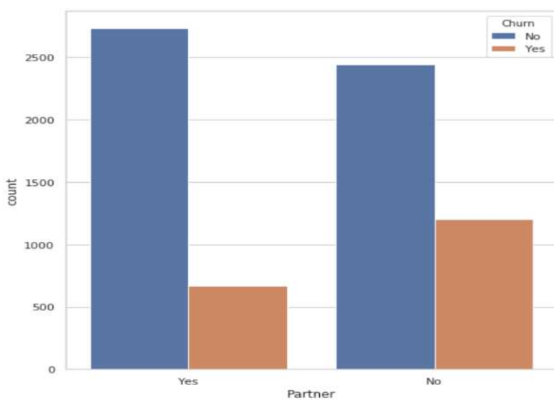




- As we can see from this graph most of the customers are in the month to month contract.
- While there are equal number of customers in the 1 year and 2-year contracts.
- Churn rate is high for the customers who has less tenure/contract with Telco company.

Inferential Statistics

- There is no behavior difference between women and men.



- Customer with partners has a very low churn rate when compared with customer without partners.

Statistical summary of data set

	count	mean	std	min	25%	50%	75%	max
gender	7043.0	0.504756	0.500013	0.00	0.00	1.000	1.0000	1.00
SeniorCitizen	7043.0	0.162147	0.368612	0.00	0.00	0.000	0.0000	1.00
Partner	7043.0	0.483033	0.499748	0.00	0.00	0.000	1.0000	1.00
Dependents	7043.0	0.299588	0.458110	0.00	0.00	0.000	1.0000	1.00
tenure	7043.0	32.371149	24.559481	0.00	9.00	29.000	55.0000	72.00
PhoneService	7043.0	0.903166	0.295752	0.00	1.00	1.000	1.0000	1.00
PaperlessBilling	7043.0	0.592219	0.491457	0.00	0.00	1.000	1.0000	1.00
MonthlyCharges	7043.0	64.761692	30.090047	18.25	35.50	70.350	89.8500	118.75
TotalCharges	7032.0	2283.300441	2266.771362	18.80	401.45	1397.475	3794.7375	8684.80
Churn	7043.0	0.265370	0.441561	0.00	0.00	0.000	1.0000	1.00
customerID_0002-ORFBO	7043.0	0.000142	0.011916	0.00	0.00	0.000	0.0000	1.00
customerID_0003-MKNFE	7043.0	0.000142	0.011916	0.00	0.00	0.000	0.0000	1.00
customerID_0004-TLHLJ	7043.0	0.000142	0.011916	0.00	0.00	0.000	0.0000	1.00

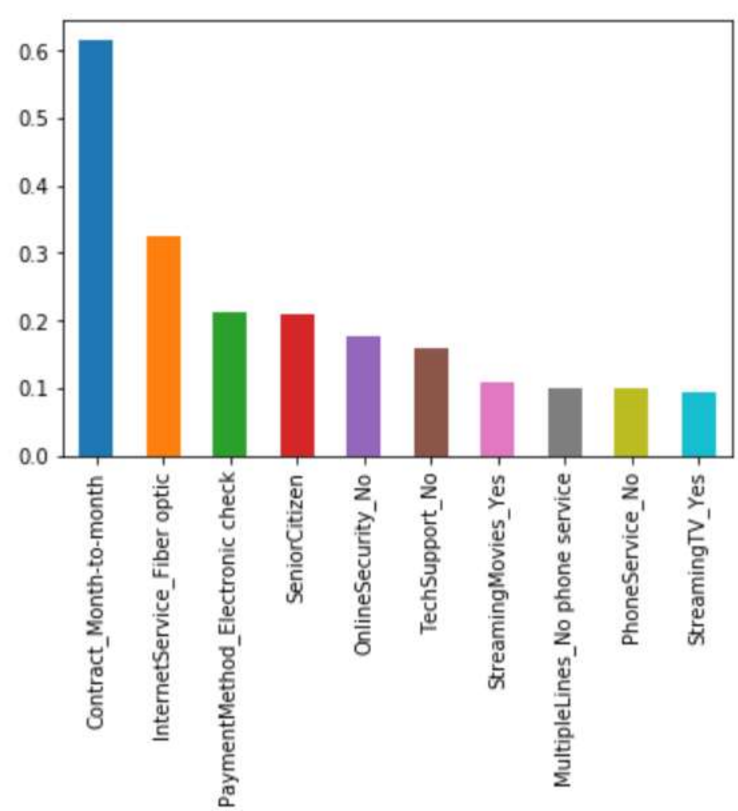
Predictive models & Compare: ¶

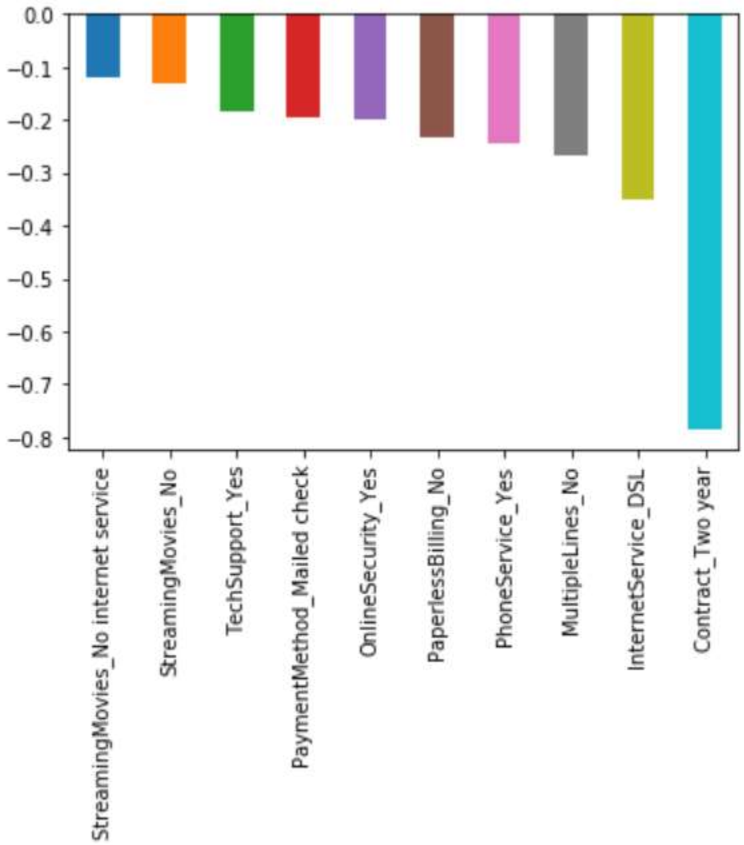
- **Models:**
  - Logistic Regression
  - Random Forest
  - SVM
  - XG Boost
  - Catboost

Logistic Regression

```
Algorithm : LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)

 Classification report :
              precision    recall  f1-score   support

           0       0.84      0.90      0.87      1294
           1       0.65      0.54      0.59       464

   micro avg       0.80      0.80      0.80      1758
   macro avg       0.75      0.72      0.73      1758
weighted avg       0.79      0.80      0.80      1758

Accuracy   Score :  0.8020477815699659
Area under curve :  0.7183103048553003
```

Weights:





Observations:

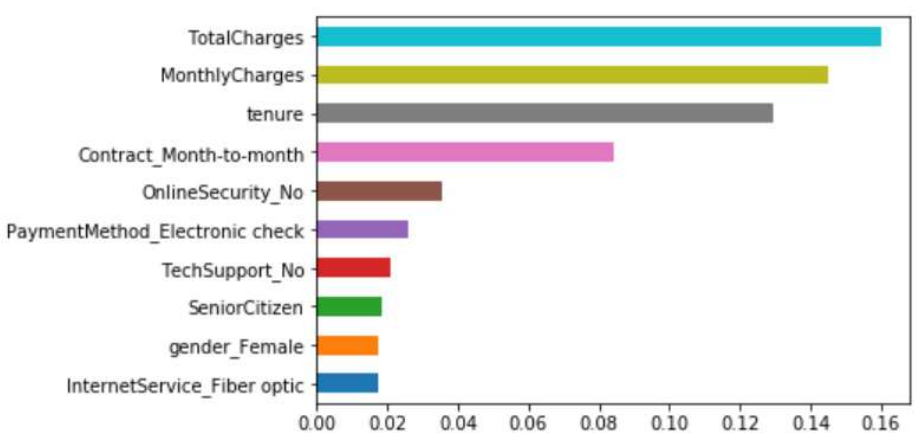
- From the above plots we can observer that some variable have a negative correlation and some has positive correlation
- Customers with Month-Month contract, no online security services and tech support seems to be positively correlated with the churn.
- Some services like streaming services, multiple lines, two-year contract seems to be negatively corelated with churn.
- We can see that some variables have a negative relation to our predicted variable (Churn), while some have positive relation. Negative relation means that likeliness of churn decreases with that variable. Let us summarize some of the interesting features below:

Random Forest

Observations:

- From the below plot we can observe that monthly contract, tenure and tenure are the most import features to predict churn.
- Algorithm, classification report details given below and the accuracy is slightly less than the logistic regression

```
Algorithm : RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=None,
            oob_score=False, random_state=0, verbose=0, warm_start=False)

 Classification report :
               precision    recall  f1-score   support

           0       0.82      0.90      0.85      1294
           1       0.60      0.44      0.51       464

   micro avg       0.78      0.78      0.78      1758
   macro avg       0.71      0.67      0.68      1758
weighted avg       0.76      0.78      0.76      1758

Accuracy   Score :  0.7758816837315131
Area under curve :  0.6673589644513137

Accuracy: 0.7758816837315131
```



SVM

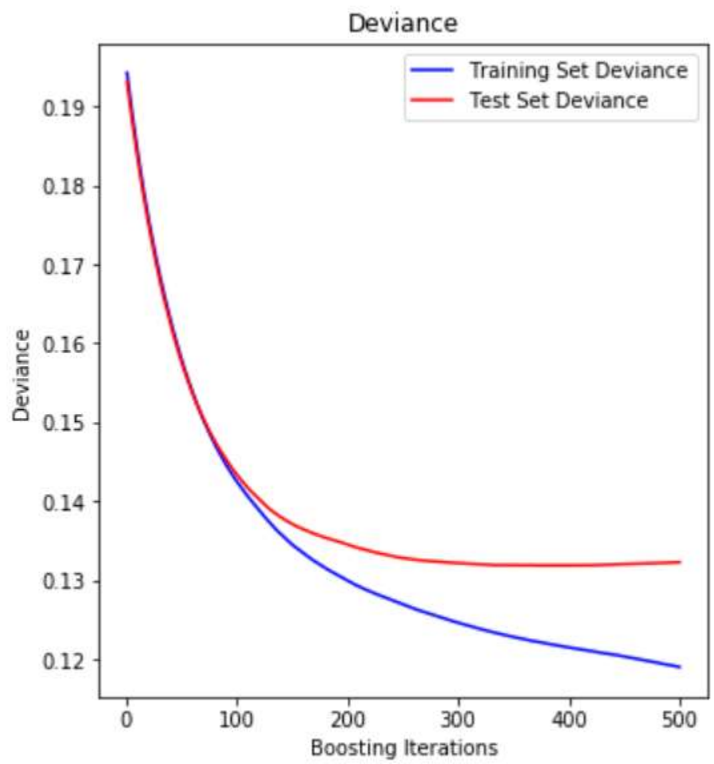
- With SVM the accuracy is 0.79 and AUC is 0.66
- Algorithm, classification report details given below, and the accuracy is in line with Random forest

```
Algorithm : SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='linear', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
accuracy score 0.7901023890784983

 Classification report :
               precision    recall  f1-score   support

           0       0.81      0.93      0.87      1294
           1       0.67      0.41      0.51       464

   micro avg       0.79      0.79      0.79      1758
   macro avg       0.74      0.67      0.69      1758
weighted avg       0.78      0.79      0.77      1758

Area under curve :  0.6687246842189415
```

Gradient Boosting Regressor

- Gradient Boosting model with least squares loss and 500 regression trees of depth 4.
- MSE: 0.1323

```
Out[10]: Text(0, 0.5, 'Deviance')
```



XG Boost

- XG Boost the accuracy on test data to almost 80%, which is in line with logistic regression and SVM.
- Algorithm, classification report details given below.

```
Algorithm : XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
accuracy score 0.8060295790671217

 Classification report :
               precision    recall  f1-score   support

           0       0.84      0.91      0.87      1294
           1       0.68      0.51      0.58       464

   micro avg       0.81      0.81      0.81      1758
   macro avg       0.76      0.71      0.73      1758
weighted avg       0.80      0.81      0.80      1758

Area under curve :  0.7113384719927517
```

Cat Boost Regressor

- Cat Boost the accuracy on test data to almost 80%, which is in line with logistic regression, XG boost and SVM.
- Algorithm, classification report details given below

```
0:      learn: 0.3982526        total: 12.5ms   remaining: 12.5ms
1:      learn: 0.3901868        total: 23.7ms   remaining: 0us
Algorithm : <catboost.core.CatBoostRegressor object at 0x000002221777C240>
accuracy score 0.8060295790671217

 Classification report :
               precision    recall  f1-score   support

           0       0.84      0.91      0.87      1294
           1       0.68      0.51      0.58       464

   micro avg       0.81      0.81      0.81      1758
   macro avg       0.76      0.71      0.73      1758
weighted avg       0.80      0.81      0.80      1758

Area under curve :  0.7113384719927517
```

Comparison matrix

Model	Accuracy	ROC
Logistic Regression	**0.802**	**0.71**
Random Forest	**0.77**	**0.66**
SVM	**0.79**	
XG Boost	**0.8**	**0.71**
Cat boost	**0.8**	**0.71**