Final Report

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Regarding:

Predicting Customer Churn

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Introduction

The project focuses on a problem that 28 million business face each day of operation, customer churn.

Definition

Customer churn, also known as customer attrition, customer turnover, or customer defection is the loss of clients or customers. Many companies include customer churn rate as part of their monitoring metrics because the cost of retaining current customers compared to acquiring new customers is much less.

Within customer churn there is the concept of voluntary and involuntary churn, where voluntary refers to customers leaving on their own choice, while involuntary refers to other circumstances, such as customer relocation to a long term care facility, death or customer relocation in a different state/geography. In most analytical models, involuntary churn is excluded from the metric.

Formulation of the Business Question

When a company first starts up, the founding members can typically handle all of the various customer concerns. As the company continues to grow, the founders can no longer service all of the various clients with support handled by a customer service team. The customer service team focuses on current issues, and a proactive approach is lost.

As the company grows, the company still cares about its clients; however, due to the large customer base, they can no longer address every customer. This is a real problem for companies. How does a company proactively predict if a customer is happy or unhappy? How does a company know if a customer is so unhappy that they are willing to leave? If a company knew if a customer was getting ready to leave, could they reach out to the customer and mend the relationship?

Hypothesis

Past customer data can predict future customer churn.

Prediction

If past customer data shows various features and whether they stayed or churned, they could be used to predict future outcomes of current customers.

Testing

To test my hypothesis, a set of customer data with various features is used along with whether they churned or not.

The data has 7043 rows and can be found at:
https://www.kaggle.com/blastchar/telco-customer-churn

The dataset has the following features:

- customerID - Customer ID
- gender - Customer gender (female, male)
- SeniorCitizen - Whether the customer is a senior citizen or not (1, 0)
- Partner - Whether the customer has a partner or not (Yes, No)
- Dependents - Whether the customer has dependents or not (Yes, No)
- tenure - Number of months the customer has stayed with the company
- PhoneService - Whether the customer has a phone service or not (Yes, No)
- MultipleLines - Whether the customer has multiple lines or not (Yes, No, No phone service)
- InternetService - Customer's internet service provider (DSL, Fiber optic, No)
- OnlineSecurity - Whether the customer has an online security or not (Yes, No, No internet service)
- OnlineBackup - Whether the customer has an online backup or not (Yes, No, No internet service)
- DeviceProtection - Whether the customer has device protection or not (Yes, No, No internet service)
- TechSupport - Whether the customer has tech support or not (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 - The contract term of the customer (Month-to-month, One year, Two year)

- PaperlessBilling - Whether the customer has paperless billing or not (Yes, No)
- PaymentMethod - The customer’s payment method (Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic))
- MonthlyCharges - The amount charged to the customer monthly
- TotalCharges - The total amount charged to the customer

The following target will be used to understand if the customer churned or not.

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

Analysis

To determine if churn rate can be predicted, various classification algorithms will be used and compared according to the appropriate performance metrics.

Approach

Data Acquisition and Wrangling

Data Investigation

The first step is to import the data and investigate the data.

The data is located in a csv file which is imported into a Panda’s DataFrame using the read_csv function. The data is stored in a subfolder under the Jupyter notebook so others can leverage the same data set.

After importing the data, a head function is ran to show the first five rows to understand what the data looked like.

Now start looking for missing values.

1. Are there any null values by column? The dataframe came back with zero null values.
2. Are there any empty strings by row? The results returned 11 rows that had empty strings.

Data Cleaning

After identifying what columns have issues, it is also important to understand if Pandas had assigned the correct types to each column. A .info method is run, and it shows almost all columns were set to object. This means there is a need to get a better understanding of each column data type.

Based on the head method, each column is listed that is categorical using the unique method and converted to a list to see the unique values. Here is the printout:

```
gender:  ['Female', 'Male']
SeniorCitizen:  [0, 1]
Partner:  ['Yes', 'No']
Dependents:  ['No', 'Yes']
tenure:  [1, 34, 2, 45, 8, 22, 10, 28, 62, 13, 16, 58, 49, 25, 69, 52, 71,
21, 12, 30, 47, 72, 17, 27, 5, 46, 11, 70, 63, 43, 15, 60, 18, 66, 9, 3,
31, 50, 64, 56, 7, 42, 35, 48, 29, 65, 38, 68, 32, 55, 37, 36, 41, 6, 4,
33, 67, 23, 57, 61, 14, 20, 53, 40, 59, 24, 44, 19, 54, 51, 26, 0, 39]
PhoneService:  ['No', 'Yes']
MultipleLines:  ['No phone service', 'No', 'Yes']
InternetService:  ['DSL', 'Fiber optic', 'No']
OnlineSecurity:  ['No', 'Yes', 'No internet service']
OnlineBackup:  ['Yes', 'No', 'No internet service']
DeviceProtection:  ['No', 'Yes', 'No internet service']
TechSupport:  ['No', 'Yes', 'No internet service']
StreamingTV:  ['No', 'Yes', 'No internet service']
StreamingMovies:  ['No', 'Yes', 'No internet service']
Contract:  ['Month-to-month', 'One year', 'Two year']
PaperlessBilling:  ['Yes', 'No']
PaymentMethod:  ['Electronic check', 'Mailed check', 'Bank transfer
(automatic)', 'Credit card (automatic)']
```

Because of this, all of them except tenure are set to a type of category.

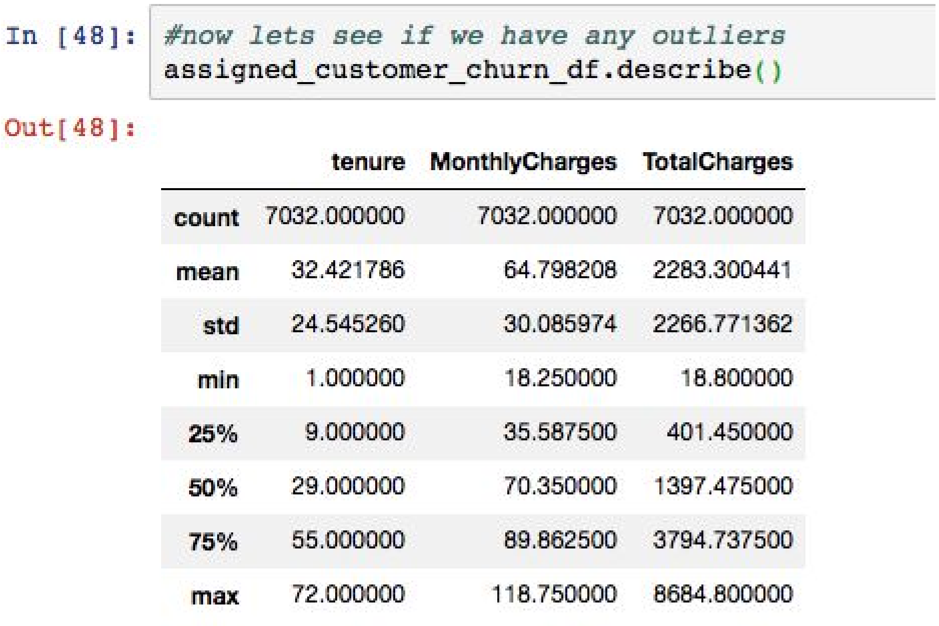
TotalCharges is an object and not a float64, which causes suspicion that something is not right. When investigated, it had 11 rows with empty strings.

Dealing with Missing Data Values

The only column that has missing values is the TotalCharges column. After looking at the 11 rows, the data look invalid, so the 11 rows are filled with zeros and then assigned the column as type float64.

Data Quality

After dealing with missing values and assigning the proper types, the describe method is used to look at the numerical types and understand if any values look odd. Based on that readout, the values appear to be typical of what is expected for monthly and total charges.



```
In [48]: #now lets see if we have any outliers
         assigned_customer_churn_df.describe()
```

Out[48]:

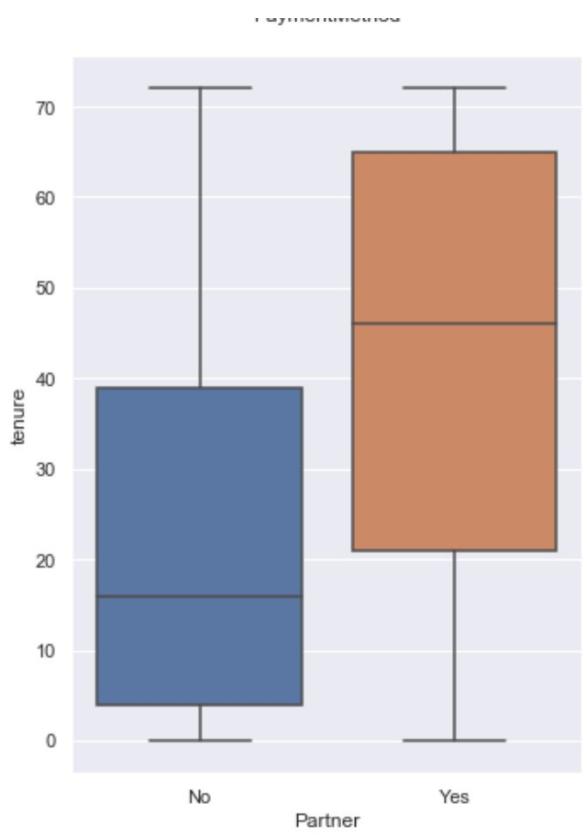
	tenure	MonthlyCharges	TotalCharges
count	7032.000000	7032.000000	7032.000000
mean	32.421786	64.798208	2283.300441
std	24.545260	30.085974	2266.771362
min	1.000000	18.250000	18.800000
25%	9.000000	35.587500	401.450000
50%	29.000000	70.350000	1397.475000
75%	55.000000	89.862500	3794.737500
max	72.000000	118.750000	8684.800000

Storytelling and Inferential Statistics

Inferential Statistics Investigation

The first step of exploratory data analysis (EDA) is to visualize the data to understand the relationship between the various features and the predictor. Initially the feature tenure is used to understand how long a customer stays, hypothesizing that the longer a customer stays, the less likely they are to churn.

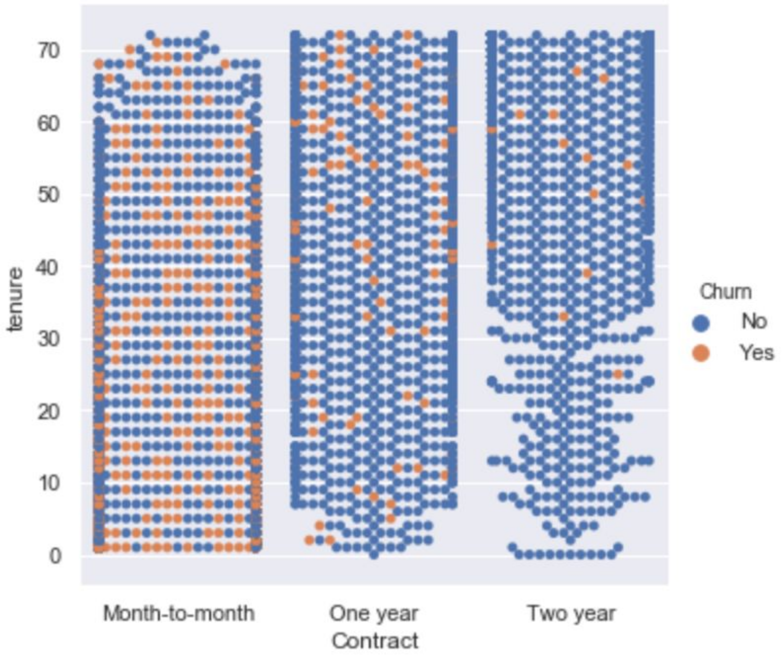
Because most of the features are categorical, boxplots are used to understand the categories within each feature against tenure. (A boxplot displays the five-number summary of a set of data: minimum, first quartile, median, third quartile and maximum) What is noticed is that some of the categories within each feature had higher levels of tenure than their counterparts. Here is an example of Partner vs. Tenure that shows those with a partner have a higher level of tenure.



The next step is to take the following features and do a catplot of the categories against tenure along with churn. A catplot shows frequencies of the categories along with occurrences of Churn in those categories, which is helpful in visualizing which category has instances of Churn.

1. Phone Service
2. Multiple Lines
3. Internet Service
4. Contract Length
5. Paperless Billing
6. Payment Method
7. Dependents
8. Senior Citizen
9. Partner

Amongst these features, distinct patterns indicate some categories are prone to churn more than others. In the below graphic, one can observe that month-to-month billing has more frequencies of churn than the other two contract types.



Leveraging Inferential Statistics

The features that provide visual correlations between the categories and churn need to be checked for statistical significance and strength.

Alpha is set equal to 0.05 or 5%.
The Null Hypothesis is no relationship between categories and churn.

P-value, Pearson Chi-Square and Cramer’s phi are leveraged for results.

Note: Cramer’s phi measures how strong the relationship between the two variables, the closer to 1 the stronger the relationship.

The following categorical features are tested against churn:

- gender
- SeniorCitizen
- Partner
- Dependents
- PhoneService
- MultipleLines
- InternetService
- Contract
- PaperlessBilling
- PaymentMethod

Here are the results for all of the categorical features:

gender

No Relationship (fail to reject H0)

Comparison of: gender to Churn.

	Churn		
	No	***Yes***	***All***
gender			
Female	*49.27*	*50.24*	*49.52*
Male	*50.73*	*49.76*	*50.48*
All	*100.00*	*100.00*	*100.00*

	Chi-square test	***results***
0	*Pearson Chi-square (1.0) =*	*0.5224*
1	*p-value =*	*0.4698*
2	*Cramer's phi =*	*0.0086*

SeniorCitizen

Relationship (reject H0)

Comparison of: SeniorCitizen to Churn.

	Churn		
	No	***Yes***	***All***
SeniorCitizen			
0	*87.13*	*74.53*	*83.79*
1	*12.87*	*25.47*	*16.21*
All	*100.00*	*100.00*	*100.00*

	Chi-square test	***results***
0	*Pearson Chi-square (1.0) =*	*160.3521*
1	*p-value =*	*0.0000*
2	*Cramer's phi =*	*0.1509*

Partner

Relationship (reject H0)

Comparison of: Partner to Churn.

	Churn		
	No	***Yes***	***All***
Partner			
Yes	*52.82*	*35.79*	*48.3*
No	*47.18*	*64.21*	*51.7*
All	*100.00*	*100.00*	*100.0*

	Chi-square test	***results***
0	*Pearson Chi-square (1.0) =*	*159.4145*
1	*p-value =*	*0.0000*
2	*Cramer's phi =*	*0.1504*

Dependents

Relationship (reject H0)

Comparison of: Dependents to Churn.

	Churn		
	No	***Yes***	***All***
Dependents			
No	*65.52*	*82.56*	*70.04*
Yes	*34.48*	*17.44*	*29.96*
All	*100.00*	*100.00*	*100.00*

	Chi-square test	***results***
0	*Pearson Chi-square (1.0) =*	*189.9403*
1	*p-value =*	*0.0000*
2	*Cramer's phi =*	*0.1642*

PhoneService

No Relationship (fail to reject H0)

Comparison of: PhoneService to Churn.

	Churn		
	No	***Yes***	***All***
PhoneService			
No	*9.9*	*9.1*	*9.68*
Yes	*90.1*	*90.9*	*90.32*
All	*100.0*	*100.0*	*100.00*

	Chi-square test	***results***
0	*Pearson Chi-square (1.0) =*	*1.0044*
1	*p-value =*	*0.3162*
2	*Cramer's phi =*	*0.0119*

MultipleLines

Relationship (reject H0)

```
Comparison of: MultipleLines to Churn.
                    Churn
             No            Yes    All
MultipleLines
No phone service  9.90            9.10   9.68
No           49.11         45.43          48.13
Yes          40.99         45.48          42.18
All                 100.00        100.00        100.00

             Chi-square test                   results
0            Pearson Chi-square ( 2.0) =       11.3304
1           p-value =                          0.0035
2            Cramer's V =                      0.0401
```

InternetService

Relationship (reject H0)

```
Comparison of: InternetService to Churn.
                    Churn
                    No            Yes    All
InternetService
DSL          37.92         24.56          34.37
Fiber optic         34.77         69.40         43.96
No                  27.31         6.05          21.67
All                 100.00        100.00        100.00

             Chi-square test                   results
0            Pearson Chi-square ( 2.0) =       732.3096
1           p-value =                          0.0000
2            Cramer's V =                      0.3225
```

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Contract

Relationship (reject H0)

Comparison of: Contract to Churn.

	Churn		
	No	***Yes***	***All***
Contract			
Month-to-month	*42.91*	*88.55*	*55.02*
One year	*25.26*	*8.88*	*20.91*
Two year	*31.83*	*2.57*	*24.07*
All	*100.00*	*100.00*	*100.00*

	Chi-square test	***results***
0	*Pearson Chi-square (2.0) =*	*1184.5966*
1	*p-value =*	*0.0000*
2	*Cramer's V =*	*0.4101*

PaperlessBilling

Relationship (reject H0)

Comparison of: PaperlessBilling to Churn.

	Churn		
	No	***Yes***	***All***
PaperlessBilling			
Yes	*53.56*	*74.91*	*59.22*
No	*46.44*	*25.09*	*40.78*
All	*100.00*	*100.00*	*100.00*

	Chi-square test	***results***
0	*Pearson Chi-square (1.0) =*	*259.1610*
1	*p-value =*	*0.0000*
2	*Cramer's phi =*	*0.1918*

PaymentMethod

Relationship (reject H0)

```
Comparison of: PaymentMethod to Churn.
                           Churn
                           No           Yes     All
PaymentMethod
Electronic check           25.01        57.30         33.58
Mailed check               25.20        16.48         22.89
Bank transfer (automatic) 24.86     13.80         21.92
Credit card (automatic)    24.93        12.41         21.61
All                        100.00       100.00        100.00

             Chi-square test                results
0            Pearson Chi-square ( 3.0) =    648.1423
1           p-value =                       0.0000
2            Cramer's V =                   0.3034
```

Initial EDA and Inferential Statistics Recap

Based on the visual EDA, it is anticipated that all of the following features have correlation or relationships between the categorical feature and churn; however, this is wrong.

- gender
- SeniorCitizen
- Partner
- Dependents
- PhoneService
- MultipleLines
- InternetService
- Contract
- PaperlessBilling
- PaymentMethod

What is found is that the gender and phone service do not have a relationship with churn which is contrary to what is expected.

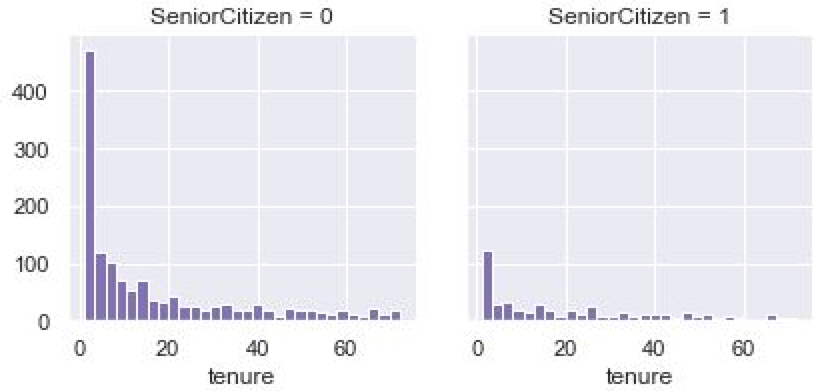
The dataset has 18 features and one target used to determine if the customer churned or not. Of the 18 features, seven features have a relationship with churn.

- SeniorCitizen
- Partner
- Dependents
- InternetService
- Contract
- PaperlessBilling
- PaymentMethod

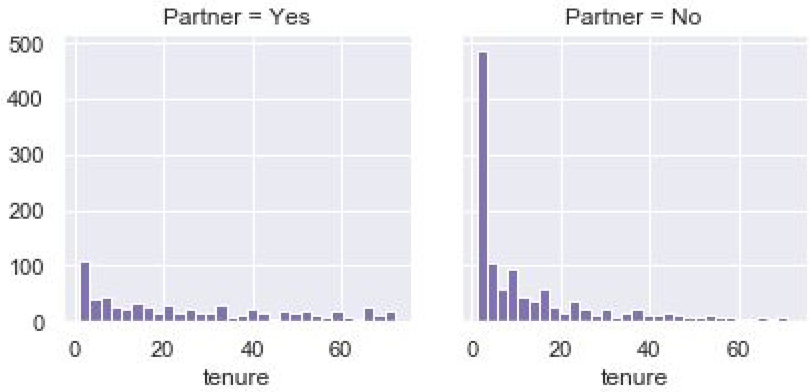
Visual EDA of Seven Features

Based on the seven features identified above, we can do a visual EDA to understand the frequency of the churned customers. The below visuals are taken from a subset of the data of only churned customers compared to tenure.

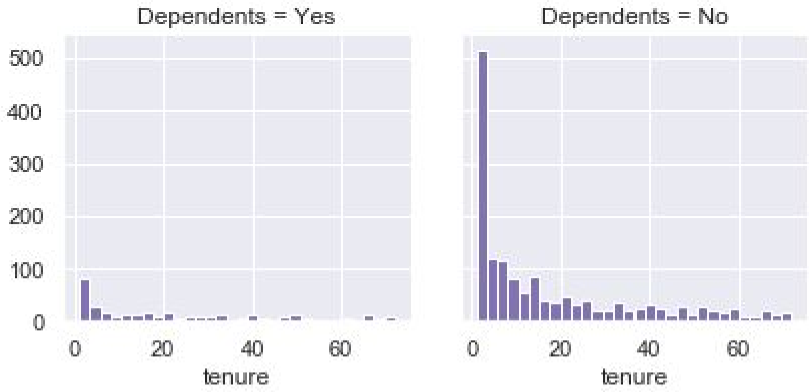
Senior Citizen



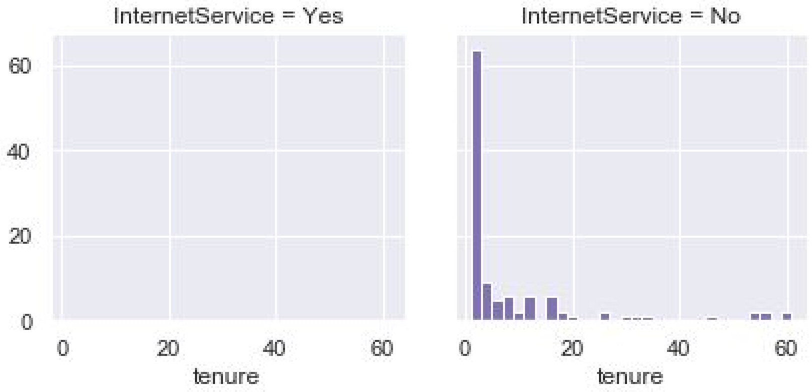
Partner



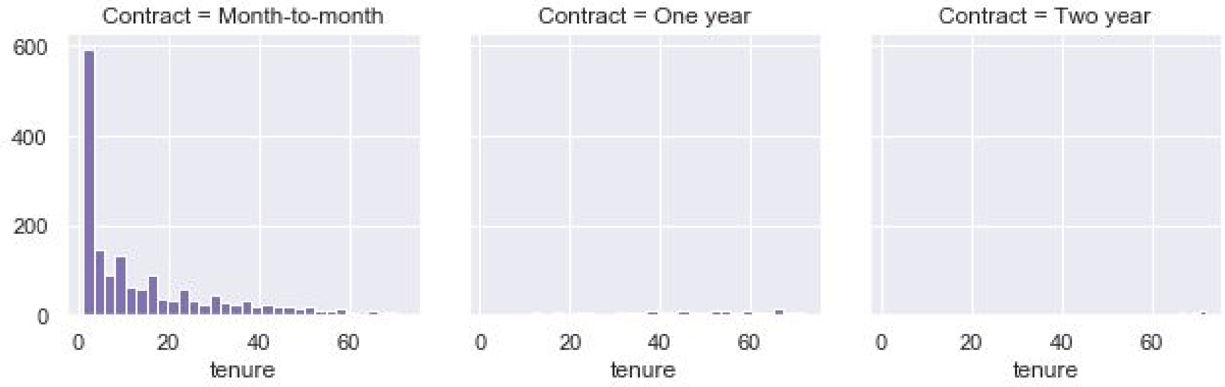
Dependents



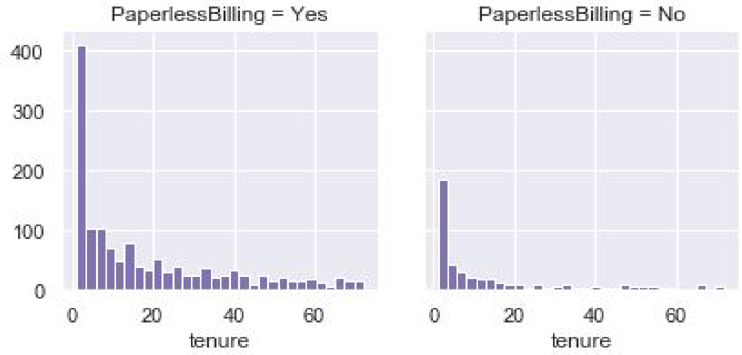
Internet Service



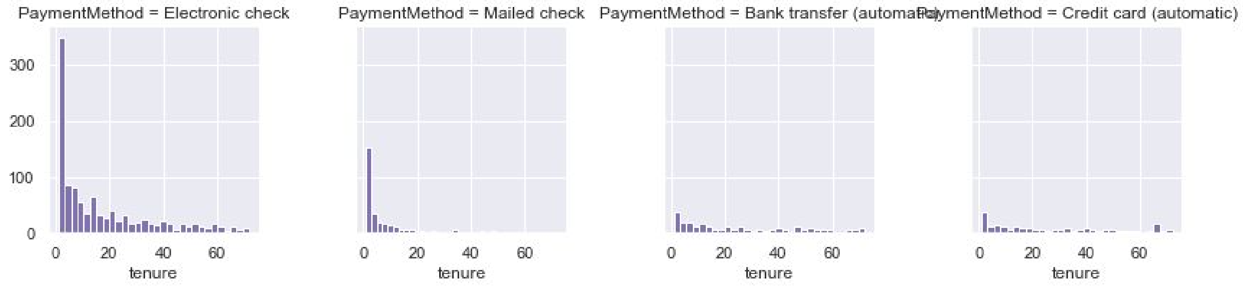
Contract



Paperless Billing



Payment Method



Visual EDA Recap of seven Features

Based on the seven feature comparisons, one observes very distinct patterns emerging. Each of the services, when broken down by their distinctive parts, now illustrate customers that have a higher rate of churn.

The following scenarios have a much higher rate of churn:

- Non-Senior Customers are more likely to churn in the first few years.
- Customers without partners are more likely to churn in the first few years.
- Customers without dependents are more likely to churn in the first few years.
- Customers without internet service are more likely to churn in the first few years.
- Customers that are on month-to-month billing are more likely to churn in the first few years.
- Customers that receive paperless billing are more likely to churn in the first few years.
- Customers that pay via Electronic Check are more likely to churn in the first few years.

Baseline Analysis and Preliminary Results

The goal of the baseline analysis is to establish a starting point and then consider whether results can be improved from there. The evaluation of the baseline model will use accuracy along with performance metrics.

The original hypothesis is that past customer data can be used to predict if future customers will churn. The baseline analysis intends to predict customer churn, and we therefore assume in this project that for our clients it is more important to know when customers are likely to churn--as opposed to knowing when customers are likely to not churn. More specifically, we assume that our clients better tolerate false positives because they are more interested in not missing a customer that might churn.

From a statistical modeling perspective, this decision translates to optimizing the recall performance metric. The recall rate is reported in the classification report computed from the confusion matrix as the proportion of test cases that are correctly classified, per class. A higher recall rate for the positive class means that the model is predicting the correct customers that might churn. However, precision is is also being used, to ensure that a balance is maintained between recall and precision.

Logistic Regression

The baseline model uses logistic regression with L1 and L2 regularization using the following features:

- SeniorCitizen
- Partner

- Dependents
- InternetService
- Contract
- PaperlessBilling
- PaymentMethod

The model uses churn as the label to indicate if a customer has churned or not.

The logistic regression model also has various hyperparameters, and the focus is on getting the optimal C value for L1 and L2, respectively. After testing various values, the optimal C values are:

L1	0.1
L2	0.01

Running the logistic regression model with those C values produced the following accuracy scores.

Logistic Model	**Training Data**	**Test Data**
L1	0.751419916698	0.743327654742
L2	0.751041272245	0.733674048836

The accuracy rate for the baseline after only optimizing the C value is roughly 75%. That is not bad for accuracy without much optimization. The next step is to run the classification report, here are the results.

L1 Training	**Precision**	**Recall**	**F1-Score**
False	0.74	0.74	0.74
True	0.27	0.27	0.27
Avg/Total	0.61	0.61	0.61

L1 Test	**Precision**	**Recall**	**F1-Score**
False	0.73	0.73	0.73
True	0.24	0.24	0.24
Avg/Total	0.60	0.60	0.60

L2 Training	**Precision**	**Recall**	**F1-Score**
False	0.74	0.74	0.74
True	0.27	0.27	0.27
Avg/Total	0.61	0.61	0.61

L2 Test	**Precision**	**Recall**	**F1-Score**
False	0.73	0.72	0.73
True	0.26	0.27	0.27
Avg/Total	0.61	0.60	0.61

The recall rate for L1 and L2 for the True classification is only ~0.27 which is low compared to the recall rate for False classification. That means customer churn will get predicted correctly 27% of the time, which is not acceptable.

What the classification report is demonstrating is a natural imbalance in the data. The data has more negative cases than positive, which is reflected in the tendency of the model to better predict negative cases. The next step is to try resampling techniques along with different models.

Extended Analysis and Final Results

In the baseline analysis, the data is fit to a Logistic Regression model using L1 and L2 regularization. The accuracy was 75% for L1 and 74% for L2. The performance of the model showed an imbalance regarding customers that churned. The F1 score for customers that did not churn was 74%, and the F1 score for customers that did churn was 27% (for L1 regularization).

The main score being optimized is the performance recall for the positive class.

Because the client is more concerned about catching customers before they churn it is okay to have a reasonable amount of false positives. When using the base Logistic Regression model, recall is 75% for 'False' and 27% for 'True'.

Recall scores split 75/27 is indicative of the data set where the customers that churned have a much lower percentage compared to those that did not churn. The data imbalance between classes is an issue that cannot be fixed by adding more data because there is an inherent imbalance between the classes--in other words, there will always be inherently less positive cases than negative cases, in any healthy business.

In this section, different models and data sampling techniques are used to test if the accuracy performance improves. We have used the imblearn package in our implementation.[1]

SMOTE

The first sampling technique is SMOTE. SMOTE stands for Synthetic Minority Over-sampling Technique. This means SMOTE will use a synthetic technique to add samples to the class with the smaller number of data points (a.k.a. minority class). After applying SMOTE, the shape of the data is changed.

[1] https://imbalanced-learn.readthedocs.io/en/stable/api.html

	False	**True**
Original Data Set Shape	3880	1402
SMOTE Data Set Shape	3880	3880

RUS

The second resampling technique used is RUS. RUS stands for Random Under-sampling. This means RUS randomly undersamples the class with more data points (a.k.a. majority class).

	False	**True**
Original Data Set Shape	3880	1402
RUS Data Set Shape	1402	1402

Hyperparameter Tuning

All models have hyperparameters that can be adjusted to improve them. For each model, one or two of the parameters are adjusted for initial model comparison.

Model Comparison

Original Dataset

Model	Precision (True)	Recall (True)	Accuracy
Logistic Regression	0.54	0.227	0.744
Naïve Bayes	0.51	0.642	0.741
Decision Tree	0.55	0.435	0.756
kNN	0.52	0.435	0.744
SVM	0.55	0.456	0.756
Random Forest	0.56	0.471	0.762
AdaBoost	0.57	0.452	0.764

ReSampled Dataset

Model	Precision (True)	Recall (True)	Accuracy
SMOTE - Logistic Regression	0.44	0.805	0.676
SMOTE - Naïve Bayes	0.46	0.773	0.699
SMOTE - Decision Tree	0.47	0.756	0.713
SMOTE - kNN	0.40	0.370	0.688
SMOTE - SVM	0.46	0.829	0.697
SMOTE - Random Forest	0.47	0.762	0.712
SMOTE - AdaBoost	0.49	0.784	0.726
RUS - AdaBoost	0.49	0.784	0.726
RUS - Boost	0.40	0.876	0.621
SMOTE - Boost	0.39	0.961	0.584

For problems with class imbalance, metrics such as precision, recall, and f1-score give good insight into how a classifier performs concerning the minority class. Depending on the problem, the goal is to optimize either precision or recall of the classifier. In this case, a model that catches the most number of instances of the minority class is desired, even if it increases the number of false positives. A classifier with a high recall score will give the most significant number of potential customer churns, or at least raise a flag on most of the cases.

The resampled datasets all have higher recall percentages except kNN when compared to the original dataset. Three of the models have recall rates (for True) that are higher than 80% (Logistic Regression, SVM, RUS Boost) while one has a recall rate of 96% (SMOTE Boost). The trade-off is the accuracy and precision which means the model will have false positives. However, since the overall goal is to predict which customers might churn and keep them as a customer, it is better to have false positives rather than miss customers that churn.

Conclusions and Future Work

The initial hypothesis was that customer churn could be predicted based on past customers. After doing exploratory data analysis, applying inferential statistics and extended analysis we have shown that customer churn can be predicted based on seven dataset features using models that combine classification algorithms with rebalancing approaches. In this project the best combination we observed is SMOTE Boost.

Future Work

Additional work can be done to improve the results further. The following areas of study are suggested:

1. Gather more data
2. Rerun the various models with differing degrees of the seven features
3. Tune the hyperparameters for each model
4. Combine multiple models using ensembles
5. Apply anomaly detection algorithms

Recommendations for the Client

With the initial analysis complete, it is recommend to gather further data to conduct additional testing on the various models to understand the top two. Once that is determined, it is recommend placing the top two models into production. It is suggested splitting the data into three groups:

1. Model #1
2. Model #2
3. Control

By having three groups, the data can be further analyzed to determine which group is performing best compared to the third group which is the control group. The control group is used to understand what would happen if no model had been deployed and it allows the data to be used as a comparison.

As testing proceeds, it is recommend that adjusting the models to improve the performance based on recall. There might also be subsets of data that can further be explored once churn is realized with the models.

Resources / Resources Used

The following is a list of the various resources used in this study.

1. https://www.kaggle.com/blastchar/telco-customer-churn
2. https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html
3. https://medium.com/greyatom/performance-metrics-for-classification-problems-in-machine-learning-part-i-b085d432082b
4. http://scikit-learn.org/stable/modules/generated/sklearn.metrics.classification_report.html#sklearn.metrics.classification_report
5. https://towardsdatascience.com/building-a-logistic-regression-in-python-step-by-step-becd4d56c9c8
6. https://imbalanced-learn.org/en/stable/generated/imblearn.over_sampling.SMOTE.html#r001eabbe5dd7-1
7. https://www.svds.com/learning-imbalanced-classes/
8. https://towardsdatascience.com/hyperparameter-tuning-the-random-forest-in-python-using-scikit-learn-28d2aa77dd74
9. https://www3.nd.edu/~dial/publications/hoens2013imbalanced.pdf
10. https://sci2s.ugr.es/keel/pdf/algorithm/congreso/kubat97addressing.pdf
11. https://curate.nd.edu/downloads/0p096684s7g
12. https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
13. https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.GaussianNB.html
14. https://scikit-learn.org/stable/modules/tree.html
15. https://scikit-learn.org/stable/modules/neighbors.html
16. https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html
17. https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
18. https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.AdaBoostClassifier.html
19. https://github.com/dialnd/imbalanced-algorithms
20. https://github.com/foutaise/texttable/