Customer Retention

By Being Proactive

A Data Science Project By Aparna Shastry

Overview

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The Business Problem

- A Telecom company observes customer “Churn”
- Estimated loss of income: $140k per month
- Attraction of new ones is more expensive than retention of current ones
- Expectations from this project: Given historical data on loyal and churn customers,
  - Understand relation between churn and certain factors
  - Provide a predictive model that ranks the customers
  - Make recommendations to the business to minimize the revenue loss.

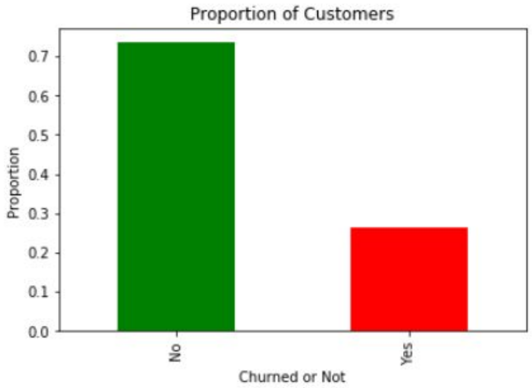
Data Set

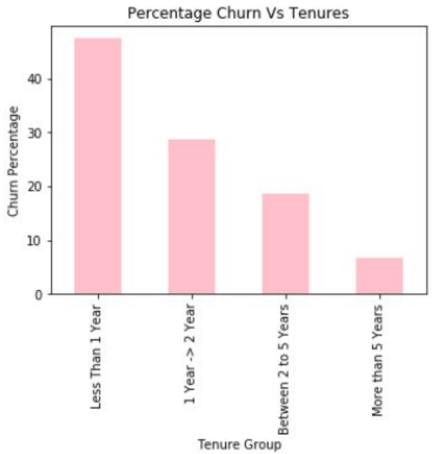
- Dataset link is given in Ref [1] in the last slide.
- 7043 records, 21 columns
- The target variable: Churn : { “Yes”, “No”} entries.
- One column has unique customer ID
- 19 Predictor Variables, which are of following types:
- Service specific :
  - Phone: Phone Service, Multiple Lines
  - Internet: Internet Service, Online Security, Online backup, Streaming TV, Streaming Movies, Tech support, Device protection
- Person specific : Gender, Senior Citizen,Partner, Dependents, Tenure (num)
- Money specific: Monthly Charges (num), Total Charges (num), Contract, Paperless billing, Payment Method
- *(num) above indicates numerical. Rest are all categorical: 2 to 4 categories

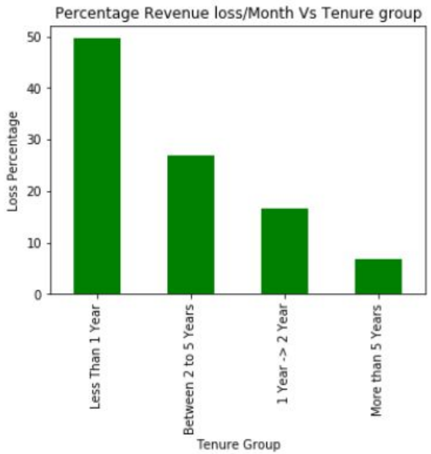
Data Wrangling

- Only Total Charges has 11 missing entries.
    - All of them are in rows with Churn “No”
    - tenure values are 0 for them
    - No other information is given.
    - Concluded that these should be for customers just registered
- Cleaning:
    - Set Total Charges to 0
    - Converted all other entries from string to float
- Observed : Total Charges is almost = tenure * Monthly Charges
- Verified: By fitting a simple linear regression through Tenure * Monthly Charges [Refer Appendix Slide 1 for statmodels OLS summary]
- Total Charges is hence redundant

Business Problem visualization

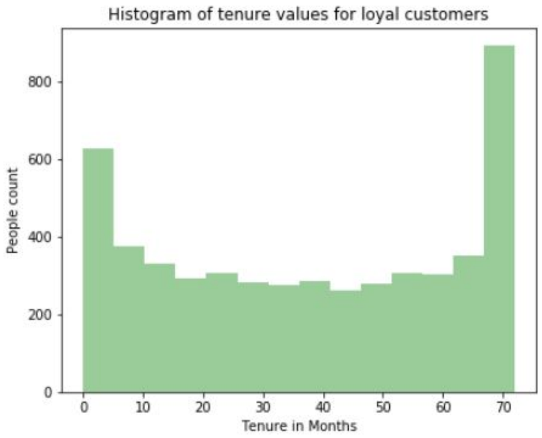


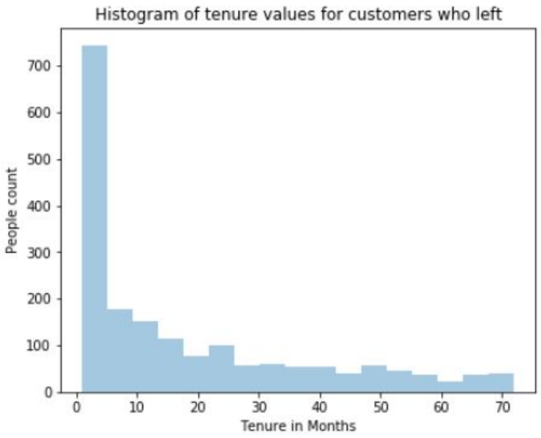




- 26.54% Churn rate overall
- $139130 loss per month, about 30% of the total income
- Less than a year tenure category has highest churn and result in highest revenue loss
- 2 to 5 year tenure category results in highest revenue loss

Data Stories (1) : Tenure in Months





- Fig 1: Drop from bin 70 to bin 60 => Huge churn happened about 5.5 years ago.
- Fig 1: Between 10 to 60 months, not much variation => Once they cross a year, they remain loyal
- Fig 2: High count in first bin, drastic drop=> Most in churn group < 5 months tenure

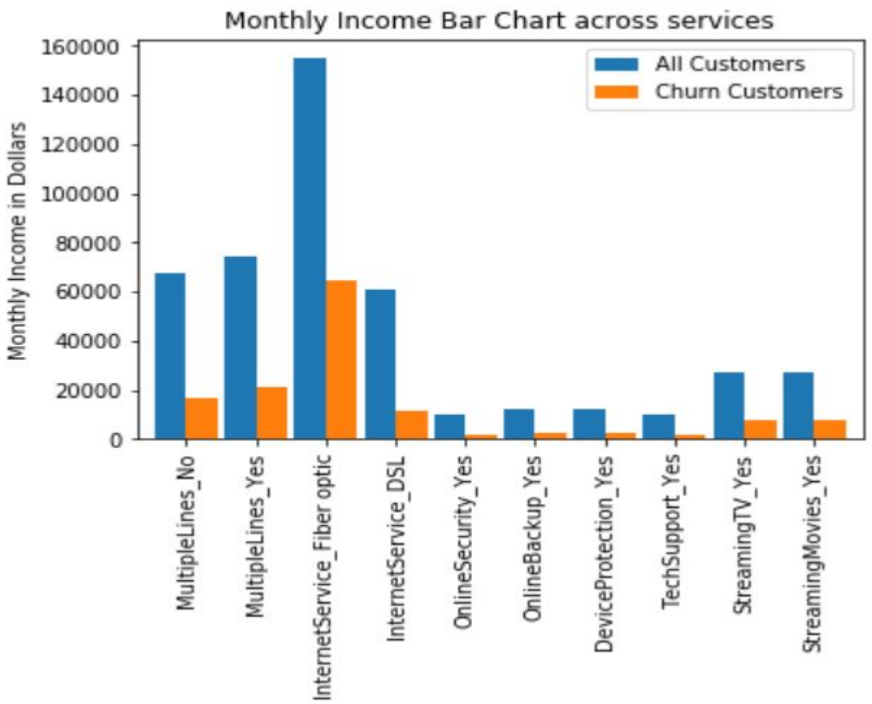
Data Stories (2) Monthly Charges Vs Services

- Rate sheet is not available, hence linear regression was done to know the rate per each service. The curve was a great fit. Intercept 0 indicated no fixed monthly charges

Type of Service	Charges
Phone Line Single	$20
Phone Line Multiple	$25
Online Security,Online Backup,Tech Support,Device Protection	$5 per service
Streaming Movies/ Streaming TV	$10 per service
Internet DSL	$25
Internet Fiber Optic	$50

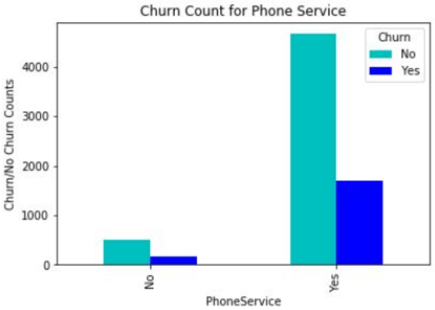
- See Appendix Slide 2 for validation of regression assumptions

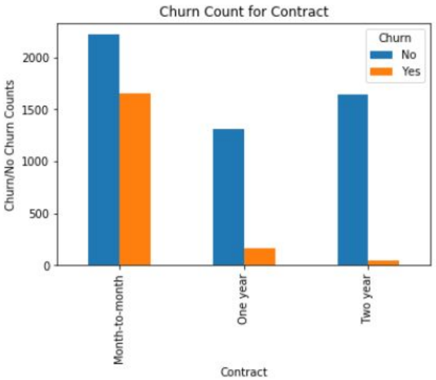
Monthly Charges Split by Services

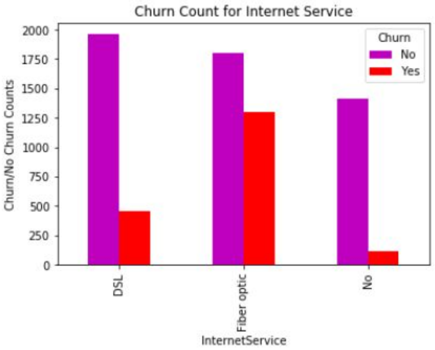


- The height of the bar = count of people subscribed * Charge as per rate table of previous slide
- Blue bars are from the entire 7043 rows
- Orange bars are from the Churn group
- The importance of Fiber Optic Service on the Monthly Income is very clear!
- MulipleLines_No essentially means Phone Line Single

Data Stories (3) Categorical Data





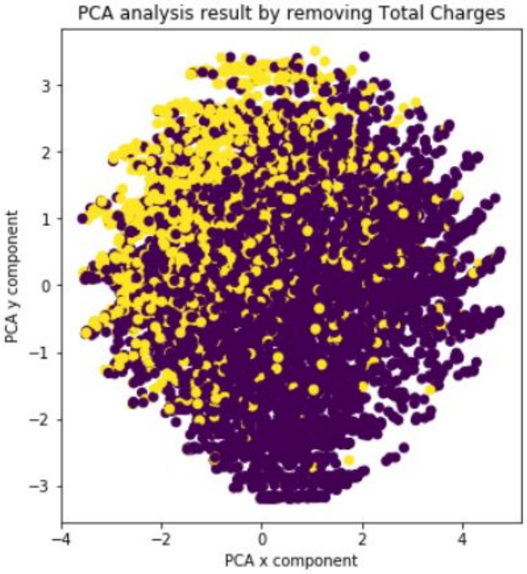


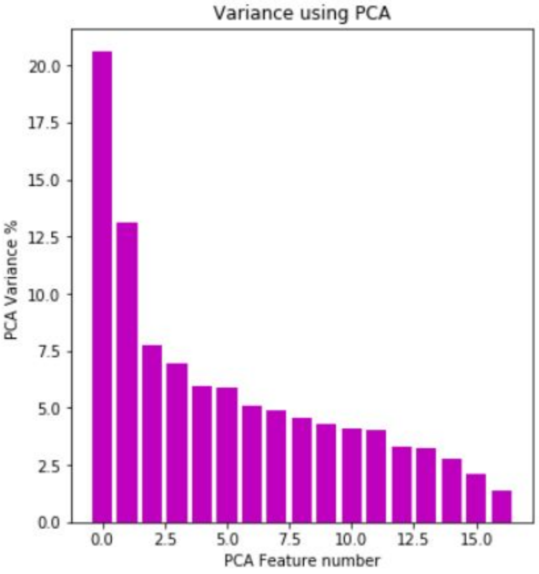

```
Mean Churn Across Contract
Month-to-month    0.427097
One year          0.112695
Two year          0.028319
Name: Ch10, dtype: float64
Mean Churn Across PhoneService
No     0.249267
Yes    0.267096
Name: Ch10, dtype: float64
Mean Churn Across InternetService
DSL            0.189591
Fiber optic    0.418928
No             0.074050
Name: Ch10, dtype: float64
```

- The bar charts show counts in each category of these variables
- Mean rate of churn shown
- Plots can show individual variations
- The effect of several combinations, and also specific types of services within internet services can be understood only by modeling

Principal Component Analysis (PCA)

- First plot: 2-D approx helps in understanding whether classes could be separable
- Second plot: Shows the explained variance. “Elbow” happens at 3. But all of them have good variance.





Predictive Modeling

- Acceptance Criteria:
  - Compared models based on Area Under ROC Curve (AUC)
  - Train and Test Accuracy approx equal or not.
  - “Recall” on the Churn class to be higher priority than overall accuracy
- Data Prep/Feature Selection :
  - Drop numerical variable Total Charges, and Monthly Charges
  - Drop the column Phone Service, as it is a subset of Multiple Lines

For logistic regression: (and previously for Monthly Charges Linear Regression)

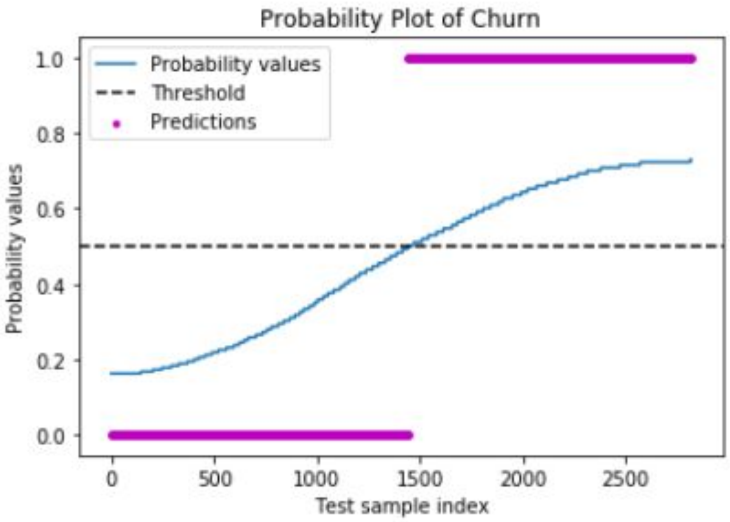
  - Convert to dummies, and drop first, drop originals
  - “No internet service” dummy in some services are dropped, correlated with Internet Services (See Appendix Slide 3 for correlations)

Training and Testing Method

- Data split to Train : Test ratio 60:40 , stratified with target
- Hyperparameter tuning done using 5-fold cross validation(CV) method on Training data
- Score function used in CV is “Recall”
  - Tried with ROC_AUC as well, did not work well.
- This is moderately imbalanced with 0.74 : 0.26 ratio on No:Yes Churn
- Misclassifications from “No” to “Yes” are fine, if helpful in capturing “Yes”
- Several methods of balancing possible
  - Undersampling No Class
  - Synthetic Oversampling Yes Class (SMOTE)
  - Giving more penalty on misclassification of Yes to No class
- In this we have attempted to do the last one.

Logistic Regression with Tenure alone

- Fitted a simple logistic regression of Tenure to find out the relation
- Between 9 and 60 months, probability curve is almost linear
- Threshold Tenure = 27 months. Samples above black dotted lines correspond to < 27

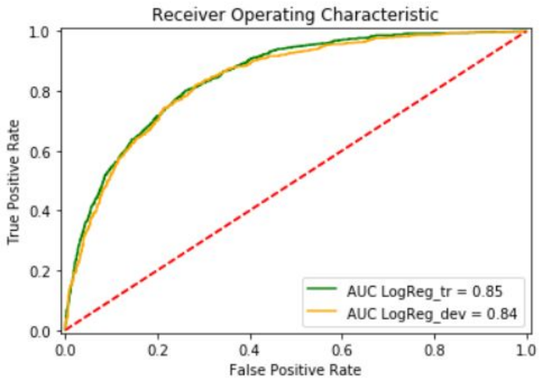


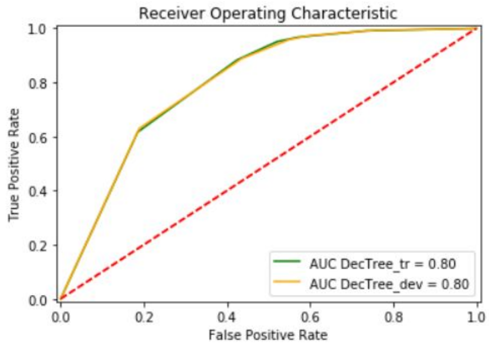

```
Coefficient:-0.037, Intercept:0.997

Train Set Accuracy :63.67%
Dev Set Accuracy 64.16%

Report:
             precision    recall  f1-score   support

          0       0.87      0.60      0.71      2070
          1       0.40      0.74      0.52       748

avg / total       0.74      0.64      0.66      2818
```

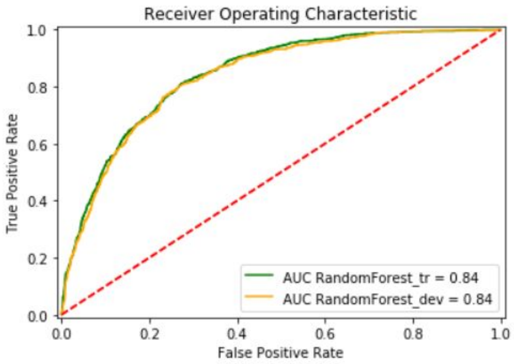
Comparison of Models Tried

Model Name	Hyperparameters Tried	Hyperparameters Selected	Sensitivity (Recall) on the Churn group, Overall Accuracy
Logistic Regression Selected	**C=[0.1,1,10,100,10000],class_weight:['balanced',None]**	**C = 0.1, class_Weight = balanced**	**0.80,0.75**
Decision Tree	max_depth: [3,4,6,8,12], min_samples_leaf: [1,2,4,8],class_weight: ['balanced',None]	max_depth=3,min_samples_leaf=1,class_Weight = balanced	0.89,0.65
Random Forests	Same as above and n_estimators: [10,50,100,200]	max_depth=3,min_samples_leaf=1,class_Weight = balanced,n_estimators=100	0.83,0.72

Comparison of Results, ROC Plots

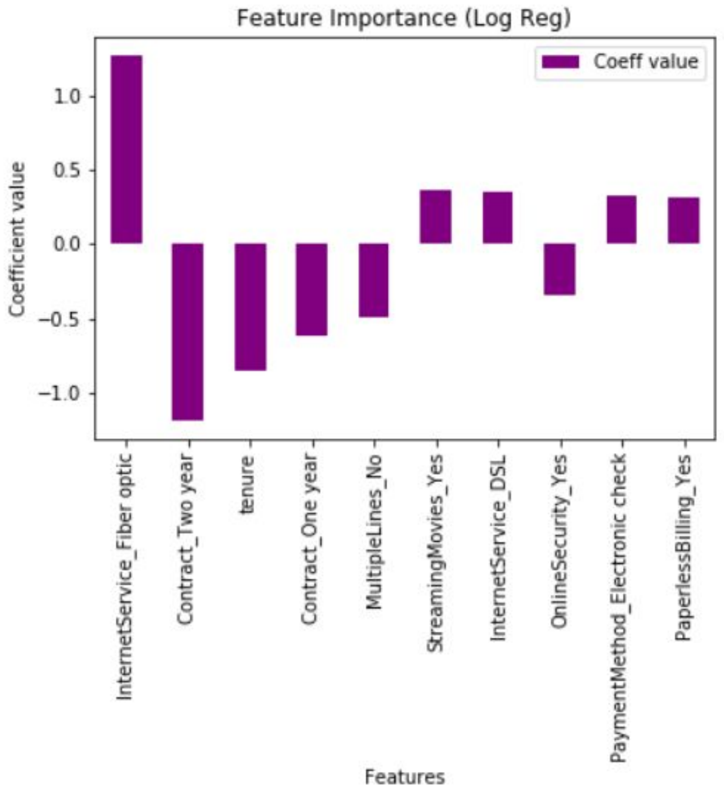






- Which one to choose: I would choose Logistic Regression because,
  - It is faster and less complex
  - More interpretable, gives me coefficients with signs
  - It gives better overall accuracy than Random Forest, and almost same recall on Churn class

Feature Importance Based on Logistic Regression



Top 10 Features with their influence shown

- Tenure is second last among 21. (not shown).
- Interpretation:
  - Features with negative coefficients are favorable, and positive not favorable
  - The services with positive coefficients need to be interpreted, or else those customers will churn

Solutions Proposed

- A predictive model is given that ranks customers based on their probability of churn and the revenue that they bring.
- Use this model to prioritize whose concerns to be addressed first. Sometimes it might be case by case basis.
- Take the following actions immediately:
    - Try striking a longer contract with new customers: two year or one year in that order of preference.
    - Leverage the time to improve the quality of services, of the high cost ones like Fiber optic.
    - Improve on the Technical support on all services like streaming, phone connection and internet.
    - Be up-to-date with current technology.
    - Collect customer feedback and act on it immediately to prevent new customer churn
- Next: It will be helpful to understand why churn started 5.5 years ago. Give more historical data to the data scientist for analysis.

Potential Money Savings!

- Assuming the business makes an attempt to convince all the customers identified as Churn (likelihood >= 0.5),
- The income loss prevented using the given dataset: $114,422 / month if all of them change their mind.
- The above statement has not accounted for the money spent in efforts to retain them, because there is not enough information. Hence the net income will be less than $114,422.

Scope for Further Work

- Collect more data through surveys, analyze them using NLP techniques.
- Can try some more balancing techniques
- Collect more historical data on customer churn. Especially it might be useful to see what happened 5+ years ago as seen from tenure plot.

References/Links

1. IBM page has many, out of that this Telecom dataset
2. Introduction to Statistical Learning by Gareth James et. al
3. Predicting Customer Churn using R by Susan Li
4. Techniques to Handle Imbalance by Jason Brownlee
5. My Code

Appendix Slide 1: Goodness of fit for Total Charges

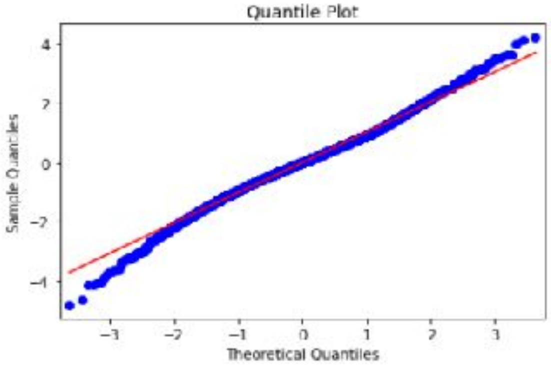
OLS Regression Results

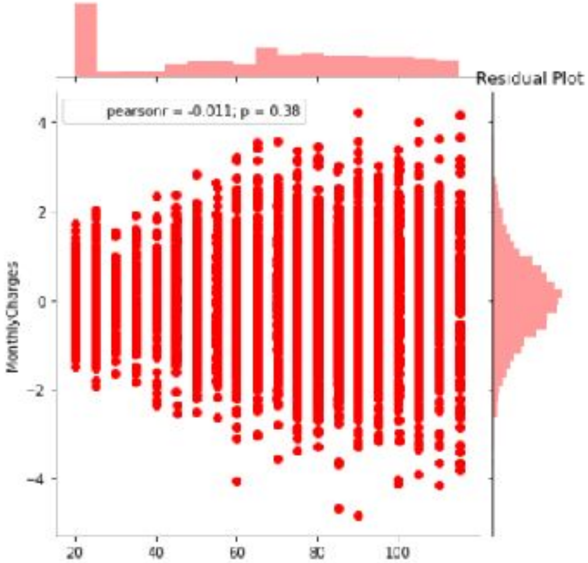
Dep. Variable:	TotalCharges	**R-squared:**	0.999
Model:	OLS	**Adj. R-squared:**	0.999
Method:	Least Squares	**F-statistic:**	8.006e+06
Date:	Mon, 12 Feb 2018	**Prob (F-statistic):**	0.00
Time:	13:31:50	**Log-Likelihood:**	-39627.
No. Observations:	7043	**AIC:**	7.926e+04
Df Residuals:	7041	**BIC:**	7.927e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-0.9229	1.136	-0.812	0.417	-3.150	1.304
Temp	1.0005	0.000	2829.477	0.000	1.000	1.001

Omnibus:	538.795	**Durbin-Watson:**	2.055
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3067.278
Skew:	-0.034	**Prob(JB):**	0.00
Kurtosis:	6.232	**Cond. No.**	4.56e+03

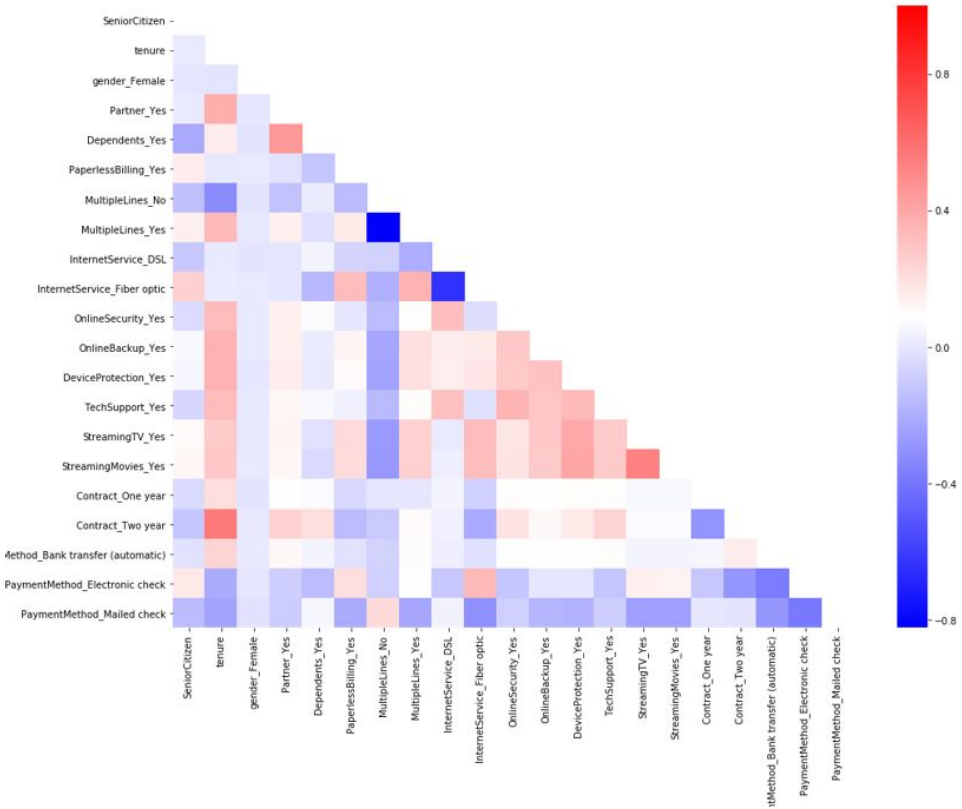
Slide 2: Quantile and Residual Plots of Monthly Charges





1. Assumptions verified as seen by plots
2. $R^2 = 0.999$
3. MSE of the fit = 1.05
4. Percentage of outliers = 3.96

Slide 3 Correlation plot for Log Reg inputs



There are hardly any highly correlated features