

TELECOM CUSTOMER CHURN PREDICTIVE SOLUTIONS

How to Limit the Churn Rate:
The definitive plan for limiting churn

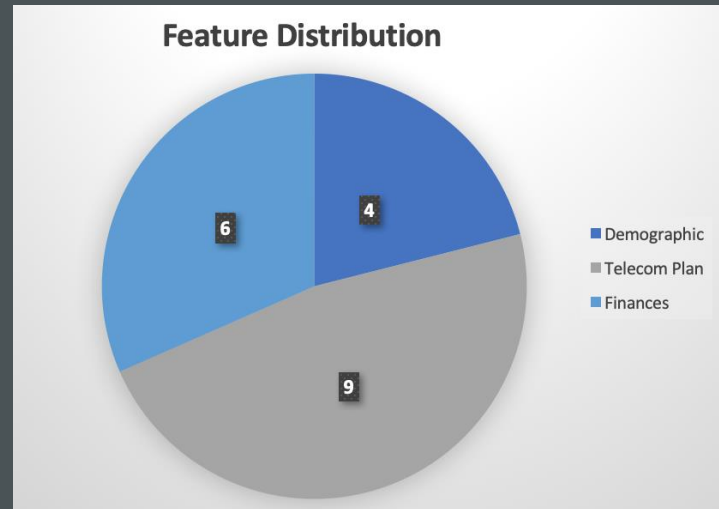
- **Goal** – Better understand churn behavior in order to retain customers
 - **Benefits** – Increase *profit margin* and improve *business reputation*
- **How** – Explore multiple *Classification* models to predict customers who churn vs. customers who do not churn
 - **Measure** – In order to limit data set bias, we will use *AUC* as our metric to determine how well our model performs
- **Success** – A definitive metric that results in $>.60$ AUC with a negligible turnaround time



RELATING

EXPLAINING

- 5282 records, 19 features, 1 target variable
- ~26% of customers churned
- Average Monthly Charge
 - Not Churn: \$61.27
 - Churn: \$73.52
 - Competition: \$50-\$85



- Majority Characteristics of Churn Customers
 - Gender neutral
 - Not Senior Citizens
 - No partner/dependents
 - Phone Service
 - Online Security
 - Tech Support
 - **Month-to-Month contract**



ADAPTING

- Data Cleaning:
 - Converted categorical variables to '0' and '1' (and '2' if necessary) integer representations
 - Converted numerical variables to float and replaced numerical null values with '0'
 - Scaled the data so that the numerical variables wouldn't overpower categorical ones
- Data Selection:
 - Explored benefits of using all variables and previously mentioned influential features
 - Best result: 'Contract', 'PaperlessBilling', 'PhoneService', 'gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure', 'MonthlyCharges'

SELECTING

Model Approach: Compare performance of four well known classification algorithms

- Logistic Regression
- Random Forest
- Gradient Boost
- Neural Network
- All Features and Specific Features
- Split Training Data
- Hyperparameter tuning
- Cross Validation

OUTLINING

- **Top Performer** – Logistic Regression using specific influential features and 60/40 train/test split
- **Success** – A definitive metric that results in $>.60$ AUC with a negligible turnaround time
 - **Results** – 0.71373 AUC which is 18% better performance than we were expecting

	Retain Customers (T)	Losing Customers (T)
Retain Customers (P)	$1708 \times \$61 = +\$104,188$	$213 \times \$73 = \underline{-\$15,549}$
Losing Customers (P)	$342 \times \$61 = \underline{+\$20,862}$	$378 \times \$73 = -\$27,594$

NAVIGATING

Because this schema is month-to-month, real-time prediction is unnecessary.



Deploy via **AWS Sagemaker** which supports Python and scikit-learn

Allows us to retrain monthly and re-deploy to production

Easy connection to BI tools for monthly reports