MSSP 608

Final Project: Telecom Customer Churn Analysis

Xuechuan Song & Ziyu Zhao

Contents

I. Project Narrative

a) Background

Customer loss can be a serious concern for most companies across various industries including telephone service, Internet service, pay TV, insurance, financial service industries, and so on. Since losing customers might harm a business's ability to grow and take away its advantages in competitions, churn analysis that evaluates a company's customer loss rate is of great significance for businesses to retain and recover long-term customers. In this project, we aim to do a customer attrition analysis for a telecommunication service company and build machine learning models to predict whether a customer might be inclining to quit services based on his/her demographic, service, and account information. Also by interpreting data and some of the models, we want to understand why customers might choose to leave. The risks of misclassification are to falsely predict clients who are highly possible to churn to be loyal and miss the opportunities of applying customer retention strategies to prevent losing them to competitors. In professional settings, inputs from the company's customer service and marketing departments and, more ideally, feedback from customers themselves in forms of survey and questionnaire should also be considered during the process of modeling.

Similar tasks of predicting potential customers to churn have been performed by many companies and researchers due to the direct effect of churn rates on the companies' revenue. Generally, it is common in telecom-sector customer churn predictions to build supervised classification models with Ensemble methods such as bagging and boosting. For example, in Ahmad et al.'s research, they experimented the algorithms of Decision Tree, Random Forest, and Gradient boosted tree on a dataset provided by SyriaTel telecom company (2019). By also extracting Social Network Analysis (SNS) features, their final model achieved 93.3% of Area Under Curve (AUC). Other classifiers used in such studies also include Logistic Regression and Supported Vector Machine (SVM) classifiers as in Gaur and Dubey's work (2018), and Naïve Bayes and Ensemble-based classifiers as in Mishra and Reddy's report (2017). Most of the articles and papers were published in telecom industry international conferences, data analysis and networking symposiums, and on related journals.

b) Dataset Description

The data we will be using is the Telco Customer Churn dataset on Kaggle. The dataset has 7043 rows and 21 columns with no null values. While each row represents a customer record, the columns show data on the customers' demographic, services, and account information. The variables of gender, age-range, partner, and dependent status will be the protected attributes for the fairness evaluation task and will not be included in the primary modeling task. The column names, data types, numbers of unique values, and the split of variable uses are as in the following table.

Column	**Datatype**	**Val**	**Use**	
customerID	String	7043	Index	
gender	Whether the customer is a male or a female	2	Protected Demographic Info	
SeniorCitizen	Whether the customer is a senior citizen or not (0/1)	2		
Partner	Whether the customer has a partner or not (Yes/No)	2		
Dependents	Whether the customer has dependents or not (Yes/No)	2		
tenure	Int, continuous	73	Service	Training Features
PhoneService	String, boolean (Yes/No)	2		
MultipleLines	String, categorical (No Phone service/Yes/No)	3		
InternetService	String, categorical (DSL/Fiber optic/No)	3		
OnlineSecurity	String, categorical (No Internet service/Yes/No)	3		
OnlineBackup	String, categorical (No Internet service/Yes/No)	3		
DeviceProtection	String, categorical (No Internet service/Yes/No)	3		
TechSupport	String, categorical (No Internet service/Yes/No)	3		
StreamingTV	String, categorical (No Internet service/Yes/No)	3		
StreamingMovies	String, categorical (No Internet service/Yes/No)	3		
Contract	String, categorical (Month-to-month/One year/Two year)	3	Account	
PaperlessBilling	String, boolean (Yes/No)	2		
PaymentMethod	String, categorical	4		
MonthluCharges	Float, continuous	1585		
TotalCharges	Float, continuous	6531		
Churn	Whether the customer left within a month or not (Yes/No)	2	Label	

The summaries of the continuous variables are as:

	tenure	MonthlyCharges	TotalCharges
mean	32.42	64.8	2283.3
std	24.55	30.09	2266.77
min	1	18.25	18.8
max	72	118.75	8684.8

II. Primary Task

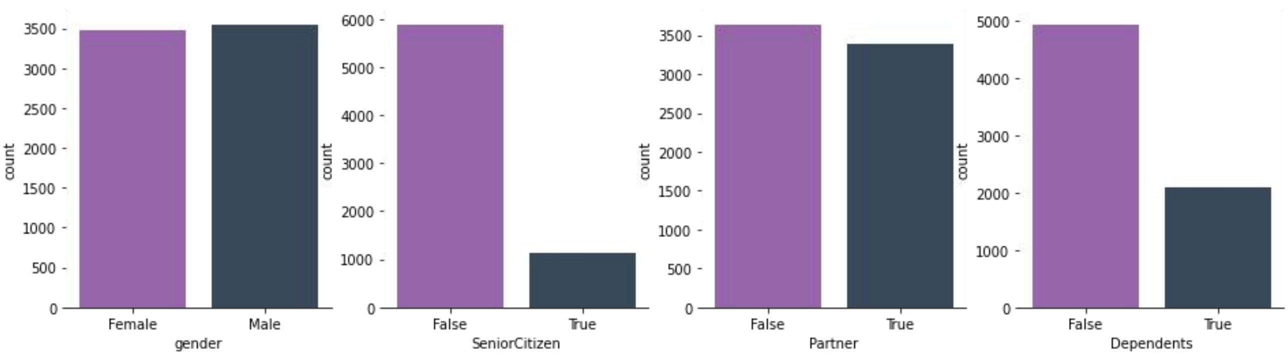
The classification task of this project is to predict whether the customers will churn, or, in other words, cancel services and stop doing business with this telecom company. The labels are binary showing whether a customer left within a month, with “True” meaning he/she left and “False” meaning the customer did not leave. There were 1869 records of customers that had left already, 26.58% of all, and 5163 of them, 73.42%, stayed for services.

a) Exploratory Data Analysis

i. General Distribution

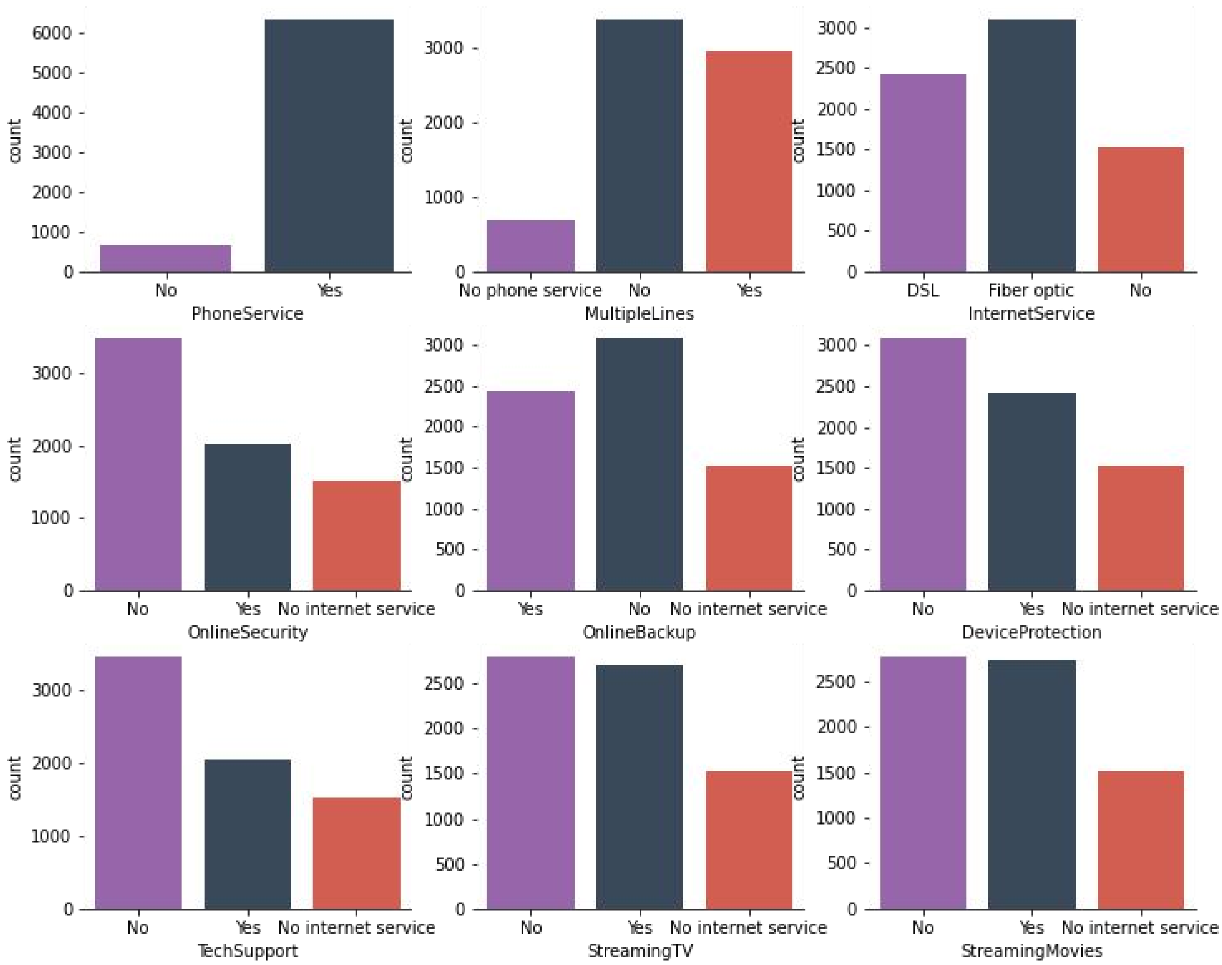
We are interested in customer features of this Telcom, so the EDA on general features and distribution will be conducted on three parts: demographic feature, service, and account.

1) Demographic features



From bar charts above, most of this Telcom are young customers without dependent. The gender of customer is balanced, and relatively more customers don’t have the partner. Young customers are the target uses of services.

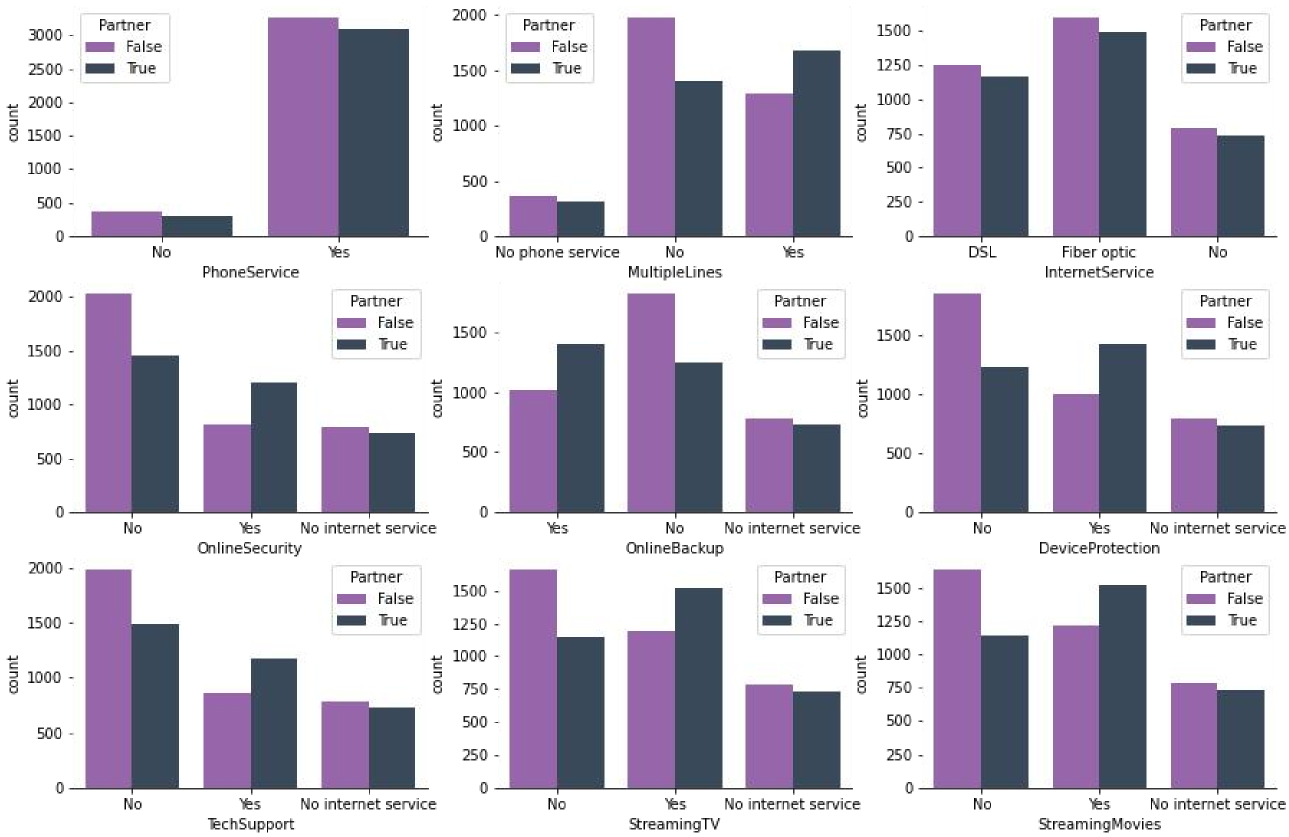
2) Service



From bar charts about service preference from customers, most customers have phone service by fiber optic without multiple lines, online security, online backup, device protection, tech support. Meanwhile, nearly half of customer choose to use streaming tv and streaming movie service to enjoy family time. Here we can conclude that most customers are only want to use the basic service with low price.

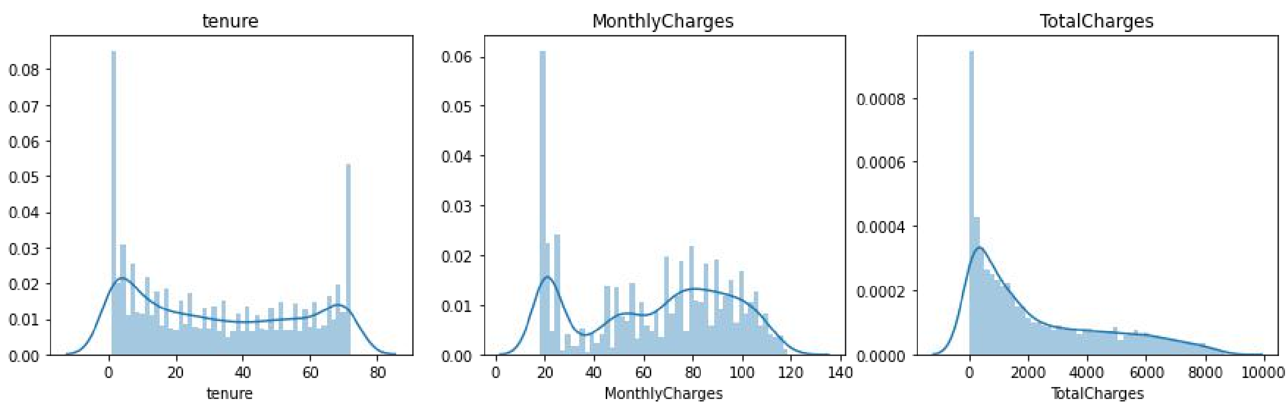
After data visualization on four demographic features, it shows that customers with partners prefer trying more kinds of service.

Customers with partners prefer multiple lines, online backup, online protection service, with streaming TV and streaming Movies to enjoy home time. Comparing with customers having dependents, having partner but no dependent customers will spend more money on protection service and entertainment items.

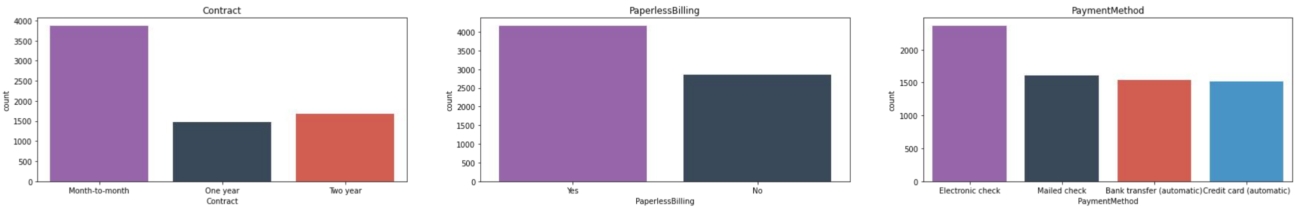


3) Account

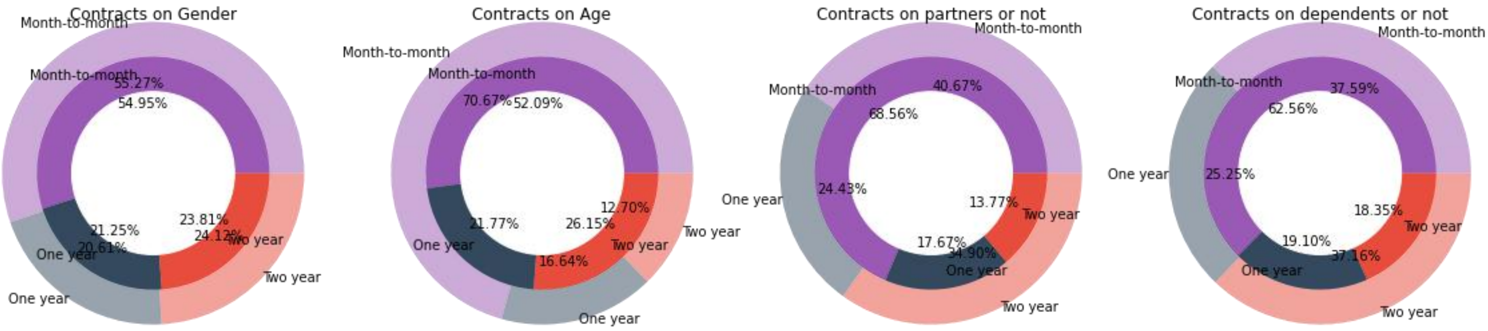
This part, we will focus on how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges.



According to distribution charts on the numerical features above, we can see this Telcom works well on both attracting new customers and developing loyal customers, though more are new uses. And customers prefer to pay less money and only use basic service, but here is another wave crest on monthly charges, which demonstrates a sum of customers are trying multiple service.



As for contract and paying, most customers choose month-to-month with the electronic check on paperless billing. We are interested in easily losing customers and loyal customers, so we draw pie charts on different contracts from demographic features.



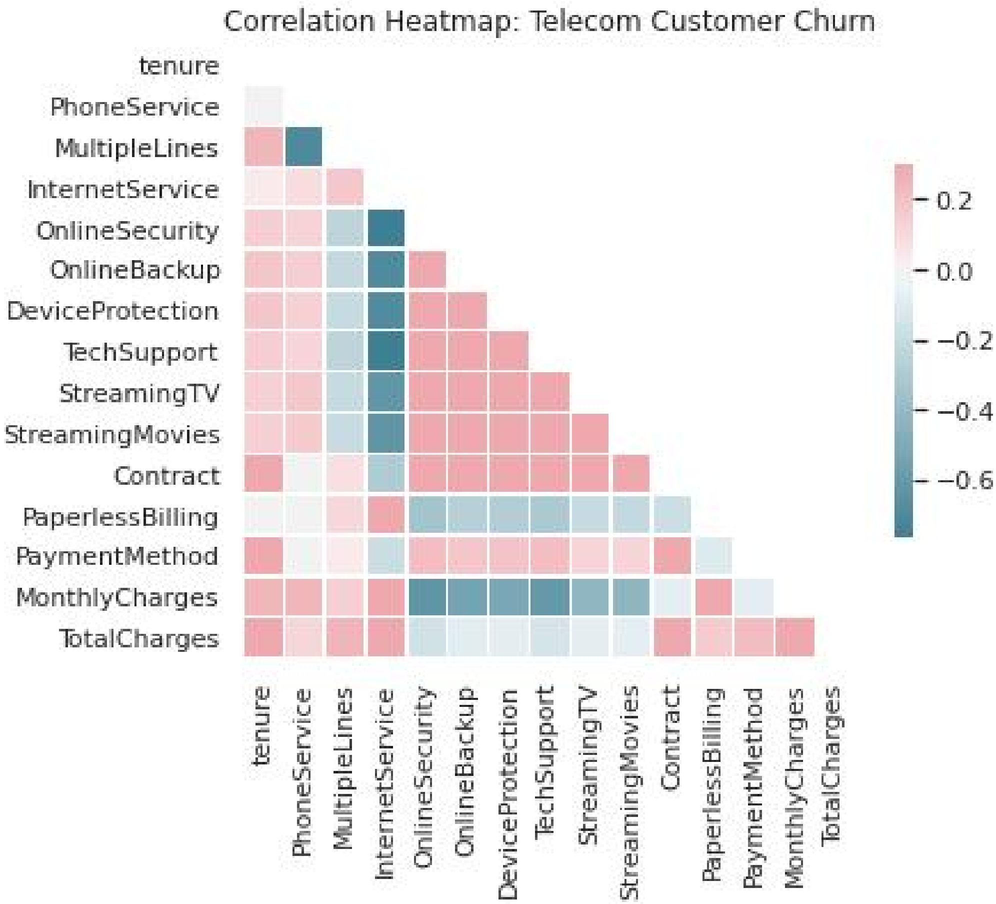
Here is no big difference in service preference from gender. However, as for contracts on age, more than 70% senior customers choose month-to-month contract (outer), while month-to-month is a welcome choice, 22% young customers choose one-year contract and 26% choose two-year one. Young customers are more loyal.

Customers with partner(Outer) really prefer one-year and two-year service, nearly 60% in sum, maybe due to benefits on pair service and a good wish on the relationship. Customers without partner prefer month-to-month service, showing they are actively on seeking new and suitable service, and they are more likely the price-leading customers.

Similar to the above one, customers with dependents prefer to use long-term services(Outer), while about 62% of customers without dependents prefer the month-to-month service.

Marketing strategy from contracts here is paying attention to young customers, or customers with partner or dependents because they are the loyal and basic customers in this Telcom. Besides, try some price strategies on senior customers, or customers without partner or dependent can be useful to attract new users.

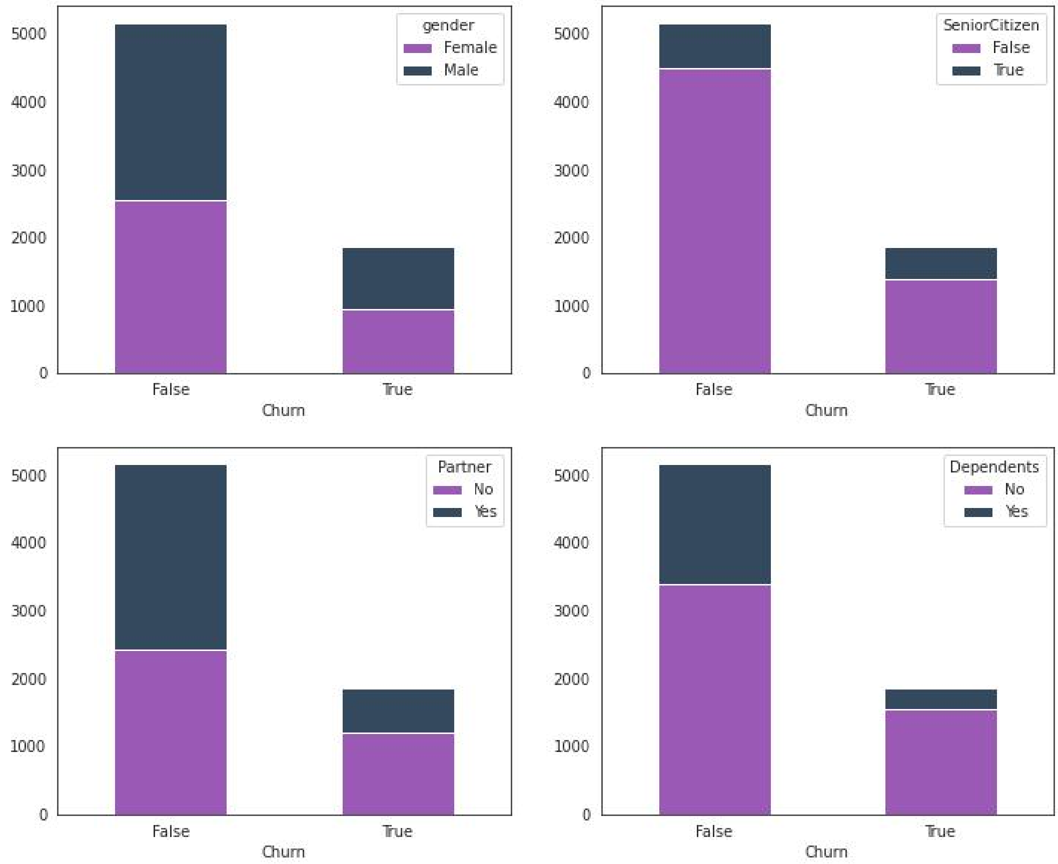
The correlation heatmap shows that the correlations between variables were not too strong. The worries for multicollinearity do seem insignificant in this case.



ii. Churn Comparison Analysis

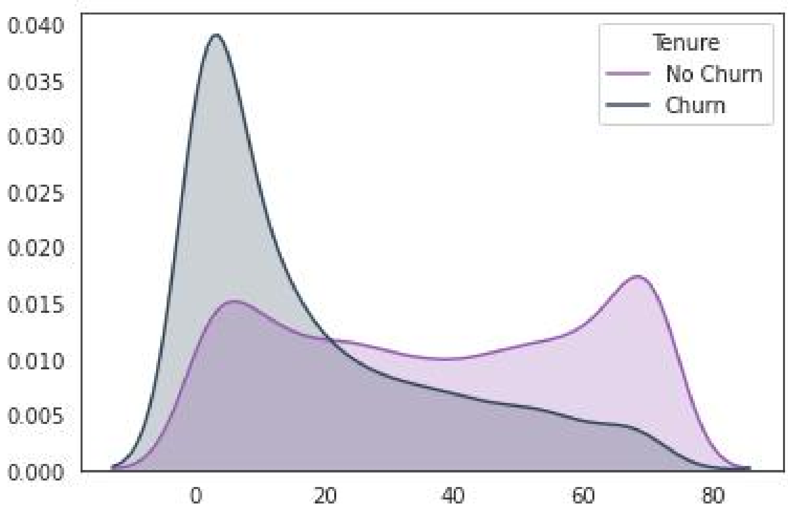
1) Demographic Features

In the subgroups of customers who left within a month and who did not, the customers' demographic distribution is as shown in the following bar plot. Female and male customers took about the same percentage of both groups. While the numbers of senior customers are about the same in the two groups, they took a larger portion, about 25.7%, in the churned group than 12.9% among the unchurned. The percents that customers with no partner or dependents took were significantly higher in the churned group: 64.2% churned customers had no partner and 82.6% of churned customers had no dependent. It suggests that customers with no partner or dependents might be less loyal and have greater flexibility to choose among and transfer business between companies that provide similar services.



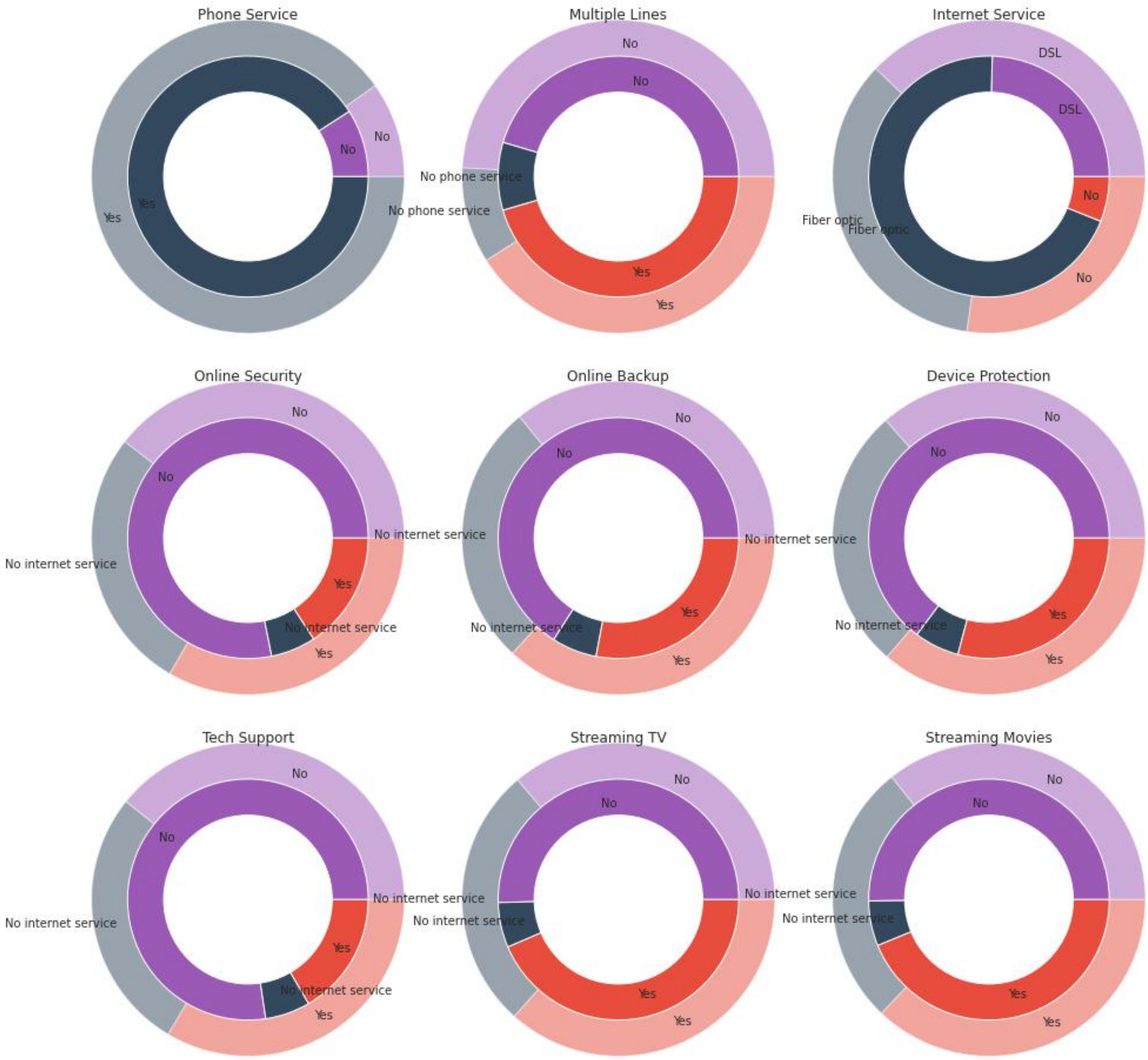
2) Service

The density plot shows the tenure of services that the customers subscribed to before they canceled services. We read that most of the churned customers left canceled services at a quite early stage for less than 10 months. The average lengths of service were 17.98 months for the churned and 37.65 months for the unchurned.



Churned customers that left before 20 months took 65.97% suggesting that the best time to implement customer retention strategies would be 6-7 month once and 14-15 months once after the service start. About 30.27% of the unchurned still-in-business customers' length of services was shorted than 20 months and they should be the ones that were worth of efforts to retain.

The following donut plots show the differences of service that churned and unchurned customers subscribed with the outer loop being the statistics for the unchurned and inner loop for the churned. Both groups of customers seemed to have a

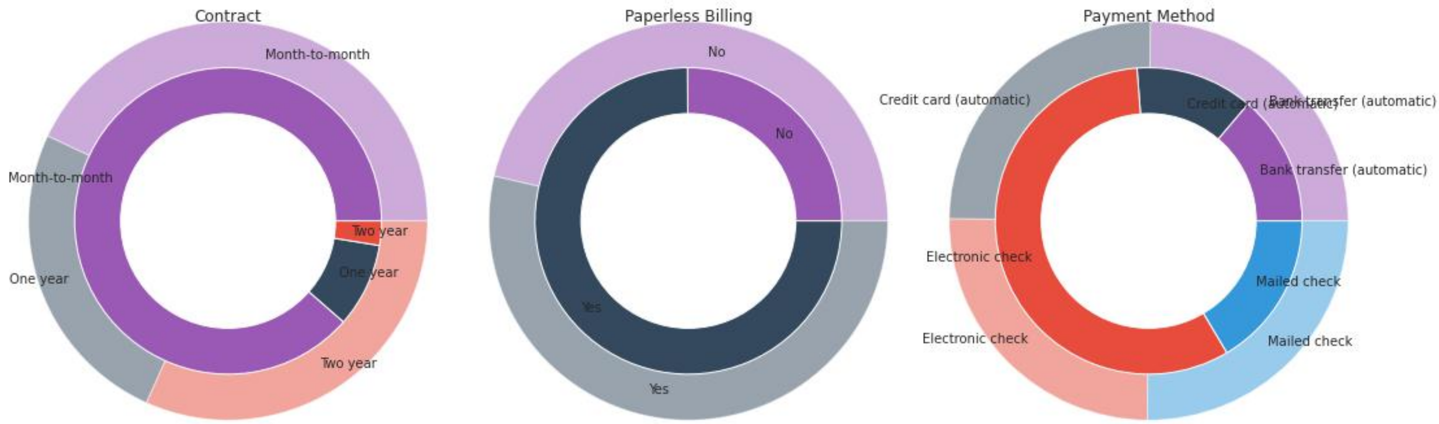


similar distribution of choices for phone service and multiple lines. The churned customers appeared to have signed up for less fancy services such as online security, online backup, device protection, tech support, streaming TV, and streaming movies.

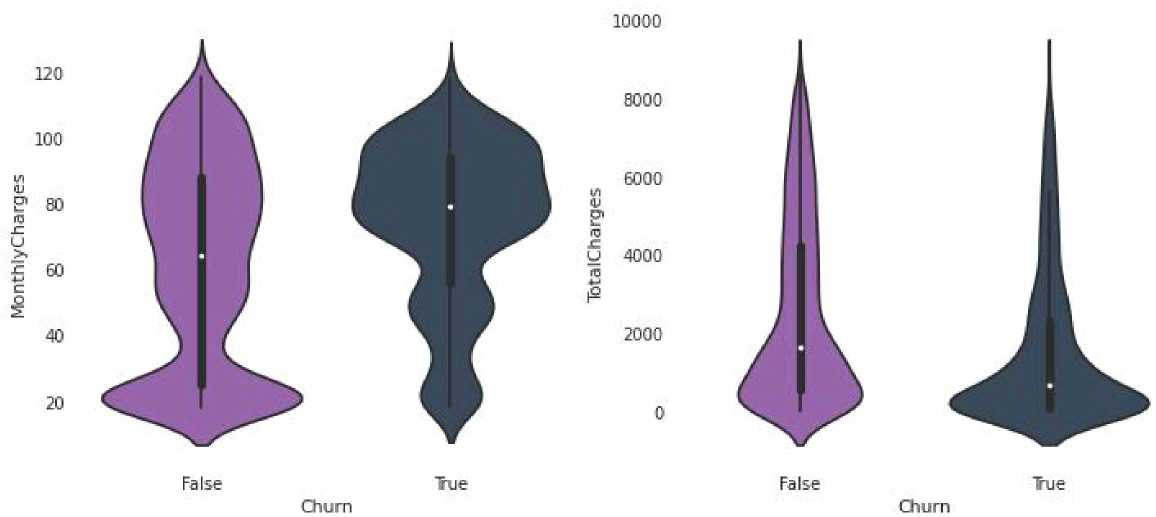
On the other hand, the percentage of churned customers to pay for Internet service, fiber optic or DSL, is greater than the unchurned, indicating that Internet service might be the major product that short-term easy-to-leave customers were most attracted to. It also came to our attention that the choices distributions looked the same between online security and tech support, online backup and device protection, and streaming TV and streaming movies. Despite that the differences between the numbers of each choice were minimal, we found there were 1863, 2213, and 1556 customers that had different options for these pairs of services' subscription.

3) Account

Customers' account info shows churned customers were mostly on a



month-to-month contract, as associated with tenure, had fewer requests for paper billing, and prefer electronic checks better. All of these simple, short-term, and worry-free automated options reflect the churned customers' high flexibility and mobility. Moreover, reading from the charges and payment information, the churned

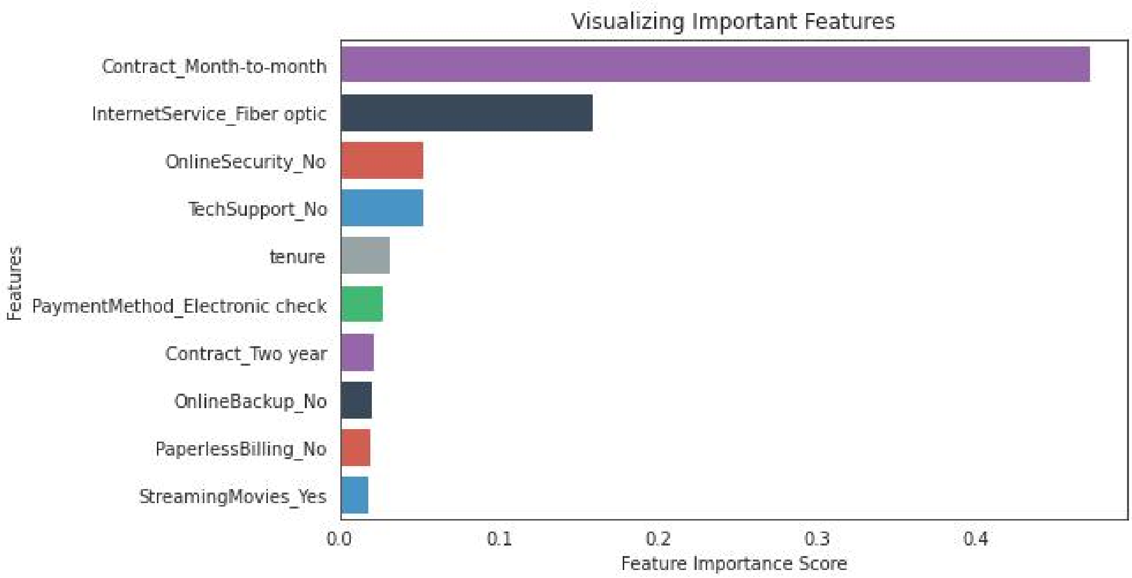


and unchurned group differed in both terms of density distributions and 5-number summaries. The churned group's average monthly charge was higher than the unchurned group with a smaller range between Q1 and Q3. A higher percentage of churned customers paid more than 70 dollars per month while the unchurned group's monthly payments had a partial concentration at 20 dollars. Besides, with regard to total charges, the unchurned group tended to have larger amounts to pay due to the length of their services. Overall, we concluded that it was more expensive to subscribe to basic services for a short term than to pay for more advanced services for longer tenures.

b) Modeling

Given above analyses and our later extension task, we divided our data into demographic, service, and account features. Demographic information will not be used for classification model training and, due to the reasonable numbers of the other

Feature Set	**Count Var**	**Variables**
1	15	Service + account
2	10	Service
3	5	Account
4	8	tenure, Internet Service, Online Security, Contract, Paperless Billing, Payment Method, Online Backup, Streaming Movies



features left, we decided to test on four feature sets and use the best one. The four feature sets: all 15 service and account attributes, only service attributes, only account attributes, and handpicked subset of attributes that maximize the variance based on EDA findings (and feature importance scores from a test model).

To perform the modeling, we firstly divided the dataset into a training set and a held-out test set with 20% of all instances. We trained the model with 10-fold cross-validation using multiple selected classifiers on the training set, used grid search to tune hyperparameters, and compared prediction results with and without normalization and PCA transformation. At last, we built our final optimized model with 100% of the training set, and tested it on the held-out test set. The target for performance was set to be at least 70% accuracy with a reasonable kappa (about 0.6) and a relatively high recall score. With a recall score ideally higher than the precision, our model would likely make fewer false-negative predictions that might lead to missed chances of retaining customers, which makes the 70% accuracy and 30% room for errors and natural customer flow acceptable for us.

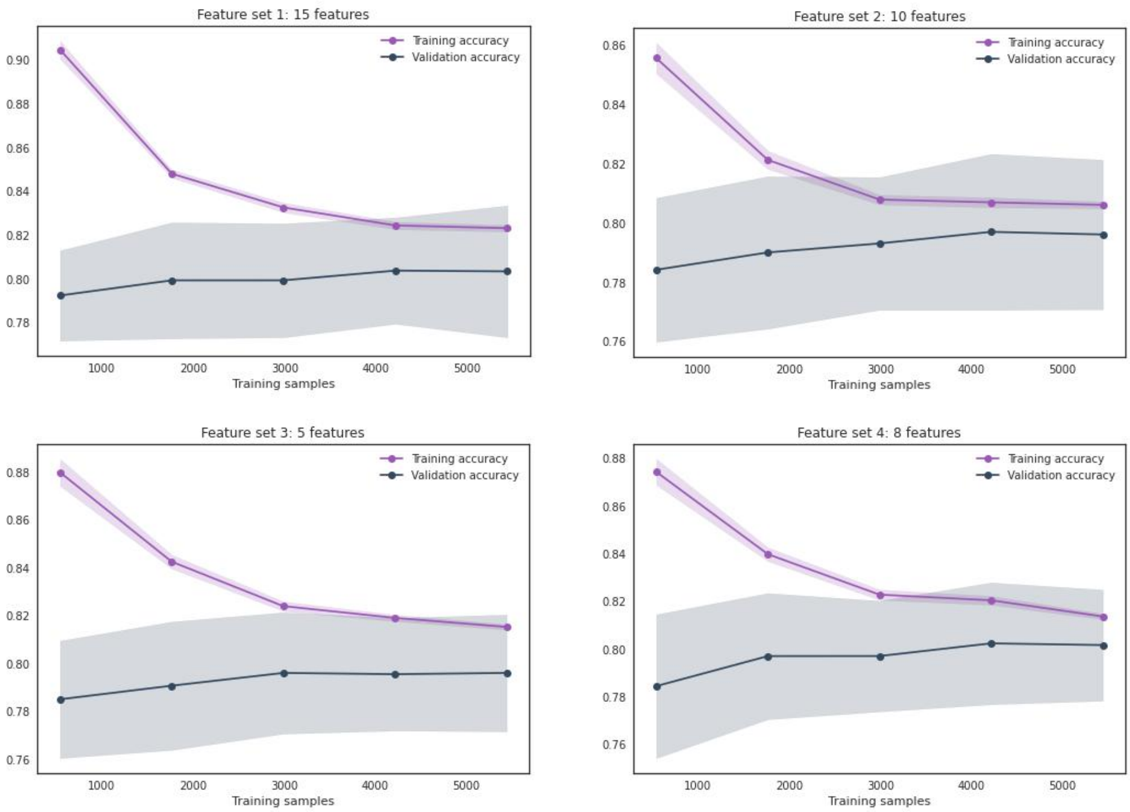
The initial set of learning algorithms we tried and the hyperparameters we tried to tune for each classifiers are as in the following table.

Classifier	**Hyperparameters**
Decision Tree	criterion, splitter, max_depth, min_impurity_decrease
Logistic Regression	penalty
Naive Bayes	Types: Gaussian, Bernoulli, Complement, Multinomial
Random Forest	max_depth, max_features, n_estimators
Linear SVM	
XGBoost	max_depth, n_estimators, learning_rate
KNN	leaf_size, n_neighbors, algorithm, weights
Multilayer Perceptron	hidden_layer_sizes, solver, activation, alpha, learning_rate, max_iter

In the first round of modeling, we used 10-fold cross-validation on the training set with the 4 features sets respectively, and compared the results of accuracy. The feature set with all 15 features included slightly outperformed other features sets (by about 0.5 points of accuracy to 8-feature set) with the following metrics.

10-fold cross-validation with default hyperparameters (training set)					
Classifier	**Accuracy**	**Kappa**	**Precision**	**Recall**	**F-Score**
XGBoost	80.32	0.46	0.67	0.53	0.59
Logistic Regression	79.86	0.45	0.64	0.54	0.59
Multilayer Perceptron	78.87	0.39	0.68	0.43	0.51
Random Forest	78.44	0.40	0.62	0.48	0.54
K-nearest Neighbors	75.92	0.34	0.56	0.45	0.50
Linear SVM	75.29	0.26	0.57	0.33	0.39
Decision Tree	73.21	0.32	0.49	0.51	0.50
Bernoulli NB	71.12	0.40	0.47	0.81	0.60
Gaussian NB	68.66	0.37	0.45	0.85	0.59
Multinomial NB	68.29	0.33	0.44	0.75	0.56
Complement NB	67.70	0.33	0.44	0.75	0.55

To measure the performance of the model, we plotted the XGBoost learning curves with the 4 feature sets.



The 15-feature set learning curve shows that both training and validation accuracy steadied around 81% without close convergence at the end, indicating that the model can be improved with more training data and is overfitting a little; the service-only feature set 2 has lower accuracy and account-only feature set 3 is underfitting. Thus, the 8-feature feature set seemed to be the best performing set in terms of variance and bias balance. But in general, the differences of performances of feature set 1 and 4 are rather insignificant. We continued with feature set 1, due to its slightly higher accuracy. Also, as the top 3 performing classifiers were XGBoost, Logistic Regression, and multilayer Perceptron, we focused on optimizing them. The results of using grid searches to tune hyperparameters are as the following.

Grid Search				
Classifier	**Hyperparameters**	**Accuracy**	**Kappa**	**Recall**
Decision Tree	'criterion': 'gini', 'max_depth': 4, 'min_impurity_decrease': 0.0, 'splitter': 'best'	78.77	0.38	0.44
Logistic Regression	'penalty': 'none'	80.99	0.45	0.51
Random Forest	'max_depth': 8, 'max_features': 4, 'n_estimators': 200	80.9	0.44	0.65
XGBoost	'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 60	81.26	0.46	0.5
KNN	'algorithm': 'ball_tree', 'leaf_size': 20, 'n_neighbors': 6, 'weights': 'uniform'	77.62	0.29	0.32
Multilayer Perceptron	'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (100,), 'learning_rate': 'adaptive', 'max_iter': 300, 'solver': 'adam'	78.42	0.4	0.51

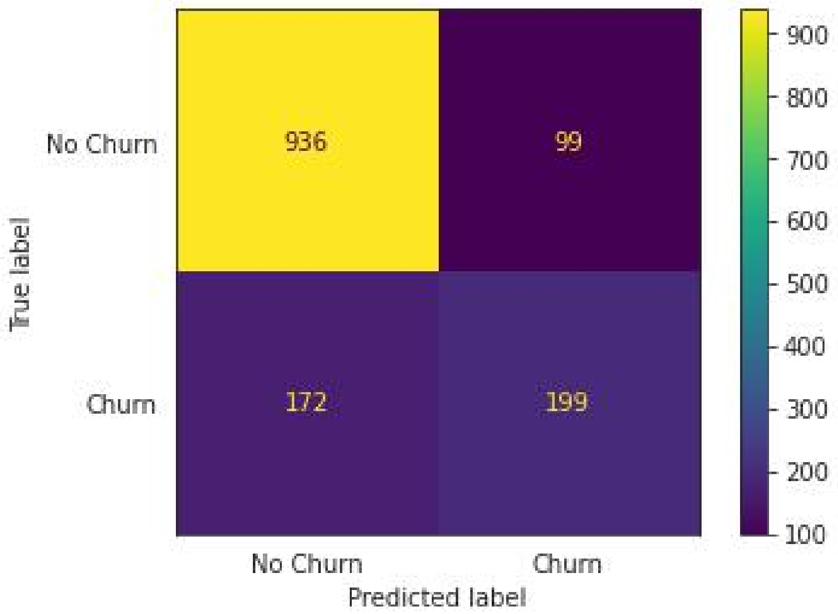
The best performing model for now is XGBoost with tuned hyperparameters. During multicollinearity diagnosis in EDA, we didn't notice strong pattern of correlations. But just in case, we did normalization and PCA transformation to address potential problems with Logistic Regression and XGBoost classifiers, and tuned hyperparameters with grid search. The results were not ideal and didn't show significant improvement from before the transformation.

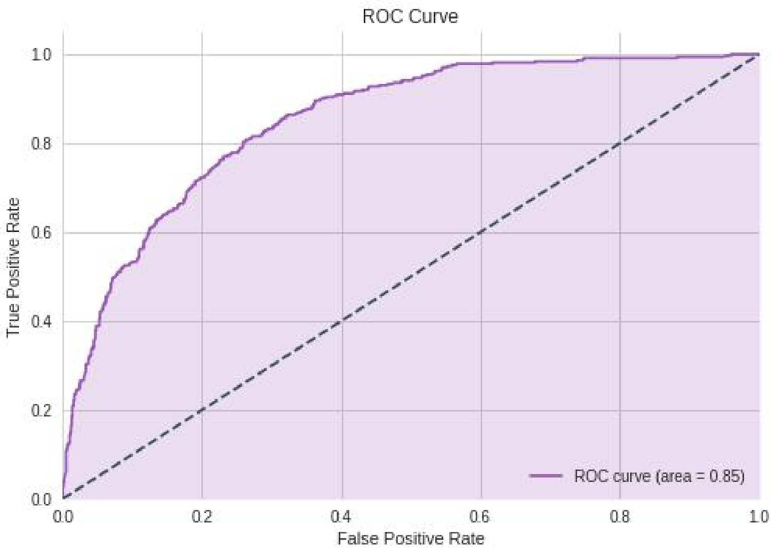
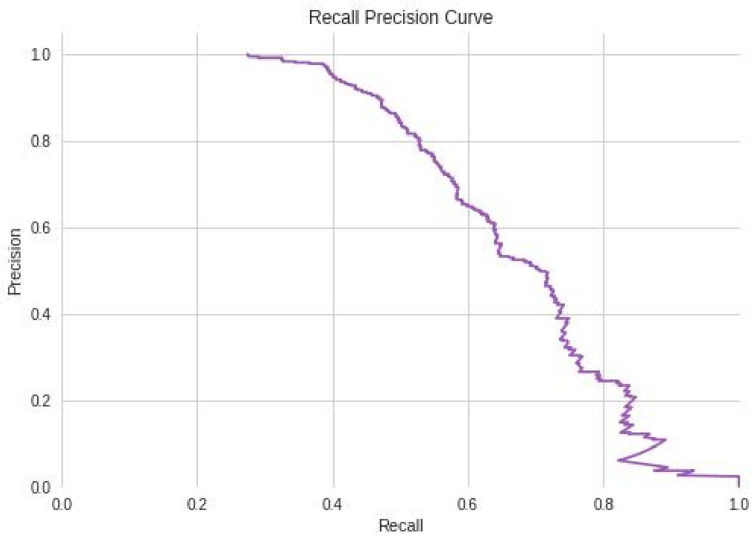
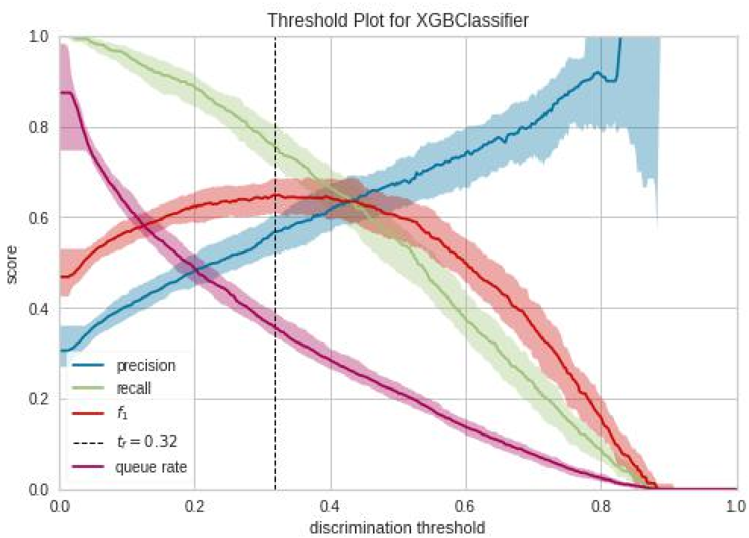
Grid Search with standardization and PCA transformation				
Classifier	**Hyperparameters**	**Accuracy**	**Kappa**	**Recall**

Logistic Regression	'penalty': 'l2'	81.26	0.5	0.55
XGBoost	'learning_rate': 0.05, 'max_depth': 5, 'n_estimators': 140	80.11	0.46	0.5

After the above experiments, we decided to build our final model with the full 15-feature training set using XGBoost classifier without StandardScaler() normalization and PCA transformation with tuned hyperparameters and test its performance on the held-out test set.

c) Results

Final Model: XGBClassifier(learning_rate= 0.1, max_depth= 3, n_estimators= 60, random_state=123)	
Accuracy	80.73%
Kappa	0.47
Precision	0.67
Recall	0.54
F-Score	0.59
Confusion Matrix	

ROC Curve	
Recall Precision Curve	
Threshold Plot	

Our final model reached an accuracy of 80.73% on the held-out test set that was not used for optimization, better than our goal of 70% accuracy. The 0.47 kappa score represented moderate inter-rater reliability, and the recall score was lower than precision, both of which failed to meet the goals we preset. Higher precision than recall was also reflected in the Confusion Matrix with more false negative errors than false positive ones. It is more likely that our model will mistakenly classify a potential customer who might leave into the won't-churn group. The ROC curve plots false positive rate (inverted specificity) vs true positive rate and the 0.85 AUC indicates that our final model distinguishes between classes pretty well and better than random guesses (0.5). With all things considered, we are satisfied with our model's performance.

III. Extension Task

a) Task Definition

We conduct the fairness audit on our best performance model, the XGBoost model, from the primary task. This task aims at exploring model performance on different subpopulations to help the marketing and other relevant departments with making cost-managing and budget-saving strategies, which means it can provide a priority order on customers when making benefit strategies on potential churn customers. Meanwhile, this task helps us know fairness or not on demographic features of the final model, providing an evaluation method and an improving direction for model accuracy improvement.

As for the work plan, we will divide the customers into several groups based on their demographic information, gender, age-range, and if they have partners and dependents in particular. Besides, we will visualize predictions from the model against the real results, and calculate accuracy, precision, and recall respectively for each subgroup. The target is to evaluate the model and report our findings, as we are not considering improving the fairness of the model at the current stage.

b) Technical Methods

To achieve our task aims, we mainly use classification_report method from metrics library and heatmap function from seaborn with python; Here are technical steps in detail:

Summary of the best model on precision, recall, f1-score, and support value.

Draw heatmap matrix on age, gender, partners or not, dependents or not, with valuation summary.

c) Results

Model summary:

	precision	**recall**	**f1-score**	**support**
False	0.83	0.91	0.87	1032
True	0.66	0.49	0.56	374
accuracy			0.80	1406
Macro avg	0.74	0.70	0.71	1406
Weighted	0.78	0.80	0.79	1406

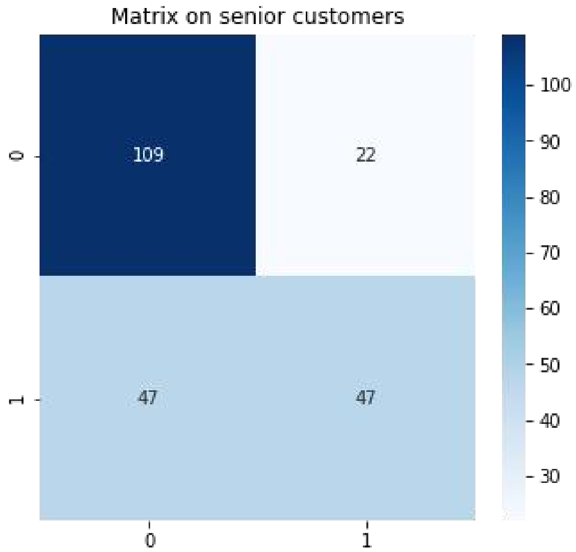
The table above shows some evaluation indexes for the classification task. Due to our aim is to predict potential churn customers, here we will focus on true(which means predict as churn customers) label. Before exploring the model on subgroups by demographic features. We can see the accuracy of the model is around 80%, higher than our estimation in the proposal, so we think this model can work. However, there is a big gap between true and false predictions on precision, recall, and f-1 score. We think the reason is the biased group volume in the training set, leading to the relatively worse prediction on churn customers. So, collecting more data on churn customers is important to improve model performance.

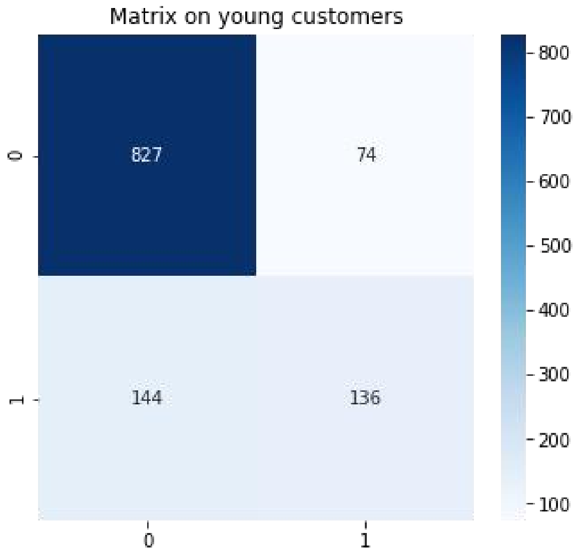
i. Fairness audit on demographic features

1) Age

According to age info, we divide customers into senior and young, these two groups.

The model works better on young customers with about 82% accuracy, compared with 69% accuracy on senior customers. However, when we focus on predictive churn customers, according to precision, the model is slightly more precisely on true churn customers from all customers predicted to be positive in senior customers. And the f1-score reconfirms the better prediction on senior customers.

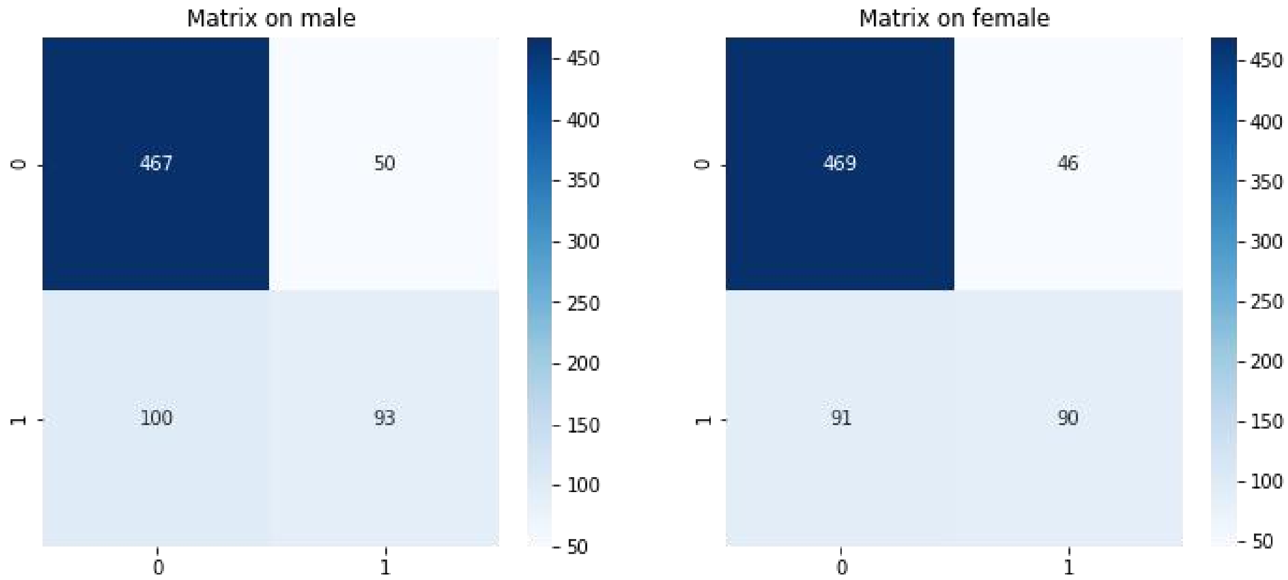




Senior				
	precision	recall	f1-score	support
False	0.70	0.83	0.76	131
True	0.68	0.50	0.58	94
accuracy			0.69	225
Macro avg	0.69	0.67	0.67	225
Weighted avg	0.69	0.69	0.68	225
Not senior				
	precision	recall	f1-score	support
False	0.85	0.92	0.88	901
True	0.65	0.49	0.56	280
accuracy			0.82	1181
Macro avg	0.75	0.70	0.72	1181
Weighted avg	0.80	0.82	0.81	1181

2) Gender

According to gender info, we divide customers into male and women two groups. The model accuracy is nearly similar to male and female groups, maybe due to the balanced training dataset. The precision of the model on the female is slightly higher than the male with 0.01, and the f-1 score is higher with 0.02 difference. Though it shows a little better on female group prediction, we believe here is no big difference in prediction between male or female customers.

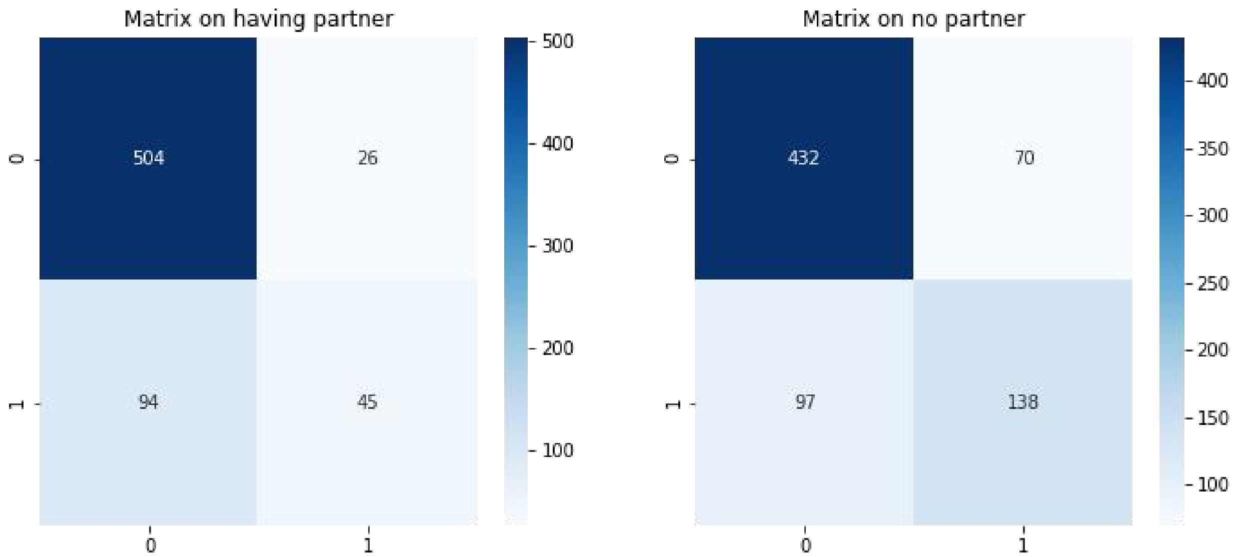


Male				
	precision	recall	f1-score	support
False	0.82	0.90	0.86	517
True	0.65	0.48	0.55	193
accuracy			0.79	710
Macro avg	0.74	0.69	0.71	710
Weighted	0.78	0.79	0.78	710
Female				
	precision	recall	f1-score	support
False	0.84	0.91	0.87	515
True	0.66	0.50	0.57	181
accuracy			0.80	696
Macro avg	0.75	0.70	0.72	696
Weighted	0.79	0.80	0.79	696

3) Partner

According to having a partner or not, we divide customers into having partner and not having partner two groups.

According to chart above, though model accuracy is higher in having partner group with 82% accuracy, our model works better on predicting potential churn customers in no partner group. The model works especially better on recall score in no partner group with 0.59, which means the model predicts more precisely from true churn customers, and the f-1 score is 0.62.

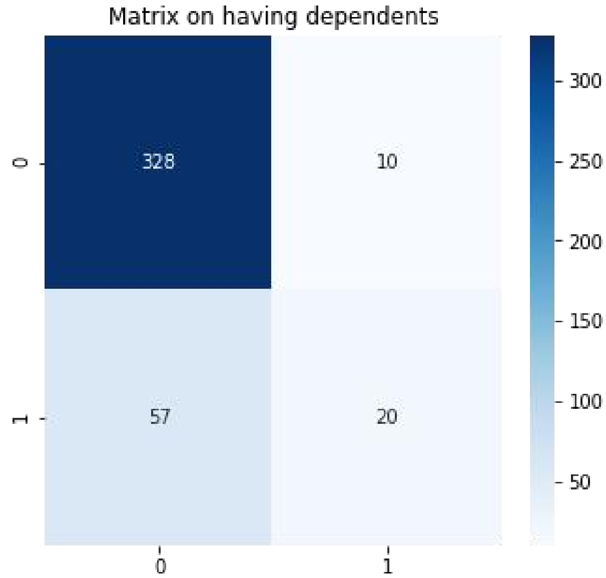


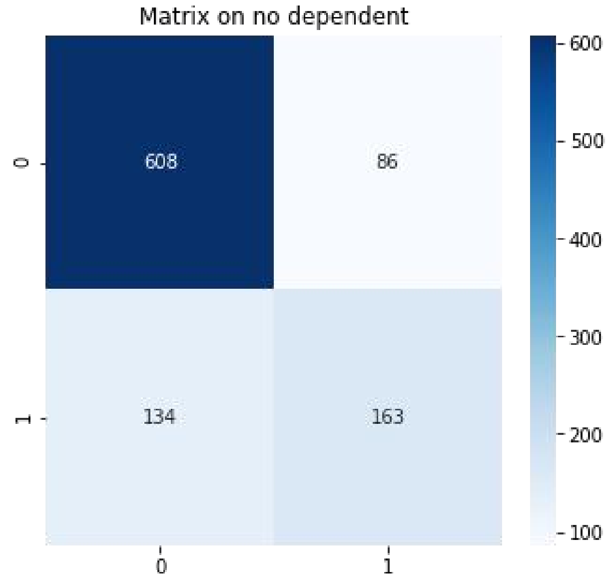
Having partner				
	precision	recall	f1-score	support
False	0.84	0.95	0.89	530
True	0.63	0.32	0.43	139
accuracy			0.82	669
Macro avg	0.74	0.64	0.66	669
Weighted	0.80	0.82	0.80	669
No partner				
	precision	recall	f1-score	support
False	0.82	0.86	0.84	502
True	0.66	0.59	0.62	235
accuracy			0.77	737
Macro avg	0.74	0.72	0.73	737
Weighted	0.77	0.77	0.77	737

From the matrix, we can understand the reason, here are more true churn customers from no-partner group. Here are two messages from it: customers with partner are more loyal to this company, so the company can consider providing the family benefit or long-term contract to customers with partner; The other strategy is to provide some short-tern discount or benefit in the telecommunication market, such as in school, mall and so on, attracting new young customers into own company's service.

4) Dependents

According to having dependents or not, we divide customers into having dependents or not two groups.





Having dependents				
	precision	recall	f1-score	support
False	0.85	0.97	0.91	338
True	0.67	0.26	0.37	77
Accuracy			0.84	415
Macro avg	0.76	0.62	0.64	415
Weighted	0.82	0.84	0.81	415
No dependent				
	precision	recall	f1-score	support
False	0.82	0.88	0.85	694
True	0.65	0.55	0.60	297
accuracy			0.78	991
Macro avg	0.74	0.71	0.72	991
Weighted	0.77	0.78	0.77	991

According to the table above, the model works better on the having-dependents group with 0.84 accuracies, but the no-dependent group performs better on recall and f-1 score. The reason behind it is the high churn rate of no-dependent customers. Considering together with precision value, we can conclude the good accuracy on predicting positive cases. So here we can take similar strategies as above, more family benefit or service to having-dependent customers, and short-term benefit strategy to no-dependent customers.

Here we use the table to summarize the predict positive result with precision, recall, f1 score, and support cases:

True (Positive)	**precision**	**recall**	**f1-score**	**support**	**Rank(f1)**
Model	0.66	0.49	0.56	374	
Senior	0.68	0.50	0.58	94	3
Young	0.65	0.49	0.56	280	5
Male	0.65	0.48	0.55	193	6
Female	0.66	0.50	0.57	181	4
Having-partner	0.63	0.32	0.43	139	7
No-partner	0.66	0.59	0.62	235	1
Dependents	0.67	0.26	0.37	77	8
No-dependent	0.65	0.55	0.60	297	2

Here we can see no-dependent customers, no-partner customers and young customers are relatively easy to lose, according to support case value. From f1 score, the model predicts precisely on no-partner, no-dependent groups, so it is possible to take short-term benefit strategy to attract these groups into service from markets, and then explore on customer characteristics to keep them stay in the service.

Meanwhile, we can see f-1 scores are low in having-partner and having-dependent groups, scarce data can account for it someway. They are target long-term customers, and we can provide family benefits to keep them.

ii. About Stakeholders

Biased data volume, missing data, wrong data, in this case, are likely to cause failures to maximize profits, minimize costs, and maintain good relationships with valuable customers. In real business settings, to lower such risks, we will work with our data managers to keep updated on customer' info and ask marketers for insights on to what extent we should subdivide our customers and how to meet their needs for customer behavioral predictions with our model.

IV. Materials

a) Source Code

Final_Project_608 (Google Colab)

b) Dataset

Kaggle - Telco Customer Churn; Data File (Google Drive)

c) Documentation

The structure of our code notebook is as the following.

Section 0: Loading Data

Section 1: EDA

1.1 General Customer Statistics (Xuechuan)

1.2 Churn Comparison (Ziyu)

Section 2: Primary Task (Ziyu & Xuechuan)

2.1 Pre-processing

2.2 Model Training

Section 3: Fairness Audit (Extension Task) (Xuechuan)

References

Ahmad, A. K., Jafar, A., & Aljoumaa, K. (2019). *Customer churn prediction in telecom using machine learning in big data platform*. Cham: Springer International Publishing. doi:10.1186/s40537-019-0191-6

Building Customer Churn Models For Business, Ruslana Dalinina - https://blogs.oracle.com/datascience/building-customer-churn-models-for-business

Gaur, A., & Dubey, R. (2018). Predicting customer churn prediction in telecom sector using various machine learning techniques. Paper presented at the 1-5. doi:10.1109/ICACAT.2018.8933783

Mishra, A., & Reddy, U. S. (2017). A comparative study of customer churn prediction in telecom industry using ensemble based classifiers. Paper presented at the 721-725. doi:10.1109/ICICI.2017.8365230

Telco Customer Churn, BlastChar - https://www.kaggle.com/blastchar/telco-customer-churn