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Final Project

Telco Customer Churn Prediction

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01

BUSINESS & DATASET UNDERSTANDING

Dataset Information

- Customer information from a **telco company**
- This company provides various services such as **streaming**, **internet**, and **phone** service

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Attribute Information

Identifier	Target variable	Demographic information	Account information	Subscribed service
Customer ID	Churn status	Gender	Tenure	Phone service
		Senior citizen	Monthly charges	Multiple lines
		Partner	Total charges	Internet service
		Dependents	Contract	Online security
			Paperless billing	Online backup
			Payment method	Device protection
				Tech support
				Streaming TV
				Streaming movies

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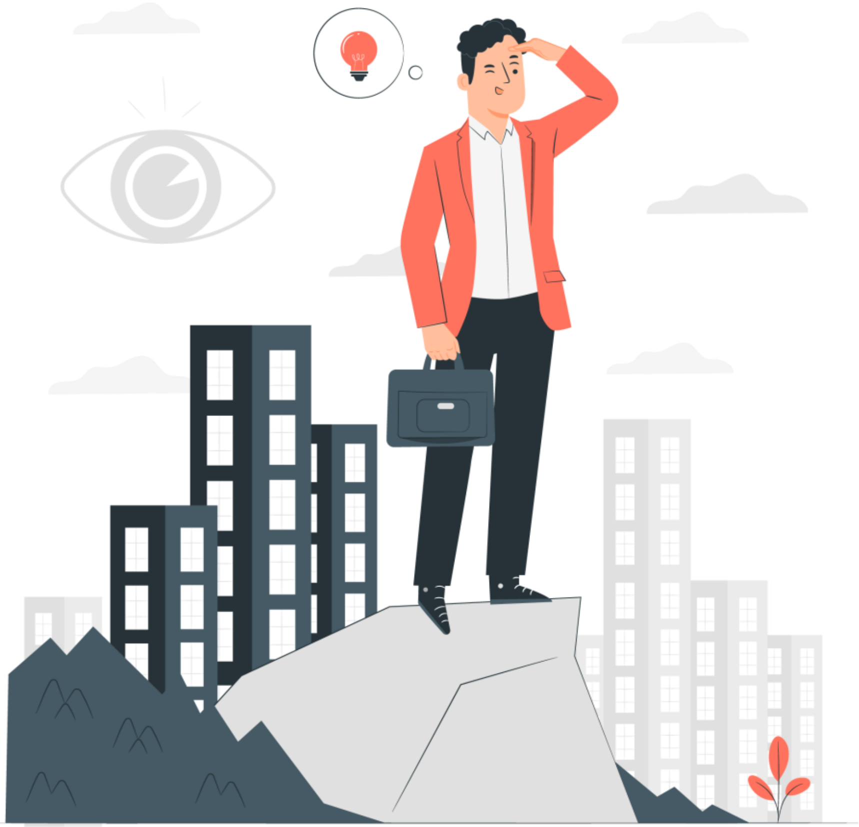
Company Goals



- **Acquiring new customers** as much as we can
- **Retaining existing customers** as much as we can

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Cost Problems

Acquiring a new customer can be

25x more expensive

Reference:
https://hbr.org/2014/10/the-value-of-keeping-the-right-customers
https://www.outboundengine.com/blog/customer-retention-marketing-vs-customer-acquisition-marketing

Objectives

- **Predict** whether the customer will still use our service or **will leave** our service

- Understanding **customer behavior**
  - What keeps customers using our service
  - What makes customers leave our service

02

EXPLORATORY DATA ANALYSIS

What Happened?

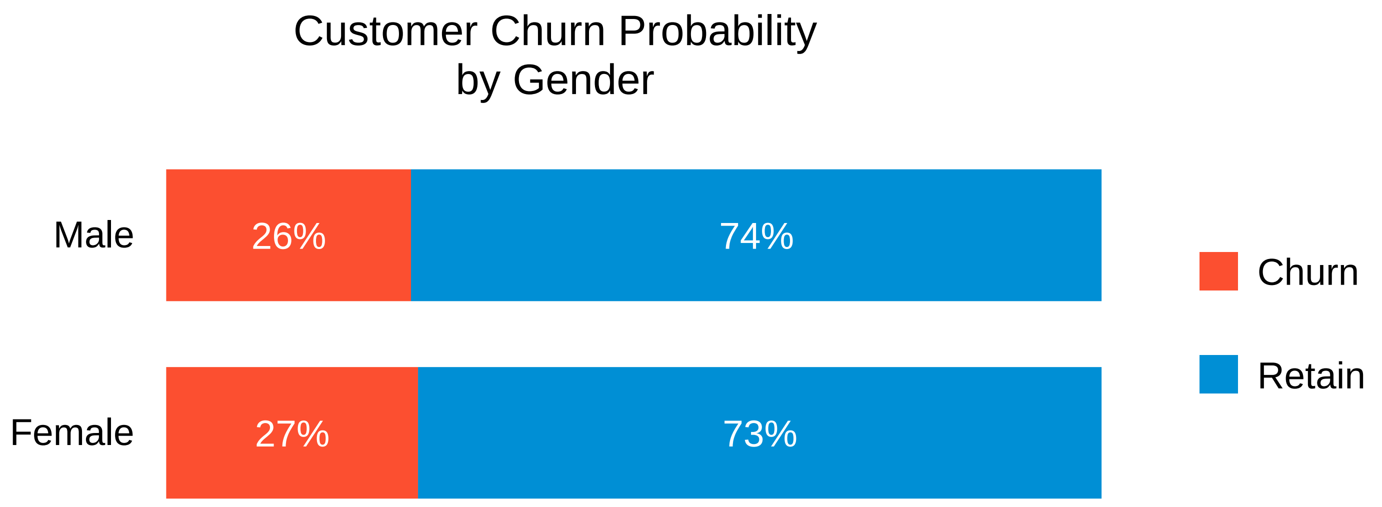
27%

Customers leave us! ☹

Technically speaking,
This is an imbalanced dataset

Why Did It Happen?

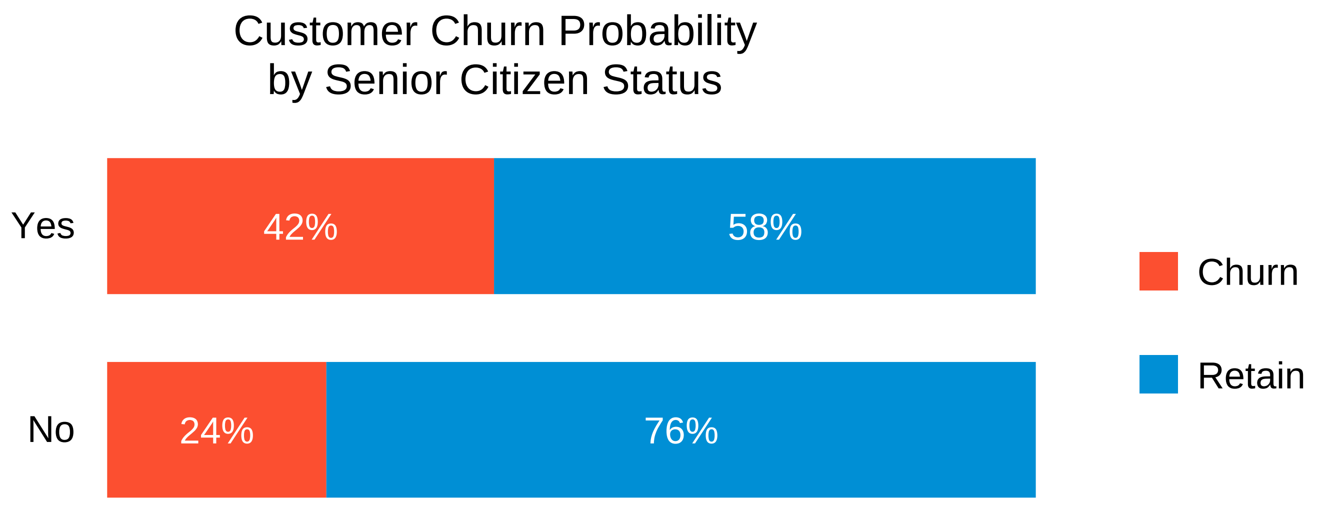
Not all attributes have a **strong relationship** with churn status



Both males and females almost have the same probability to churn
We can say that customer's gender **has no relationship** with their churn status

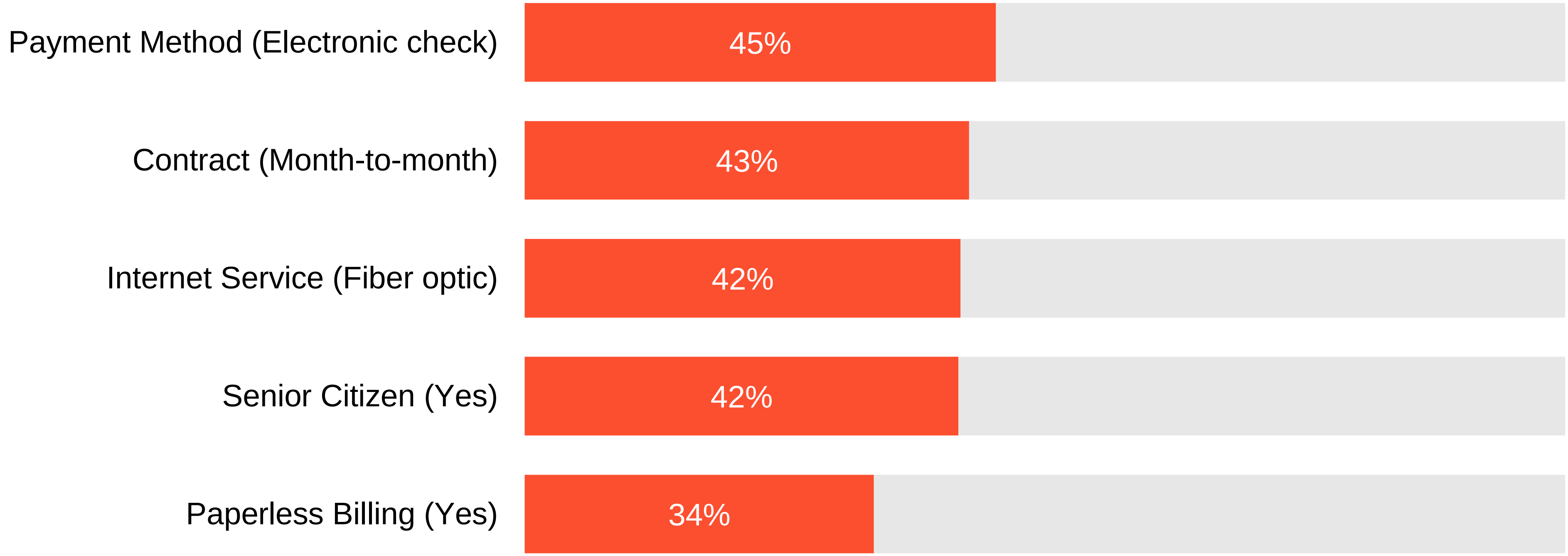
Why Did It Happen?

Not all attributes have a **strong relationship** with churn status

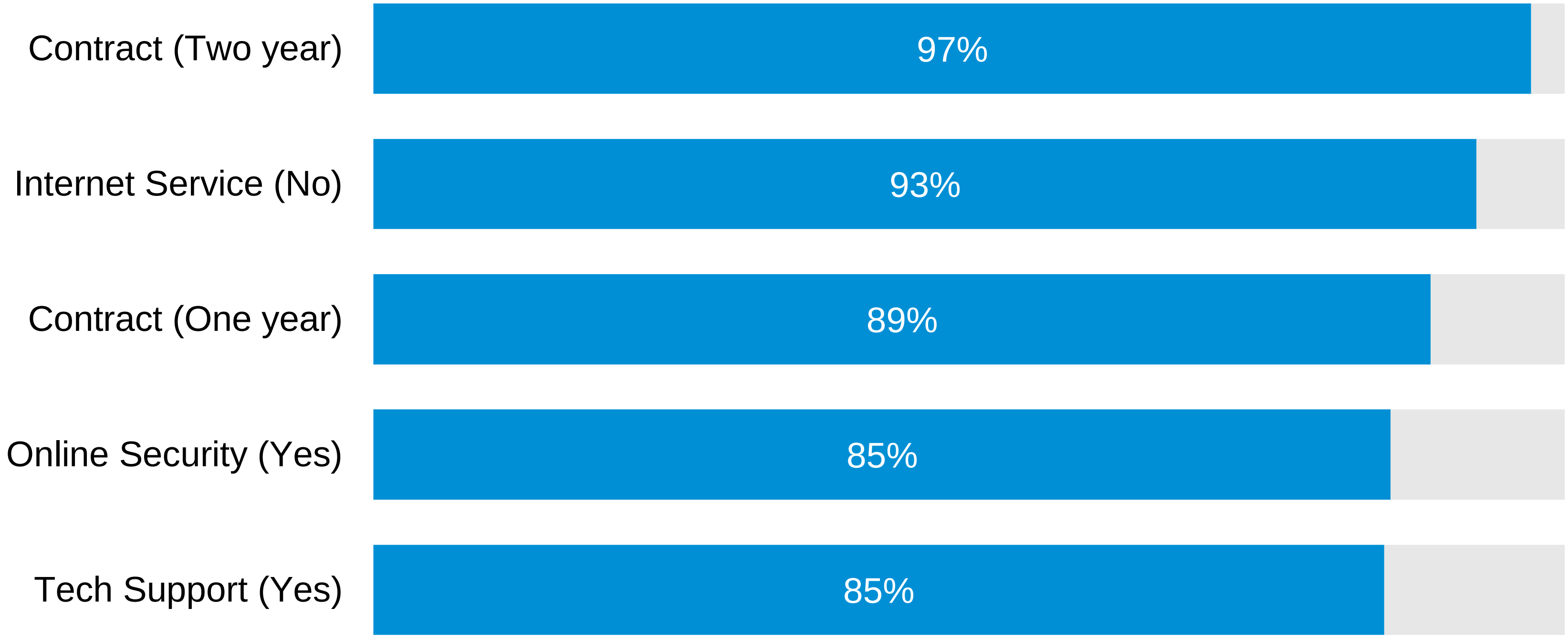


Senior citizens have a higher probability of churn than younger citizens
We can say this attribute **has a relationship** with churn status

Top 5 Churn Probability



Top 5 Retain Probability



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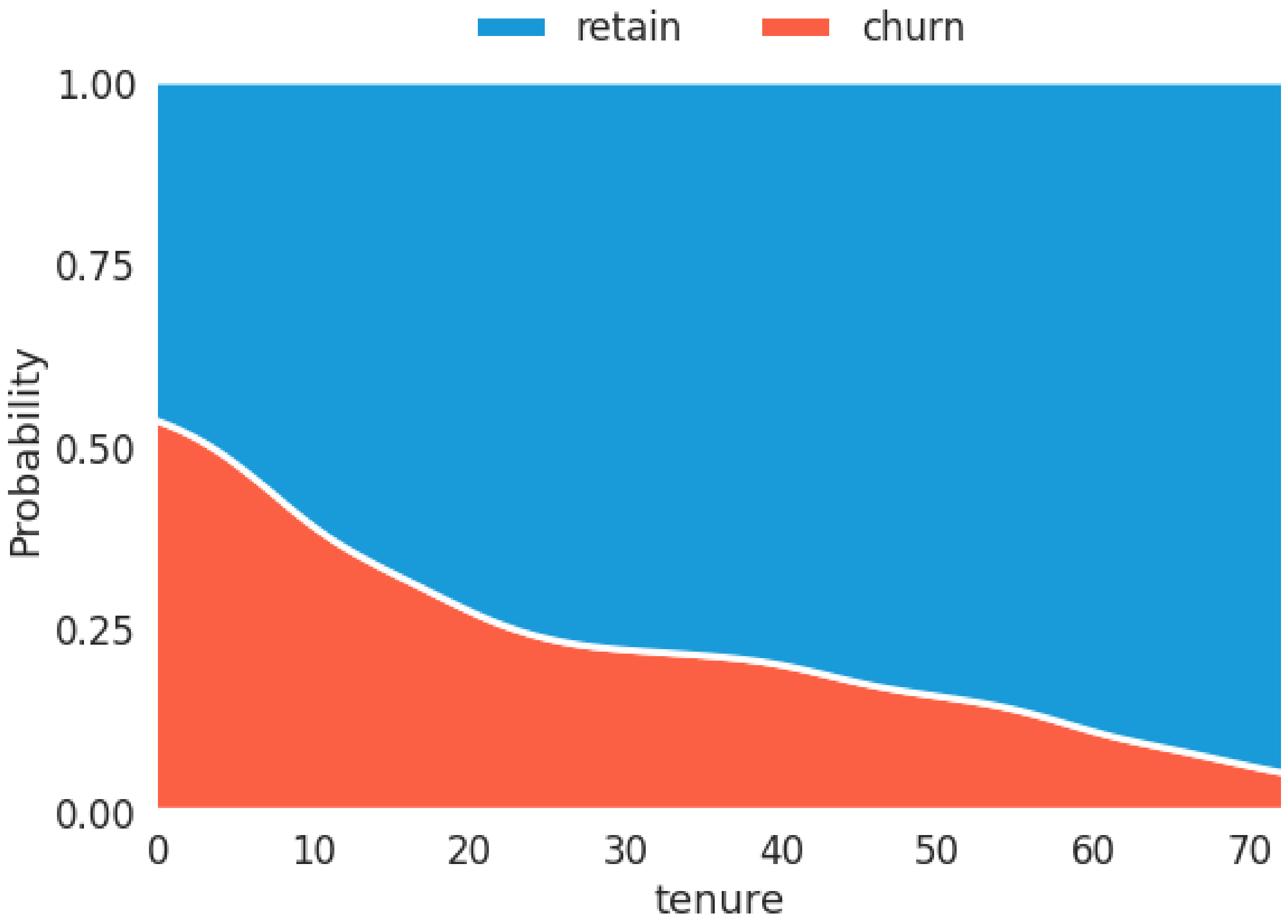
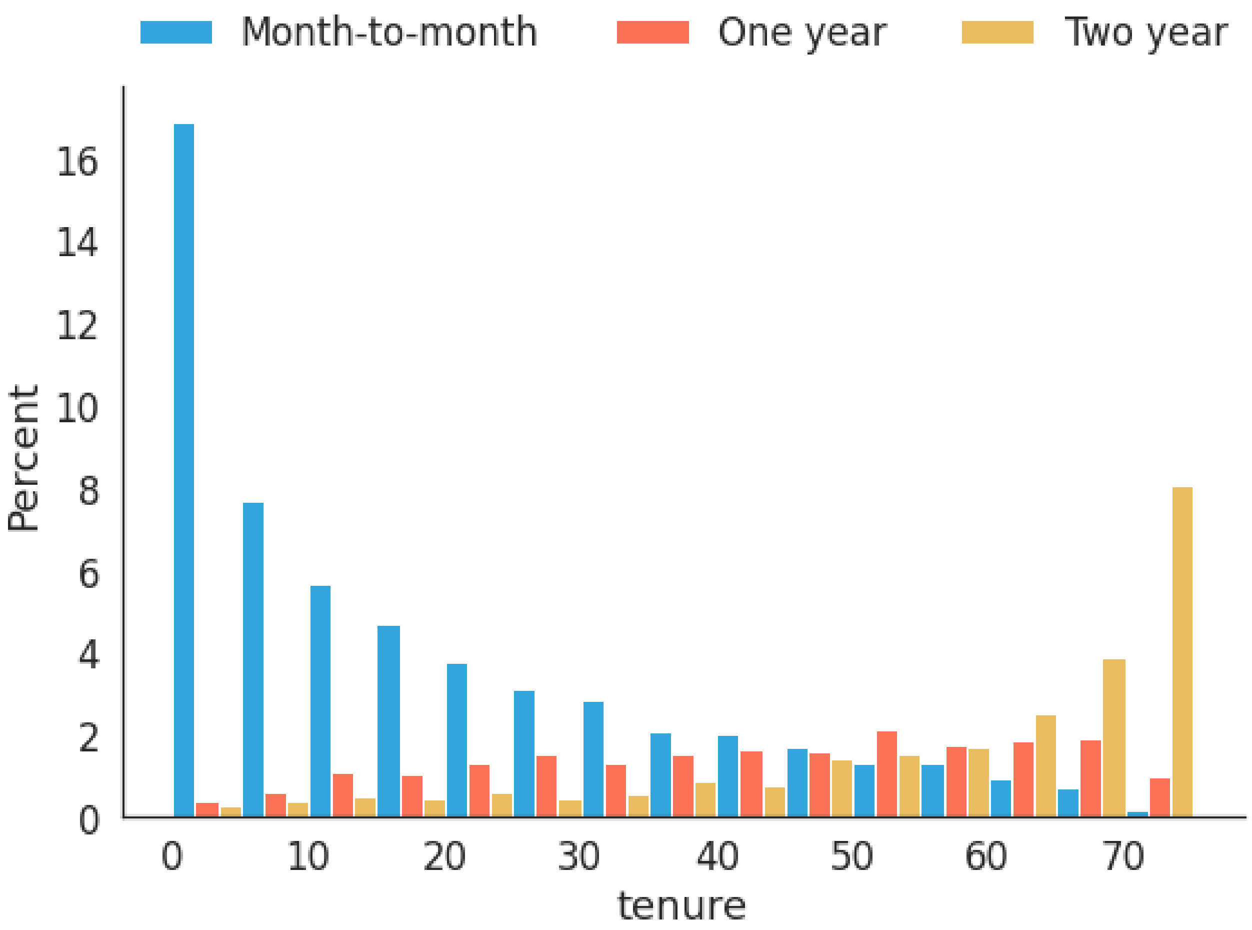
Tenure



It has a clear trend!

Negative correlation with the probability of churn

Tenure by Contract



Customers with **short tenure** are more likely to have a **month-to-month** contracts

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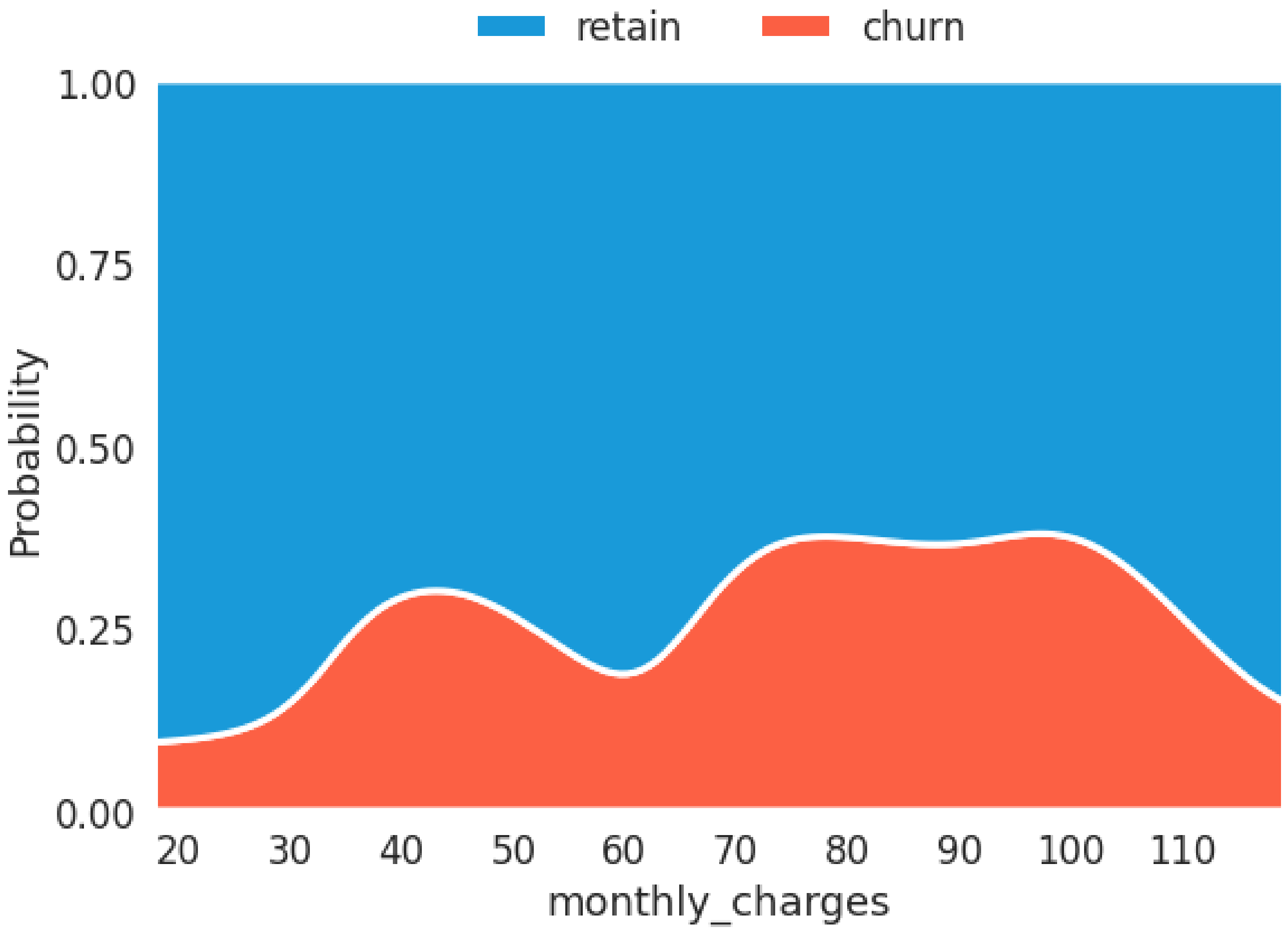
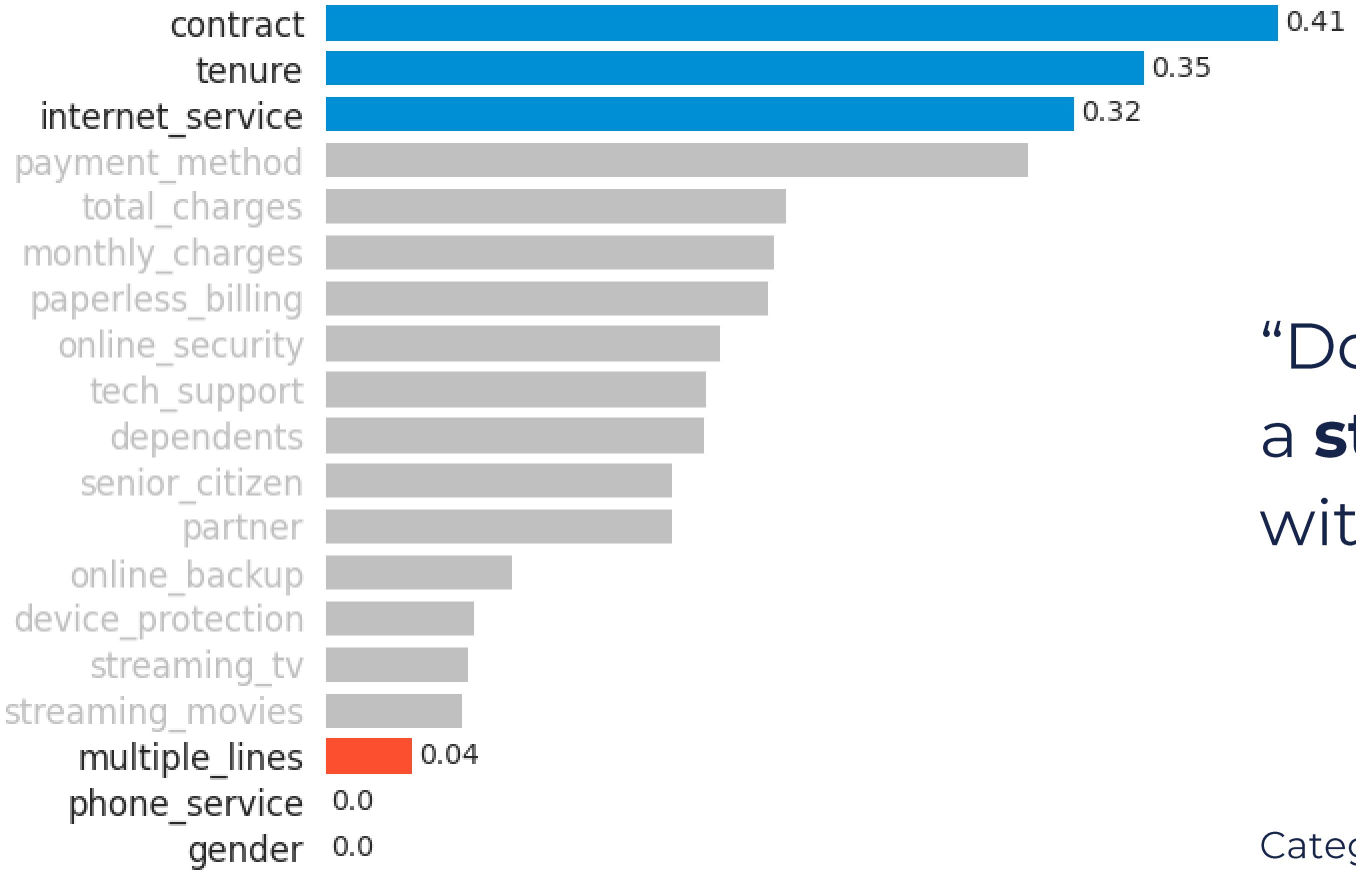
Monthly Charges



It has no clear trend

Attribute Associations to Churn Status



“Does this attribute have a **strong relationship** with churn status?”

Categorical-categorical : Cramer’s V
Categorical-numerical : Correlation ratio

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DATA PREPROCESSING

Missing Values

	tenure	total_charges	churn
488	0		No
753	0		No
936	0		No
1082	0		No
1340	0		No
3331	0		No
3826	0		No
4380	0		No
5218	0		No
6670	0		No
6754	0		No

	tenure	total_charges	churn
488	0	0	No
753	0	0	No
936	0	0	No
1082	0	0	No
1340	0	0	No
3331	0	0	No
3826	0	0	No
4380	0	0	No
5218	0	0	No
6670	0	0	No
6754	0	0	No

Redundant Values

Attribute	Data variation
multiple_lines	No, Yes, **No phone service**
online_security	No, Yes, **No internet service**
online_backup	No, Yes, **No internet service**
device_protection	No, Yes, **No internet service**
tech_support	No, Yes, **No internet service**
streaming_tv	No, Yes, **No internet service**
streaming_movies	No, Yes, **No internet service**

→

Attribute	Data variation
multiple_lines	No, Yes
online_security	No, Yes
online_backup	No, Yes
device_protection	No, Yes
tech_support	No, Yes
streaming_tv	No, Yes
streaming_movies	No, Yes

Replace to "No"

Avoiding multicollinearities & reducing the dimension

Train – Test Split

Train : Test

70% : 30%

	Variable	Shape
Original	X	(7043, 19)
	Y	(7043,)
Train set	X_train	(4930, 19)
	y_train	(4930,)
Test set	X_test	(2113, 19)
	y_test	(2113,)

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Feature Encoding

		6427	6971	96	5640
input	internet_service	No	Fiber optic	DSL	Fiber optic
output	churn	No	Yes	No	Yes

LabelEncoder for target variable
OneHotEncoder for input variables

		6427	6971	96	5640
input	internet_service_dsl	0.0	0.0	1.0	0.0
input	internet_service_fiber_optic	0.0	1.0	0.0	1.0
input	internet_service_no	1.0	0.0	0.0	0.0
output	churn	0.0	1.0	0.0	1.0

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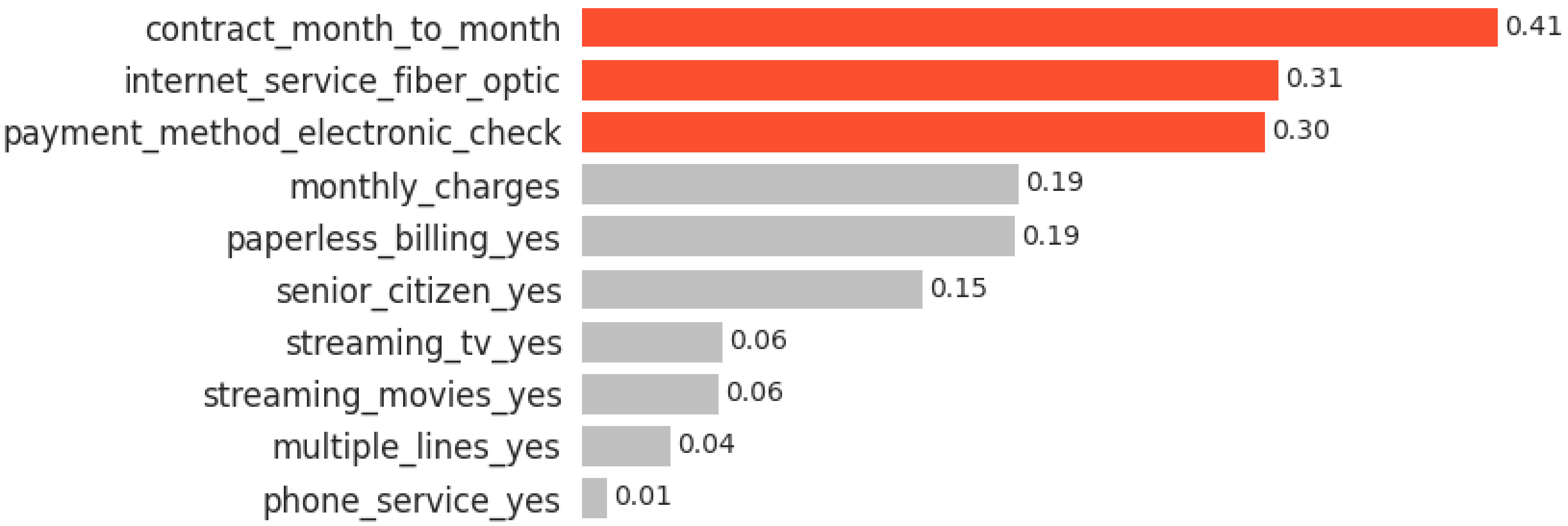
Positive Correlation to Churn Status



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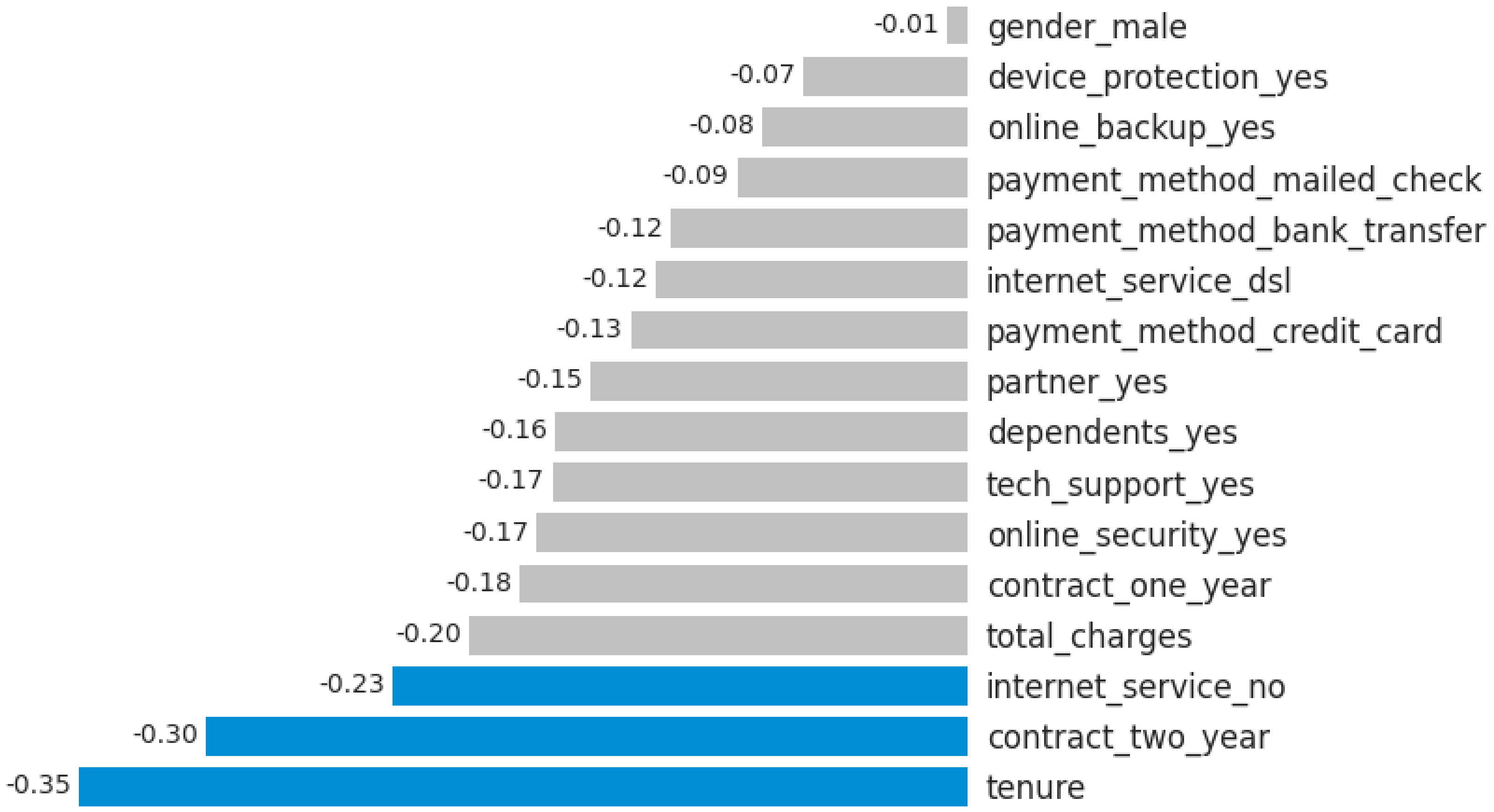
Negative Correlation to Churn Status



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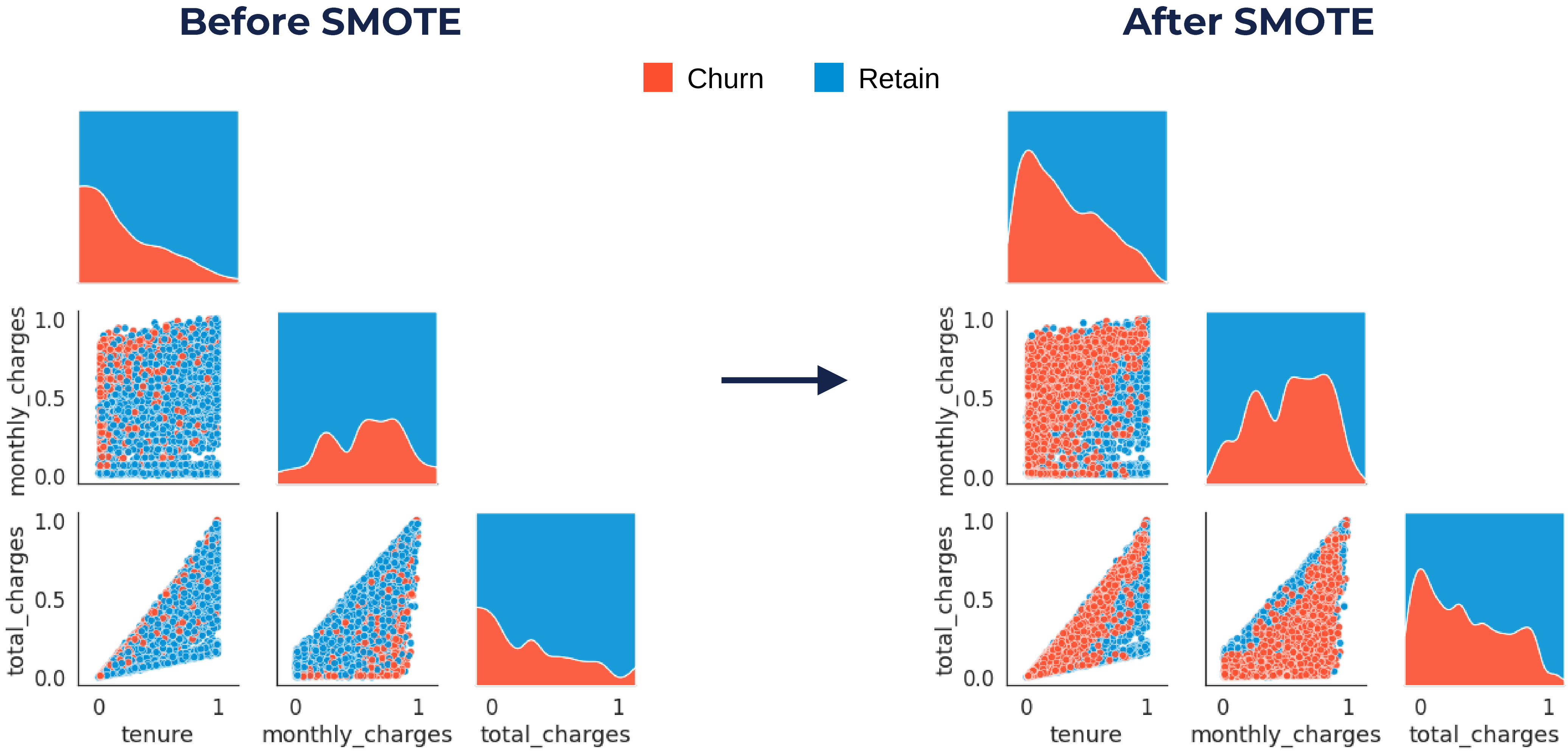
Feature Scaling

	6427	6971	96	5640
tenure	41.00	18.00	71.00	1.0
monthly_charges	20.15	99.75	66.85	79.6
total_charges	802.35	1836.25	4748.70	79.6

MinMaxScaler (range 0-1)

	6427	6971	96	5640
tenure	0.57	0.25	0.99	0.01
monthly_charges	0.02	0.81	0.48	0.61
total_charges	0.09	0.21	0.55	0.01

Oversampling with SMOTE



05

MODEL DEVELOPMENT

Model List

Logistic Regression
Ridge Classifier
KNN
SVC
Neural Network
Decision Tree
Random Forest
Gradient Boosting Classifier
AdaBoost Classifier
CatBoost Classifier
Histogram Gradient Boosting
XGBoost
LightGBM

SMOTE vs ADASYN

The average metrics of all models using default parameter

	SMOTE	ADASYN
Accuracy	0.760	0.752
Precision	0.707	0.704
Recall	0.732	0.731
F1 Score	0.713	0.707
ROC AUC	0.732	0.731

high

low

Note:
Precision, recall, F1 score, and ROC AUC score are calculated using **macro average**

SMOTE has a higher performance than ADASYN,
So, for the next step, I will **only use SMOTE** for simplicity reason

Metrics using Default Parameter

	Accuracy	Precision	Recall	F1 Score	ROC AUC
Logistic Regression	0.747	0.707	0.755	0.714	0.755
Ridge Classifier	0.744	0.707	0.756	0.713	0.756
KNN	0.696	0.660	0.699	0.661	0.699
SVC	0.765	0.713	0.747	0.724	0.747
Neural Network	0.752	0.686	0.696	0.690	0.696
Decision Tree	0.731	0.666	0.682	0.672	0.682
Random Forest	0.771	0.708	0.714	0.711	0.714
Gradient Boosting Classifier	0.788	0.734	0.763	0.744	0.763
AdaBoost Classifier	0.755	0.712	0.756	0.720	0.756
CatBoost Classifier	0.786	0.725	0.728	0.727	0.728
Hist Gradient Boosting	0.780	0.719	0.722	0.721	0.722
XGBoost	0.784	0.731	0.762	0.741	0.762
LightGBM	0.785	0.725	0.732	0.728	0.732

high

low

Note:
Precision, recall, F1 score, and ROC AUC score are calculated using **macro average**

Overall, **boosting methods** show a good performance

Can we improve it?

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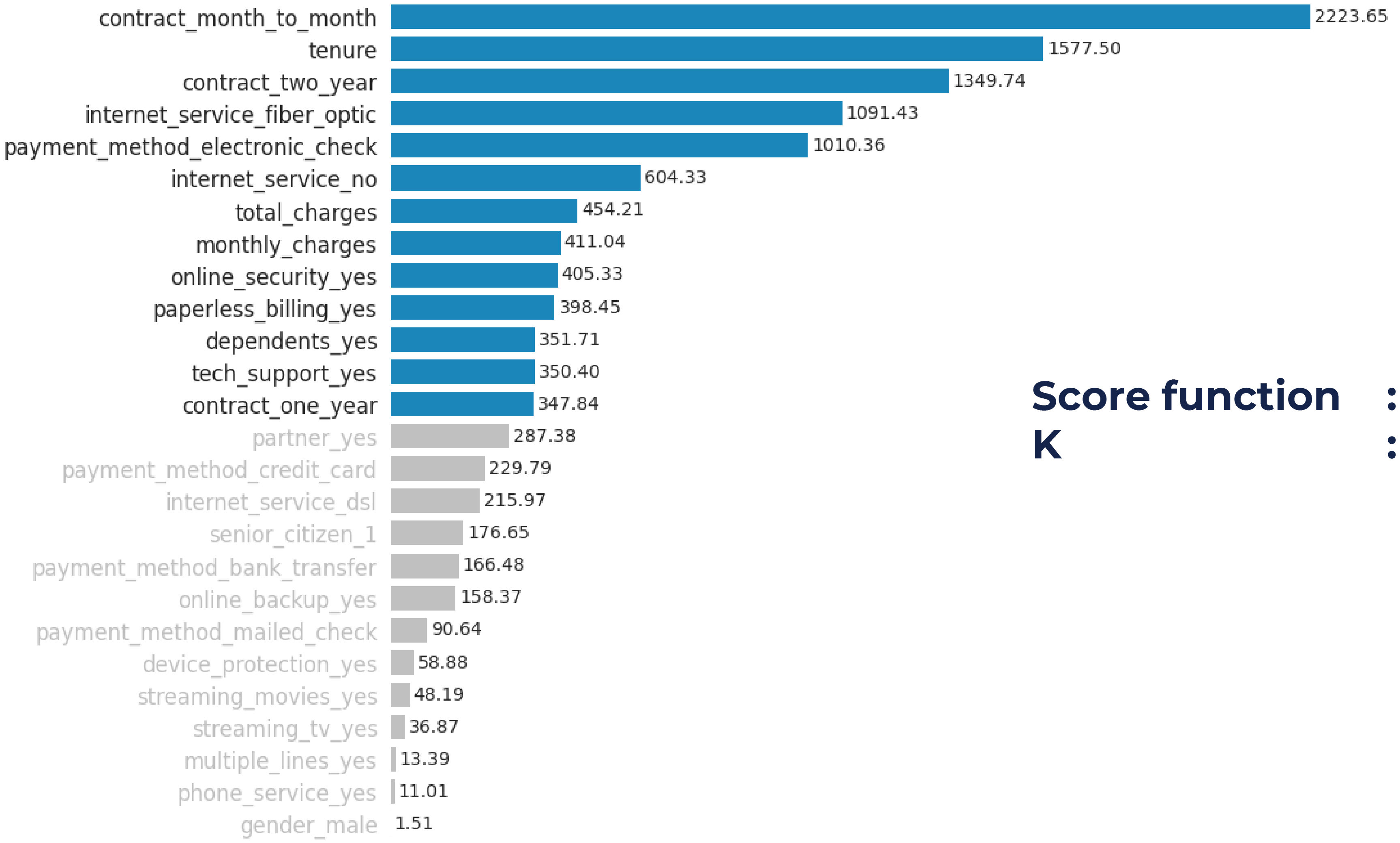
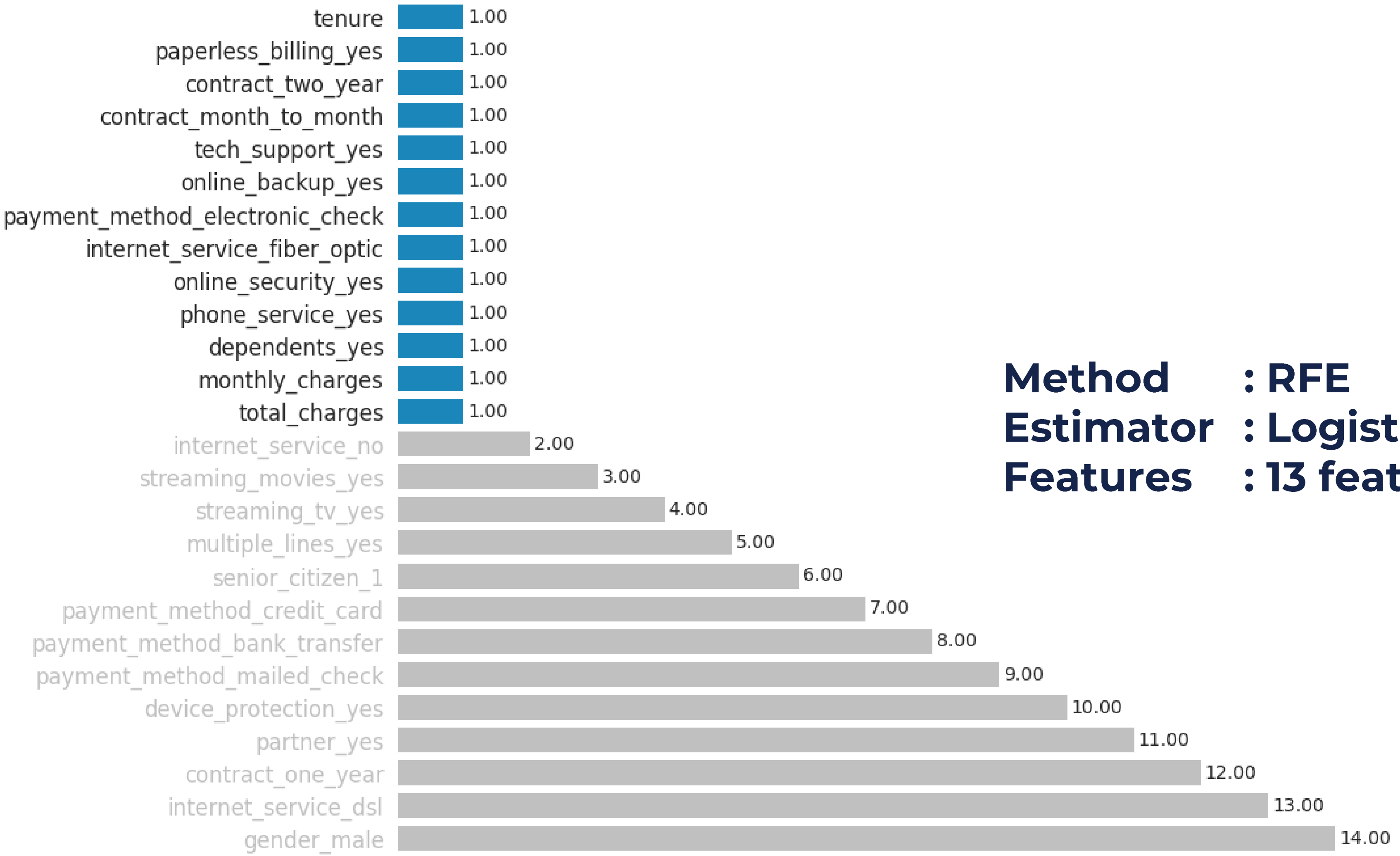
Feature Selection – Filter Method



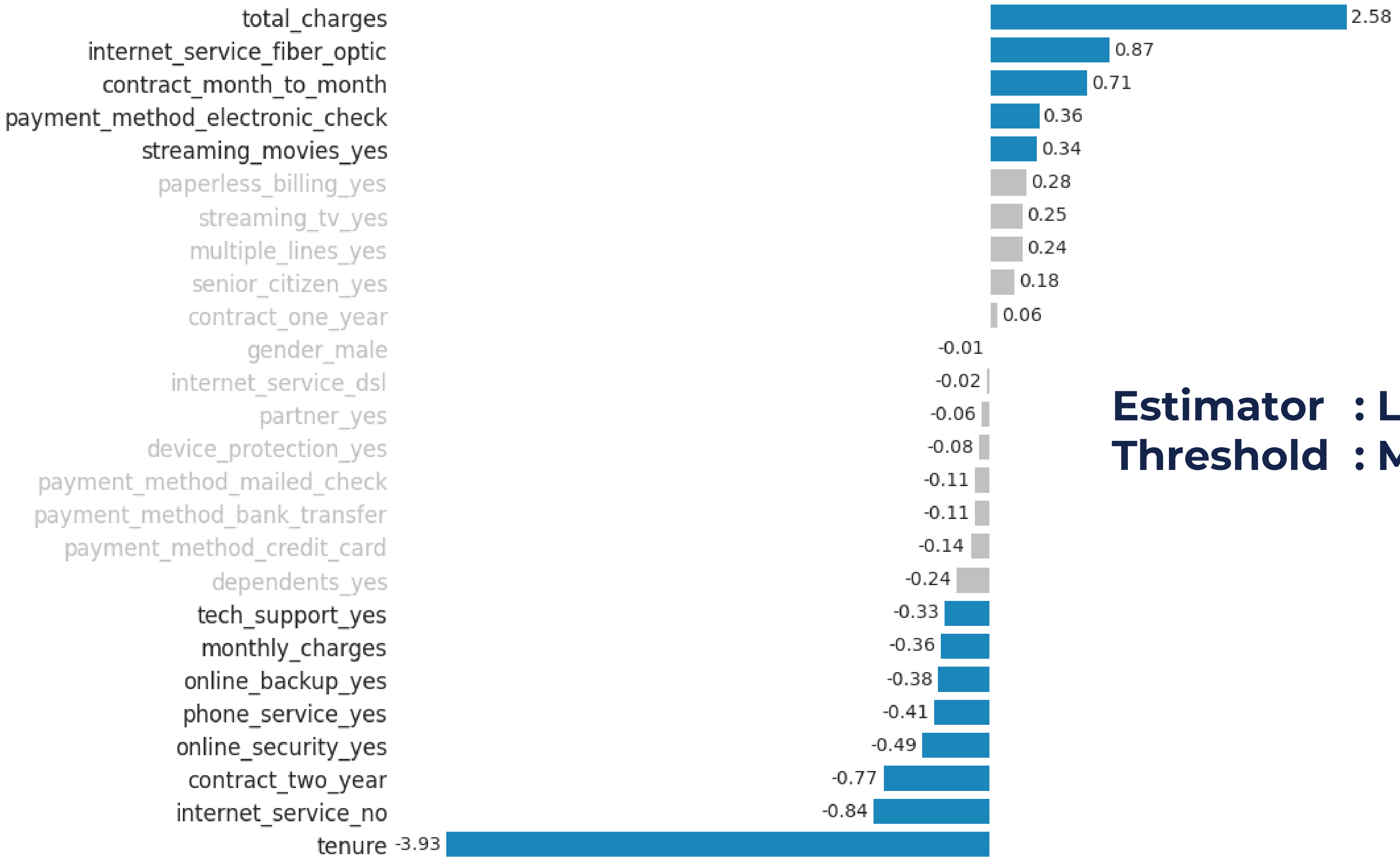
Score function : ANOVA
K : 13 features

Feature Selection – Wrapper Method



Method : RFE
Estimator : Logistic Regression
Features : 13 features

Feature Selection – Embedded Method



Estimator : Logistic Regression
Threshold : Median

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Feature Selection Comparison

The average metrics of boosting models using default parameter

	Accuracy	Precision	Recall	F1 Score	ROC AUC
Without Feature Selection	0.780	0.724	0.744	0.730	0.744
Filter Method	0.773	0.722	0.753	0.731	0.753
Wrapper Method	0.775	0.722	0.751	0.731	0.751
Embedded Method	0.766	0.714	0.746	0.723	0.746

high

low

In general, the **filter method** shows the best result
Moreover, it has the **highest recall** score

Note:
Precision, recall, F1 score, and ROC AUC score are calculated using **macro average**

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Hyperparameter Tuning Strategy

Adaboost classifier without feature selection

Default Parameter

	precision	recall	f1-score
0	0.896	0.753	0.819
1	0.527	0.759	0.622
macro avg	0.712	0.756	0.720
weighted avg	0.798	0.755	0.766
accuracy			0.755
roc auc			0.756

Tuning 1

	precision	recall	f1-score
0	0.872	0.841	0.856
1	0.600	0.660	0.628
macro avg	0.736	0.750	0.742
weighted avg	0.800	0.793	0.796
accuracy			0.793
roc auc			0.750

Tuning 2

	precision	recall	f1-score
0	0.902	0.758	0.824
1	0.536	0.772	0.633
macro avg	0.719	0.765	0.728
weighted avg	0.805	0.762	0.773
accuracy			0.762
roc auc			0.765

I choose the second tuning because it has a higher positive recall than the first tuning

The hyperparameter tuning strategy is focused on
Maximizing the **recall** score of the **positive class** (churn), not the average
But still paying attention to the **accuracy** score

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Metrics after Tuning

Without Feature Selection

	Accuracy		Recall (Positive)	
	Before	After	Before	After
Gradient Boosting Classifier	0.788	0.783	0.709	0.742
AdaBoost Classifier	0.755	0.762	0.759	0.772
CatBoost Classifier	0.786	0.772	0.606	0.740
Hist Gradient Boosting	0.780	0.763	0.599	0.774
XGBoost	0.784	0.772	0.715	0.763
LightGBM	0.785	0.760	0.619	0.783

high

low

After tuning, the accuracy score is mostly decreased
But, the recall score has increased dramatically

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Metrics after Tuning

With feature selection

	Accuracy		Recall (Positive)	
	Ori	Tuned	Ori	Tuned
Gradient Boosting Classifier	0.772	0.775	0.725	0.766
AdaBoost Classifier	0.755	0.759	0.777	0.783
CatBoost Classifier	0.788	0.761	0.677	0.765
Hist Gradient Boosting	0.773	0.756	0.668	0.781
XGBoost	0.774	0.761	0.752	0.779
LightGBM	0.777	0.762	0.663	0.791

high

low

After tuning, the accuracy score is mostly decreased
But, the recall score has increased dramatically

Model Selection

Using **harmonic mean** of the accuracy and recall scores

$$F_\beta = (1+\beta^2)\frac{(accuracy\ * recall)}{\beta^2 * accuracy + recall}$$

	Without feature selection			With feature selection		
	Accuracy	Recall (Positive)	F-beta	Accuracy	Recall (Positive)	F-beta
Gradient Boosting Classifier	0.783	0.742	0.762	0.775	0.766	0.770
AdaBoost Classifier	0.762	0.772	0.767	0.759	0.783	0.771
CatBoost Classifier	0.772	0.740	0.756	0.761	0.765	0.763
Hist Gradient Boosting	0.763	0.774	0.768	0.756	0.781	0.768
XGBoost	0.772	0.763	0.767	0.761	0.779	0.770
LightGBM	0.760	0.783	0.771	0.762	0.791	0.776

Conclusion

Final Model

- LightGBM with feature selection using filter method

Recommendation and Request

- We should **pay more attention** to customers who meet the criteria below
  - Contract : Month-to-month
  - Tenure : Short tenure
  - Internet service : Fiber optic
  - Payment method : Electronic check

- Please, **evaluate our service!**
  Especially for internet service (fiber optic) and payment method (electronic check)

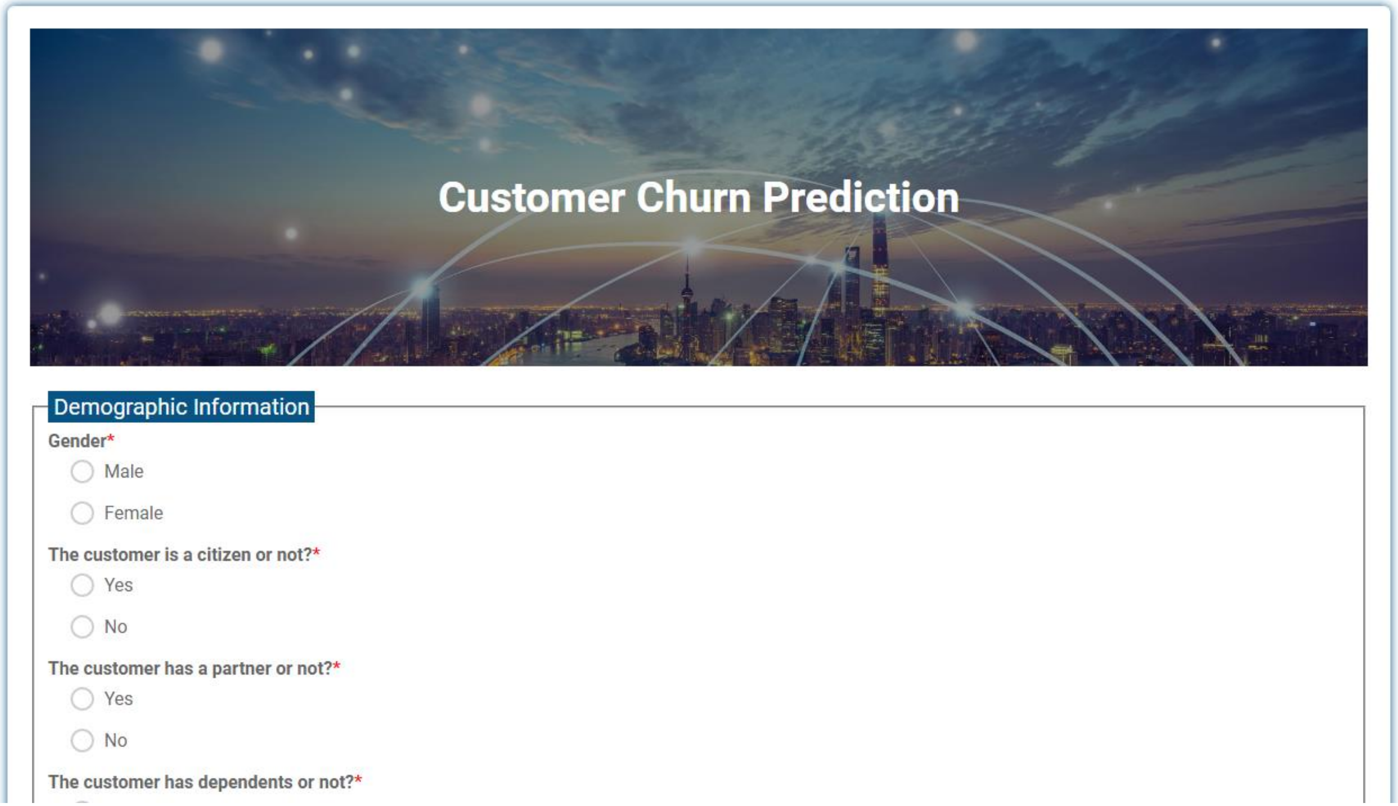
- Can we **give more benefit** to a new customer?
  Because the new customer has a high probability to churn

06

BONUS!

Last but not least

Model Deployment



Model deployment using **Flask** and **Heroku**

https://adhang-churn.herokuapp.com/

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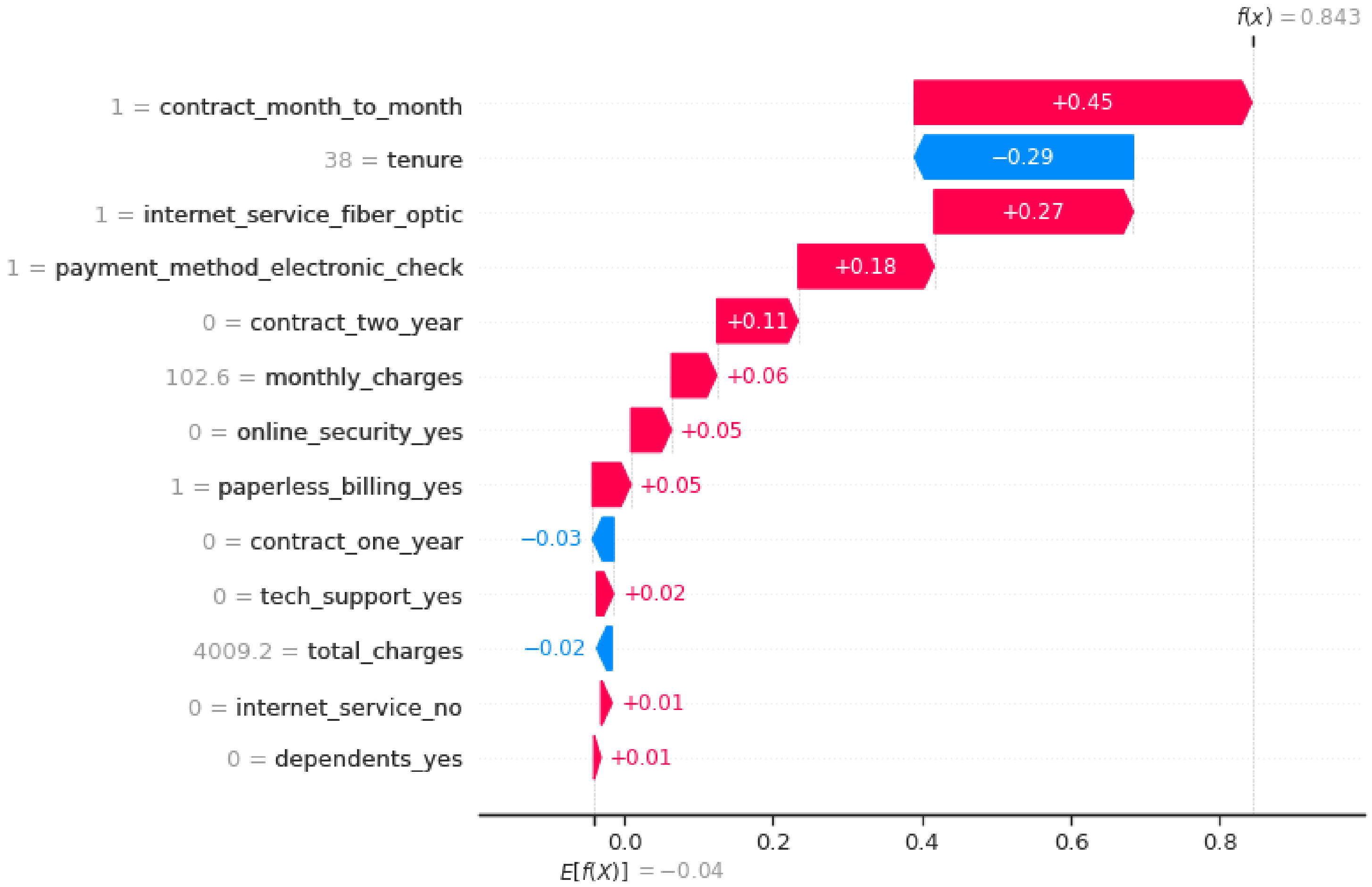
SHAP Explainable AI



SHAP (SHapley Additive exPlanations) is a game theoretic approach to explain the output of any machine learning model.

I have included it on my Heroku app

THANKS

Adhang Muntaha Muhammad