TELCO CHURN PREDICTION MODEL

A Model for Predicting Customer Retention in Telecom

Peerapat.t

For project's material please visit : github.com/peerapat-t

TELCO CHURN PREDICTION MODEL

Problem context
- Retaining existing customers is usually cheaper than acquiring new ones.
- A Bain & Company study found it can be 5 to 7 times more expensive to get new customers.
- Existing customers are often more loyal and likely to continue their relationship with your business.

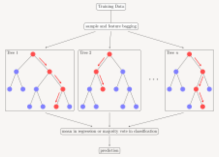
Challenges
- Imbalanced dataset
- Metrics for measurement
- Threshold selection

Tools

python

pandas

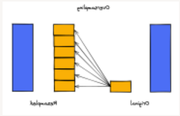
Methods



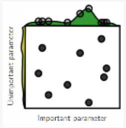
Random forest

LightGBM

XGBoost



Resampling



Randomized search

SHAP

Business impact

The model improved revenue by 164.24% compared to the 'do nothing' program and by 44.51% compared to the 'retain all' program.

TABLE OF CONTENT

1. PROBLEM STATEMENT

- The cost of retaining a customer is typically much lower than the cost of acquiring a new customer.
- For example, a study by Bain & Company found that it costs 5 to 7 times more to acquire a new customer than it does to retain an existing customer.
- This is because existing customers are already familiar with your product or services and they are more likely to continue doing business with you.

2. BUSINESS VALUE

- A churn prediction model in a telco company provides substantial business value by forecasting which customers are likely to leave the service.
- This predictive capability allows the company to take proactive measures to retain customers, such as offering personalized incentives or addressing their concerns.
- By reducing churn, the company can achieve cost savings associated with customer acquisition, preserve existing revenue streams, and enhance overall customer satisfaction.

3. METHODOLOGY

Do nothing

- Business not take any action to retain customers.

Retain all customers

- Business take action to retain every customer.

Use a churn prediction model

- Business use churn prediction model to predict the probability of churning and use this score to decide whether a customer will churn.
- Churn prediction can help businesses identify customers who are at risk of leaving.
- This allows businesses to take action to retain those customers, such as offering them discounts or special promotions.

Option	Cost	Effectiveness
Do nothing	Least expensive	Least effective
Retain all customers	Most expensive	Most effective
Use a churn prediction model	More cost-effective than retaining all customers	More effective than doing nothing

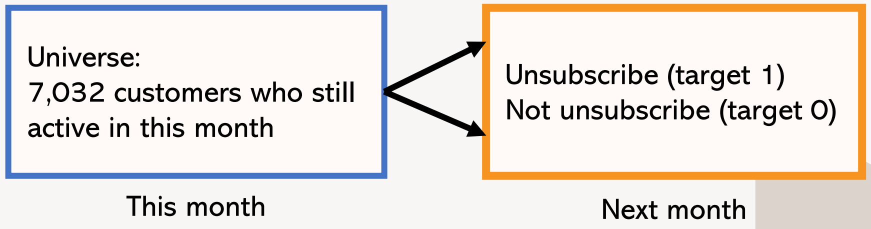
3. METHODOLOGY

Target

- There are 7,043 customers in the dataset, including churn and not-churn customers.
- Churn customers are those who have unsubscribed within the last month.

Features

- The dataset contains 22 features, which can be categorized into 3 groups:
  1. Services that each customer has signed up for: This includes phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies.
  2. Customer account information: This includes how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges.
  3. Demographic info about customers: This includes gender, age range, and if they have partners and dependents.



4. RESULT

Model result

Method	Total (Test)	Actual churn	Overspend (FP)	Save (TP)	Gains (or Loss)
Do nothing	1,409	373	0	0	-186,500
Retain all	1,409	373	1,036	373	82,900
Churn prediction model	1,409	373	253	302	119,800

* These calculations are based on the assumption that the cost of promotion is 100, the cost of loss is 500, and the savings per customer is 500.

- Utilizing data from the test set involving approximately 1,409 customers, the churn prediction model yielded a gain of 164.24% when compared to the 'do nothing' program, and 44.51% when compared to the 'retain all' program.

4. RESULT

Feature importance

Rank	Features	Sign	Meaning
1	Contract	+	Customers on contract or top-up plans are more likely to churn, possibly due to the ease of changing numbers for top-up customers.
2	Tenure	+	Long-time customers have a higher churn probability, potentially due to elderly individuals reducing phone usage to cut expenses.
3	Monthly charges	-	Customers paying lower charges are more likely to churn, influenced by industry trends towards appealing, low-priced packages from other operators.
4	Internet service	-	Customers without internet in their package are at a higher churn risk, as competitors offer inclusive internet services, reflecting its growing importance.
5	Payment method (electronic check)	-	Non-users of electronic payment for bills are more likely to churn, possibly due to the inconvenience of payment, prompting a switch to other providers.

5. CONCLUSIONS/RECOMMENDATIONS

Conclusion

- The churn prediction model, based on the analysis of a test set comprising around 1,409 customers, has demonstrated its effectiveness in reducing customer churn significantly.
- When compared to the 'do nothing' program, which involves no proactive retention efforts, the model achieved a remarkable gain of 164.24%. Additionally, in comparison to the 'retain all' program, which indiscriminately attempts to retain all customers, the model still outperformed with a gain of 44.51%. These results underscore the value of predictive modeling in identifying and mitigating customer churn.

Recommendation

- Implement the churn prediction model as a core part of your customer retention strategy to identify at-risk customers.
- Develop personalized retention strategies based on the model's insights to optimize resource allocation.
- Regularly monitor and improve the churn prediction model to ensure its accuracy and effectiveness over time.

6. FUTURE WORK

- Improve model performance by creating more features and performing feature engineering.
- Experiment with different machine learning models, such as SVC and deep learning.
- Tune hyperparameters using sequential search techniques, such as Optuna.
- Segment customers using clustering and retain them with personalized promotions.

END OF PRESENTATION

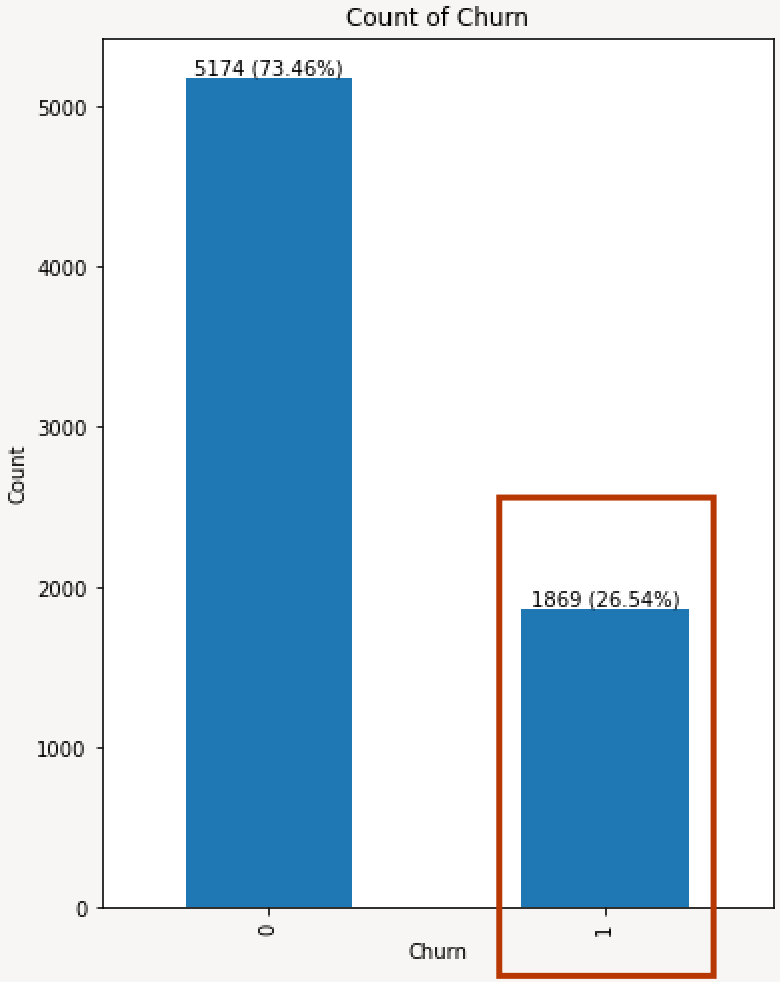
7. APPENDIX

Technique

Step	Topic	Cost
1	Dataset	• Split the data into train, test, and validation sets. • Use the train set to train the model, the validation set to tune the threshold, and the test set to evaluate the model.
2	Normalized	• Use Min-Max scaling to normalize the data.
3	Resampling	• Try oversampling (SMOTE, ANASYN) and undersampling (Random undersampling).
4	Model	• Try random forest, LightGBM, and XGBoost.
5	Hyperparameter tuning	• Use RandomizedCV to find the best hyperparameters for each model.
6	Threshold tuning	• Use cost-sensitive learning to tune the threshold. • Assign a cost of 5 times more to acquiring new customers than to retaining existing customers.
7	Interpreting	• Use SHAP values.

7. APPENDIX

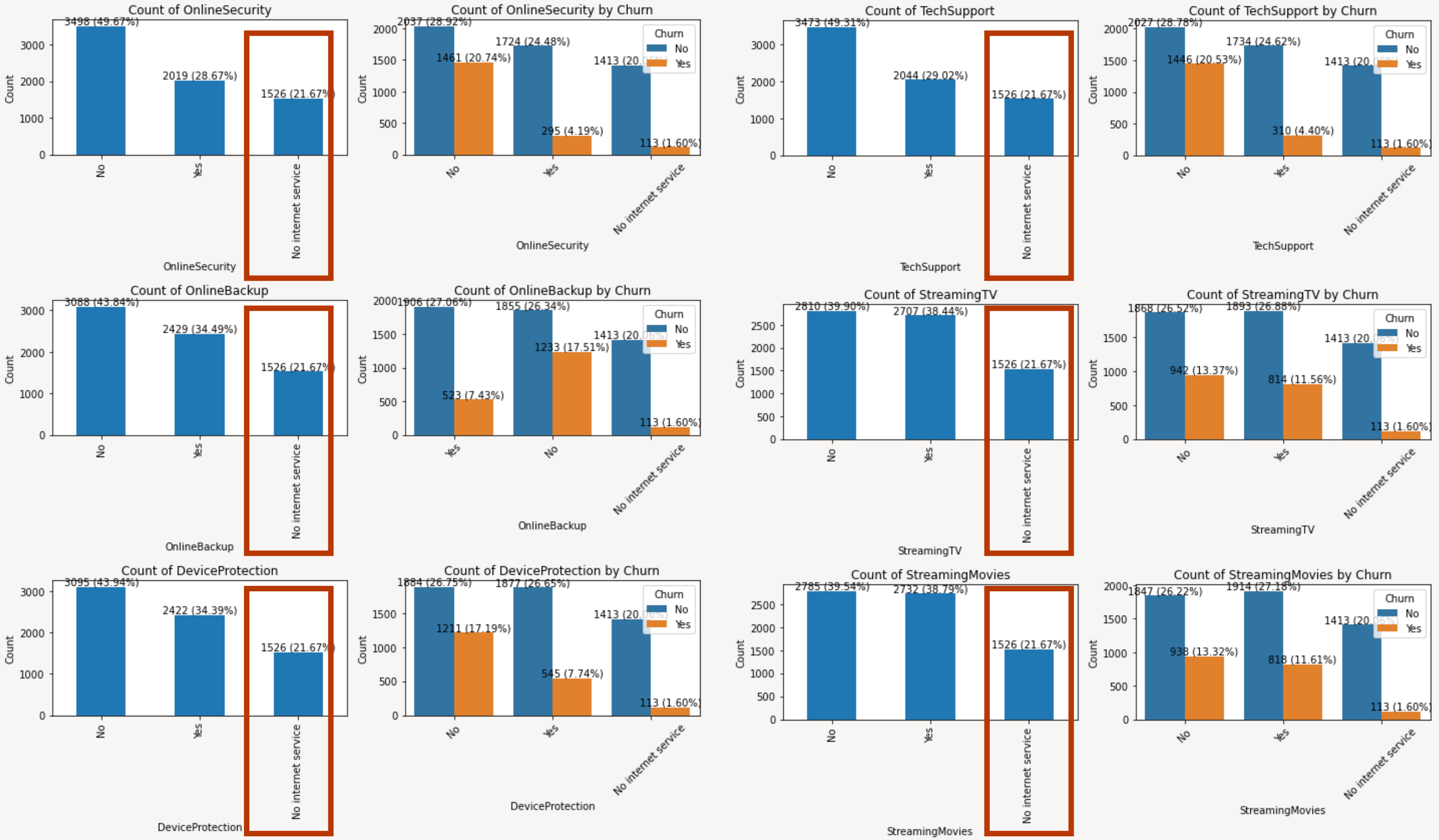
Exploratory data analysis (EDA)



- If we look at the target distribution, There are only 27% of churn customers that the data is imbalanced.
- Resampling method or threshold tuning should be applied to handle this problem.
- Metrics like accuracy can be misleading and ineffective. Instead, it is essential to explore alternative evaluation measures, such as precision, recall, F1-score, or AUC-ROC.

7. APPENDIX

Exploratory data analysis (EDA)



- The phrase "No internet service" appears in 6 variables, all with the same frequency of 1,526.

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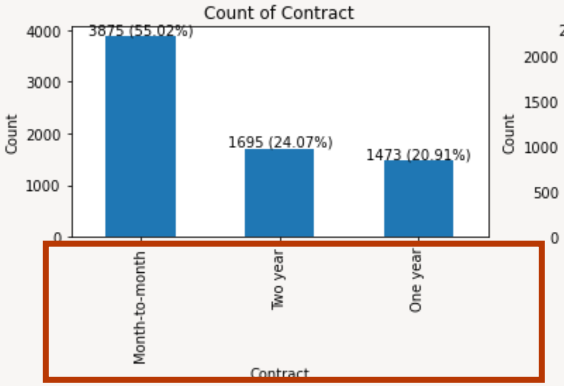
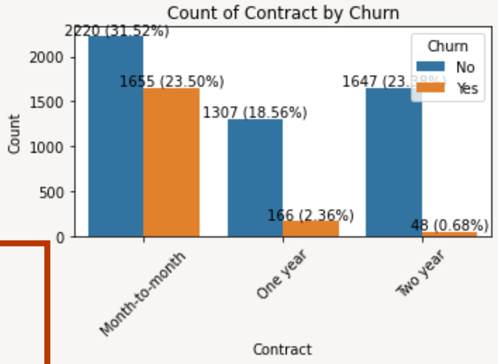
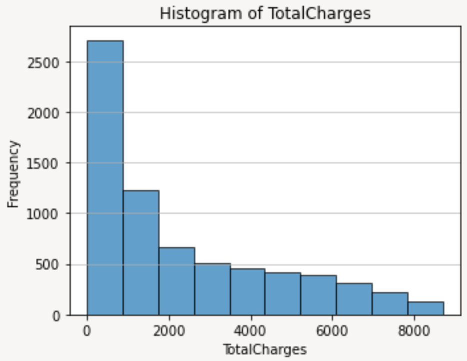
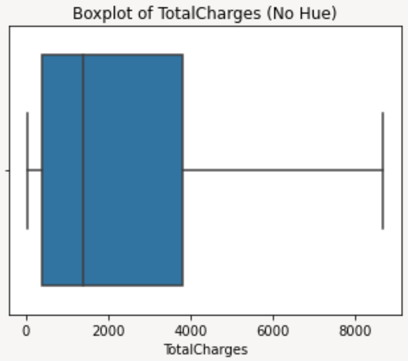


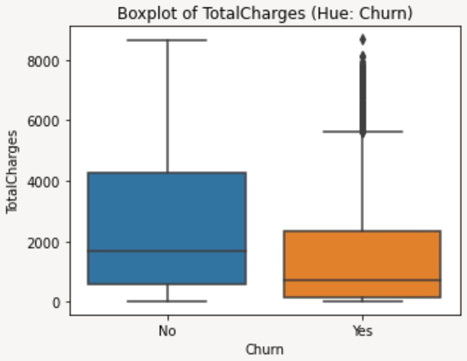


0, 1, 2

- Can represent the "Contract" variable as an ordinal variable with values 0, 1, and 2.







- The distribution of 'TotalCharges' is right-skewed. Use the median to replace missing values instead of the mean.

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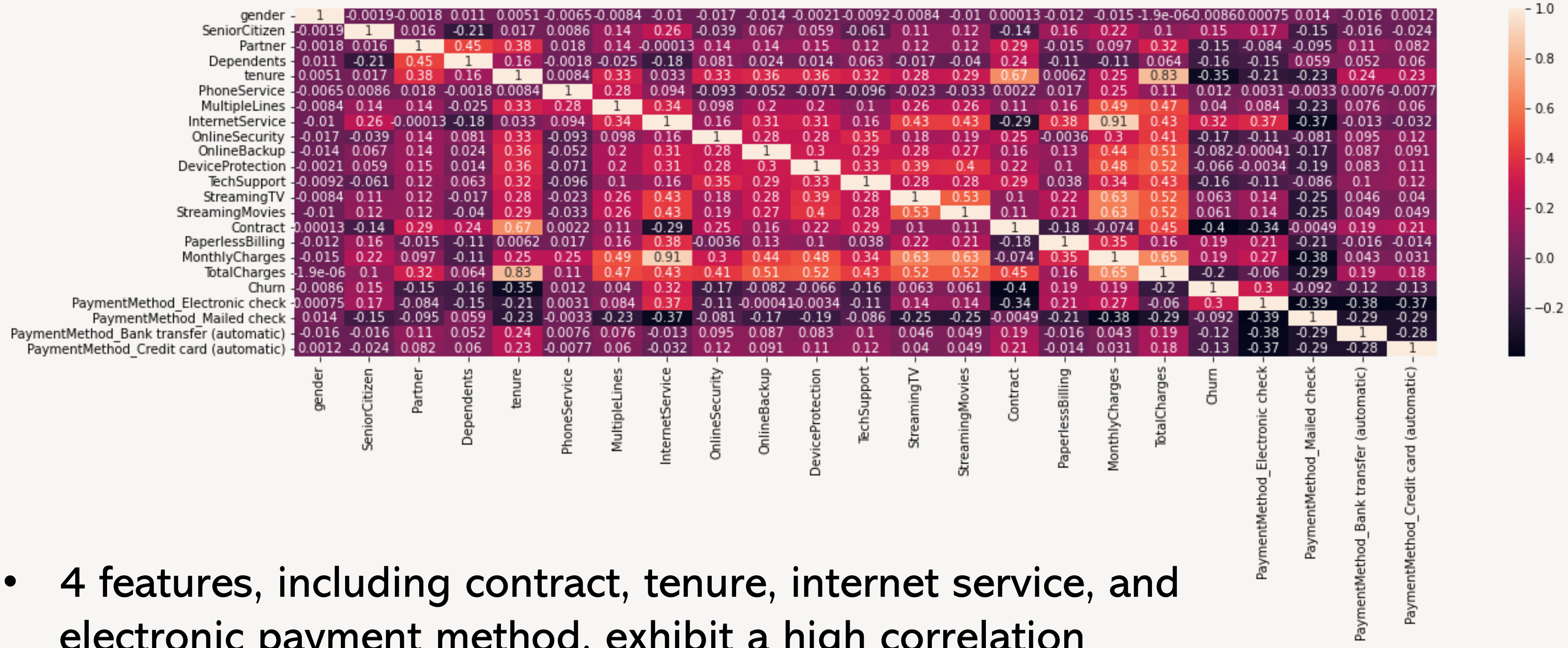


```
Churn                                      1.000000
Contract                                   0.396713
tenure                                     0.352229
InternetService                            0.316846
PaymentMethod_Electronic check             0.301919
TotalCharges                               0.199037
MonthlyCharges                             0.193356
PaperlessBilling                           0.191825
OnlineSecurity                             0.171226
TechSupport                                0.164674
Dependents                                 0.164221
SeniorCitizen                              0.150889
Partner                                    0.150448
PaymentMethod_Credit card (automatic)      0.134302
PaymentMethod_Bank transfer (automatic)    0.117937
PaymentMethod_Mailed check                 0.091683
OnlineBackup                               0.082255
DeviceProtection                           0.066160
StreamingTV                                0.063228
StreamingMovies                            0.061382
MultipleLines                              0.040102
PhoneService                               0.011942
gender                                     0.008612
Name: Churn, dtype: float64
```

- 4 features, including contract, tenure, internet service, and electronic payment method, exhibit a high correlation (greater than 0.3 in absolute terms) with the target variable.

7. APPENDIX

Model evaluation

	Model	Observation	TP	TN	FP	FN	Precision	Recall	AUCROC
0	Dummy Model (All Churn)	1409	373	0	1036	0	0.264727	1.000000	0.500000
1	Dummy Model (All Not Churn)	1409	0	1036	0	373	NaN	0.000000	0.500000
2	Random Forest (SMOTE)	1409	212	901	135	161	0.610951	0.568365	0.839842
3	LightGBM (SMOTE)	1409	216	888	148	157	0.593407	0.579088	0.838736
4	XGBoost (SMOTE)	1409	253	885	151	120	0.626238	0.678284	0.857387
5	Random Forest (ADASYN)	1409	208	894	142	165	0.594286	0.557641	0.835892
6	LightGBM (ADASYN)	1409	217	895	141	156	0.606145	0.581769	0.840977
7	XGBoost (ADASYN)	1409	245	880	156	128	0.610973	0.656836	0.855058
8	Random Forest (RUS)	1409	302	783	253	71	0.544144	0.809651	0.861091
9	LightGBM (RUS)	1409	306	764	272	67	0.529412	0.820375	0.857970
10	XGBoost (RUS)	1409	313	749	287	60	0.521667	0.839142	0.862201

	Model	Observation	TP	TN	FP	FN	Precision	Recall	AUCROC	Best Threshold	Validation Gain	Test Gain
0	Dummy Model (All Churn)	1409	373	0	1036	0	0.264727	1.000000	0.500000	0.00	70300	82900
1	Dummy Model (All Not Churn)	1409	0	1036	0	373	NaN	0.000000	0.500000	0.00	-152500	-186500
2	Random Forest (SMOTE)	1409	212	901	135	161	0.610951	0.568365	0.839842	0.05	88000	109700
3	LightGBM (SMOTE)	1409	216	888	148	157	0.593407	0.579088	0.838736	0.01	92700	115700
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6	LightGBM (ADASYN)	1409	217	895	141	156	0.606145	0.581769	0.840977	0.02	88100	111500
7	XGBoost (ADASYN)	1409	245	880	156	128	0.610973	0.656836	0.855058	0.08	97700	117700
8	Random Forest (RUS)	1409	302	783	253	71	0.544144	0.809651	0.861091	0.22	96400	119800
9	LightGBM (RUS)	1409	306	764	272	67	0.529412	0.820375	0.857970	0.16	95800	111700
10	XGBoost (RUS)	1409	313	749	287	60	0.521667	0.839142	0.862201	0.19	97300	114900

- Before performing threshold tuning, XGBoost (RUS) seems good because it has a highest AUCROC.
- However, prior to that, Random forest (RUS) is the better model as it achieves maximum gains.
- Ultimately, for the final decision, we choose Random forest (RUS) to deploy.

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Threshold selection with business

	Model	Observation	TP	TN	FP	FN	Precision	Recall	AUCROC	Best Threshold	Validation Gain	Test Gain
0	Dummy Model (All Churn)	1409	373	0	1036	0	0.264727	1.000000	0.500000	0.00	70300	82900
1	Dummy Model (All Not Churn)	1409	0	1036	0	373	NaN	0.000000	0.500000	0.00	-152500	-186500
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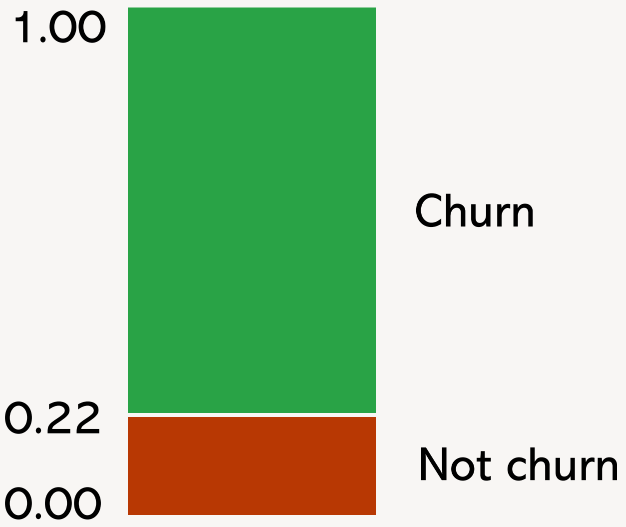

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SHAP

Features	Sign	Meaning
Contract	+	Customers on contract or top-up plans are more likely to churn, possibly due to the ease of changing numbers for top-up customers.
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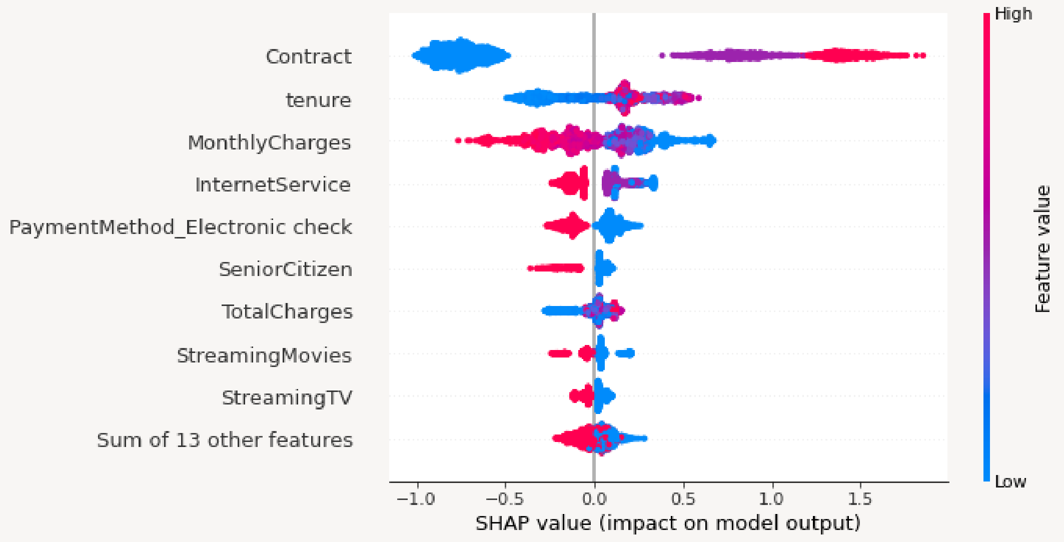
Monthly charges	-	Customers paying lower charges are more likely to churn, influenced by industry trends towards appealing, low-priced packages from other operators.
Internet service	-	Customers without internet in their package are at a higher churn risk, as competitors offer inclusive internet services, reflecting its growing importance.
Payment method (electronic check)	-	Non-users of electronic payment for bills are more likely to churn, possibly due to the inconvenience of payment, prompting a switch to other providers.



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Reference

- https://medium.com/@stephen.blount99/putting-a-price-on-customer-churn-38a184e530b8

- https://www.kaggle.com/datasets/blastchar/telco-customer-churn/data

- https://www.kaggle.com/code/bandiatindra/telecom-churn-prediction

- https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/

8. ABOUT ME

- Peerapat Tancharoen holds a Bachelor's degree in Economics from Srinakharinwirot University, graduating with first honors and a GPA of 3.67. He also earned a Master's degree in Economics from Thammasat University, achieving a GPA of 3.98.

Contact me on

- linkedin.com/in/peerapat-tancharoen-664759220/
- peerapat.tcr@gmail.com