TELCO CHURN PREDICTION MODEL

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

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1. BUSINESS PROBLEM

1.1 Cost of acquiring a new customer

- 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 service and they are more likely to continue doing business with you.

2. HOW TO SOLVE THIS PROBLEM

2.1 Do nothing

- Business not take any action to retain customers.

2.2 Retain all customers

- Business take action to retain every customer.

2.3 Use a churn prediction model

- Business use churn prediction to predicts who are at risk of churning.
- 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. DATA

3.1 Target

- There are 7,032 customers in the dataset, including churn and not-churn customers.
- Churn customers are those who have unsubscribed within the last month.

3.2 Features

- The dataset contains 22 features, which can be categorized into 3 groups:
    - 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.
- Customer account information: This includes how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges.
- Demographic info about customers: This includes gender, age range, and if they have partners and dependents.

4. SOLUTION

4.1 Churn prediction model performance

Option	Total (Test)	Actual churn	Overspend (FP)	Save (TP)	Gains (or Loss)
Do nothing	1,407	374	0	0	-187,000
Retain all	1,407	374	1,033	374	83,700
Churn prediction model	1,407	374	307	295	110,700

* 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 1,407 customers, the churn prediction model yielded a gain of 159.03% when compared to the 'do nothing' program, and 32.23% when compared to the 'retain all' program.

4. SOLUTION

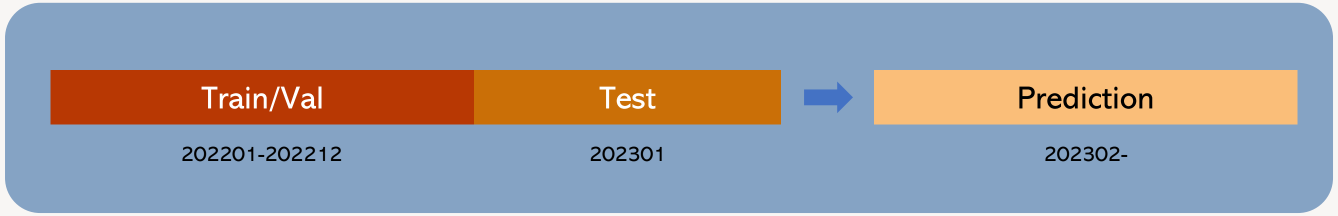
4.2 Promotion/campaign to retain customers

- **For customers who have signal of churning and using a top-up package,** we should introduce promotions to transition them to a contract package. Additionally, provide a limited-time offer like free 10GB internet for 6 months.
- **For customers who have signal of churning and they are elder,** we should offer a budget-friendly package accompanied by a message like "Stay connected with your number.
- **For customers who have signal of churning and using a low-price package,** we should be presented with a comparison of our package against competitors' offerings, followed by a strategic response.
- **For customers who have signal of churning and no current internet service,** we should introduce an affordable internet package.
- **For customers who have signal of churning and still pay bills physically,** we should encourage them to explore more convenient payment options, such as automatic credit card billing.

4. SOLUTION

4.3 Use of model in the future

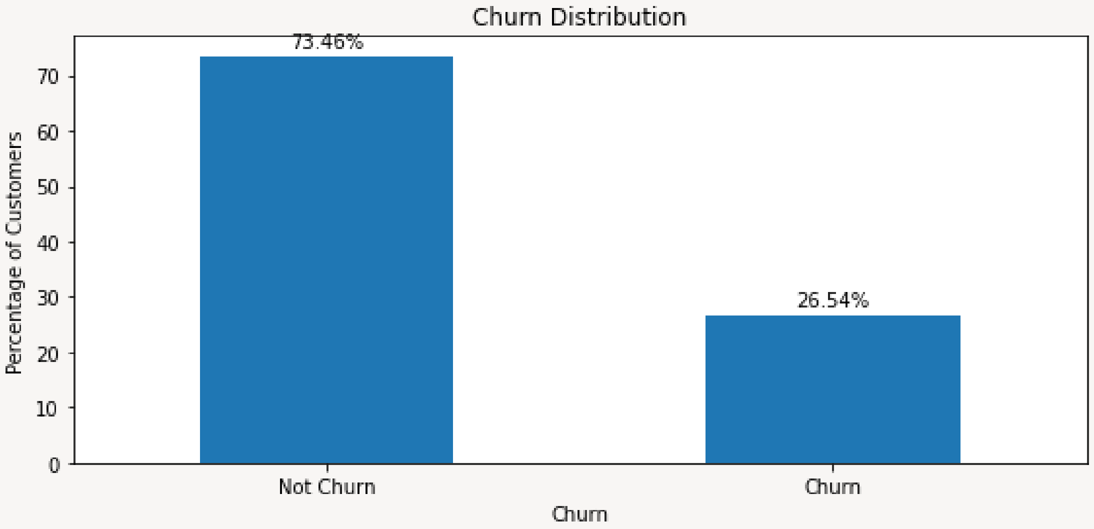
- Predict customer who are at risk to churn in the next month using the model and send leads to marketing team for retention campaign.



END OF BUSINESS SESSION

4. MODEL

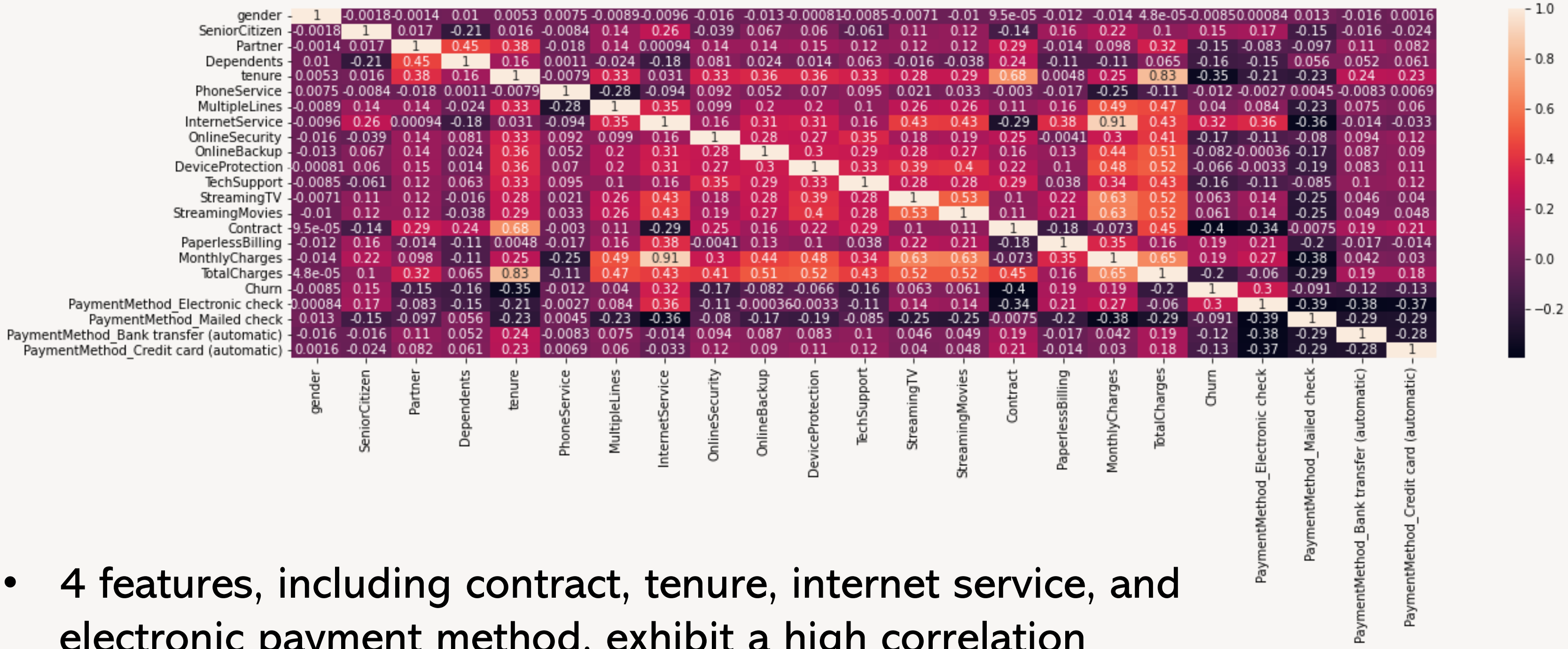
4.1 Data understanding



- 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.

4. MODEL

4.1 Data understanding (cont.)




```
Churn                                      1.000000
Contract                                   0.396150
tenure                                     0.354049
InternetService                            0.316350
PaymentMethod_Electronic check             0.301455
TotalCharges                               0.199484
MonthlyCharges                             0.192858
PaperlessBilling                           0.191454
OnlineSecurity                             0.171270
TechSupport                                0.164716
Dependents                                 0.163128
SeniorCitizen                              0.150541
Partner                                    0.149982
PaymentMethod_Credit card (automatic)      0.134687
PaymentMethod_Bank transfer (automatic)    0.118136
PaymentMethod_Mailed check                 0.090773
OnlineBackup                               0.082307
DeviceProtection                           0.066193
StreamingTV                                0.063254
StreamingMovies                            0.060860
MultipleLines                              0.040033
PhoneService                               0.011691
gender                                     0.008545
```

- 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."

4. MODEL

4.2 Technique used

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) 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.

4. MODEL

4.3 Model evaluation

	Model	Observation	TP	TN	FP	FN	Precision	Recall	AUCROC
0	Dummy Model (All Churn)	1407	374	0	1033	0	0.265814	1.000000	0.500000
1	Dummy Model (All Not Churn)	1407	0	1033	0	374	NaN	0.000000	0.500000
2	Random Forest (SMOTE)	1407	252	812	221	122	0.532770	0.673797	0.824113
3	LightGBM (SMOTE)	1407	256	808	225	118	0.532225	0.684492	0.819451
4	XGBoost (SMOTE)	1407	289	742	291	85	0.498276	0.772727	0.828354
5	Random Forest (RUS)	1407	294	729	304	80	0.491639	0.786096	0.828529
6	LightGBM (RUS)	1407	295	726	307	79	0.490033	0.788770	0.828037
7	XGBoost (RUS)	1407	306	688	345	68	0.470046	0.818182	0.826978

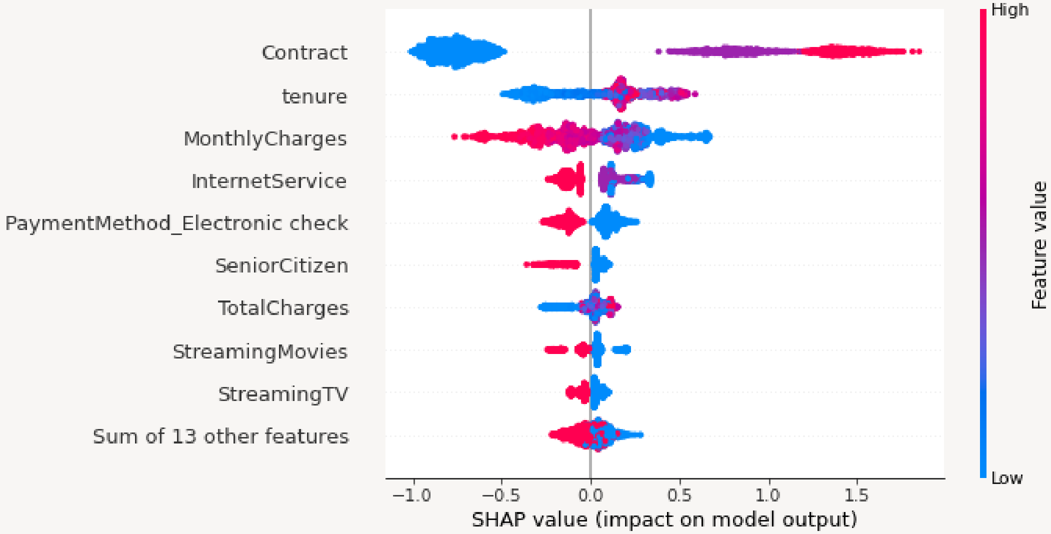
	Model	Best Threshold	Validation Gain	Test Gain
0	Dummy Model (All Churn)	0.00	69300	83700
1	Dummy Model (All Not Churn)	0.00	-151500	-187000
2	Random Forest (SMOTE)	0.18	95500	108400
3	LightGBM (SMOTE)	0.25	95900	102400
4	XGBoost (SMOTE)	0.19	97900	108000
5	Random Forest (RUS)	0.28	96500	109400
6	LightGBM (RUS)	0.25	94700	110700
7	XGBoost (RUS)	0.31	96800	108200

- Before performing threshold tuning, XGBoost (RUS) seems good because it has a high AUCROC and the highest Recall.
- However, prior to that, LightGBM (RUS) is the better model as it achieves maximum gains.
- Ultimately, for the final decision, we choose LightGBM (RUS) to deploy in our system."

4. MODEL

4.4 Feature importance (cont.)

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.
Tenure	+	Long-time customers have a higher churn probability, potentially due to elderly individuals reducing phone usage to cut expenses.
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.



5. 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

6. REFERENCE

- https://medium.com/@stephen.blount99/putting-a-price-on-customer-churn-38a184e530b8
- https://www.kaggle.com/code/bandiatindra/telecom-churn-prediction
- https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/

7. 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.

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