Telco churn prediction model

Peerapat.t, Data scientist

…@gmail.com, github.com/

Table of content

1. **Business problem**
   - Cost of acquiring a new customer
   - Why does churn prediction matter?
2. **How to solve this problem**
   - Do nothing
   - Retain all customers
   - Use a churn prediction model
3. **Data**
   - Target
   - Features
3. **Solution**
   - Churn prediction model performance
   - Promotion/campaign to retain customers
   - Use of model in the future
4. **Model**
   - Data understanding
   - Technique used
   - Model evaluation
   - Feature importance
5. **Future work**
6. **References**
7. **Author**

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.

1.2 Why does churn prediction matter?

- 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.
- Churn prediction can also help businesses to identify trends in customer behavior that may lead to churn, so that they can address those issues before they cause customers to leave.

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.

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 four 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)	Actually 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

- Utilizing churn prediction results in a cost savings of 3.38X compared to the 'do nothing' program and 0.32X compared to the 'retain all' program.
- Costs are calculated under the assumption that acquiring new customers costs 5X more than retaining existing customers."

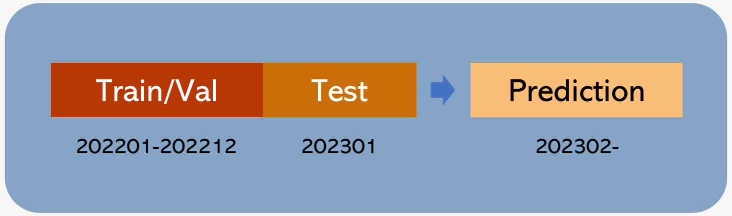
4. Solution

4.2 Promotion/campaign to retain customers

- **Rewards**: Launch a loyalty rewards program with points for every action, redeemable for discounts and upgrades.
- **Upgrade**: Limited-time offers for plan and device upgrades with special incentives.
- **Refer & Earn**: Incentivize referrals with rewards for both referrers and new customers.
- **Data Week**: Offer free data upgrades for a week to enhance connectivity.
- **Community Connect**: Engage customers in community service, rewarding them with discounts and donations.

4.3 Use of model in the future

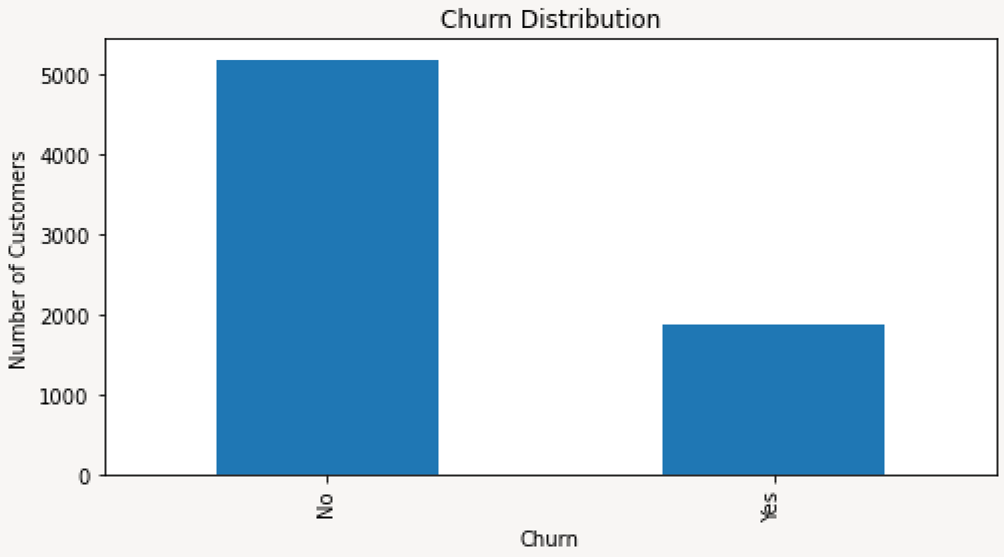
- Predict customer who are at risk to churn in the next month using the model and send leads to marketing team for retention campaign.



End of business session

4. Model

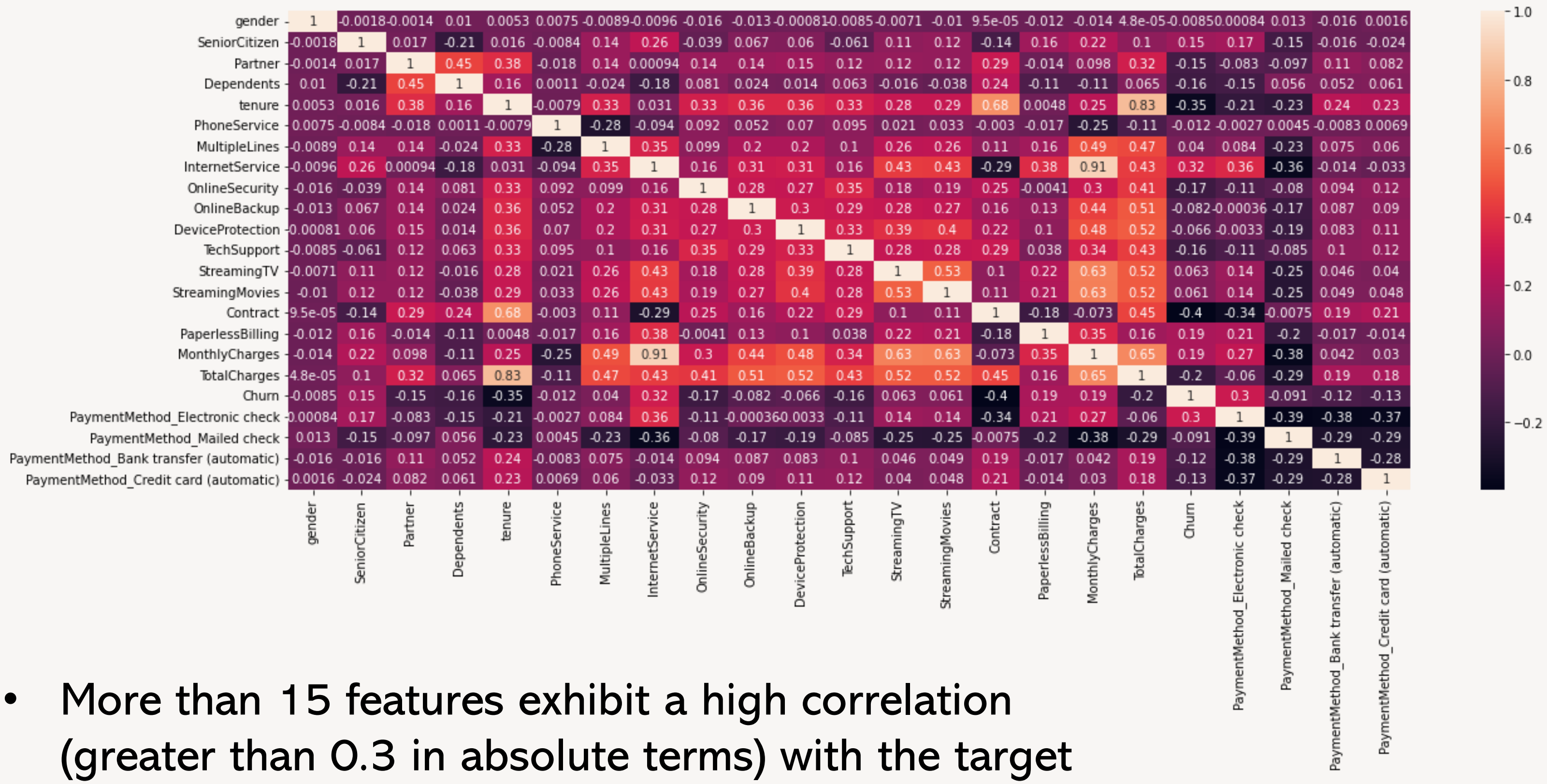
4.1 Data understanding



- If we look at the target distribution, we can see that the data is imbalanced.
- In such scenarios, relying solely on metrics like accuracy can be misleading and ineffective. Instead, it is essential to explore alternative evaluation measures, such as precision, recall, F1-score, or area under the precision-recall curve (AUC-PR), which provide a more accurate result.
- Resampling method or threshold tuning should be applied to handle this problem.

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
```

- More than 15 features 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."

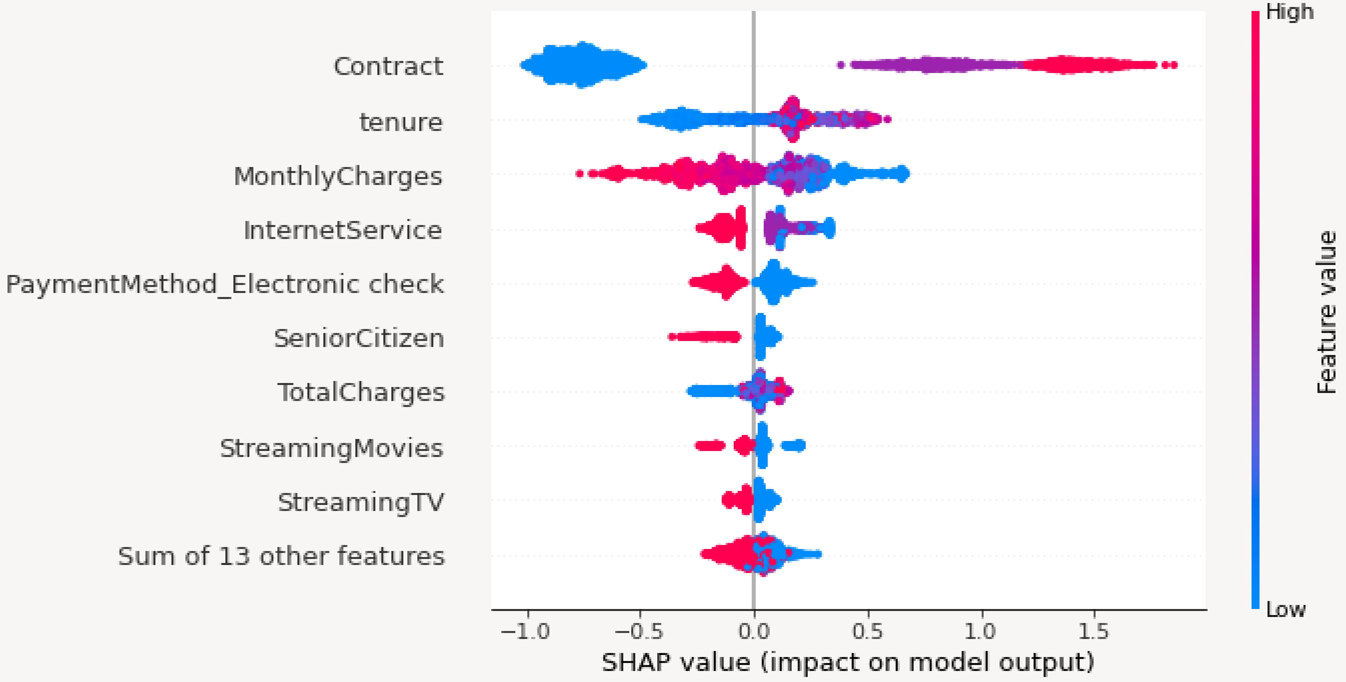
4. Model

4.4 Feature importance

Features	Sign	Meaning
Contract	+	Customers on contract packages are more prone to switching due to enticing promotions from other operators, offering benefits like data roaming. In contrast, top-up package users, who primarily make calls, show lower inclination to switch.
Tenure	+	Customers who have been with us for a long time have a higher probability of churning. This might be because they are more likely to be older and more hesitant to cancel our service.
Monthly charges	-	Customers who pay lower charges may have a higher probability of churning. This is because the industry's current trend offers attractive low-priced packages for new customers, possibly causing them to cancel and apply with other operators.
Internet service	-	Customers without internet included in their package are more likely to churn. In today's context, internet has become a crucial factor, leading customers to cancel our package in favor of competitors offering inclusive internet services.
Payment method (electronic check)	-	Customers who do not use electronic payment methods may be more inclined to churn. This aligns with the tenure-related churn reason, indicating that older customers may decide to cancel our service.

4. Model

4.4 Feature importance (cont.)



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 this presentation

6. About me

- A
- B
- C
- D

Contact me on

- Linkin.com/
- Github.com/