Predicting Customer Churn

Microsoft Azure

Agenda

- The Problem
- Methodology
- Conclusions & Suggestions

The Problem

- Companies lose $1.6 trillion per year due to customer churn!
- It costs 5 times more to acquire new customers than retaining an existing one
- The more customers a business retains, the more revenue it makes!
- Customers at high risk of churning, represent a huge additional potential revenue source

Analyze and predict customer churn

"There is a big difference between a satisfied customer and a loyal customer."

Shep Hyken

"If your customer retention is poor then nothing else matters."

Brian Balfour

Methodology

Data Processing

- Data Acquisition
- Data Wrangling
- Feature Engineering

Model Building

- Data Splitting
- Model Training
- Feature Importance
- Model Scoring

Model Evaluation

- Confusion Matrix
- Performance Measurements

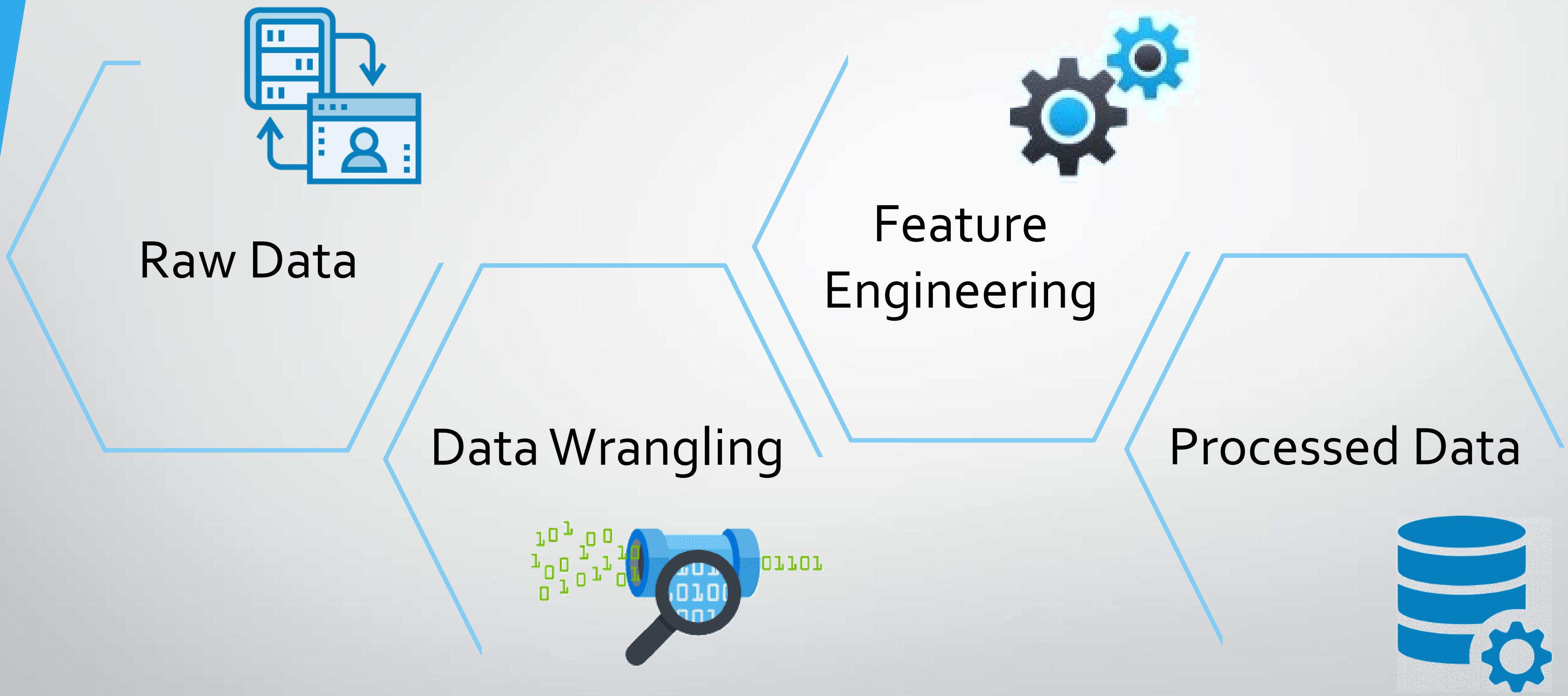
Model Deployment

- Batch Inference

Conclusions

- Results
- Suggestions

Data Processing



Features Used

- Number of times a customer collected (Sum_collect_points)
- Total collected points (Sum_collect_points)

- Number of times a customer redeemed (Sum_redeem)

- Years passed since customer's registration to the program (Years_in_the_program)

- Months passed since customer's last action (Months_since_last_transaction)

✓ <u>Target Feature</u>: Customer's lapsed status (State)

0 = Active

1 = Lapsed

Model Building

<u>Data Splitting:</u>

- 80% training, 20% testing
- Stratified sampling based on target variable (i.e. State)

<u>Model Training:</u>

- Binary classification problem (Active, Lapsed)

Two-Class Boosted Decision Tree

Model Building

Two-Class Boosted Decision Tree:

✓ Non-parametrical method
- Classify customers to active & lapsed
- Hyper-parameter tuning
- Feature Importance
- Score Model
- Model Evaluation
- Model Deployment

Hyper-parameters	Values
Maximum number of leaves per tree	20
Minimum number of samples per leaf node	10
Learning rate	0.2
Number of trees constructed	300

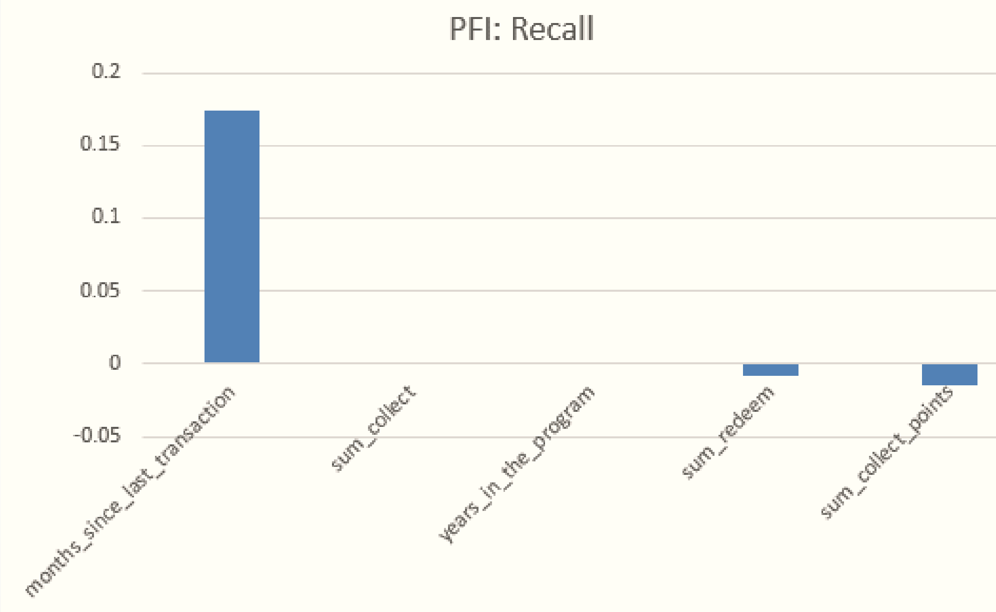
Permutation Feature Importance

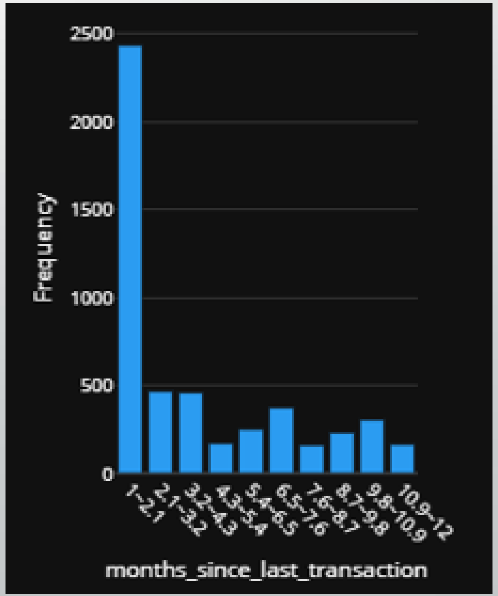
❖ More customers lapsed identified, more unnecessary retention costs saved

↳ Main performance metric used: **Recall**

- Month's passed since customer's last action
  - ✓ Most important feature for classification
  - ✓ Most customers collected or redeemed points less than 2 months ago

- All other features seem to have insignificant effect





Model Evaluation

		Actual	
		Lapsed	Active
Predicted	Lapsed	409	93
	Active	90	408

From confusion matrix:

✓ Good classifier (values accumulated on the diagonal)

From other typical performance metrics:

✓ High accuracy, precision, recall, AUC

Accuracy	81.7% (of customers correctly classified)
Precision	81.5% (of predicted lapsed customers correctly classified)
Recall	82% (of actual lapsed customers correctly classified)
AUC	.895 (higher the AUC, better the classifier)

✓ Good classification model (will generalize well to out-of-sample data)

Model Deployment

- Deploy model to a given batch of observations
- Use model to generate customer predictions (active, lapsed in the next 12 months) based on their previous behavior

sum_collect	sum_redeem	sum_collect_points	years_in_the_program	months_since_last_transaction	Scored Labels	Scored Probabilities
13	0	1,269	19	1	0	.0071
6	0	2,890	10	10	1	.9998
2	0	422	7	9	1	.9999
7	1	2,690	16	1	0	.0144
7	0	211	2	3	0	.4053

<u>Customers whose last action (collection or redemption) was:</u>

- more than 9 months ago, have a huge probability to lapse (more than 99%).
- one month ago, have a very small probability to lapse (about 1%).

Conclusions

- About 1 out of 2 customers were lapsed customers
- 82% of the lapsed customers correctly identified via the model
- Months passed since customer's last action was the only feature that revealed an evident pattern for customer churn probabilities (also suggested from PFI technique)
- The fewer the months passed without a transaction the more loyal the customer
- The best customers are those who are active on a monthly basis
- Customers who are active quarterly are at a high risk of churning

Suggestions

- Keep the most loyal customers as satisfied as possible
- Reward the more active customers
- Provide incentives to customers who are active once per quarter or per trimester to prevent them from lapsing (e.g. discounts, special offers)
- Save retention costs from customers who are very likely to lapse

✓ Note: For a successful retention campaign, the decision threshold for identifying a lapsed customer should be decided by the management team or calculated from the profit matrix

Thank you for your attention!