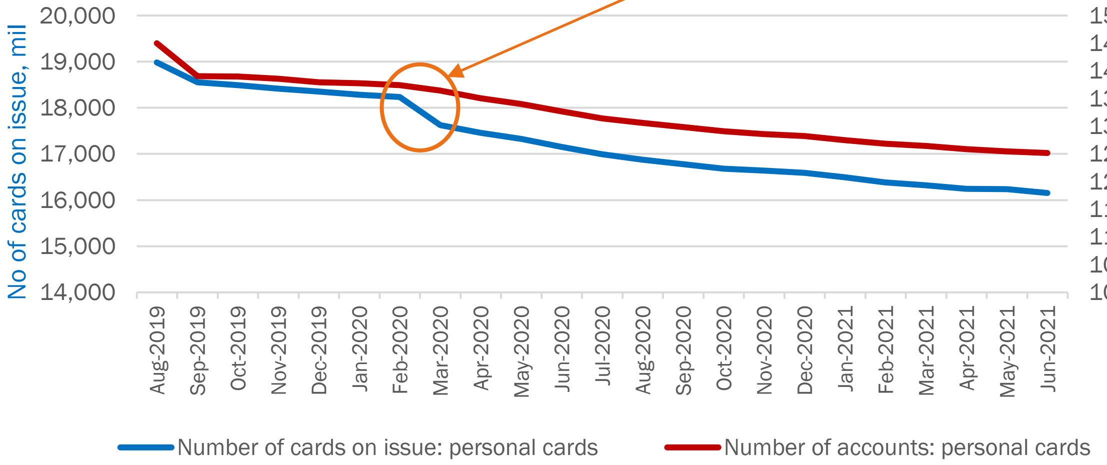
Credit Card Market Summary Overview

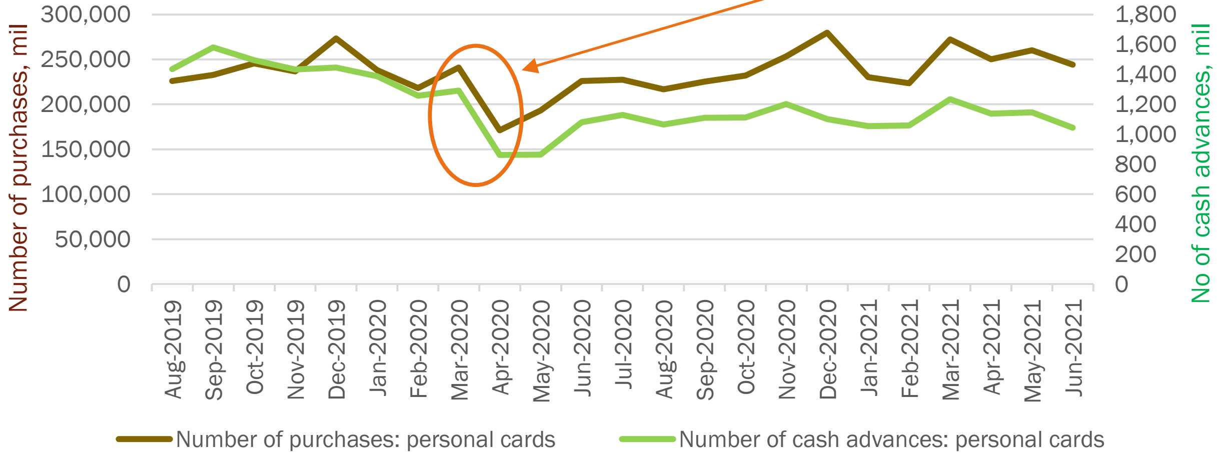
Source: [Payments Statistics | RBA]

1. **Impact from COVID19 – affecting most metrics**: accounts/cards, transactions volume especially overseas & balances
2. **Continued area of concern** – accounts / cards on issue (**low acquisition + high churn rate**)

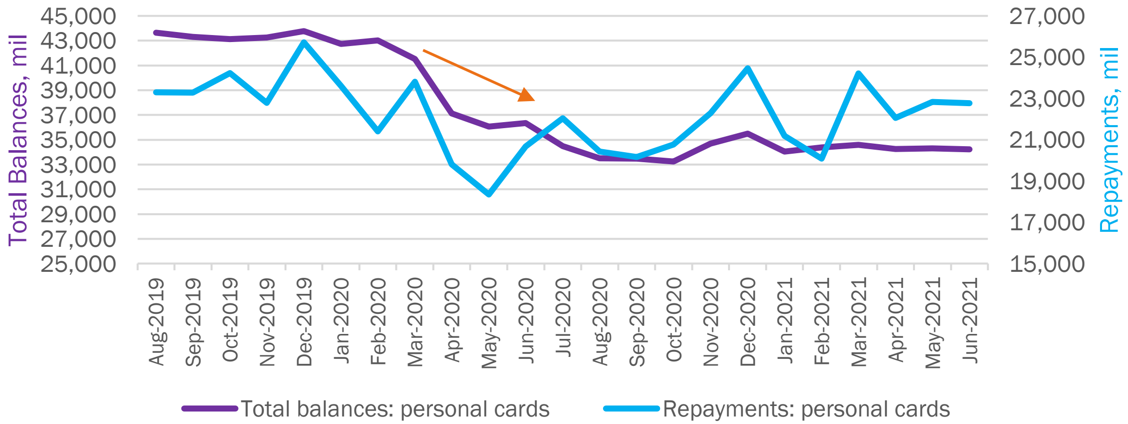
1. **No of cards/accounts** are trending down over time.
The decline accelerated post COVID19 lockdown Mar last year



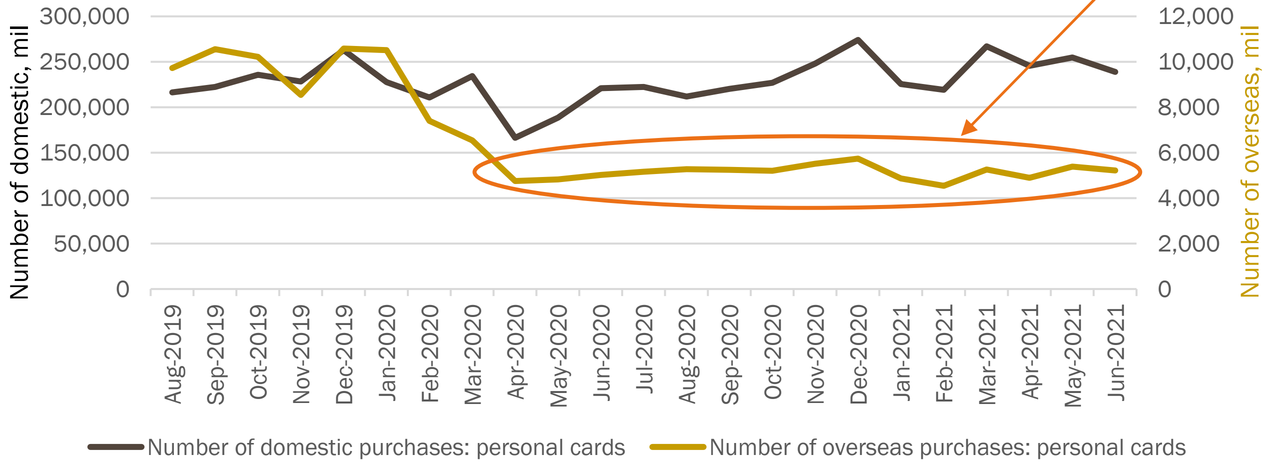
2. **Transactions volume** remained strong despite hiccup in Mar2020



4. A dip in balances post COVID19 which may be due to economy uncertainty

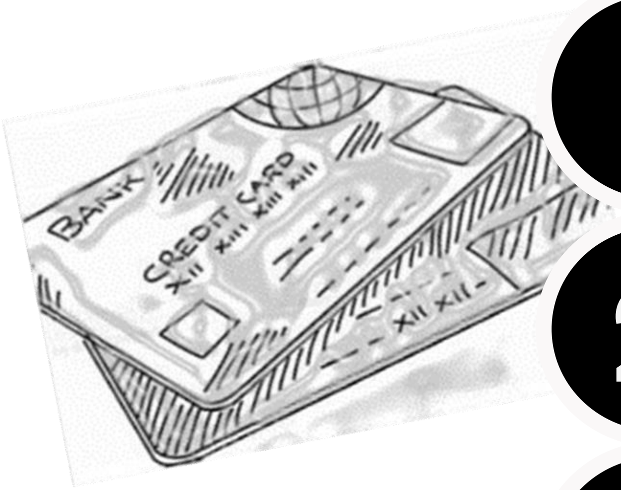


3. Huge impact on overseas purchases post COVID19 but reached plateau



Credit Card Churn

DANIEL CHOW



1. Purpose
2. Methodology
3. Data Exploratory
4. Model Results
5. Synopsis

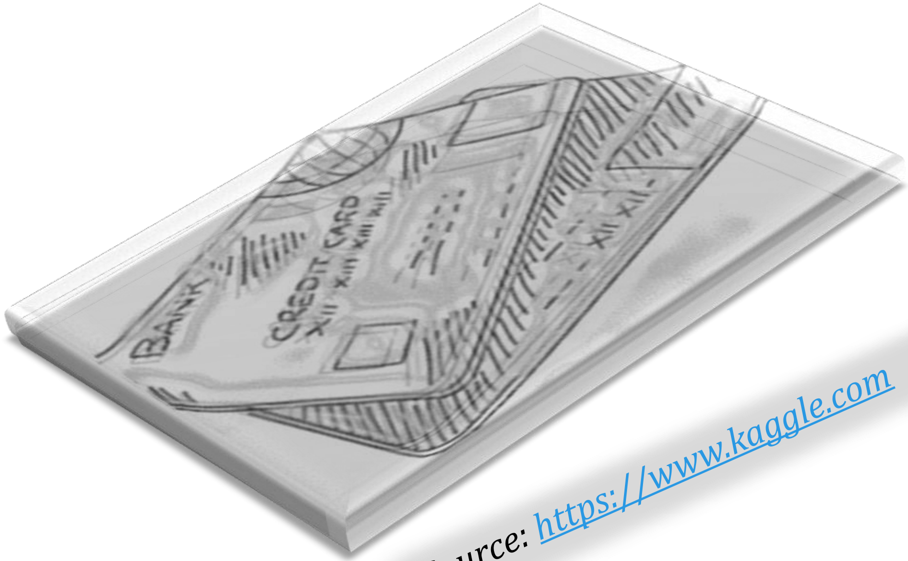
Purpose

Executive Summary

More and more credit card customers are leaving the bank. The business wants to find **a way of predicting** which customers are most likely to stop using their credit card product in order to proactively check in on the customer to provide them better services in order to convince them to change their minds.

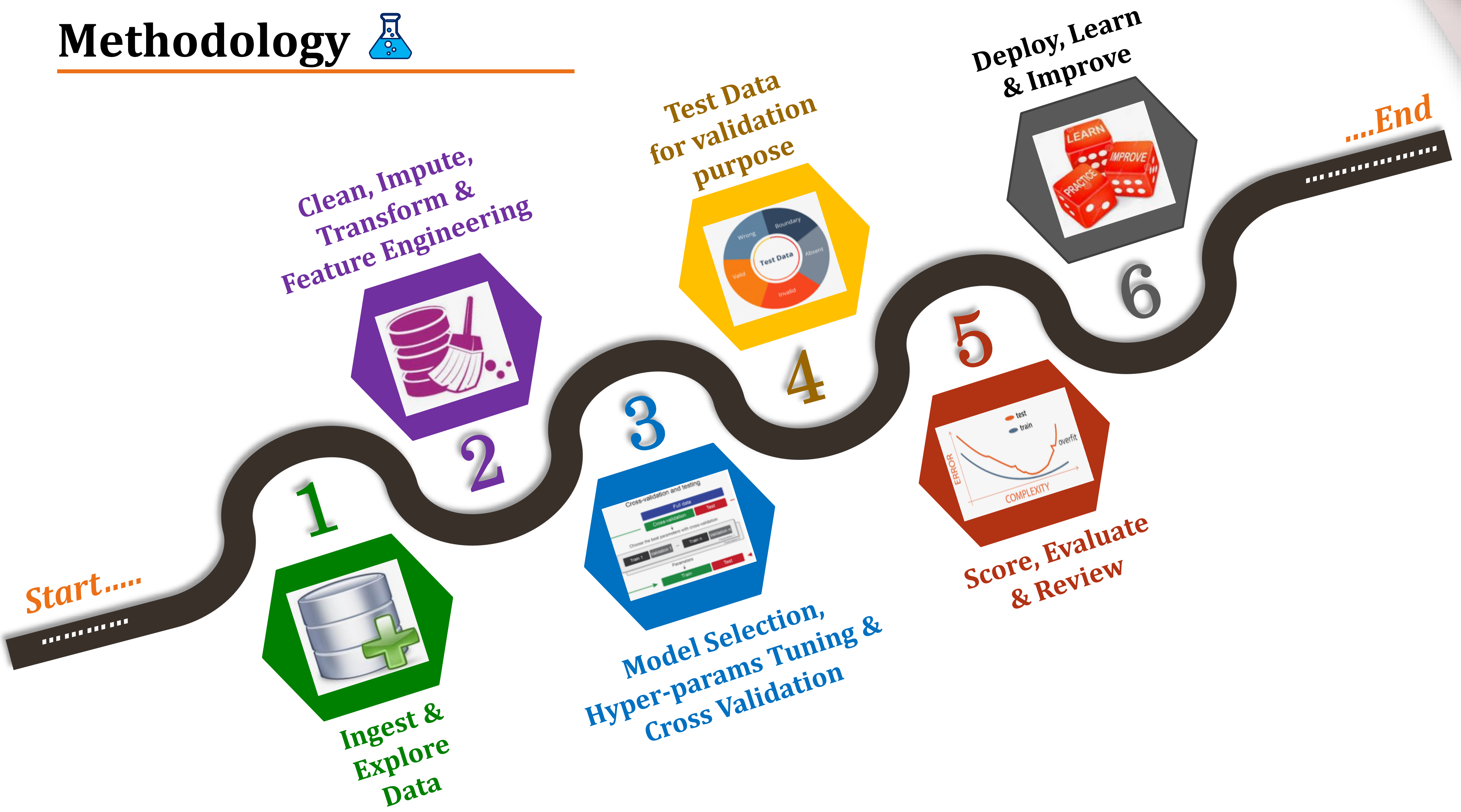
Our objectives are to:-

- identify any **significant influential factors** that lead to a customer's decision of leaving the bank.
- leverage on the results from the model and **explore possibility of reaching out to customers** to recover the relationship.
- quantify the **benefits gained** from using the model vs. natural attrition.



Source: https://www.kaggle.com

Methodology



Data Exploration

A Quick Glance
What do we know about the data?

1. Data consists of **10,127** customers.
2. There are **20** features and grouped into **8** broad category:-

Behavioural

- 8 Usage Behaviour
  (Revolving Bal, Months Inactive last 12mo, Avg Util Rate, # Contacts last 12mo)
- 7 Total Transactions Value / Volume
- 6 Months-on-Book / Products Holding

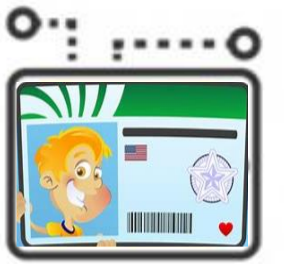
Demo/Ethnogrpahic

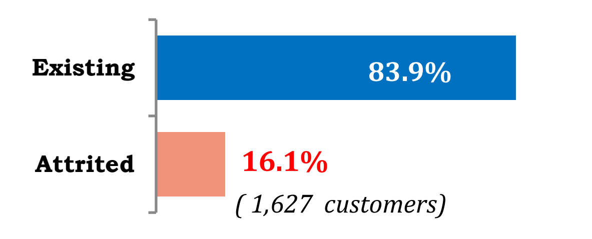
- 5 Declared Income / Card Category / Credit Limit
- 4 Marital Status / No of dependents
- 3 Education Level
- 2 Gender
- 1 Age

**** PERSONA ****

CHURNED CUST. PROFILE

- has higher level of education: **Doctorate**
- hold **Platinum** / low **Credit Limit**
- lower **revolving balance / avg util. ratio**
- longer **tenure**
- had **3-5X contacts** in last 12 months





EDUCATION LEVEL

Relatively higher number of churned customers who hold ***Doctorate***

Education	Relative Index
College	94
Doctorate	139
Graduate	96
High School	94
Post-Graduate	113
Uneducated	99
Unknown	106

CARD TYPE / CREDIT LIMIT

More churned customers hold ***Platinum*** *and/or* ***lower Credit Limit***

Card Category	Relative Index
Blue	100
Silver	91
Gold	115
Platinum	174

REVOLVING BAL/AVG UTIL.

Lower ***Revolving Balance & low Avg Utilisation Ratio***

Avg Utilisation Ratio	Relative Index
01. LT 10%	187
02. 11%-25%K	53
03. 26%-50%	55
04. 51%-75%	35
05. 75%+	96

MONTHS-ON-BOOK

Relatively ***longer vintage*** *customers are leaving the bank*

MOB	Relative Index
03. 1-2yr	91
04. 2-3yr	100
05. 3-4yr	101
06. 4-5yr	107

CONTACTS LAST 12 MTHS

Customers with ***3-5 contacts*** *in the last 12 months*

# Contacts Last 12Months	Relative Index
0	9
1	41
2	75
3	132
4	153
5	263

Relative Index *measures the strength/weakness within each features and compare them between existing and churned customers.*

Model Results

T - treat outliers / missing values & data transformation

A - apply principal component analysis (PCA) on correlated features

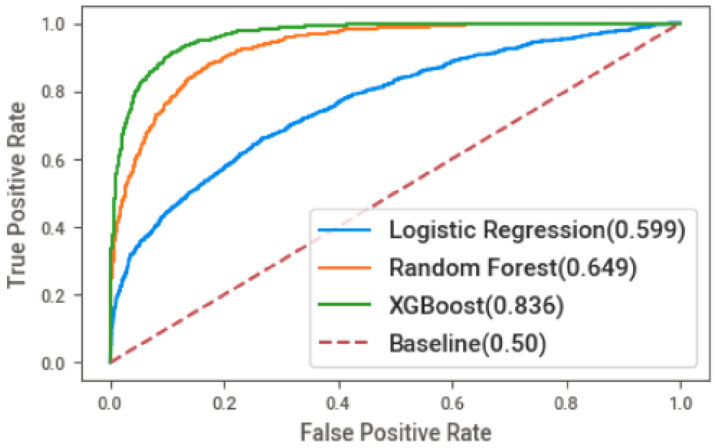
S - synthesize minority oversampling tech (SMOTE) on imbalanced dataset

T - test & tune using 2 or more machine learning algorithms

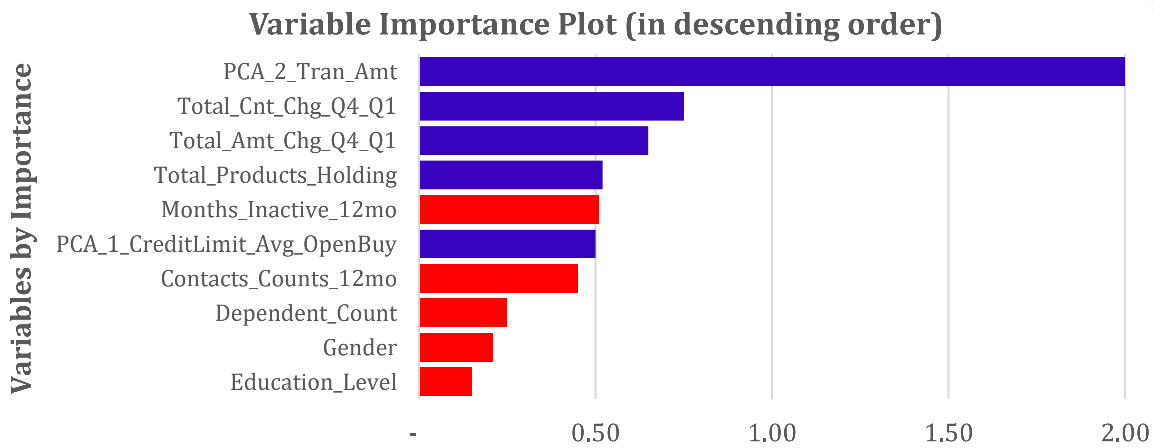
E - ensure no over/under-fitting & consistent results between train & test

SUMMARY Classification Model	Test Dataset: Accuracy Score	Test Dataset: AUC Score
Logistic Regression	0.861	0.599
Random Forest	0.885	0.649
XGBoost	**0.930**	**0.836**

Receiver Operating Characteristic [ROC]

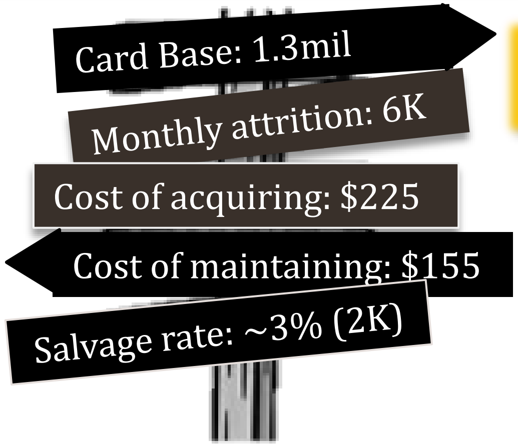


Significant Influential Factors



SHAP Value (Red = Positive Impact, Blue = Negative Impact)

Projected Benefits



If we are able to salvage **2K** custs. per month by…

Possible Offers:

1. **Appreciation vouchers**
2. **Annual fee waiver**
3. **Cash reward**
4. **New product offering**
5. **SMART Plan**

Synopsis

1

Data showed **distinct characteristics** between **existing** and **churned** customers.

2

Model has **>80% predictive capability** when predicting customer's likelihood to leave the bank.

3

It is cheaper to retain an existing customer than acquiring a new one. By **targeting customers who are likely to churn,** we maybe able to salvage **2K** customers.

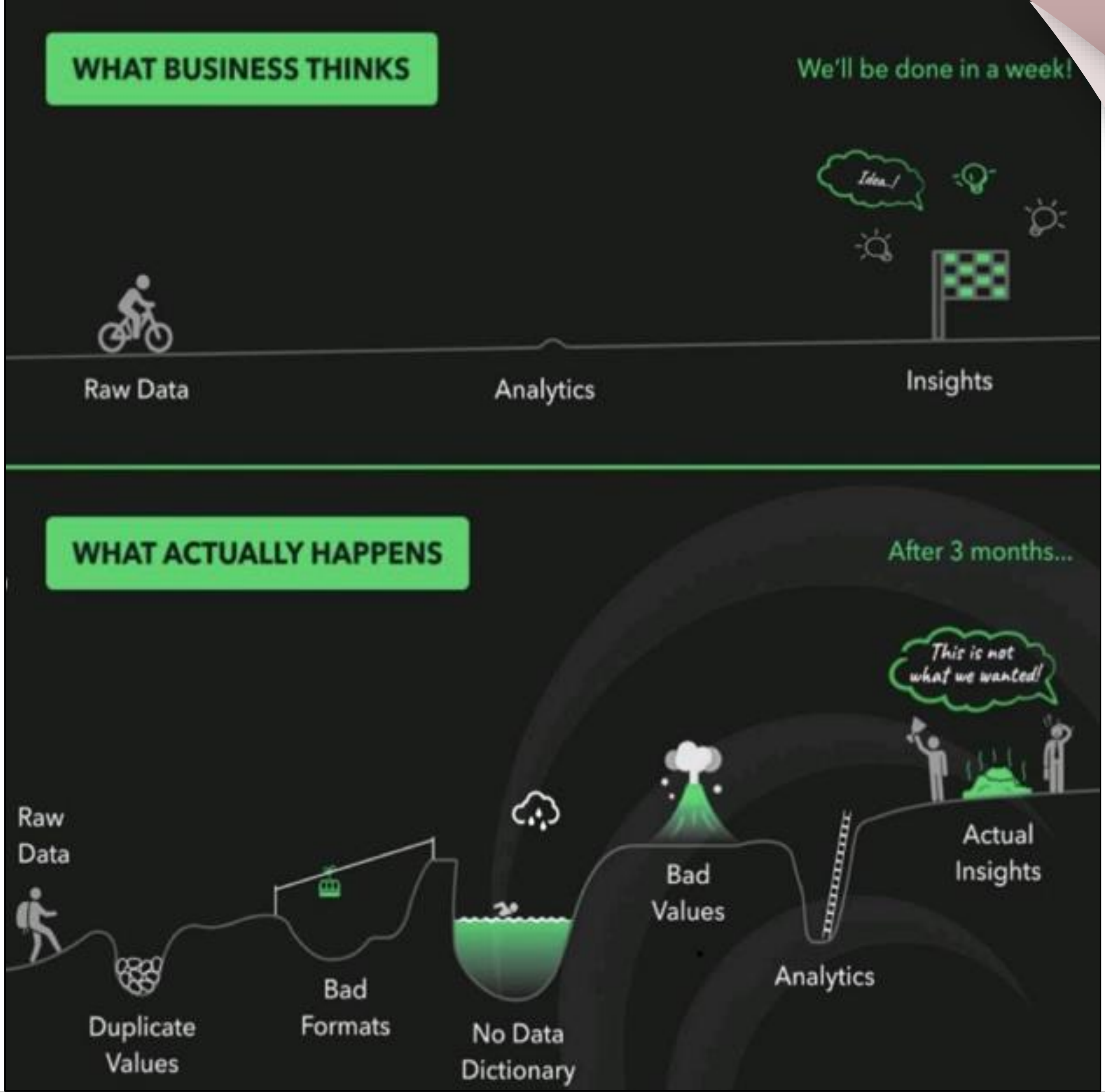
4

Propose to deploy using **test-and-control** groups **(i.e. A/B testing)** to gauge model effectiveness and constantly improve the model through **different offers** and/or adding various touch-points like digital side of things, geo-locations, behaviour score or creating bespoke **customer segmentation** via clustering.

Conclusion

If you interested on how the models are constructed, please find details in the following link:
https://github.com/ucdcsl55/projects

Thank you.



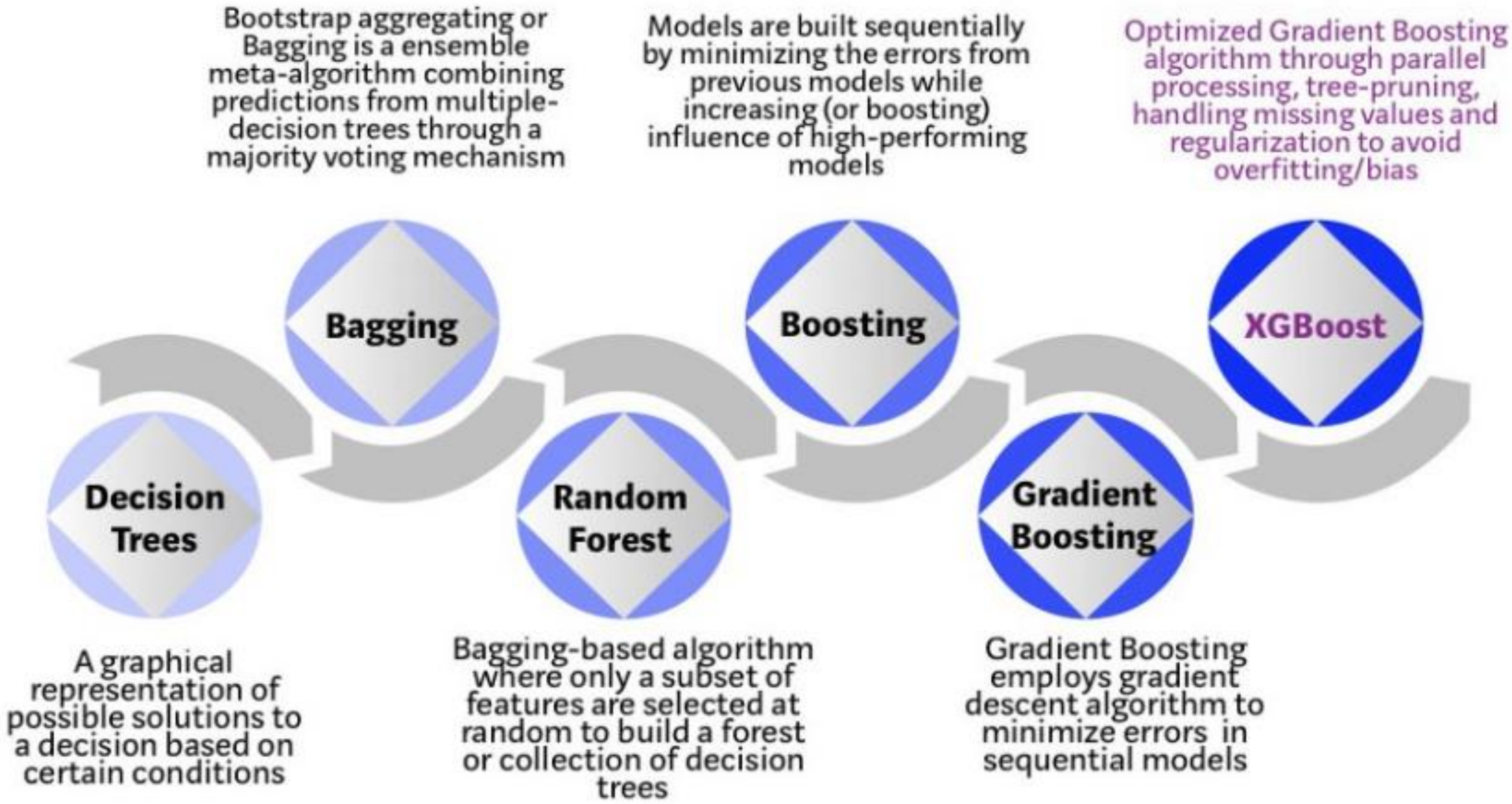
WHAT BUSINESS THINKS
We'll be done in a week!
Idea.!
Raw Data
Analytics
Insights
WHAT ACTUALLY HAPPENS
After 3 months...
This is not what we wanted!
Raw Data
Duplicate Values
Bad Formats
No Data Dictionary
Bad Values
Analytics
Actual Insights

Appendix

Feature	Description
Customer_Age	Demographic variable - Customer's Age in Years
Gender	Demographic variable - M=Male, F=Female
Dependent_count	Demographic variable - Number of dependents
Education_Level	Demographic variable - Educational Qualification of the account holder
Marital_Status	Demographic variable - Married, Single, Divorced, Unknown
Income_Category	Demographic variable - Annual Income Category of the account holder
Card_Category	Product Variable - Type of Card (Blue, Silver, Gold, Platinum)
Months_on_book	Period of relationship with bank
Total_Products_Holding	Total no. of products held by the customer
Months_Inactive_12_mon	No. of months inactive in the last 12 months
Contacts_Count_12_mon	No. of Contacts in the last 12 months
Credit_Limit	Credit Limit on the Credit Card
Total_Revolving_Bal	Total Revolving Balance on the Credit Card
Avg_Open_To_Buy	Open to Buy Credit Line (Average of last 12 months)
Total_Trans_Amt	Total Transaction Amount (Last 12 months)
Total_Trans_Ct	Total Transaction Count (Last 12 months)
Avg_Utilization_Ratio	Average Card Utilization Ratio
Total_Amt_Chng_Q4_Q1	Change in Transaction Amount (Q4 over Q1)
Total_Ct_Chng_Q4_Q1	Change in Transaction Count (Q4 over Q1)

Evolution of XGBoost

Appendix



Evolution of XGBoost Algorithm from Decision Trees