Santander Product Recommendation

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AGENDA

01 Introduction

02 Data Cleaning and EDA

03 Feature Engineering

04 Training Model

05 Result and Finding

06 Future Steps

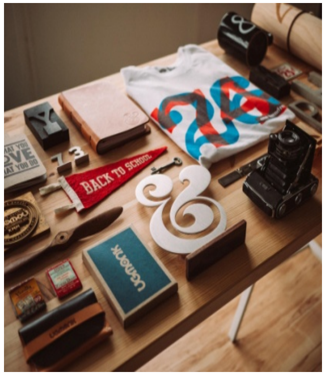
Introduction

Project Description

Santander Bank offers their customers personalized product recommendations time to time, in order to meet the individuals needs and satisfaction.
This challenge seeks to improve the recommendation system by predicting which products their existing customers will use in the next month based on their past behavior.

Goal

Achieve top 5% ranking and MAP@7 score on Kaggle leader board



Introduction

01

Data Size

Training Set:
13,647,409

Test Set: 929,615

02

Input Features

Categorical: 21
Continuous: 3

Customer Info. :
1: 24

2015.1 – 2016.5

03

Output Features

Product Purchased Info:
25:48

2015.1 – 2016.5

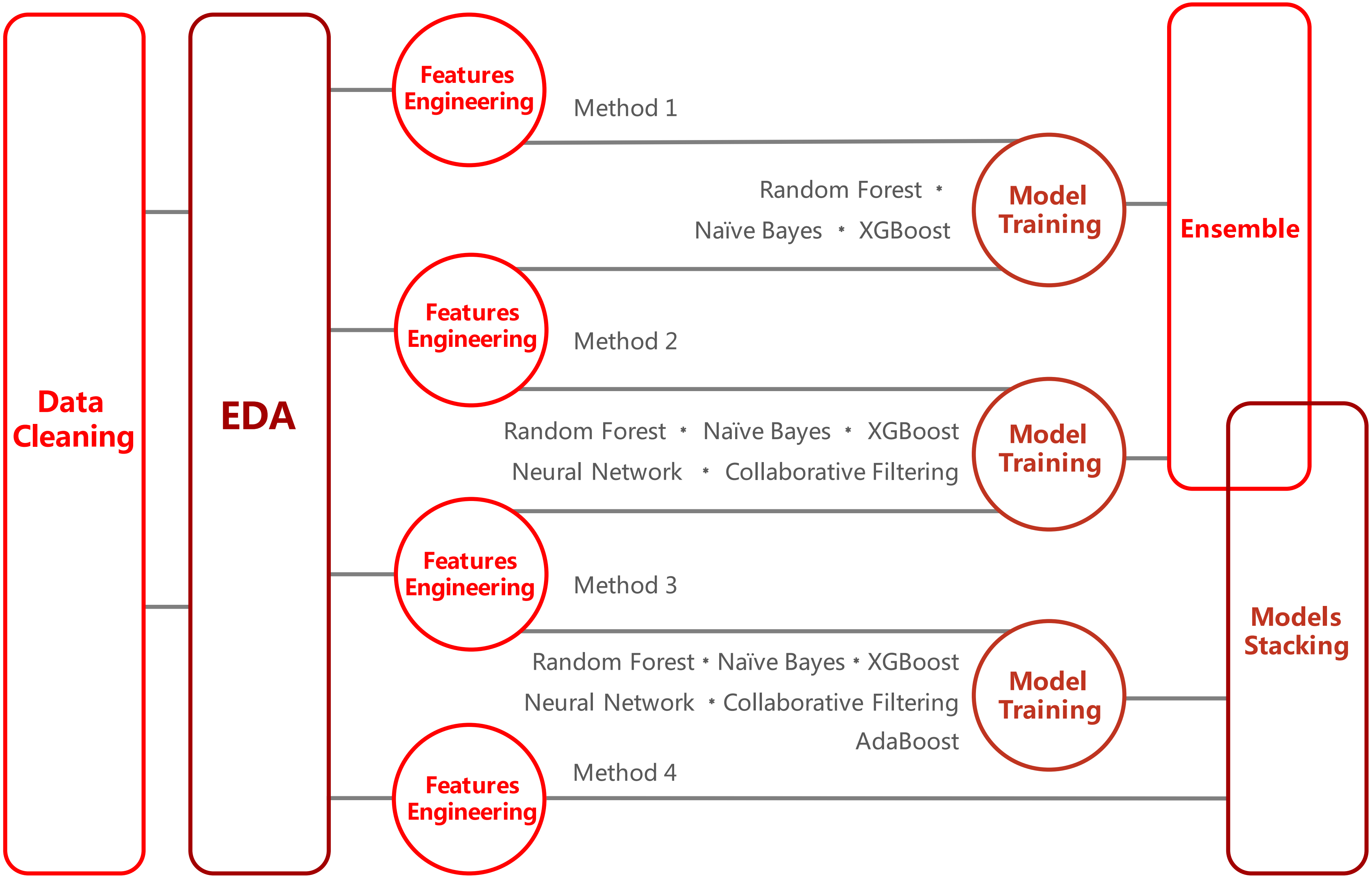
04

Evaluation

MAP@7

Multi-Classifier
Recommended
Products : 7

Workflow


Data Cleaning
EDA
Features Engineering
Method 1
Random Forest • Naïve Bayes • XGBoost
Model Training
Ensemble
Features Engineering
Method 2
Random Forest • Naïve Bayes • XGBoost
Neural Network • Collaborative Filtering
Model Training
Features Engineering
Method 3
Random Forest • Naïve Bayes • XGBoost
Neural Network • Collaborative Filtering
AdaBoost
Model Training
Models Stacking
Features Engineering
Method 4

Data Cleaning

Imputation

Contain Missing Values:

24 Features

Time Series – Customer Info.

Dropping Features

Drop 5 Features:

- Having over 95% missing value
- Repetitive of other features

Imputation

Unknown

- Sex
- Employee Index
- Country Residency
- Segmentation
- Residence Index
- Foreigner Index
- Channel to Join
- Primary
- Province Name

Common Type

- Customer Type
- Activity Index
- Income

Others

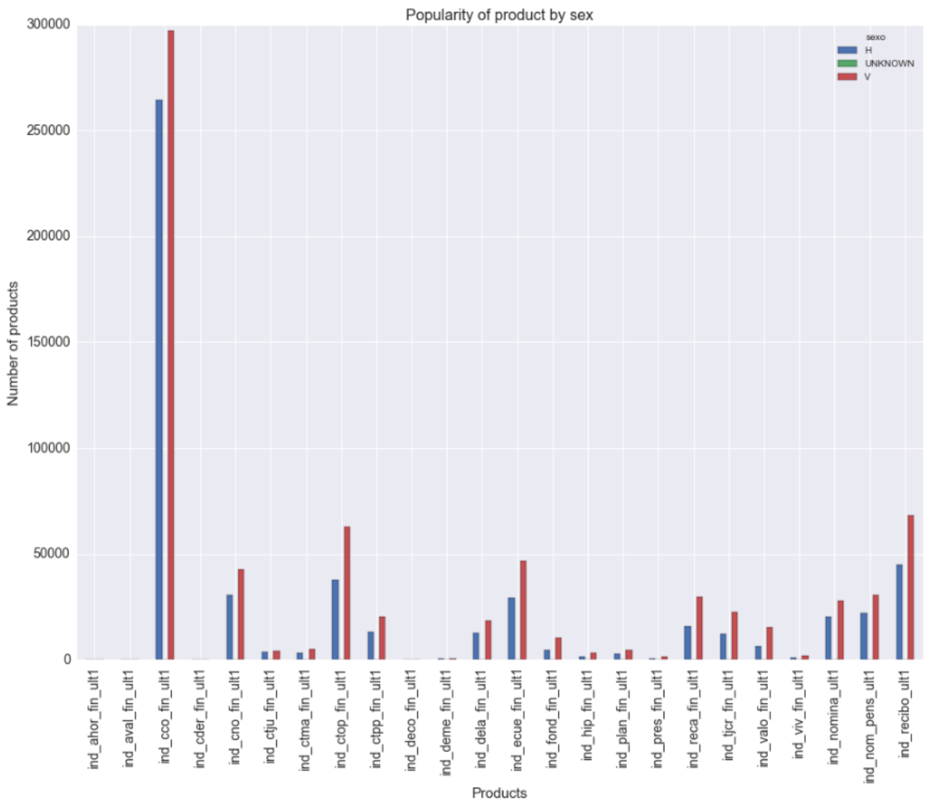
- New Customer – New
- Seniority – Min
- Age – Scale, Mean
- Relationship Type – 'A'
- Deceased Index – 'N'

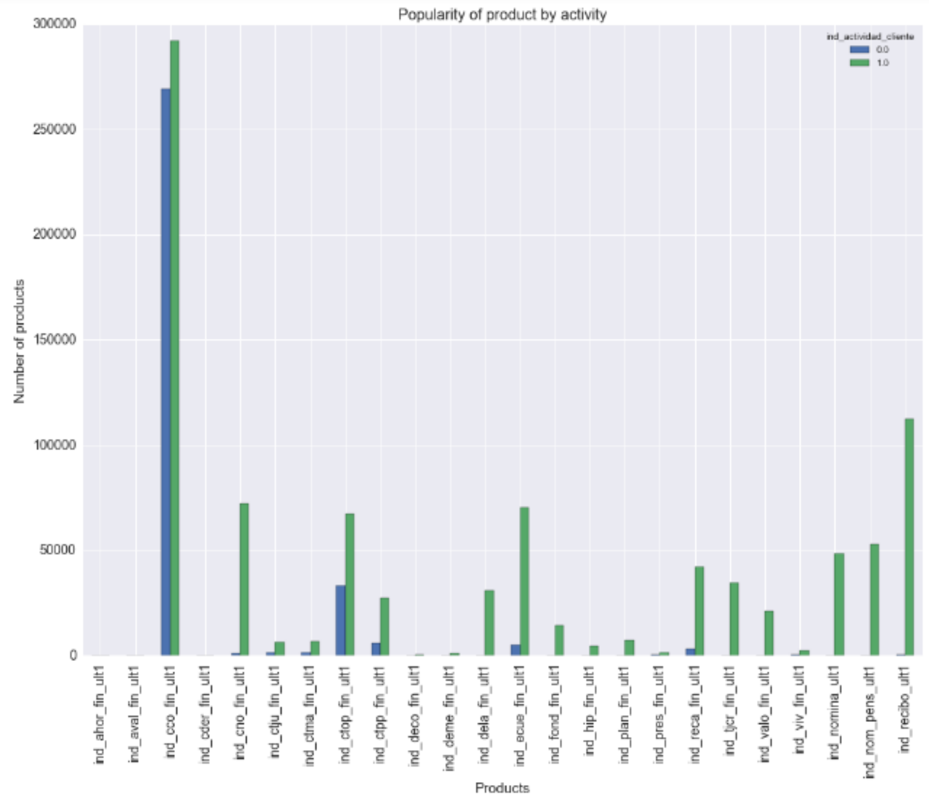
Products

- Payroll - 0
- Pensions - 0

EDA

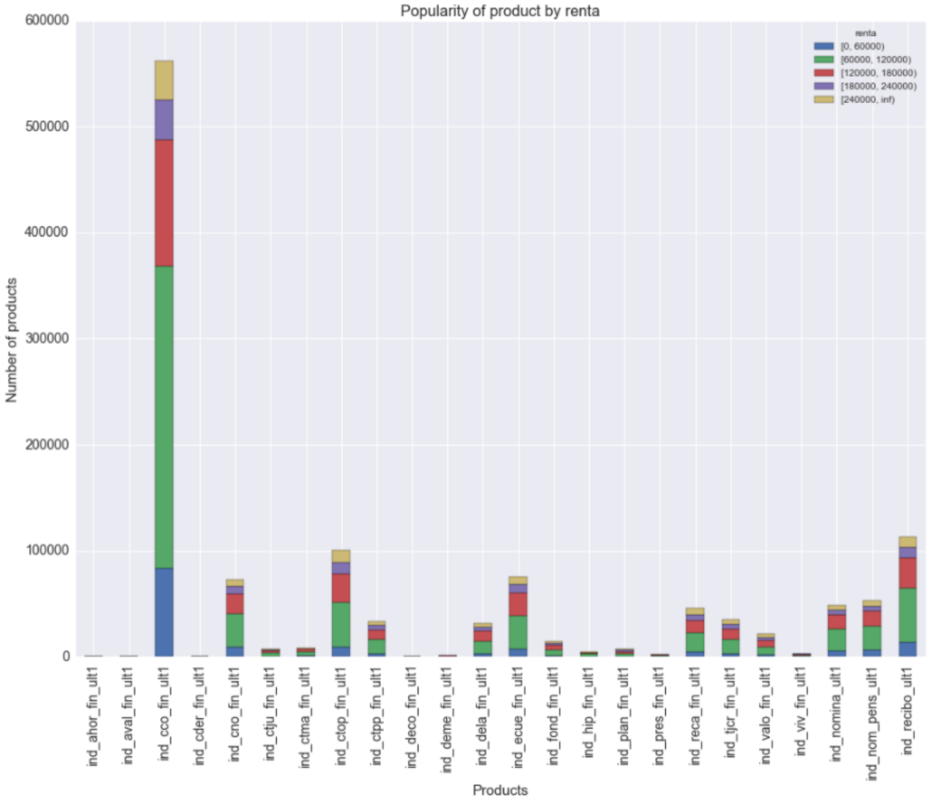
Product Sales Related to Customer’s Info - 2016.5

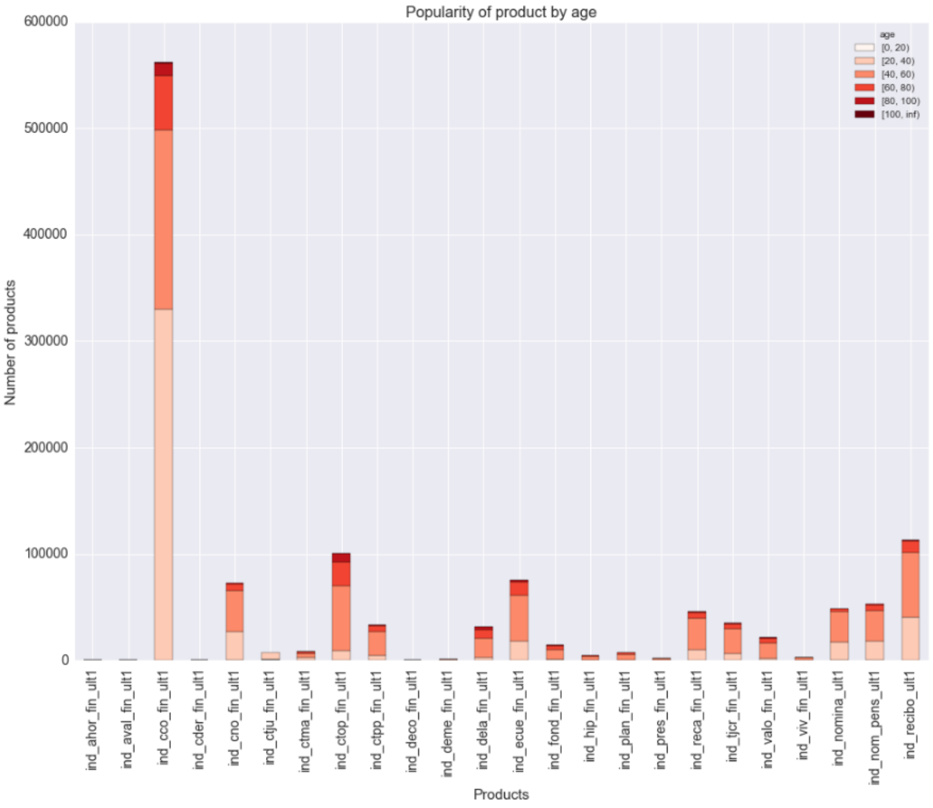




EDA

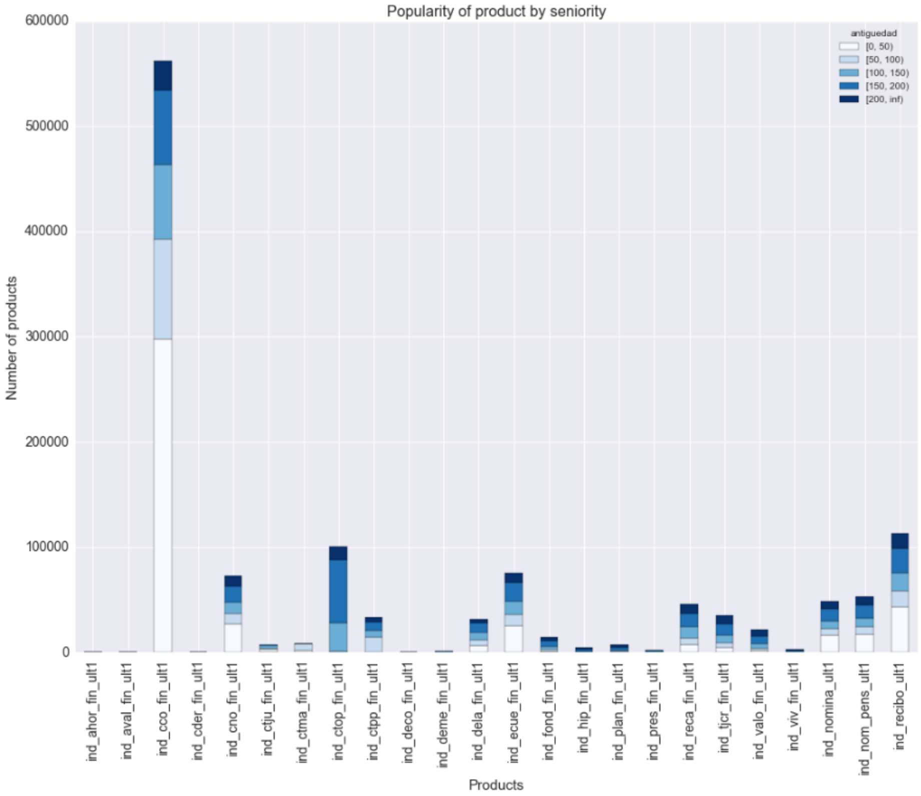
Product Sales Related to Customer’s Info - 2016.5

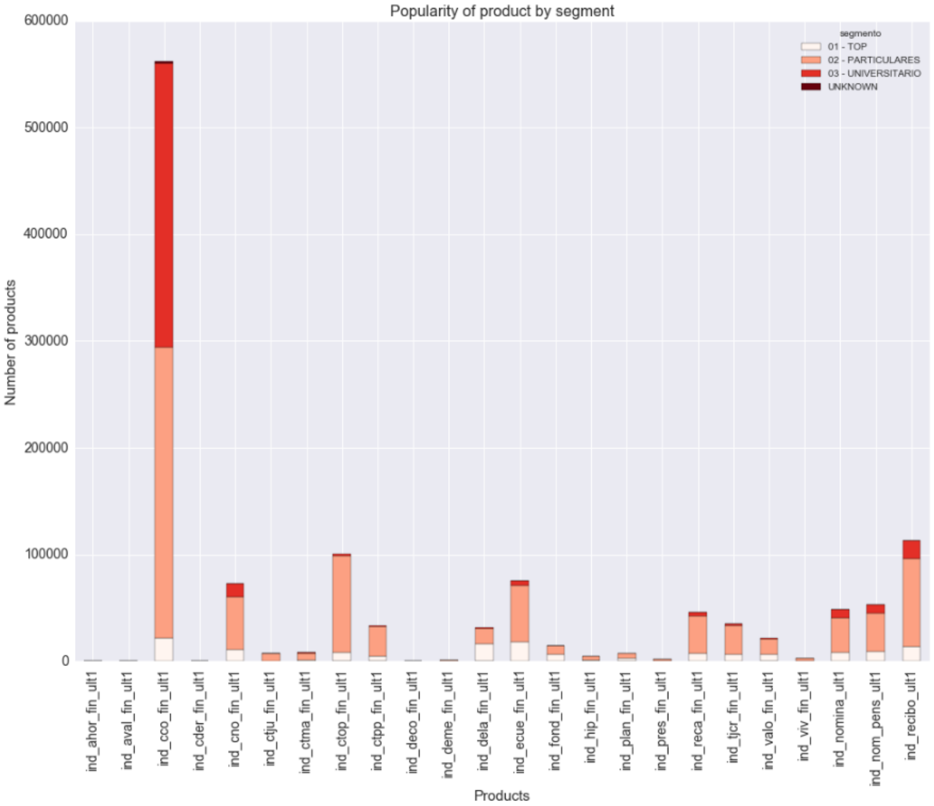




EDA

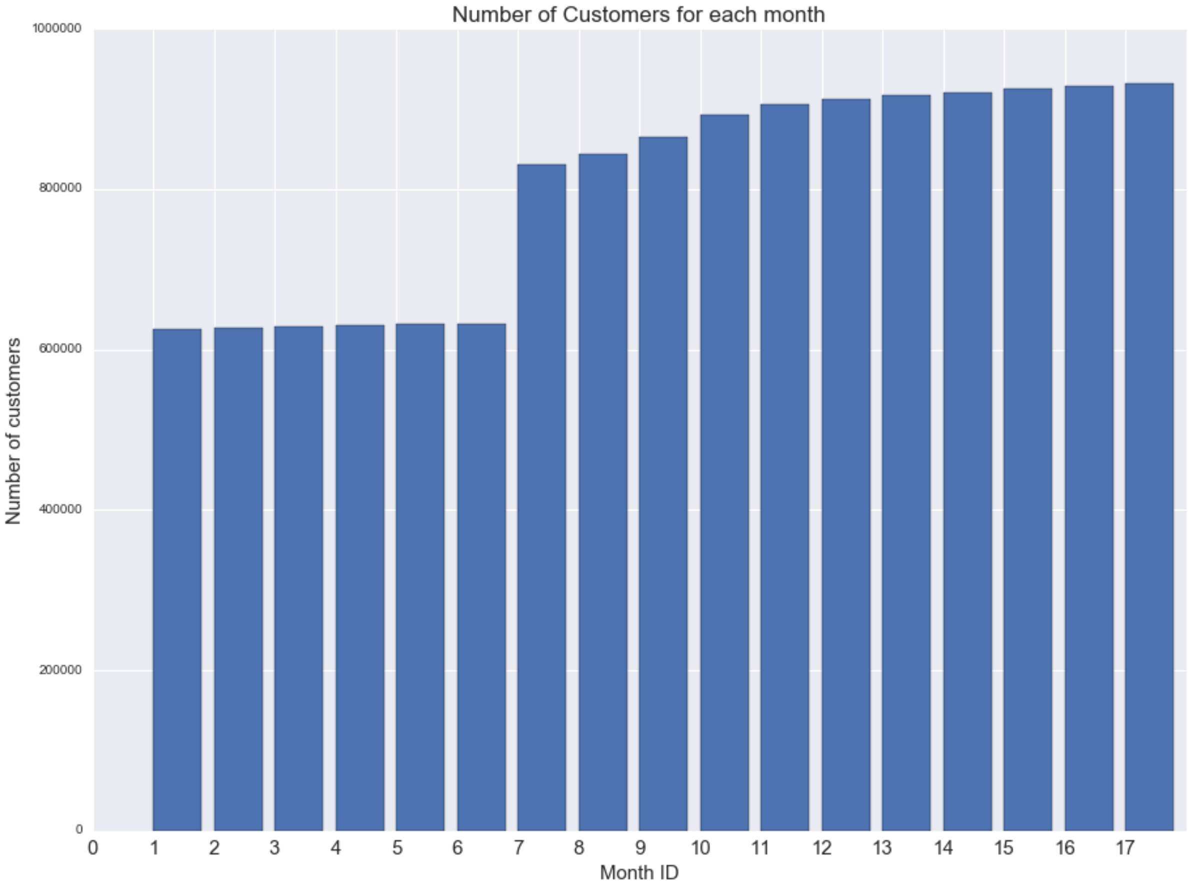
Product Sales Related to Customer’s Info - 2016.5





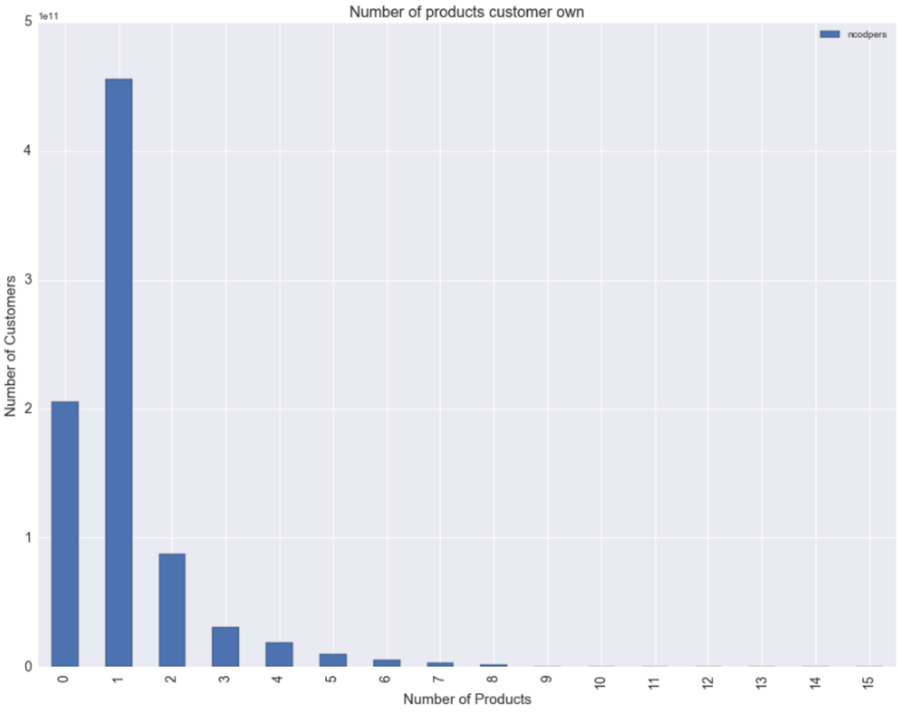
EDA

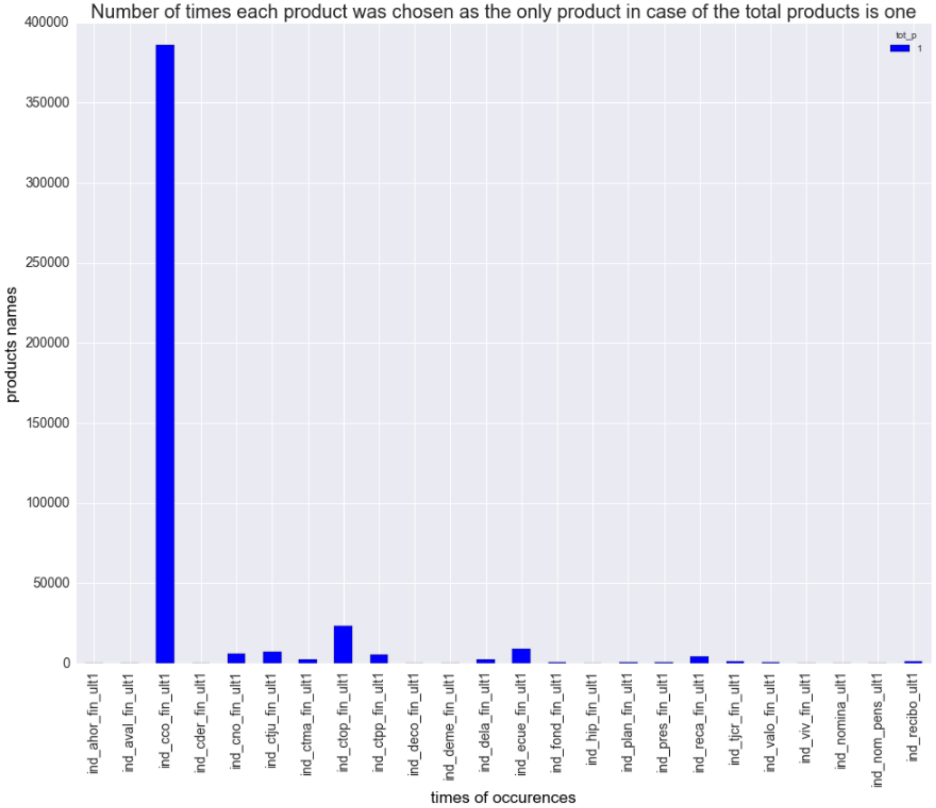
Number of Customers by Time



EDA

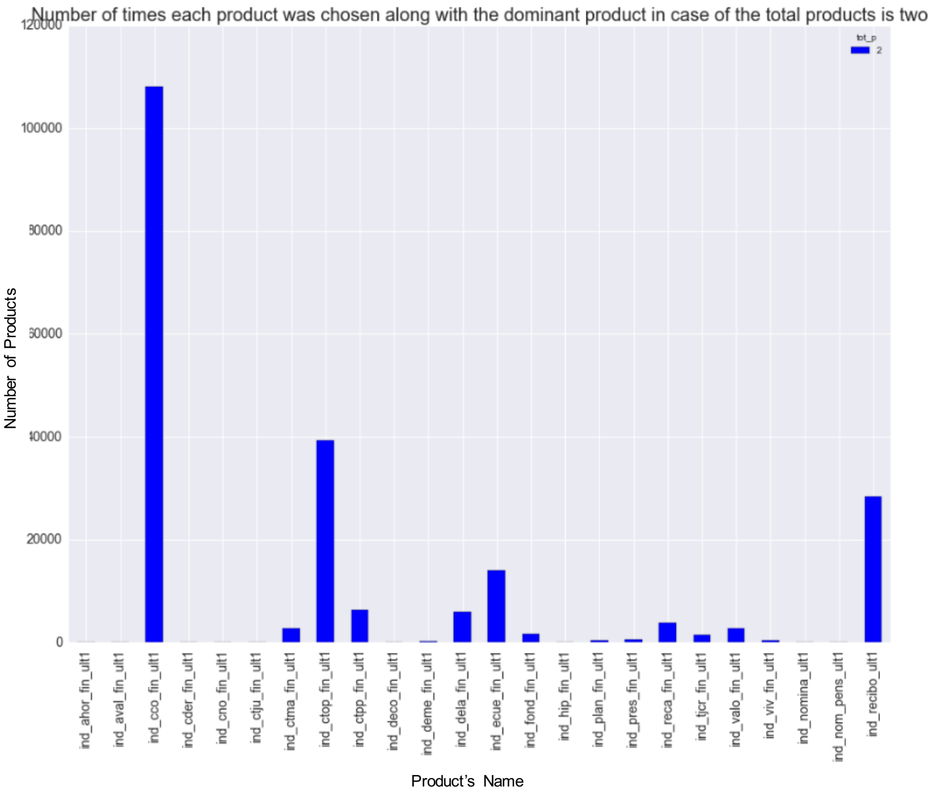
Number of Product Own - 2016.5

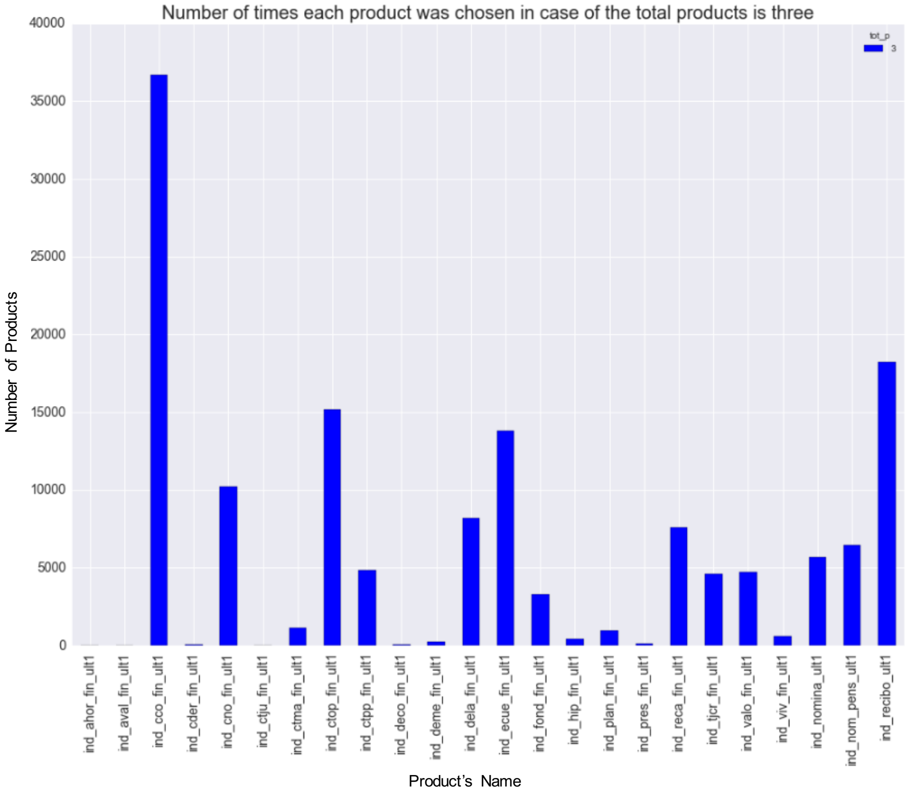

Number of products customer own


Number of times each product was chosen as the only product in case of the total products is one

EDA

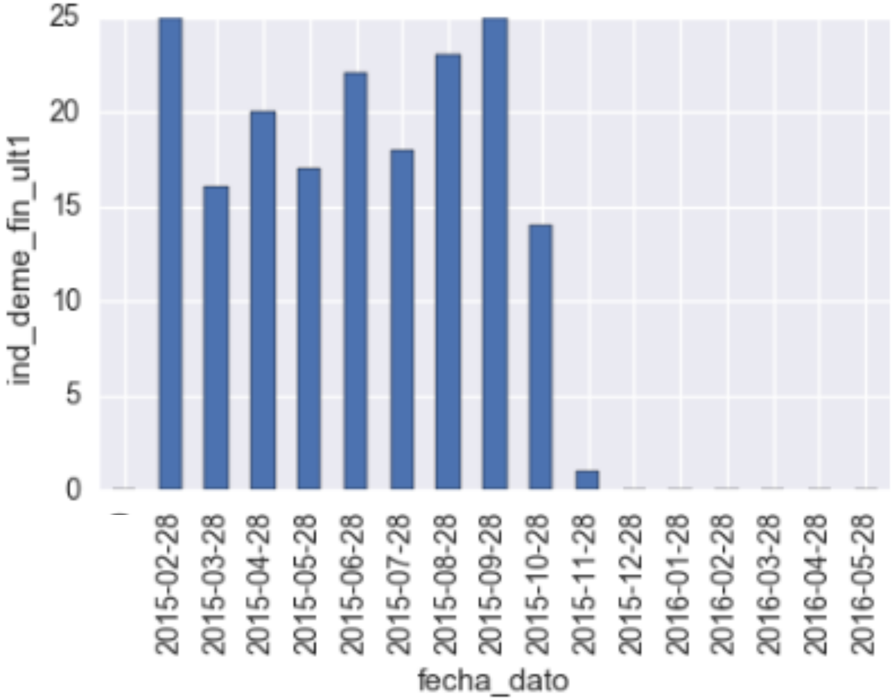
Number of Product Own - 2016.5

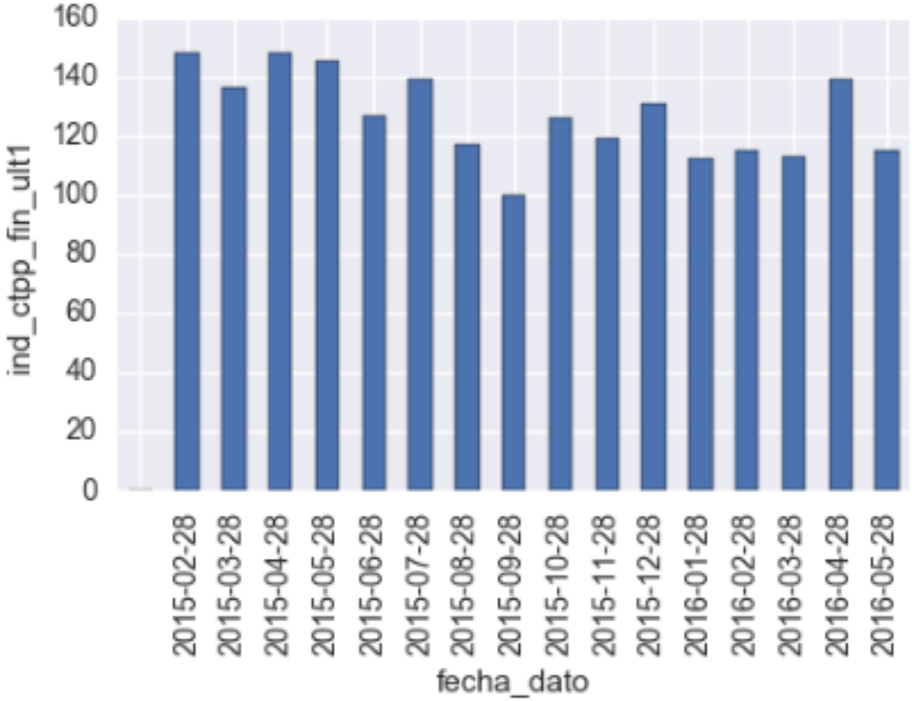

Number of times each product was chosen along with the dominant product in case of the total products is two


Number of times each product was chosen in case of the total products is three

EDA

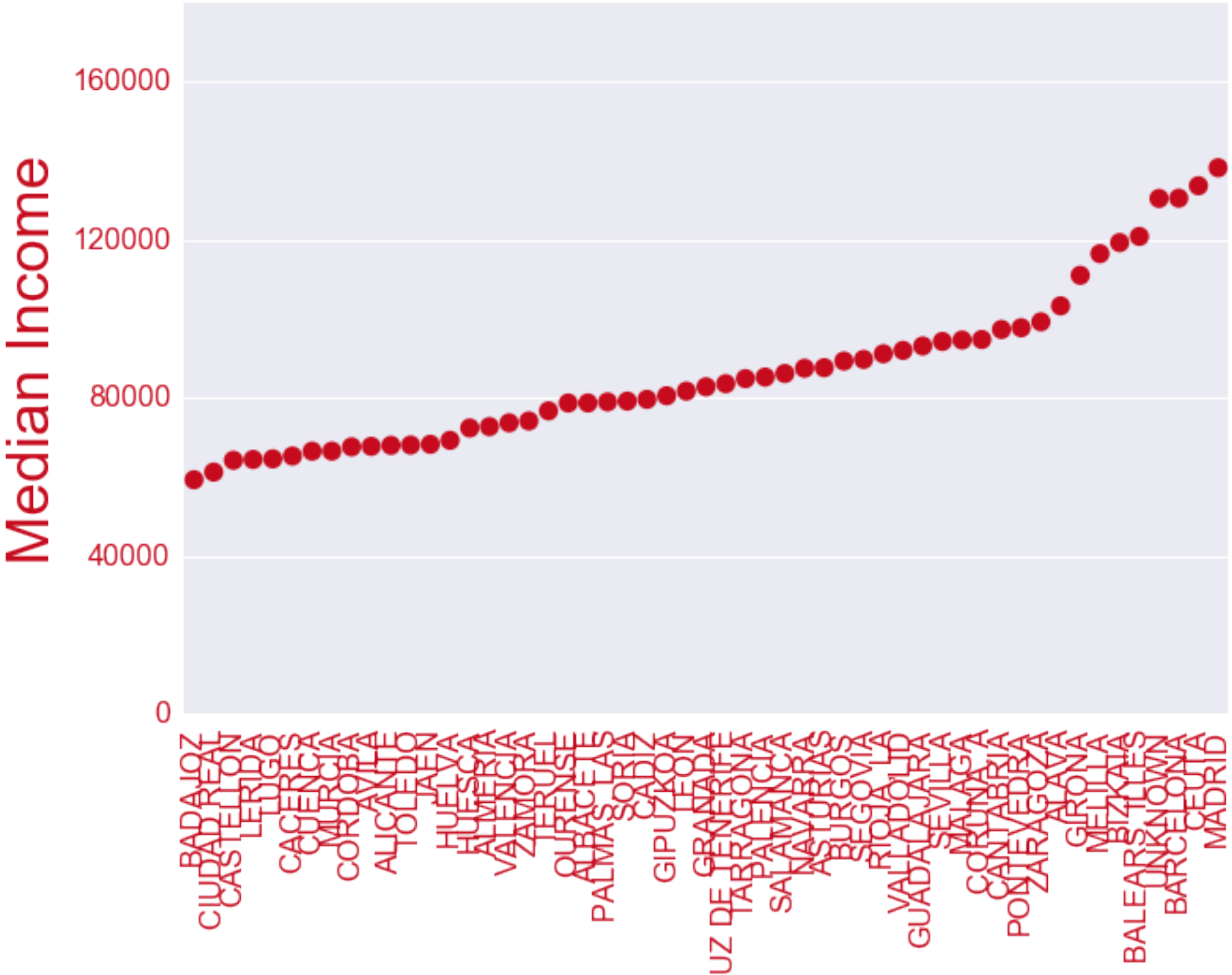
Number of Product Sales by Time



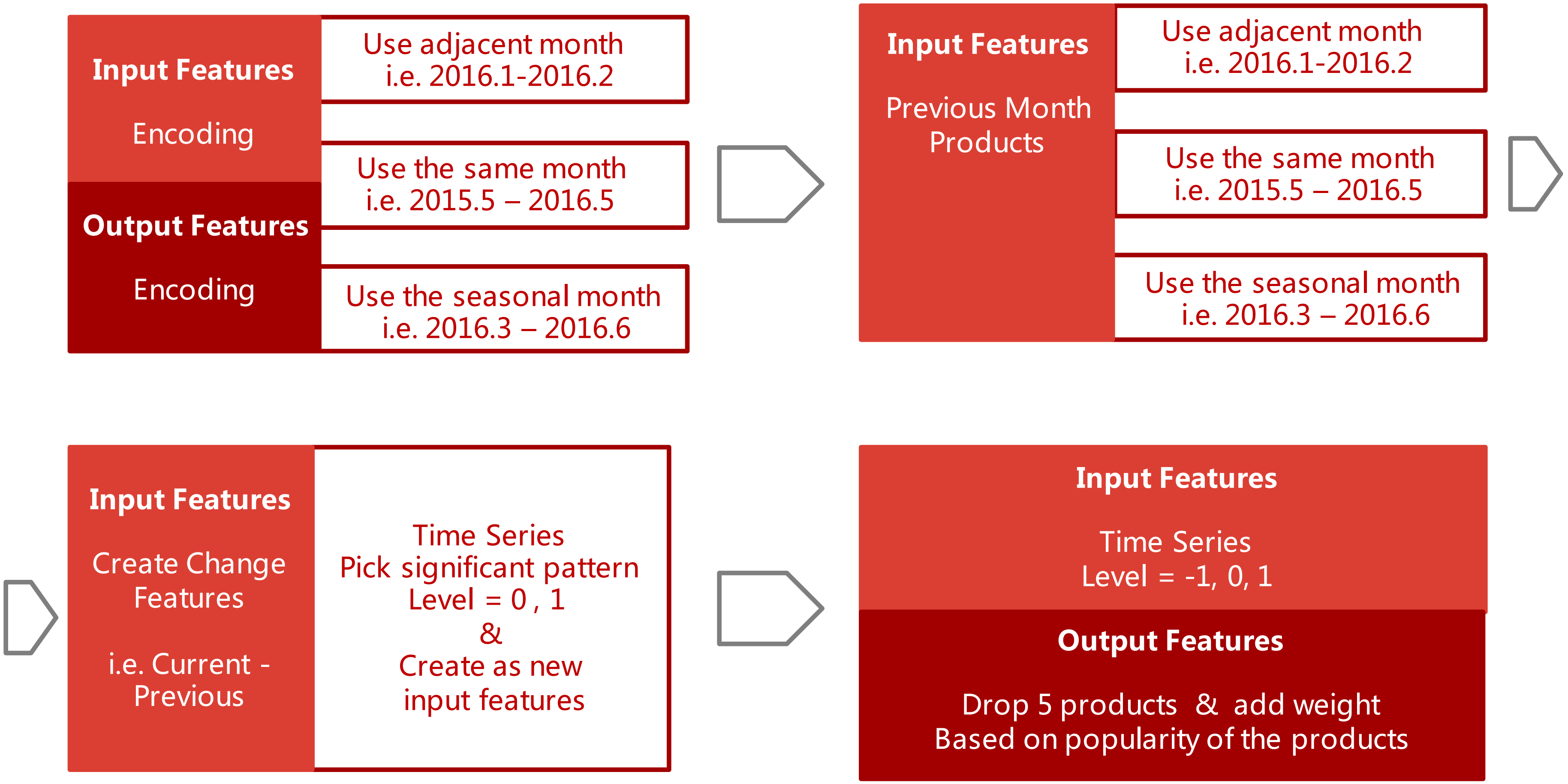


EDA

Income Distribution by City



Feature Engineering



Input Features

Encoding

Output Features

Encoding

Use adjacent month
i.e. 2016.1-2016.2

Use the same month
i.e. 2015.5 – 2016.5

Use the seasonal month
i.e. 2016.3 – 2016.6

Input Features

Previous Month
Products

Use adjacent month
i.e. 2016.1-2016.2

Use the same month
i.e. 2015.5 – 2016.5

Use the seasonal month
i.e. 2016.3 – 2016.6

Input Features

Create Change
Features

i.e. Current -
Previous

Time Series
Pick significant pattern
Level = 0 , 1
&
Create as new
input features

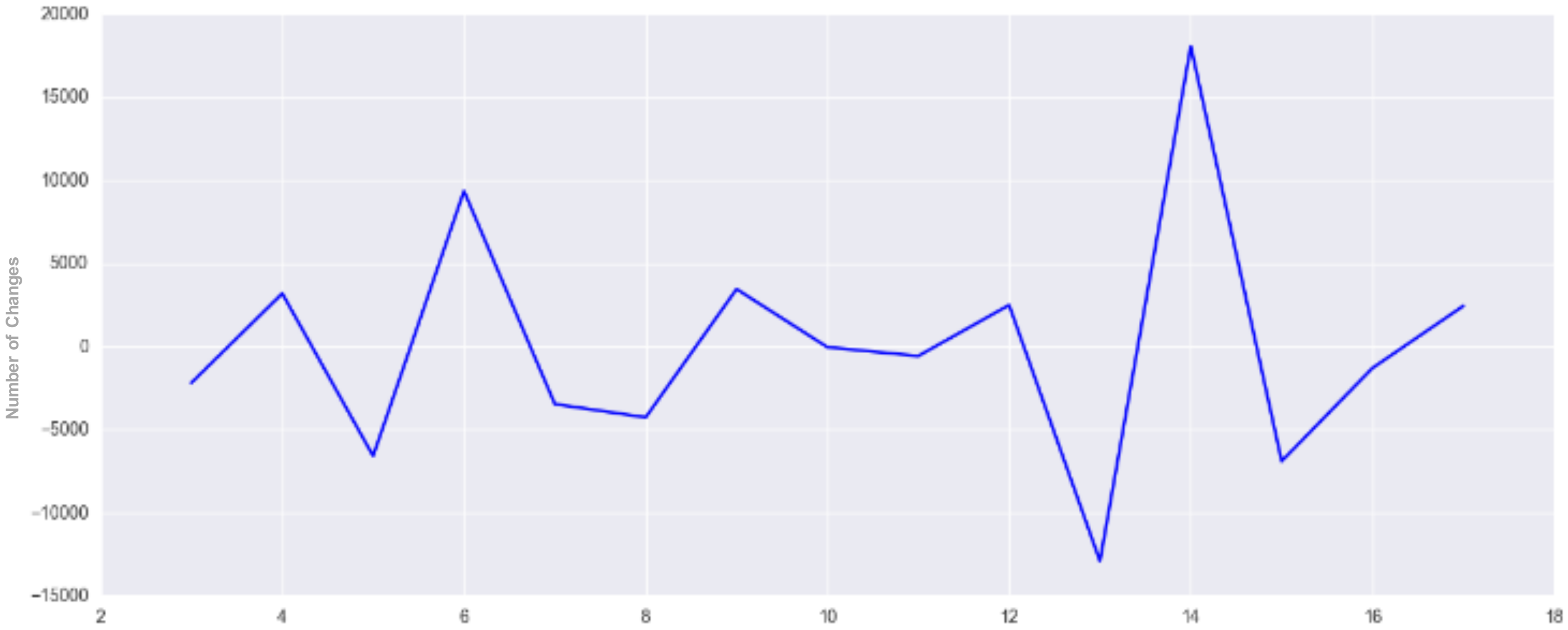
Input Features

Time Series
Level = -1, 0, 1

Output Features

Drop 5 products & add weight
Based on popularity of the products

Time Series



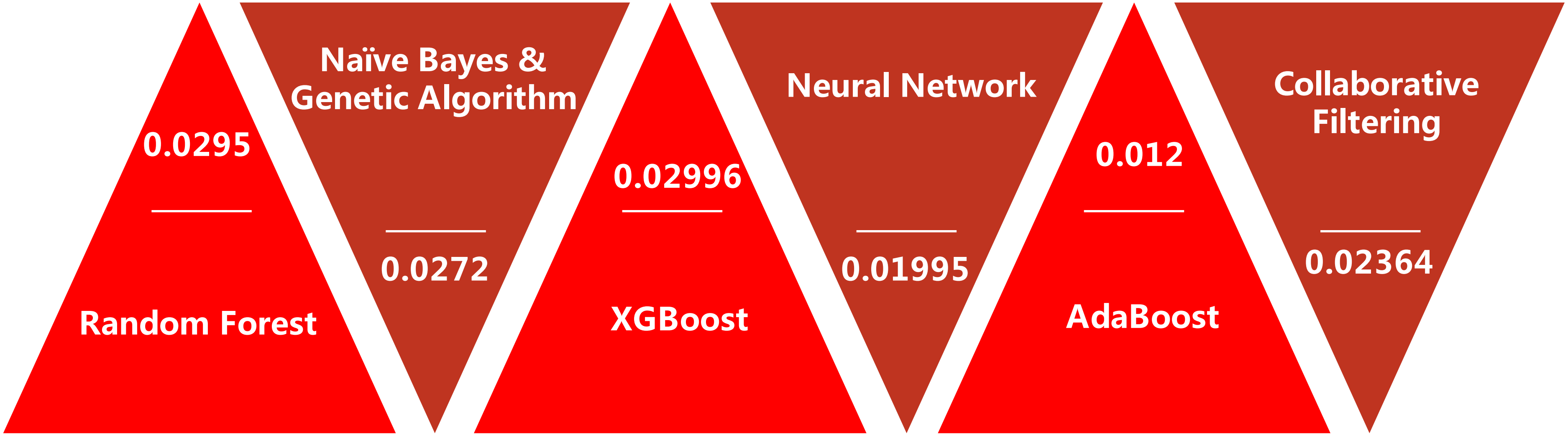
Results of ADF Test

Pension Account

Test Statistic	-3.163039
p-value	0.022226
No. Lags Used	4.000000
Critical Value (5%)	-3.232950
Critical Value (1%)	-4.331573
Critical Value (10%)	-2.748700

Models Training

Multi-label and Multi-class algorithms



0.0295

Random Forest

Naïve Bayes & Genetic Algorithm

0.0272

0.02996

XGBoost

Neural Network

0.01995

0.012

AdaBoost

Collaborative Filtering

0.02364

Make recommendation based on products’ popularity | 0.0225

Ensemble - Voting

0.0276

Popularity
0.0225

Collaborative Filter
0.0236

Naïve Bayes
0.0272

01
02
03
04
05
06

Popularity
0.0225

Collaborative Filter
0.0236

Naïve Bayes
0.0272

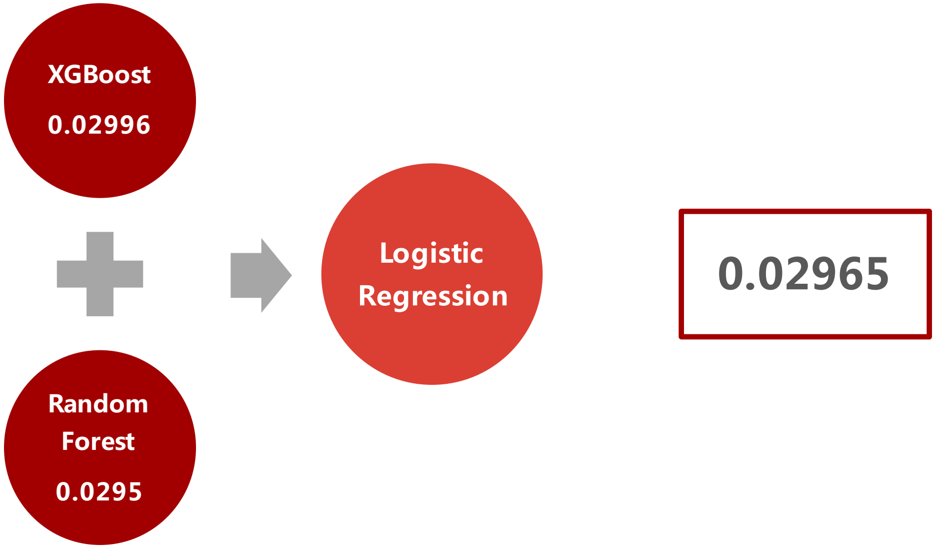
XGBoost
0.0269

XGBoost (new Features)
0.0289

Random Forest (multiclass)
0.0225

0.0230108

Ensemble - Stacking



XGBoost

0.02996

Random Forest

0.0295

Logistic Regression

0.02965

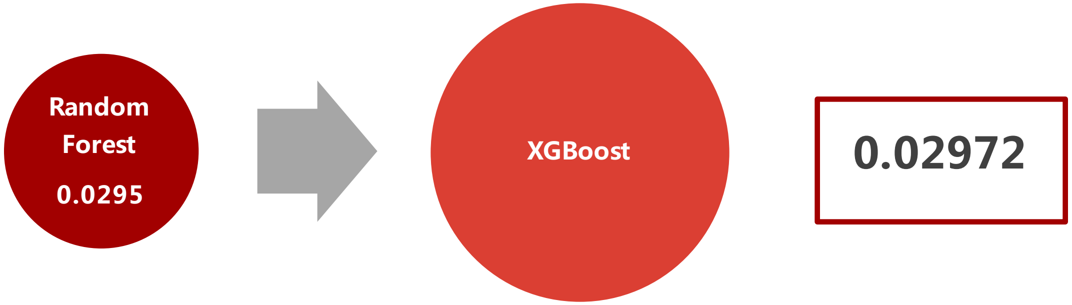
New Features Used

5 previous months' account history

Marriage index (age, sex and income)

Combined city and income

Removed 5 products



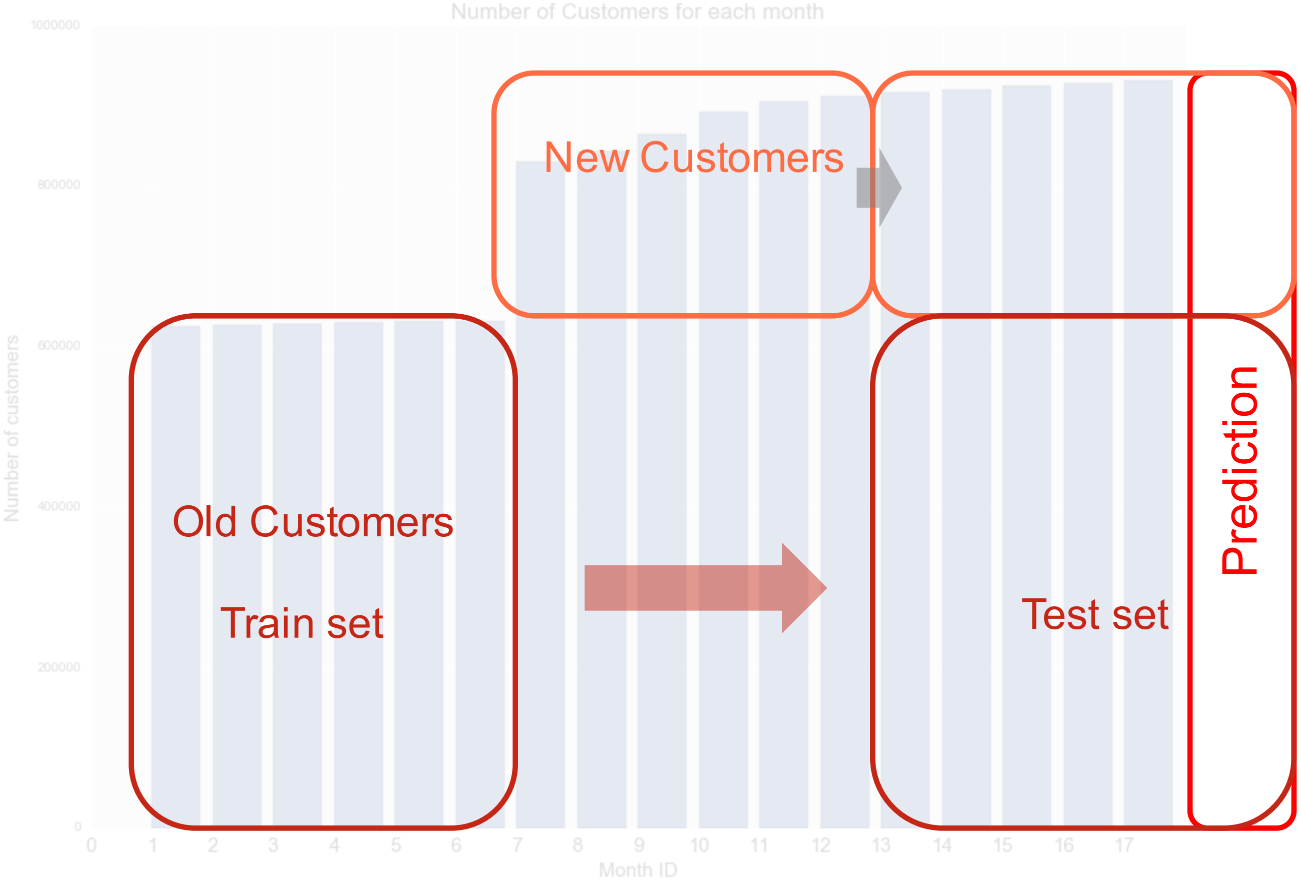
Random Forest

0.0295

XGBoost

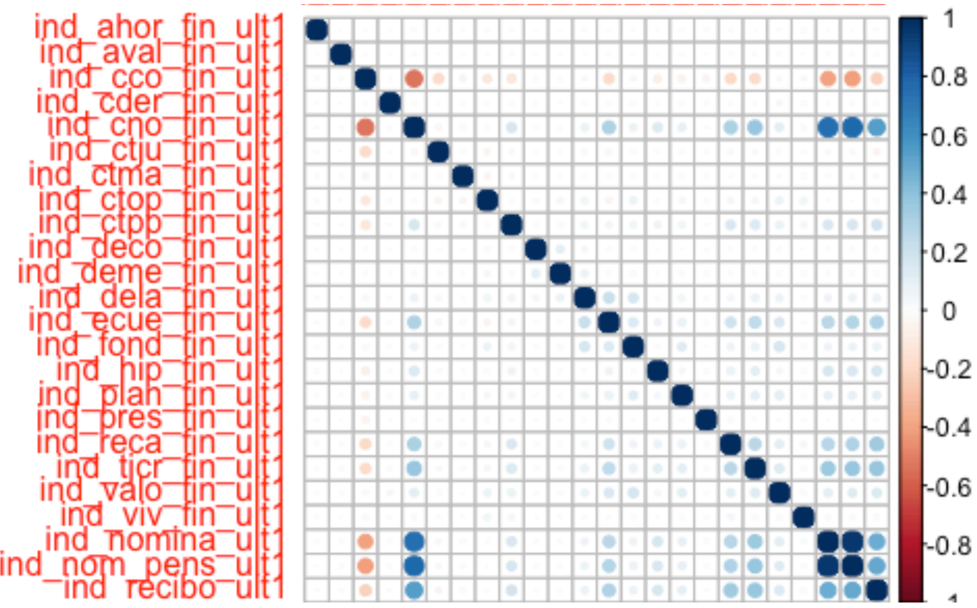
0.02972

Work-in-progress

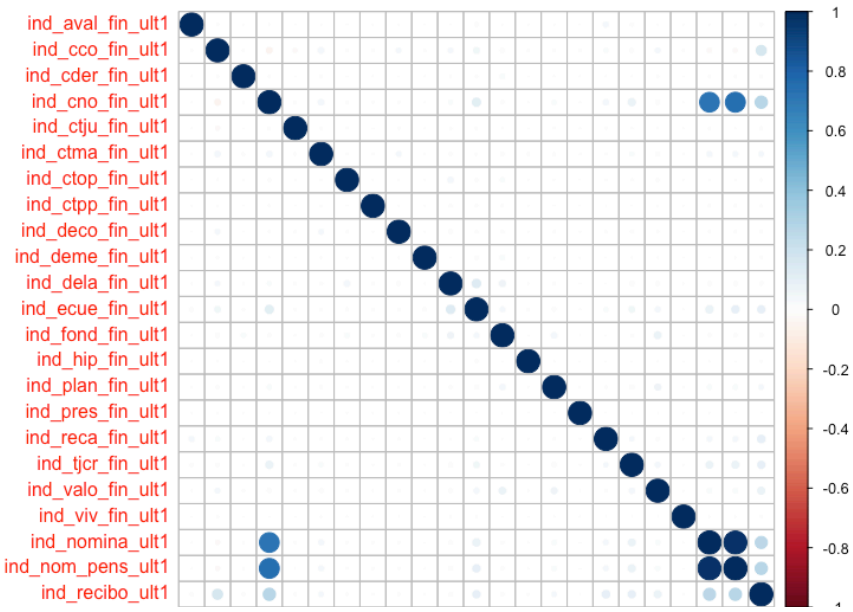


Work-in-progress

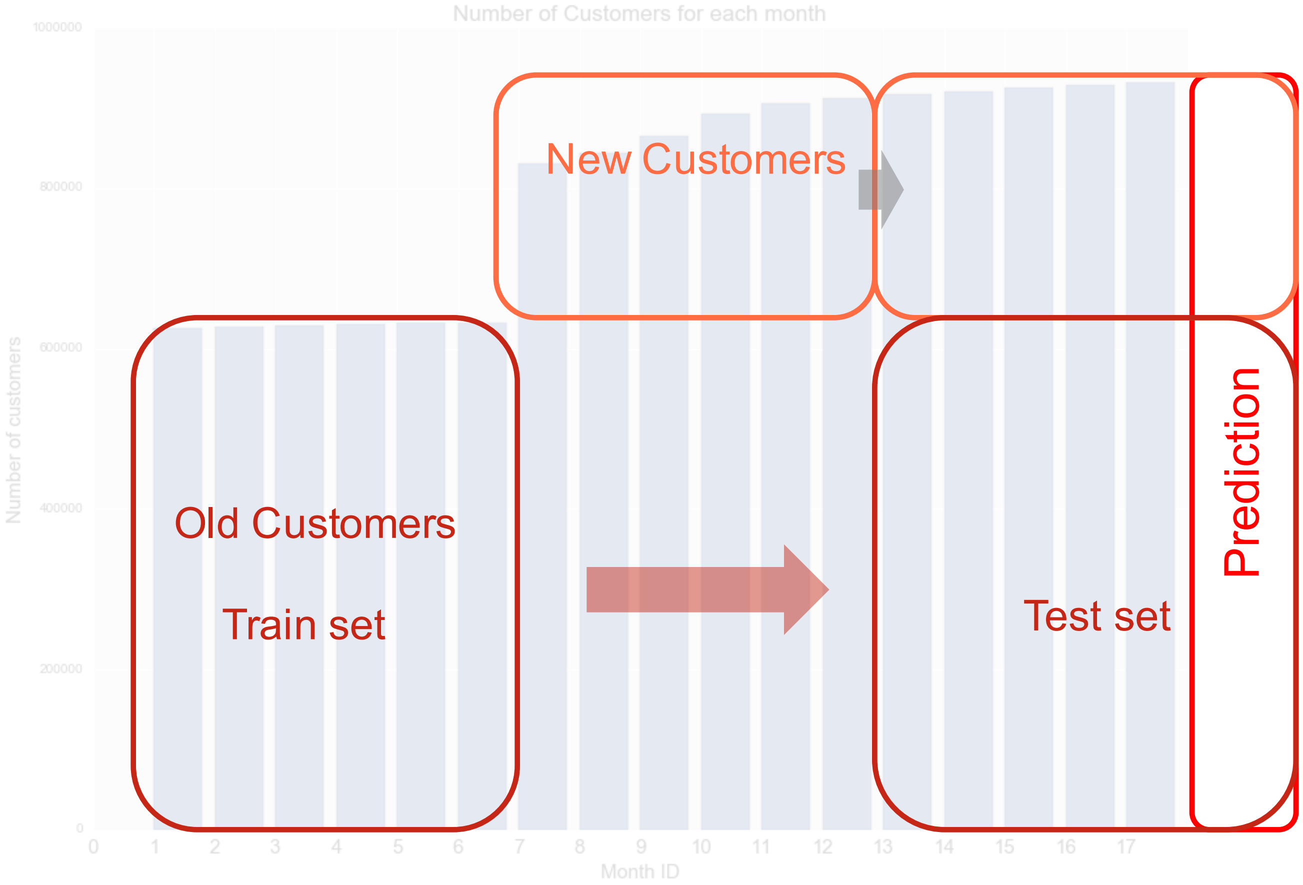
Old Customers



New Customers



Work-in-progress



New Customers

Old Customers

Train set

Test set

Prediction

0.0297

Insights & Findings

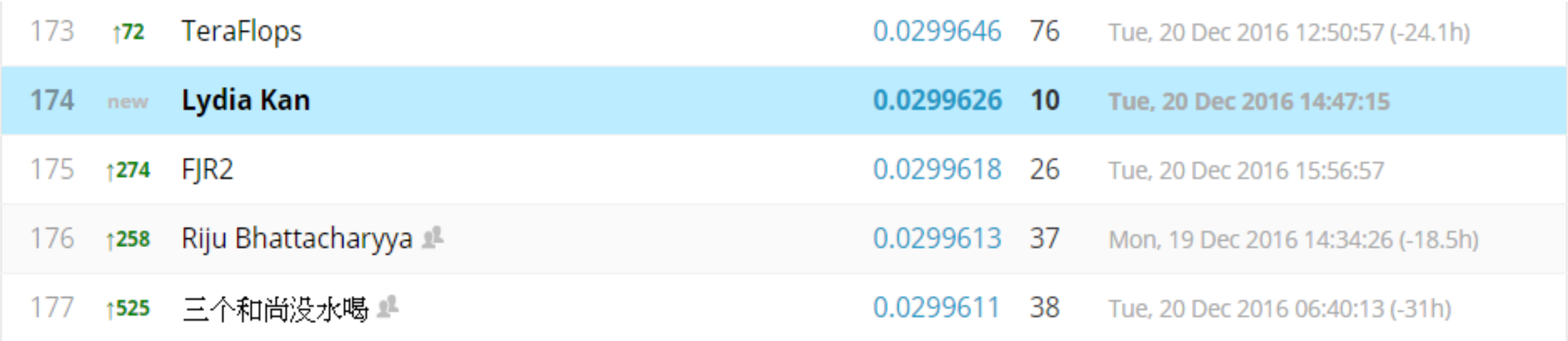
Building the model on 2015-06 is key to predict 2016-06.

Single Models, XGBoost has the best performance

Most helpful features: · 5 previous months · removing 5 products

Multi-class vs. multi-labels algorithms

Final Result



173	↑72	TeraFlops	0.0299646	76	Tue, 20 Dec 2016 12:50:57 (-24.1h)
174	new	**Lydia Kan**	**0.0299626**	**10**	**Tue, 20 Dec 2016 14:47:15**
175	↑274	FJR2	0.0299618	26	Tue, 20 Dec 2016 15:56:57
176	↑258	Riju Bhattacharyya	0.0299613	37	Mon, 19 Dec 2016 14:34:26 (-18.5h)
177	↑525	三个和尚没水喝	0.0299611	38	Tue, 20 Dec 2016 06:40:13 (-31h)

Total Teams : 1806

Top 9 %