

# Customers segmentation and probability to purchase modelling

## **Agenda**

- Introduction & objective
- Data source & data preparation
- Exploratory analysis
- Main analysis
  - RFM customer segmentation
  - O Customer lifetime value (CLV) Analysis
- Probability to purchase prediction
  - Logistic regression
- Key Insights & recommendations

#### Introduction

**Objective:** Enhance customer experience, elevate satisfaction levels, boost revenue

**Methodology:** RFM Customers Segmentation, Customer Lifetime Value (CLV) using BigQuery and Looker Studio, Logistic Regression using Python.

Target Audience: Transacted and non-transacted electronics company portal customers

**Goal:** Provide actionable insights to ensure growth and improve operations

#### **Introduction to Data Source**

E-Commerce Data Source for 2016 Aug 1 – 2017 July 31.

**Dataset information:** visitors data including geographical, technological, marketing channels usage, transactional revenue

**Dataset size:** ~243k rows, 55 attributes

Selected Time Coverage: marketing analytics dataset ( 2016 Aug 1 - 2016 Oct 31)

## **Data Preparation**

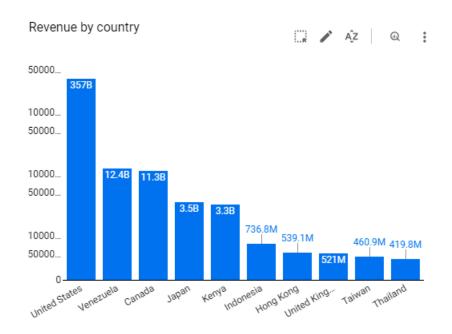
Main analysis	Probability of purchase analysis	Features selected
Feature Engineering: Checking the revenue values of customer	Handling Missing Values and Duplicates: checking for missing and duplicated data to fix or replace it by median or mode.	24
transactions data, creating a necessary transactional field for further analysis.	Outlier Identification and Management: checking and identifying outliers to manage them and normalize the variables distribution.	
	Variables encoding: categorical and boolean variables encoding to make them suitable for logistic regression modelling.	
	Feature Selection Based on Correlation and Multicollinearity	20
	<b>Feature Selection by Significance:</b> variables have been chosen for modeling based on their significance.	14 (10)

## **Exploratory Analysis (1)**

#### **Key Metrics:**

- ~200k unique visitors, ~2k unique transactions.
- \$394.03 billion in revenue, \$138,2 millions average transactions value

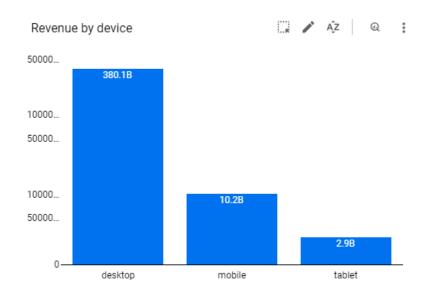
## **Exploratory Analysis (2)**



#### **Key Metrics:**

Customers from USA generates ~ 91% of the revenue, compared to other countries only ~9%.

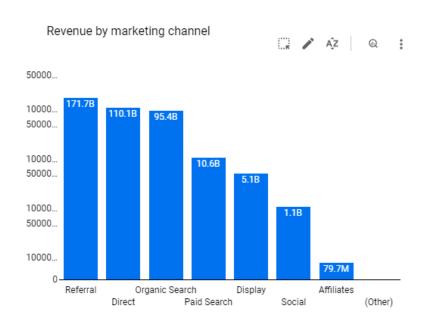
## **Exploratory Analysis (3)**



#### **Key Metrics:**

Desktop user generates ~ 97% of the revenue, compared to mobile and tablet only ~3%.

## **Exploratory Analysis (4)**



#### **Key Metrics:**

Most of revenue is generated from Referral,

Direct and Organic Search marketing channels

## **Exploratory Analysis (5)**

RFM segment	# of custo	% of custo	Revenue • •
Loyal Customers	529	21%	\$130.18B
Customers Needing Attention	708	28%	\$84.3B
At Risk	168	7%	\$71.87B
Best Customers	127	5%	\$65.93B
Hibernating	348	14%	\$22.27B
Cant Lose Them	25	1%	\$8.66B
Recent Customers	186	7%	\$3.04B
Promising	171	7%	\$2.83B
About to Sleep	146	6%	\$2.57B
Lost Customers	133	5%	\$2.38B

#### **Key Metrics:**

Best customers and Customers Needing

**Attention** generates most of the revenue

across customers segments

## **Exploratory Analysis (2)**

**Key Metrics:** 

• Transacted visitors show high engagement rate in average - 34 pagevies vs non-transacted – only 4.

## **RFM Analysis**

- Customer Segmentation based on Recency, Frequency, Monetary values:
  - o Non-transacted **engagement**: visit recency, number of visits, number of pageviews
  - o Transacted **purchase**: transaction recency, number of transactions, average revenue
- Customer distribution across segments
- Revenue distribution across segments

## **RFM Analysis – Transacted customers**

#### **Key Insights**

- Top Segments: **Best Customers** and **At Risk**
- Segments Cant Loose Them,
   Customers Needing Attention
   need extra care
- Segment Loyal customers need to be nurtured and up-selling and cross-selling strategies should be applied
- Need to adjust the marketing strategies for segments.

#### Customers Revenue Distribution across segments

	RFM segment	# of visitors	% of visitors	Recency (Average	Frequency (Av	Monetary (Averag
1.	Best Customers	127	5%	25	2.55	\$519.12M
2.	At Risk	168	7%	75.79	1.4	\$427.78M
3.	Cant Lose Them	25	1%	77.84	2.16	\$346.53M
4.	Loyal Customers	529	21%	18.99	1.02	\$246.09M
5.	Customers Needing	708	28%	52.27	1	\$119.06M
6.	Hibernating	348	14%	80.45	1	\$64M
7.	Lost Customers	133	5%	81.73	1	\$17.86M
8.	About to Sleep	146	6%	61.72	1	\$17.6M
9.	Promising	171	7%	36.4	1	\$16.57M
1	Recent Customers	186	7%	13.4	1	\$16.34M

### **RFM Analysis – Non-transacted customers**

#### **Key Insights**

- Top Engaged Segments: At Risk, Cant Loose Them, Best Customers, Loyal Customers.
- Segments Customers Needing Attention and Hibernating need extra care.
- Need to improve user experience and maintain re-engagement strategies for segments with higher monetary (engagement) metrics).

#### Customers Engagement rate by segments

RFM segment	# of visitors	% of visitors	Recency (Av	Frequency (A	Monetary (A
At Risk	16,005	8%	70.8	4.39	8.43
Cant Lose Them	4,991	3%	79.09	7.4	7.72
Best Customers	9,672	5%	18.89	25.67	6.55
Loyal Customers	28,788	14%	15.31	1.37	5.92
Customers Nee	31,823	16%	44.18	1.14	4.7
Hibernating	9,172	5%	79.36	1	2.3
Promising	22,464	11%	27.36	1	1
About to Sleep	24,305	12%	53.08	1	1
Lost Customers	23,887	12%	79.42	1	1
Recent Custom	28,154	14%	8.1	1	1

## **Customer Lifetime Value (CLV) Analysis**

- Monthly Customer Lifetime value for 2016 Aug 1 2016 Oct 31
- Cohort analysis and Predictive Modeling results shows Overall CLV = \$2,09 M

## **CLV Analysis**

#### **Key Insights**

Predictive Modeling of CLV calculation

All Customers CLV: \$2,09 M

Last 3 weekly cohorts shows higher predictive values



## **Probability of purchase analysis**

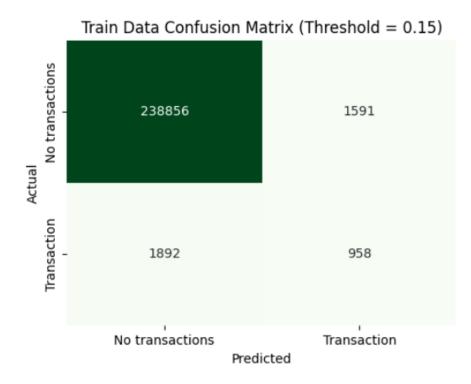
- Selecting significant attributes for predictive modelling
- Logistic regression model creation
- Probability of purchase estimation

## Probability of purchase model creation

#### **Key Insights**

- Model created with precision 37,58%, accuracy 98.57%, recall -33.6%.
- True Positive Rate
  (Sensitivity/Recall): 0.3361, False
  Positive Rate: 0.0066
- Need to balance dataset to have a better prediction for positive cases
- It is recommended to use alternative methods as KNN and decision tree to compare the model performance

Logistic regression model

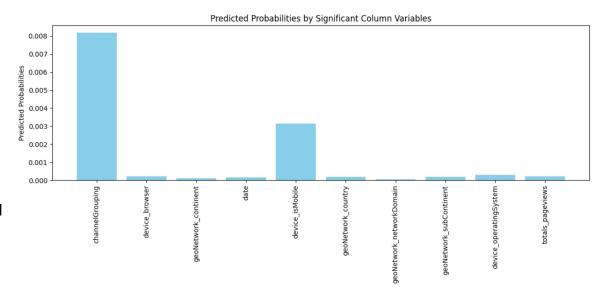


## **Probability of purchase**

#### **Key Insights**

- Higher probabilities has variables as marketing channels and devices related data (type)
- Possibilities to scale most significant categories involving feature engineering by they options
- Additional data required for model improvement

#### Most significant factors predicting probability of purchase



**Key insights & Recommendations** 

## **Key Insights**

1

Referral, direct and organic search channels brings most traffic and revenue

2

USA market generates the most revenue

K

Majority transactions and revenue comes from desktop users

4

**Best Customers & Customers Needing Attention** customers
bring 54,4% of all revenue
(\$214,48 billion).

5

Predictive Customer lifetime value (\$2.09 M)

6

The highest impact for purchase probability has marketing channel and device type related data

## Recommendations

1

Improve user experience for desktop and mobile users to maximize revenue and number of transactions 2

Focus on retention and reengagement strategies 3

Focus on High-Value Segments, tailor marketing messages to maximize engagement and generated revenue

4

Engage with At Risk and Loyal Customers which account is 34,9% of customers (\$156,16 billion)

5

Improve probability of purchase estimation by using strategies like balancing dataset, feature engineering with WoE estimation 6

Use alternative models such as decision trees (e.g., Random Forest) and KNN to capture complex patterns.



## Thank you!