CUSTOMER LIFETIME VALUE

Group 4 - May 2024

Customer
lifetime value

OUR TEAM

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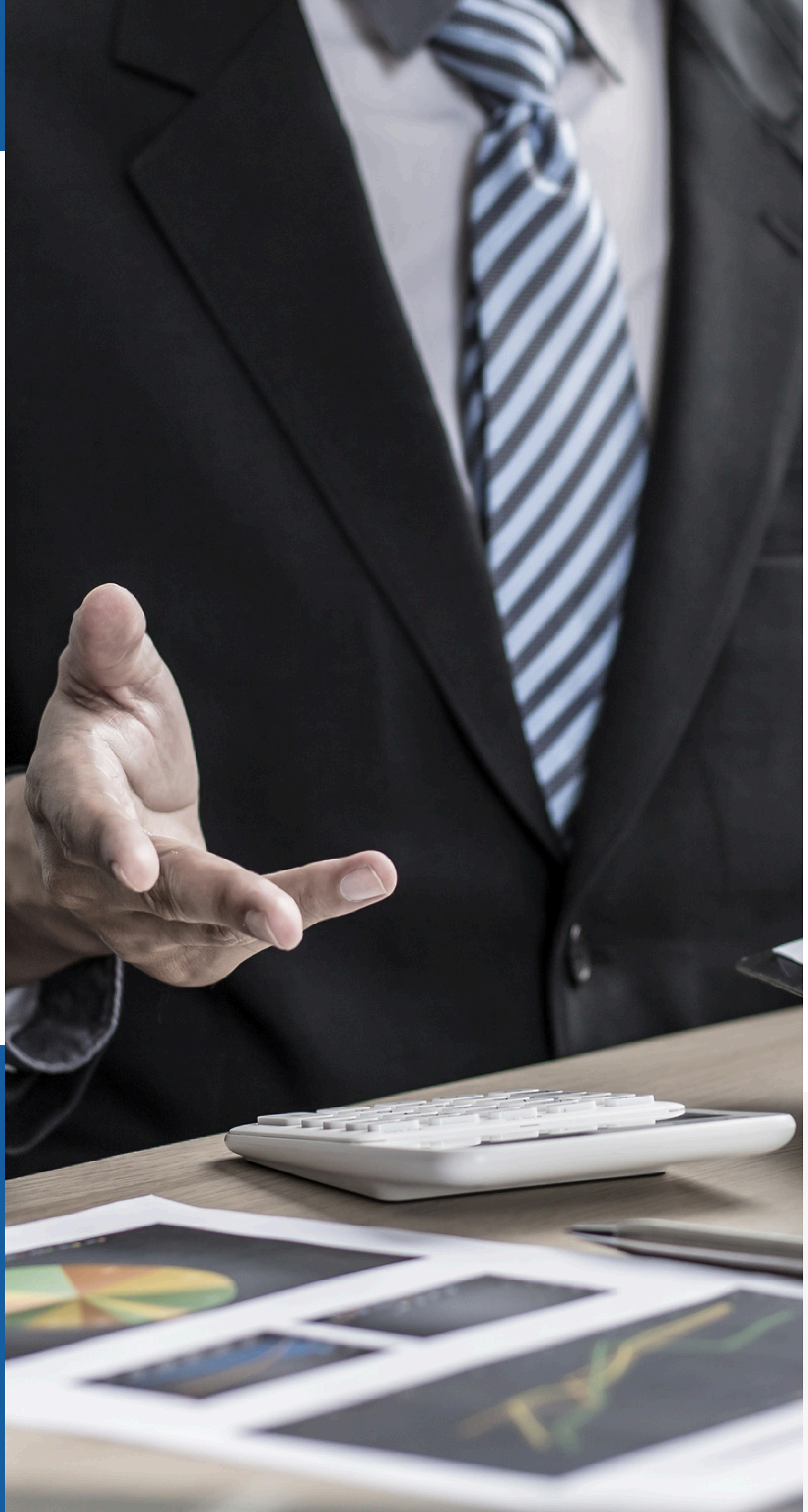


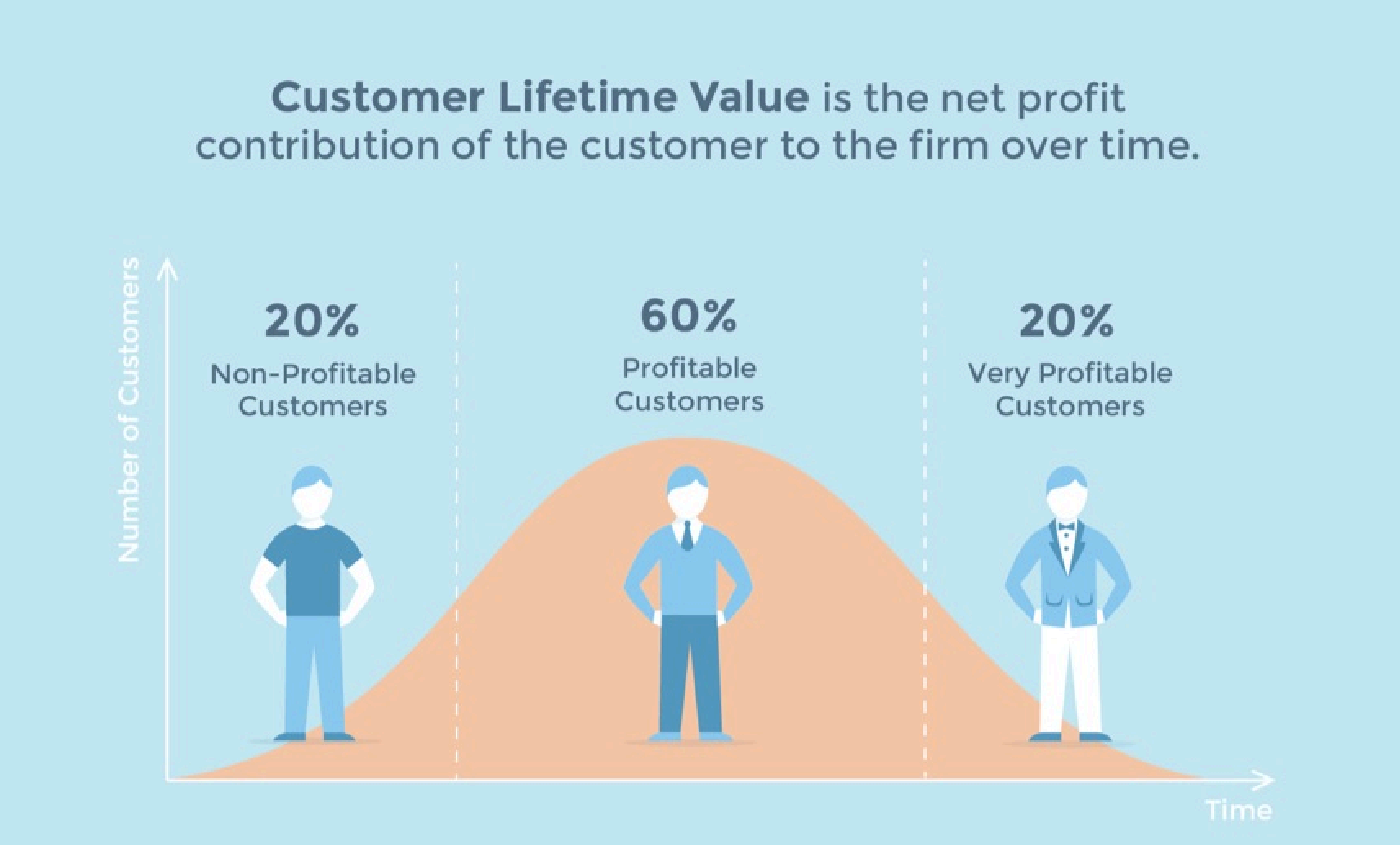
CONTENT

Customer
lifetime value

INTRODUCTION

Customer lifetime value

1. PROBLEM DEFINITION



Customer lifetime value is a metric that represents the total net profit a company can expect to generate from a customer throughout their entire relationship. It takes into account the customer's initial purchase, repeat purchases, and the average duration of their relationship with the company.

2. MOTIVATION

Measuring Marketing Efforts

Understanding Customer Behavior

Understanding Marketing Objectives

Segmentation

ROI and Budget Allocation

Customer lifetime value

3. PROBLEM SETTING

	id	zone	state	gender	age_category	age	date	cds	amt
0	1	Pacific	Oregon	M	young	26	1997-01-01	1	11.77
1	2	Eastern	New Jersey	M	medium	36	1997-01-12	1	12.00
2	2	Eastern	New Jersey	M	medium	36	1997-01-12	5	77.00
3	3	Central	Minnesota	M	young	17	1997-01-02	2	20.76
4	3	Central	Minnesota	M	young	17	1997-03-30	2	20.76
...	...	...	...	...	...	...	...	...	...
69654	23568	Eastern	New Jersey	F	medium	44	1997-04-05	4	83.74
69655	23568	Eastern	New Jersey	F	medium	44	1997-04-22	1	14.99
69656	23569	Mountain	Utah	M	old	63	1997-03-25	2	25.74
69657	23570	Central	Illinois	F	young	21	1997-03-25	3	51.12
69658	23570	Central	Illinois	F	young	21	1997-03-26	2	42.96

69659 rows × 9 columns

The first dataset we use is **Online Retail II** data set which contains all the transactions occurring for a UK-based and registered, non-store online retail between 01/12/2009 and 09/12/2011. The company mainly sells unique all-occasion gift-ware. Many customers of the company are wholesalers.

The second dataset is the **CD NOW** dataset. which contains the entire purchase history up to the end of June 1998 of the cohort of 23,570 individuals who made their first-ever purchase at CDNOW in the first quarter of 1997.

	Invoice	StockCode	Description	Quantity	InvoiceDate	Price	Customer ID	Country
0	489434	85048	15CM CHRISTMAS GLASS BALL 20 LIGHTS	12	2009-12-01 07:45:00	6.95	13085.0	United Kingdom
1	489434	79323P	PINK CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	United Kingdom
2	489434	79323W	WHITE CHERRY LIGHTS	12	2009-12-01 07:45:00	6.75	13085.0	United Kingdom
3	489434	22041	RECORD FRAME 7" SINGLE SIZE	48	2009-12-01 07:45:00	2.10	13085.0	United Kingdom
4	489434	21232	STRAWBERRY CERAMIC TRINKET BOX	24	2009-12-01 07:45:00	1.25	13085.0	United Kingdom
...	...	...	...	...	...	...	...	...
1067366	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2011-12-09 12:50:00	2.10	12680.0	France
1067367	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2011-12-09 12:50:00	4.15	12680.0	France
1067368	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2011-12-09 12:50:00	4.15	12680.0	France
1067369	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2011-12-09 12:50:00	4.95	12680.0	France
1067370	581587	POST	POSTAGE	1	2011-12-09 12:50:00	18.00	12680.0	France

1067371 rows × 8 columns

Customer
lifetime value

LITERATURE REVIEW

RESEARCH ON CUSTOMER LIFE CYCLE VALUE

Based on the customer perspective

DEFINE CUSTOMER VALUE

Based on the enterprise perspective

BUSINESS RELATIONSHIP

Contractual relationship

customers sign long-term contracts with a single business. If the contract is not renewed or transactions cease, the customer is considered lost permanently.

Non-contractual relationships

customers engage with multiple businesses concurrently with minimal switching costs. Pausing transactions doesn't necessarily mean customer loss

CUSTOMER LIFE CYCLE MODEL

Customer lifetime value

Scholars have identified shortcomings in CLV models

They are often overly conceptual and idealized, making practical application difficult.

CLV typically focuses only on customer profitability, neglecting the broader value customers bring beyond revenue

In the information age, the abundance of product options leads to intense competition among businesses, making it challenging to retain customers and gather comprehensive data for CLV calculation

PROBABILISTIC MODEL

Disadvantages

Reliance on assumptions that may not always hold true

Limited use of purchase information in some models

Complexity may require expertise in statistical analysis

Advantages

Utilize historical data to estimate customer behavior

Provide insights into customer retention and purchase frequency

Adaptations enhance predictive accuracy by considering various factors

MACHINE LEARNING MODEL

Advantages

- Flexibility in modeling complex relationships in data
- Potential for high predictive performance
- Can incorporate various data types and features

Disadvantages

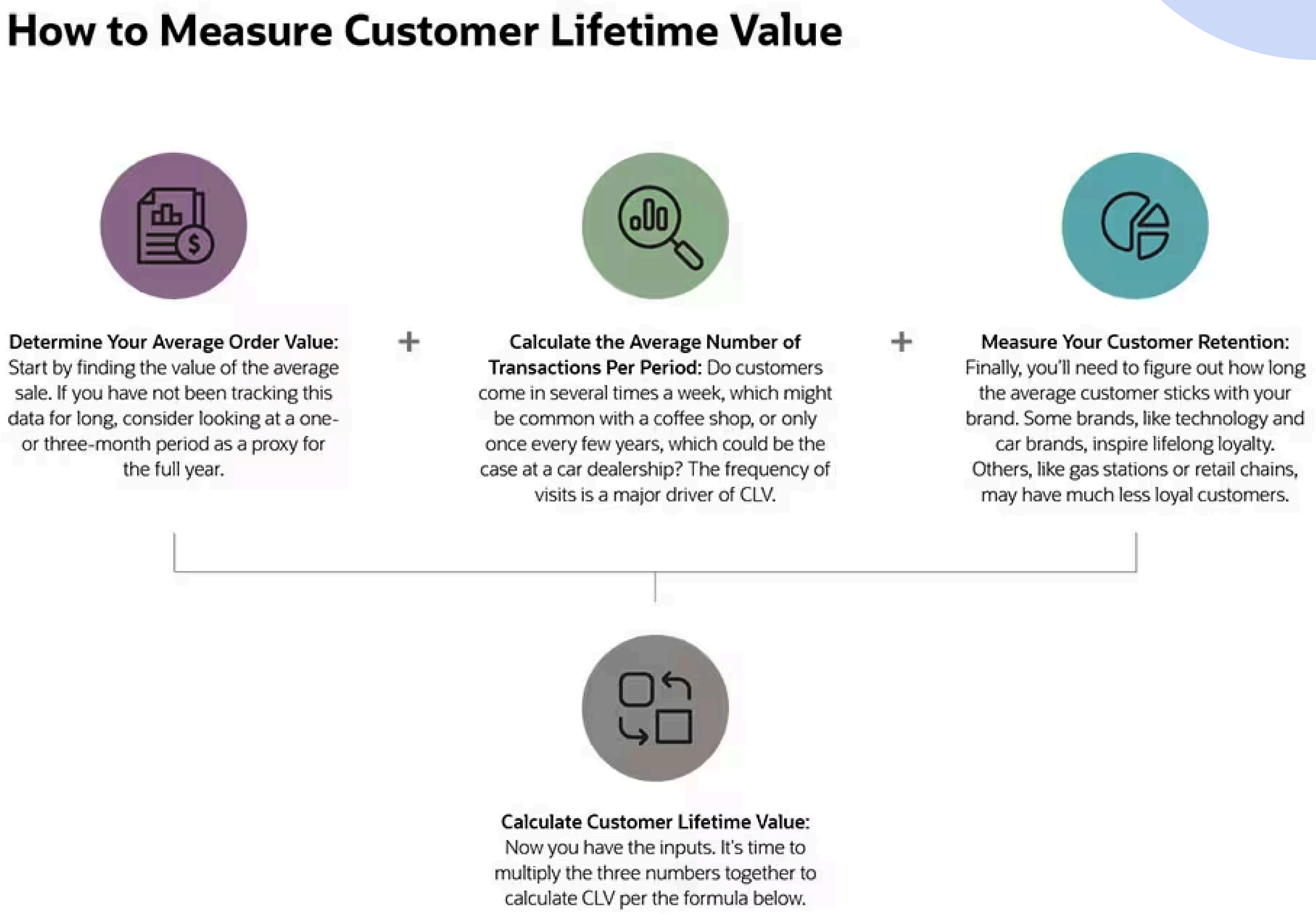
- Requires parameter tuning and careful model selection
- Prone to overfitting, especially with large datasets
- Computational complexity may be high, leading to longer training times

Customer
lifetime value

SOLUTION & RESULT

TRADITIONAL
CLV

TRADITIONAL CLV



CLTV = ((Average Order Value x Purchase Frequency) / Churn Rate) x Profit Margin.

CUSTOMER LIFETIME VALUE

$$CLV = \sum_{t=0}^{T} \frac{(p_t - c_t)r_t}{(1+i)^t} - AC$$

CLV for a customer

$$CLV = \sum_{t=0}^{\infty} \frac{(p - c)r^t}{(1+i)^t} = m\frac{r}{(1+i-r)}.$$

Arbitrary time horizon or expected customer lifetime

where

pt= price paid by a consumer at time t,

ct = direct cost of servicing the customer at time t,

i = discount rate or cost of capital for the firm,

rt = probability of customer repeat buying or being “alive” at time t,

AC = acquisition cost, and

T = time horizon for estimating CLV

PROBABILISTIC MODEL

CLTV = NUMBER OF TRANSACTIONS × AVERAGE ORDER VALUE

BG / NBD Model

Buy till you Die

Models 2 processes probabilistically

Transaction Process (BUY)

⦿ If Alive, the number of transactions to be performed by a client in a given time period is poisson distributed with the transaction rate parameter.

Dropout Process (DIE)

⦿ Each customer has a dropout rate with probability of p. After a customer makes a purchase, there is a certain probability that they will drop.

Gamma Gamma Submodel

⦿ Models expected average profit distribution and will predict the expected average profit for each customer.

⦿ The monetary value of a customer's transactions is randomly distributed around the average of their transaction values.

ASSUMPTION | BG/NBD MODEL

Step 1:

Poisson distribution for the number of transactions

$$f(t_j \mid t_{j-1}; \lambda) = \lambda e^{-\lambda(t_j - t_{j-1})}, \qquad t_j > t_{j-1} \geq 0.$$

Step 2:

Gamma distribution for the nonuniformity of transaction rate

$$f(\lambda \mid r, \alpha) = \frac{\alpha^r \lambda^{r-1} e^{-\lambda\alpha}}{\Gamma(r)}, \qquad \lambda > 0.$$

Step 3:

Binomial distribution for customer churn

$$P(\text{inactive immediately after } j\text{th transaction}) = p(1-p)^{j-1}, \qquad j = 1, 2, 3, \ldots .$$

Step 4:

Beta distribution for the nonuniformity of churn probability

$$f(p \mid a, b) = \frac{p^{a-1}(1-p)^{b-1}}{B(a, b)}, \qquad 0 \leq p \leq 1,$$

Apply Probabilistic Model

PHASE 1

Preparing Lifetime Value metrics

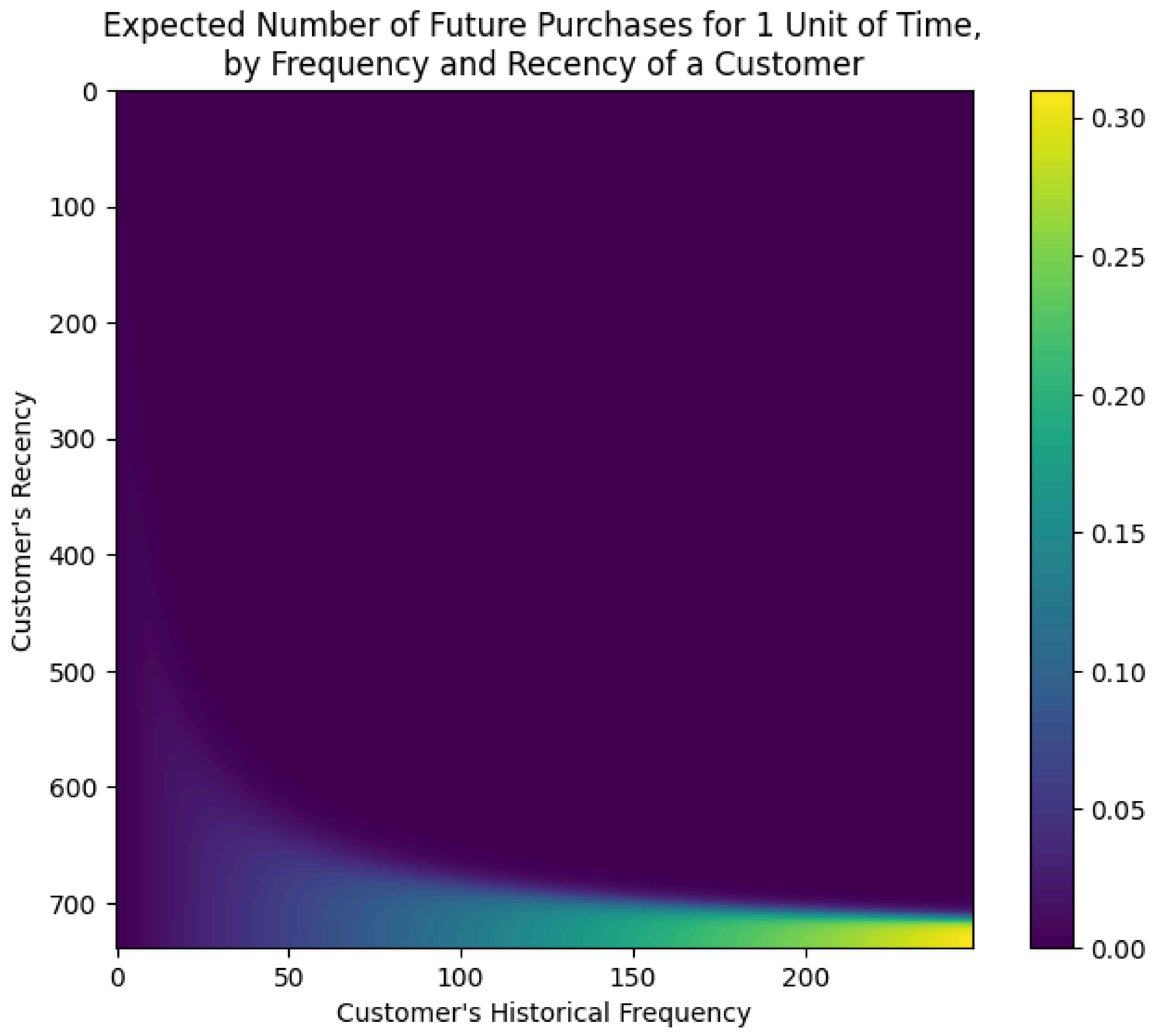
- **recency** — the time between the first and the last transaction
- **frequency** — the number of repeat purchases (more than 1 purchases)
- **T** — the time between the first purchase and the end of the transaction period (last date of the time frame considered for the analysis)
- **monetary_value** — it is the mean of a given customers sales value

Customer ID	frequency	recency	T	monetary_value	predicted_purchases
14606.0	176.0	735.0	736.0	167.237216	0.220695
17841.0	192.0	736.0	737.0	354.136667	0.240394
15311.0	195.0	738.0	738.0	583.837949	0.243872
12748.0	195.0	735.0	735.0	251.135333	0.244788
14911.0	248.0	737.0	738.0	1123.968387	0.309916

Apply Probabilistic Model

PHASE 2 **Apply BG/NBD model**

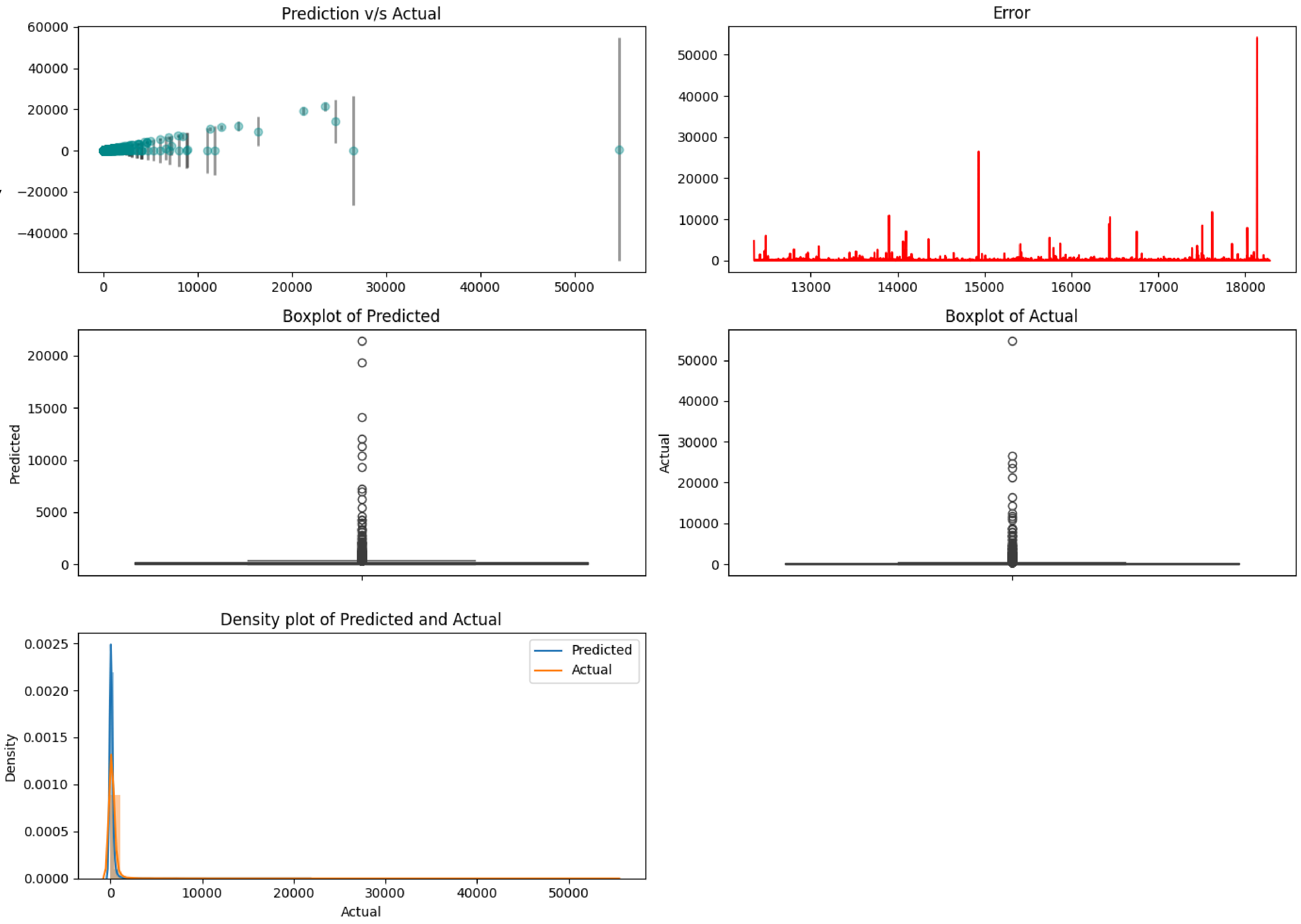
- The above matrix shows that the expected number of future purchases starts low (top-left), increases around (100, 600) days, and rises towards the bottom-right.
- The top-right section doesn't reflect a high number of purchases and instead shows that those customers who bought more frequently at the beginning didn't return.
- The customers who made 200 purchases when they were 700 days old are the loyal customers the company should focus on.



Apply Probabilistic Model

PHASE 3 **Apply Gamma-Gamma model**

- To add the monetary aspect of the problem, we have to model the monetary value using the Gamma-Gamma Model.
- We use GammaGammaFitter from Lifetimes package and fit the model to our data to calculate the expected average profit. Then we calculate CLTV by adding gamma gamma model to BG/NBD model.



=> The model is built on strong assumptions, which might not be accurate in practical application. True data often doesn't follow the distribution.

MACHINE LEARNING
MODEL

CUSTOMER CLASSIFICATION

Based on RFM Model

R

Recency

To calculate recency, we need to find out the most recent purchase date of each customer and see how many days they are inactive.

F

Frequency

Frequency represents the total number orders for each customer

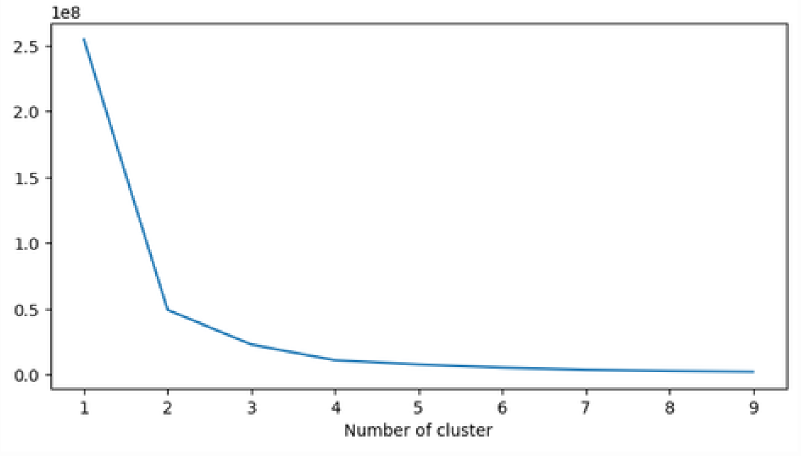
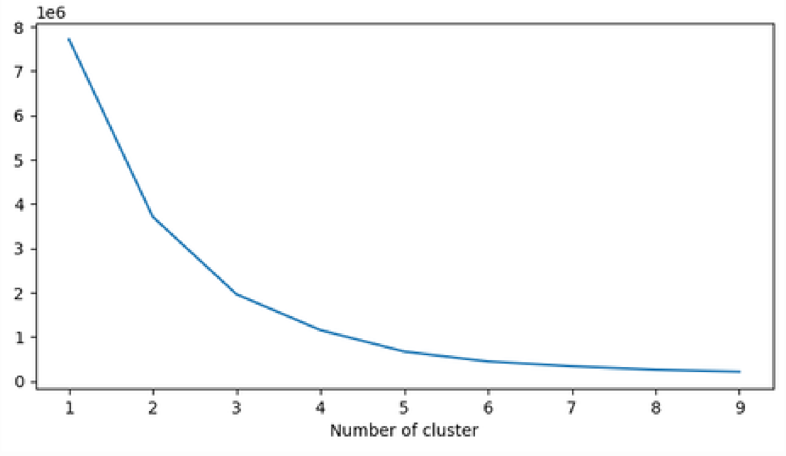
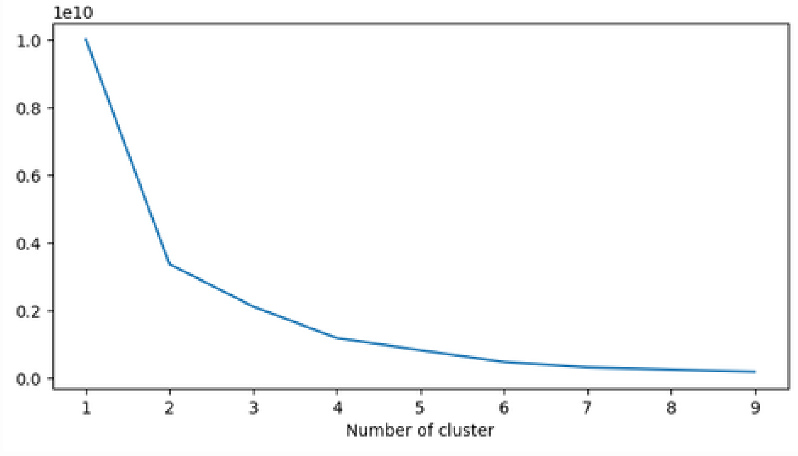
M

Monetary (Revenue)

Monetary value represents the total amount of money a customer has spent over a given period

CUSTOMER CLASSIFICATION

Based on RFM Model

<table>
<tr><th></th><th>Recency</th><th>Frequency</th><th>Revenue</th></tr>
<tr><td>KMeans</td>
<td></td>
<td></td>
<td></td></tr>
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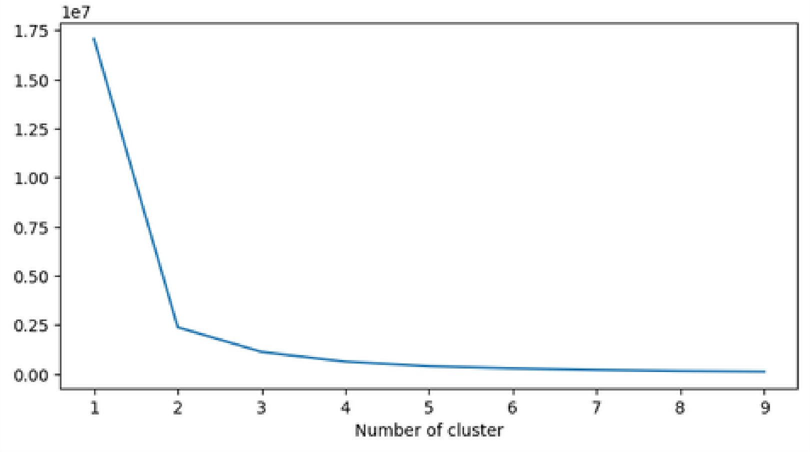
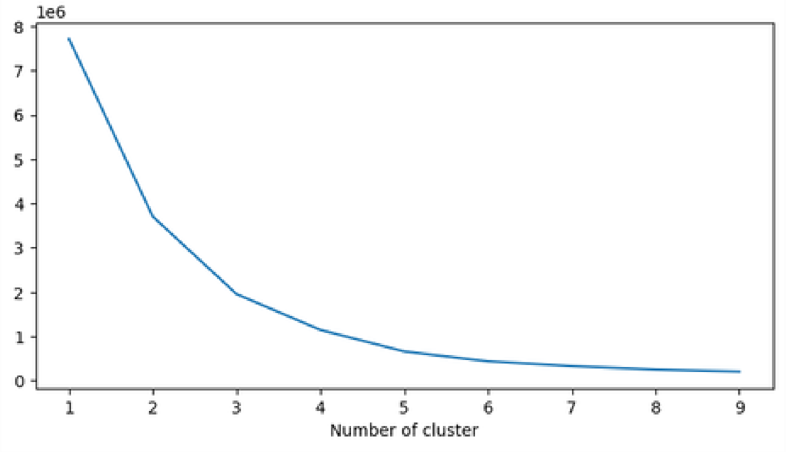
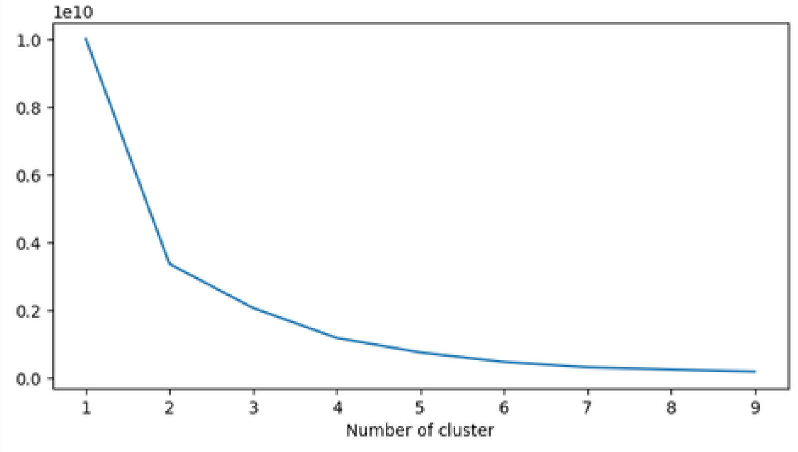
<td></td>
<td></td>
<td></td></tr>
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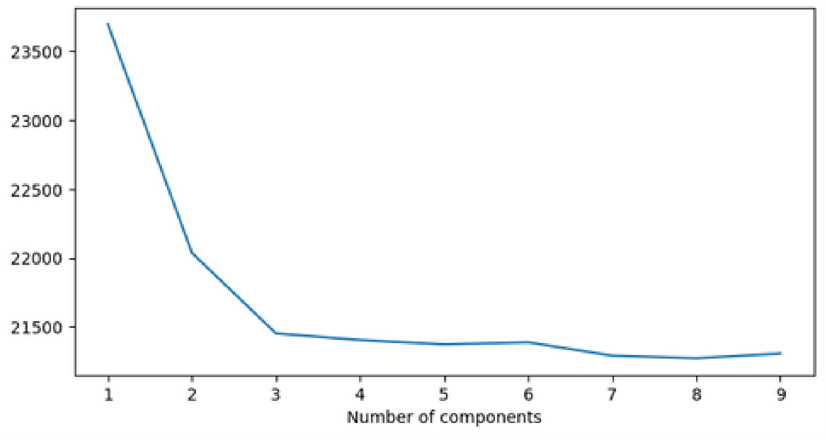
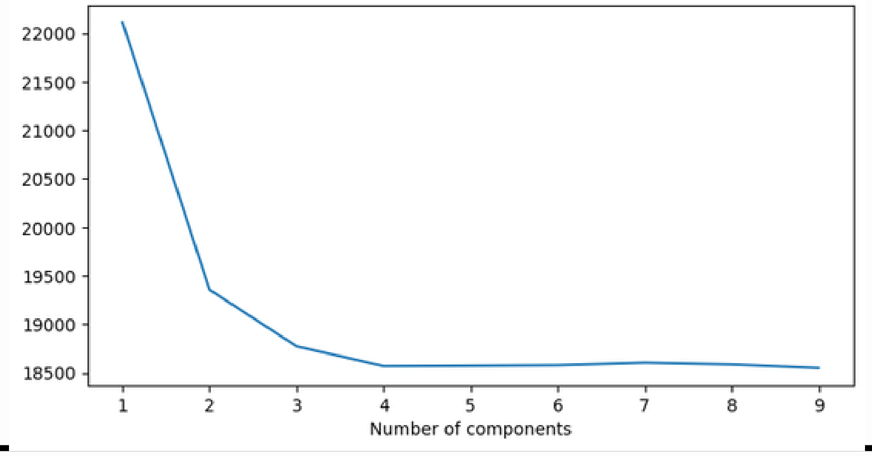
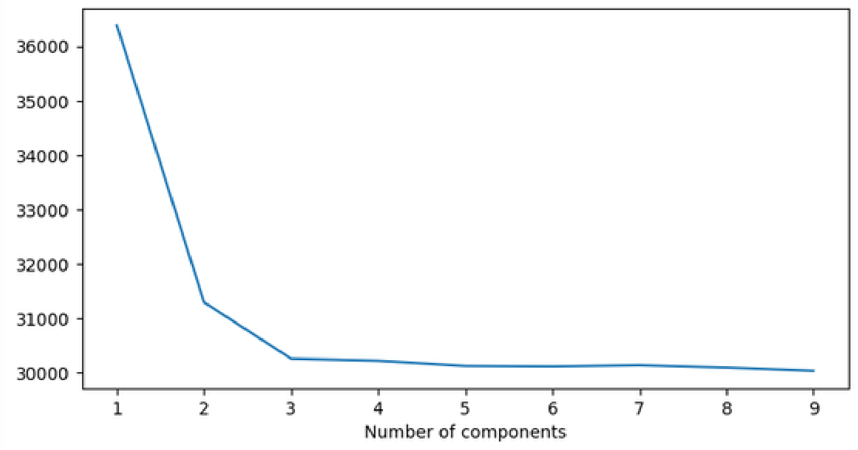
<td></td>
<td></td>
<td></td></tr>
</table>

CUSTOMER CLASSIFICATION

Based on RFM Model

0-2

Low value

customers who are less active than others, not very frequent buyer, and generates very low revenue

3-4

Mid value

This segment in the middle of everything. Often uses the platform, fairly frequent and generates moderate revenue

>=5

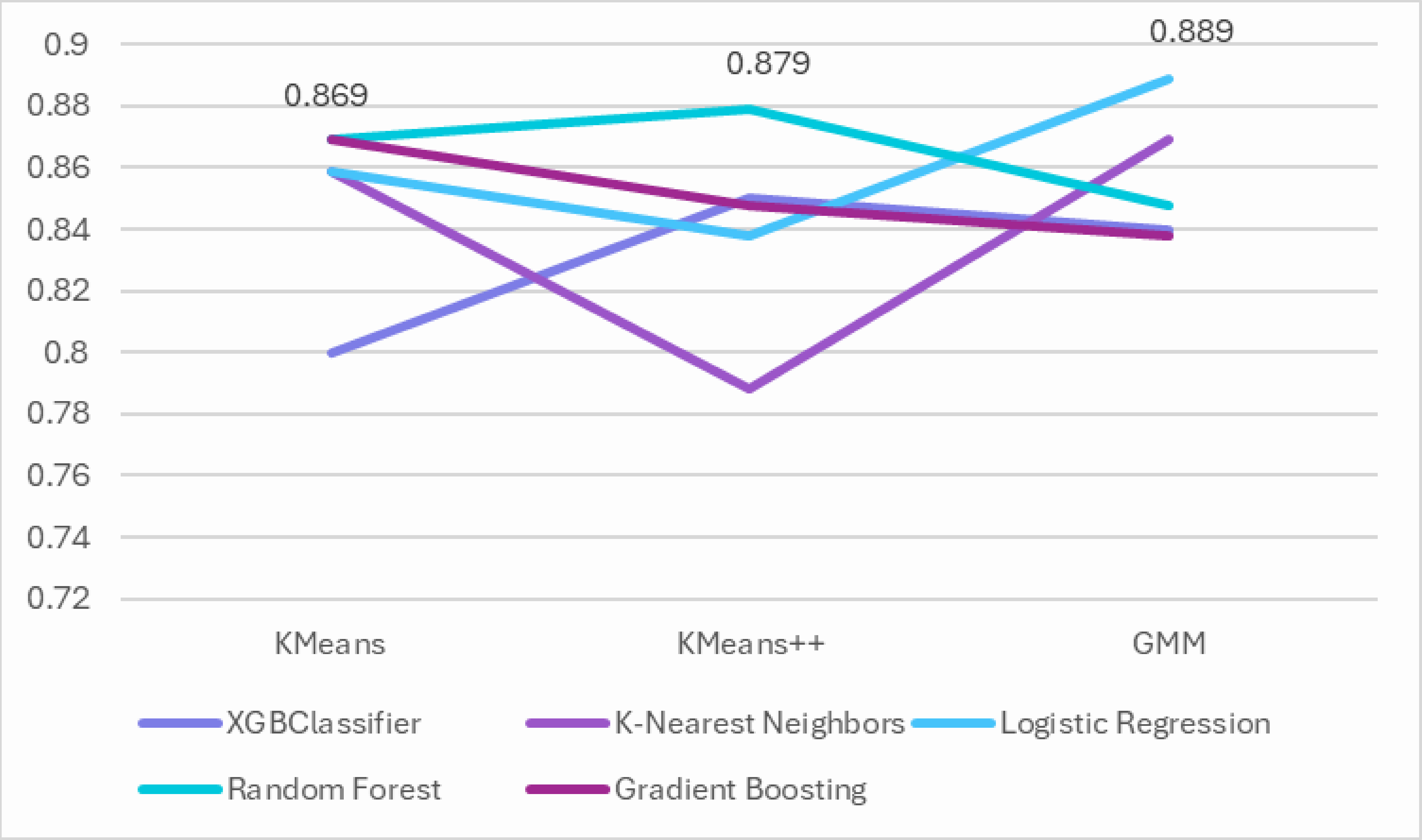
High value

The group you don’t want to lose. High revenue and frequency, very active

RFM score = R + F + M

CUSTOMER CLASSIFICATION

Based on RFM Model



REGRESSION MODEL

- Light GBM
- Logistic Regression
- XG Boost
- Decision Tree
- Gradient Boosting
- Random Forest
- Cat Boost

FEATURE ENGINEERING

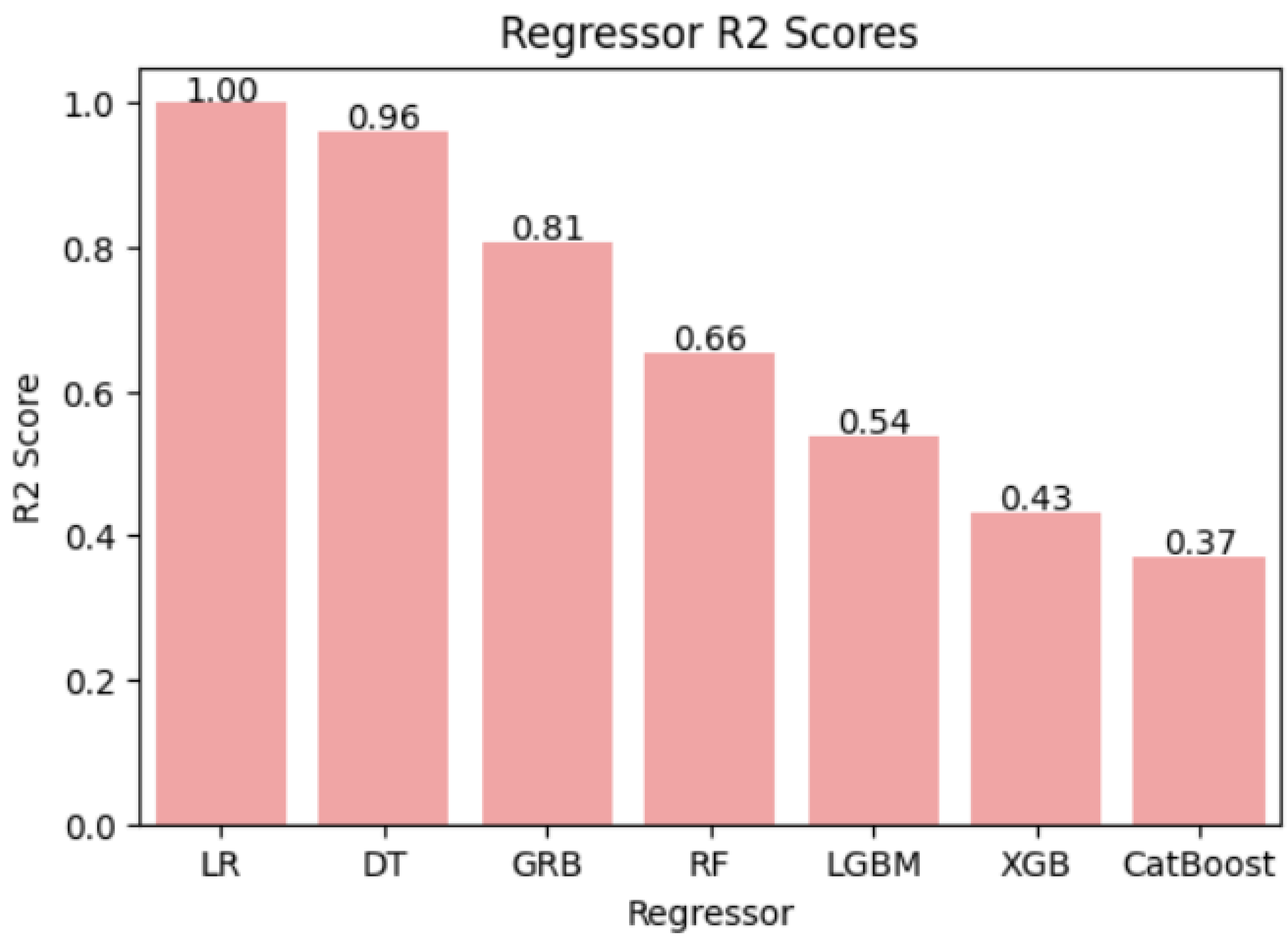
Online Retail II

- New features based on CLV customer behavior
- Features representing these monthly CLV values

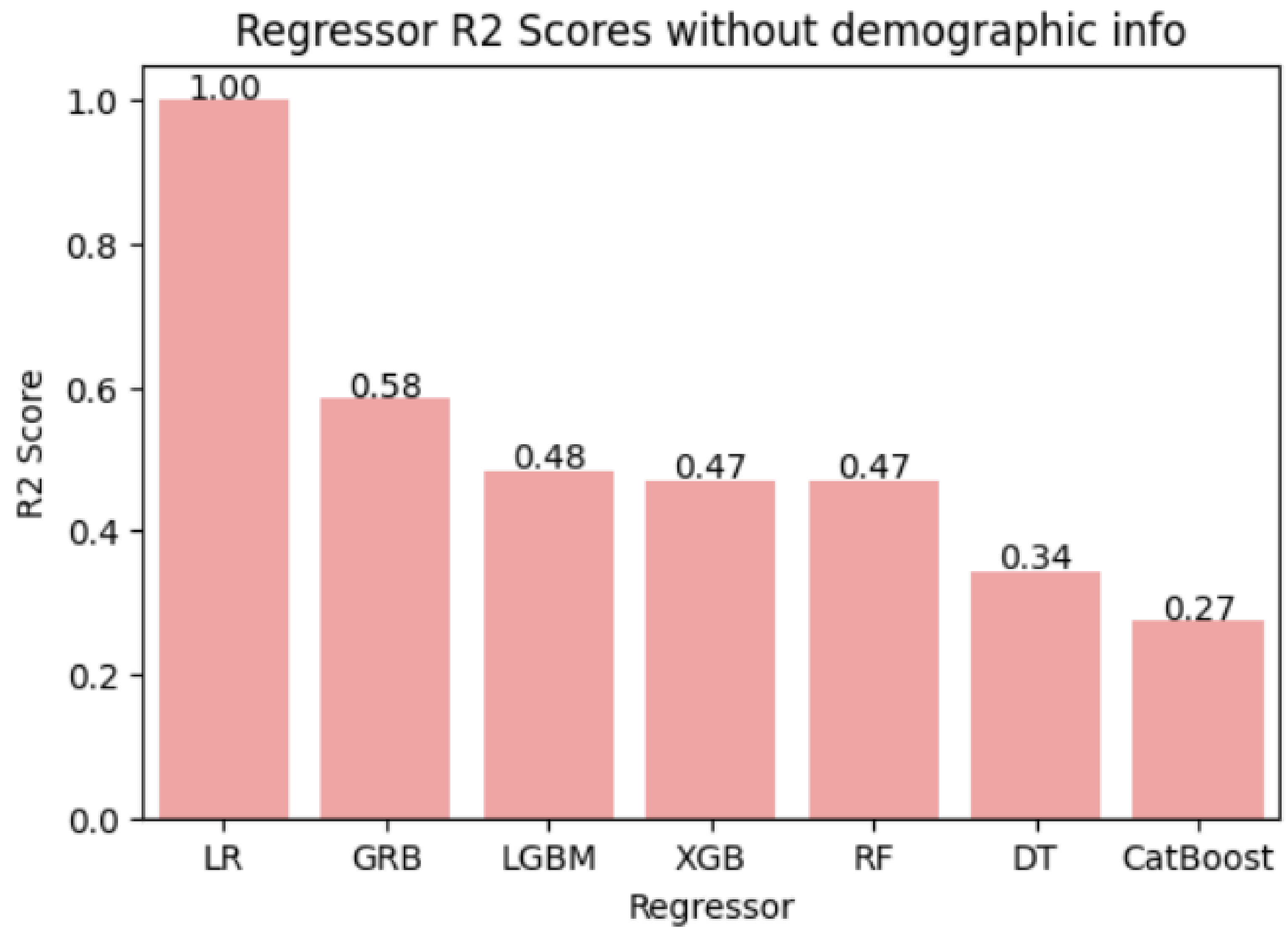
CD NOW

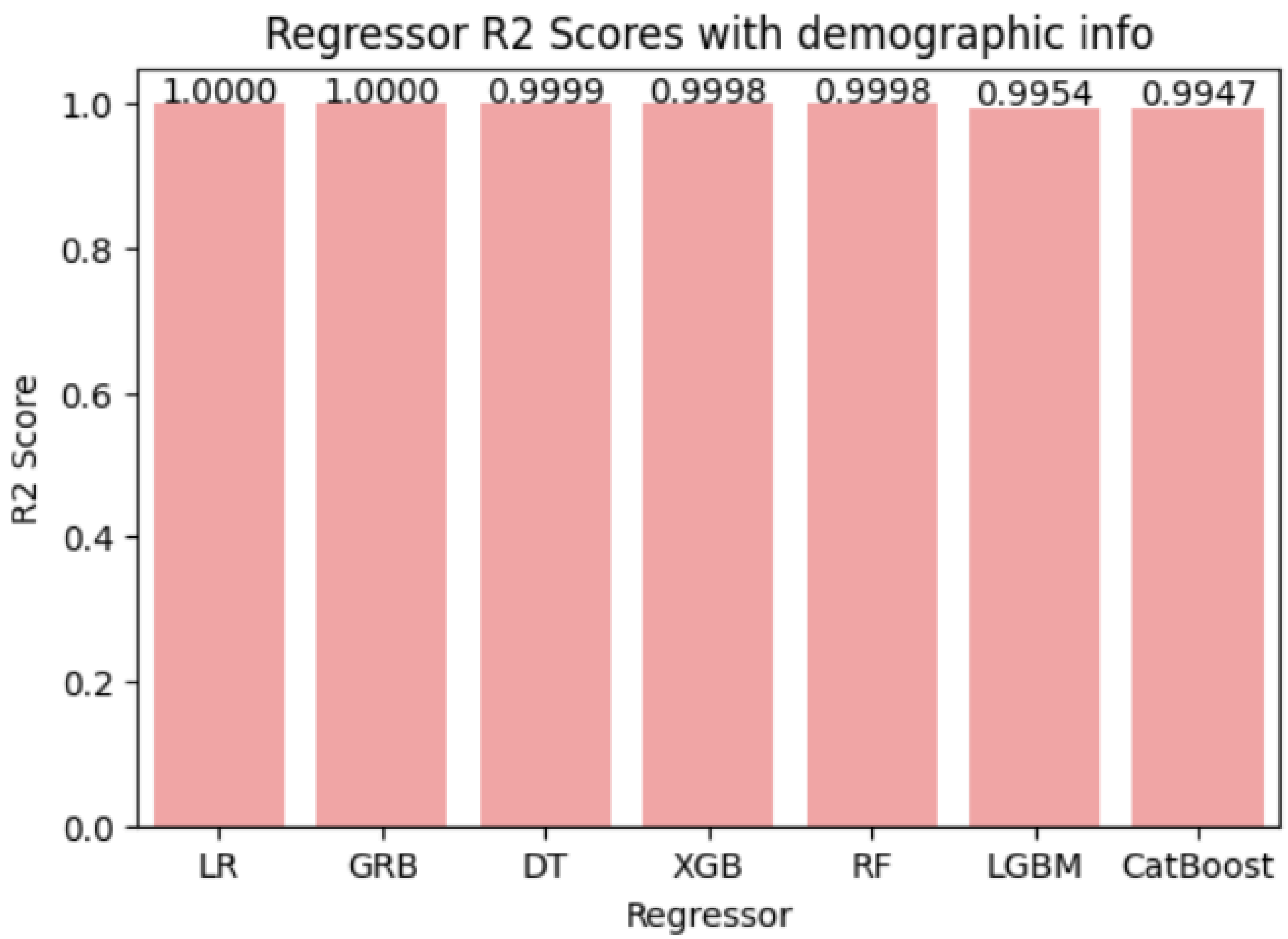
- New features based on CLV customer behavior
- Features representing these monthly CLV values
- Demographic Information

ONLINE RETAIL II RESULT



CD NOW RESULT





DEEP LEARNIG MODEL

1. **Model - Deep Neural Network**

2. **Feature Engineering**

- RFM analysis
- Average Basket Value
- Order count

3. **Training Target Interval**

- Training: 70–80% for learning model weights.
- Evaluation: 10–15% for preventing overfitting.
- Test: 10–15% for final performance measure.

DEEP LEARNIG MODEL

4. Model Development

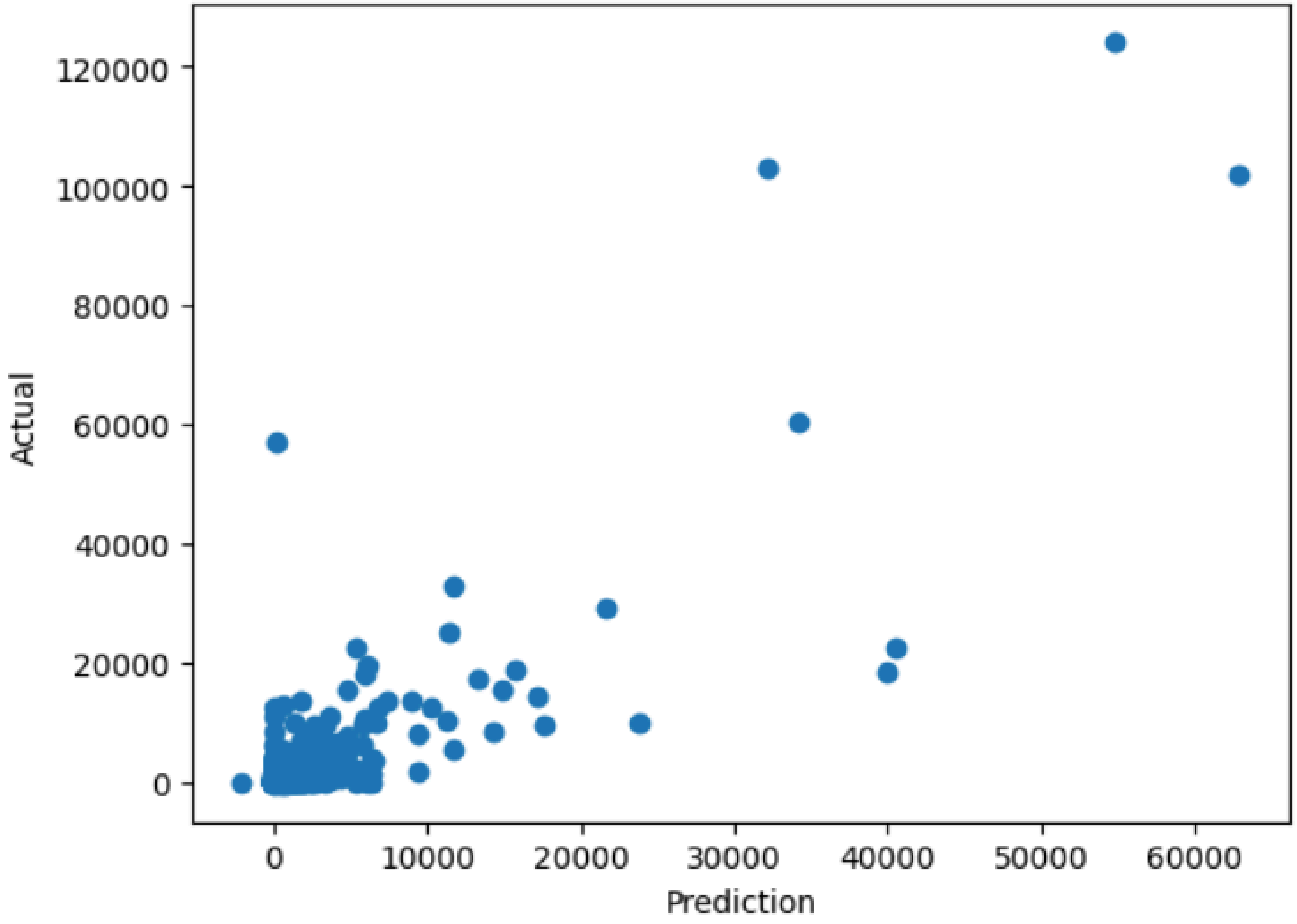
- Select appropriate neural network architecture.
- Define layers, neurons, activation functions, and optimization algorithms.
- Train model by adjusting parameters to minimize prediction error.

5. Evaluation Metrics

- Metrics include MSE, RMSE, MAE, R^2, Adjusted R^2, MAPE

DEEP NEURAL NETWORK RESULT

```
Total Sales Actual: 3167590.0
Total Sales Predicted: 1923765.0
Individual R2 score: 0.605188067899621
Individual Mean Absolute Error: 424.96891402384927
Individual Mean Squared Error: 3597224.6679413314
Individual Mean Absolute Percentage Error: 3.1266417311318374e+17
```



CONCLUSION

Thynk Unlimited

- BG/NBD has different performance based on duration holdout
- Feature Engineering is important, affect alot for Machine Learning Models
- Regression Model is the best model with demographic info
- Deep Learning is potential, we need improve model, feature engieering ,...

CONCLUSION

In conclusion, implementing CLV offers advantages such as strategic alignment, enhanced marketing, and optimized resource allocation. Potential drawbacks include misalignment, segmentation errors, unrealistic expectations, and inflexibility

Traditional CLV methods offer a foundational framework, while . Traditional methods provide a foundation, while probabilistic models offer sophistication. Machine learning models enhance predictions, and deep learning shows promise for accuracy.

Choose CLV models based on data availability, interaction complexity, and desired accuracy. Integrate insights for better decision-making and sustainable growth.

FUTURE WORK

- Adding more datasets for other fields such as: Banking Retail,...
- Advanced Probabilistic Modeling Techniques
- Continuous Model Monitoring and Updating
- Dynamic Segmentation Strategies and Customer Journey Mapping
- Utilizing multi-source data, evaluating and comparing models

THANK YOU

FOR YOUR ATTENTION