Q1

A screenshot of a computer program

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Q2

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A graph of a graph

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Customers are assigned RFM scores using a 5-quantile method. A score of **1 in R, F, or M** indicates the **best case** (e.g., recent purchase, highest frequency, or highest monetary value), while **5 indicates the worst case**. This creates 125 unique combinations.

Customers with a R score of 1 have the highest offer used rate, which is expected as these customers have purchased more recently. We observe a general incremental trend in the likelihood of the offer acceptance as R score goes from 5 to 1. The rise is rather steady and we don’t see any unexpected or surprising findings.

A graph with a bar graph

Description automatically generated

Customers with the best-case frequency, which is 1, have the highest chances of redeeming the offer. These are the most engaged customers, and the graph shows that it could be very profitable if these users are targeted. Moreover, we notice a steep decline in the probability of offer acceptance as F goes from 1 to 5.

A graph with a bar graph

Description automatically generated

Likewise, we notice a similar trend in the monetary graph with the best performing segment as M = 1. It means that customers who have spent the highest amount are most likely to use the offer.

Q3

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A graph of a number of rectangular objects

Description automatically generated with medium confidenceA graph of a number of rectangular objects

Description automatically generated with medium confidenceA graph of a number of rectangular objects

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Interestingly, we could say from the above graphs that the normal price paid is more or less very similar across customer of varying RFM indices. It means that the customers are likely purchasing items with similar prices as they use the offer. We also see an exception wherein M = 5 customers are on and average purchase less costly items with the offer coupon. The exception is understandable as this segment has the least purchasing power, historically, in terms of monetary amount.

Q4

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Q5

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Q6

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Q7

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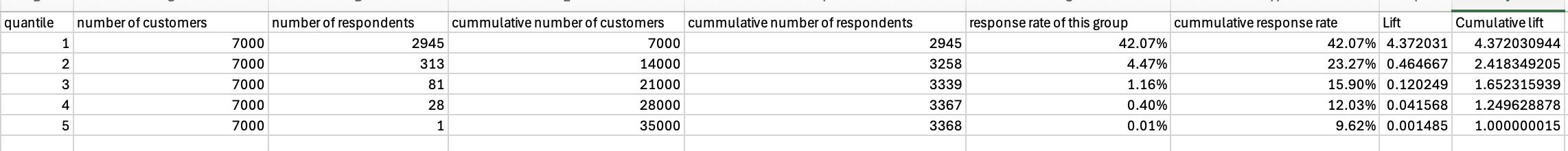
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In the previous case, we were sending offer coupons to Sephora’s entire customer base and wasting a lot of money on people who were not likely to respond to the offer. RFM analysis is based on the principle of reducing these costs and increasing the overall profitability of the marketing campaign. After RFM, we only target customers who are above the breakeven rate, and hence significantly decrease campaign costs. The target\_customer\_share is the corresponding share of customers we want to target. We can see the Return on Marketing cost has significantly jumped from 27.83% to 396.28% while the profits have increased to $39861567.

Q8

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Liftis based on comparing the response rate within each quantile to the overall average response rate. Higher lift values are observed in top quantiles. Whereas, gain measures the cumulative percentage of total responses captured as more quantiles are included.

Life curve steeply declines after the top quantile, showing that the highest-probability segments drive most of the response. Gain curve demonstrates that a small portion of high-value customers account for the majority of responses.

Both Lift and gain analyses confirm that targeting lower performing quantiles adds minimal value while incurring higher costs.

Q9

**Shortcomings**:

* + Equal RFM Weighting: We have treated R, F, and M as equally important. Now this is oversimplifying customer behavior. Some metrics might hold greater predictive power.
  + Static Customer Behavior: Assumes that RFM scores and response probabilities remain constant, ignoring seasonal changes.
  + Fixed Marginal Costs: Also assumed a static cost of annoyance, which may vary based on email content or campaign frequency.

**Assumptions**:

* + Uniform Revenue Margins: Assuming the same profit margin (24%) across all purchases may not account for product-specific variability.
  + Predictive Accuracy: Relies on historical behavior as a perfect predictor of future actions, which may not account for evolving preferences.
  + Exclusion Effects: Ignores potential alienation of lower RFM segments who might still respond positively under certain conditions.

**Conclusion:** While the analysis provides actionable insights, adding dynamic RFM weighting, temporal behavior changes, or campaign-specific variations would improve accuracy in real-world scenarios.