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Optimizing Customer Relationship Management with Surprise Program: A Quantitative Approach

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ABSTRACT

This research explores the implementation of customer relationship marketing strategies through the a program launched by PT XYZ. The program was designed to enhance customer loyalty with personalized special offers and exclusive promotions. This study employs quantitative methods and the data were obtained from the analysis of company reports and customer demographics, geography, behaviour, and psychology. Using K-means clustering, this study analyses data collected from XYZ's CRM surprise program, focusing on customer interests in video, games, and music, as well as their payment methods (prepaid or postpaid). The findings reveal significant variations in digital content consumption between prepaid and postpaid users. This segmentation enables XYZ to tailor its service offerings more effectively. The study highlights the potential for increasing customer satisfaction and loyalty through personalized offers, underscoring the importance of behavioural and psychographic data in optimizing service delivery.

1. Introduction

According to Buttle et al., (2019) Customer Relationship Management (CRM) plays a crucial role in the telecommunications industry by helping companies deeply understand customer needs and preferences, enabling them to provide more relevant and satisfying services. In this highly competitive industry, where customers have many choices, the ability to build and maintain long-term relationships with customers is key to increasing loyalty and reducing churn rates. Through CRM, telecommunications companies can collect and analyse customer data, allowing them to develop more effective marketing strategies and deliver better customer experiences. This, in turn, helps companies maintain a competitive edge and drive sustainable business growth. PT XYZ is a leading player in the broadband services sector in Indonesia, with the largest customer base in the country. To maintain and strengthen its relationships with customers, XYZ has launched a customer relationship marketing initiative known as the "Surprise" program. This program has gained significant popularity among customers due to its customized offerings and personalized approach to delivering special offers and promotions (Aditya, 2023).

Currently, the segmentation strategy in the "Surprise" program largely relies on the Average Revenue Per User (ARPU) metric. ARPU serves as the primary determinant in grouping customers based on their usage patterns from the previous month. For instance, if a customer spent 6,15 USD in the previous month and made no purchases in the current month, they would receive a "Surprise" offer priced slightly higher than 6,15 USD. However, while ARPU offers a quantitative metric for segmentation, its effectiveness alone remains limited in achieving the desired revenue targets. This was evidenced by the program's performance in October 2023, where it failed to meet the company's revenue projections, achieving only 61.1% on the first day and 92.6% on the second day.

Given the existing challenges, there arises a pressing need to explore whether augmenting the segmentation approach with additional variables beyond ARPU could yield more robust outcomes. This necessitates a comprehensive investigation into alternative segmentation parameters and their potential impact on customer engagement and revenue generation within the "Surprise" framework. By delving deeper into these considerations, XYZ aims to refine its CRM strategies, enhance customer satisfaction, and ultimately propel the company towards achieving its revenue objectives. This research aims to identify significant factors or variables that play a role in optimizing customer segmentation in XYZ's "Surprise" program. By deepening the understanding of the factors influencing customer preferences and behaviours, the study seeks to find more effective ways to categorize customers into more homogeneous and responsive groups for the program's offerings. Additionally, to clearly determine the primary target market for XYZ's "Surprise" program. By more accurately identifying which customers are most potential and responsive to the program, XYZ can direct their resources more efficiently and maximize the impact of their marketing strategies. Through in-depth analysis of customer preferences and needs, as well as evaluation of existing marketing strategies, the research seeks to formulate tactical recommendations that can enhance customer engagement and participation in the program.

2. Literature Review

2a. CRM in Telecommunication Industry

A study exploring the interplay between CRM, knowledge management, and organizational commitment in the telecommunications industry found that the synergy between these elements is critical for managing customer satisfaction, profitability, and loyalty. The integration of CRM with knowledge management systems helps in better understanding customer needs and behaviours, thus improving service delivery and customer satisfaction. Customer Relationship Management (CRM) and clustering algorithms are closely related in the context of market segmentation, which is crucial for businesses to understand and cater to the needs of different customer groups effectively (Ullah et al., 2020; Indrawati, 2024, 2024, p. 20224; Iskamto, 2024; Jaenudin & Fauziana, 2022)

2b. Clustering and K-Means

Clustering is a type of unsupervised machine learning technique used to group similar data points together based on their attributes. In the context of Customer Relationship Management (CRM), clustering algorithms can analyse customer data to identify distinct segments within a customer base. The K-means algorithm is one of the most widely used clustering techniques in market segmentation. This algorithm works by dividing customer data into a predetermined number of clusters based on similarities in various attributes such as purchasing behaviour, demographics, or psychographics. K-means offers several advantages, including simplicity and computational efficiency, but it also has drawbacks, such as sensitivity to the selection of the number of clusters and initial points (Han et al., 2011; (Adhania et al., 2024; Agaba et al., 2023, p. 20024; Setiasih & Dandono, 2022)).

In market segmentation, K-means helps companies gain a better understanding of their customers by grouping them into homogeneous segments. This enables companies to develop more targeted marketing strategies, enhance customer satisfaction, and maximize customer lifetime value (Al-Dabbas et al., 2023).

2c. Behavioural and Psychographic Segmentation

The paper by Zdziebko et al. provides an in-depth review of behavioural and psychographic segmentation to create detailed customer segments. Behavioural segmentation involves categorizing customers based on their interactions with the company, such as usage patterns, purchase history, and engagement with services. This approach enables telecommunications companies to identify high-risk churn groups by analysing how frequently and intensively customers use their services.

Psychographic segmentation, on the other hand, delves deeper into customers' lifestyles, values, interests, and attitudes. By understanding these psychological aspects, telecommunications companies can tailor their marketing and retention strategies to better align with different customer segments. This segmentation is particularly valuable because it goes beyond observable behaviour to capture the underlying motivations driving customer actions. The study emphasizes the importance of integrating behavioural and psychographic data to enhance customer retention efforts. Behavioural data provides concrete evidence of usage patterns, while psychographic data offers deeper insights into customer mindsets (Kotler et al., 2016; (Adhania et al., 2024))

3. Research Method

Quantitative research employing the K-means clustering method aims to group data into several clusters based on similar characteristics. This method is frequently used in the analysis of large datasets to uncover patterns or segmentations that are not immediately apparent. K-means operates by identifying centroids, or central points, for each cluster, then grouping data into clusters based on the nearest distance to the centroids. This process is repeated until there are no significant changes in the clustering (Ghosal et al., 2019)

The data obtained consists of purchase data from the Surprise customer relationship management (CRM) program at XYZ. This data is categorized into at least three main categories: behavioral, psychographic, and demographic. These categories are represented by MSISDN data (customer identification number) and the type of payment made, either postpaid or prepaid. Behavioral and psychographic data is represented by data on interests in digital content such as videos, games, and music. This data is used as one of the variables in the K-means clustering process, an algorithm that aims to divide the data into a number of K clusters based on the similarity of certain features.

3a. Preprocessing

1. **Data Cleaning.** The data cleaning process for XYZ "Surprise" program begins with gathering raw data, including MSISDNs and their activity logs. This step involves removing duplicates to avoid bias and ensuring the integrity of the data. Handling missing values is crucial; for example, if there are MSISDNs with incomplete access logs, these could be labeled as '0' for no access to maintain consistency across the dataset. This preparation ensures that the data used for further analysis is accurate and reliable.

2. **Alias Creation (Labelling).** In the aliasing process, binary labels (0 or 1) are assigned to each MSISDN based on their activity in accessing digital content such as videos, music, and games. This involves creating new features for each content type and assigning a '1' if the content was accessed and '0' if it was not. For instance, if an MSISDN accessed video and games but not music, it would be labeled as 1, 0, 1 respectively.

   Example:

   MSISDN : 628123456789
   Video : 1 (accessed)
   Music : 0 (not accessed)
   Games : 1 (accessed)

This results in a data entry:
628123456789, 1, 0, 1

3. **Data Transformation.** Involves compiling these binary features into a matrix format where each row represents an MSISDN and each column represents a type of content accessed. This matrix is then normalized if necessary, although binary data typically does not require this step. The feature selection ensures that only relevant data (in this case, content access) is included in the clustering algorithm, which helps in creating meaningful customer segments. Ensure that the selected features (in this case, video, music, and games access) are the most relevant for clustering. Irrelevant features can introduce noise and affect the clustering outcome.

Example Matrix:

MSISDN	Video	Music	Games
628123456789	1	0	1
628987654321	0	1	1
628192837465	1	1	0

3b. Clustering Process

```
[1] import pandas as pd # untuk data analisis
    import numpy as np # untuk array dan matriks
    from sklearn.cluster import KMeans # algoritma k means
    import matplotlib.pyplot as plt # plotting
    from sklearn.metrics import silhouette_score

[2] df = pd.read_csv('/content/dataset_syaban_rev2.csv')

[4] X = df.to_numpy() # ubah ke numpy

[5] kmeans = KMeans(n_clusters=16, random_state=42,verbose=1).fit(X) # proses training/klastering dengan 16 klaster, index random = 42

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from
  warnings.warn(
Initialization complete
Iteration 0, inertia 0.0.
Iteration 1, inertia 2.5459535447714676e-22.
Iteration 2, inertia 5.433393153139814e-22.
Converged at iteration 2: strict convergence.
Initialization complete
Iteration 0, inertia 0.0.
Iteration 1, inertia 2.5459535447714676e-22.
Iteration 2, inertia 5.433393153139814e-22.
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Initialization complete
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Iteration 1, inertia 2.5459535447714676e-22.
Iteration 2, inertia 5.433393153139814e-22.
Converged at iteration 2: strict convergence.
```

Figure 1 Clustering process

```
[8] df['cluster'] =  cluster #klaster nya dimasukkan ke data
```

```
[9] df
```

	pre_post_flag	bcp_interest_games	bcp_interest_music	bcp_interest_video	cluster
0	1	0	0	0	14
1	1	0	0	0	14
2	1	0	0	0	14
3	1	0	0	0	14
4	1	0	0	0	14
...	...	...	...	...	...
40885	1	1	1	1	0
40886	1	1	1	1	0
40887	1	1	1	1	0
40888	1	1	1	1	0
40889	1	0	0	0	14

40890 rows × 5 columns

Figure 2 Preview dataset result after clustering

3c. The process of getting the best K number

To determine the optimal number of clusters (K) in K-means clustering, one can use a brute force approach by evaluating a range of K values and assessing the clustering quality for each. The algorithm involves iterating through a predefined range of K values, initializing and running the K-means algorithm for each K, and then calculating evaluation metrics such as the Sum of Squared Errors (SSE) and the Silhouette Score (SS). SSE measures the total within-cluster variation, with lower values indicating better clustering. The Elbow Method is used to plot SSE against K and identify the point where the rate of decrease slows, suggesting the optimal K. The Silhouette Score, ranging from -1 to 1, evaluates how well clusters are separated, with higher values indicating better-defined clusters. By plotting both SSE and Silhouette Scores for each K, the optimal K can be selected based on the elbow

```
[11] kmeans_kwargs = {
         "init": "random",
         "n_init": 16,
         "max_iter": 300, # maksimum iterasi
         "random_state": 42,
     }

     # ini brute force dari 1 - 16 klaster
     sse = []
     sc = []
     for k in range(2, 21):
         kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
         kmeans.fit(X)
         label = kmeans.predict(X)
         sc.append(silhouette_score(X,label))
         sse.append(kmeans.inertia_) #didapatkan nilai SSE nya per masing2 klaster 1 - 16
```

point in the SSE plot and the highest Silhouette Score. This method provides a systematic way to determine the most appropriate number of clusters for a given dataset (Rousseeuw, 1987).

Figure 3 Evaluate K-means using SC & SSE

4. Result

According to journal by Rousseeuw (1987), the Silhouette Index (HSI) is a method used to measure how well objects in a cluster are grouped. This index provides an indication of the validity and quality of clusters produced by clustering algorithms, such as K-means. The HSI value ranges between -1 and 1, where values closer to 1 indicate that objects within a cluster are more similar to each other and different from objects in other clusters.

The formula for calculating the Silhouette Index is:

$$s(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}}$$

Where:

- $a(i)$ is the average distance between the object i and all other objects in the same cluster.
- $b(i)$ is the average distance between the object i and all objects in the nearest different cluster.

SC values range from -1 to 1, with higher values indicating better clustering quality.

Based on the Silhouette Coefficient (SC) plot, initializing with K=16 clusters yields very good clustering results, with high SC values close to 1. This indicates that using 16 clusters produces highly cohesive groups that are well separated from each other. The stability of SC values after 16 clusters also suggests that adding more clusters will not significantly enhance the clustering quality.

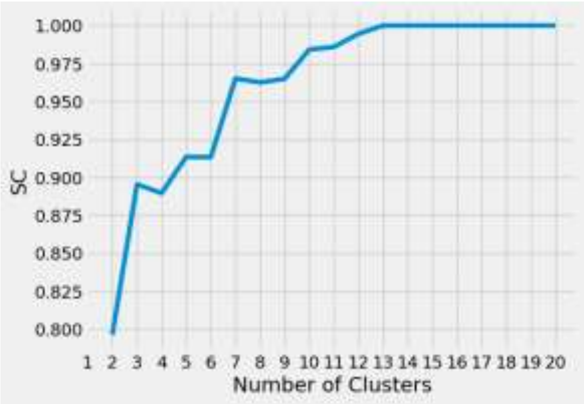

Figure 4 Evaluating result using SC

In the other hand on the Sum of Squared Errors (SSE) plot, initializing with K=16 clusters results in a low SSE value, indicating effective clustering with well-defined clusters. However, the plot also shows that the most significant improvements in SSE occur around 4-6 clusters, which could be considered the optimal range. Using 16 clusters still yields a good clustering outcome, but the incremental benefit over fewer clusters is marginal.

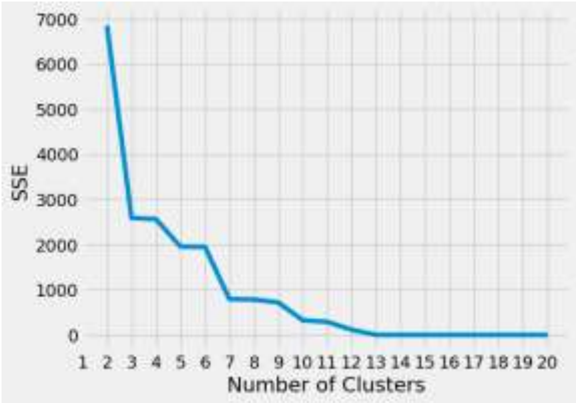

Figure 5 Evaluating result using SSE

The clustering results are evaluated using the Silhouette Index (HSI) and other indicators to determine the optimal number of clusters. In this case, the most appropriate number of clusters is 16.

The sixteen clusters are as follows :

cluster	total msisdn	Usage Profile				payment
		broadband	music	video	games	
1	22330	yes	yes	yes	yes	prepaid
2	212	yes	yes	yes		prepaid
3	4	yes	yes		yes	prepaid
4	5	yes	yes			prepaid
5	4993	yes		yes	yes	prepaid
6	793	yes		yes		prepaid
7	35	yes			yes	prepaid
8	10807	yes				prepaid
9	1086	yes	yes	yes	yes	postpaid
10	7	yes	yes	yes		postpaid
11	0	yes	yes		yes	postpaid
12	1	yes	yes			postpaid
13	124	yes		yes	yes	postpaid
14	10	yes		yes		postpaid
15	0	yes			yes	postpaid
16	483	yes				postpaid

Table 1 Clustering Result Profile

The provided table contains the results of a clustering analysis based on the usage profiles of XYZ's surprise program, focusing on digital content access (broadband, music, video, games) and the payment type (prepaid or postpaid).

The highlighted clusters indicate the most significant segments based on the number of MSISDNs and their usage profiles. These clusters predominantly consist of prepaid users (Clusters 1, 5, and 8) with a substantial number of MSISDNs, while Cluster 9 represents a smaller but notable segment of postpaid users.

From the provided clustering table, several important patterns emerge in the usage of digital services by XYZ customers. Below is the interpretation of the clustering results:

A. *Major Clusters with Significant Number of Users*
   - Cluster 1 (22,330 MSISDNs): Users in this cluster access all types of digital content (broadband, music, video, and games) and are all prepaid users.
   - Cluster 5 (4,993 MSISDNs): Similar to Cluster 1, users in this cluster also access all types of digital content, mostly video & games and are all prepaid users.
   - Cluster 8 (10,807 MSISDNs): Users in this cluster use only broadband service and consist of prepaid users.

B. *Medium-Size Clusters*
   - Cluster 6 (793 MSISDNs): All users in this cluster access broadband and only video content, and are all prepaid users.
   - Cluster 9 (1,086 MSISDNs): Users in this cluster also access all types of digital content and are all postpaid users.

C. *Small-Size Clusters*
   - Clusters with a very small number of users (fewer than 100 MSISDNs) indicate that there are user segments that might not be significant in terms of numbers but could provide important insights if explored further.

5. Discussion

The interpretation of clustering results provides crucial insights into the behavioral patterns of XYZ customers, allowing for the development of targeted marketing strategies. By segmenting users based on their engagement with digital services and payment methods, XYZ can tailor its surprise program to meet the specific needs and preferences of different customer groups. This approach ensures that promotional offers are relevant and appealing, thereby enhancing customer engagement and service utilization (Dolnicar et al., 2018)

Targeting Strategy Based on Payment Type

- Prepaid Users: Clusters 1, 5 and 8, with a large number of users who are all prepaid, represent ideal targets for surprise deal offers that can increase engagement and service usage. The surprise program can focus on offering bonus data or free access to certain content during the promotional period.

- Postpaid Users: Clusters 9 show that postpaid users also have high engagement with digital services. Surprise program offers could include bundling additional services or discounts on monthly bills.

Cluster-Based Program Development

- High-Engagement Clusters (Clusters 1, 5, and 8): Users in these clusters show active usage patterns. The surprise deal program can be designed to enhance loyalty by providing exclusive offers such as early access to new content or bonus data for specific usage.

- Medium-Engagement Clusters (Clusters 6 and 9): For users in these clusters, the surprise deal program can focus on increasing usage of underutilized services or promoting cross-sell initiatives that encourage them to try new services with attractive incentives.

To determine new market segments from the clustering results, we can focus on the characteristics of the largest clusters and explore opportunities to target underrepresented segments or create tailored offers for the identified clusters (Payne et al,. 2005).

Clusters	Segments	Strategy
High-Engagement Prepaid Users	Cluster 1, 5, and 8	Develop exclusive prepaid plans with enhanced benefit for digital content, such as bundled offers for unlimited access to video, music, and games. Loyalty programs and personalized recommendations based on usage patterns can further engage these users (WhistleOut, 2024).
Postpaid Users with Full Access	Cluster 9	Introduce premium postpaid plans that offer superior benefits for high digital content consumption. Emphasize the advantages of postpaid services such as higher data limits, priority customer service, and additional perks for content access (Airtel, 2024; Gadgets 360, 2024).
Underrepresented Segments	Clusters with fewer MSISDNs (Clusters 2, 3, 4, 6, 7, 10-16)	Investigate the specific needs and preferences of these smaller clusters to create niche offerings. For example, tailored plans for occasional users or targeted promotions to encourage higher engagement with specific types of digital content (e.g., special offers on music streaming for Cluster 6) (Optimove, n.d.).
Cross-Promotion Opportunities		Identify opportunities to cross-promote services to users who access only specific types of content. For instance, users who primarily engage with music and video (Cluster 4) can be targeted with gaming promotions to expand their content usage (Buffer, 2023).

Table 2 Marketing strategy offering

6. Conclusion

By understanding usage patterns from clustering, XYZ can create more personalized and relevant offers, thereby increasing acceptance and customer satisfaction. For instance, users who predominantly access video content could receive special offers streaming services. Personalization also helps optimize marketing costs by avoiding irrelevant promotions for certain segments, thus enhancing the efficiency and effectiveness of the surprise deal campaigns. The clustering process allows XYZ to understand user usage patterns and preferences more deeply. With this information, the company can create new segmentation that is more specific and relevant. This new segmentation enables XYZ to develop more personalized and effective marketing and service strategies, improving user experience and overall company performance.

Clustering produces homogeneous groups of users in terms of interests and behaviors, allowing the company to offer more tailored products and services. By leveraging the detailed segmentation provided by the clustering analysis, XYZ can optimize its marketing strategies, create personalized offers, and enhance customer satisfaction across different user segments. This approach ensures that both high-value and niche segments are adequately addressed, driving overall growth and customer loyalty.

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