Customer Segmentation & Persona Creation in the Banking Industry

A Case Study Using K-Means Algorithm

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Contents

Problem Statement

The banking industry struggles with understanding and meeting the diverse needs of customers, resulting in generic marketing approaches to financial product offerings that fall short of creating personalized experiences. To address this challenge, a data-driven solution is required to effectively segment customers and create targeted personas for improved customer engagement and satisfaction, thus leading to increased revenue for banks/financial institutions.

Solution

Customer segmentation can be achieved through the powerful **k-means** algorithm. By leveraging data analytics and machine learning techniques, financial institutions (banks & credit card companies) gain valuable insights into customer behavior, preferences, and characteristics. This enables the identification of distinct customer segments and the development of personalized offerings. This has several advantages including enhanced customer understanding, improved customer engagement with product offerings, a healthier customer base, and increased revenue for financial institutions.

Implementation Strategy

To implement customer segmentation and using the k-means algorithm, financial institutions should follow these steps:

1. Data Collection and Integration: Gather customer data from various sources, including transaction records, demographic information, and customer interactions.
2. Preprocessing and Feature Selection: Cleanse and preprocess the data, selecting relevant features for analysis, such as transaction frequency, average balance, age, and customer preferences.
3. K-Means Clustering: Apply the k-means algorithm to segment customers based on similar behavioral patterns. Determine the optimal number of clusters and assign customers to their respective segments.
4. Persona Creation: Develop personas for each customer segment, incorporating demographic information, behaviors, preferences, and goals. These personas should be representative of the segment's characteristics and serve as a guide for targeted marketing strategies.
5. Implementation and Iteration: Implement personalized marketing campaigns and track the performance of the tailored strategies. Continuously evaluate and refine the segments and personas based on customer feedback and evolving market dynamics.

The following pages, walk through a detailed case study of customer segmentation and persona creation using the k-means algorithm.

Introduction

In today's competitive marketplace, financial institutions must focus on developing effective strategies to attract and retain customers. One key approach to customer targeting is customer segmentation, which involves dividing a customer base into groups based on shared characteristics or needs. By understanding the unique needs and preferences of different customer segments, financial institutions can tailor their marketing efforts, product offerings, and customer service to better meet the expectations of each group. This analysis will explore how to use customer data to segment customers in the banking and credit card industry and provide insights on how financial institutions can effectively segment their customer base to drive growth, profitability and create as win-win strategy for themselves and their customers.

Creating a win-win strategy for any business and it's customers is crucial for maintaining a long-term, mutually beneficial relationship. In today's marketplace, customers have more choices than ever before, and they are more empowered to switch to a competitor if they feel that their needs are not being met. Therefore, it is in the best interest of financial institutions to ensure that their customers feel satisfied and valued. By creating a win-win strategy, financial institutions can achieve their business objectives while also addressing the needs and preferences of their customers. This can result in increased customer loyalty, higher retention rates, and ultimately, greater profitability for the business. Additionally, a win-win strategy can help to foster a positive reputation and brand image, which can attract new customers and enhance the overall success of the organization. What does a win-win strategy for financial institutions look like?

- Providing personalized services: This can create a win-win situation by offering customized products and services that cater to the specific needs of individual customers. For example, offering credit cards with rewards and benefits that are tailored to a customer's spending habits and preferences.
- Maintaining transparency: It is important for financial institutions to be transparent about their policies, fees, and charges. This can help to build trust and confidence with customers and ensure that they feel valued and respected.
- Offering competitive rates and terms: Financial institutions can attract and retain customers by offering competitive rates and terms on their products and services. This can help to ensure that customers feel that they are getting good value for their money.
- Providing excellent customer service: Customer service is a key factor in creating a win-win strategy. financial institutions that provide excellent customer service can differentiate themselves from competitors and build strong relationships with their customers.

In general, a win-win strategy must ensure that customers are able to get access to the credit they need at reasonable terms and conditions to reduce their risk of default, which in-turn reduces the risk to the financial institutions.

Analysis Approach

The analysis approach involves several steps, starting with explanatory data analysis to gain insights into the data. Next, the k-means algorithm is used to identify clusters in the data based on shared characteristics of customers. The UMAP algorithm is then used to plot the clusters in two or three dimensions, making it easier to visualize the clusters. The analysis of the clusters is then performed to understand the unique characteristics and needs of each group and then create customer personas. Finally, based on the insights gained, recommendations on product offerings are made to address the needs of each cluster/persona and improve the overall customer experience. This approach can be used in a variety of industries to better understand customer behavior and tailor services and products to meet their needs.

Data Understanding

The dataset used in this is part of the resource files for the Udemy course Data Science for Business. See data descriptions below -

- **CUST_ID**: Identification of credit card holder.
- **BALANCE**: Balance amount left in customer's account to make purchases.
- **BALANCE_FREQUENCY**: How frequently the Balance is updated, score between 0 and 1.
- **PURCHASES**: Amount of purchases made from account.
- **ONEOFFPURCHASES**: Maximum purchase amount done in one-go.
- **INSTALLMENTS_PURCHASES**: Amount of purchase done in installment.
- **CASH_ADVANCE**: Cash in advance given by the user.
- **PURCHASES_FREQUENCY**: Frequency of purchases, score between 0 and 1.
- **ONEOFF_PURCHASES_FREQUENCY**: Frequency of purchases in one-go.
- **PURCHASES_INSTALLMENTS_FREQUENCY**: Frequency of purchases in installments.
- **CASH_ADVANCE_FREQUENCY**: Frequency of cash advance payments.
- **CASH_ADVANCE_TRX**: Number of Transactions made with "Cash in Advance".
- **PURCHASES_TRX**: Number of purchase transactions made.
- **CREDIT_LIMIT**: Limit of Credit Card for customer.
- **PAYMENTS**: Amount of Payment done by customer.
- **MINIMUM_PAYMENTS**: Minimum amount of payments made by customer.
- **PRC_FULL_PAYMENT**: Percent of full payment paid by customer.
- **TENURE**: Tenure of credit card service for customer.

A few things to note on the dataset -

- For features with values between 0 and 1, values closer to 1 mean it happens frequently while values close to 0 means it happens less frequently.
- For this analysis, I'll be making the assumption that *tenure* is in months, since this is not stated explicitly.

Exploratory Data Analysis

The `skim()` function from the skimr package can be used to get an overview of features in the dataset.

Table 1: Data summary

Name	customer_tbl
Number of rows	8950
Number of columns	18
Column type frequency:	
character	1
numeric	17
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
cust_id	0	1	6	6	0	8950	0

Variable type: numeric

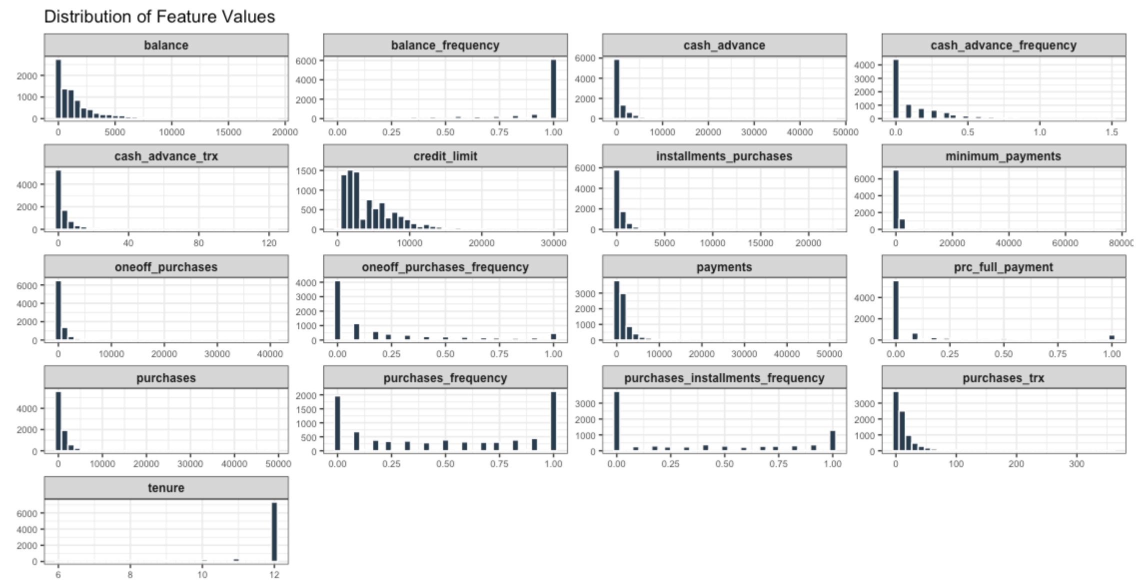
skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
balance	0	1.00	1564.47	2081.53	0.00	128.28	873.39	2054.14	19043.14	
balance_frequency	0	1.00	0.88	0.24	0.00	0.89	1.00	1.00	1.00	
purchases	0	1.00	1003.20	2136.63	0.00	39.63	361.28	1110.13	49039.57	
oneoff_purchases	0	1.00	592.44	1659.89	0.00	0.00	38.00	577.41	40761.25	
installments_purchases	0	1.00	411.07	904.34	0.00	0.00	89.00	468.64	22500.00	
cash_advance	0	1.00	978.87	2097.16	0.00	0.00	0.00	1113.82	47137.21	
purchases_frequency	0	1.00	0.49	0.40	0.00	0.08	0.50	0.92	1.00	
oneoff_purchases_frequency	0	1.00	0.20	0.30	0.00	0.00	0.08	0.30	1.00	
purchases_installments_frequency	0	1.00	0.36	0.40	0.00	0.00	0.17	0.75	1.00	
cash_advance_frequency	0	1.00	0.14	0.20	0.00	0.00	0.00	0.22	1.50	
cash_advance_trx	0	1.00	3.25	6.82	0.00	0.00	0.00	4.00	123.00	
purchases_trx	0	1.00	14.71	24.86	0.00	1.00	7.00	17.00	358.00	
credit_limit	1	1.00	4494.45	3638.82	50.00	1600.00	3000.00	6500.00	30000.00	
payments	0	1.00	1733.14	2895.06	0.00	383.28	856.90	1901.13	50721.48	
minimum_payments	313	0.97	864.21	2372.45	0.02	169.12	312.34	825.49	76406.21	
prc_full_payment	0	1.00	0.15	0.29	0.00	0.00	0.00	0.14	1.00	
tenure	0	1.00	11.52	1.34	6.00	12.00	12.00	12.00	12.00	

Observations:

- Missing Values - Dataset is complete except for 313 null values in *minimum_payments* and 1 missing value in *credit_limit*.
- The dataset contains only numeric values.

- Although the output from the `skim()` function does not show it here, all the features in the dataset are highly left or right skewed, with the exception of *purchases_frequency* that appears to have a bi-modal distribution. We can get a sense of this by observing the values for the mean and median (p50) in the `skim()` output. the large variance between those values indicates highly skewed features.

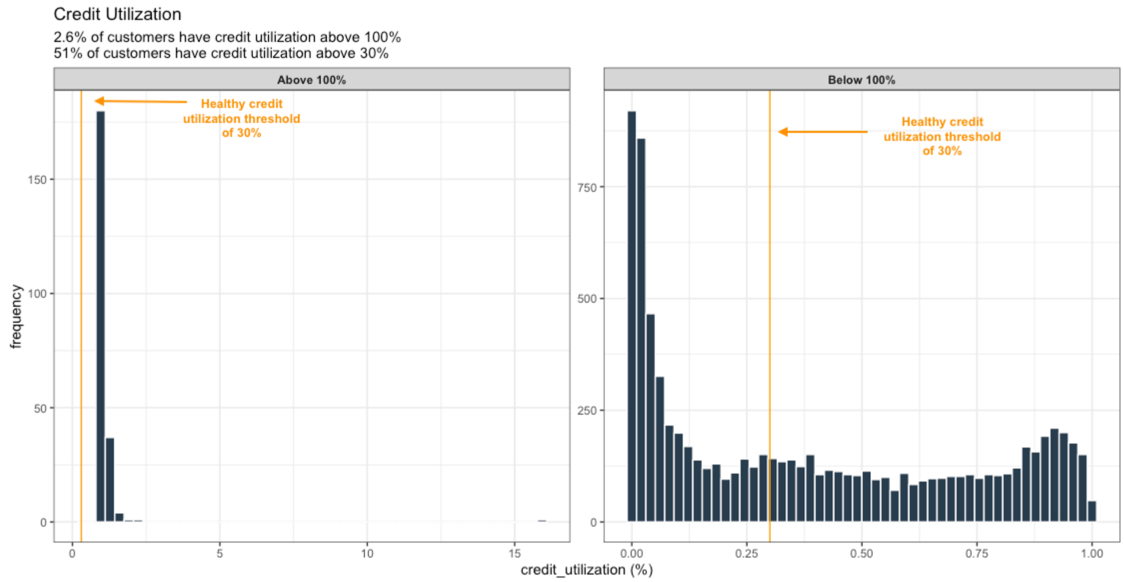
To further illustrate the skewness, we can plot histograms of all numeric features -



While there are many features to explore in the dataset, one that I am particularly interested in is the **credit card utilization**. While not explicitly shown in the dataset, we can easily add this feature by dividing the *balance* by *credit_limit*.

What is Credit Utilization. Credit Utilization is a measure of how much a customer's available credit they are currently using. It is calculated by dividing the amount of credit the customer is currently using by their total available credit limit. Credit utilization is an important factor for banks and credit card companies because it is one of the key metrics used to assess a borrower's credit worthiness. High levels of credit utilization can indicate that the customer may be struggling to manage their credit debt and may be at higher risk of defaulting on their payments. On the flip side, customers with low levels of credit utilization are generally viewed as lower risk and may be more likely to be approved for new credit or offered more favorable terms.

What does credit utilization look like for customers in this dataset. Below I plot histograms for customers who's credit utilization is above 100% (meaning their current balance is higher then their credit limit) and customers who's credit utilization is below 100% (meaning their balance is currently lower than their credit limit).

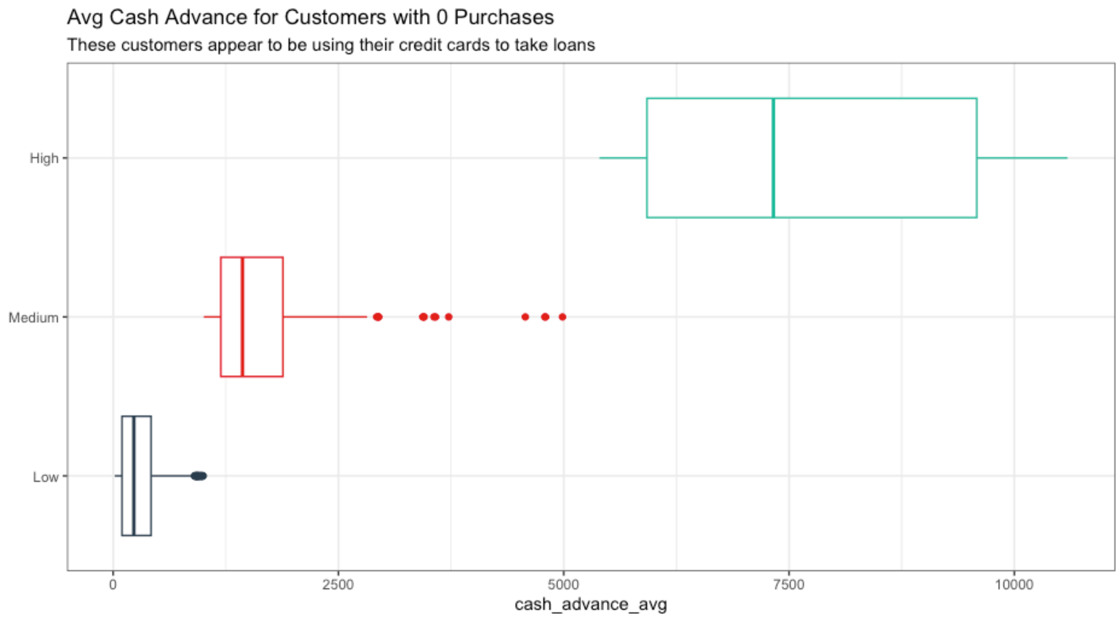


Observations:

- 2.6% of customers have credit utilization above 100%. These customers would be considered extremely risky and have high chances of defaulting on their payments.
- A general threshold for healthy credit utilization is 30% or below. This would mean about half (51%) of customers in this dataset are above the healthy threshold.

There are several ways financial institutions can address customers with high levels of credit utilization. We'll explore some of these ideas later on.

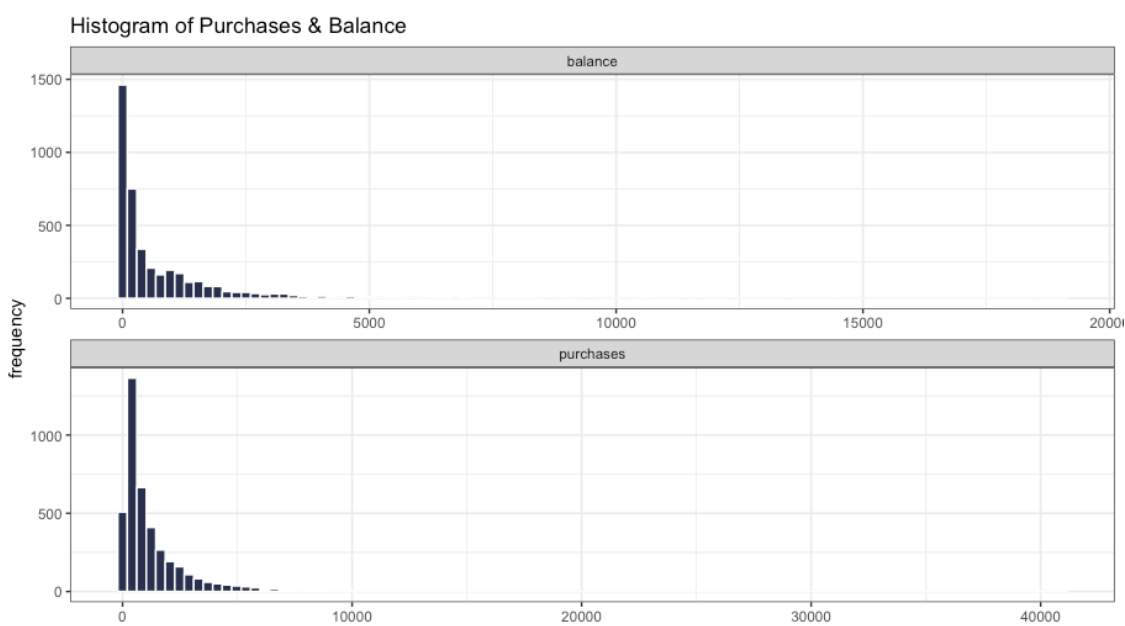
What other insights can we draw from this dataset before exploring the k-means algorithm. We just saw the distribution of *credit_utilization.* Another way we may want to segment customers is by looking at *cash_advance.* Given the high credit utilization we saw for some customers, it is obvious that some customers might be using their credit cards as a means to take out loans. The plot below shows average *cash_advance* for 3 cohorts of customers taking out cash advances. Low = less than $1000, Medium = $1001 - $5000, High = above $5000.



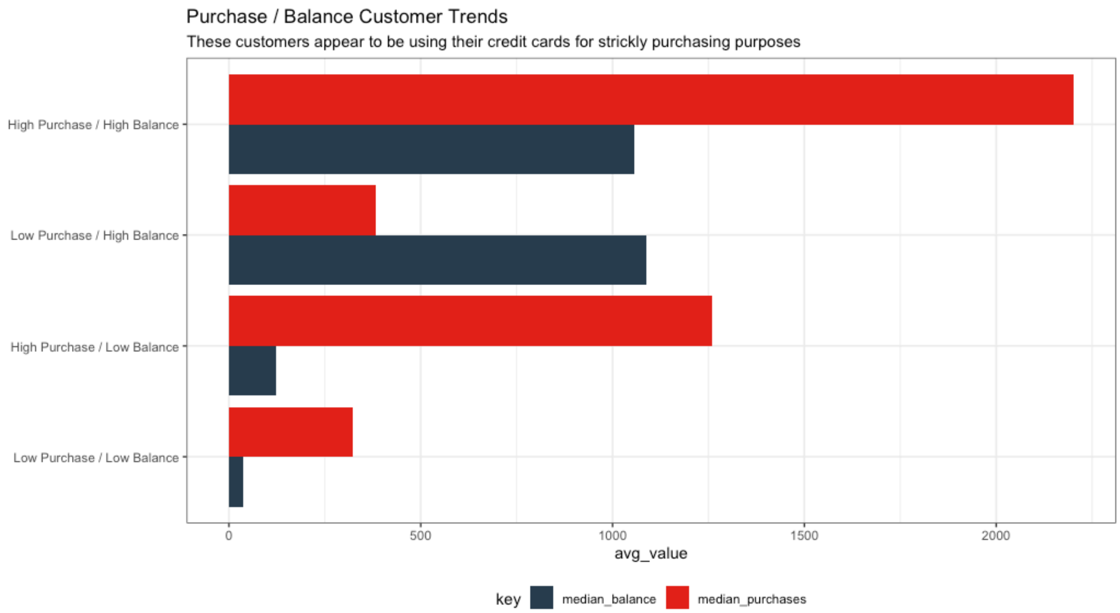
Observations:

- The average *cash_advance* plotted above are for customers with 0 *purchases* on their credit cards. We can see certain customers with *cash_advance* upwards of $10,000. The max *cash_advance* for a customer is $47,000. These customers appear to be using their credit card as means to take out loans for other purposes. Cash advances are generally considered bad financial practice for several reasons including high fees, high interest rates and negative impact on credit scores. Financial institutions may need to target these customers with better financial products, perhaps low interest loans. We'll explore this later on.

Another way we might want to segment customers is looking at *purchases* and *balance* to understand the spending habits of customers. In the plot below, we can see the distribution of *purchases* and *balance* for customers who have spent at least $100 on purchases -



We notice a fairly wide distribution of *purchases* and *balance*. We can look deeper and categorize customers into high/low purchase and balance cohorts based on median values. The plot below shows that categorization. Note that data used in the plot is filtered for customers with 0 *cash_advance*. We want to ensure that we are excluding the customers who are potentially using their credit cards for taking out loans:



Observation: We can observe a few standout cohorts:

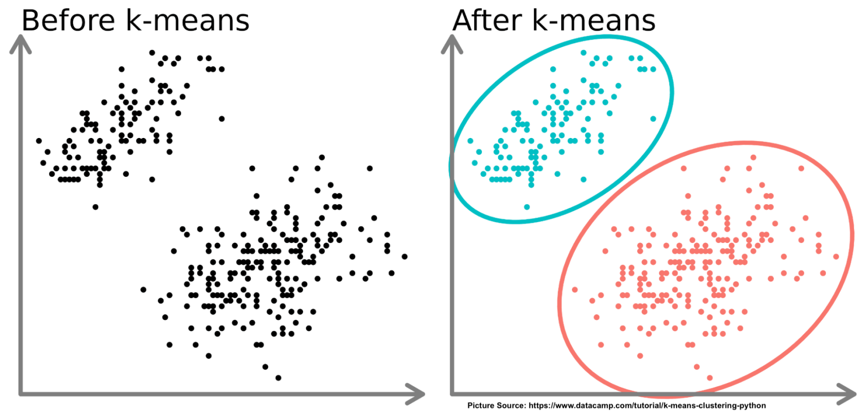
- High Purchase / High Balance - These customers are potentially using their credit card for all of their purchases to perhaps accumulate points, and are maintaining a high balance.
- Low Purchase / High Balance - These customers are potentially making some high value purchases on their credit card and are taking time to pay of the balance.
- High Purchase / Low Balance - These customers are potentially making frequent purchases with their credit card but are paying off the balance immediately.
- Low Purchase / Low Balance - These customers are potentially making very few purchases and paying off the balance immediately. These could be young customers looking to build their credit.

Based on this, the bank could design financial products these groups of customers. For example for those with high purchases/high balance, the bank could offer high credit limits to ensure their credit utilization stays low. The bank could also offer lower annual fees or balance transfer options. For customers in the low purchase/low balance cohort, the bank could offer more cash back, points based rewards and lower interest rates, to encourage them to use their credit card more.

We have used explanatory data analysis to understand characteristics about customers and get ideas of how we could segment customers. This initial step will help to shed light on how a k-means algorithm may cluster customers later on in the project.

K-Means Algorithm

K-Means algorithm is a popular unsupervised machine learning technique used for clustering data. The algorithm works by dividing a set of data points into k clusters based on their similarity. Initially, k centroids are chosen randomly from the data points, and each data point is assigned to the nearest centroid. Then, the centroids are moved to the center of their respective clusters, and the data points are re-assigned to the nearest centroid. This process is repeated until the centroids no longer move or a maximum number of iterations is reached.



The k-means algorithm is widely used in various applications, such as customer segmentation, and anomaly detection. To learn more about the k-means algorithm, you can read up on the following sources:

- K-Means Clustering.
- Benefits & challenges of k-means for customer segmentation
- How to use k-means clustering for customer segmentation

Before proceeding with k-means clustering, I decided to filter the dataset down to a particular cohort of customers, in order to ease computational time and ease of analyzing/visualizing clusters. I'll be picking customers with *tenure* at 10 months for my analysis cohort. This cohort has 236 customers and makes up 2.6% of the dataset.

Data Prep

To prepare the dataset for k-means clustering, I performed the following steps:

- Create an analysis cohort by filtering for customers with *tenure* = 10.
- Drop any rows with null values. This leaves an analysis cohort of 226 customers.
- Create a *credit_utilization* feature by dividing *balance* by *credit_limit*.

Feature Engineering

Feature engineering is an important step in preparing data for k-means clustering. I used the following techniques for feature engineering in order to improve the accuracy and effectiveness of the algorithm:

- Remove unwanted features - Remove the *cust_id* column. This is not needed for k-means and is used only as a customer identifier. I also make the executive decision to remove the *installment_purchases* column. This feature is defined as the "amount of purchases done in installments". I would assume that *purchases* is the important feature in this dataset and regardless of the number of purchase installments.
- Normalization - This step scales each feature to have a mean of zero and standard deviation of one. This helps prevent features with larger values from dominating the clustering results.
- Dimensionality Reduction (PCA) - Reducing the dimensionality of the data can reduce the computational complexity and improve the interpretability of the clustering results. A popular dimensionality reduction technique is called PCA (Principal Component Analysis). PCA works by identifying a smaller number of variables, known as principal components, that can explain the maximum amount of variance in the original dataset. These principal components are linear combinations of the original variables, and each one represents a different direction in the data. The first principal component

captures the most variance in the data, while each subsequent component captures as much of the remaining variance as possible. For a video explanation of how PCA works, see this link.

Setting a PCA threshold of 80%, meaning generating enough components to capture 80% of the variability in the features, PCA identified 5 principal components from 16 features. See sample below:

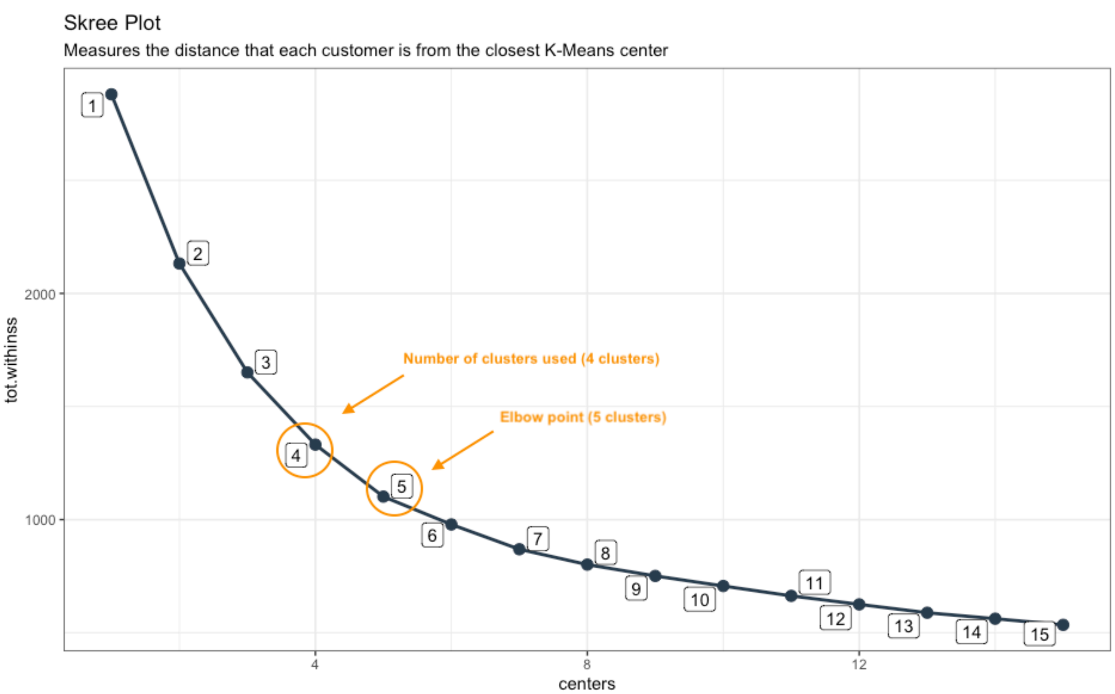
PC1	PC2	PC3	PC4	PC5
0.2049298	0.3212283	-1.3122685	-0.9975037	-1.1368777
0.9377245	-1.8638414	0.9362858	-0.9723859	0.2042461
-0.9079890	-1.4975342	1.6820455	0.1346647	0.5887907
-6.7562686	2.3631080	1.9160285	2.7912623	-2.2666350
-6.0881237	2.5280460	0.8651978	2.2398511	1.5534325
4.2063411	7.6499074	4.7965948	-1.8409245	-0.1582811
-4.0846875	2.5808683	0.0549524	-0.8657810	-3.1829249
1.4572424	-2.2281695	1.4621123	0.5023197	0.0765203
2.2612432	0.9303650	-1.2289065	0.1982712	-0.2531780
-2.6964624	-0.6164209	-0.4961045	-0.3428046	-0.7074959

Optimal Number of Clusters

To determine the optimal number of clusters, we can use a **Skree Plot**. A skree plot is used to determine the appropriate number of clusters to use in a k-means clustering analysis. The skree plot displays the within-cluster sum of squares (WCSS) on the y-axis, plotted against the number of clusters on the x-axis.

The within-cluster sum of squares measures the total squared distance between each point and it's assigned cluster center, summed over all clusters. The scree plot helps identify the **elbow point**, or the point on the plot where adding more clusters does not significantly improve the clustering performance, i.e., the WCSS is not significantly reduced by adding more clusters.

The elbow point is typically used as a guide for deciding how many clusters to retain in the analysis. However, there is no hard and fast rule for selecting the number of clusters, this can be based on domain knowledge and knowledge about the dataset. The plot below is the skree plot for our analysis cohort:

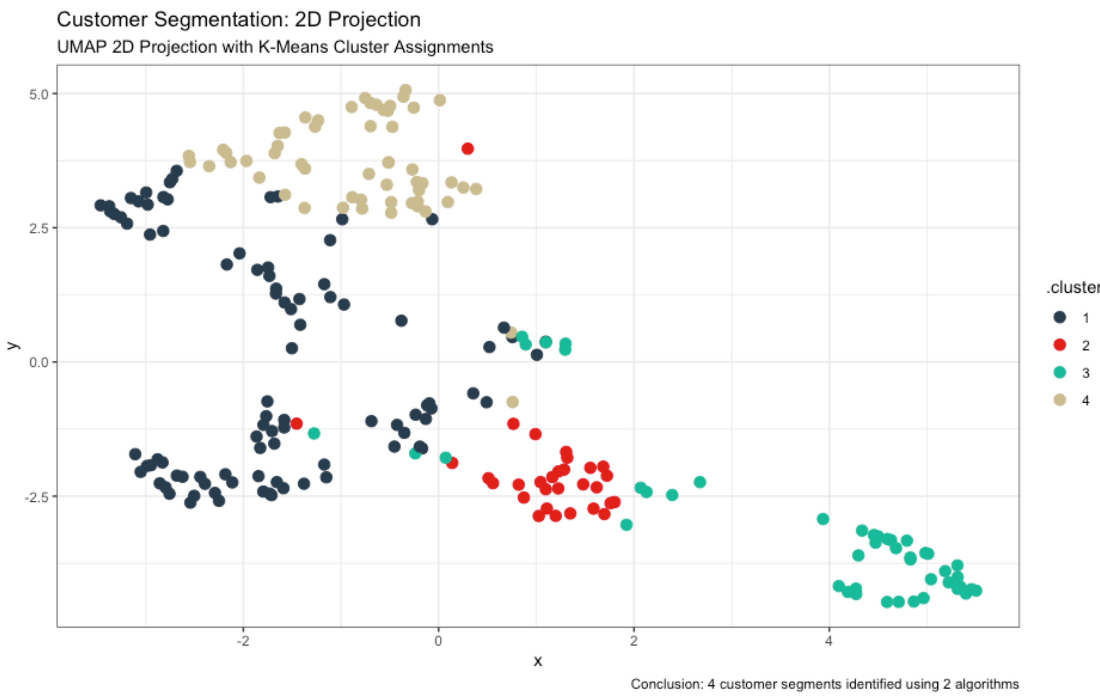


Observation: We can see that the elbow point appears to be 5 clusters. However after running the first iteration of the k-means algorithm, I noticed that only 1 customer (*cust_id* C11004) was being assigned to cluster 1. I would assume that this customer has certain characteristics that stand out for the rest of the cohort. For this particular analysis, I just decided to exclude this customer and re-cluster again, using 4 clusters.

Visualizing Clusters

UMAP (Uniform Manifold Approximation & Projection) is a machine learning technique for dimensionality reduction and data visualization. In order to visualize the cluster assignments, I used UMAP for the sole purpose of generating x and y axis coordinates for visualizing clusters. Recall our dataset for k-means was reduced to 5 principal components. I wanted to still be able to visualize the clusters in 2 dimensions.

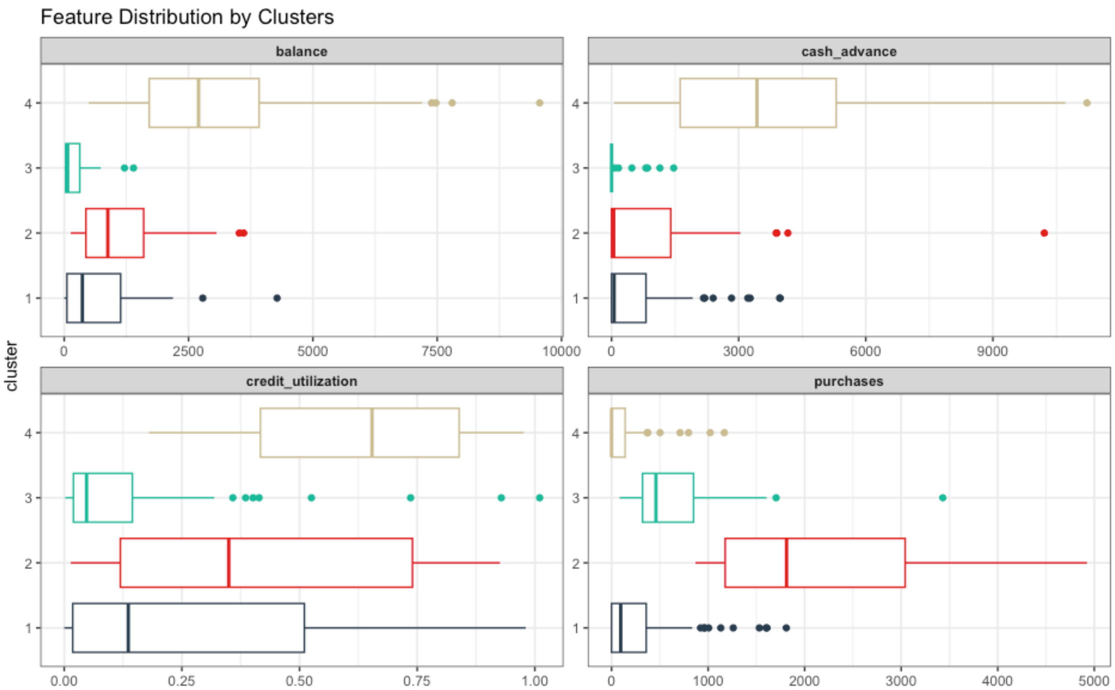
The plot below shows our cluster assignments from the k-means algorithm:



Observation: We can see the k-means algorithm does a good job of segmenting customers. While not completely perfect, we can see 4 distinct segments with a few customers that should probably be re-clustered, although a 3 dimensional plot may present a different perspective. Next we can analyze these clusters in-depth.

Cluster Analysis

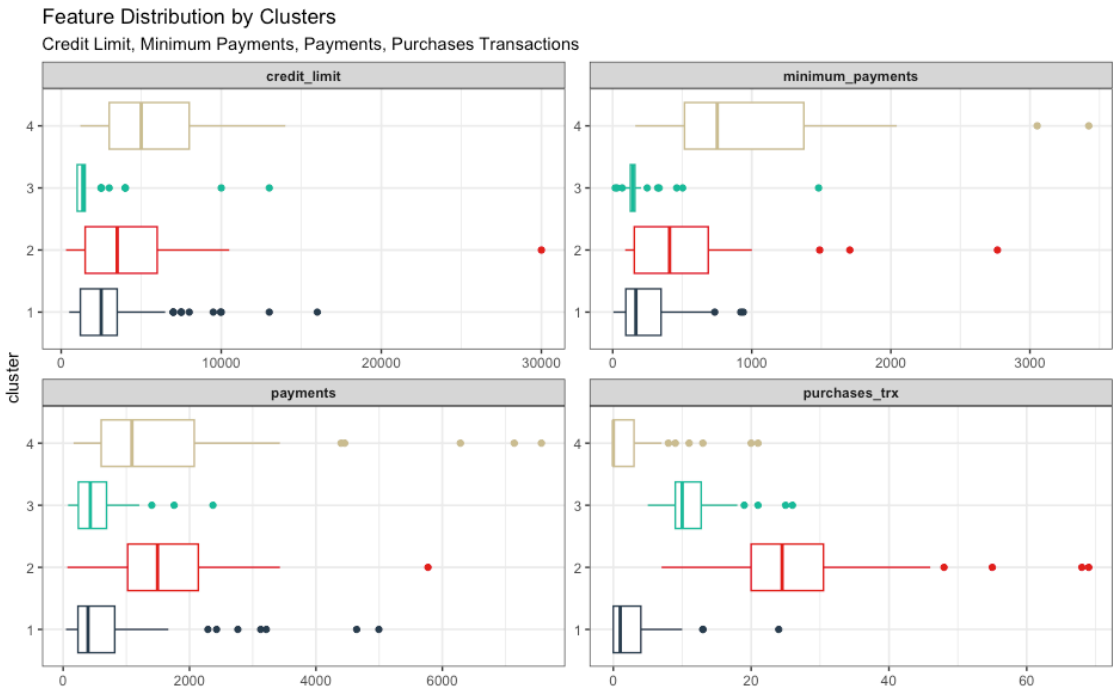
Now that we have our clusters of customers, we can begin analyzing these clusters to understand trends in customer characteristics of the different clusters. Note that we have already seen some of these trends during the explanatory data analysis phase, thus we can better understand how the k-means algorithm is working. To start, we can plot the distribution of some features of interest by cluster using boxplots. Let's start by plotting the distribution of *balance*, *cash_advance*, *credit_utilization* and *purchases*.



Observation: Looking at the plot above, 2 distinct clusters stand out at first glance, cluster 4 and cluster 2:

- **Cluster 4:** Include customers with high *balance*, *cash_advance* and *credit_utilization*. However, these customers have very low *purchases*. As we outlined earlier, these are customers that appear to be using their credit cards as a means to take out loans.
- **Cluster 2:** Includes customers with high *credit_utilization*, slightly high *balance* and high *purchases*. These customers appear to be using their credits strictly for making purchases, and tend to pay off the balance frequently.
- **Cluster 3:** These customers have lower values for all these features. However we know that this analysis cohort includes customers with *tenure* of 10 months, so these customers have had their credit cards for a while. This clusters appears to include customers who are cautious about using their credit cards and tend to make some low value purchases.
- **Cluster 1:** These customers are similar to those in cluster 2, however they tend to have higher credit utilization. These customers appear to have much lower *credit_limit* (median of $2,500) compared to cluster 1 ($5,000) and cluster 3 ($3,500). Cluster 2 has the lowest median *credit_limit* ($1,350).

Let us take a look at a few other feature distributions for our clusters. Below I show boxplots for *credit_limit*, *minimum_payments*, *payments* and *purchase_trx* for each cluster.



Observation: Once again we can gleam a few insights:

- **Cluster 4:** Appears to have higher *credit_limit* and also, customers in this cluster tend to make make higher minimum payments, suggesting that some of these customers (who are using their credit cards to take out loans) are indeed making efforts to pay off their balance.
- **Cluster 2:** These customers have high the highest *purchase_trx* but also have *payments*, *minimum_payment*, *credit_limit* and similar to clusters 1 and 4. These customers while making frequent purchases with their credit tend to pay just the minimum required payments and thus always maintain some balance on their credit card.
- **Clusters 1 and 3:** These customers appear to have similar characteristics and maintain low levels of use for their credit cards.

Customer Persona / Product Recommendations

Based on the analysis in the previous section. We can thus finalize our customer personas and come up with product recommendations to be marketed to these customers. We'll do this using the following format; ***Cluster***, ***Persona Name***, ***Description***, ***Stats***, ***Product Recommendations***.

1. **Cluster 4: Loanee Customer**

    - **Description:** These customers tend to use their credit cards a means for taking out loans. They use their credit card to bridge the gap between their financial needs, thus resulting in high cash advances, high balance and high credit utilization.

    - **Stats:** Range (medium - max).

        - Credit Utilization - 65% - 97% (High)
        - Cash Advance - $3,431 - $11,221 (High)
        - Purchases - $0 - $1,168 (Low)
        - Balance - $2,701 - $9,560 (High)

    - **Product Recommendations:**

        - Balance Transfer Card Options: Option to transfer their balance to 0% APR cards to save on interests rates.
        - Debt Consolidation / Personal Loans: Provide debt consolidation loans with lower interest rates, allowing these customers to combine their high-interest debts into a single manageable payment, thus reducing their interest charges and simplifying their repayment strategy.
        - Credit Counselling: Provide guidance on managing debt, creating budgets and financial improvements.
        - Credit Builder Loans: Credit builder loans are specifically designed to help individuals build/improve their credit scores. Such loans are secured by the borrower's savings account and timely payments are reported to the credit bureaus. These loans benefit both the financial institution through interest earned and also benfit the customer by establishing/rebuiliding positive credit history.

2. **Cluster 3: Purchasing Customer**
   - **Description:** These customers use their credit cards as a means for making frequent purchases. This may be due to the convenience and rewards earned by using their credit cards.
   - **Stats:** Range (medium - max).
     - Credit Utilization - 35% - 93% (Medium to High)
     - Cash Advance - $49 - $4,161 (Low to High, excluding outliers)
     - Purchases - $1,813 - $4,924 (High)
     - Balance - $365 - $4,279 (Low to Medium)
   - **Product Recommendations:**
     - Rewards Programs: Reward programs where customers earn points, cashback, or airline miles based on their spending. These programs encourage customers to use their credit cards and provide incentive for loyalty.
     - Premium Cards: This bank could offer premium cards with enhanced benefits for frequent users. While these cards typicall come with higher annual fees (value for the bank), but also provide additional perks such as airport lounge access, concierge services, travel insurance, etc. (value for the customer).
     - Installment Plans: This bank could offer installment plans to these customers, enabling them to convert larger purchases in smaller, more manageable monthly payments.
     - Credit Lines / Lower Interest Rates: Frequent card users who have established positive credit history could be eligible for increased credit lines and lower interest cards.
3. **Cluster 3: Prudent Customer**
   - **Description:** These customers take a cautious and thoughtful approach to their credit card usage. They have a sense of responsible financial behavior and consider their spending decisions carefully.
   - **Stats:** Range (medium - max).
     - Credit Utilization - 4% - 52% (Low to Medium, excluding outliers)
     - Cash Advance - $0 - $1,465 (Low to Medium)
     - Purchases - $460 - $3,431 (Low to Medium)
     - Balance - $70 - $1,393 (Low to Medium)
   - **Product Recommendations:**
     - Low Interest Cards: Offer credit cards with low annual percentage rates (APRs). These cards offer a lower cost of borrowing, allowing customers to manage their balances with minimal interest charges. Banks benefit from interest earned, while customers can maintain their cautious approach without worrying about excessive interest fees.
     - Secured Credit Cards: Secured credit cards are an option for customers who want to build or rebuild their credit while maintaining control over their spending. These cards require a security deposit as collateral, which sets the credit limit. This offers an opportunity for cautious customers to establish a positive credit history while banks benefit from the security deposit and the potential to convert customers to unsecured credit cards in the future.
     - Fraud Protection and Monitoring: Banks can provide enhanced fraud protection and monitoring services for cautious customers. These services include real-time transaction alerts, identity theft protection, and advanced security features to safeguard against fraudulent activities. Customers gain peace of mind knowing that their accounts are closely monitored and protected, while banks can reduce the risk of financial losses due to fraud.

4. **Cluster 1: Selective Customer**
   - **Description:** These customers also have a careful and deliberate approach to credit card usage, primarily for low/medium value infrequent purchases. They are selective in their spending choices and prioritize making low/medium value purchases rather than frequent small transactions.
   - **Stats:** Range (medium - max).
     - Credit Utilization - 13% - 98% (Low to High)
     - Cash Advance - $60 - $3,980 (Low to Medium)
     - Purchases - $95 - $1,810 (Low to Medium)
     - Balance - $365 - $4,279 (Low to Medium)
   - **Product Recommendations:**
     - Value Purchase Financing: Banks can offer specialized financing options for infrequent purchases, allowing customers to pay for these purchases over time with low or 0% interest rates. This benefits customers by providing affordable installment plans and flexibility in managing their cash flow, while banks generate interest revenue and foster customer loyalty.
     - Extended Warranty Protection: Banks can provide extended warranty protection as an added benefit for customers making certain infrequent high-value purchases. This extends the manufacturer's warranty of these high-value purchases, offering coverage against unexpected repairs or replacements, providing peace of mind to customers. The bank benefits from increased card usage and customer satisfaction, potentially leading to long-term loyalty.
     - Personalized Spending Insights: Banks can offer personalized spending insights and analysis for customers who make infrequent purchases. This includes detailed transaction categorization, spending trends, and recommendations tailored to their unique spending patterns. It benefits customers by helping them make informed financial decisions and optimize their spending, while banks enhance customer engagement and strengthen relationships by providing valuable financial insights.

These are just a few examples of how this bank can build customer personas from the various customer segments/clusters and market financial products to them. It is important that these financial products are mutually beneficial to both the bank and the customers.

The bank can test the success of these financial products through various ways including experimentation (a/b testing), surveys, user analytics, net promoter score (NPS), pilot programs, etc.

Conclusion

In conclusion, customer segmentation and persona creation using the k-means algorithm have emerged as powerful tools in the banking industry. By leveraging data analytics and machine learning techniques, banks can gain a deeper understanding of their customers, tailor their offerings to specific segments, and deliver personalized experiences. The k-means algorithm enables the identification of distinct customer groups based on behavioral patterns and characteristics, allowing banks to develop targeted strategies, design relevant financial products, and enhance customer satisfaction. With customer segmentation and persona creation at the core of their business strategies, banks can foster stronger customer relationships, drive growth, and stay ahead in today's competitive landscape.