WARWICK BUSINESS SCHOOL
THE UNIVERSITY OF WARWICK

Master's Programmes: Assignment Cover Sheet

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Module Code:	IB98D0
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Question Attempted: *(question number/title, or description of assignment)*	1 (Cluster Analysis)
Have you used Artificial Intelligence (AI) in any part of this assignment?	**No**

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Table of Contents

Executive Summary

This report outlines the results of a cluster analysis conducted on a random sample of 500 observations from a loan dataset. The goal of the analysis was to gain insights into customer behavior, identify distinct segments for targeted marketing strategies, and refine loan offerings to meet the unique needs of each segment. By using KMeans Clustering, the samples were grouped into 3 clusters based on their characteristics. However, the study's limitation is that the sample size represents only 1% of the population, so it is important to consider larger sample sizes in future studies.

1. Introduction

This report seeks to utilise Cluster Analysis (CA) to gain comprehension of customer behaviour, identify segments to group borrowers with similar characteristics in loan data, and refine loan offerings for the company by implementing targeted marketing strategies and better customer support process to serve the unique needs of each segment. A sample of 500 observations from the loan data was used to perform the CA, which identified various segments that can be utilised for better loan portfolio management. The findings from the experiment will be analysed and used to provide appropriate recommendations for the company.

2. Data Preparation

2.1. The Variables

During the process of selecting variables to identify the characteristics of a cluster, we experimented with different options and ultimately chose 10 out of 53 variables that we believed were significant. Our selection was based on domain knowledge, experimentation, and references (Appendix 1). The chosen variables include annual income; home ownership; loan amount; interest rate; interest, late fees, principal received to date; monthly debts; grade; and term.

2.2. Make Pre-Analysis Decisions

Before delving into data analysis, it is essential to make informed decisions that will directly impact the accuracy and reliability of the analysis. In the initial phase, we began by verifying the integrity

of the data by checking for any duplicated values, which were not found. We also confirmed that there were no missing values in our cluster variables. To detect any outliers, we employed a graphical method, which did not identify any outliers in our new dataset. Lastly, we observed that there was no evident pattern in the preceding section, and hence we proceeded to generate 500 random samples through the random-sampling process.

2.3. Encode

We used the labelling data encoding technique to encode categorical variables to numeric variables, as indicated in Table 2.1.

Table 2.1 Encoding Variables

Categorical Variable	Encoding to Numeric Variable
home_ownership	Own: 1, Mortgage: 2, Rent: 3, Other: 4, None: 5
term	36 (short-term): 0, 60 (long-term): 1
grade	A: 1, B: 2, C: 3, D: 4, E: 5, F: 6, G: 7

2.4. Check Assumptions

Before proceeding, we conducted a thorough analysis of the data to ensure that there are no issues with multicollinearity, which can affect the accuracy of the results. To do this, we performed three different tests. The first test involved examining the correlation coefficient, as shown in Figure 2.1. We observed that there were 12 correlation coefficients that were greater than 0.3, and more than one pair of variables had a correlation coefficient higher than 0.8, which indicates that there is a high correlation between these variables.

	annl_	ln_mn	int_r	ttl_rc_n	ttl_rc_p	dti	tt___	term	hm_wn	grade
annual_inc	1.00									
loan_amnt	0.29	1.00								
int_rate	0.06	0.37	1.00							
total_rec_int	0.27	0.76	0.55	1.00						
total_rec_prncp	0.20	0.81	0.17	0.52	1.00					
dti	-0.22	0.05	0.13	0.06	0.03	1.00				
total_rec_late_fee	0.02	0.10	0.03	0.09	0.11	0.01	1.00			
term	0.15	0.50	0.49	0.60	0.22	0.02	-0.05	1.00		
home_ownership	-0.07	-0.21	-0.01	-0.16	-0.20	0.03	0.03	-0.15	1.00	
grade	0.07	0.39	0.96	0.56	0.20	0.11	0.04	0.51	-0.02	1.00

Figure 2.1. Correlation Coefficient

The results of the KMO test in Figure 2.2. reveal that all variables in the dataset have a MSA score greater than 0.5, and the overall MSA score is 0.71. This suggests that some variables are strongly correlated.

```
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = sample)
Overall MSA =  0.71
MSA for each item =
        annual_inc          loan_amnt           int_rate      total_rec_int    total_rec_prncp
              0.75               0.67               0.65               0.86               0.61
               dti total_rec_late_fee               term     home_ownership              grade
              0.55               0.60               0.83               0.88               0.65
```

Figure 2.2. KMO Test Results

Similarly, the Bartlett Test's p-value is less than 0.05, which indicates that the identity matrix and the correlation coefficient matrix are significantly different, implying that there is considerable multicollinearity among variables.

```
$chisq
[1] 2917.021

$p.value
[1] 0

$df
[1] 45
```

Figure 2.3 Bartlett's Test Results

Since all three tests indicate a high correlation between variables, we decided to use Principal Component Analysis (PCA) and Factor Analysis (FA) to get uncorrelated observations and reduce dimensionality.

3. Principal Component Analysis (PCA)

We performed a PCA on the sample described above using both original and standardised observations, with no notable differences observed. The conditions for applying this methodology were met, and the following results were obtained:

```
Principal Components Analysis
Call: principal(r = sample, nfactors = 5, rotate = "none", scores = TRUE,
    weights = TRUE)
Standardized loadings (pattern matrix) based upon correlation matrix

                        PC1  PC2  PC3  PC4  PC5
SS loadings           3.69 1.56 1.13 1.05 0.86
Proportion Var        0.37 0.16 0.11 0.10 0.09
Cumulative Var        0.37 0.53 0.64 0.74 0.83
Proportion Explained  0.45 0.19 0.14 0.13 0.10
Cumulative Proportion 0.45 0.63 0.77 0.90 1.00

Mean item complexity =  2.1
Test of the hypothesis that 5 components are sufficient.

The root mean square of the residuals (RMSR) is  0.07
 with the empirical chi square  236.16  with prob <  5.1e-49

Fit based upon off diagonal values = 0.95
```

Figure 3.1 PCA Results (1)

	item <S3: AsIs>	PC1 <S3: AsIs>	PC2 <S3: AsIs>	PC3 <S3: AsIs>	PC4 <S3: AsIs>	PC5 <S3: AsIs>	h2 <dbl>	u2 <dbl>
total_rec_int	4	0.88					0.7875693	0.21243075
loan_amnt	2	0.84	-0.39				0.9192587	0.08074129
grade	10	0.77	0.54				0.9154141	0.08458591
int_rate	3	0.75	0.56				0.9169095	0.08309050
term	8	0.71					0.5977978	0.40220215
total_rec_prncp	5	0.63	-0.53	0.34			0.8330084	0.16699159
annual_inc	1		-0.46	-0.51			0.6388566	0.36114345
dti	6		0.37	0.72			0.7560960	0.24390402
total_rec_late_fee	7			0.37	0.77	-0.47	0.9751412	0.02485881
home_ownership	9		0.36		0.57	0.67	0.9523251	0.04767491

1-10 of 10 rows | 1-9 of 9 columns

Figure 3.2 PCA Results (2)

As expected, the first component group has the largest number of variables (having a correlation greater than 0.3 with 6 variables). On the other hand, in the case of “Principal received to date” a contrast can be made between PC1 and PC2 since it does have a significant positive correlation with the first and negative with the second. According to the analysis of SS loadings, it can be determined that the ideal number of components is 4 (having eigen value higher than 1), which group together 74% of variability. However, as can be observed in the following Scree plot, there was no striking variation between PC3 and PC4.

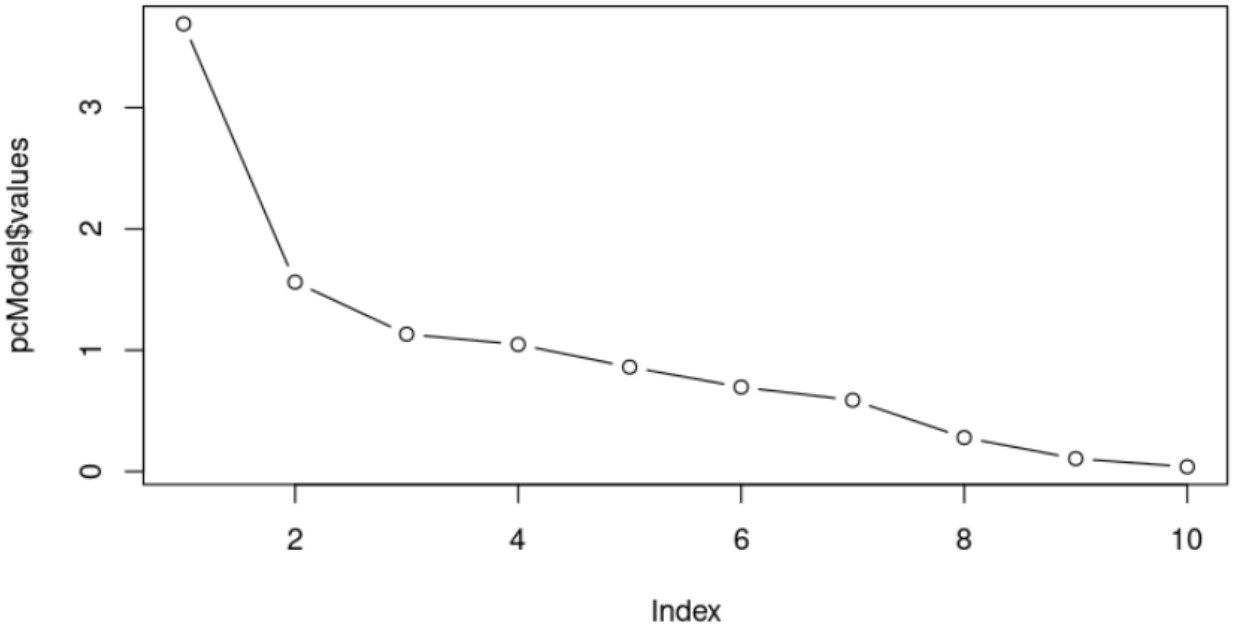


Figure 3.2 Scree Plot

4. Factor Analysis

By scrutinising the Scree plot, we ascertain the optimal number of factors to retain, which, in this case, is 2. This determination is made based on an inflection point observed after the second factor.

For our analysis, we conducted factor analysis with no rotation, oblique rotation, and orthogonal rotation. We found that the most favourable outcome was orthogonal rotation with two factors

(varimax). We also performed factor analysis using both original and standardized observations, but we did not observe any significant differences.

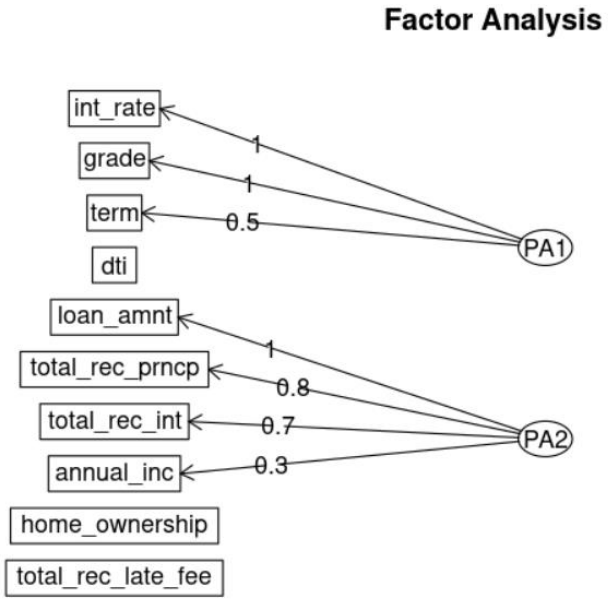


Figure 4.1 Factor Analysis Result

Based on Figure 4.1. which shows the result of the FA, we were able to interpret that:

- PA1 groups attributes such as interest rate, grade, term, indicating a factor correlated with the customer's credit score.
- PA2 encompasses variables such as loan amount, annual income, principal and interest received to date, suggesting a factor associated with the customer’s current financial status.

This comprehensive analysis underscores the efficacy of FA in uncovering latent variables and their relationship with observed variables, thereby facilitating insightful interpretations of complex datasets.

5. Cluster Analysis and Validation

After performing some scenarios, we decided to use factors resulted from FA for clustering analysis (CA) to interpret components in a meaningful way.

Before performing the CA on the selected two factors, we again calculated the Mahalanobis distance to identify potential outliers, and no outlier was found. We also checked for multicollinearity, finding no substantial number of correlations of more than 0.3, and standardised the two-factor dataset, since it was necessary for CA. Finally, we calculated the agglomerative coefficient for each clustering linkage method and the gap statistic for each number of clusters.

Here are the plots of optimal number of clusters using gap statistic method that we got from the hierarchical model (Figure 5.1) and non-hierarchical K-means model (Figure 5.2):

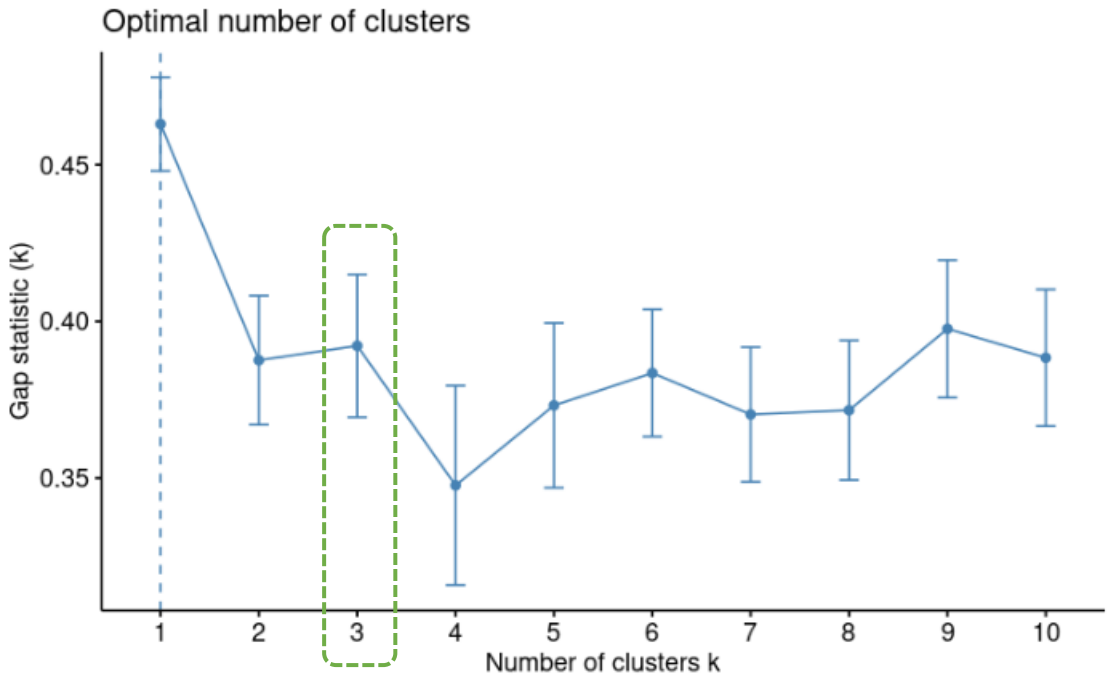


Figure 5.1 Optimal Number of Clusters in the Hierarchical Model

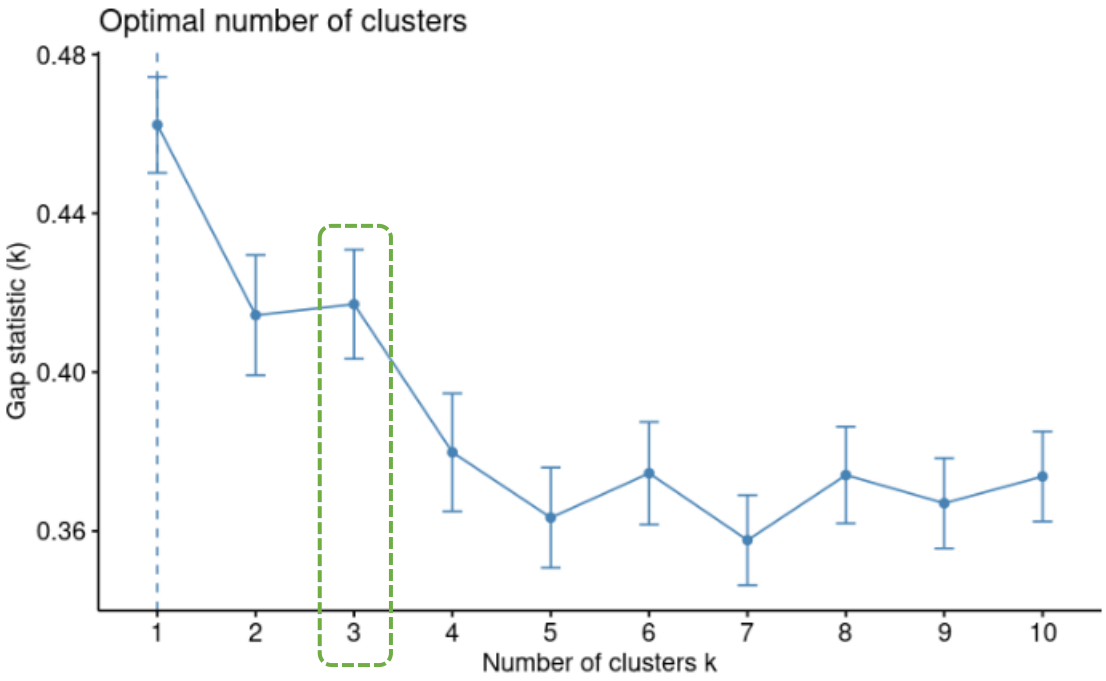


Figure 5.2 Optimal Number of Clusters in the Non-Hierarchical Model

According to the plots, the optimal number of clusters in the hierarchical and non-hierarchical models were both 3. For the hierarchical model, we found the distance matrix using Euclidian distance, and we used the "ward" method to fit it. For the non-hierarchical clustering model, we set with 3 clusters, giving us between SS / total SS of 59.5%. Although the optimal number of clusters were same, we used the Silhouette Coefficient Index to compare hierarchical and non-hierarchical solutions. The average silhouette width of hierarchical clustering is 0.366, and non-hierarchical clustering is 0.385. From this, the non-hierarchical model has a higher Silhouette Coefficient Index, meaning concentration within clusters and dispersion between clusters. We also

used Silhouette plots in Figure 5.3 and Figure 5.4 to compare Hierarchical and Non-Hierarchical solutions:

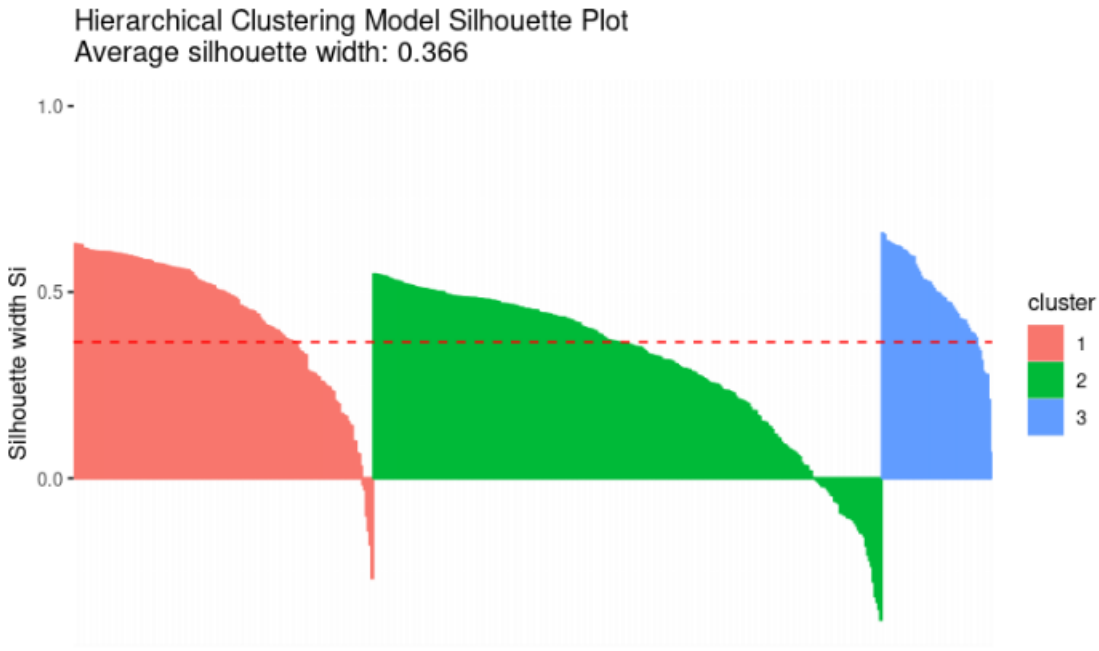


Figure 5.3 Silhouette Plot of Hierarchical Clustering Model

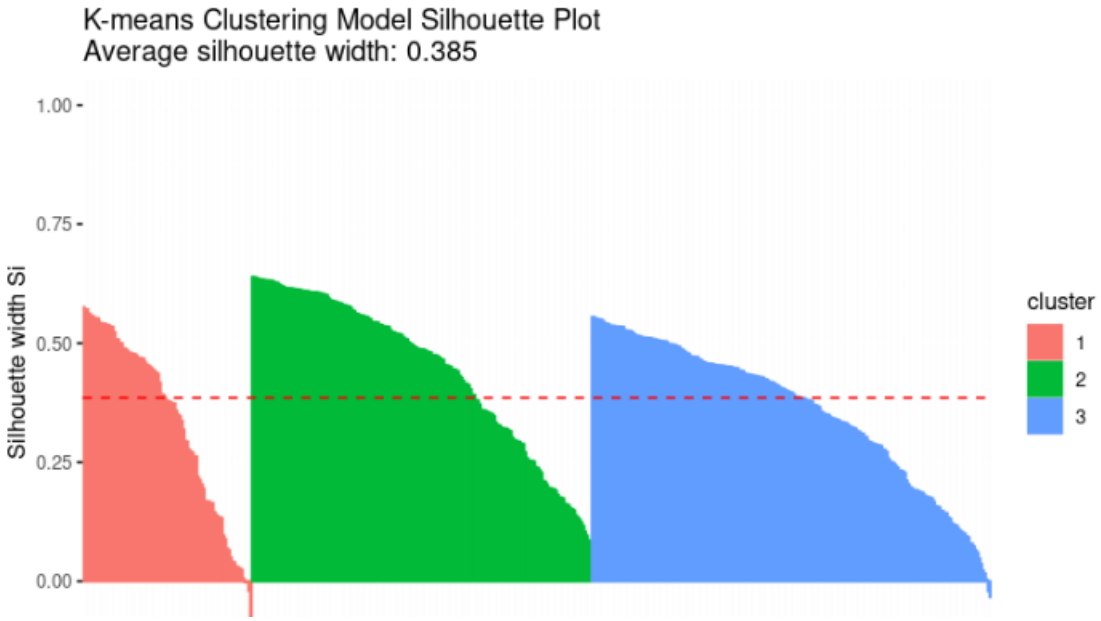


Figure 5.4 Silhouette Plot of K-means Clustering Model

According to these, the K-means clustering model provides better clustering quality, with higher average silhouette width and more consistent intra-group similarity. In the hierarchical clustering model, many observations in clusters 1 and 2 had a negative silhouette coefficient, meaning they are not in the right cluster. Hence, we used a K-means clustering model with 3 clusters as our solution in this project.

The validation of results for the dataset posed several challenges due to the small sample size and the variability observed in clustering outcomes with each random seed. For internal cluster validation, an average silhouette width of 0.387 for new clustering from the same sample set is similar to the origin clustering model 0.385. This shows that the clustering effects are alike, and our cluster model has stability within the sample set.

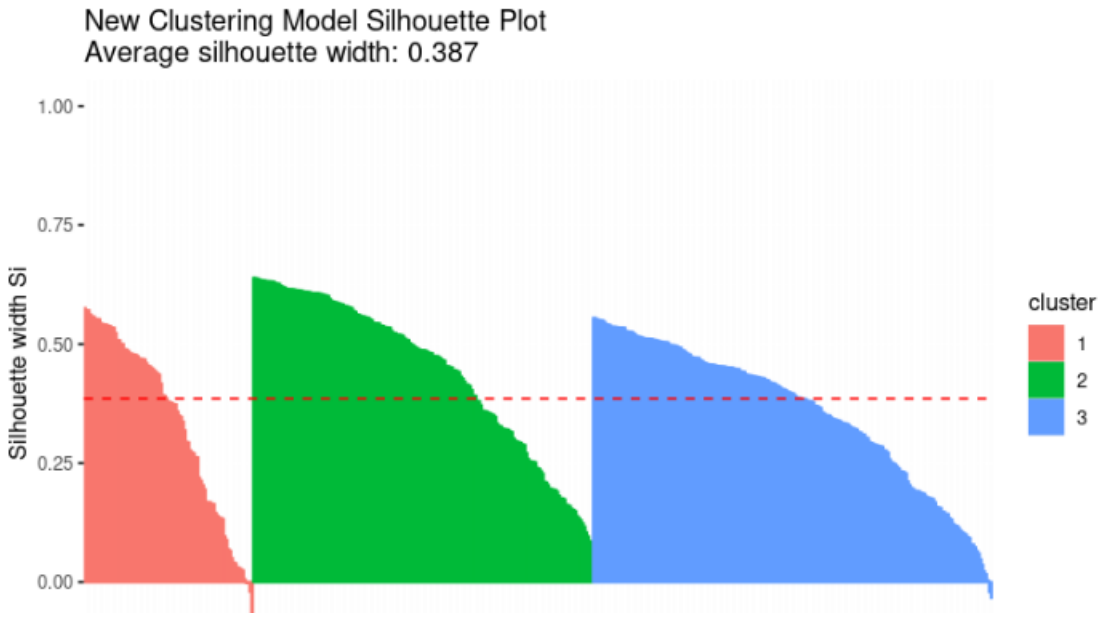


Figure 5.5 Silhouette Plot of the New Clustering (Subset) Model

We repeated the previous process, conducting Factor Analysis and determining the number of clusters on a new sample with the same size (500 observations). To compare the clusters from the initial and new samples, we used the Adjusted Rand Index (ARI). The ARI value obtained was -0.0000675, indicating that the two cluster solutions are essentially independent or no better than random chance, suggesting a lack of similarity between them.

6. Results Analysis and Recommendations

As mentioned in Section 5, we have chosen the KMean method with 3 clusters as the optimal result. Specifically, each cluster contained 93, 187, and 220 observations. Also, the within-cluster sum of squares indicates that 59.5% of the total variation in the dataset is accounted for within the individual clusters, suggesting that the clusters were compact and the observations within each cluster were alike.

We plotted the clusters to visualise the result of clustering analysis. A lower PA1 index indicates better current loan conditions since A-grade loans and short-term loans were encoded as 1 and 0, respectively. Furthermore, low-interest rates signify better loan conditions. Conversely, as a higher annual income, a larger loan amount, and a consistent history of payment imply stable financial status, a higher PA2 index suggests fair financial stability.

As described in Figure 6.1, Cluster 1 represents financially stable borrowers with unfavourable current loan conditions. In contrast, Cluster 2 refers to those who are financially unstable and have average and relatively poor loan conditions. Customers in Cluster 3 mostly have fair loan conditions and financially fair stability.

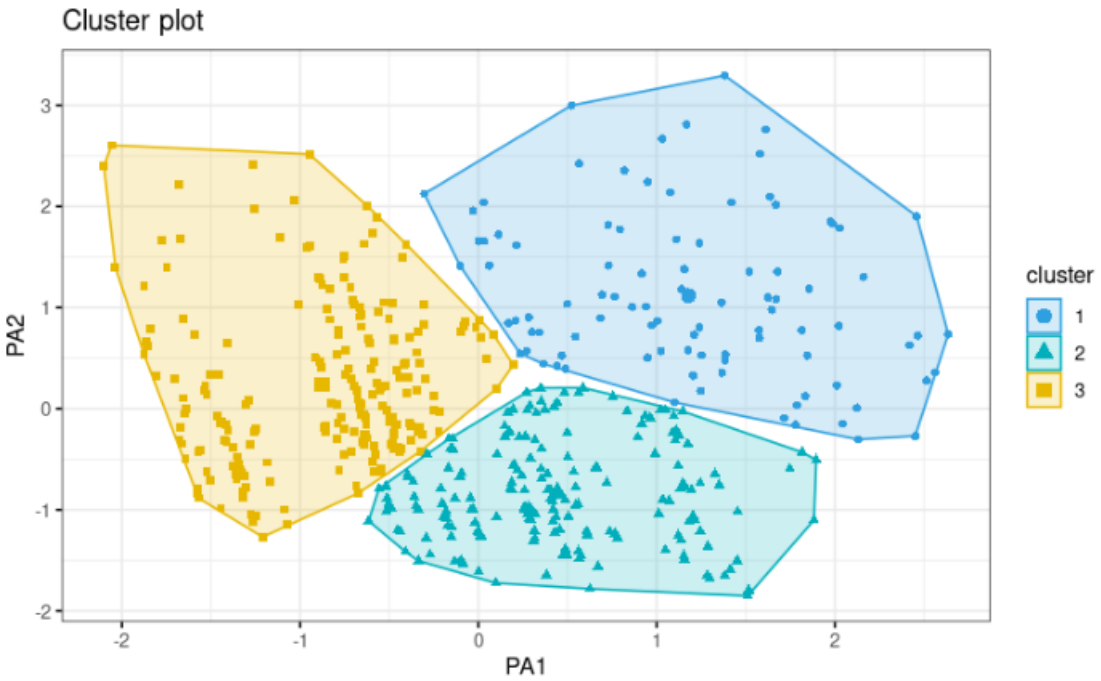


Figure 6.1. KMean clustering: 3 Clusters

Regarding marketing strategy and customer support, we recommend offering customers enhanced loyalty benefits in Cluster 1. As the customers are financially stable and may be able to borrow a more significant loan, they may consider moving to another company for better loan conditions. On the other hand, the company could reconsider or monitor the current loan conditions for customers in Cluster 3, as some have relatively favourable loan terms based on their financial stability.

7. Conclusion

By analysing 10 selected variables, we were able to uncover meaningful patterns and relationships within the data. Additionally, the assessment of multicollinearity prompted FA to obtain factors for CA. The validation of CA results, including the determination of the optimal number of clusters and the assessment of clustering quality using the Silhouette Coefficient Index, provided further confidence in the segmentation outcomes.

However, it is essential to acknowledge the study's limitations. Primarily, the sample size representing only 1% of the population potentially limits the generalisability of the results to other data sets. Additionally, whilst random sampling was employed, the use of stratified sampling would have provided a more representative sample. Furthermore, computational limitations hindered our ability to compare the sample to the entire population.

Despite these limitations, the findings offer valuable insights into customer segmentation, guiding decision-making for loan portfolio management. Moving forward, it is essential to address the limitations by considering larger sample sizes, utilising alternative sampling techniques, and leveraging advanced computational resources for more comprehensive analyses.

References

Luthi, B. (2023) *What's a Good Interest Rate for a Personal Loan?* Available at: https://www.experian.com/blogs/ask-experian/whats-a-good-interest-rate-for-a-personal-loan/ (Accessed: 15 March 2024).

Murphy, C.B. (2024) *Debt-to-Income (DTI) Ratio: What's Good and How to Calculate It*. Available at: https://www.investopedia.com/terms/d/dti.asp (Accessed: 15 March 2024).

Venner, S. (2023) *How will a lender make a decision on my loan application?* Available at: https://www.novunapersonalfinance.co.uk/hints-tips/money/lender-decisions/ (Accessed: 15 March 2024).

Appendix 1: Cluster Variables

No	Variables	Description	Justification
1	annual_inc	The self-reported annual income provided by the borrower during registration	When evaluating a borrower's ability to repay a loan, their annual income is an essential factor to consider. This is because it is important to ensure that their income is enough to cover their day-to-day expenses and other necessary costs (Venner, 2023). Hence, it is crucial to consider this income variable in this particular case.
2	loan_amnt	The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.	The possibility of getting a loan approved is directly influenced by the amount of money the borrower wants to borrow. Lenders evaluate whether the borrowers can repay the loan based on their income, outstanding debts, and credit score. If someone applies for a larger loan, the lender's financial risk goes up, which may lead to a more rigorous approval process.
3	int_rate	Interest Rate on the loan	Lenders often use a risk-based pricing strategy to determine the interest rates they offer for personal loans. This means that they evaluate the probability of the borrower being unable to repay the loan and use that information to decide what interest rate to charge (Luthi, 2023).
4	total_rec_int	Interest received to date	Lenders may consider the interest received thus far when assessing a loan's performance. A significant interest amount may suggest that the loan is doing well, which can positively impact the lender's decision to approve future loans for similar borrowers.

5	total_rec_prncp	Principal received to date	When lenders evaluate the risk of lending money to borrowers, they may consider the rate at which the borrower repays the original loan amount. If the borrower consistently repays the principal amount, it can have a positive impact on their risk profile, which could lead to better loan terms in the future or influence the lender's decision to offer more credit to the borrower.
6	dti	A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower’s self-reported monthly income.	When lenders consider lending money, they evaluate its risk level using a ratio called DTI. If someone's DTI ratio is high, they may have more debt than monthly income (Murphy, 2024).
7	total_rec_late_fee	Late fees received to date	Frequent late fees can indicate to lenders that borrowers are struggling to manage their finances and prioritize their debt payments. This may lead to an increase in the borrower's perceived risk, as lenders may view them as less capable of meeting their financial obligations.
8	term	The entire period of the loan	Lenders consider the loan term when assessing the risk associated with lending money. A longer loan term implies a higher risk of default since it increases the possibility of adverse changes in economic or personal financial circumstances over an extended period.
9	home_ownership	The home ownership status provided by the borrower during registration or obtained from the credit report. The values are RENT, OWN, MORTGAGE, OTHER	People who own homes are typically seen as having better financial stability and creditworthiness than those who do not. Owning a home suggests that the individual has a track record of managing significant financial responsibilities effectively, which can have a positive

			impact on the lender's evaluation of the borrower's loan request.
10	grade	The grade of loan	The interest rate that a borrower is offered for a loan depends on its grade. Loans with higher grades, which indicate lower risk, usually have lower interest rates. This shows that the lender is confident that the borrower will be able to pay back the loan.

Appendix 2: Project Management

Meeting Minutes

No	Date & Place	Discussion Items	Things to do
1	Thursday 15/02/2024 15:00 – 16:00	• Introduction of team members • Overview of the overall timeline • Understanding the question • Initial distribution of tasks among team members • Agreement on our working methods, including regular weekly meetings. • Decided to do question 1: cluster analysis	• Requirement for each member to conduct data verification and assumption checking. • Finalise data verification and assumption checking in the next meeting
2	Tuesday 20/02/2024 14:00 – 15:00	• Update on the stages of data verification and assumption checking. • Selection of variables for clustering	• Completion of the PCA (Principal Component Analysis) and FA (Factor Analysis) processes • Definition of variables for CA • Preparation of the report format • Request for Posit Cloud access for our group from the PG team
3	Tuesday 27/02/2024 15:00 – 16:00	• Observation from the Scree plot indicating 3 factors. • In the next step of CA, consideration of 7 variables with the highest PC scores • Documentation of all attempted scenarios in an Excel file	• Assignment of CA performance to Selina, Kshitij, and Dan • Allocation of PCA section reporting to Amal and Santiago • Assignment of FA section reporting to Sola and Nitya
4	Tuesday 05/03/2024 15:00 – 16:00	• Update on the progress of Cluster Analysis	• Completion of the report for each section and the Cluster Analysis process
5	Thursday 14/03/2024 11:00 – 13:00	• Update on Cluster Analysis with standardized and normalized data.	• Finalisation of each part of the report

		• Discussion and execution of the internal validation step • Task distribution for the remaining sections of the report	
6	Saturday 16/03/2024 17:00 – 20:00	Finalise R code and report	Submit the assignment

Task Distribution

Student ID	Technical Process	Report
2292213	• Principal Component Analysis • Validation	Principal Component Analysis
5587165	• Cluster Analysis • Validation	• Define the Problem • Check Assumptions • Cluster Analysis
5581250	• Factor Analysis • Validation • Visualisation	• Check Assumptions • Factor Analysis • Result Analysis
5582755	• Factor Analysis • Validation	• Factor Analysis • Validation • Conclusion
5528141	• Cluster Analysis	• Pre-Analysis Decision • Cluster Analysis
5588409	• Principal Component Analysis • Validation • Finalise code	• Principal Component Analysis • Cluster Variables • Project Management (Meeting Minutes and Task Distribution) • Finalise report
5589718	• Cluster Analysis • Validation	• Introduction • Cluster Analysis

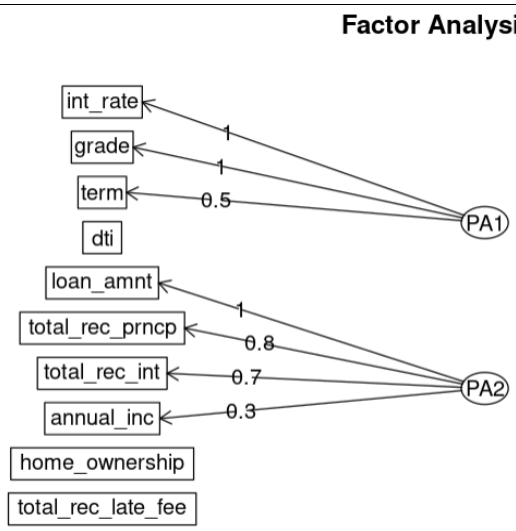
Appendix 3: Experiment Log

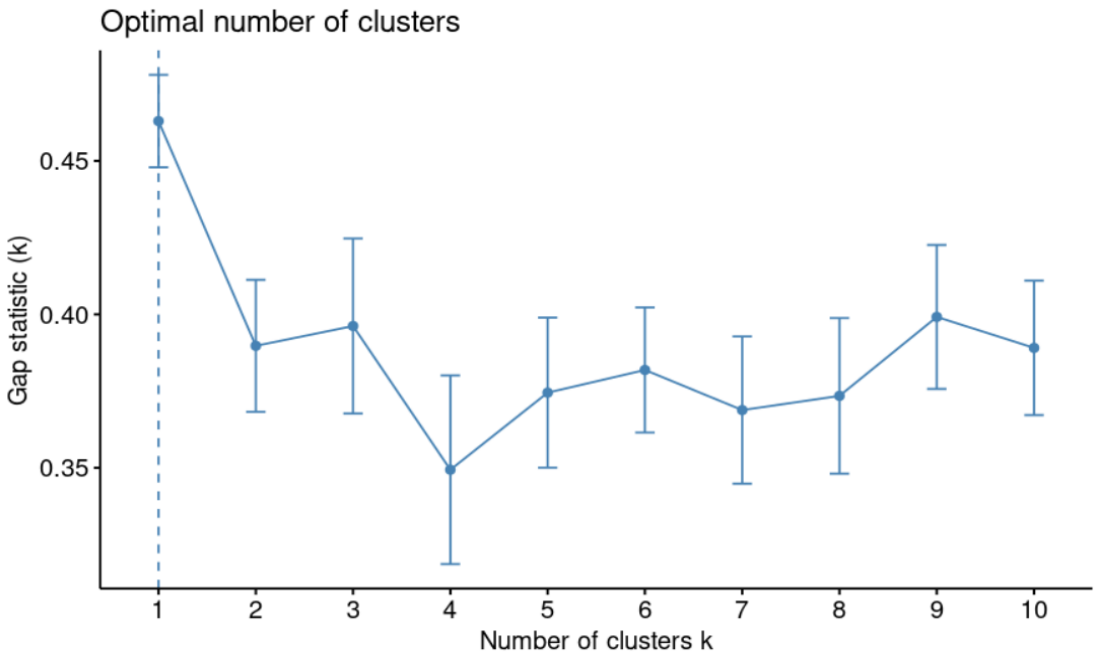
- Initial Scenarios (Scenario 1-7)

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Method	PCA	PCA	PCA	Factor Analysis
Step 1	Filtering only 14 variables (based on domain knowledge)	Filtering only 14 variables (based on domain knowledge)	Filtering only 14 variables (based on domain knowledge)	Filtering only 12 variables (based on domain knowledge)
Step 2	Check duplicate values	Check duplicate values	Check duplicate values	Check duplicate values
Step 3	Check missing values	Check missing values	Check missing values	Check missing values
Step 4	Convert term, grade, home_ownership, purpose, loan_is_bad to factor	Convert term, grade, home_ownership, purpose, loan_is_bad to factor	Convert term, grade, home_ownership, purpose, loan_is_bad to factor	Convert term, grade, home_ownership, purpose, loan_is_bad to factor
Step 5	Recode term, grade, home_ownership, loan_is_bad using label encoding	Recode term, grade, home_ownership, loan_is_bad using label encoding	Recode term, grade, home_ownership, loan_is_bad using label encoding	Recode term, grade, home_ownership, loan_is_bad using label encoding
Step 6	See data distribution to check outliers	See data distribution to check outliers	See data distribution to check outliers	See data distribution to check outliers
Step 7	Create new dataset without purpose to continue to the PCA process as it will be used only for interpretation purpose only	Create new dataset without purpose to continue to the PCA process as it will be used only for interpretation purpose only	Create new dataset without purpose to continue to the PCA process as it will be used only for interpretation purpose only	Create new dataset without purpose to continue to the PCA process as it will be used only for interpretation purpose only
Step 8	Convert all columns in the new dataset to numeric	Convert all columns in the new dataset to numeric	Convert all columns in the new dataset to numeric	Convert all columns in the new dataset to numeric
Step 9	Compute correlation matrix	**Standardise the data**	**Normalise the data**	Try and check the correlation results by normalising the data
Step 10	Check for multicollinearity using correlation coefficients	Compute correlation matrix	Compute correlation matrix	Compute correlation matrix
Step 11	Kaiser-Meyer-Olkin	Check for multicollinearity using correlation coefficients	Check for multicollinearity using correlation coefficients	Check for multicollinearity using correlation coefficients
Step 12	Cortest Bartlett Test	Kaiser-Meyer-Olkin	Kaiser-Meyer-Olkin	Kaiser-Meyer-Olkin
Step 13	Perform PCA	Cortest Bartlett Test	Cortest Bartlett Test	Cortest Bartlett Test
Step 14	Produce the scree plot	Perform PCA	Perform PCA	Perform FA
Step 15		Produce the scree plot	Produce the scree plot	Produce the scree plot

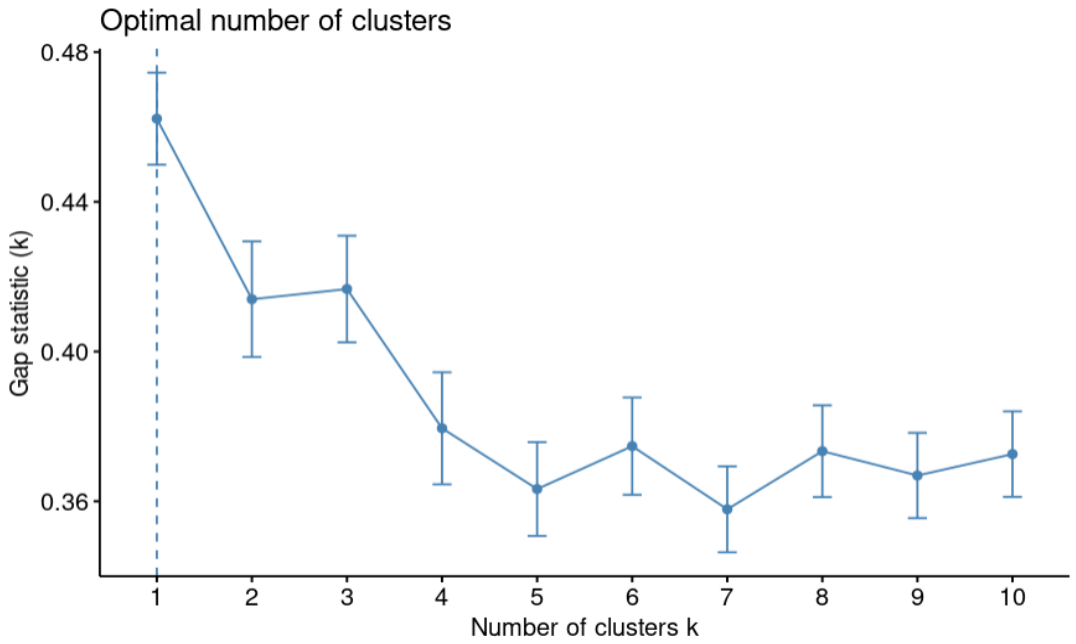
	Scenario 5	Scenario 6	Scenario 7
Method	FA + CA	FA + CA	FA and CA
Step 1	Filtering only 14 variables (based on domain knowledge)	Filtering only 14 variables (based on domain knowledge)	Filter 14 vars
Step 2	Check duplicate values	Check duplicate values	Check dupes
Step 3	Check missing values	Check missing values	Check missing/NA
Step 4	Convert term, grade, home_ownership, purpose, loan_is_bad to factor	Convert term, grade, home_ownership, purpose, loan_is_bad to factor	Data coversion to factors
Step 5	Recode term, grade, home_ownership, loan_is_bad using label encoding	Recode term, grade, home_ownership, loan_is_bad using label encoding	Recoding
Step 6	See data distribution to check outliers	See data distribution to check outliers	Check distribution of data
Step 7	Create new dataset without purpose to continue to the PCA process as it will be used only for interpretation purpose only	Create new dataset without purpose to continue to the PCA process as it will be used only for interpretation purpose only	New dataset creation
Step 8	Convert all columns in the new dataset to numeric	Convert all columns in the new dataset to numeric	Convert columns to numeric
Step 9	Select 500 random samples	Select 500 random samples	Sample of 500 with a set seed
Step 10	Check whether sample represents the population	Check whether sample represents the population	Check whether sample represents the population
Step 11	Compute correlation matrix	Compute correlation matrix	Corr matrix
Step 12	Check for multicollinearity using correlation coefficients	Check for multicollinearity using correlation coefficients	Check for multicollinearity using correlation coefficients
Step 13	Kaiser-Meyer-Olkin	Kaiser-Meyer-Olkin	Kaiser-Meyer-Olkin
Step 14	Cortest Bartlett Test	Cortest Bartlett Test	Cortest Bartlett Test
Step 15	Perform FA	Perform FA	Perform FA(3)
Step 16	Produce FA diagram (3 Factors Solution with Orthogonal rotation)	Produce FA diagram (3 Factors Solution with Orthogonal rotation)	FA diagram
Step 17	Perform CA	Perform CA	Perform CA
Step 18	Check outliers using Mahalanobis distance	Check outliers using Mahalanobis distance	Mahalanobis distance
Step 19	Check multicollinearity	Check multicollinearity	Multicollinearity
Step 20	Standardize data	Normalize data	Normalisation
Step 21	Calculate agglomerative coefficient	Calculate agglomerative coefficient	Calculate agglomerative coefficient
Step 22	Produce plot of clusters vs. gap statistic	Produce plot of clusters vs. gap statistic	Produce plot of clusters vs. gap statistic
Step 23	Distance matrix (using Euclidean distance)	Distance matrix (using Euclidean distance)	Distance matrix (using Euclidean distance)
Step 24	Plotting dendrogram	Plotting dendrogram	Hierarchical clustering with ward.D
Step 25	Hierarchical clustering (6 clusters)	Hierarchical clustering (6 clusters)	Plot dendrogram
Step 26	Non-hierarchical clustering - Kmeans (5 clusters)	Non-hierarchical clustering - Kmeans (5 clusters)	hcut clutsering (6)
Step 27			kmeans clustering (5)

- Final Scenarios (Scenario 1-3)

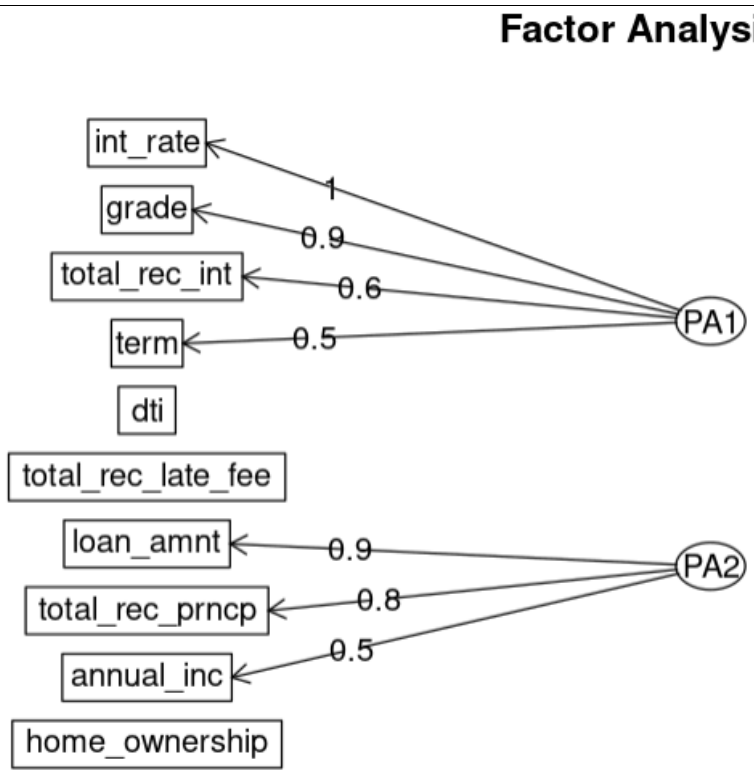
<table>
<tr><th colspan="2">Scenario 1</th></tr>
<tr><td>Variables</td><td>10 variables: annual_inc, loan_amnt, int_rate, total_rec_int, total_rec_prncp, dti, total_rec_late_fee, term, home_ownership, grade</td></tr>
<tr><td>KMO</td><td>
<pre>
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = sample)
Overall MSA = 0.71
MSA for each item =
        annual_inc   loan_amnt   int_rate   total_rec_int   total_rec_prncp
              0.75   0.67   0.65   0.86   0.61
               dti total_rec_late_fee   term   home_ownership   grade
              0.55   0.60   0.83   0.88   0.65
</pre>
</td></tr>
<tr><td>FA</td><td>


</td></tr>
<tr><td>Num. of clusters</td><td>Hierarchical:


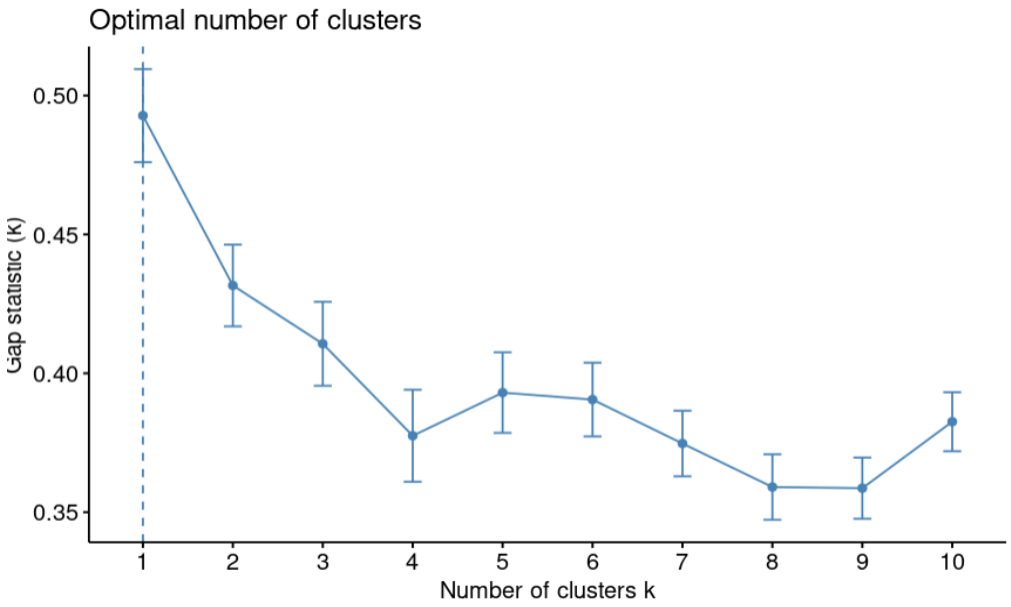
</td></tr>
</table>

<table>
<tr><td></td><td>Non-Hierarchical (KMeans):
 
</td></tr>
<tr><td>Cluster size distribution</td><td>Based on hierarchical, cluster=3
<pre>fit_fa3
  1   2   3
163 277 60</pre>
Based on KMeans, cluster=3
<pre>K-means clustering with 3 clusters of sizes 93, 187, 220</pre></td></tr>
<tr><td>Similarity using Sihouette</td><td><pre>[1] "Hierarchical clustering average silhouette width: 0.365886930628537"
[1] "K-means clustering average silhouette width: 0.385485019803922"</pre>
<pre>[1] "New clustering average silhouette width: 0.387436909751364"</pre></td></tr>
</table>

FA new sample



CA new sample

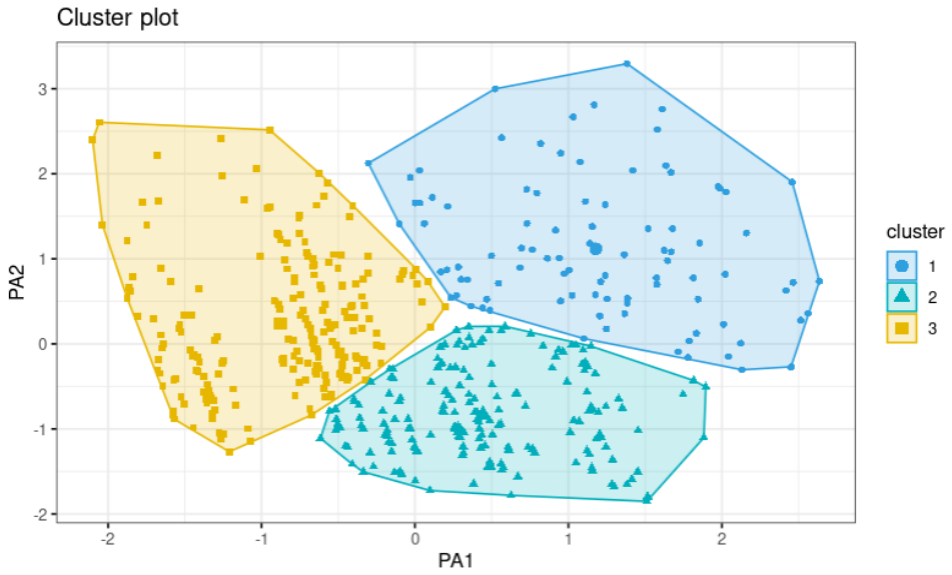


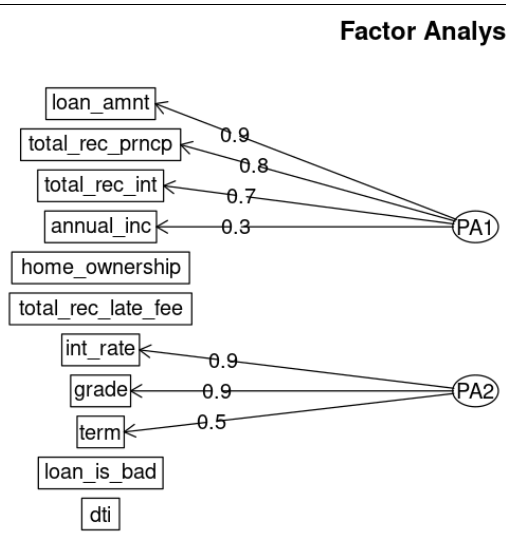
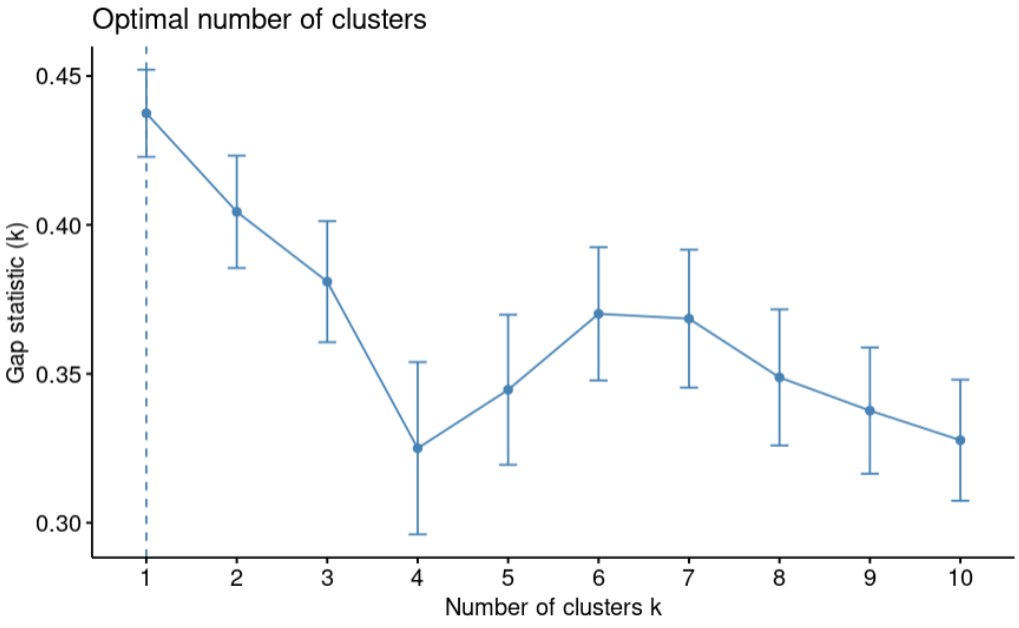
Cluster=5

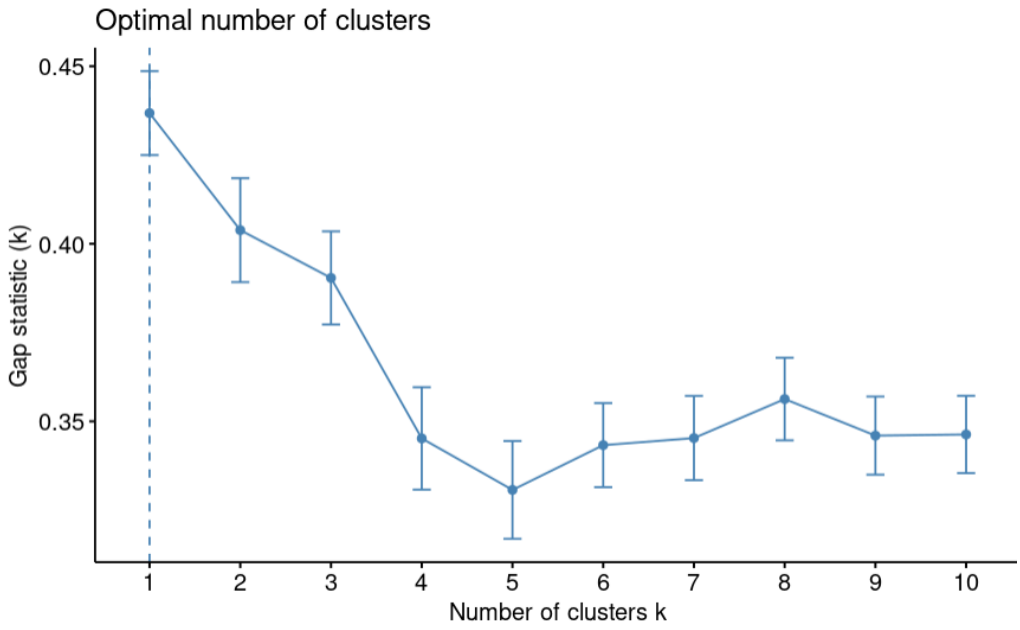
```
K-means clustering with 5 clusters of sizes 151, 79, 104, 114, 52
```

Compare two different

```
[1] -0.00550285
```

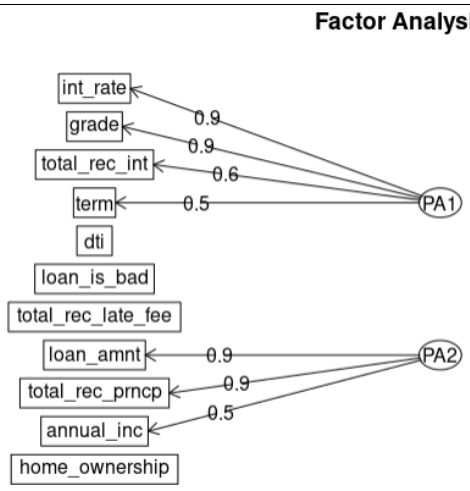
samples using ARI	
Cluster plot	Initial sample with KMeans: 

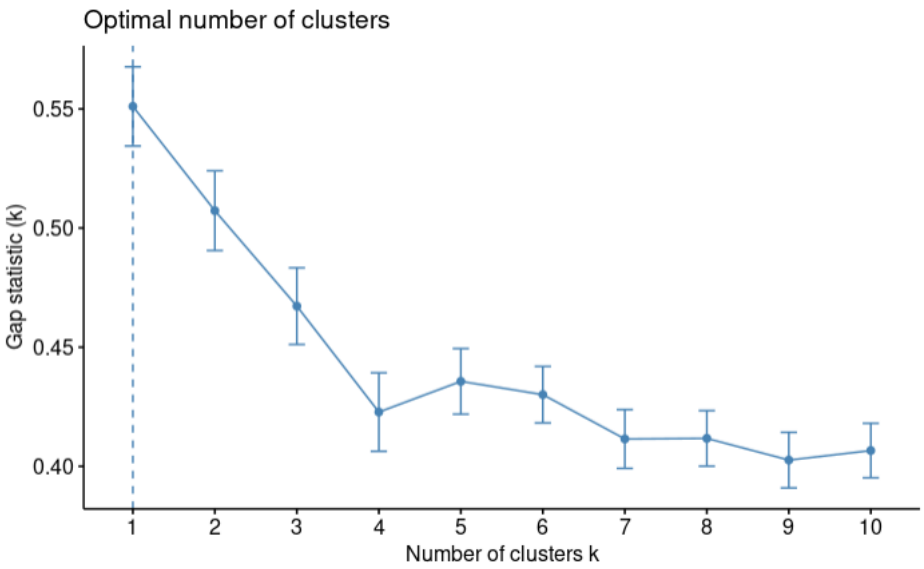
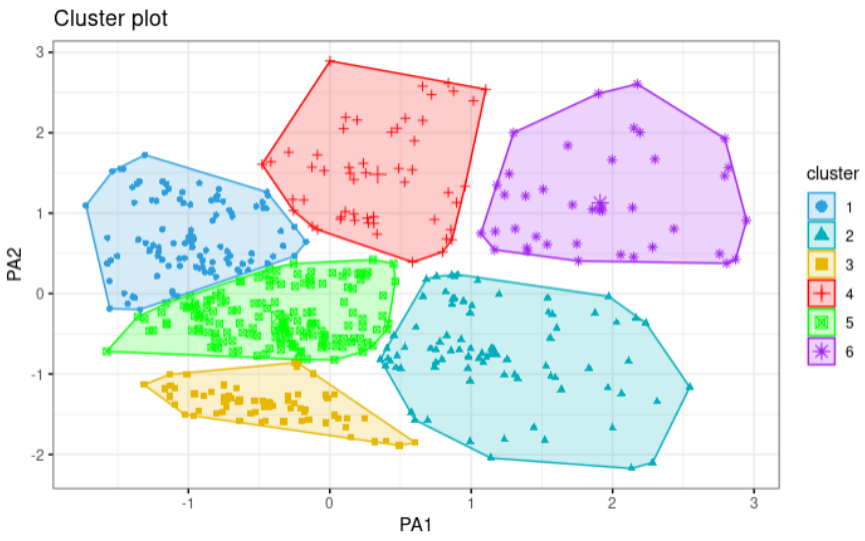
Scenario 2	
Variables	11 variables: annual_inc, loan_amnt, int_rate, total_rec_int, total_rec_prncp, dti, total_rec_late_fee, term, home_ownership, grade, loan_is_bad
KMO	Kaiser-Meyer-Olkin factor adequacy Call: KMO(r = sample) Overall MSA = 0.58 MSA for each item = annual_inc 0.70 / loan_amnt 0.52 / int_rate 0.65 / total_rec_int 0.77 / total_rec_prncp 0.44 dti 0.54 / total_rec_late_fee 0.34 / term 0.77 / home_ownership 0.89 / grade 0.66 loan_is_bad 0.13
FA	
Num. of clusters	Hierarchical: 

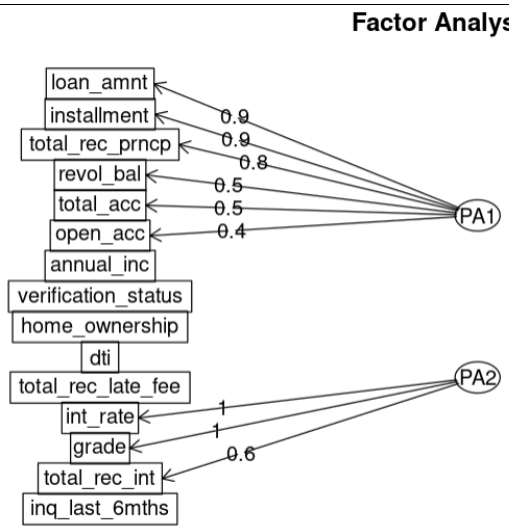
	Non-Hierarchical (KMeans): 

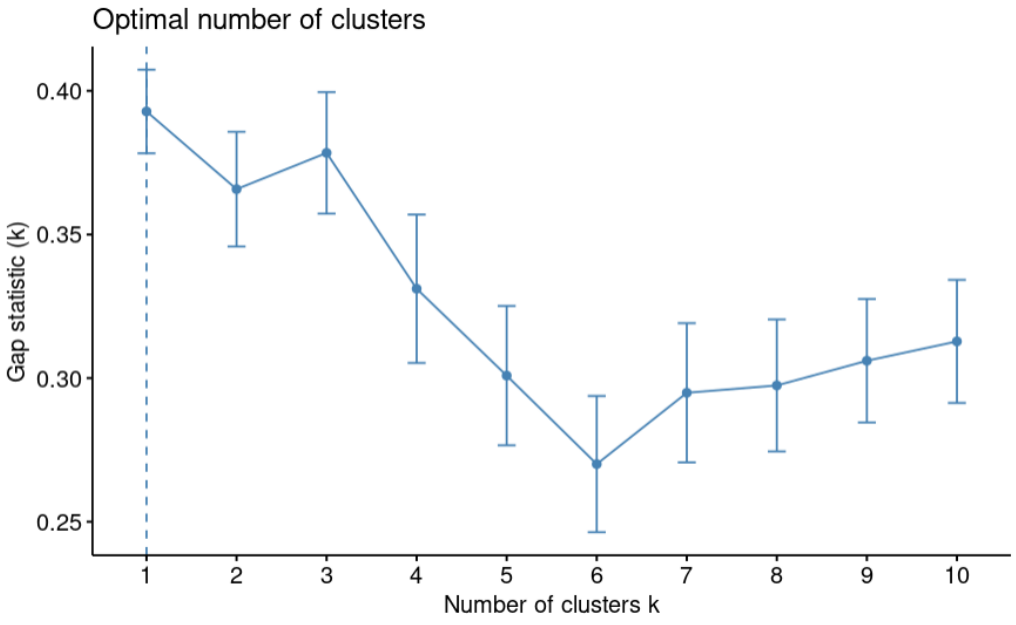
Cluster size distribution	Based on hierarchical, cluster=5
	`fit_fa3`
	`1 2 3 4 5`
	`128 119 121 48 84`
	
	Based on KMeans, cluster=6
	`K-means clustering with 6 clusters of sizes 105, 82, 64, 53, 156, 40`

Similarity using Sihouette	`[1] "Hierarchical clustering average silhouette width: 0.318538347338661"`
	`[1] "K-means clustering average silhouette width: 0.361004837808972"`
	
	`[1] "New clustering average silhouette width: 0.441510763769024"`

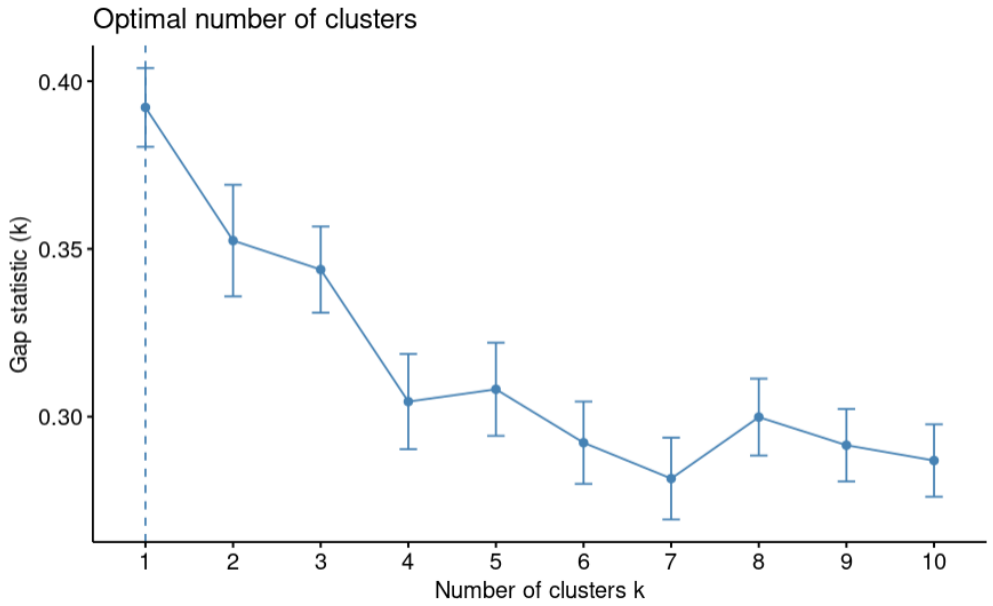
FA new sample	

CA new sample	 Cluster=5 `K-means clustering with 5 clusters of sizes 53, 98, 124, 75, 150`
Compare two different samples using ARI	`[1] 0.0005045034`
Cluster plot	Initial sample with KMeans: 

<table>
<tr><td colspan="2">Scenario 3</td></tr>
<tr><td>Variables</td><td>15 variables: loan_amnt, int_rate, home_ownership, annual_inc, verification_status, dti, total_rec_prncp, total_rec_int, installment, grade, inq_last_6mths, open_acc, total_acc, revol_bal, total_rec_late_fee</td></tr>
<tr><td>KMO</td><td>
<pre>
Kaiser-Meyer-Olkin factor adequacy
Call: KMO(r = sample)
Overall MSA = 0.76
MSA for each item =
          loan_amnt   int_rate   home_ownership   annual_inc verification_status
               0.75   0.64   0.79   0.71   0.86
                dti   total_rec_prncp   total_rec_int   installment   grade
               0.58   0.93   0.89   0.76   0.65
     inq_last_6mths   open_acc   total_acc   revol_bal total_rec_late_fee
               0.72   0.67   0.69   0.87   0.53
</pre>
</td></tr>
<tr><td>FA</td><td>


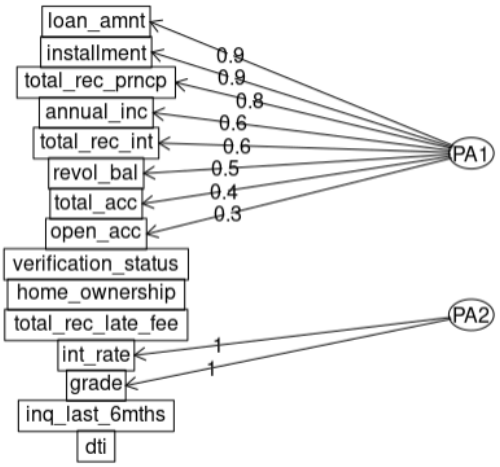
</td></tr>
<tr><td>Num. of clusters</td><td>Hierarchical:


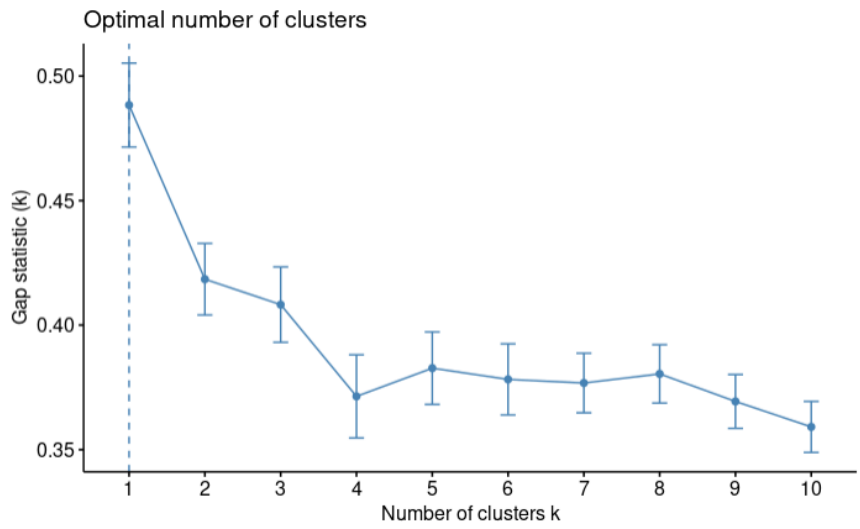
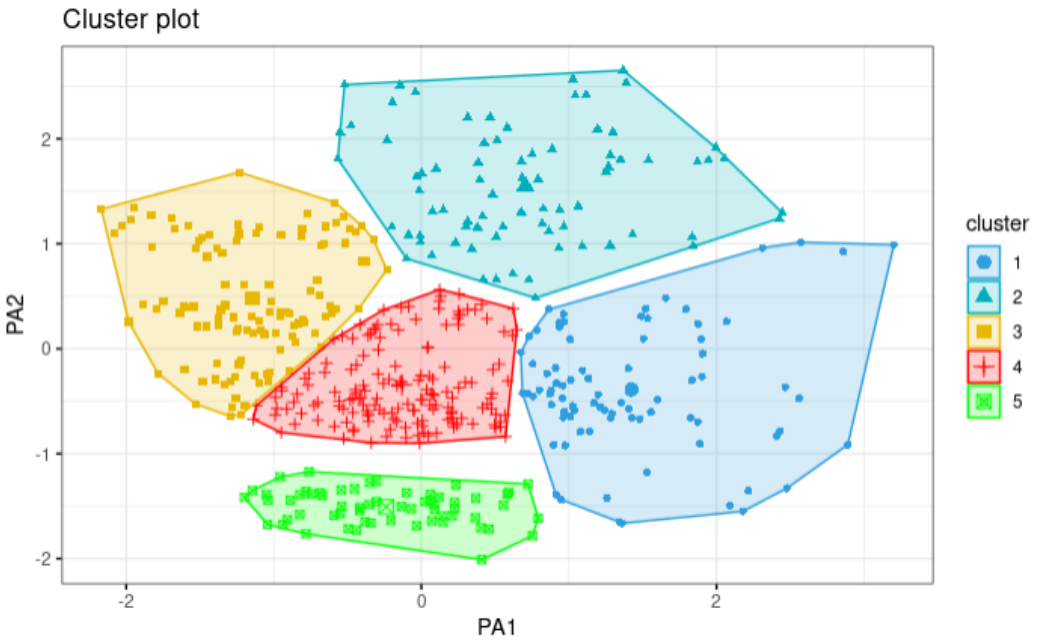
</td></tr>
</table>

	Non-Hierarchical (KMeans): 

Cluster size distribution	Based on hierarchical, cluster=3
	`fit_fa3`
	`  1   2   3`
	`164 163 173`
	
	Based on KMeans, cluster=5
	`K-means clustering with 5 clusters of sizes 81, 79, 118, 161, 61`

Similarity using Sihouette	`[1] "Hierarchical clustering average silhouette width: 0.331167670530194"`
	`[1] "K-means clustering average silhouette width: 0.377141556511043"`
	
	`[1] "New clustering average silhouette width: 0.394640230455599"`

FA new sample	**Factor Analysis** 

CA new sample	 Cluster=5 `K-means clustering with 5 clusters of sizes 114, 83, 113, 116, 74`
Compare two different samples using ARI	`[1] -0.002549345`
Cluster plot	Initial sample with KMeans: 

ADA Groupwork Assignment

2292213, 5528141, 5581250, 5582755, 5587165, 5588409, 5589718

2024-03-08

```
# import loan data as df
df <- read_excel("loan_data_ADA_assignment.xlsx")
```

```
summary(df)
```

```
##        id            member_id         loan_amnt      funded_amnt
##  Min.   :  58524   Min.   : 149512   Min.   : 1000   Min.   : 1000
##  1st Qu.:1443048   1st Qu.:1695278   1st Qu.: 8000   1st Qu.: 8000
##  Median :1587758   Median :1857296   Median :12000   Median :12000
##  Mean   :1918444   Mean   :2283786   Mean   :13901   Mean   :13896
##  3rd Qu.:2311939   3rd Qu.:2744578   3rd Qu.:19200   3rd Qu.:19200
##  Max.   :3304574   Max.   :4076727   Max.   :35000   Max.   :35000
##
##  funded_amnt_inv      term          int_rate      installment
##  Min.   :  950   Min.   :36.00   Min.   : 6.00   Min.   :  25.81
##  1st Qu.: 7950   1st Qu.:36.00   1st Qu.:11.14   1st Qu.: 255.66
##  Median :12000   Median :36.00   Median :14.09   Median : 399.26
##  Mean   :13878   Mean   :40.49   Mean   :14.00   Mean   : 436.95
##  3rd Qu.:19175   3rd Qu.:36.00   3rd Qu.:17.27   3rd Qu.: 567.04
##  Max.   :35000   Max.   :60.00   Max.   :24.89   Max.   :1388.45
##
##     grade            sub_grade          emp_title           emp_length
##  Length:50000       Length:50000       Length:50000       Min.   : 1.000
##  Class :character   Class :character   Class :character   1st Qu.: 3.000
##  Mode  :character   Mode  :character   Mode  :character   Median : 6.000
##                                                           Mean   : 5.993
##                                                           3rd Qu.:10.000
##                                                           Max.   :10.000
##                                                           NA's   :1802
##  home_ownership       annual_inc      verification_status
##  Length:50000       Min.   :   5000   Length:50000
##  Class :character   1st Qu.:  45000   Class :character
##  Mode  :character   Median :  60000   Mode  :character
##                     Mean   :  71317
##                     3rd Qu.:  85000
##                     Max.   :7141778
##
##     issue_d                       loan_status         pymnt_plan
##  Min.   :2012-05-01 00:00:00.00   Length:50000       Length:50000
##  1st Qu.:2012-08-01 00:00:00.00   Class :character   Class :character
##  Median :2012-10-01 00:00:00.00   Mode  :character   Mode  :character
##  Mean   :2012-09-29 03:53:13.33
##  3rd Qu.:2012-12-01 00:00:00.00
```

```
##  Max.   :2013-02-01 00:00:00.00
##
##      desc             purpose             title             zip_code
##  Length:50000       Length:50000       Length:50000       Length:50000
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##   addr_state             dti         delinq_2yrs
##  Length:50000       Min.   : 0.00   Min.   : 0.0000
##  Class :character   1st Qu.:11.51   1st Qu.: 0.0000
##  Mode  :character   Median :17.16   Median : 0.0000
##                     Mean   :17.37   Mean   : 0.2244
##                     3rd Qu.:23.05   3rd Qu.: 0.0000
##                     Max.   :34.99   Max.   :18.0000
##
##  earliest_cr_line                 inq_last_6mths   mths_since_last_delinq
##  Min.   :1951-12-01 00:00:00.000   Min.   :0.0000   Min.   :  0.00
##  1st Qu.:1994-05-01 00:00:00.000   1st Qu.:0.0000   1st Qu.: 18.00
##  Median :1999-01-01 00:00:00.000   Median :1.0000   Median : 33.00
##  Mean   :1997-09-29 09:34:28.416   Mean   :0.8389   Mean   : 36.08
##  3rd Qu.:2002-05-01 00:00:00.000   3rd Qu.:1.0000   3rd Qu.: 52.00
##  Max.   :2009-12-01 00:00:00.000   Max.   :8.0000   Max.   :152.00
##                                                     NA's   :28126
##  mths_since_last_record    open_acc        pub_rec          revol_bal
##  Min.   :  2.0          Min.   : 0.00   Min.   :0.00000   Min.   :      0
##  1st Qu.: 76.0          1st Qu.: 8.00   1st Qu.:0.00000   1st Qu.:   7102
##  Median : 93.0          Median :10.00   Median :0.00000   Median :  12368
##  Mean   : 87.7          Mean   :11.01   Mean   :0.05648   Mean   :  16011
##  3rd Qu.:106.0          3rd Qu.:14.00   3rd Qu.:0.00000   3rd Qu.:  20515
##  Max.   :119.0          Max.   :53.00   Max.   :8.00000   Max.   :1743266
##  NA's   :47468
##    revol_util       total_acc      total_pymnt    total_pymnt_inv
##  Min.   :0.0000   Min.   : 2.00   Min.   :    0   Min.   :    0
##  1st Qu.:0.4310   1st Qu.:16.00   1st Qu.: 7614   1st Qu.: 7601
##  Median :0.6150   Median :23.00   Median :12858   Median :12842
##  Mean   :0.5885   Mean   :24.31   Mean   :14828   Mean   :14808
##  3rd Qu.:0.7750   3rd Qu.:31.00   3rd Qu.:20051   3rd Qu.:20024
##  Max.   :1.1390   Max.   :99.00   Max.   :57778   Max.   :57778
##  NA's   :31
##  total_rec_prncp total_rec_int   total_rec_late_fee   recoveries
##  Min.   :    0   Min.   :    0   Min.   :  0.0000   Min.   :    0.0
##  1st Qu.: 6000   1st Qu.: 1058   1st Qu.:  0.0000   1st Qu.:    0.0
##  Median :10000   Median : 2047   Median :  0.0000   Median :    0.0
##  Mean   :11611   Mean   : 3071   Mean   :  0.8419   Mean   :  144.2
##  3rd Qu.:15479   3rd Qu.: 3737   3rd Qu.:  0.0000   3rd Qu.:    0.0
##  Max.   :35000   Max.   :22778   Max.   :286.7476   Max.   :33520.3
##
##  collection_recovery_fee  last_pymnt_d                    last_pymnt_amnt
##  Min.   :   0.00          Min.   :2012-06-01 00:00:00.00   Min.   :    0.0
##  1st Qu.:   0.00          1st Qu.:2014-03-01 00:00:00.00   1st Qu.:  353.1
##  Median :   0.00          Median :2015-03-01 00:00:00.00   Median :  723.6
```

```
##  Mean   :  10.66         Mean   :2014-11-26 07:40:19.91   Mean   : 3569.0
##  3rd Qu.:   0.00         3rd Qu.:2015-10-01 00:00:00.00   3rd Qu.: 4675.9
##  Max.   :3896.24         Max.   :2015-12-01 00:00:00.00   Max.   :35683.2
##                          NA's   :43
##   next_pymnt_d                    last_credit_pull_d
##  Min.   :2016-01-01 00:00:00.00   Min.   :2012-05-01 00:00:00.00
##  1st Qu.:2016-01-01 00:00:00.00   1st Qu.:2015-03-01 00:00:00.00
##  Median :2016-01-01 00:00:00.00   Median :2015-11-01 00:00:00.00
##  Mean   :2016-01-06 08:08:08.33   Mean   :2015-06-01 13:41:50.21
##  3rd Qu.:2016-01-01 00:00:00.00   3rd Qu.:2015-12-01 00:00:00.00
##  Max.   :2016-02-01 00:00:00.00   Max.   :2015-12-01 00:00:00.00
##  NA's   :42864
##  collections_12_mths_ex_med mths_since_last_major_derog  policy_code
##  Min.   :0.00000            Min.   :  0.00              Min.   :1
##  1st Qu.:0.00000            1st Qu.: 25.00              1st Qu.:1
##  Median :0.00000            Median : 40.00              Median :1
##  Mean   :0.00114            Mean   : 42.31              Mean   :1
##  3rd Qu.:0.00000            3rd Qu.: 59.00              3rd Qu.:1
##  Max.   :2.00000            Max.   :152.00              Max.   :1
##                             NA's   :42880
##  acc_now_delinq     tot_coll_amt    tot_cur_bal      total_credit_rv
##  Min.   :0.00000   Min.   :    0   Min.   :      0   Min.   :      0
##  1st Qu.:0.00000   1st Qu.:    0   1st Qu.:  26298   1st Qu.:  14000
##  Median :0.00000   Median :    0   Median :  72117   Median :  22800
##  Mean   :0.00082   Mean   :   52   Mean   : 133594   Mean   :  29300
##  3rd Qu.:0.00000   3rd Qu.:    0   3rd Qu.: 202362   3rd Qu.:  36600
##  Max.   :4.00000   Max.   :55009   Max.   :8000078   Max.   :2013133
##                    NA's   :14618   NA's   :14618     NA's   :14618
##  loan_is_bad
##  Mode :logical
##  FALSE:42186
##  TRUE :7814
##
##
##
##
```

1. Define the Problem

1.1. Objective

- Utilising cluster analysisrouping borrowers with similar characteristics
- Identify distinct borrower's segments
- Enabling personalised loan products, targeted marketing strategies, and a better customer support process to serve the unique needs of each segment

1.2. Select cluster variables

1. annual_inc: The self-reported annual income provided by the borrower during registration.
2. loan_amnt: The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
3. int_rate: Interest Rate on the loan
4. total_rec_int: Interest received to date
5. total_rec_prncp: Principal received to date

6. dti: A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income.
7. total_rec_late_fee: Late fees received to date
8. term : The entire period of the loan
9. home_ownership: The home ownership status provided by the borrower during registration or obtained from the credit report. Our values are: RENT, OWN, MORTGAGE, OTHER
10. grade : The grade of loan

```
# create new df with essential variables (10 variables)
df_ess <- df %>% select(annual_inc,
                        loan_amnt,
                        int_rate,
                        total_rec_int,
                        total_rec_prncp,
                        dti,
                        total_rec_late_fee,
                        term,
                        home_ownership,
                        grade)
```

2. Pre-Analysis Decision

2.1. Data checking (duplicate, missing values, outliers)

- Check duplicate value

```
# total row of data
df_row <- nrow(df_ess)

# distinct data
unique_row <- nrow(distinct(df_ess))

# verification. No duplicated data
duplicated <- df_row - unique_row
print(duplicated)
```

```
## [1] 0
```

- Check missing value

```
missing_counts <- numeric(length(df_ess))

for (col in names(df_ess)) {
  missing_counts[col] <- sum(is.na(df_ess[[col]]))
}

missing_counts
```

```
##
##                   0                   0                   0                   0
##
##                   0                   0                   0                   0
##                                                  annual_inc          loan_amnt
##                   0                   0                   0                   0
##            int_rate      total_rec_int    total_rec_prncp                 dti
##                   0                   0                   0                   0
## total_rec_late_fee                term     home_ownership               grade
```

```
##                    0                    0                    0                    0
```

No missing value in cluster variables.

- Detect outliers using graphical method

```
df_summary <- dfSummary(df_ess)
filename <- "df_summary.html"
view(df_summary, file = filename)
```

```
summary(df_ess)
```

```
##    annual_inc        loan_amnt        int_rate     total_rec_int
##  Min.   :   5000   Min.   : 1000   Min.   : 6.00   Min.   :    0
##  1st Qu.:  45000   1st Qu.: 8000   1st Qu.:11.14   1st Qu.: 1058
##  Median :  60000   Median :12000   Median :14.09   Median : 2047
##  Mean   :  71317   Mean   :13901   Mean   :14.00   Mean   : 3071
##  3rd Qu.:  85000   3rd Qu.:19200   3rd Qu.:17.27   3rd Qu.: 3737
##  Max.   :7141778   Max.   :35000   Max.   :24.89   Max.   :22778
##  total_rec_prncp      dti        total_rec_late_fee      term
##  Min.   :    0   Min.   : 0.00   Min.   :  0.0000   Min.   :36.00
##  1st Qu.: 6000   1st Qu.:11.51   1st Qu.:  0.0000   1st Qu.:36.00
##  Median :10000   Median :17.16   Median :  0.0000   Median :36.00
##  Mean   :11611   Mean   :17.37   Mean   :  0.8419   Mean   :40.49
##  3rd Qu.:15479   3rd Qu.:23.05   3rd Qu.:  0.0000   3rd Qu.:36.00
##  Max.   :35000   Max.   :34.99   Max.   :286.7476   Max.   :60.00
##  home_ownership        grade
##  Length:50000       Length:50000
##  Class :character   Class :character
##  Mode  :character   Mode  :character
##
##
##
```

2.2. Data encoding

1) Home-ownership: recode to metric variables - sequence order by financial stability (1-highest, 5-lowest)

1. OWN -1
2. MORTGAGE-2
3. RENT -3
4. OTHER-4
5. NONE-5

2) grade : 1 - 7 (A - G) 1: Highest (A) 7: Lowest (G)

3) Term: 0 -> 36 (short-term) 1 -> 60 (long-term)

```
# Change into factor
df_ess$home_ownership <- as.factor(df_ess$home_ownership)
df_ess$grade <- as.factor(df_ess$grade)
df_ess$term <- as.factor(df_ess$term)

# Recode
df_ess$home_ownership <- revalue(df_ess$home_ownership,
                                 c('OWN' = 1, 'MORTGAGE' = 2, 'RENT' = 3, 'OTHER' = 4, 'NONE' = 5)
```

```
df_ess$grade <- revalue(df_ess$grade,
                            c('A' = 1, 'B' = 2, 'C' = 3, 'D' = 4, 'E' = 5, 'F' = 6, 'G' = 7))

df_ess$term <- revalue(df_ess$term,
                            c('36' = 0, '60' = 1))
```

```
summary(df_ess)
```

```
##    annual_inc        loan_amnt        int_rate     total_rec_int
##  Min.   :   5000   Min.   : 1000   Min.   : 6.00   Min.   :    0
##  1st Qu.:  45000   1st Qu.: 8000   1st Qu.:11.14   1st Qu.: 1058
##  Median :  60000   Median :12000   Median :14.09   Median : 2047
##  Mean   :  71317   Mean   :13901   Mean   :14.00   Mean   : 3071
##  3rd Qu.:  85000   3rd Qu.:19200   3rd Qu.:17.27   3rd Qu.: 3737
##  Max.   :7141778   Max.   :35000   Max.   :24.89   Max.   :22778
##
##  total_rec_prncp      dti        total_rec_late_fee term      home_ownership
##  Min.   :    0   Min.   : 0.00   Min.   :  0.0000   0:40641   2:24784
##  1st Qu.: 6000   1st Qu.:11.51   1st Qu.:  0.0000   1: 9359   5:   42
##  Median :10000   Median :17.16   Median :  0.0000             4:   45
##  Mean   :11611   Mean   :17.37   Mean   :  0.8419             1: 3836
##  3rd Qu.:15479   3rd Qu.:23.05   3rd Qu.:  0.0000             3:21293
##  Max.   :35000   Max.   :34.99   Max.   :286.7476
##
##  grade
##  1: 8533
##  2:17859
##  3:12171
##  4: 7065
##  5: 2926
##  6: 1227
##  7:  219
```

```
# Convert all selected columns to numeric
loanDataFiltered <- apply(df_ess, 2, as.numeric)
loanDataFiltered_df <- as.data.frame(loanDataFiltered)
summary(loanDataFiltered_df)
```

```
##    annual_inc        loan_amnt        int_rate     total_rec_int
##  Min.   :   5000   Min.   : 1000   Min.   : 6.00   Min.   :    0
##  1st Qu.:  45000   1st Qu.: 8000   1st Qu.:11.14   1st Qu.: 1058
##  Median :  60000   Median :12000   Median :14.09   Median : 2047
##  Mean   :  71317   Mean   :13901   Mean   :14.00   Mean   : 3071
##  3rd Qu.:  85000   3rd Qu.:19200   3rd Qu.:17.27   3rd Qu.: 3737
##  Max.   :7141778   Max.   :35000   Max.   :24.89   Max.   :22778
##  total_rec_prncp      dti        total_rec_late_fee      term
##  Min.   :    0   Min.   : 0.00   Min.   :  0.0000   Min.   :0.0000
##  1st Qu.: 6000   1st Qu.:11.51   1st Qu.:  0.0000   1st Qu.:0.0000
##  Median :10000   Median :17.16   Median :  0.0000   Median :0.0000
##  Mean   :11611   Mean   :17.37   Mean   :  0.8419   Mean   :0.1872
##  3rd Qu.:15479   3rd Qu.:23.05   3rd Qu.:  0.0000   3rd Qu.:0.0000
##  Max.   :35000   Max.   :34.99   Max.   :286.7476   Max.   :1.0000
##  home_ownership      grade
##  Min.   :1.000   Min.   :1.000
##  1st Qu.:2.000   1st Qu.:2.000
```

```
##  Median :2.000   Median :2.000
##  Mean   :2.353   Mean   :2.651
##  3rd Qu.:3.000   3rd Qu.:3.000
##  Max.   :5.000   Max.   :7.000
```

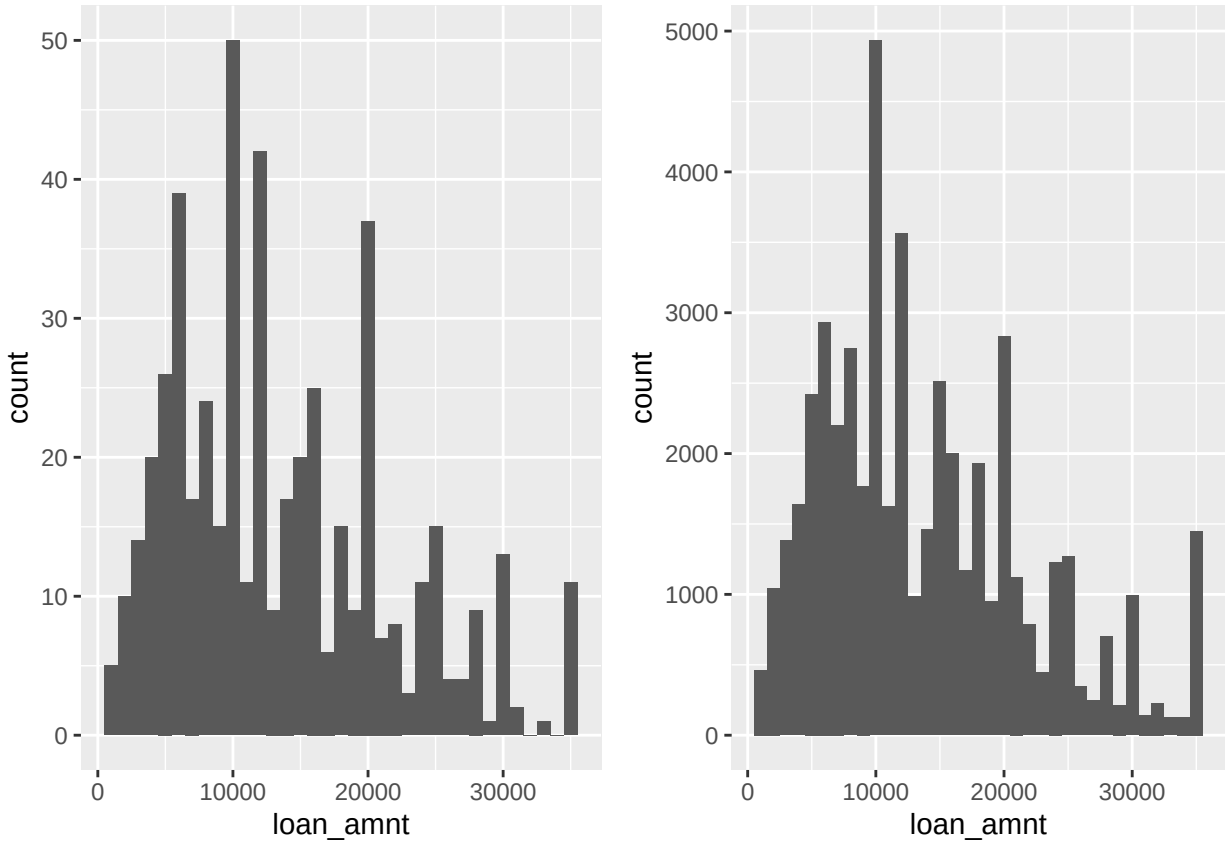
2.3. Sampling

```
set.seed(10)
sample <- sample_n(loanDataFiltered_df, 500)
```

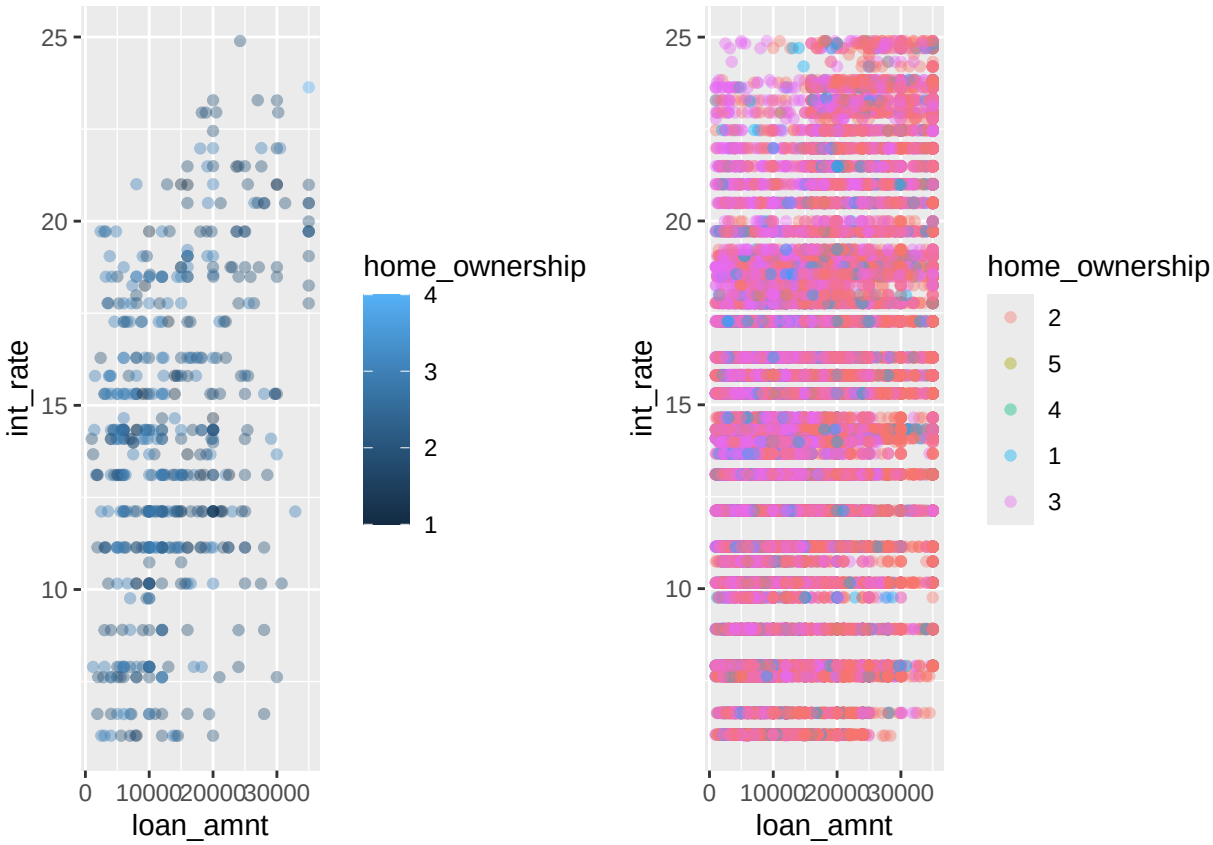
3. Check Assumptions

3.1. Data checking

```
# Distribution of loan amount of sample vs population
grid.arrange(ggplot(sample, aes(x = loan_amnt)) + geom_histogram(binwidth = 1000),
                        ggplot(df_ess, aes(x = loan_amnt)) + geom_histogram(binwidth = 1000),
                        ncol = 2)
```




```
# Scatter plot of interest rate and loan amount based on home ownership
grid.arrange(ggplot(sample, aes(x = loan_amnt, y = int_rate, color = home_ownership)) +
                          geom_point(position = "jitter", alpha = 0.4),
                        ggplot(df_ess, aes(x = loan_amnt, y = int_rate, color = home_ownership)) +
                          geom_point(position = "jitter", alpha = 0.4),
                        ncol = 2)
```



3.2. Multicollinearity: Pairwise Correlation

```
sampleMatrix<-cor(sample)
```

```
# round(sampleMatrix, 2)
```

```
lowerCor(sample)
```

```
##                   annl_ ln_mn int_r ttl_rc_n ttl_rc_p dti   tt___ term  hm_wn
## annual_inc         1.00
## loan_amnt          0.29  1.00
## int_rate           0.06  0.37  1.00
## total_rec_int      0.27  0.76  0.55  1.00
## total_rec_prncp    0.20  0.81  0.17  0.52     1.00
## dti               -0.22  0.05  0.13  0.06     0.03     1.00
## total_rec_late_fee 0.02  0.10  0.03  0.09     0.11     0.01  1.00
## term               0.15  0.50  0.49  0.60     0.22     0.02 -0.05  1.00
## home_ownership    -0.07 -0.21 -0.01 -0.16    -0.20     0.03  0.03 -0.15  1.00
## grade              0.07  0.39  0.96  0.56     0.20     0.11  0.04  0.51 -0.02
##                   grade
## annual_inc
## loan_amnt
## int_rate
## total_rec_int
## total_rec_prncp
## dti
## total_rec_late_fee
```

```
## term
## home_ownership
## grade               1.00
```

3.3. Multicollinearity: Kaiser-Meyer-Olkin (KMO)

```
KMO(sample)
```

```
## Kaiser-Meyer-Olkin factor adequacy
## Call: KMO(r = sample)
## Overall MSA =  0.71
## MSA for each item =
##         annual_inc          loan_amnt           int_rate      total_rec_int
##               0.75               0.67               0.65               0.86
##    total_rec_prncp                dti total_rec_late_fee               term
##               0.61               0.55               0.60               0.83
##     home_ownership              grade
##               0.88               0.65
```

Kaiser-Meyer-Olkin (KMO) test is a standard to assess the suitability of a data set for factor analysis. We are looking for a KMO value of 0.5 or more. Here it is 0.71, so this is good.

3.4. Multicollinearity: Bartlett's test

```
cortest.bartlett(sample)
```

```
## R was not square, finding R from data
```

```
## $chisq
## [1] 2917.021
##
## $p.value
## [1] 0
##
## $df
## [1] 45
```

P-value is 0, which means there is a sufficient correlation between variables. We can use factor analysis in this case.

4. Perform Principal Component Analysis (PCA)

```
pcModel<-principal(sample, 5, rotate="none", weights=TRUE, scores=TRUE)
print(pcModel)
```

```
## Principal Components Analysis
## Call: principal(r = sample, nfactors = 5, rotate = "none", scores = TRUE,
##     weights = TRUE)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                      PC1   PC2   PC3   PC4   PC5   h2    u2 com
## annual_inc          0.30 -0.46 -0.51  0.22  0.19 0.64 0.361 3.4
## loan_amnt           0.84 -0.39  0.19 -0.01  0.16 0.92 0.081 1.6
## int_rate            0.75  0.56 -0.14  0.08 -0.10 0.92 0.083 2.0
## total_rec_int       0.88 -0.09  0.01  0.02  0.05 0.79 0.212 1.0
## total_rec_prncp     0.63 -0.53  0.34  0.01  0.21 0.83 0.167 2.8
```

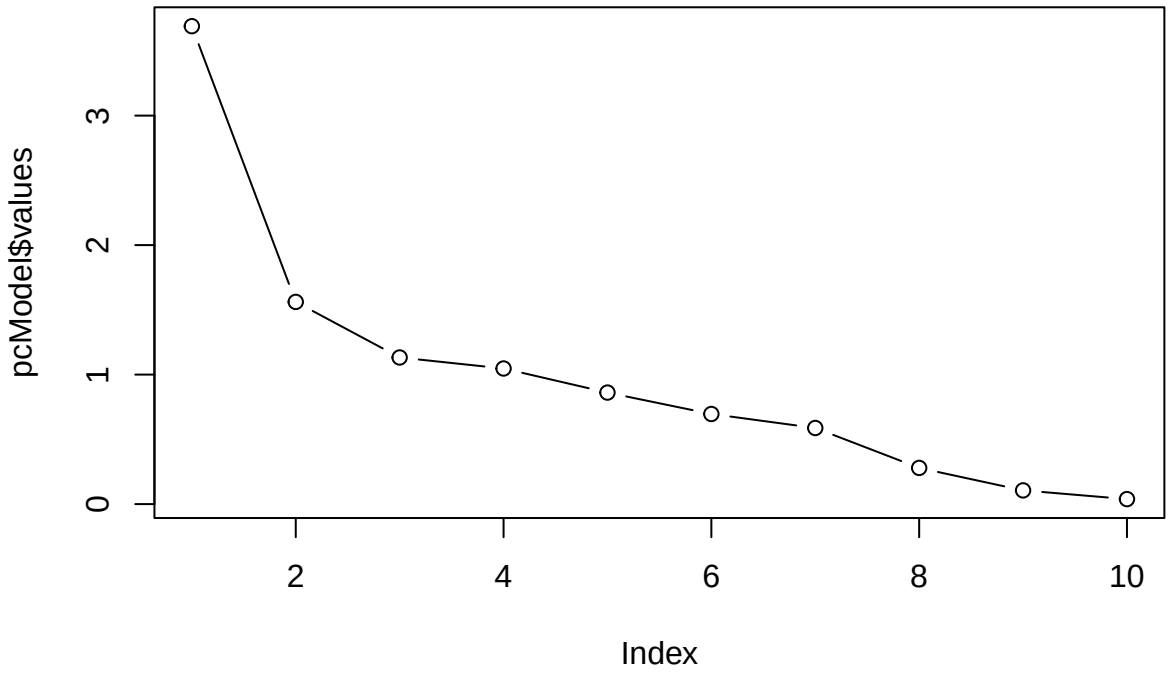
```
## dti                 0.09  0.37  0.72 -0.20  0.24 0.76 0.244 2.0
## total_rec_late_fee  0.09 -0.12  0.37  0.77 -0.47 0.98 0.025 2.3
## term                0.71  0.14 -0.19 -0.17 -0.06 0.60 0.402 1.4
## home_ownership     -0.22  0.36 -0.07  0.57  0.67 0.95 0.048 2.8
## grade               0.77  0.54 -0.14  0.08 -0.11 0.92 0.085 1.9
##
##                        PC1  PC2  PC3  PC4  PC5
## SS loadings           3.69 1.56 1.13 1.05 0.86
## Proportion Var        0.37 0.16 0.11 0.10 0.09
## Cumulative Var        0.37 0.53 0.64 0.74 0.83
## Proportion Explained  0.45 0.19 0.14 0.13 0.10
## Cumulative Proportion 0.45 0.63 0.77 0.90 1.00
##
## Mean item complexity =  2.1
## Test of the hypothesis that 5 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.07
##  with the empirical chi square  236.16  with prob <  5.1e-49
##
## Fit based upon off diagonal values = 0.95
```

```
print.psych(pcModel, cut=0.3, sort=TRUE)
```

```
## Principal Components Analysis
## Call: principal(r = sample, nfactors = 5, rotate = "none", scores = TRUE,
##     weights = TRUE)
## Standardized loadings (pattern matrix) based upon correlation matrix
##                     item   PC1   PC2   PC3   PC4   PC5   h2    u2 com
## total_rec_int          4  0.88                         0.79 0.212 1.0
## loan_amnt              2  0.84 -0.39                   0.92 0.081 1.6
## grade                 10  0.77  0.54                   0.92 0.085 1.9
## int_rate               3  0.75  0.56                   0.92 0.083 2.0
## term                   8  0.71                         0.60 0.402 1.4
## total_rec_prncp        5  0.63 -0.53  0.34             0.83 0.167 2.8
## annual_inc             1       -0.46 -0.51             0.64 0.361 3.4
## dti                    6        0.37  0.72             0.76 0.244 2.0
## total_rec_late_fee     7              0.37  0.77 -0.47 0.98 0.025 2.3
## home_ownership         9        0.36        0.57  0.67 0.95 0.048 2.8
##
##                        PC1  PC2  PC3  PC4  PC5
## SS loadings           3.69 1.56 1.13 1.05 0.86
## Proportion Var        0.37 0.16 0.11 0.10 0.09
## Cumulative Var        0.37 0.53 0.64 0.74 0.83
## Proportion Explained  0.45 0.19 0.14 0.13 0.10
## Cumulative Proportion 0.45 0.63 0.77 0.90 1.00
##
## Mean item complexity =  2.1
## Test of the hypothesis that 5 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.07
##  with the empirical chi square  236.16  with prob <  5.1e-49
##
## Fit based upon off diagonal values = 0.95
```

To produce the scree plot

```
plot(pcModel$values,type="b")
```




```
pcModel$weights
```

```
##                          PC1         PC2         PC3          PC4         PC5
## annual_inc          0.08077978 -0.29386453 -0.44702185  0.211336565  0.21505306
## loan_amnt           0.22724608 -0.25017527  0.16852750 -0.012608901  0.19006420
## int_rate            0.20388818  0.35981820 -0.12090356  0.075981427 -0.11638677
## total_rec_int       0.23875150 -0.05686243  0.01128327  0.016732186  0.06257646
## total_rec_prncp     0.16944389 -0.34076013  0.30067456  0.005422551  0.24069513
## dti                 0.02405031  0.24000061  0.63163640 -0.192318501  0.27421682
## total_rec_late_fee  0.02435222 -0.07721672  0.32343541  0.735819109 -0.55046943
## term                0.19347312  0.08751756 -0.16911285 -0.164221480 -0.06470958
## home_ownership     -0.05908698  0.23224573 -0.05769586  0.541198712  0.77708951
## grade               0.20839761  0.34281299 -0.11965181  0.076032355 -0.13105886
```

We can then access these scores by using

```
head(pcModel$scores, 10)
```

```
##              PC1        PC2        PC3         PC4        PC5
##  [1,] -0.9362977  0.5689859 -0.4954174  0.46310447  0.3189131
##  [2,] -0.4007959 -1.0803219 -0.1582872 -1.95481543 -1.9494720
##  [3,] -0.9696421 -1.4644904 -0.5948107  0.62450428  1.1336938
##  [4,] -0.3813357  0.5408023 -0.5210639  0.59892546  0.3624829
##  [5,] -0.4367595  0.5162278  1.1664280  0.03463419  1.3807775
##  [6,]  1.2747127 -1.3723158  1.0637235 -0.31856468  0.6282800
##  [7,] -0.2453597 -0.4118408  1.0225689  0.24853833  1.7307205
##  [8,] -0.6120398  0.3670978  0.9451526  0.10681232  1.1682691
##  [9,] -0.1046778 -0.2993457  0.6658561  0.38867458  1.5204344
## [10,] -0.6689182  1.3380139 -0.1416283  0.39483528  0.3665061
```

We can use the principal component scores for further analysis, before doing that we need to add them into our dataframe:

```
sample_pca <- cbind(sample, pcModel$scores)
```

```
summary(sample_pca)
```

```
##    annual_inc        loan_amnt        int_rate     total_rec_int
##  Min.   :  14000   Min.   : 1000   Min.   : 6.03   Min.   :   59.7
##  1st Qu.:  45000   1st Qu.: 7200   1st Qu.:11.14   1st Qu.:  998.4
##  Median :  60000   Median :12000   Median :14.09   Median : 1970.6
##  Mean   :  73102   Mean   :13662   Mean   :14.03   Mean   : 2982.6
##  3rd Qu.:  85000   3rd Qu.:19600   3rd Qu.:17.27   3rd Qu.: 3813.5
##  Max.   :1250000   Max.   :35000   Max.   :24.89   Max.   :17175.1
##  total_rec_prncp        dti        total_rec_late_fee      term
##  Min.   :  265.9   Min.   : 1.02   Min.   : 0.0000    Min.   :0.000
##  1st Qu.: 5971.4   1st Qu.:11.22   1st Qu.: 0.0000    1st Qu.:0.000
##  Median :10000.0   Median :16.48   Median : 0.0000    Median :0.000
##  Mean   :11545.0   Mean   :17.02   Mean   : 0.9973    Mean   :0.186
##  3rd Qu.:16000.0   3rd Qu.:23.02   3rd Qu.: 0.0000    3rd Qu.:0.000
##  Max.   :35000.0   Max.   :34.88   Max.   :64.3400    Max.   :1.000
##  home_ownership      grade            PC1               PC2
##  Min.   :1.000   Min.   :1.000   Min.   :-1.6576   Min.   :-4.815475
##  1st Qu.:2.000   1st Qu.:2.000   1st Qu.:-0.6791   1st Qu.:-0.638184
##  Median :2.000   Median :2.000   Median :-0.2757   Median : 0.002815
##  Mean   :2.368   Mean   :2.676   Mean   : 0.0000   Mean   : 0.000000
##  3rd Qu.:3.000   3rd Qu.:3.000   3rd Qu.: 0.4054   3rd Qu.: 0.741524
##  Max.   :4.000   Max.   :7.000   Max.   : 3.7382   Max.   : 2.345764
##       PC3                PC4               PC5
##  Min.   :-8.30745   Min.   :-1.9548   Min.   :-6.5452
##  1st Qu.:-0.60411   1st Qu.:-0.5538   1st Qu.:-0.5323
##  Median :-0.04166   Median :-0.1339   Median : 0.1074
##  Mean   : 0.00000   Mean   : 0.0000   Mean   : 0.0000
##  3rd Qu.: 0.56248   3rd Qu.: 0.4210   3rd Qu.: 0.6567
##  Max.   : 4.22046   Max.   : 7.6188   Max.   : 4.1670
```

5. Perform Factor Analysis

Two Factors Solution with Orthogonal rotation (Varimax Rotation)

```
fa3v<-(fa(sample,2, n.obs=500, rotate="varimax", fm="pa"))
```

```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs = np.obs, :
## The estimated weights for the factor scores are probably incorrect.  Try a
## different factor score estimation method.
```

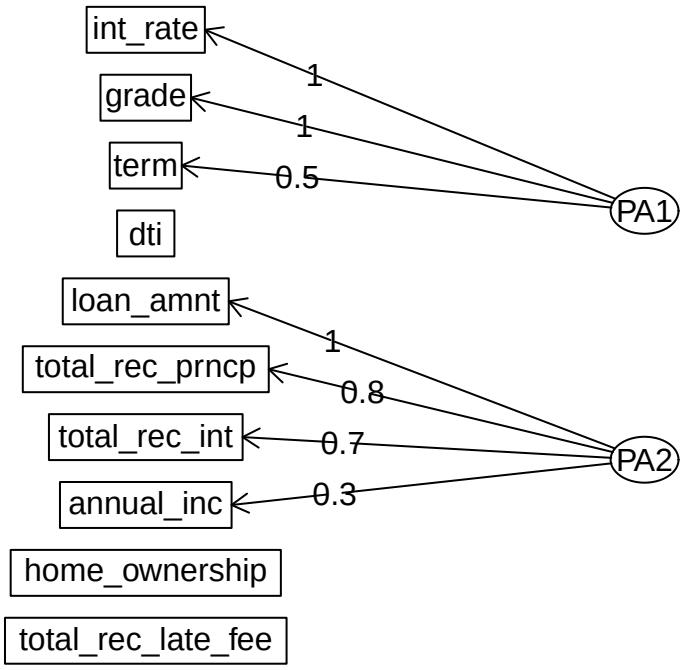
```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate = rotate, : An
## ultra-Heywood case was detected.  Examine the results carefully
```

```
print.psych(fa3v, cut=0.3,sort="TRUE")
```

```
## Factor Analysis using method =  pa
## Call: fa(r = sample, nfactors = 2, n.obs = 500, rotate = "varimax",
##     fm = "pa")
## Standardized loadings (pattern matrix) based upon correlation matrix
##                    item  PA1   PA2     h2     u2 com
## int_rate              3 0.97       0.9538  0.046 1.0
## grade                10 0.95       0.9310  0.069 1.1
## term                  8 0.48  0.39 0.3831  0.617 1.9
```

```
## dti                   6            0.0178  0.982 1.1
## loan_amnt             2       1.00 1.0487 -0.049 1.1
## total_rec_prncp       5       0.75 0.5704  0.430 1.0
## total_rec_int         4 0.50  0.68 0.7128  0.287 1.8
## annual_inc            1       0.30 0.0925  0.908 1.0
## home_ownership        9            0.0587  0.941 1.0
## total_rec_late_fee    7            0.0087  0.991 1.0
##
##                        PA1  PA2
## SS loadings           2.41 2.37
## Proportion Var        0.24 0.24
## Cumulative Var        0.24 0.48
## Proportion Explained  0.50 0.50
## Cumulative Proportion 0.50 1.00
##
## Mean item complexity =  1.2
## Test of the hypothesis that 2 factors are sufficient.
##
## df null model =  45  with the objective function =  5.89 with Chi Square =  2917.02
## df of  the model are 26  and the objective function was  0.43
##
## The root mean square of the residuals (RMSR) is  0.05
## The df corrected root mean square of the residuals is  0.06
##
## The harmonic n.obs is  500 with the empirical chi square  100.75  with prob <  9.6e-11
## The total n.obs was  500  with Likelihood Chi Square =  211.73  with prob <  4.9e-31
##
## Tucker Lewis Index of factoring reliability =  0.888
## RMSEA index =  0.12  and the 90 % confidence intervals are  0.105 0.135
## BIC =  50.15
## Fit based upon off diagonal values = 0.98
```

```
fa.diagram(fa3v)
```



Once we have decided best solution, we can set scores to regression.

```
fa3v<-(fa(sample,2, n.obs=500, rotate="varimax", fm="pa", scores="regression"))
```

```
## Warning in fa.stats(r = r, f = f, phi = phi, n.obs = n.obs, np.obs = np.obs, :
## The estimated weights for the factor scores are probably incorrect.  Try a
## different factor score estimation method.
```

```
## Warning in fac(r = r, nfactors = nfactors, n.obs = n.obs, rotate = rotate, : An
## ultra-Heywood case was detected.  Examine the results carefully
```

```
head(fa3v$scores, 10)
```

```
##                PA1        PA2
##  [1,] -0.18085623 -1.1381673
##  [2,] -1.25971881 -0.3675690
##  [3,] -1.84634926  0.5655897
##  [4,]  0.19832737 -0.5813052
##  [5,] -0.73987157  1.5818343
##  [6,] -0.03012164  2.0481682
##  [7,] -0.90231757  0.5370203
##  [8,] -0.61937263 -0.1590261
##  [9,] -0.45304492  0.4046091
## [10,]  0.48182208 -1.4589098
```

We can use the factor scores for further analysis, before doing that we need to add them into our dataframe:

```
sample_fa3 <- fa3v$scores
```

```
summary(sample_fa3)
```

```
##       PA1                PA2
##  Min.   :-2.0672   Min.   :-1.9379
```

```
##  1st Qu.:-0.6513   1st Qu.:-0.8054
##  Median :-0.1008   Median :-0.1588
##  Mean   : 0.0000   Mean   : 0.0000
##  3rd Qu.: 0.6534   3rd Qu.: 0.7085
##  Max.   : 2.5941   Max.   : 3.4486
```

6. Create Clusters

1) Check outliers again after selecting 3 factors

- Calculate Mahalanobis distance to identify potential outliers

```
Maha <- mahalanobis(sample_fa3,colMeans(sample_fa3),cov(sample_fa3))
```

```
MahaPvalue <-pchisq(Maha,df=10,lower.tail = FALSE)
# print(MahaPvalue)
print(sum(MahaPvalue<0.001)) # no outlier
```

```
## [1] 0
```

2) Check multicollinearity again after selecting 3 factors

```
SampleMatrix<-cor(sample_fa3)
```

```
#round(sample_fa3, 2)
```

```
lowerCor(sample_fa3)
```

```
##     PA1   PA2
## PA1  1.00
## PA2 -0.01  1.00
```

There is no substantial number of correlations > 0.3

6.1. Standardise/normalise data

```
# Standardize data set
sample_s <- scale(sample_fa3)

# View the standardized data
head(sample_s)
```

```
##             PA1        PA2
## [1,] -0.1837921 -1.0875018
## [2,] -1.2801680 -0.3512067
## [3,] -1.8763213  0.5404125
## [4,]  0.2015468 -0.5554284
## [5,] -0.7518820  1.5114189
## [6,] -0.0306106  1.9569939
```

6.2. Select clustering method

- **Find the Linkage Method to Use**
- Define linkage methods

```
m <- c( "average", "single", "complete", "ward")
names(m) <- c( "average", "single", "complete", "ward")
```

- Function to compute agglomerative coefficient

```
ac <- function(x) {
  agnes(sample_s, method = x)$ac
}
```

- Calculate agglomerative coefficient for each clustering linkage method

```
sapply(m, ac)
```

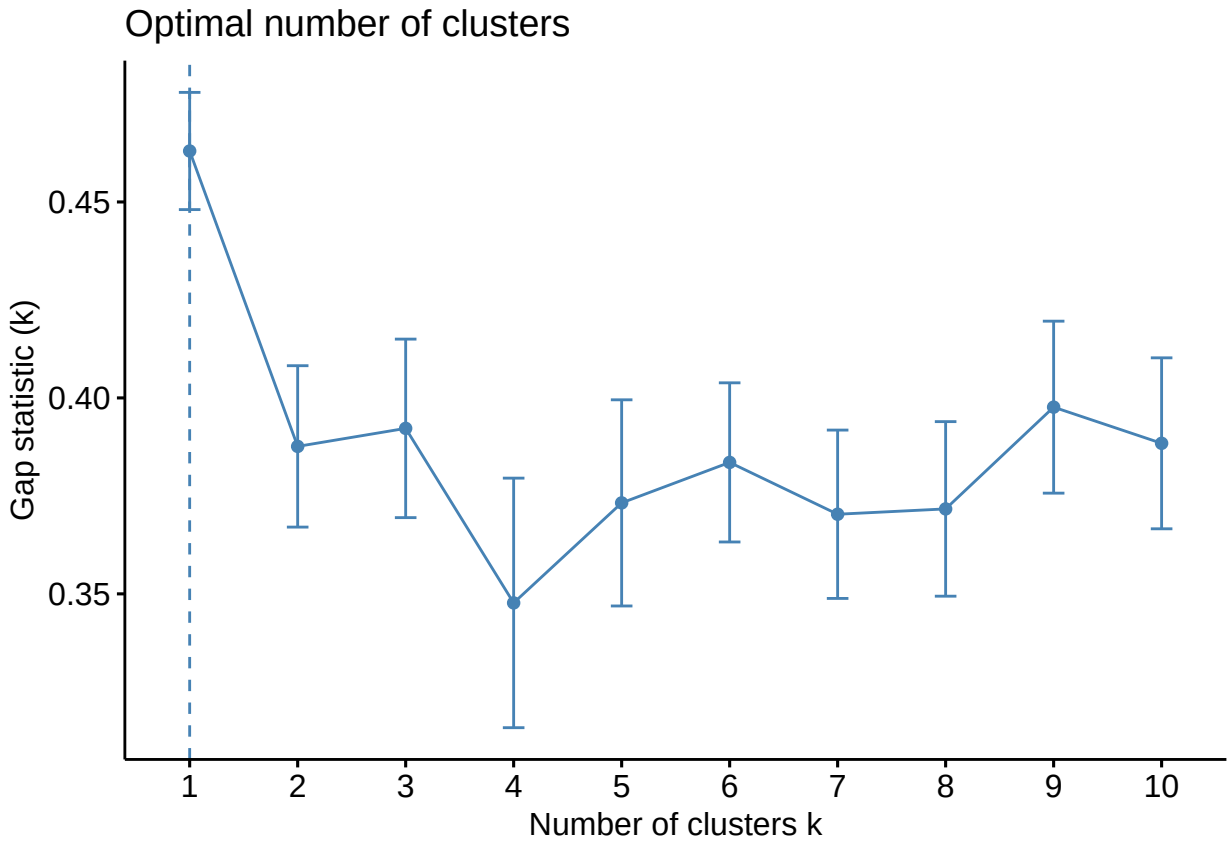
```
##   average    single  complete      ward
## 0.9643149 0.8638402 0.9834904 0.9961041
```

- Calculate gap statistic for each number of clusters (up to 10 clusters)

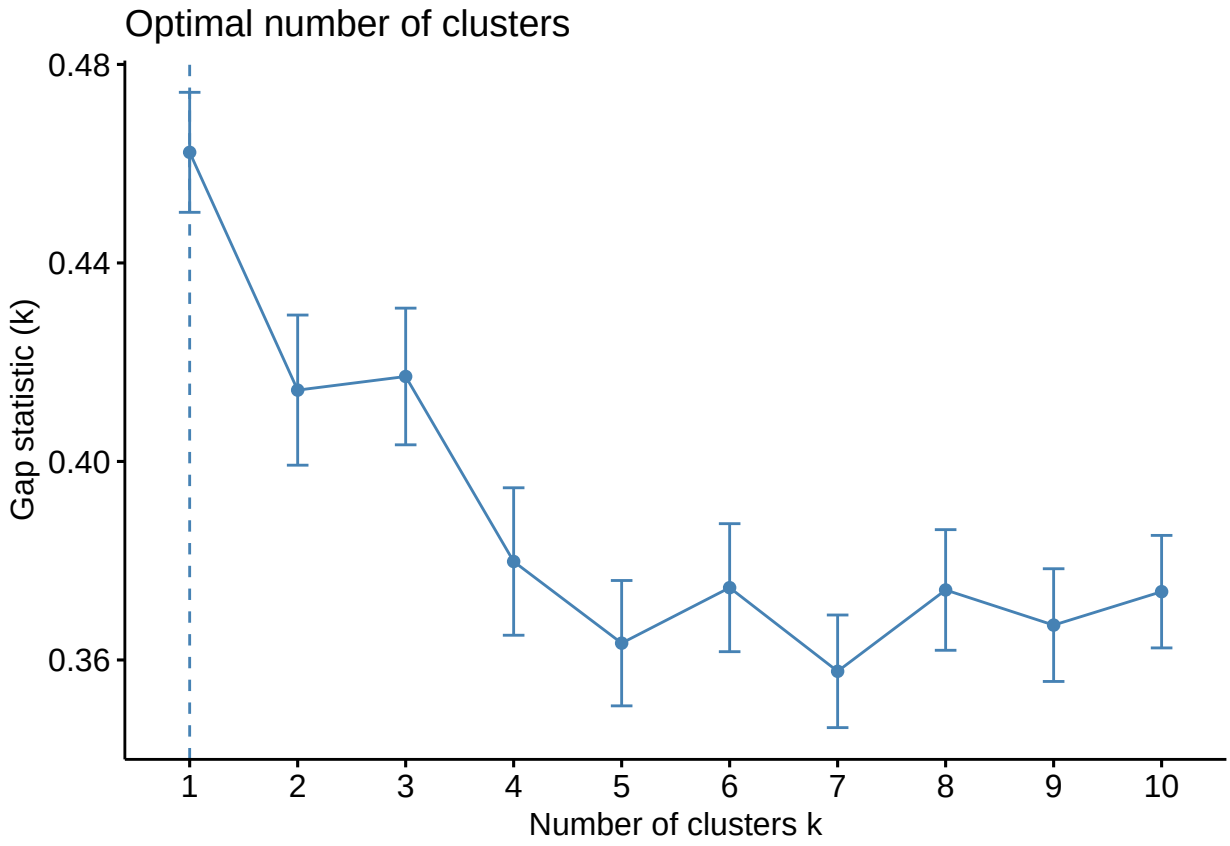
```
gap_stat_h_fa3 <- clusGap(sample_s, FUN = hcut, nstart = 25, K.max = 10, B = 50)
gap_stat_k_fa3 <- clusGap(sample_s, FUN = kmeans, nstart = 25, K.max = 10, B = 50)
```

- Produce plot of optimal number of clusters using gap statistic method

```
fviz_gap_stat(gap_stat_h_fa3) # 3 clusters for hierarchical
```




```
fviz_gap_stat(gap_stat_k_fa3) # 3 clusters for Non-hierarchical (Kmeans)
```



- Finding distance matrix

```
#using Euclidean distance
distance_mat_fa3 <- dist(sample_s, method = 'euclidean')
```

7. Comparing results & choosing solution

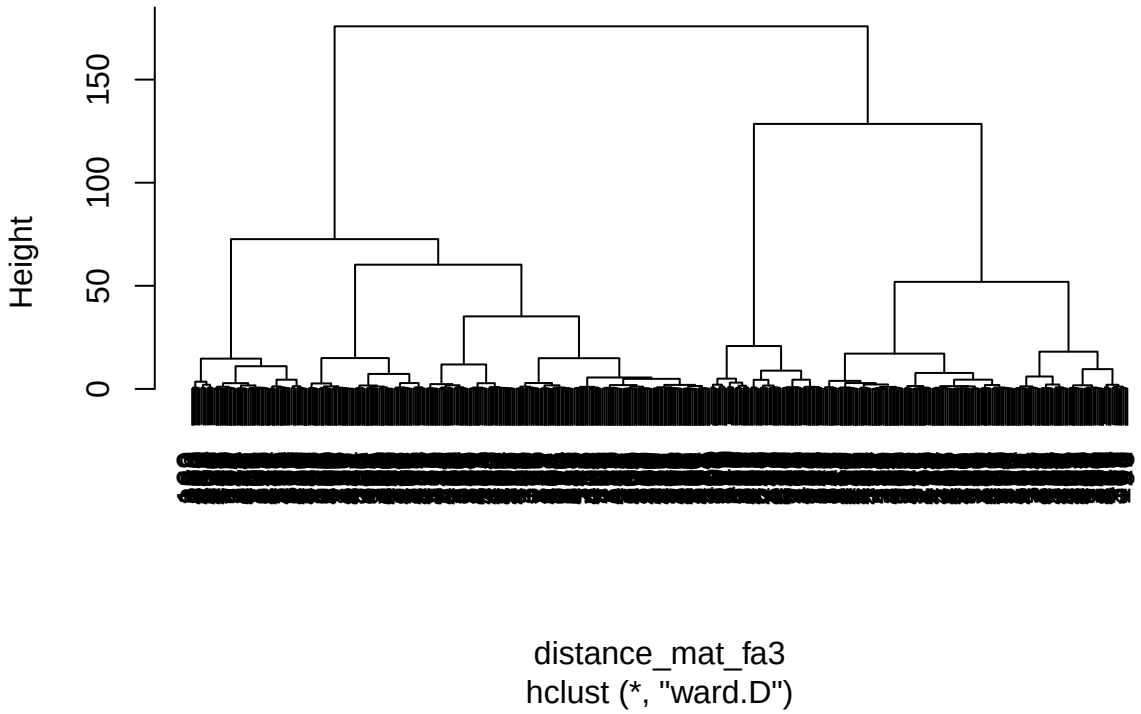
- **Hierarchical clustering Model**
- Fitting Hierarchical clustering Model to dataset

```
set.seed(240)  # Setting seed
Hierar_cl_fa3 <- hclust(distance_mat_fa3, method = "ward.D")
Hierar_cl_fa3
```

```
##
## Call:
## hclust(d = distance_mat_fa3, method = "ward.D")
##
## Cluster method   : ward.D
## Distance         : euclidean
## Number of objects: 500
```

- Plotting dendrogram

```
plot(Hierar_cl_fa3)
```



- Choosing no. of clusters: 3 clusters

```
fit_fa3 <- cutree(Hierar_cl_fa3, k = 3)
fit_fa3
```

```
##   [1] 1 2 2 1 2 2 2 2 2 1 3 1 1 1 2 2 3 2 1 2 1 3 2 2 1 3 2 1 2 2 2 1 2 1 1 2 2
##  [38] 1 2 3 1 2 2 2 2 1 1 1 2 3 1 2 3 1 2 3 2 3 3 2 2 2 2 2 2 2 2 1 1 2 2 2 3 2
##  [75] 2 2 2 2 3 2 2 1 2 2 2 1 1 1 2 1 2 1 2 1 1 1 2 3 3 1 2 2 1 3 2 2 1 1 3 1 2
## [112] 2 2 2 1 2 2 2 1 2 2 1 1 1 3 1 2 1 3 2 2 2 3 1 2 2 2 1 1 3 2 1 1 2 1 1 1 2
## [149] 2 2 1 1 1 1 2 1 1 2 2 2 1 2 3 3 1 2 2 1 2 2 2 1 1 3 2 2 2 2 2 2 1 2 1 2 3
## [186] 1 2 2 1 2 1 2 1 2 2 2 2 2 2 2 2 1 1 2 2 2 2 1 2 2 2 1 1 2 1 1 1 1 2 3 2 1
## [223] 2 2 2 1 3 2 2 2 2 3 2 1 2 2 2 1 2 2 1 2 2 2 2 1 2 2 1 2 1 2 1 1 2 2 2 2 3
## [260] 3 1 2 2 2 2 2 2 1 2 1 2 1 2 1 2 2 1 3 1 2 1 2 2 1 2 2 2 2 3 1 1 2 2 2 1 2
## [297] 2 3 1 2 2 2 2 2 2 3 2 2 3 2 2 3 3 2 1 2 2 1 3 1 2 1 2 2 1 3 2 2 2 2 2 2 3
## [334] 1 1 3 2 1 1 2 1 1 1 1 3 2 3 1 2 1 2 2 2 1 2 2 2 2 3 2 2 3 1 1 2 1 1 2 2 2
## [371] 2 2 2 2 1 3 2 2 1 2 2 2 1 3 2 2 2 1 1 2 2 1 2 2 1 2 2 3 3 2 1 2 1 2 1 1 1
## [408] 2 1 1 2 1 2 2 1 1 2 2 2 2 2 2 1 2 2 1 3 2 2 3 1 2 1 1 1 1 2 3 3 1 1 2 2 2
## [445] 2 2 2 2 1 2 2 3 2 2 1 2 3 3 3 2 2 2 1 1 1 3 1 1 2 2 1 2 1 2 1 1 1 2 2 2 1
## [482] 2 1 2 2 3 2 2 2 2 2 3 2 2 2 1 1 1 3 2
```

- Find number of observations in each cluster

```
table(fit_fa3)
```

```
## fit_fa3
##   1   2   3
## 163 277  60
```

```
final_data_fa3 <-cbind(sample_s, cluster = fit_fa3)
```

- Display first six rows of final data

```r
head(final_data_fa3)
```

```
##             PA1        PA2 cluster
## [1,] -0.1837921 -1.0875018       1
## [2,] -1.2801680 -0.3512067       2
## [3,] -1.8763213  0.5404125       2
## [4,]  0.2015468 -0.5554284       1
## [5,] -0.7518820  1.5114189       2
## [6,] -0.0306106  1.9569939       2
```

- Find mean values for each cluster

```r
hcentres_fa3<-aggregate(x=final_data_fa3, by=list(cluster=fit_fa3), FUN="mean")
print(hcentres_fa3)
```

```
##   cluster        PA1        PA2 cluster
## 1       1  0.5967203 -0.9183870       1
## 2       2 -0.6591268  0.2544071       2
## 3       3  1.4218784  1.3204386       3
```

- **Non-hierarchical clustering Model (Kmeans)**

```r
# 3 clusters
set.seed(55)
k_cl_fa3 <- kmeans(sample_s, 3, nstart=25)
k_cl_fa3
```

```
## K-means clustering with 3 clusters of sizes 93, 187, 220
##
## Cluster means:
##          PA1        PA2
## 1  1.1785205  1.1181371
## 2  0.4430026 -0.8371817
## 3 -0.8747450  0.2389374
##
## Clustering vector:
##   [1] 2 3 3 2 3 1 3 3 3 2 1 2 2 2 3 3 1 3 2 1 1 1 3 3 2 1 2 2 3 3 3 2 3 2 2 3 3
##  [38] 2 3 1 2 3 3 1 3 2 2 2 3 1 2 3 1 2 3 1 2 1 1 3 3 3 3 2 1 3 3 2 1 3 2 2 1 1
##  [75] 1 3 3 3 1 3 3 2 3 3 3 2 2 2 3 2 3 2 3 2 2 1 3 1 1 2 3 3 2 1 3 3 1 2 1 2 3
## [112] 3 1 3 2 1 3 3 2 3 3 2 2 2 1 2 3 2 1 2 3 3 1 2 3 3 3 2 2 1 3 2 2 2 2 2 2 3
## [149] 3 3 2 2 2 2 3 2 2 3 1 3 2 3 1 1 1 3 3 2 3 2 3 2 2 1 2 3 3 3 3 3 2 3 2 2 1
## [186] 2 3 3 1 3 2 3 2 3 3 3 3 3 2 3 3 2 2 1 3 3 3 2 1 3 1 2 2 3 2 2 2 2 3 1 3 2
## [223] 1 3 3 2 1 3 1 3 3 1 3 2 3 3 3 2 3 3 2 3 3 3 3 2 3 3 2 3 1 3 2 2 3 3 3 3 1
## [260] 1 2 3 3 3 3 3 3 2 2 2 3 2 3 2 3 3 2 1 2 2 2 3 3 2 1 3 2 3 1 2 2 3 3 2 2 3
## [297] 1 1 2 3 2 3 3 3 3 1 3 2 1 3 3 1 1 2 1 3 3 2 1 2 2 2 3 3 2 1 2 1 3 3 3 3 1
## [334] 2 2 1 3 2 2 3 2 2 2 2 1 3 1 2 3 2 3 3 3 2 3 3 3 3 1 1 1 1 2 2 3 2 2 2 3 2
## [371] 3 3 3 3 2 1 3 3 2 3 3 3 2 1 3 3 2 2 2 3 3 2 3 3 1 3 3 1 1 2 2 2 2 3 2 2 2
## [408] 3 2 2 3 2 3 3 2 2 3 1 2 3 1 3 2 2 3 2 1 1 3 1 2 3 2 2 2 2 3 1 1 2 2 3 3 3
## [445] 3 3 3 3 2 3 3 1 3 3 2 3 1 1 1 3 2 2 2 2 2 1 2 2 3 3 2 2 2 2 1 2 2 3 1 3 2
## [482] 3 2 3 2 1 3 3 3 3 3 1 2 2 3 2 2 2 1 3
##
## Within cluster sum of squares by cluster:
## [1] 107.2371 107.8363 188.8248
##  (between_SS / total_SS =  59.5 %)
##
## Available components:
```

```
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

- **Choose final cluster solution**

Similarity measure

- Using Silhouette Coefficient Index to compare hierarchical and Non-hierarchical solutions

```
# Hierarchical model
silhouette_score_hierar <- silhouette(fit_fa3, dist(sample_s))
avg_sil_width_hierar <- mean(silhouette_score_hierar[, 'sil_width'])

# Non-hierarchical model  (K-means)
silhouette_score_kmeans <- silhouette(k_cl_fa3$cluster, dist(sample_s))
avg_sil_width_kmeans <- mean(silhouette_score_kmeans[, 'sil_width'])

# Compare Silhouette Coefficient Index
print(paste("Hierarchical clustering average silhouette width:", avg_sil_width_hierar))
```

```
## [1] "Hierarchical clustering average silhouette width: 0.365886930628537"
```

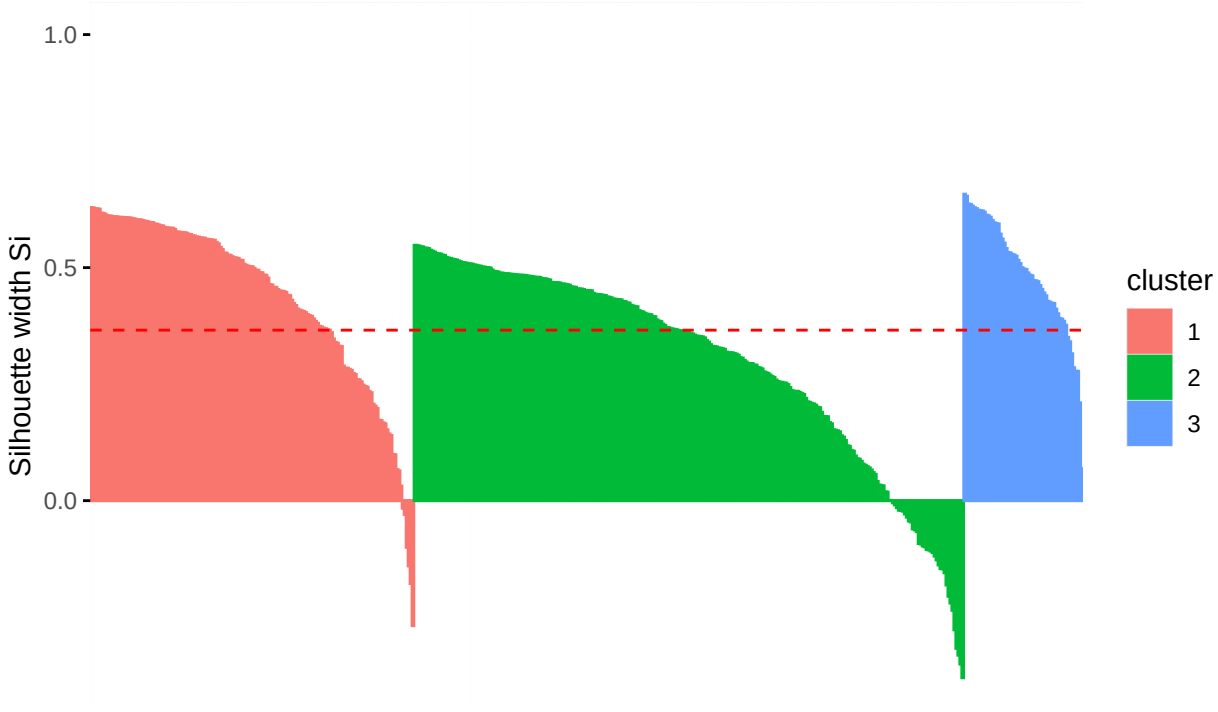
```
print(paste("K-means clustering average silhouette width:", avg_sil_width_kmeans))
```

```
## [1] "K-means clustering average silhouette width: 0.385485019803922"
```

Based on the result above, non-hierarchical model has a higher Silhouette Coefficient Index, which means clusters are closely connected within each other, while clusters are relatively separated from each other.

```
# Silhouette plot
fviz_silhouette(silhouette_score_hierar) +
    ggtitle(paste("Hierarchical Clustering Model Silhouette Plot\nAverage silhouette width:", round(avg
```

```
##   cluster size ave.sil.width
## 1       1  163          0.44
## 2       2  277          0.30
## 3       3   60          0.49
```




```
fviz_silhouette(silhouette_score_kmeans) +
    ggtitle(paste("K-means Clustering Model Silhouette Plot\nAverage silhouette width:", round(avg_sil_
```

```
##   cluster size ave.sil.width
## 1       1   93          0.33
## 2       2  187          0.44
## 3       3  220          0.36
```

According to these two figures, the K-means clustering model provides better clustering quality, with higher average silhouette width and more consistent intra-group similarity. In hierarchical clustering model, it can be seen that many samples, in cluster 1 and 2, have a negative silhouette coefficient. This means that they are not in the right cluster.

Hence, we choose to use K-means clustering (3 clusters) solution in our case.

8. Validate & Profile cluster solution

8.1. Stability check

1) Using Silhouette Coefficient Index again to test internal new cluster (subset)

```
#Save the initial cluster results
initial_cluster <- k_cl_fa3$cluster

set.seed(55)  # Ensure reproducibility
indices <- sample(1:nrow(sample_s), size = 100)  # Random indices for the subset
subset <- sample_s[indices, ]  # Extract the subset
new_cluster <- kmeans(subset, 3, nstart = 25)  # Perform KMeans clustering on the subset
```

```
silhouette_score_new_cluster <- silhouette(new_cluster$cluster, dist(subset))
avg_sil_width_new_cluster <- mean(silhouette_score_new_cluster[, 'sil_width'])
```

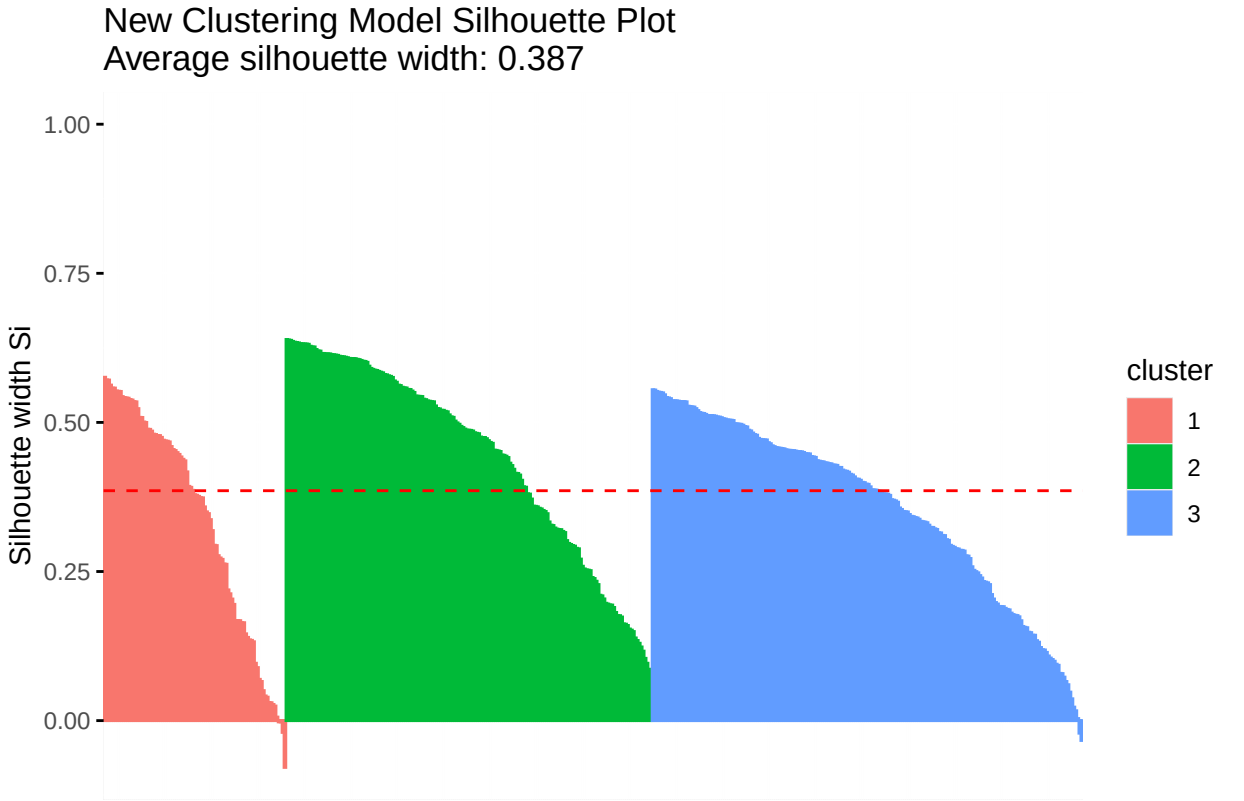
```
print(paste("New clustering average silhouette width:", avg_sil_width_new_cluster))
```

```
## [1] "New clustering average silhouette width: 0.387436909751364"
```

- Silhouette plot

```
fviz_silhouette(silhouette_score_kmeans) +
    ggtitle(paste("New Clustering Model Silhouette Plot\nAverage silhouette width:", round(avg_sil_width
```

```
##   cluster size ave.sil.width
## 1       1   93          0.33
## 2       2  187          0.44
## 3       3  220          0.36
```



2) Choosing different sample Sample size: 500 (given) No explicit pattern detected from the previous section. Therefore, random sampling will be used to sample 500.

```
set.seed(1)
sample_2 <- sample_n(loanDataFiltered_df, 500)
```

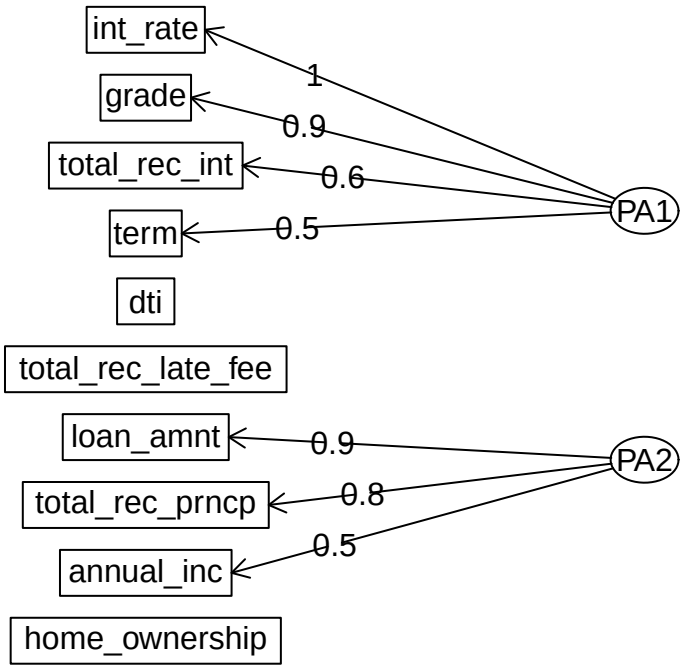
3) Performing Factor Analysis to new sample Two Factors Solution with Orthogonal rotation (Varimax Rotation)

```
fa3v_2<-(fa(sample_2,2, n.obs=500, rotate="varimax", fm="pa"))
print.psych(fa3v_2, cut=0.3,sort="TRUE")
```

```
## Factor Analysis using method =  pa
## Call: fa(r = sample_2, nfactors = 2, n.obs = 500, rotate = "varimax",
##     fm = "pa")
## Standardized loadings (pattern matrix) based upon correlation matrix
##                     item   PA1   PA2     h2    u2 com
## int_rate               3  0.95       0.9136 0.086 1.0
## grade                 10  0.94       0.8929 0.107 1.0
## total_rec_int          4  0.63  0.55 0.7009 0.299 2.0
## term                   8  0.49       0.2846 0.715 1.4
## dti                    6             0.0406 0.959 1.2
## total_rec_late_fee     7             0.0026 0.997 1.5
## loan_amnt              2  0.31  0.93 0.9684 0.032 1.2
```

```
## total_rec_prncp       5        0.83 0.6993 0.301 1.0
## annual_inc            1        0.53 0.2778 0.722 1.0
## home_ownership        9             0.0643 0.936 1.3
##
##                         PA1  PA2
## SS loadings            2.57 2.27
## Proportion Var         0.26 0.23
## Cumulative Var         0.26 0.48
## Proportion Explained   0.53 0.47
## Cumulative Proportion  0.53 1.00
##
## Mean item complexity =  1.3
## Test of the hypothesis that 2 factors are sufficient.
##
## df null model =  45  with the objective function =  6.22 with Chi Square =  3076.63
## df of  the model are 26  and the objective function was  0.96
##
## The root mean square of the residuals (RMSR) is  0.05
## The df corrected root mean square of the residuals is  0.07
##
## The harmonic n.obs is  500 with the empirical chi square  133.56  with prob <  2e-16
## The total n.obs was  500  with Likelihood Chi Square =  474.92  with prob <  5.3e-84
##
## Tucker Lewis Index of factoring reliability =  0.743
## RMSEA index =  0.186  and the 90 % confidence intervals are  0.172 0.201
## BIC =  313.34
## Fit based upon off diagonal values = 0.97
## Measures of factor score adequacy
##                                                 PA1  PA2
## Correlation of (regression) scores with factors   0.97 0.98
## Multiple R square of scores with factors          0.95 0.96
## Minimum correlation of possible factor scores     0.90 0.93
```

```
fa.diagram(fa3v_2)
```



Once we have decided best solution, we can set scores to regression.

```
fa3v_2<-(fa(sample_2,2, n.obs=500, rotate="varimax", fm="pa", scores="regression"))
head(fa3v_2$scores, 10)
```

```
##              PA1        PA2
##  [1,] -0.7191392  1.9333363
##  [2,]  1.3926625 -1.8066480
##  [3,]  0.7798019 -1.3619908
##  [4,]  1.1832440 -1.3560982
##  [5,] -0.5811087 -0.8124614
##  [6,] -0.4392972  0.8691897
##  [7,]  0.6707179 -1.4386772
##  [8,] -0.3613264 -0.1282618
##  [9,] -0.8703624 -0.8852356
## [10,]  0.3600808  0.0441758
```

We can use the factor scores for further analysis, before doing that we need to add them into our dataframe:

```
sample_fa3_2 <- fa3v_2$scores
```

4) Create clusters

- Standardize data

```
# Standardise data set
sample_fa3_s_2 <- scale(sample_fa3_2)

# View the standardized data
head(sample_fa3_s_2)
```

```
##             PA1        PA2
```

```
## [1,] -0.7378579  1.9681100
## [2,]  1.4289125 -1.8391430
## [3,]  0.8000996 -1.3864881
## [4,]  1.2140430 -1.3804895
## [5,] -0.5962346 -0.8270747
## [6,] -0.4507318  0.8848233
```

- **Find the Linkage Method to Use**
- Define linkage methods

```
m <- c( "average", "single", "complete", "ward")
names(m) <- c( "average", "single", "complete", "ward")
```

- Function to compute agglomerative coefficient

```
ac <- function(x) {
  agnes(sample_fa3_s_2, method = x)$ac
}
```

- Calculate agglomerative coefficient for each clustering linkage method

```
sapply(m, ac)
```

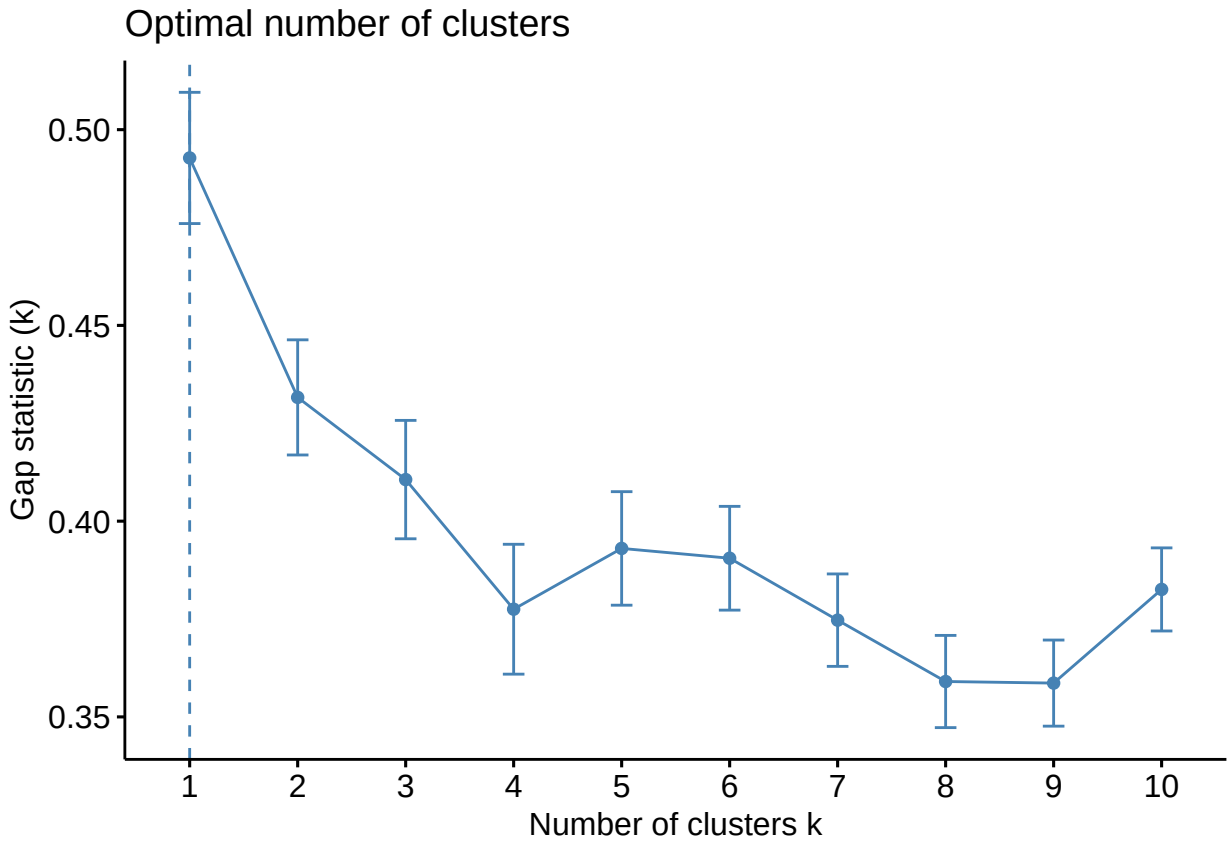
```
##   average    single  complete      ward
## 0.9715927 0.8857328 0.9827171 0.9959920
```

- Calculate gap statistic for each number of clusters (up to 10 clusters)

```
gap_stat_k_fa3_2 <- clusGap(sample_fa3_s_2, FUN = kmeans, nstart = 25, K.max = 10, B = 50)
```

- Produce plot of potential number of clusters using gap statistic method

```
fviz_gap_stat(gap_stat_k_fa3_2) # 5 clusters for Non-hierarchical (Kmeans)
```



- Finding distance matrix

```
#using Euclidean distance
distance_mat_fa3_2 <- dist(sample_fa3_s_2, method = 'euclidean')
```

```
# 5 clusters
#(between_SS / total_SS =  73.6 %)
set.seed(55)
k_cl_fa3_2 <- kmeans(sample_fa3_s_2, 5, nstart=25)
k_cl_fa3_2
```

```
## K-means clustering with 5 clusters of sizes 151, 79, 104, 114, 52
##
## Cluster means:
##          PA1        PA2
## 1 -0.8712874 -0.4062146
## 2 -0.7169792  1.4760163
## 3  0.3841964  0.2305968
## 4  0.4457889 -1.0753481
## 5  1.8736423  0.8334758
##
## Clustering vector:
##   [1] 2 4 4 4 1 2 4 1 1 3 3 3 4 3 4 1 1 3 1 1 5 4 1 2 5 1 1 4 5 4 3 2 2 1 3 5 5
##  [38] 4 2 3 1 3 1 1 4 3 1 4 3 1 1 4 1 5 3 1 1 4 1 4 1 4 2 2 2 3 1 3 1 1 1 3 3 1
##  [75] 2 1 3 2 1 3 3 4 3 5 1 1 1 5 2 4 3 1 3 1 1 3 3 4 1 1 1 4 3 2 1 5 1 1 3 4 2
## [112] 4 3 4 3 3 1 2 4 4 2 3 1 1 1 4 1 3 3 4 2 1 5 2 2 1 1 2 4 1 1 1 2 5 3 3 2 1
## [149] 4 1 2 4 3 1 3 2 1 2 3 3 4 3 4 4 4 4 4 4 4 4 2 1 5 4 5 4 4 3 5 1 3 1 1 4 3
## [186] 5 2 1 5 4 3 1 4 1 1 3 3 1 2 4 4 3 4 3 3 1 3 1 2 4 3 3 3 5 5 3 5 4 2 5 1 3
```

```
## [223] 1 4 5 5 1 2 3 2 1 1 4 1 1 2 4 5 3 3 5 1 4 1 1 1 4 3 5 1 1 4 2 4 3 2 3 3 3
## [260] 3 1 3 3 2 1 4 2 1 3 1 4 2 2 1 2 3 3 4 1 3 4 1 3 2 4 1 4 2 5 2 2 2 1 2 4 1
## [297] 2 3 1 1 4 5 1 1 2 2 3 5 2 5 3 1 1 4 5 1 3 1 2 4 1 1 5 2 4 1 4 4 1 1 3 4 5
## [334] 2 3 1 1 2 3 3 1 1 1 2 2 3 2 5 2 4 3 3 1 4 1 2 3 4 2 5 3 3 5 1 5 3 5 5 5 1
## [371] 1 3 1 2 1 4 5 4 5 1 1 1 2 4 4 1 4 1 1 4 2 3 2 1 1 1 4 1 3 1 4 5 2 3 1 4 2
## [408] 4 4 5 1 3 4 4 2 4 5 3 5 2 1 5 5 4 2 4 3 4 4 4 3 1 3 1 5 1 1 4 4 4 4 3 1 2
## [445] 4 4 4 1 4 1 1 4 4 2 1 3 4 5 5 2 1 4 4 4 1 1 2 1 2 4 4 1 2 3 3 1 4 3 5 1 3
## [482] 3 4 5 1 2 1 1 2 4 2 4 1 1 4 3 3 3 2 1
##
## Within cluster sum of squares by cluster:
## [1] 61.38244 64.81063 32.52642 39.65720 53.32022
##  (between_SS / total_SS =  74.8 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```
k_cl_fa3
```

```
## K-means clustering with 3 clusters of sizes 93, 187, 220
##
## Cluster means:
##          PA1        PA2
## 1  1.1785205  1.1181371
## 2  0.4430026 -0.8371817
## 3 -0.8747450  0.2389374
##
## Clustering vector:
##   [1] 2 3 3 2 3 1 3 3 3 2 1 2 2 2 3 3 1 3 2 1 1 1 3 3 2 1 2 2 3 3 3 2 3 2 2 3 3
##  [38] 2 3 1 2 3 3 1 3 2 2 2 3 1 2 3 1 2 3 1 2 1 1 3 3 3 3 2 1 3 3 2 1 3 2 2 1 1
##  [75] 1 3 3 3 1 3 3 2 3 3 3 2 2 2 3 2 3 2 3 2 2 1 3 1 1 2 3 3 2 1 3 3 1 2 1 2 3
## [112] 3 1 3 2 1 3 3 2 3 3 2 2 2 1 2 3 2 1 2 3 3 1 2 3 3 3 2 2 1 3 2 2 2 2 2 2 3
## [149] 3 3 2 2 2 2 3 2 2 3 1 3 2 3 1 1 1 3 3 2 3 2 3 2 2 1 2 3 3 3 3 3 2 3 2 2 1
## [186] 2 3 3 1 3 2 3 2 3 3 3 3 3 2 3 3 2 2 1 3 3 3 2 1 3 1 2 2 3 2 2 2 2 3 1 3 2
## [223] 1 3 3 2 1 3 1 3 3 1 3 2 3 3 3 2 3 3 2 3 3 3 3 2 3 3 2 3 1 3 2 2 3 3 3 3 1
## [260] 1 2 3 3 3 3 3 3 2 2 2 3 2 3 2 3 3 2 1 2 2 2 3 3 2 1 3 2 3 1 2 2 3 3 2 2 3
## [297] 1 1 2 3 2 3 3 3 3 1 3 2 1 3 3 1 1 2 1 3 3 2 1 2 2 2 3 3 2 1 2 1 3 3 3 3 1
## [334] 2 2 1 3 2 2 3 2 2 2 2 1 3 1 2 3 2 3 3 3 2 3 3 3 3 1 1 1 1 2 2 3 2 2 2 3 2
## [371] 3 3 3 3 2 1 3 3 2 3 3 3 2 1 3 3 2 2 2 3 3 2 3 3 1 3 3 1 1 2 2 2 2 3 2 2 2
## [408] 3 2 2 3 2 3 3 2 2 3 1 2 3 1 3 2 2 3 2 1 1 3 1 2 3 2 2 2 2 3 1 1 2 2 3 3 3
## [445] 3 3 3 3 2 3 3 1 3 3 2 3 1 1 1 3 2 2 2 2 2 1 2 2 3 3 2 2 2 2 1 2 2 3 1 3 2
## [482] 3 2 3 2 1 3 3 3 3 3 1 2 2 3 2 2 2 1 3
##
## Within cluster sum of squares by cluster:
## [1] 107.2371 107.8363 188.8248
##  (between_SS / total_SS =  59.5 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

- Compare two clusters using Adjusted Rand Index (ARI)

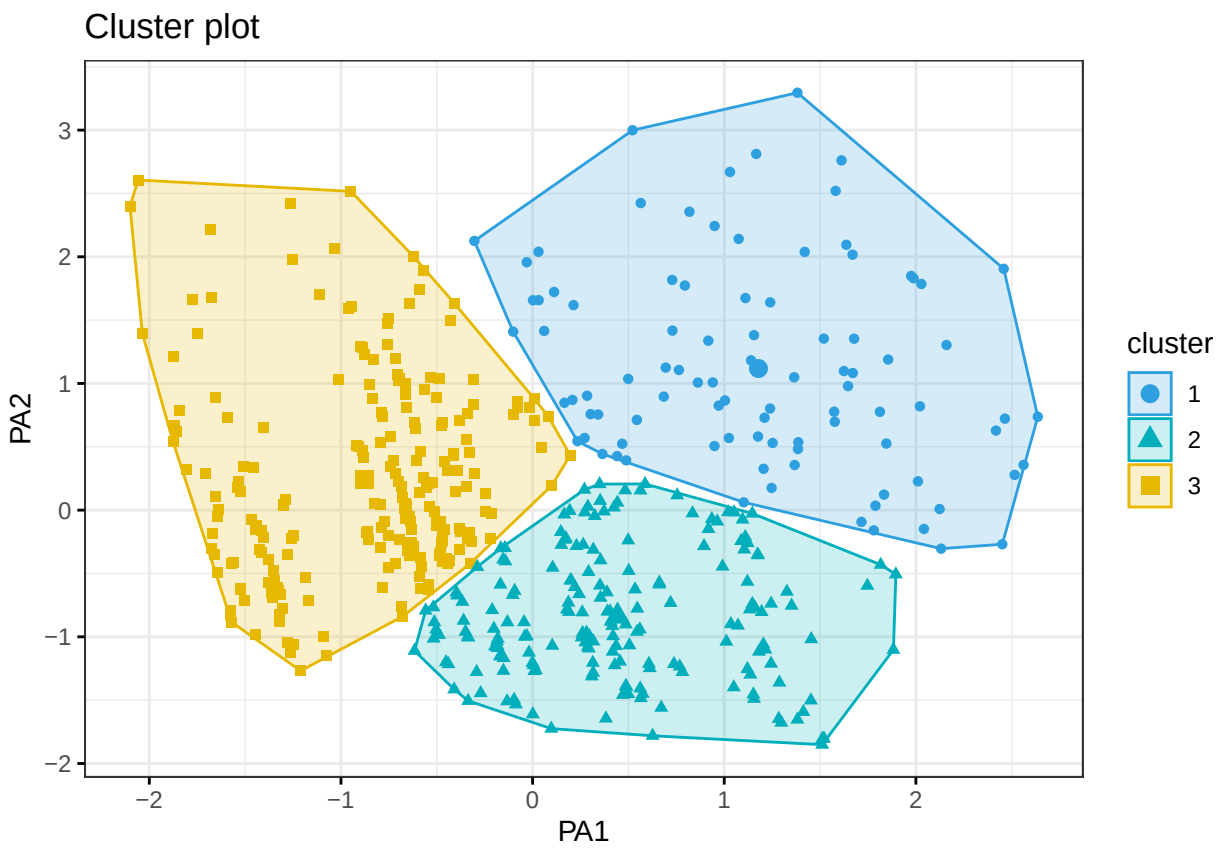
```r
# ARI
adjustedRandIndex(k_cl_fa3$cluster, k_cl_fa3_2$cluster)
```

```
## [1] -6.749255e-05
```

8.2. Cluster segmentation

Cluster plot

```r
# Plot the result of CA for the initial sample
fviz_cluster(k_cl_fa3, data = sample_s,
                         palette = c("#2E9FDF", "#00AFBB", "#E7B800", "red", "green", "purple", "grey",
                         geom = "point",
                         ellipse.type = "convex",
                         ggtheme= theme_bw())
```



Cluster characteristics

From the cluster plot above, we have 3 clusters for the initial sample with the following characteristics:

- Cluster 1: representing customers with higher creditworthiness, as it correlates with variables like interest rate, grade, and term, which are typically better for customers with good credit.
- Cluster 2: Customers in this cluster could have lower credit scores but relatively higher current financial activities or responsibilities.
- Cluster 3: representing customers with lower creditworthiness and less active or lower financial status.

Recommendation

Based on the clustering outcomes, here are some recommendations for the loan company tailored to each customer cluster:

- **Cluster 1 (Higher Creditworthiness):**

1. Premium Services: To retain low-risk customers, offer high-quality loan options with attractive interest rates and adjustable repayment terms.
2. Loyalty Programs: Encourage customer loyalty by implementing loyalty programs or offering incentives to retain their business and encourage referrals.
3. Credit Line Increases: Consider offering higher credit lines or larger loans based on the excellent credit standing of such customers.
4. Cross-Selling Opportunities: Given their probable financial stability, target these customers by cross-selling other financial products, such as investment opportunities or insurance.

- **Cluster 2 (Lower Credit Scores, Higher Financial Activity):**

1. Financial Planning Services: Provide financial planning services to help these customers manage their finances and improve their credit scores.
2. Credit Education: To aid these customers in improving their credit scores over time, offer credit counseling or educational resources.
3. Monitoring and Alerts: Introduce monitoring services that notify customers of possible credit issues or opportunities to improve their credit status.

- **Cluster 3 (Lower Creditworthiness and Financial Status):**

1. Secured Loan Options: Offer secured loans that require collateral, which can help mitigate risk while providing these customers access to credit.
2. Credit Building Products: Create products aimed at helping customers build or rebuild their credit, such as secured credit cards or small credit-builder loans.
3. Risk-Adjusted Pricing: Use risk-adjusted pricing models to ensure that the interest rates and fees compensate for the higher risk associated with this group.
4. Financial Assistance Programs: Implement hardship programs or financial assistance to support customers who may struggle with repayments.

By tailoring our approach to each customer segment, the lending company can more effectively manage risk, maximise profitability, and enhance customer satisfaction.