Assignment 99 (Unit 99): KMeans Clustering

MSDS 422: Machine Learning
Author: Stefan Jemss
Instructor: Donald Wedding, PhD
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Phase 1: Assignment Setup

Missing Value Imputation Methods Used:

> For this assignment, I elected to use the same imputation methods I have been using in previous assignments for mental consistency with the data.

1. Fill in missing jobs with the category "MISSING"
2. Perform missing value imputation for "VALUE" based on the "JOB" class
3. Perform missing value imputation for "LOAN" based on the "JOB" class
4. Perform missing value imputation for "DEBTINC" based on the "JOB" class
5. Perform a general missing value imputation for the rest of the numeric variables based on the median values

`.head()` **preview of the numeric-only Data Frame (missing value imputation completed):**

IMP_VALUE	IMP_LOAN	IMP_DEBTINC	IMP_MORTDUE	IMP_YOJ	IMP_DEROG	IMP_DELINQ	IMP_CLAGE	IMP_NINQ	IMP_CLNO
39025.0	1100	35.247328	25860.0	10.5	0.0	0.0	94.366667	1.0	9.0
68400.0	1300	35.247328	70053.0	7.0	0.0	2.0	121.833333	0.0	14.0
16700.0	1500	35.247328	13500.0	4.0	0.0	0.0	149.466667	1.0	10.0
78227.0	1500	30.311902	65019.0	7.0	0.0	0.0	173.466667	1.0	20.0
112000.0	1700	36.158718	97800.0	3.0	0.0	0.0	93.333333	0.0	14.0

Description of the numeric-only Data Frame (missing value imputation completed):

Statistic	IMP_VALUE	IMP_LOAN	IMP_DEBTINC	IMP_MORTDUE	IMP_YOJ	IMP_DEROG	IMP_DELINQ	IMP_CLAGE	IMP_NINQ	IMP_CLNO
Count	5960.000000	5960.000000	5960.000000	5960.000000	5960.000000	5960.000000	5960.000000	5960.000000	5960.000000	5960.000000
Mean	101553.336668	18607.969799	34.011474	73001.041812	8.756166	0.224329	0.405705	179.440725	1.170134	21.247819
Std	56906.419451	11207.480417	7.667363	42552.726779	7.259424	0.798458	1.079256	83.574697	1.653866	9.951308
Min	8000.000000	1100.000000	0.524499	2063.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	66489.500000	11100.000000	30.507400	48139.000000	3.000000	0.000000	0.000000	117.371430	0.000000	15.000000
50%	89094.500000	16300.000000	35.247328	65019.000000	7.000000	0.000000	0.000000	173.466667	1.000000	20.000000
75%	119144.750000	23300.000000	37.949892	88200.250000	12.000000	0.000000	0.000000	227.143058	2.000000	26.000000
Max	855909.000000	89900.000000	203.312149	399550.000000	41.000000	10.000000	15.000000	1168.233561	17.000000	71.000000

Phase 2: Transform the Data

`.head()` **preview of the transformed DataFrame:**

Variable	0	1	2	3	4
trn_IMP_VALUE	-1.098885	-0.582643	-1.491228	-0.409941	0.183592
trn_IMP_LOAN	-1.562299	-1.544453	-1.526606	-1.526606	-1.508759
trn_IMP_DEBTINC	0.161197	0.161197	0.161197	-0.482550	0.280073
trn_IMP_MORTDUE	-1.107920	-0.069286	-1.398407	-0.187596	0.582831
trn_IMP_YOJ	0.240237	-0.241936	-0.655226	-0.241936	-0.792990
trn_IMP_DEROG	-0.280976	-0.280976	-0.280976	-0.280976	-0.280976
trn_IMP_DELINQ	-0.375943	1.477341	-0.375943	-0.375943	-0.375943
trn_IMP_CLAGE	-1.018026	-0.689350	-0.358680	-0.071488	-1.030391
trn_IMP_NINQ	-0.102879	-0.707574	-0.102879	-0.102879	-0.707574
trn_IMP_CLNO	-1.230878	-0.728389	-1.130380	-0.125403	-0.728389

Description of the transformed DataFrame:

Variable	count	mean	std	min	25%	50%	75%	max
trn_IMP_VALUE	5960.0	3.814995e-17	1.000084	-1.644124	-0.616218	-0.218954	0.309155	13.257185
trn_IMP_LOAN	5960.0	-1.525998e-16	1.000084	-1.562299	-0.669963	-0.205948	0.418687	6.361645
trn_IMP_DEBTINC	5960.0	-4.387244e-16	1.000084	-4.367836	-0.457050	0.161197	0.513703	22.082544
trn_IMP_MORTDUE	5960.0	-9.537486e-17	1.000084	-1.667202	-0.584313	-0.187596	0.357215	7.674628
trn_IMP_YOJ	5960.0	-1.192186e-16	1.000084	-1.206280	-0.792990	-0.241936	0.446882	4.442025
trn_IMP_DEROG	5960.0	1.371014e-17	1.000084	-0.280976	-0.280976	-0.280976	-0.280976	12.244215
trn_IMP_DELINQ	5960.0	5.960929e-17	1.000084	-0.375943	-0.375943	-0.375943	-0.375943	13.523685
trn_IMP_CLAGE	5960.0	-2.098247e-16	1.000084	-2.147250	-0.742743	-0.071488	0.570823	11.832239
trn_IMP_NINQ	5960.0	3.576557e-17	1.000084	-0.707574	-0.707574	-0.102879	0.501815	9.572237
trn_IMP_CLNO	5960.0	5.722492e-17	1.000084	-2.135358	-0.627892	-0.125403	0.477583	4.999982

Phase 3: Variable Selection

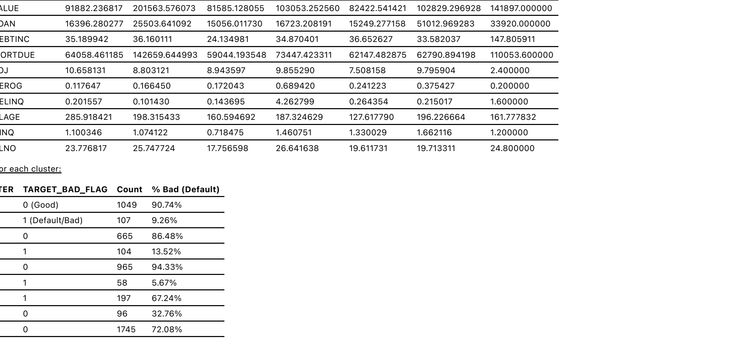
Variable Selection Methodology: I will select my variables based on the results of the important variables included in the random forest model that I created in the Tree-Based Methods assignment. The reason for choosing the random forest model is that this model had the greatest AUC and the greatest accuracy. I will select the top 5 important numeric variables in the model.

Selected Variables from the Important Random Forest Model Variables:

1. DEBTINC
2. CLAGE
3. DELINQ
4. LOAN
5. VALUE

Phase 4: Determining the Number of Clusters

Elbow Plots for the Inertia, Silhouette, and Calinski Harabasz Scores:



Interpretation:

1. **Inertia Plot**: There is a relatively smooth decrease throughout the inertia plot, without any apparent "elbow" shape. However, there is a slight change in the pattern of decline between 7 and 8 clusters. Therefore, the Initeria plot suggests that between 7-8 clusters is best.
2. **Silhouette Plot**: Since the higher the Silhouette score, the better the object is matched to its own cluster and worse to neighboring clusters, this Silhouette plot suggests that using 7 clusters is the best.
3. **Calinski-Harabasz Plot**: This plot shows a relatively steady decrease up until 7 clusters, followed by a sharp decrease after this. This likely suggests that up to 7 clusters is a viable number of clusters and likely indicates that more than 7 clusters is suboptimal.

> **Conclusion**: 7 clusters will be used.

Phase 5: Find the KMeans Clusters

K = 7

Preview of the data:

Variable	0	1	2	3	4
TARGET_BAD_FLAG	1	1	1	1	0
TARGET_LOSS_AMT	641.0	1109.0	767.0	1425.0	NaN
IMP_REASON	HomeImp	HomeImp	HomeImp	MISSING	HomeImp
IMP_JOB	Other	Other	Other	MISSING	Office
IMP_VALUE	39025.0	68400.0	16700.0	78227.0	112000.0
IMP_LOAN	1100	1300	1500	1500	1700
IMP_DEBTINC	35.247328	35.247328	35.247328	30.311902	36.158718
IMP_MORTDUE	25860.0	70053.0	13500.0	65019.0	97800.0
IMP_YOJ	10.5	7.0	4.0	7.0	3.0
IMP_DEROG	0.0	0.0	0.0	0.0	0.0
IMP_DELINQ	0.0	2.0	0.0	0.0	0.0
IMP_CLAGE	94.366667	121.833333	149.466667	173.466667	93.333333
IMP_NINQ	1.0	0.0	1.0	1.0	0.0
IMP_CLNO	9.0	14.0	10.0	20.0	14.0
CLUSTER	4	4	4	2	4

Means for each cluster:

CLUSTER	0	1	2	3	4	5	6
TARGET_BAD_FLAG	0.092561	0.135241	0.056696	0.672355	0.279223	0.143345	1.000000
TARGET_LOSS_AMT	10217.345794	20943.278846	5705.534483	17735.852792	10585.579882	36396.547619	33836.800000
IMP_VALUE	91882.236817	201563.576073	81585.128055	103053.252560	82422.541421	102829.296928	141897.000000
IMP_LOAN	16396.280277	25503.641092	15056.011730	16723.208191	15249.277158	51012.969283	33920.000000
IMP_DEBTINC	35.189942	36.160111	24.134981	34.870401	36.652627	33.582037	147.805911
IMP_MORTDUE	64058.461185	142659.644993	59044.193548	73447.423311	62147.482875	62790.894198	110053.600000
IMP_YOJ	10.658131	8.803121	8.943597	9.855290	7.508158	9.795904	2.400000
IMP_DEROG	0.117647	0.166450	0.172043	0.689420	0.241223	0.375427	0.200000
IMP_DELINQ	0.201557	0.101430	0.143695	4.262799	0.264354	0.215017	1.600000
IMP_CLAGE	285.918421	198.315433	160.594692	187.324629	127.617790	196.226664	161.777832
IMP_NINQ	1.100346	1.074122	0.718475	1.460751	1.330029	1.662116	1.200000
IMP_CLNO	23.776817	25.747724	17.756598	26.641638	19.611731	19.713311	24.800000

Count for each cluster:

CLUSTER	TARGET_BAD_FLAG	Count	% Bad (Default)
0	0 (Good)	1049	90.74%
	1 (Default/Bad)	107	9.26%
1	0	665	86.48%
	1	104	13.52%
2	0	965	94.33%
	1	58	5.67%
3	1	197	67.24%
	0	96	32.76%
4	0	1745	72.08%
	1	676	27.92%
5	0	251	85.67%
	1	42	14.33%
6	0	0	0.00%
	1	5	100.0%

Interpretation:

Overview of Cluster Characteristics:

1. **Cluster 0:** This cluster is relatively safe, with only 9.26% of loans defaulting. This cluster is characterized by relatively low loss amounts upon default ($10,217). The values for IMP_VALUE ($91,882), IMP_LOAN ($16,396), IMP_DEBT (35.19), and IMP_MORTDUE ($64,058) suggest that these are moderate loans with moderate property values. The borrowers in this cluster had the largest average IMP_YOJ, which is likely an indicator of stable income and a reliable borrower. Also notable is that this cluster also has the largest IMP_CLAGE, which likely further contributes to these borrowers' being a relatively low-risk group.
2. **Cluster 1:** This is a moderately safe cluster, with a loan default percentage of 13.52%. The defining characteristics of this cluster are that they have the largest IMP_VALUE ($201,563), with the next highest being $141,897. Additionally, this cluster has the largest IMP_MORTDUE ($142,659). While this cluster is moderately safe, due to the large IMP_VALUE amount, this cluster has a relatively large average TARGET_LOSS_AMT value ($20,943), meaning that default in this cluster can be more costly.
3. **Cluster 2:** This is the safest cluster with the lowest percentage of bad loans (5.67%) and the lowest average TARGET_LOSS_AMT ($5,705). The borrowers in this cluster are categorized by smaller loan amounts (IMP_LOAN: $15,056), lower property values (IMP_VALUE: $81,585), and the lowest debt-to-income ratios (IMP_DEBTINC: 24.13). New borrowers with these characteristics are likely very low risk to the lender.
4. **Cluster 3:** Very different from the first 3 clusters, this cluster has a high percentage of loan default (67.24%), making it the 2nd most unsafe cluster. This cluster is characterized by a moderately high average loss amount upon default (TARGET_LOSS_AMT: $17,735); however, the most defining features of this cluster are having the highest average number of derogatory marks (IMP_DEROG: 0.689) and the highest average number of delinquencies (IMP_DELINQ: 4.26).
5. **Cluster 4:** While not quite as risky as Cluster 3, Cluster 4 also has a significant proportion of defaults (27.92%) with a moderate average loss amount upon default (TARGET_LOSS_AMT: $10,585). Surprisingly, Cluster 4 has a similar profile of characteristics to Cluster 2, which is the safest cluster; however, the most marked difference is that Cluster 4 has a significantly larger debt-to-income ratio than Cluster 2 (36.65 vs. 24.13).
6. **Cluster 5:** One of the most interesting clusters, Cluster 5 has a moderately low percentage of default (14.33%); however, it has the highest average loss amount upon default (TARGET_LOSS_AMT: $26,296). This indicates that while this is a relatively safe borrower cluster, they are significantly more costly when default does occur. This cluster is characterized by very high average IMP_VALUE ($102,829), paired with the highest average loan amount (IMP_LOAN: $51,012), but relatively low average mortgage amounts due (IMP_MORTDUE: $62,790).
7. **Cluster 6:** Cluster 6 is unique in that it is very small (containing only five borrowers) but has a default rate of 100%. These borrowers have the second-highest average loss amount upon default (TARGET_LOSS_AMT: $33,837), indicating they are extremely costly. This small cluster is characterized by the highest IMP_VALUE ($141,897), a large average loan amount (IMP_LOAN: $33,920), and an extremely high average debt-to-income ratio (IMP_DEBTINC: 147.81). An interesting feature of this cluster is that they have the shortest average years on current job (IMP_YOJ: 2.4). This feature suggests that these borrowers might be individuals who recently started very high-paying yet unstable jobs that result in them taking on large amounts of debt that they are then unable to pay off when they lose the high-paying job.

> **Application of these clusters:** Given the unique characteristics of each cluster described above in the overview, these clusters could be used to determine the probability of loan default and the probable loss amount given default. New borrower's information could be compared to the characteristic profiles of the clusters outlined above, and such comparison could shed light on the potential risk of a new borrower.