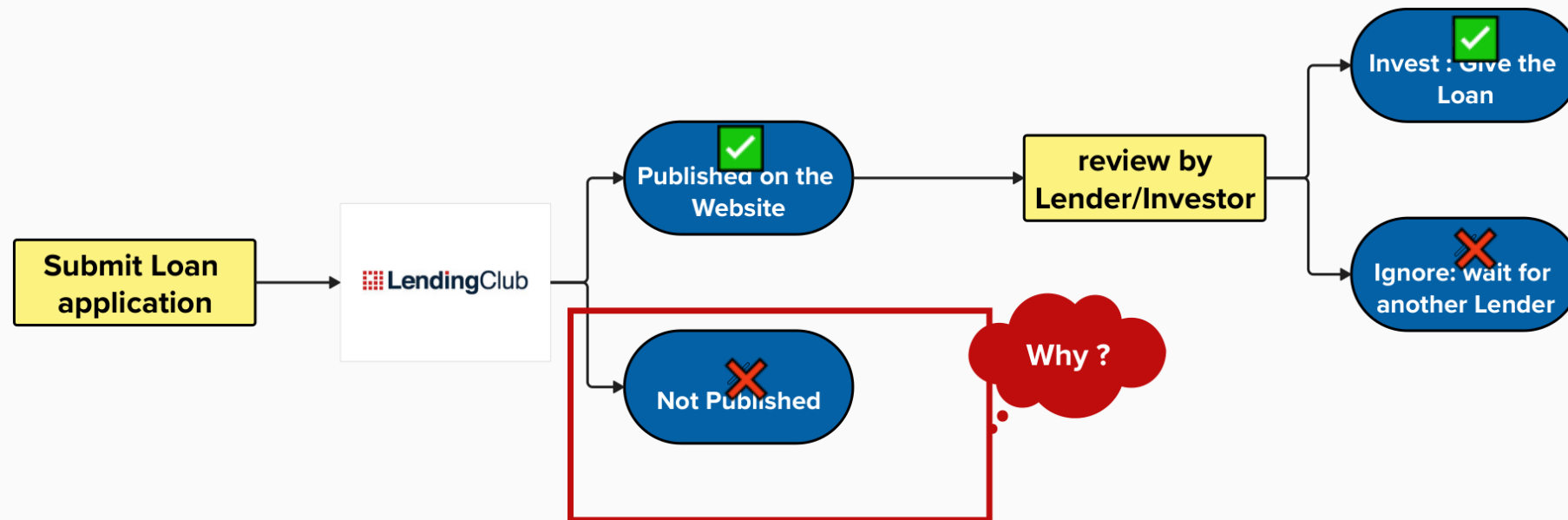


Understanding Rejected Loan Application on Lending Club Data

By Charles K

LOAN APPLICATION PROCESS



DATASET



NATHAN GEORGE · UPDATED 6 YEARS AGO

All Lending Club loan data

2007 through current Lending Club accepted and rejected loan data

kaggle.com/datasets/wordsforthewise/lending-club

GZIP

FEATURES	METRICS
amount_requested	US Dollars
application_date	YYYY-MM-DD
loan_title	Txt
risk_score	Int
debt_to_income_ratio	Pourcentage
zip_code	Code
state	Code
employment_length	Txt
policy_code	Int

Project Phase

PROJECT PHASE	COMMENTS	TECHNIQUES
Step 1 : Exploratory Data Analysis	Load the Dataset	<i>Read .gzip with Pandas on Google Colab</i>
	Understand the Metrics	<i>Matplotlib</i>
	Convert the features	<i>Python Built-in functions</i>
	Delete useless rows	<i>Python Built-in functions</i>
Step 2 : Preprocess the Data	Delete useless Features	<i>Python Built-in functions</i>
	Correlation matrix	<i>.corr Pandas function</i>
	Impute missing values on employment_length and policy_code	<i>Python Built-in functions</i>
	Normalise 'loan_title'	<i>Regular Expression and Manual regrouping</i>
	Scale the features	<i>.StandardScaler Sklearn</i>
	Encode 'state'	<i>.OneHotEncoder Sklearn</i>
	Transform loan_title to numeric	<i>TF-IDF Sklearn</i>
Step 3 : Building the Model	Topic Modeling on 'loan_title'	<i>Non-Negative Matrix Factorization (NMF)</i>
	Clustering	<i>K-Means++</i>
Step 4 : Conclusion and Data Viz	Visualize the Topics	<i>Principal Component Analysis (PCA)</i>
	Result of the Topic Modeling	<i>Centroids, and Summary</i>

KEY CONCEPTS

TF-IDF

OneHotEncoder

Non-Negative Matrix Factorization (NMF)

K-Means++

Principal Component Analysis (PCA)

EDA & PRE-PROCESS 1/6

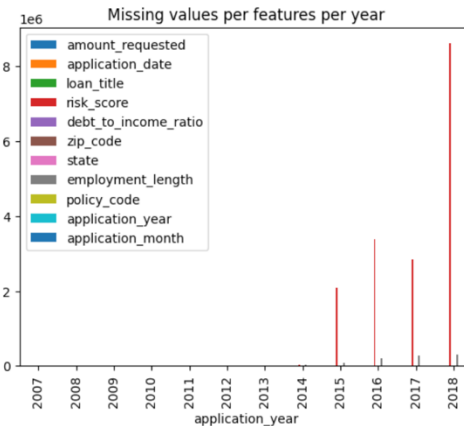
Sum of Null values:

amount_requested	0
application_date	0
loan_title	1305
risk_score	18497630
debt_to_income_ratio	0
zip_code	293
state	22
employment_length	951355
policy_code	918

#	Column	Dtype
0	amount_requested	float64
1	application_date	object
2	loan_title	object
3	risk_score	float64
4	debt_to_income_ratio	object
5	zip_code	object
6	state	object
7	employment_length	object
8	policy_code	float64

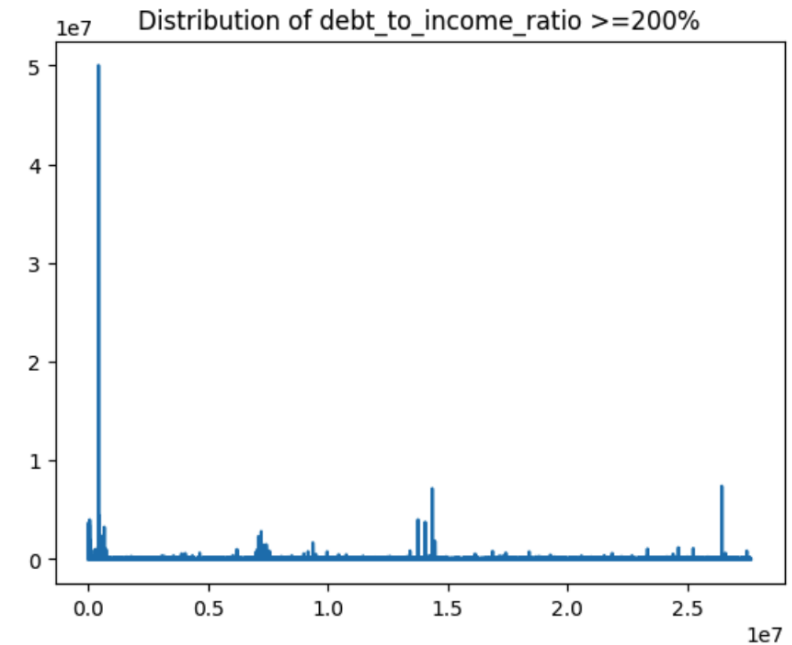
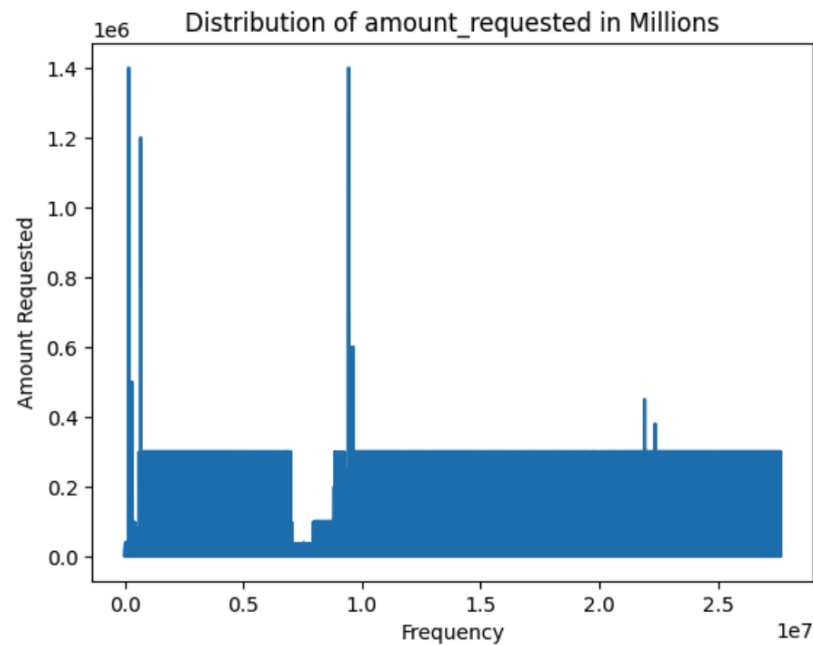
Description of numeric values:

	amount_requested	risk_score	policy_code
count	2.764874e+07	9.151111e+06	2.764782e+07
mean	1.313324e+04	6.281721e+02	6.375113e-03
std	1.500964e+04	8.993679e+01	1.127368e-01
min	0.000000e+00	0.000000e+00	0.000000e+00
25%	4.800000e+03	5.910000e+02	0.000000e+00
50%	1.000000e+04	6.370000e+02	0.000000e+00
75%	2.000000e+04	6.750000e+02	0.000000e+00
max	1.400000e+06	9.900000e+02	2.000000e+00

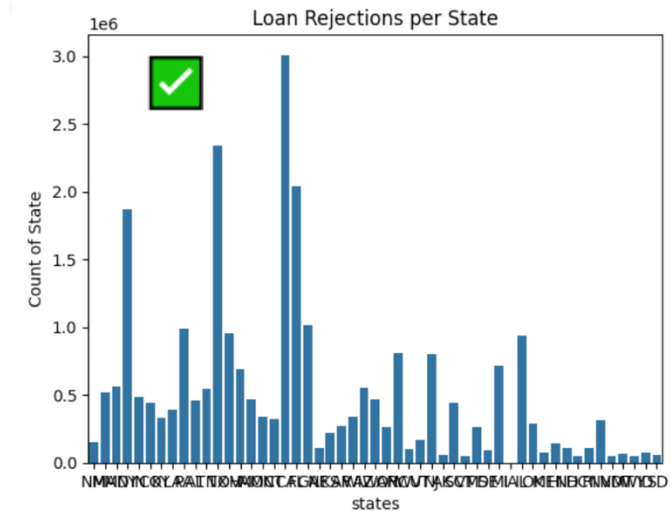
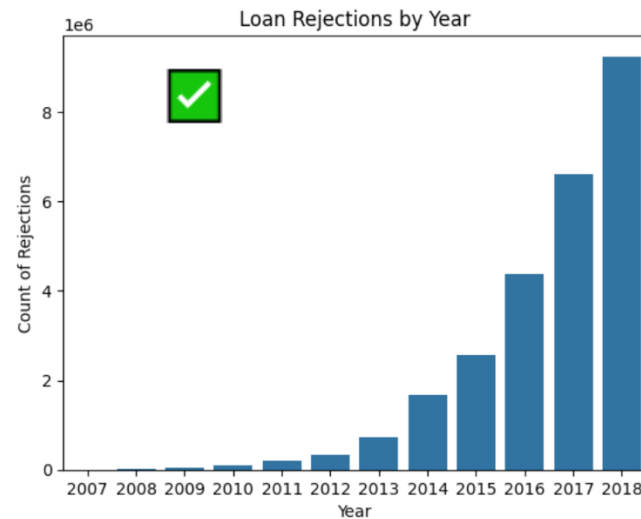


- 27 Millions rejected loans
- Max of \$1.4 Millions amount_requested
- Empty values on amount_requested
- Empty loan_title
- 18 Millions (67%) missing risk_score
- 5% missing values on employment_length
- Debt_to_income & state in bad format

EDA & PRE-PROCESS 2/6

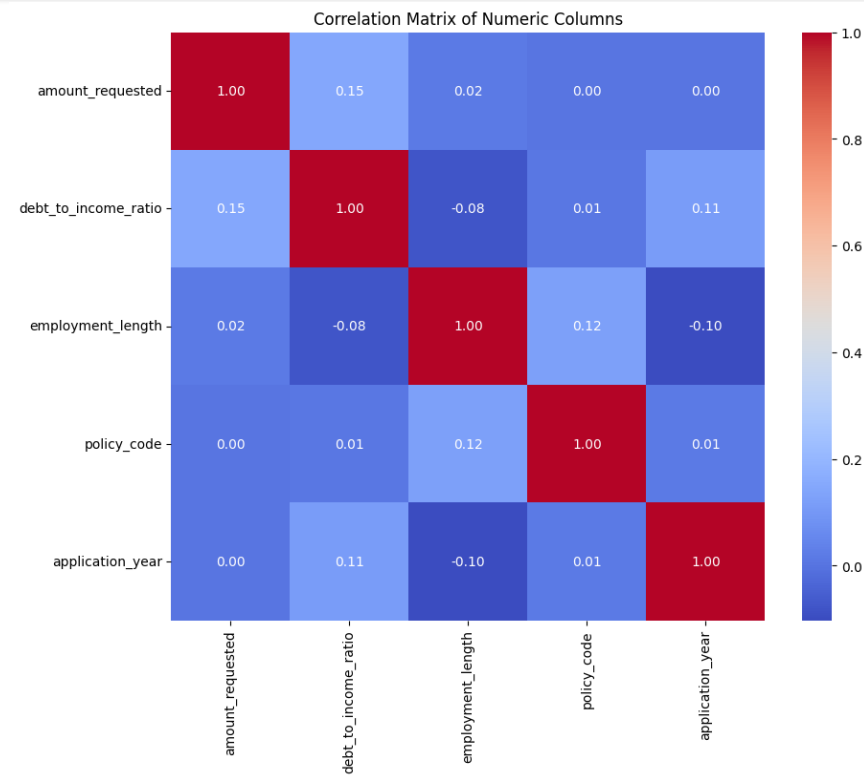


EDA & PRE-PROCESS 3/6



EDA & PRE-PROCESS 4/6

FINAL FEATURES
amount_requested
debt_to_income_ratio
employment_length
policy_code
application_year
loan_title_grouped (loan_title)



EDA & PRE-PROCESS 5/6

TECHNIQUES	FEATURES
Filling missing value : Media imputation	employment_length
Standar Scaler	amount_requested
	debt_to_income_ratio
	employment_length
One-hot encoder	State
IF-IDF	loan_title_grouped (loan_title)

EDA & PRE-PROCESS 6/6

```

loan_title
debt consolidation      6296497
debtconsolidation      5461852
other                   4443147
credit card refinancing 2248845
creditcard              1259856
car financing           751178
homeimprovement         655212
home buying             485627
major purchase          474369
car                     468824
home improvement        457402
majorpurchase           425006
medical expenses        381935
moving                  338413
medical                 324225
moving and relocation   311483
vacation                282705
smallbusiness           280819
business                208786
house                   165065
renewableenergy         27752
green loan              23436
wedding                 17701
consolidation           3183
personal loan           3107
personal                2459
debt consolidation loan 2106
educational             2012
student loan            1258
credit card consolidation 1187
Name: count, dtype: int64

```



```

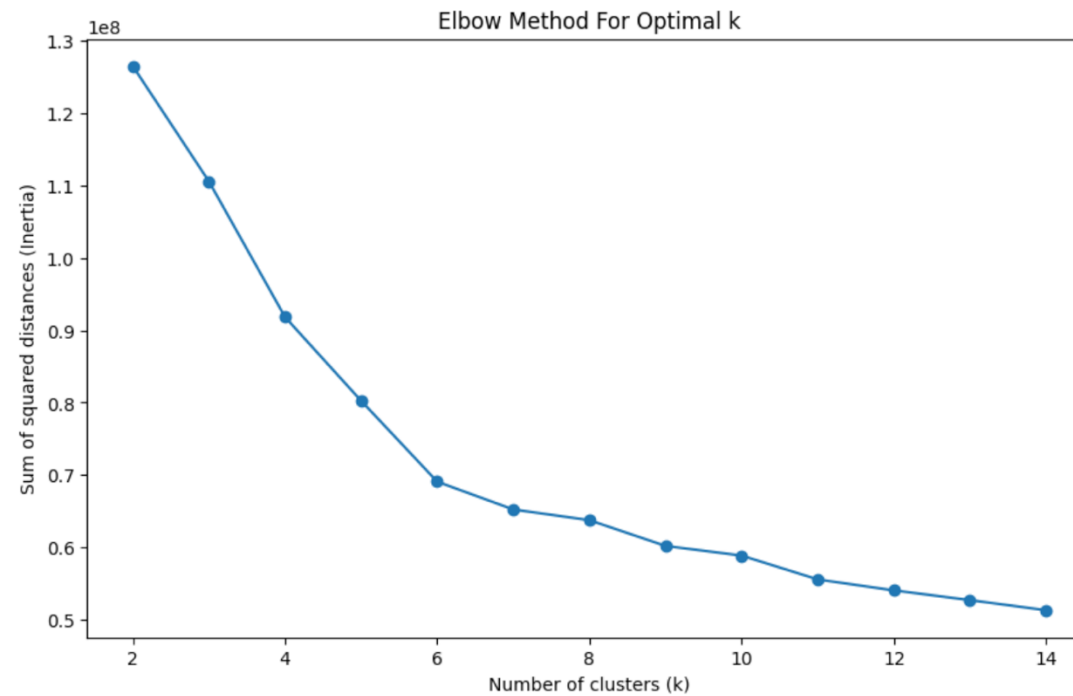
loan_title_grouped
Debt Consolidation      11771139
Other                   4444090
Credit Card             3516496
Car Financing            1221367
Home Improvement         1113817
Major Purchase           899375
Medical                  706348
Home Buying              650981
Moving and Relocation    650160
Small Business           492037
Vacation                 282705
Green Loan               51199
Wedding                  18188
Personal Loan            7818
Educational Loan         3954
Student Loan             1258
Freedom                  548
Pool Loan                296
New Start                279
major purchase loan      171
Name: count, dtype: int64

```

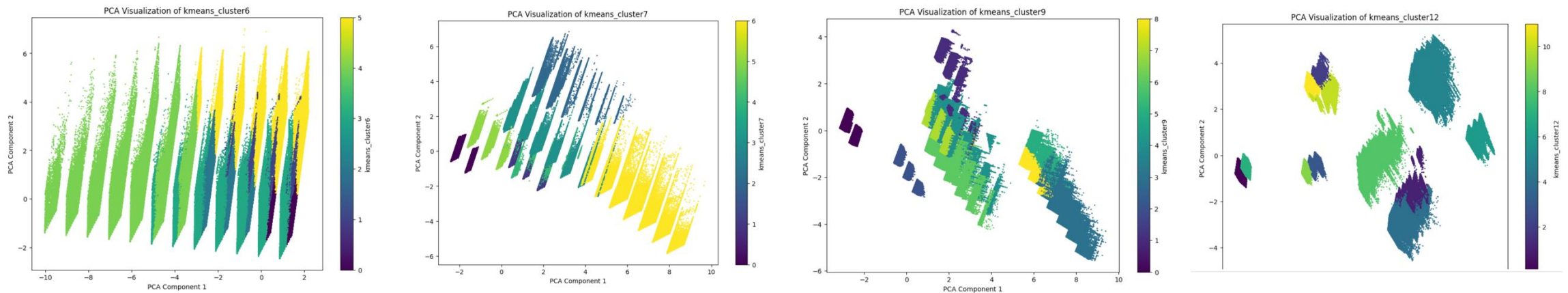
TOPIC MODELING: NMF

```
Topic 0:
consolidation debt pay loan consolidate free help consolidating paying payoff personal cc
Topic 1:
card credit pay cards payoff consolidate refinance loan high paying payment help
Topic 2:
improvement home loan payment new project repair improvment repairs purchase consolidate help
Topic 3:
financing car need new repair used repairs pay loan purchase payment buy
Topic 4:
major purchase loan car home motorcycle equipment vehicle inventory auto business new
Topic 5:
medical bills expenses pay expense help school loan need consolidate payoff cards
Topic 6:
relocation moving expenses loan forward expense job new help school need home
Topic 7:
small business start loan startup new expansion capital investment starting expanding expand
Topic 8:
buying home payment new repair improvment repairs purchase loan help car need
Topic 9:
vacation loan family dream summer money time pay needed need hawaii home
Topic 10:
loan green personal educational student pay pool need payoff school refinance cc
Topic 11:
wedding expenses expense dream help daughters loan fund day pay ring sons
```

CLUSTERING : K-MEANS



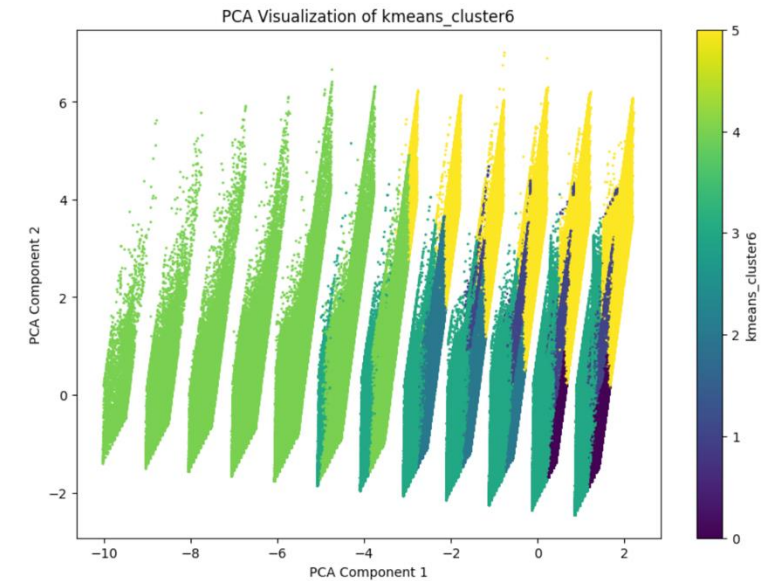
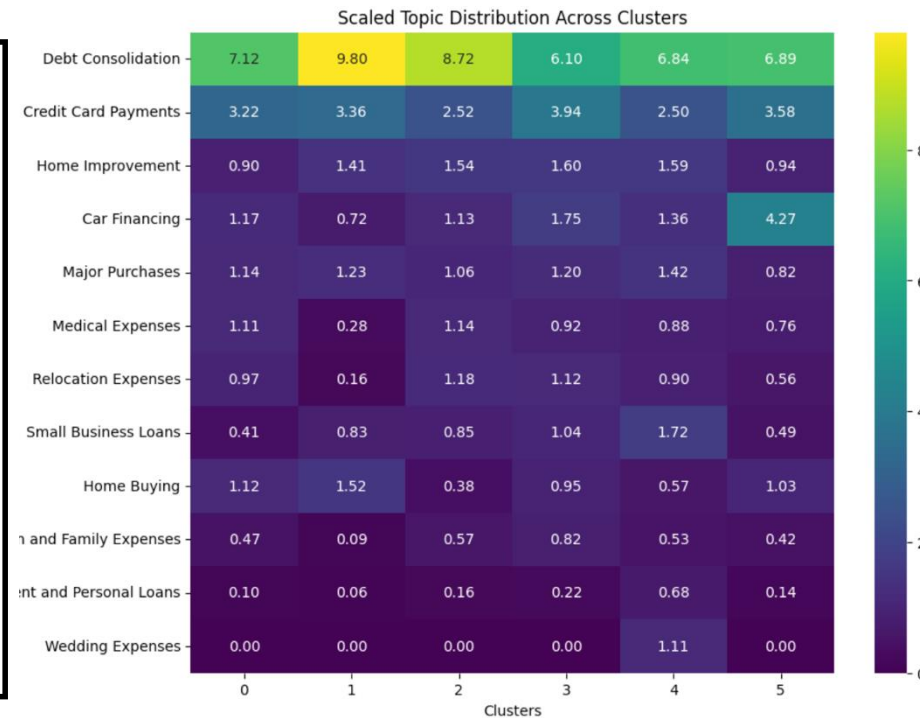
CLUSTERING : K-MEANS



SILHOUETTE SCORE	
k=6	0.25
k=7	0.26
k=9	0.10
k=12	0.13

VISUALISATION

Topic_0	Debt Consolidation
Topic_1	Credit Card Payments
Topic_2	Home Improvement
Topic_3	Car Financing
Topic_4	Major Purchases
Topic_5	Medical Expenses
Topic_6	Relocation Expenses
Topic_7	Small Business Loans
Topic_8	Home Buying
Topic_9	Vacation and Family Expenses
Topic_10	Student and Personal Loans
Topic_11	Wedding Expenses



CONCLUSION : TAKEAWAY

