EDA+ Data Cleaning and Pre-Processing

March 7, 2025

1 Introduction

1.1 Objective

This report provides an exploratory analysis (EDA) of the Auto Loan Credit Decisioning dataset. It includes data visualization, missing value analysis, and necessary pre-processing steps to prepare the data for modeling.

1.2 Data Overview

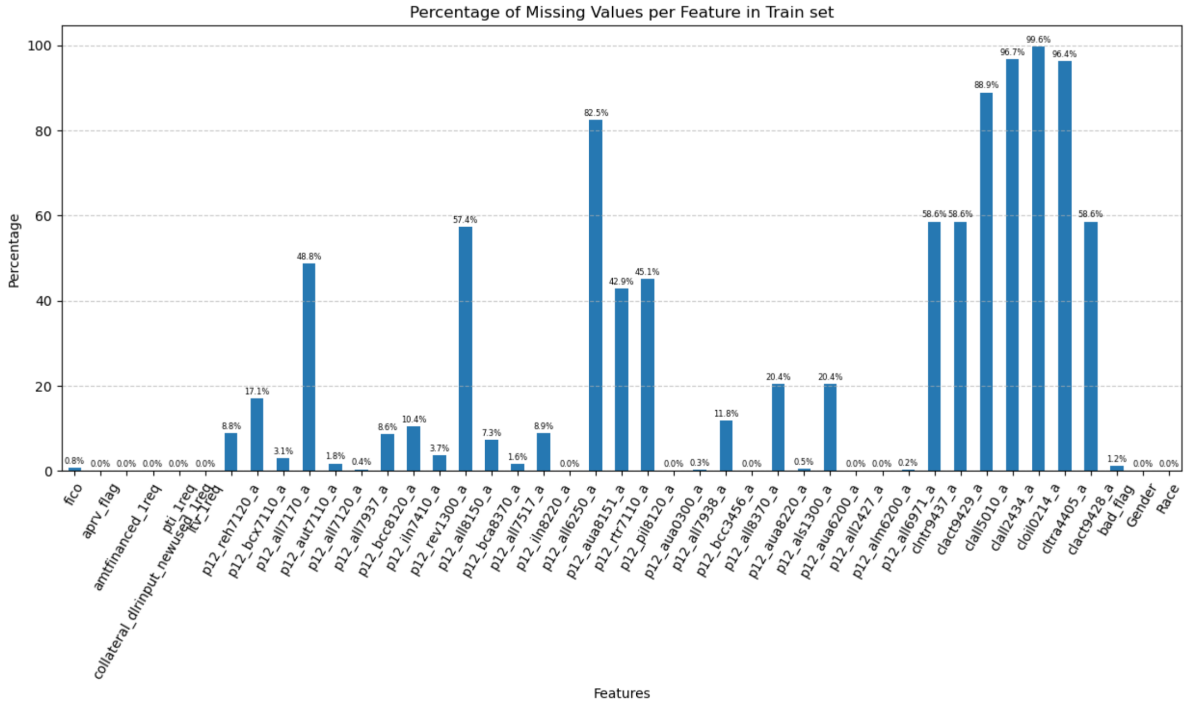
1. Training Dataset: ∼ 21,000 records
2. Testing Dataset: ∼ 5,400 records
3. Target variable: bad_flag (Loan performance in recent 12 months. =1 Never delinquent or 2 times or less 30 DPD. =0 One-time 60 DPD or worse, charge off, bankruptcy and repossession.)
4. Key Variables:
   (a) Fico: FICO score
   (b) amtfinanced_1req: Requested loan amount
   (c) pti_1req: Payment-to-income ratio
   (d) ltv_1req: Loan-to-Value ratio

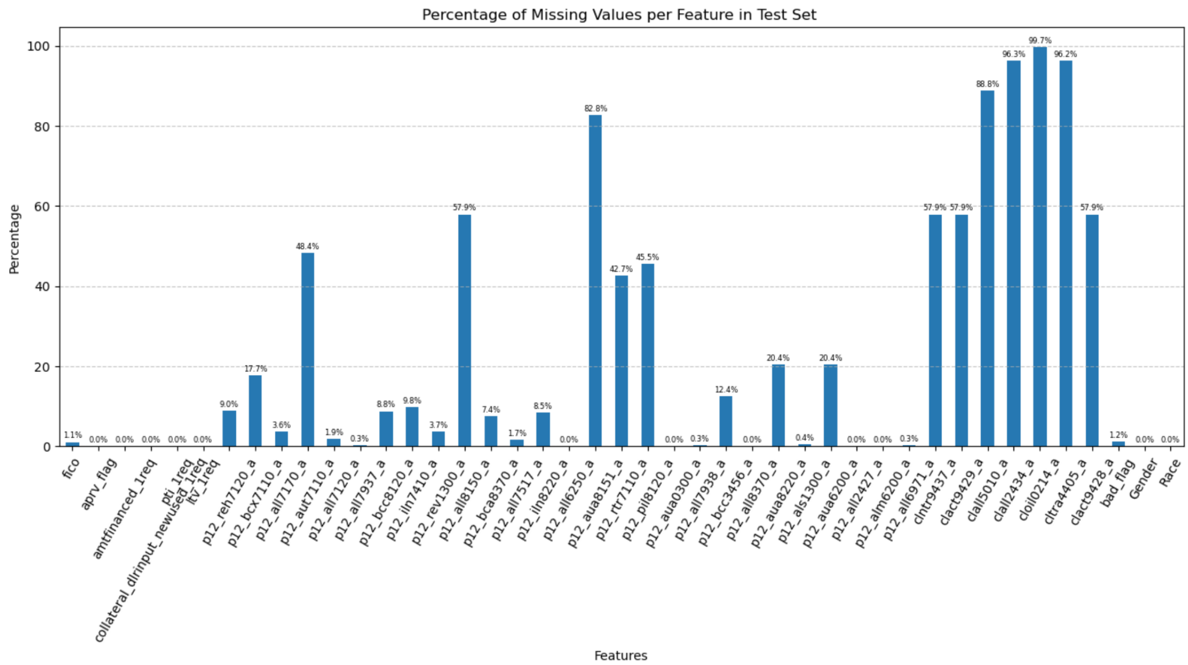
2 EDA

2.1 Data Summary

2.1.1 General Information

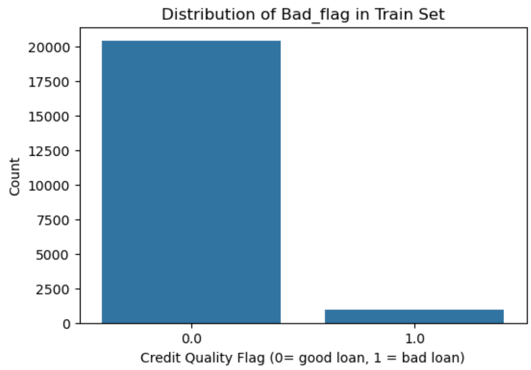
1. Number of features: 42
2. Number of Numerical features: 39
3. Number of Categorical features: 3 which are Race, Gender and collateral_dlrinput_newused_1req (if the vehicle is used or not). Note that we removed the Race and Gender as features to ensure fairness in the models.
4. Number of Missing Values per column:

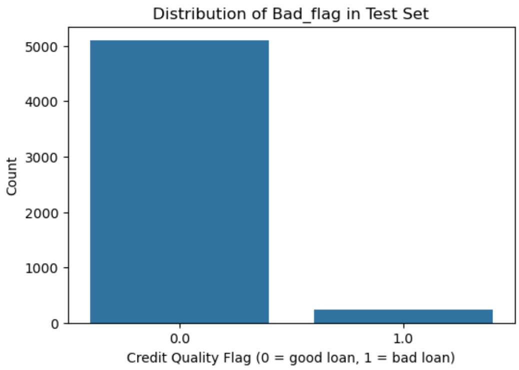




2.1.2 Target Distribution

The target is the bad_flag (REVERSED THE DEFINITION OF IT)





2.1.3 Statistical Summary

Statistics for some columns in the train set:

	fico	aprv_flag	amtfinanced_1req	pti_1req
count	21431.000000	21606.000000	21606.000000	21603.000000
mean	703.643087	0.738313	29870.867118	9.025000
std	82.786470	0.439563	15311.300550	4.803567
min	372.000000	0.000000	0.000000	0.080000
25%	644.000000	0.000000	19370.000000	5.930000
50%	701.000000	1.000000	26806.000000	8.590000
75%	766.000000	1.000000	36931.250000	11.580000
max	894.000000	1.000000	189729.000000	207.090000

	ltv_1req	p12_reh7120_a	p12_bcx7110_a	p12_all7170_a
count	21601.000000	19694.000000	17917.000000	20943.000000
mean	101.188938	51.866406	35.863370	3.597288
std	23.245966	37.352331	33.225946	14.888786
min	10.350000	0.000000	0.000000	0.000000
25%	90.520000	16.000000	6.000000	0.000000
50%	103.470000	52.000000	26.000000	0.000000
75%	113.800000	88.000000	63.000000	0.000000
max	955.260000	415.000000	290.000000	100.000000

	p12_aut7110_a	p12_all7120_a	...	p12_alm6200_a	p12_all6971_a
count	11070.000000	21226.000000	...	21606.000000	21562.000000
mean	66.256459	85.351362	...	149.763445	58.454271
std	24.470168	37.630013	...	181.349594	133.394966
min	0.000000	0.000000	...	1.000000	0.000000
25%	50.000000	73.000000	...	1.000000	1.000000
50%	72.000000	94.000000	...	30.000000	1.000000
75%	86.000000	100.000000	...	400.000000	1.000000
max	152.000000	711.000000	...	400.000000	400.000000

	clntr9437_a	clact9429_a	clall5010_a	clall2434_a	cloil0214_a
count	8952.000000	8952.000000	2390.000000	719.000000	78.000000
mean	1.391309	2.264187	2427.658996	0.020862	0.217949
std	3.433233	6.929704	4421.540329	0.143023	0.415525
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	1.000000	2.000000	2798.250000	0.000000	0.000000
max	73.000000	178.000000	33549.000000	1.000000	1.000000

Statistics for some columns in the test set:

	fico	aprv_flag	amtfinanced_1req	pti_1req	ltv_1req
count	5343.000000	5400.000000	5400.000000	5398.000000	5398.000000
mean	702.706719	0.741481	29782.550317	9.114783	101.516121
std	82.291798	0.437861	14843.983207	4.375332	22.239436
min	416.000000	0.000000	3786.000000	0.260000	12.350000
25%	644.000000	0.000000	19638.000000	5.990000	91.170000
50%	701.000000	1.000000	26894.000000	8.710000	103.675000
75%	765.000000	1.000000	36946.500000	11.687500	113.705000
max	893.000000	1.000000	134500.000000	79.270000	304.230000

	p12_reh7120_a	p12_bcx7110_a	p12_all7170_a	p12_aut7110_a
count	4916.000000	4442.000000	5206.000000	2788.000000
mean	51.010985	35.400495	3.892816	66.228121
std	37.081701	33.378023	15.486130	24.474930
min	0.000000	0.000000	0.000000	0.000000
25%	15.000000	5.000000	0.000000	51.000000
50%	51.000000	24.000000	0.000000	71.000000
75%	88.000000	63.000000	0.000000	86.000000
max	279.000000	154.000000	100.000000	104.000000

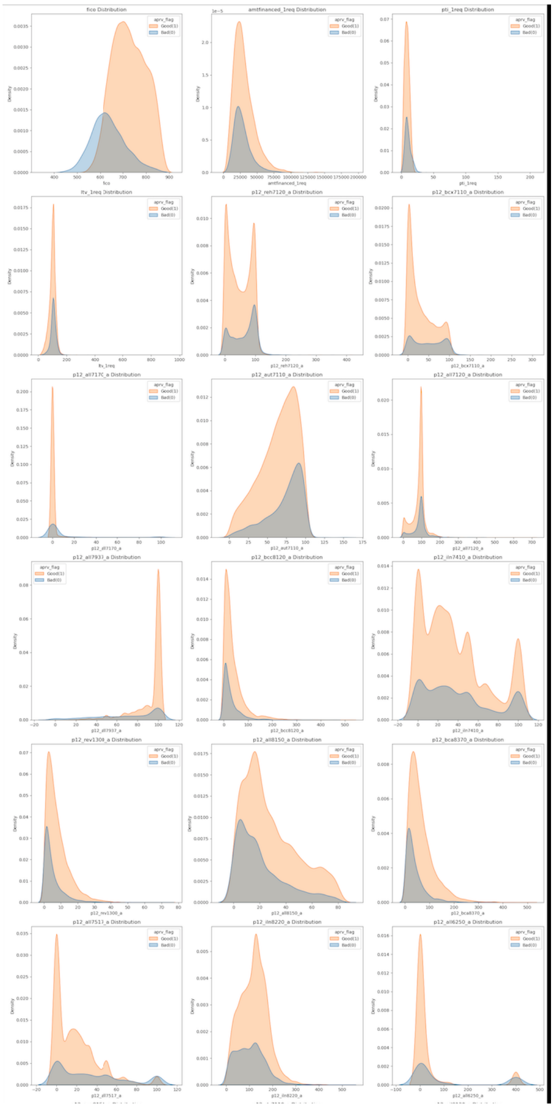
	p12_all7120_a	...	p12_alm6200_a	p12_all6971_a	clntr9437_a
count	5295.000000	...	5400.000000	5385.000000	2272.000000
mean	85.011331	...	150.206481	59.554875	1.428257
std	39.007500	...	181.471627	134.574791	3.305008
min	0.000000	...	1.000000	0.000000	0.000000
25%	71.000000	...	1.000000	1.000000	0.000000
50%	94.000000	...	30.000000	1.000000	0.000000
75%	100.000000	...	400.000000	1.000000	2.000000
max	603.000000	...	400.000000	400.000000	61.000000

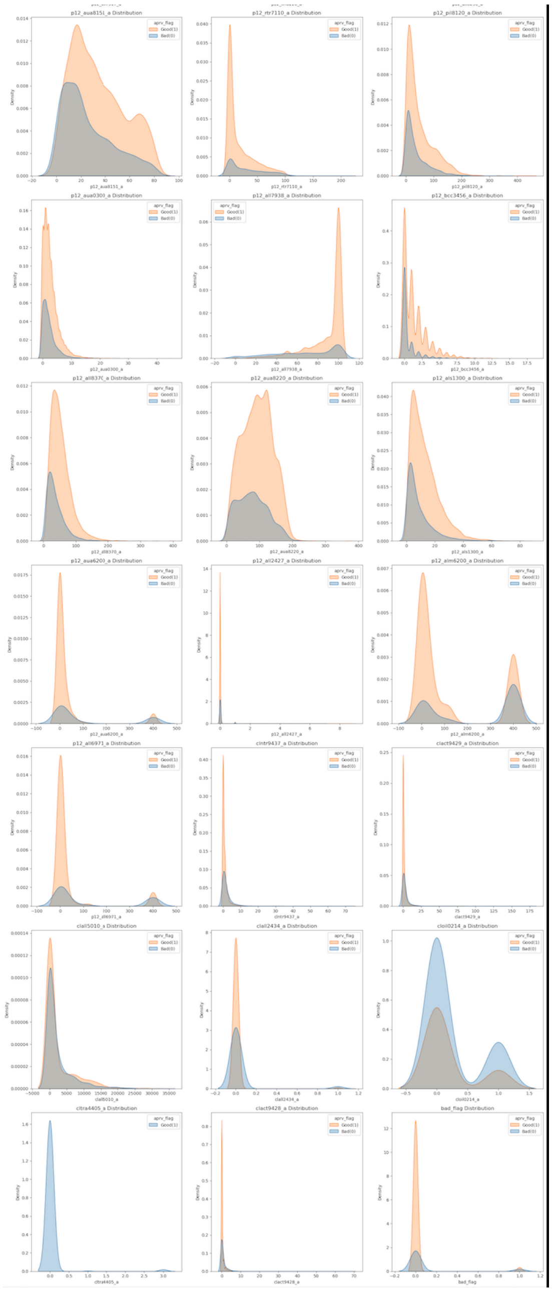
	clact9429_a	clall5010_a	clall2434_a	cloil0214_a	cltra4405_a
count	2272.000000	607.000000	200.000000	18.000000	203.000000
mean	2.311620	2902.642504	0.030000	0.333333	0.004926
std	6.601955	5030.618640	0.198233	0.485071	0.070186
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	2.000000	3885.000000	0.000000	1.000000	0.000000
max	117.000000	38755.000000	2.000000	1.000000	1.000000

3 Visualization

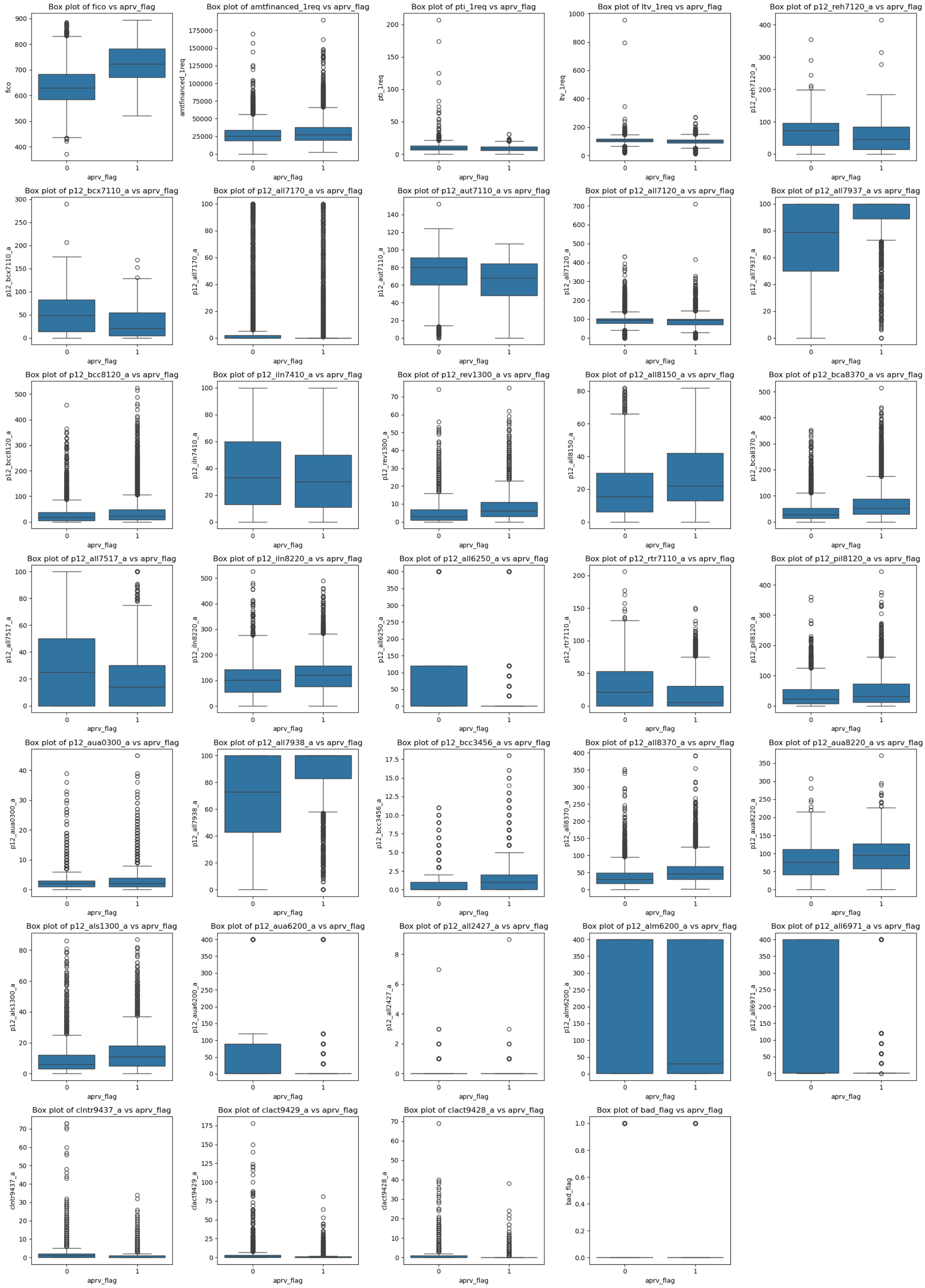
3.1 Univariate Analysis

1. Histogram and KDE plots





2. Box plots

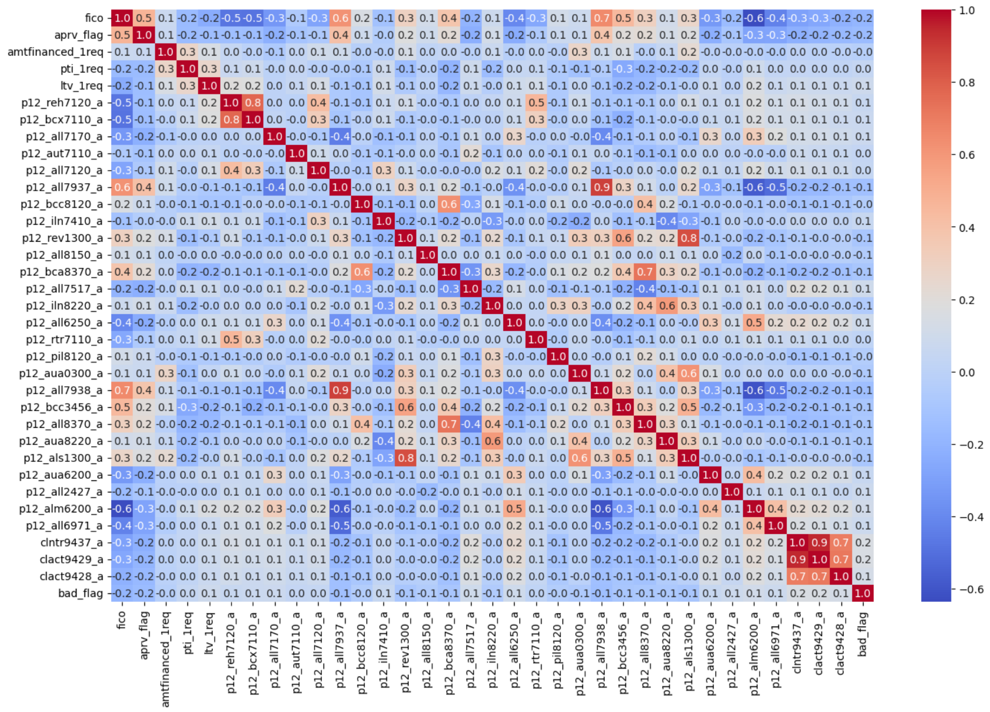


3. Log Transformation of Skewed Features:

   We aimed to address features with significant skewness in their distribution. Skewed features can negatively impact the performance of certain machine learning models, which assume more symmetric, normal distributions.

3.2 Bivaiate Analysis

1. Correlation Heatmap



I Removed features that are highly correlated (|correlation| > 0.7).

3.3 Outliers Detection

Using the above boxplots, we saw that there is a lot of outliers. To handle them the values in numerical features were capped at the 99th percentile.

4 Data Cleaning and Pre-Processing

4.1 Reversing definition of Target Variable

I reversed the definition of bad_flag to now represent =0 Never delinquent or 2 times or less 30 DPD. =1 One-time 60 DPD or worse, charge off, bankruptcy and repossession.

4.2 Handling Missing Values

1. Drop features that have more than 80% mising data.
2. For categorical features, I used SimpleImputer using the most frequent strategy.
3. For numerical features, I used SimpleImputer using the median strategy.

4.3 Scaling

Scaling Method: RobustScaler was chosen to transform numerical features, which is effective in handling outliers by using the median and interquartile range (IQR) instead of mean and standard deviation.

4.4 Encoding Categorical Variables

One-hot encoding was applied, creating separate binary columns for each category in a categorical variable.

4.5 Removing Features

I removed Race and Gender for fairness and aprv_flag to avoid data leakage.