Early Warning for Collections tool

Executive presentation

Funding Credit team

Analysts:

Kevin M. Figueroa

September 19th, 2022

About me

- BA in Economics and finance
- MA in Economics and data science
- 5 years in economic and financial consulting
- Fintech consultant: Risk Analysis
- Last week: Stride Credit Risk Analyst

Navigating repository

24 lines (17 sloc) | 1.12 KB

Raw | Blame

Early warning model for credit default

Repository

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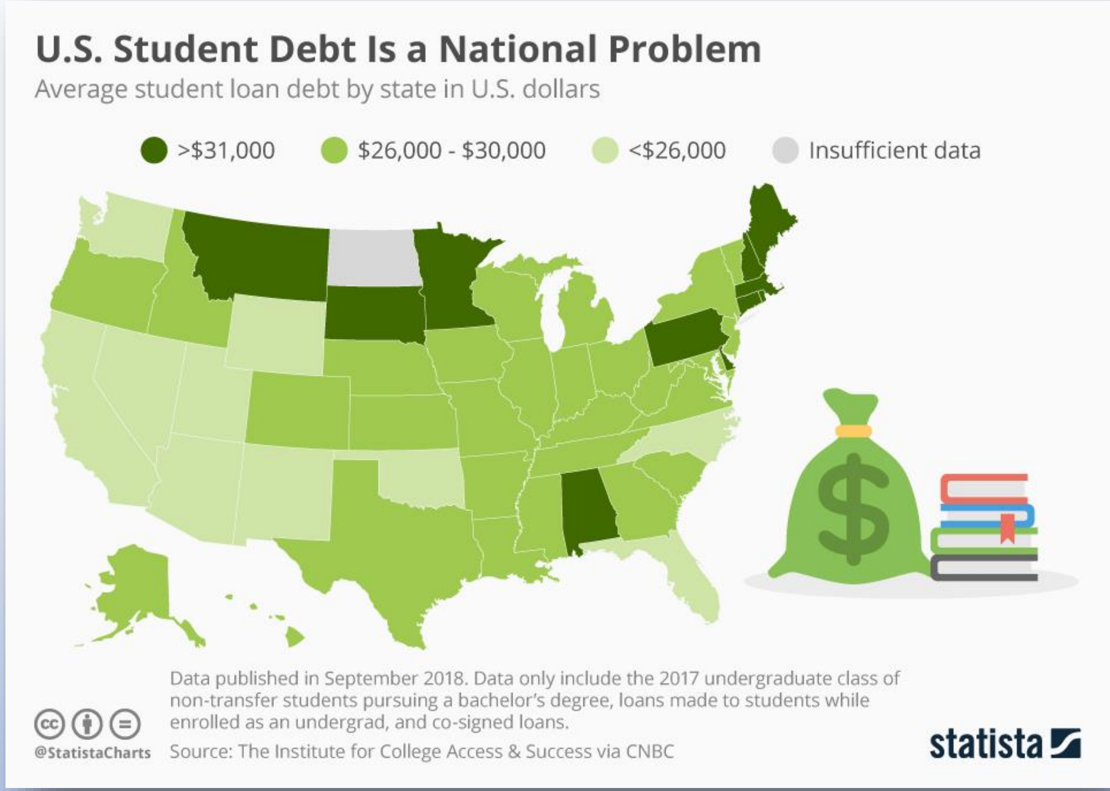
Documents:

- Executive report notebook
- Methodologic report notebook
- Library of functions created
- Final predictions
- Case dashboard

Fintechs' challenge in the growing student loan market

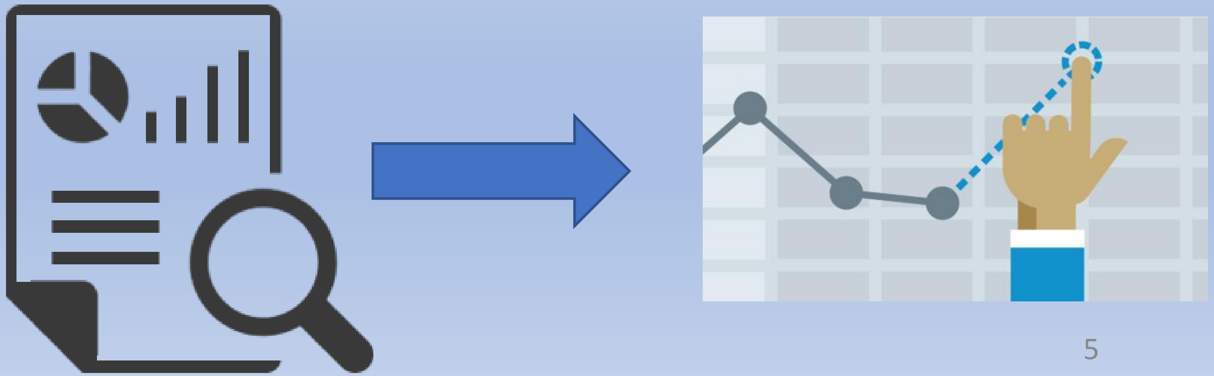
- Fintech → Competition : Reduce the cost of credit and increase financial inclusion
- Market size: 44 million borrowers who collectively owed USD 1.5 trillion in student loan debt
- Average student in the Class of 2016: $37,000
- Student loan evaluation challenge!
    - Longer terms than BL
    - Drastical conditions change for a graduate, unlike mortgages
    - No collateral
    - 1-4 yrs to first payment



Stride

Purpose

- Leverage all data available
- Database found but documentation is missing
- Our task: obtain as much insight as possible that could be useful to improve Stride's operations
- Specific objectives:
    - Perform a deep exploratory data analysis process to understand as much of the data as possible.
    - Clean the data.
    - Produce a model that can help identify loans at risk of default.
    - Predict defaults in current portfolio loans.
    - Propose a business strategy that can take advantage of the predictive power of the model.



Exploratory data analysis s results

- Description of the data and new features
- Score mistery: source? date?
- Number of dependants issue: (-1)
- Age issue
- Scales to standarize and Weak correlations

Table 1. Summary of variables training set

	count	mean	std	min	25%	50%	75%	max	Missing vals	Variable type
number_dependants	16671.0	0.49	0.72	-1.00	0.00	0.00	1.00	6.00	False	int64
credit_utilization	16671.0	0.05	0.05	0.00	0.01	0.03	0.07	0.54	False	float64
debt_to_income_ratio	16671.0	0.33	0.12	0.03	0.25	0.33	0.41	0.80	False	float64
monthly_income	16671.0	2289.90	319.47	2000.00	2100.00	2200.00	2400.00	5000.00	False	int64
number_open_credit_lines	16671.0	5.00	2.25	0.00	3.00	5.00	6.00	15.00	False	int64
number_open_loans	16671.0	2.03	1.43	0.00	1.00	2.00	3.00	9.00	False	int64
number_90_days_past_due	16671.0	0.10	0.32	0.00	0.00	0.00	0.00	3.00	False	int64
number_charged_off	16671.0	0.10	0.32	0.00	0.00	0.00	0.00	3.00	False	int64
score1	16671.0	669.90	98.01	500.00	585.00	669.00	756.00	839.00	False	int64
score2	16671.0	669.49	98.61	500.00	583.00	670.00	754.00	839.00	False	int64
target	16671.0	0.10	0.30	0.00	0.00	0.00	0.00	1.00	False	int64
age	16671.0	58.44	20.58	23.00	41.00	58.00	76.00	193.00	False	int32
total_debt	16671.0	765.01	291.69	62.30	556.40	734.38	941.70	2663.30	False	float64
number_accounts	16671.0	7.03	2.66	0.00	5.00	7.00	9.00	19.00	False	int64
avg_loan	16671.0	131.26	97.10	0.00	74.74	107.93	157.12	1895.99	False	float64
90_days_pct	16671.0	0.02	0.07	0.00	0.00	0.00	0.00	2.00	False	float64
charged_off_pct	16671.0	0.02	0.06	0.00	0.00	0.00	0.00	2.00	False	float64
avg_score	16671.0	669.70	69.95	502.00	619.00	670.00	720.00	839.00	False	float64
score_change	16671.0	-0.40	138.15	-337.00	-99.00	0.00	97.00	338.00	False	int64

Figure 4. Correlation heatmaps

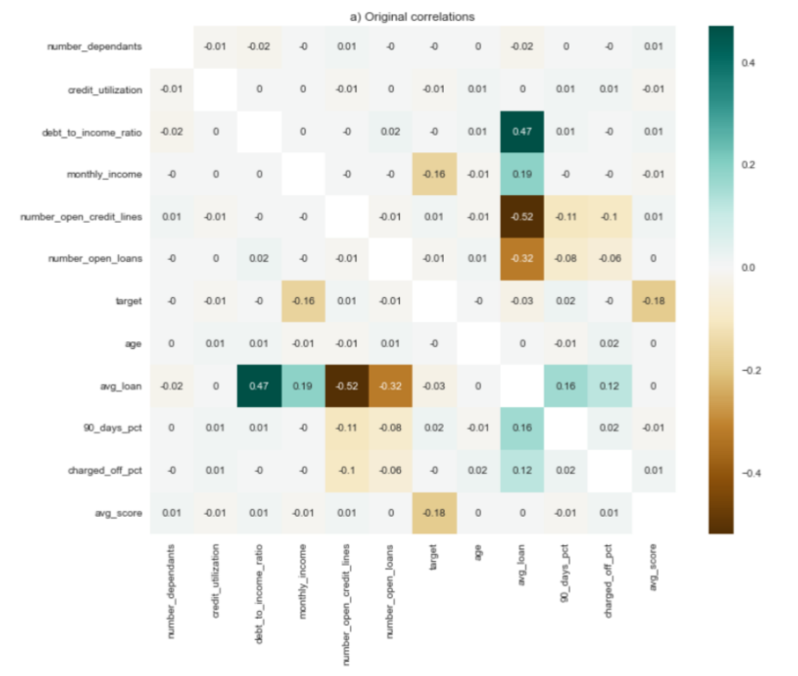
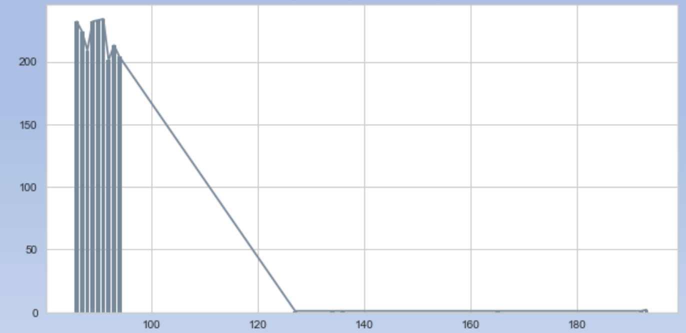


Figure 6. Age discontinuity



Exploratory data analysis results

- Description of the data
- Unbalanced Terget distribution
- Features Distributions
- No clear segmentation → Weak correlations

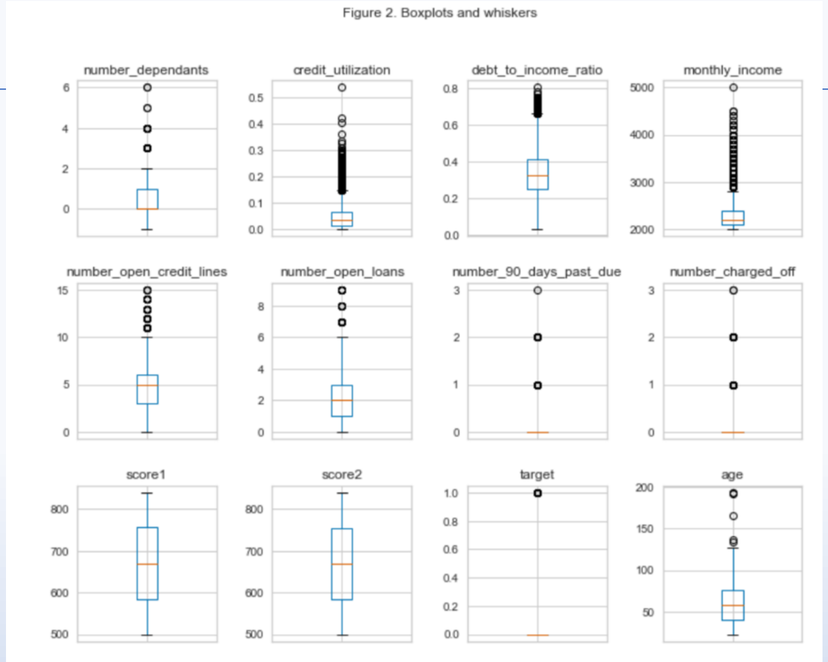


Figure 2. Boxplots and whiskers

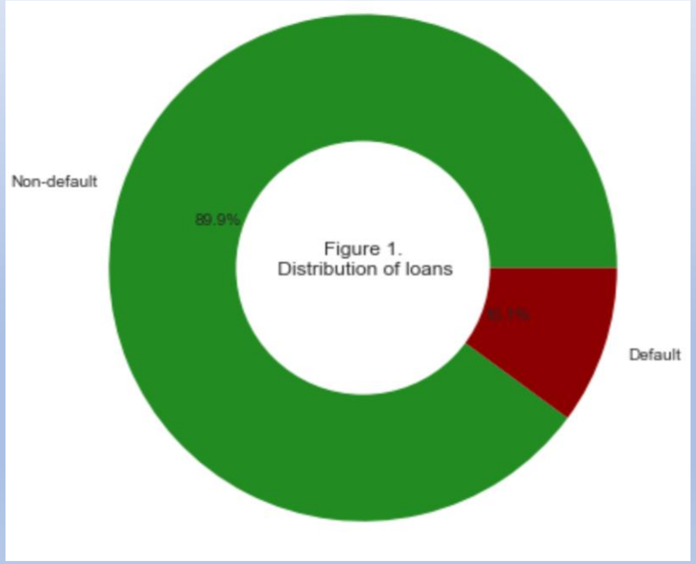


Figure 1.
Distribution of loans

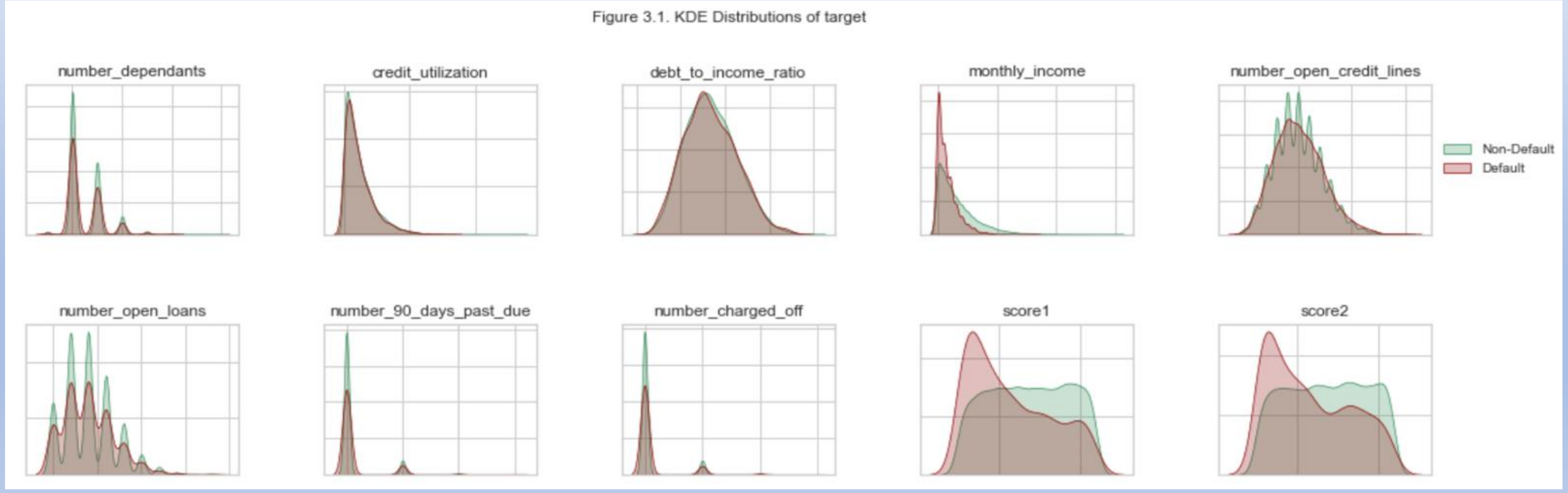


Figure 3.1. KDE Distributions of target

Stride

Evaluating if both samples were drawn from the same population

- Kolmogorov-Smirnov tests for 2 samples
  - H0: Both samples share the same distribution
  - Reject if p-val <= 0.05

- Testing and objective data come from the same population

- All variables for both sets were drawn from the same distribution → Same populations

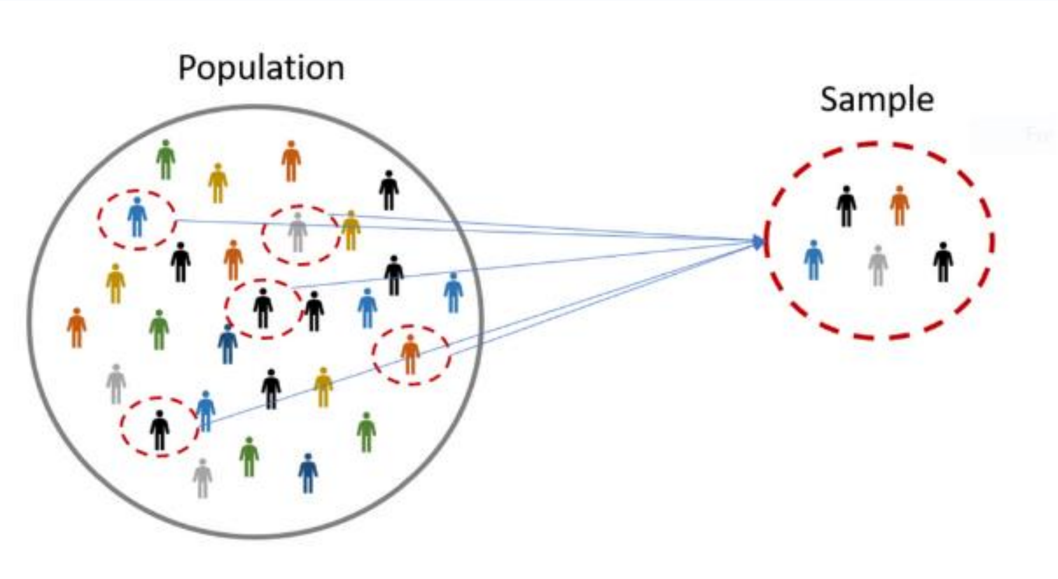
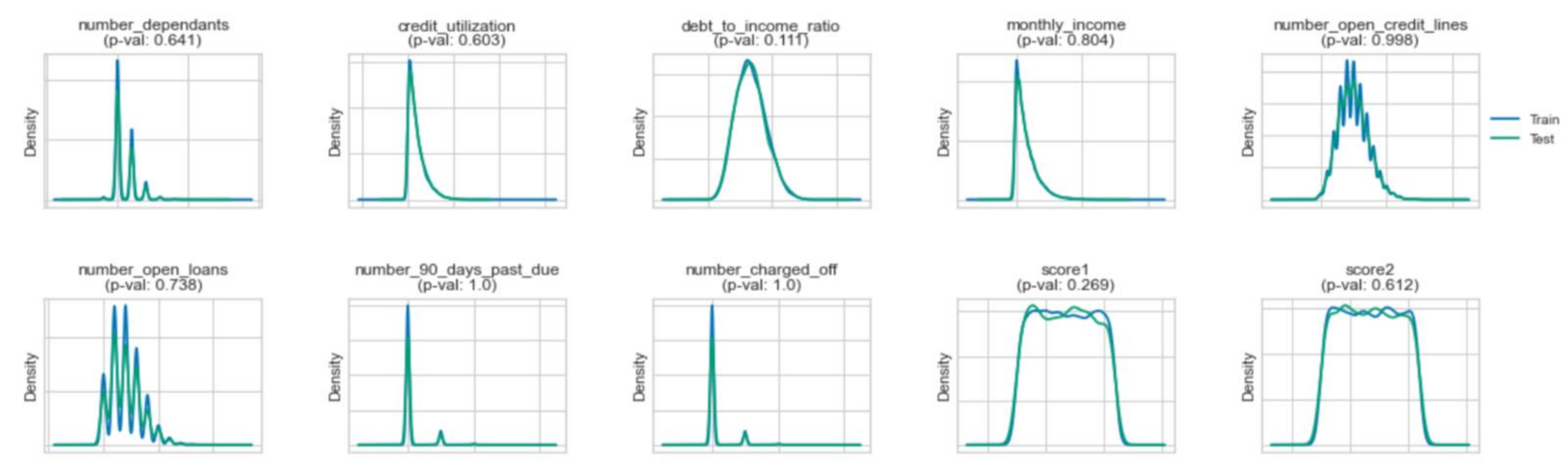


Figure 5. Train vs Test Distribution tests



Stride

What can be done with this dataset? Early Warnings for Collections (EWC) tool

- Not useful data the evaluate loan applications
- Timing mistery: 75% of ages over 41 years → follow-up data during collection.
- Useful to track loans and predict if an already existing loan is likely to default any time soon

Table 1. Summary of variables training set

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number_dependants	16671.0	0.49	0.72	-1.00	0.00	0.00	1.00	6.00	False	int64
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number_charged_off	16671.0	0.10	0.32	0.00	0.00	0.00	0.00	3.00	False	int64
score1	16671.0	669.90	98.01	500.00	585.00	669.00	756.00	839.00	False	int64
score2	16671.0	669.49	98.61	500.00	583.00	670.00	754.00	839.00	False	int64
target	16671.0	0.10	0.30	0.00	0.00	0.00	0.00	1.00	False	int64
age	16671.0	58.44	20.58	23.00	41.00	58.00	76.00	193.00	False	int32
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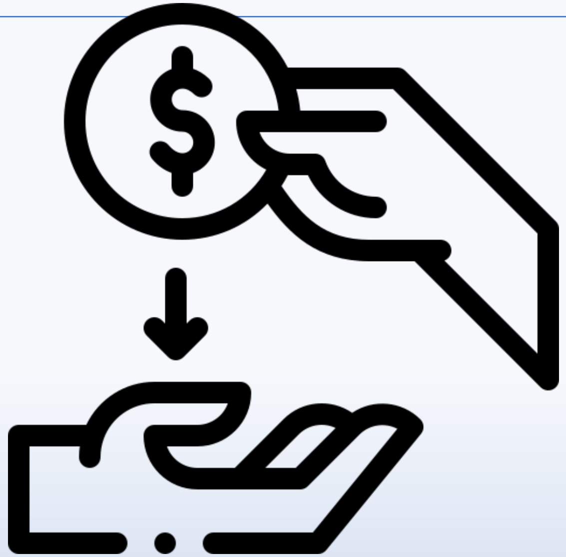
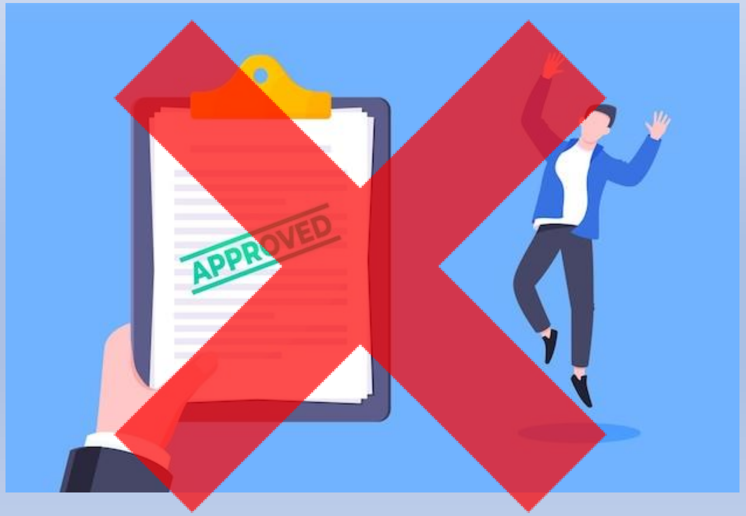




Additional variables to consider

•Number of loans with stride (internal data)

•Loan terms (internal data

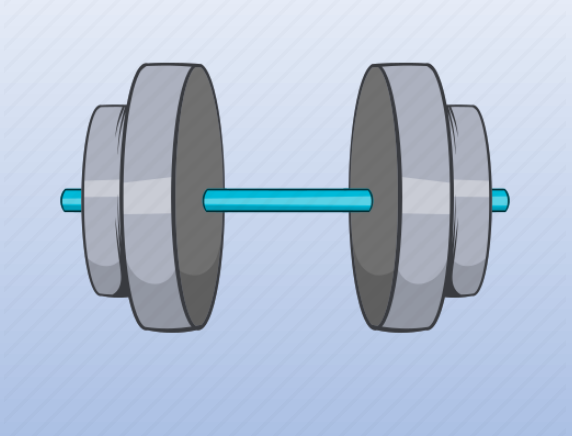
•Initial date (internal data)

•Information about the program to attend (require acceptance letter during the application.

•GPA (require transcripts of previous academic levels and follow-up after graduation

•Gym membership (ask during application)

•Loan percentage repaid (internal data):

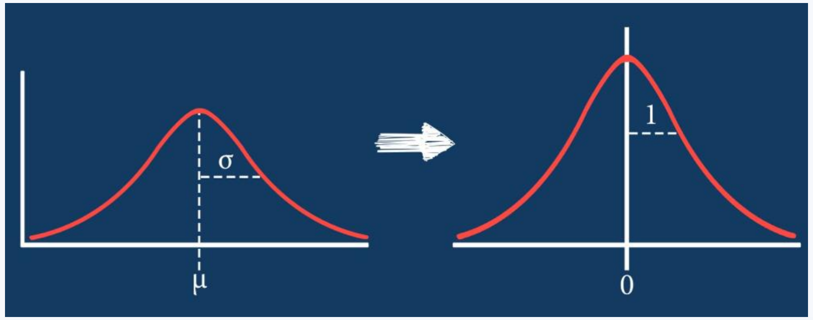


Data cleaning

- Filling missing values (-1): Mode

- Fixing ages: Subtracting 100 years to faulty observations

- Standardization (after splitting to avoid leakage)



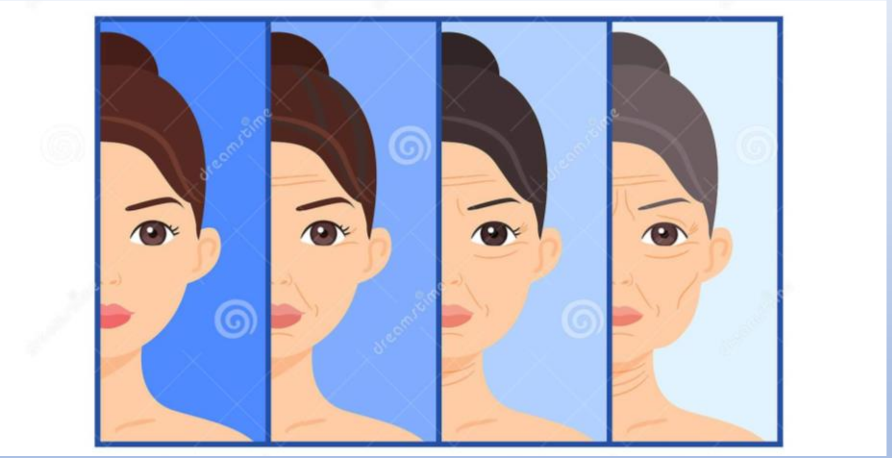


Table 3: Summary after corrections

	count	mean	std	min	25%	50%	75%	max	Missing vals	Variable type
number_dependants	16671.0	0.50	0.71	0.00	0.00	0.00	1.00	6.00	False	int64
credit_utilization	16671.0	0.05	0.05	0.00	0.01	0.03	0.07	0.54	False	float64
debt_to_income_ratio	16671.0	0.33	0.12	0.03	0.25	0.33	0.41	0.80	False	float64
monthly_income	16671.0	2289.90	319.47	2000.00	2100.00	2200.00	2400.00	5000.00	False	int64
number_open_credit_lines	16671.0	5.00	2.25	0.00	3.00	5.00	6.00	15.00	False	int64
number_open_loans	16671.0	2.03	1.43	0.00	1.00	2.00	3.00	9.00	False	int64
target	16671.0	0.10	0.30	0.00	0.00	0.00	0.00	1.00	False	int64
age	16671.0	58.40	20.47	23.00	41.00	58.00	76.00	94.00	False	int64
avg_loan	16671.0	131.26	97.10	0.00	74.74	107.93	157.12	1895.99	False	float64
90_days_pct	16671.0	0.02	0.07	0.00	0.00	0.00	0.00	2.00	False	float64
charged_off_pct	16671.0	0.02	0.06	0.00	0.00	0.00	0.00	2.00	False	float64
avg_score	16671.0	669.70	69.95	502.00	619.00	670.00	720.00	839.00	False	float64

Model creation : contextualizing concepts

• Positives observation: Defaulted loans (Contain the target we want to predict)

• Negatives observations: Non-defaulted loans (Doesn't contain the target we want to predict)

Evaluation metrics

• Accuracy: How is the model predicting both defaulters and non-defaulters?

• Precision: What percentage of the default cases predicted were actual defaulters?

• Recall: What percentage of the actual defaulters was the model able to predict?

• **Best evaluation metric → Recall**

Table 4. Possible outcomes

	Predicted Non-default	Predicted Default
Non-default	True negative	False positive
Default	False negative	True positive

Stride

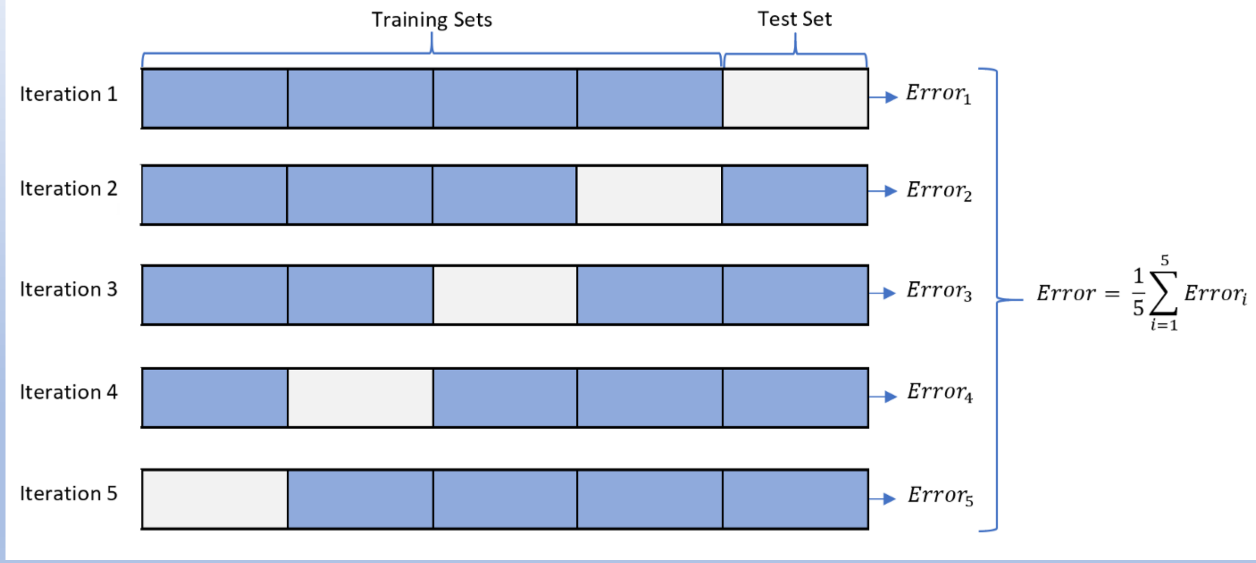
Model creation: Splitting data and null model

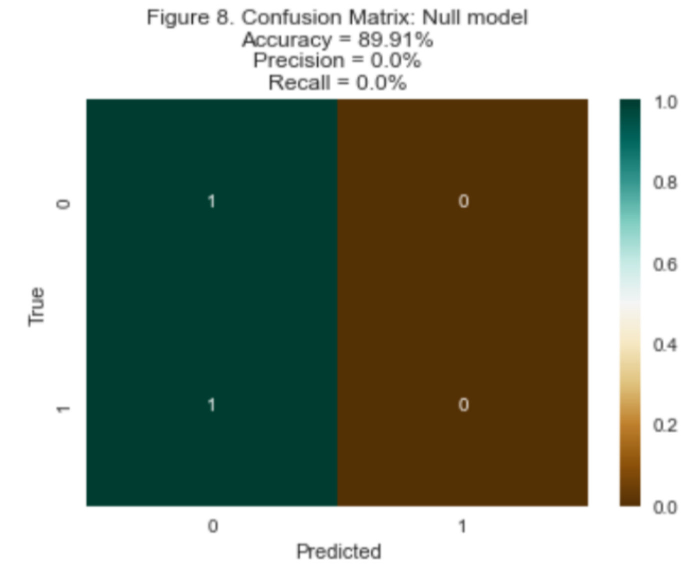
- 80% of the observations (13,336) will be used for training purposes.

- 20% (3,335) of the observations for testing purposes.

- Stratifying: keeping default proportions

- Null model no defaulters





Stride

Model creation: PyCaret

- PyCaret is an open-source, low-code machine learning library in Python that automates machine learning workflows.

- Best model → Decision Tree

-

```
DecisionTreeClassifier(

                        ccp_alpha=0.0,
                        class_weight=None,
                        criterion='gini',
                        max_depth=None,
                        max_features=None,
                        max_leaf_nodes=None,
                        min_impurity_decrease=0.0,
                        min_impurity_split=None,
                        min_samples_leaf=1,
                        min_samples_split=2,
                        min_weight_fraction_leaf=0.0,
                        presort='deprecated',
                        random_state=0,
                        splitter='best'

                        )
```

Table 6. Summary of models

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
dt	Decision Tree Classifier	0.8134	0.5228	0.1579	0.1373	0.1464	0.0425	0.0428	0.0210
nb	Naive Bayes	0.8860	0.7197	0.0358	0.2121	0.0605	0.0289	0.0446	0.0070
knn	K Neighbors Classifier	0.8885	0.5852	0.0316	0.1945	0.0540	0.0270	0.0399	0.0730
qda	Quadratic Discriminant Analysis	0.8881	0.7190	0.0253	0.1935	0.0440	0.0181	0.0315	0.0080
xgboost	Extreme Gradient Boosting	0.8884	0.7054	0.0253	0.1750	0.0439	0.0184	0.0289	0.2990
lightgbm	Light Gradient Boosting Machine	0.8959	0.7181	0.0168	0.3655	0.0318	0.0212	0.0553	0.1280
catboost	CatBoost Classifier	0.8969	0.7248	0.0095	0.3683	0.0183	0.0122	0.0415	1.6990
rf	Random Forest Classifier	0.8975	0.6958	0.0063	0.4200	0.0124	0.0084	0.0381	0.2710
gbc	Gradient Boosting Classifier	0.8975	0.7365	0.0042	0.2000	0.0082	0.0051	0.0163	0.3570
et	Extra Trees Classifier	0.8964	0.6888	0.0042	0.2083	0.0082	0.0030	0.0131	0.1980
lr	Logistic Regression	0.8982	0.7418	0.0000	0.0000	0.0000	0.0000	0.0000	0.6440
svm	SVM - Linear Kernel	0.8982	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0080
ridge	Ridge Classifier	0.8982	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0050
ada	Ada Boost Classifier	0.8977	0.7286	0.0000	0.0000	0.0000	-0.0011	-0.0049	0.1150
lda	Linear Discriminant Analysis	0.8981	0.7380	0.0000	0.0000	0.0000	-0.0002	-0.0011	0.0080
dummy	Dummy Classifier	0.8982	0.5000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0040

Creating and understanding the model

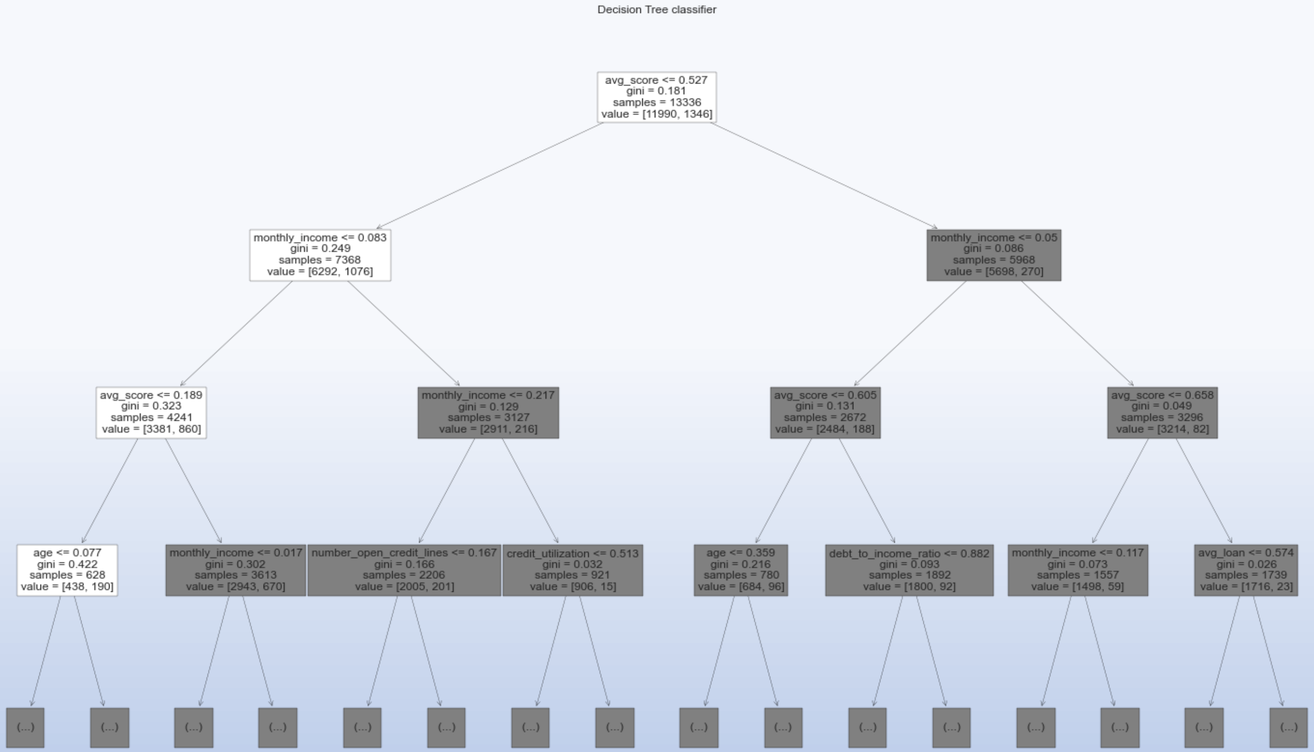
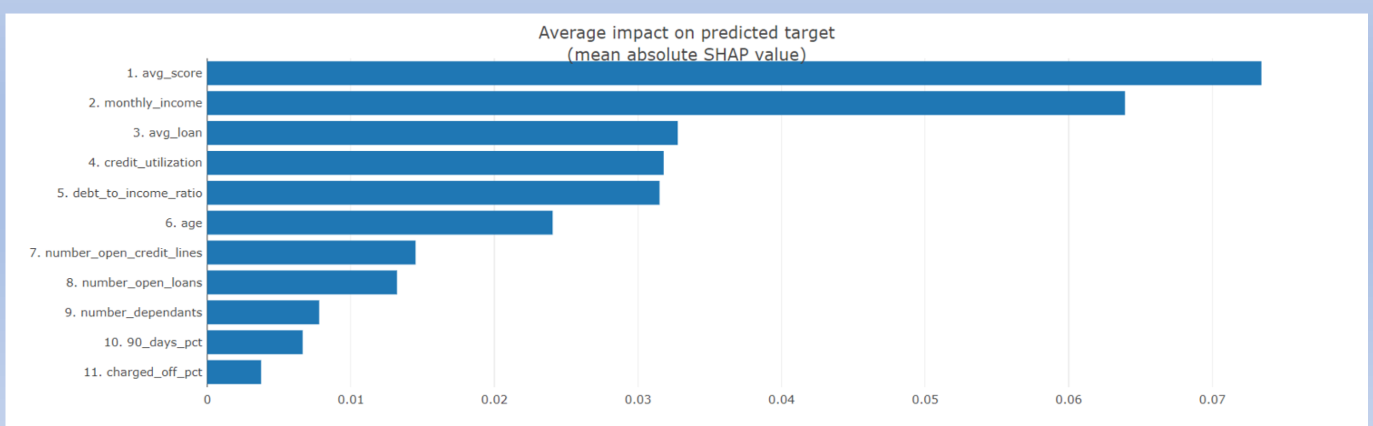
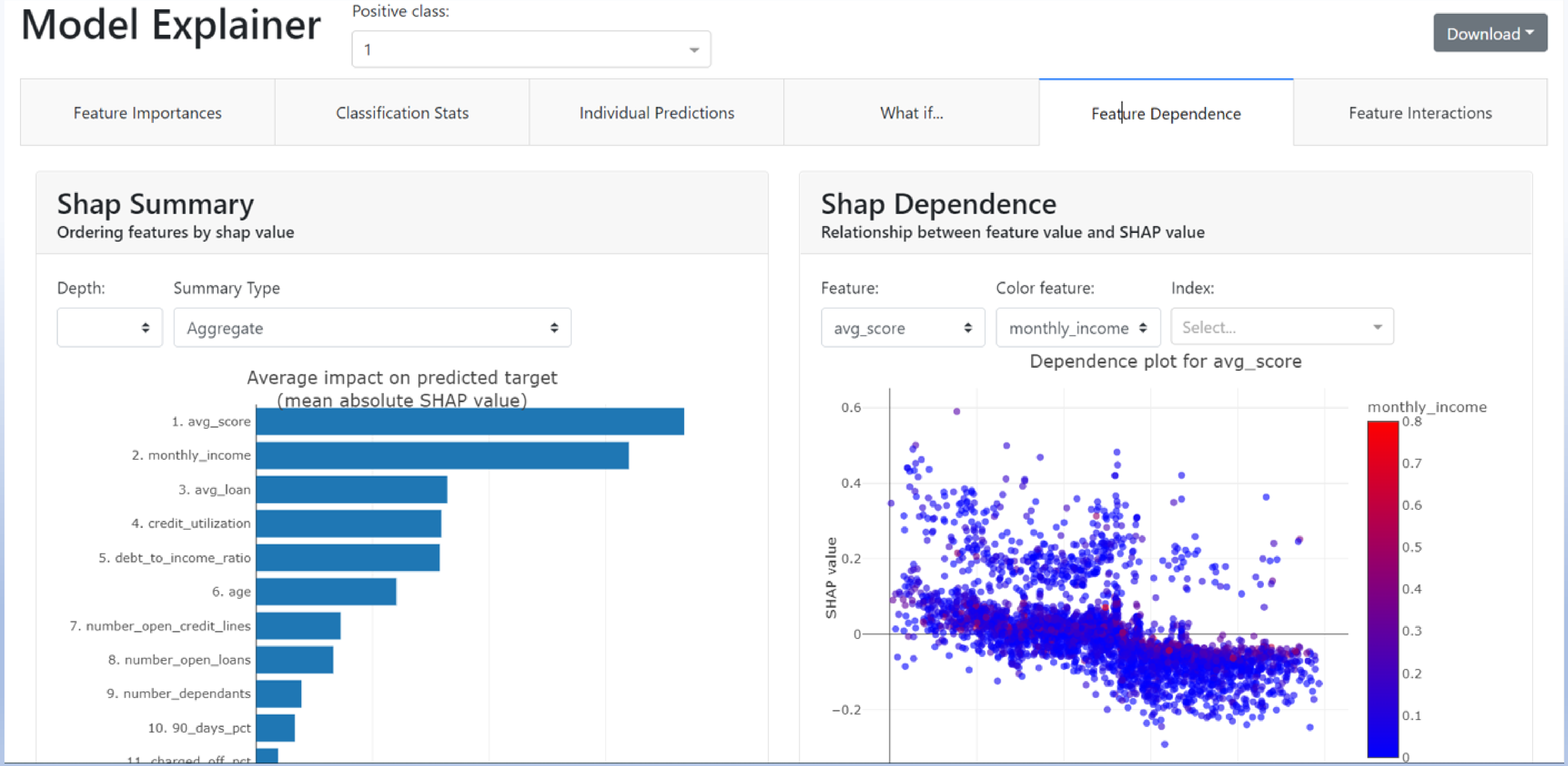


Table 7. Summary of models

Fold	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.8298	0.5552	0.2105	0.1923	0.2010	0.1060	0.1061
1	0.8148	0.5049	0.1158	0.1100	0.1128	0.0095	0.0095
2	0.8030	0.5263	0.1789	0.1382	0.1560	0.0465	0.0470
3	0.8126	0.5130	0.1368	0.1226	0.1294	0.0247	0.0248
4	0.8041	0.5362	0.2000	0.1508	0.1719	0.0633	0.0641
5	0.8199	0.5124	0.1263	0.1237	0.1250	0.0247	0.0247
6	0.7899	0.5144	0.1684	0.1203	0.1404	0.0245	0.0249
7	0.8178	0.5299	0.1684	0.1495	0.1584	0.0567	0.0568
8	0.8264	0.5160	0.1263	0.1319	0.1290	0.0327	0.0327
9	0.8156	0.5194	0.1474	0.1333	0.1400	0.0370	0.0371
Mean	0.8134	0.5228	0.1579	0.1373	0.1464	0.0425	0.0428
Std	0.0112	0.0140	0.0309	0.0220	0.0247	0.0262	0.0263

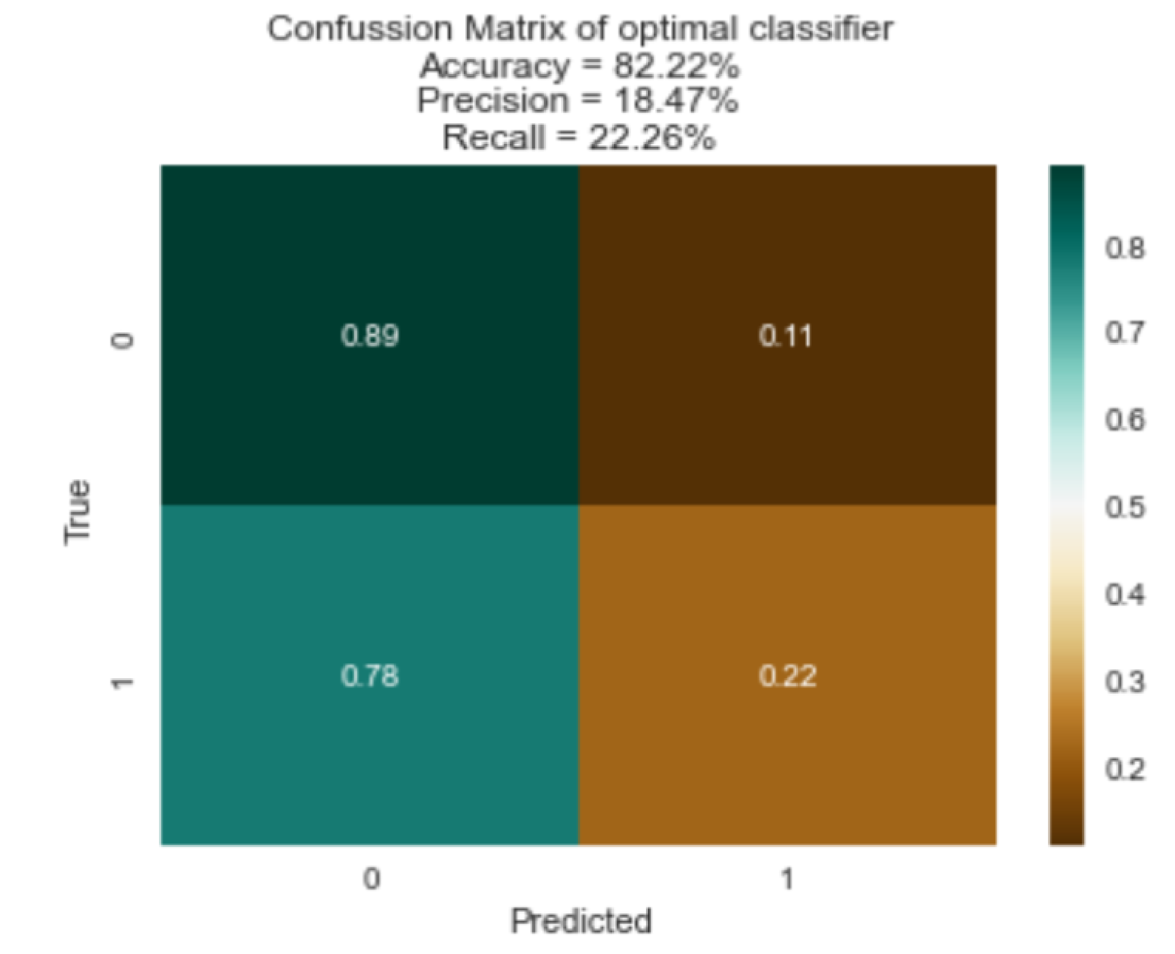


Dashboard



Model Explainer
Positive class:
1
Download
Feature Importances
Classification Stats
Individual Predictions
What if...
Feature Dependence
Feature Interactions
Shap Summary
Ordering features by shap value
Depth:
Summary Type
Aggregate
Average impact on predicted target
(mean absolute SHAP value)
1. avg_score
2. monthly_income
3. avg_loan
4. credit_utilization
5. debt_to_income_ratio
6. age
7. number_open_credit_lines
8. number_open_loans
9. number_dependants
10. 90_days_pct
11. charged_off_pct
Shap Dependence
Relationship between feature value and SHAP value
Feature:
avg_score
Color feature:
monthly_income
Index:
Select...
Dependence plot for avg_score
SHAP value
0.6
0.4
0.2
0
−0.2
monthly_income
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

Testing the model



10. EWC to alert current portfolio defaults

Based on our overall analysis we can expect a similar outcome when evaluating the target data provided of the current portfolio. The predictions can be found in the README file of the main repository, or clicking here

Projecting current portfolio

The current portfolio is composed of 4,168 open loans. The model is alerting about 489 potential defaults (11.73% of the total portfolio). However, these alerts have a 20% precision, meaning that around 391 are false alerts and 98 are real defaults. Additionally, since the model is able to correctly predict 20% of the real potential defaulters, we could approximate the total number of defaulters that the current portfolio has, which is around 489 (98/0.2), around 11% of the total portfolio. Coincidently, because the precision and recall values are very close, the model will be able to predict correctly the number of potential defaulters.

On the other hand, the model will not send alerts for 3,679 loans (88.27% of the total portfolio), out of which 391 (489 - 98) are potential defaulters (11% of the non-alerts).

Case scenario

The proposal is simple, with the results described in the last section, the collections team can better allocate their resources in the following way.

The model will divide the total portfolio in 2 groups:

- Low maintenance portfolio (3,679 loans): These loans have a probability of default of 11% and can be treated with standard prevention.
- High maintenance portfolio (489 loans); These loans have a probability of default of 20%, which is almost twice that of the low maintenance group. This loans require intensive follow-up and attention.

Stride

EWC to alert current portfolio defaults : See report

Assumptions:

- Assume a scenario in which a collections firm provider offers intensive follow-ups, and Stride has budget to get up to 500 of this specialized follow-ups.
- Traditional standard prevention has a recovery rate of 20%, while intensive follow-up has a recovery rate of 50%.
- The cost of a standard prevention is USD 100 per loan, and intensive follow-up costs USD 300.
- Using the data presented at the begining about the loan market in the U.S. we can estimate that a portfolio with 4,168 student loans to be around USD 83 million (4,168 *25,000* 0.6) (total loans *max loan stride* outstanding proportion)

Projections (See Case scenario of collections dashboard)

Using all information available we get:

- Total portfolio: 4,168
- Model will produce 489 alerts
- Out of the 489 alerts, 98 will be true
- The portfolio contains 489 real defaulters, hence it also contains 3,679 good loans
- The probability that a randomly picked loan in the non-alert group is a default is 11%
- The probability that a randomly picked loan in the non-alert group is a good loan is 89%
- The probability that a randomly picked loan in the alert group is a default is 20%
- The probability that a randomly picked loan in the alert group is a good loan is 80%

Case summary figure shows the percentage of charged off % that the portfolio would have depending on what % of the 500 intense follow ups are allocated to the alert group.

EWC to alert current portfolio defaults : See report

Outcome	Reduction poin	Imrpovement
8.673%	**-0.284**	**-3.175%**

Scenario		**Random**			**Even**				**Optimal**
Alerts %	0%	**10%**	20%	40%	50%	60%	80%	90%	**100%**
Charged-off !	8.99%	**8.96%**	8.93%	8.86%	8.83%	8.80%	8.73%	8.70%	**8.67%**

Avg loan	$25,000
Outstanding	80%
Portfolio level	$83,360,000
Portfolio saved	$237,060