Predicting Loan Approval:

Binary Classification of Financial Risk Dataset

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Executive Summary

Summary of findings

- Objective: Use ML models to predict loan classification from a Financial Risk dataset.
- Use case: ML model can reduce the number of false positives (based on specificity), saving the bank millions of pounds in customer mortgage defaults that would otherwise be avoided.
- Data Summary:
  - (Before processing): 20000 rows, 36 columns. (After cleaning and pre-processing): 5452 rows, 42 columns.
  - Target variable: y, Loan Approval, 1 for approved, 0 for rejected.
  - Key preprocessing steps: Removal of outliers, Drop irrelevant columns, Train-test split, Transform and scale categorical columns using Transformer, get.dummies() and StandardScaler.
- Modelling and results:
  - Models used: kNN, SVC, Decision Tree, Bagging, Pasting, Random Forest, XGBoost, lightgbm.
  - Evaluation metrics: Precision, Accuracy, Recall, Specificity, with a focus on precision and specificity to maximise business benefit financially.
  - Findings: Best performing model overall = SVC. All models (apart from kNN) had over 0.96 in all metrics scored, very good fitting of data to model.
  - Key Insights: EDA highlighted that higher educated applicants were more likely to be successful. Feature importance and SHAP analysis highlighted key predictors of loan approval as RiskScore, Annual Income and Total DTI.
- Recommendations and further study:
  - Recommendations:
    - Use best predictive SVC model to implement classification of loan applications.
  - Further study:
    - Use local SHAP analysis of best performing model to further validate conclusions.
    - Either improve the performance of feature-compatible models, or find a way to show feature analysis for the best performing SVC model.
    - Estimate business impact for a single bank: request and use a company dataset in a similar manner to this study.

Introduction

Background, Motivation, why data-driven approach?

- “Lenders view loan approval from a risk management standpoint”. https://fastercapital.com/topics/understanding-the-importance-of-loan-approval.html

- By carefully assessing each applicant's creditworthiness, lenders minimise the chances of default.

- When a customer defaults on their loan, Banks typically lose 30-50% of the total loan amount. Average mortgage is 200K in the UK. Default rate is 5%.

- Predictive models could save banks millions. Hence banking sector needs a data-driven analysis to better assess customer creditworthiness.

Method

Data pre-processing

- Datasets from Kaggle: https://www.kaggle.com/datasets/lorenzozoppelletto/financial-risk-for-loan-approval, https://www.kaggle.com/datasets/taweilo/loan-approval-classification-data. I chose to focus solely on the Financial Risk dataset as it had a greater depth of columns to choose from.
- Dropped columns: UtilityBillsPaymentHistory, BankruptcyHistory, PreviousLoanDefaults - these columns were irrelevant to my analysis.
- Dropped column - MonthlyIncome. This column was very similar in correlation to Annual Income so to get greater contrast in the model, I removed MonthlyIncome rather than have both columns.
- Outliers - errors I saw in the dataset were removed:
  - Experience > 50 years
  - Loan duration > 40 years
  - Credit score < 430
  - Savings >> 100k and current account balances >> 50k.
- Final Dataset size: x_train = (5452 rows, 42 columns), x_test = (1364 rows, 42 columns).
- Used get_dummies on categorical columns, transformed data with OneHotEncoder and StandardScaler.

Method (cont.)
Choice of ML models

- I used a broad range of ML models for classification analysis.
- RandomForest, XGBoost, kNN, SVC, Pasting, Bagging, lightgbm, DecisionTree classifiers.
- Approach: fit all the models and compare performance.
- I used GridSearchCV and Bayesian Optimisation to find the optimal combination of hyper-parameters for each model.
- Hyper-parameter scoring prioritised test precision, as the cost of false positives is high (banks who approve too many risky loans can lose a lot of money if the customer defaults).

EDA insights
Summary: Part 1

- Loan approval rate = 27.58%. 7 in 10 loans are not approved.
- Education is a key factor in getting approval for a loan:
  - The number of high school graduates is 33% for rejection, and 18% for approval.
  - The proportion of approved applicants increases with the level of higher education. Doctorates are most likely to be approved, followed by Masters and then Bachelor applicants.
- Annual Income: high annual income correlates with loan approval.
  - All applicants with >200k yearly salary were successful in getting a loan.
  - >100k, 85.63% were approved for a loan.
  - <100k, 80.68% were not approved for a loan.

EDA insights
Summary: Part 2

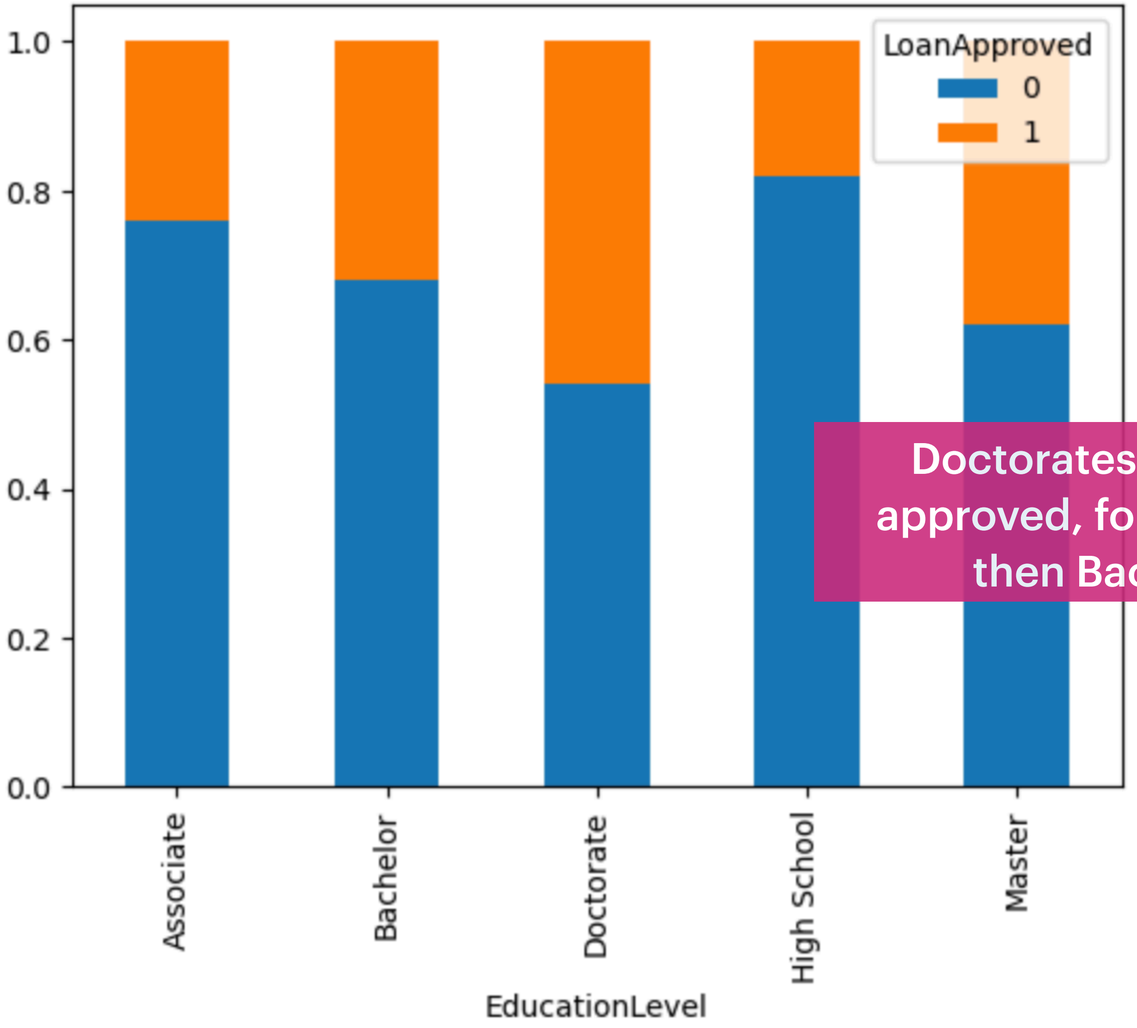
- Self employed more likely to have their loan approved than employed/ unemployed.
- Loan amount/Monthly Loan Payment: Applicants asking for a higher loan amount and who would be paying off a large amount of debt monthly on a proposed loan are more likely to be rejected, as the lender views them as a high risk investment. Below a proposed monthly loan payment of 1k, 38% of applicants were successful in getting a loan. Above 2k: 90.10% of applicants were rejected for a loan.
- TotalDTI: Low DTI combined with high annual income leads to loan approval. mean|Total DTI| = 0.139 with an annual income of 115k+, 90% of loans were approved.

EDA insights

Graphical Summary: Part 1

LoanApproved	proportion
0	72.42%
1	27.58%

Loan approval rate = 27.58%

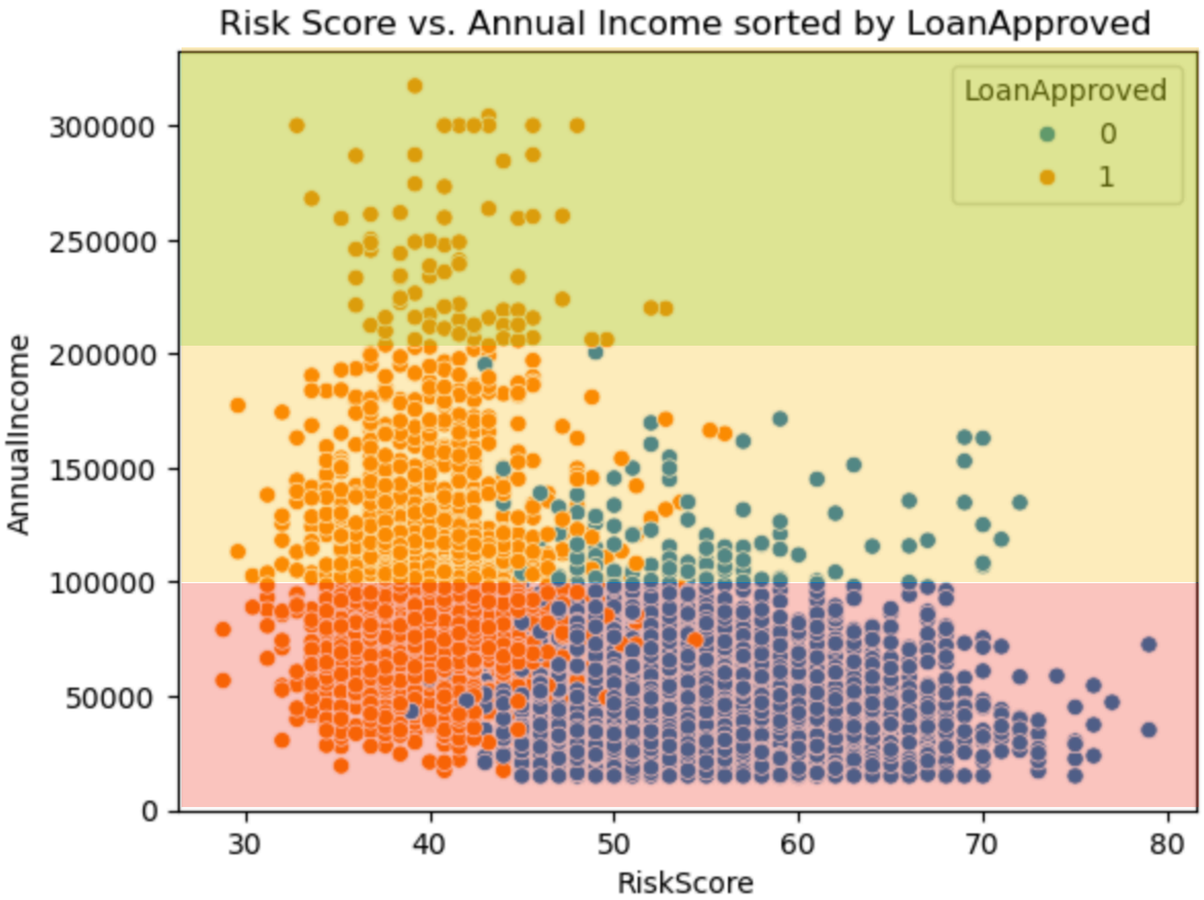


Doctorates are most likely to be approved, followed by Masters and then Bachelor applicants.

LoanApproved	EducationLevel	proportion
0	High School	33.55%
	Bachelor	29.11%
	Associate	20.77%
	Master	13.07%
	Doctorate	3.50%
1	Bachelor	35.21%
	Master	21.22%
	High School	18.72%
	Associate	16.86%
	Doctorate	7.98%

EDA insights

Graphical Summary: Part 2



All applicants with >200k yearly salary were successful in getting a loan.
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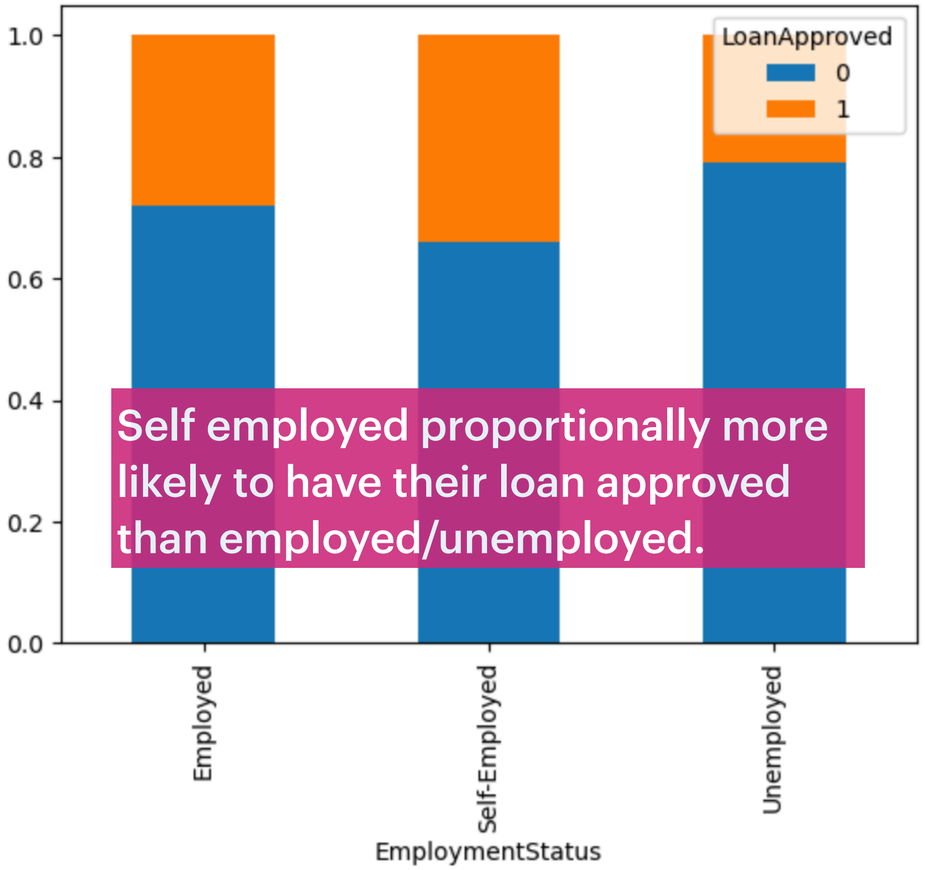
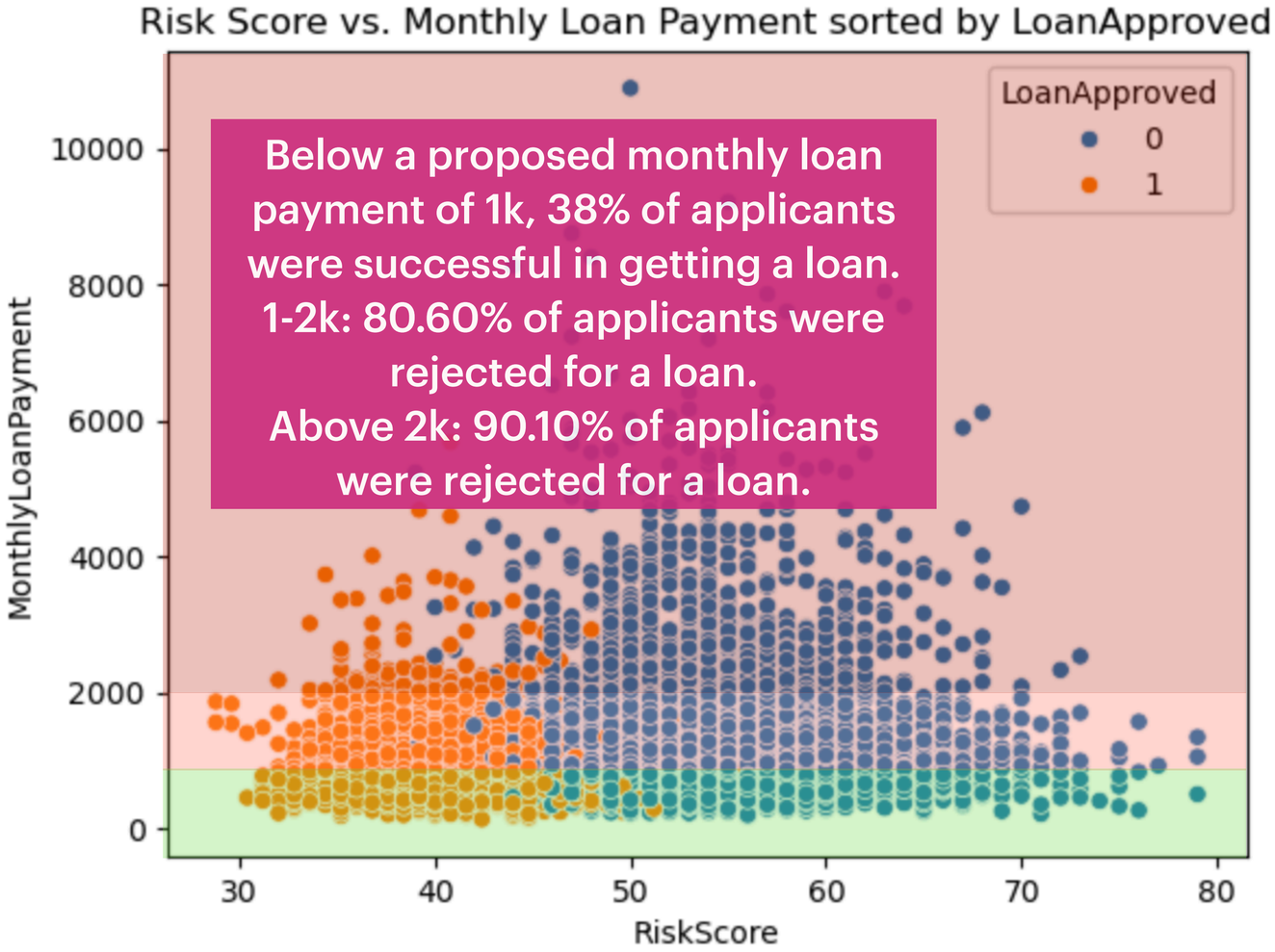
EDA insights

Graphical Summary: Part 3



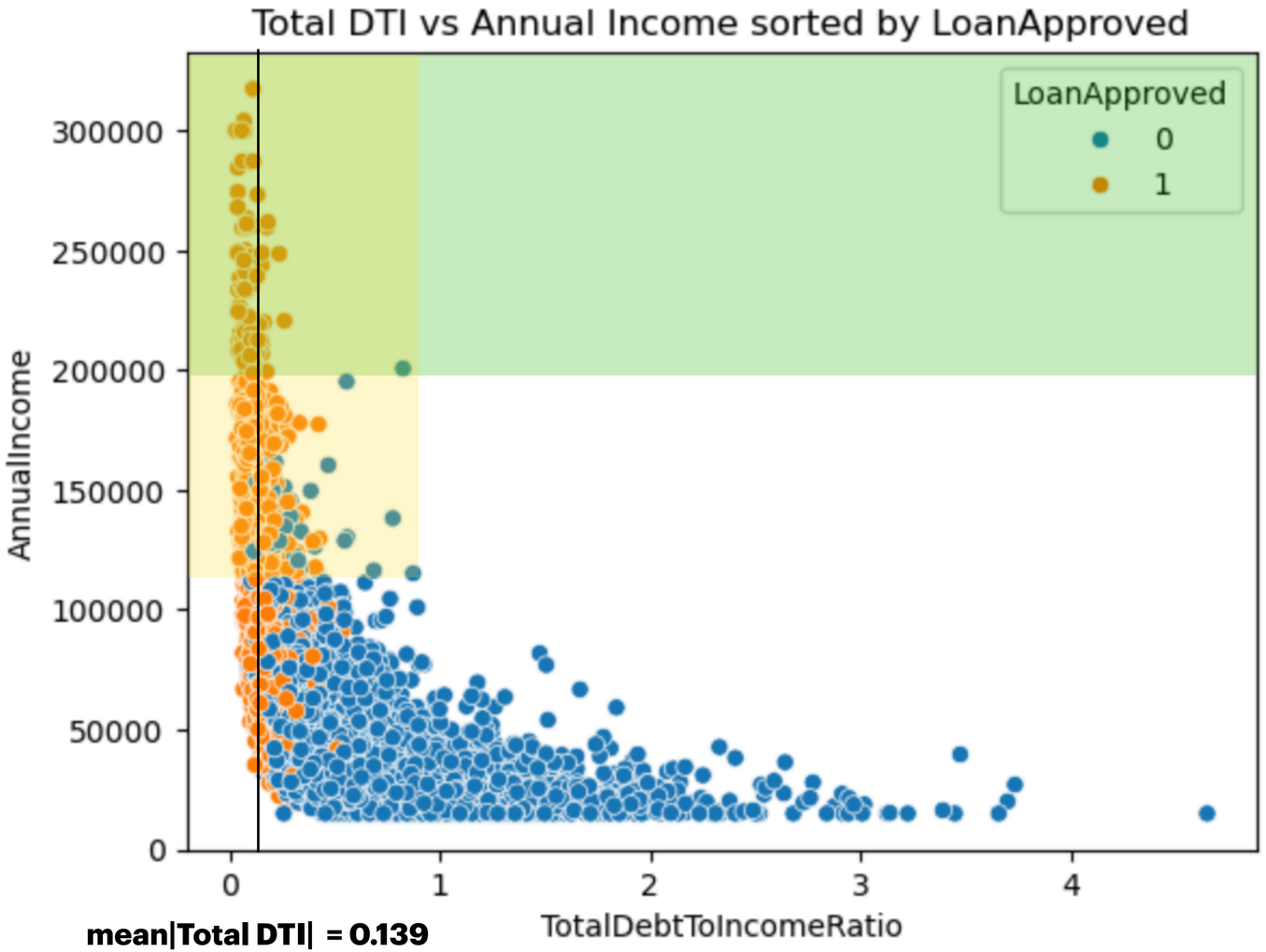
Self employed proportionally more likely to have their loan approved than employed/unemployed.



Below a proposed monthly loan payment of 1k, 38% of applicants were successful in getting a loan.
1-2k: 80.60% of applicants were rejected for a loan.
Above 2k: 90.10% of applicants were rejected for a loan.

EDA insights

Graphical Summary: Part 4



All applicants with >200k yearly salary were successful in getting a loan.

mean|Total DTI| = 0.139 with an annual income of 115k+, 90% of loans were approved.

Modelling Results

Performance Evaluation: Table

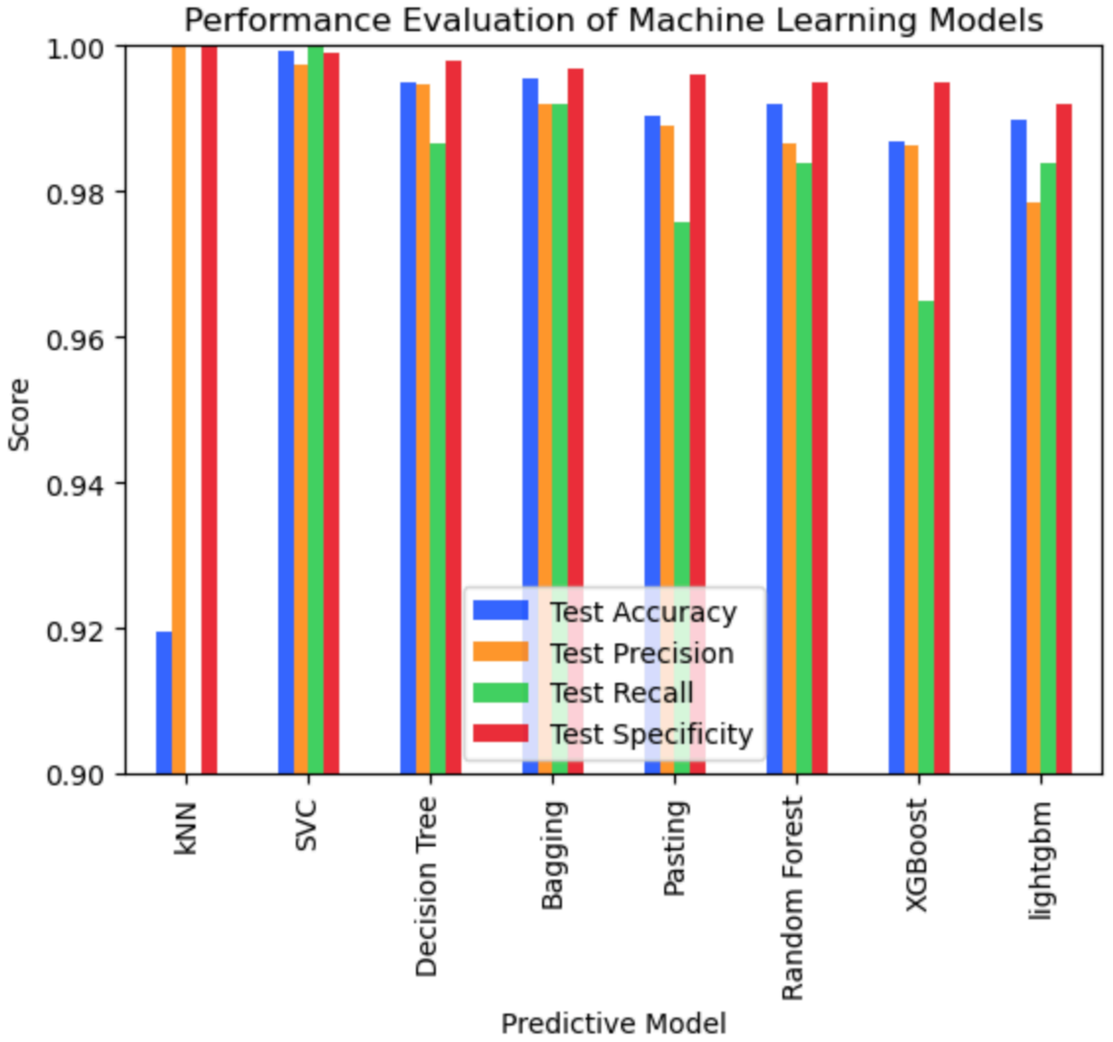
- Models sorted by test precision.
- Most precise model: kNN
- Most accurate model: SVC
- Best performing model overall: SVC

	Model	Test Accuracy	Test Precision	Test Recall	Test Specificity
0	kNN	0.919355	1.000000	0.703504	1.000000
1	SVC	0.999267	0.997312	1.000000	0.998993
7	lightgbm	0.994868	0.994565	0.986523	0.997986
6	XGBoost	0.995601	0.991914	0.991914	0.996979
4	Pasting	0.990469	0.989071	0.975741	0.995972
3	Bagging	0.991935	0.986486	0.983827	0.994965
2	Decision Tree	0.986804	0.986226	0.964960	0.994965
5	Random Forest	0.989736	0.978552	0.983827	0.991944

Modelling Results

Performance Evaluation: Graphical Comparison

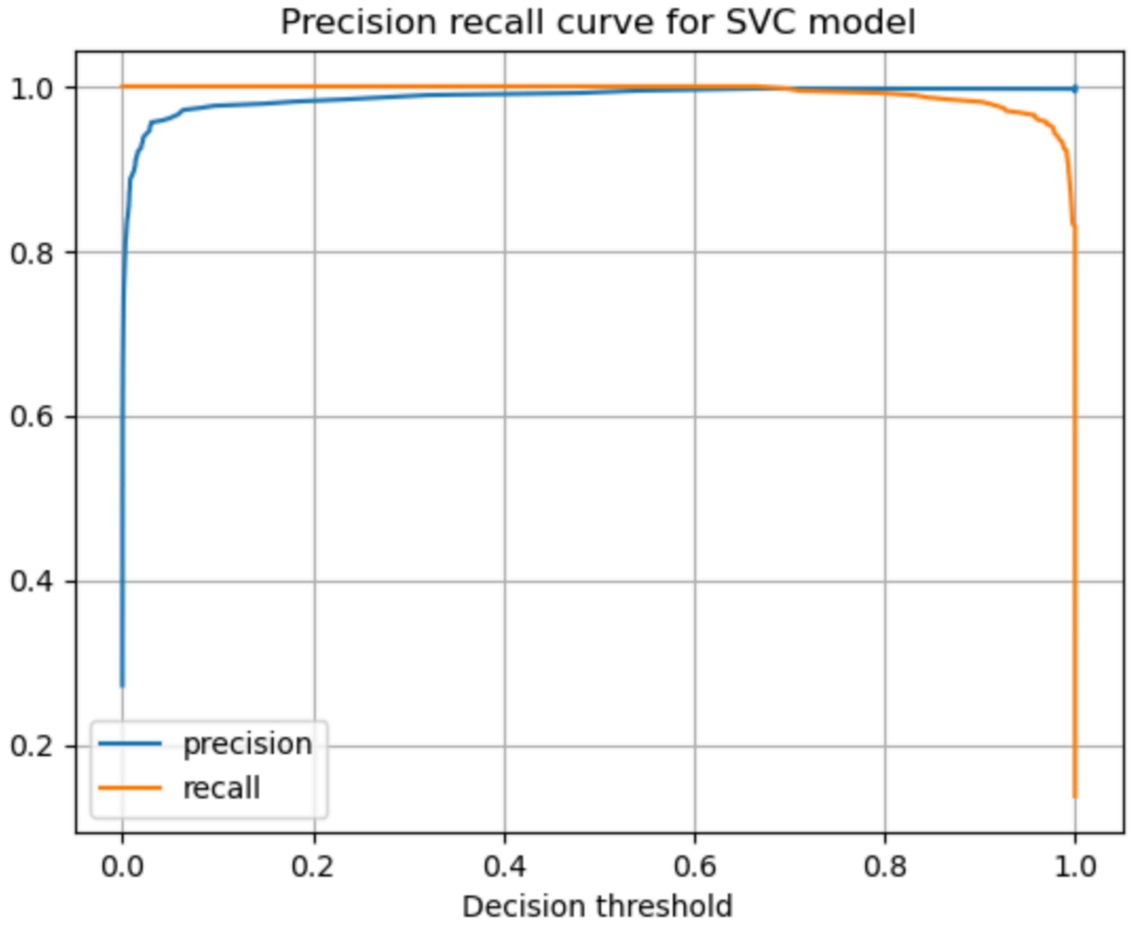
- kNN precise but less accurate.
- SVC strong all round performance
- Apart from kNN, none of the models dropped below 0.96 - very well fitted models and strong classification performance.
- Validates feature importances in next slides



Modelling Results

PR curve for overall best performing SVC model

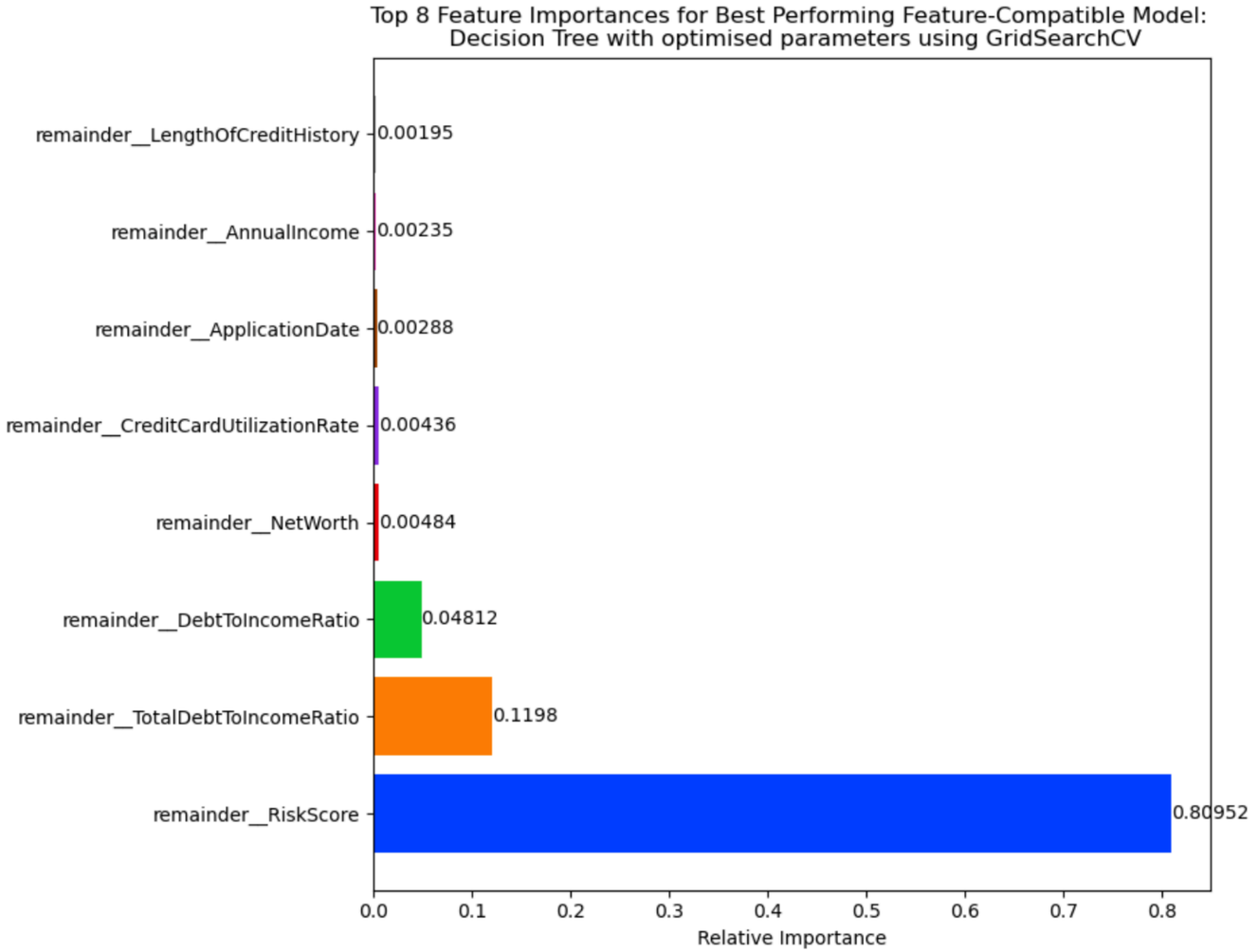
- Very sharply defined decision threshold.
- AUC (Area under curve) is approximately 1 (or very close to 1).
- This suggests an optimal, near-perfect fit.
- Performance in classification is very high, near 100%.



Modelling Results

Feature importances: Decision Tree model

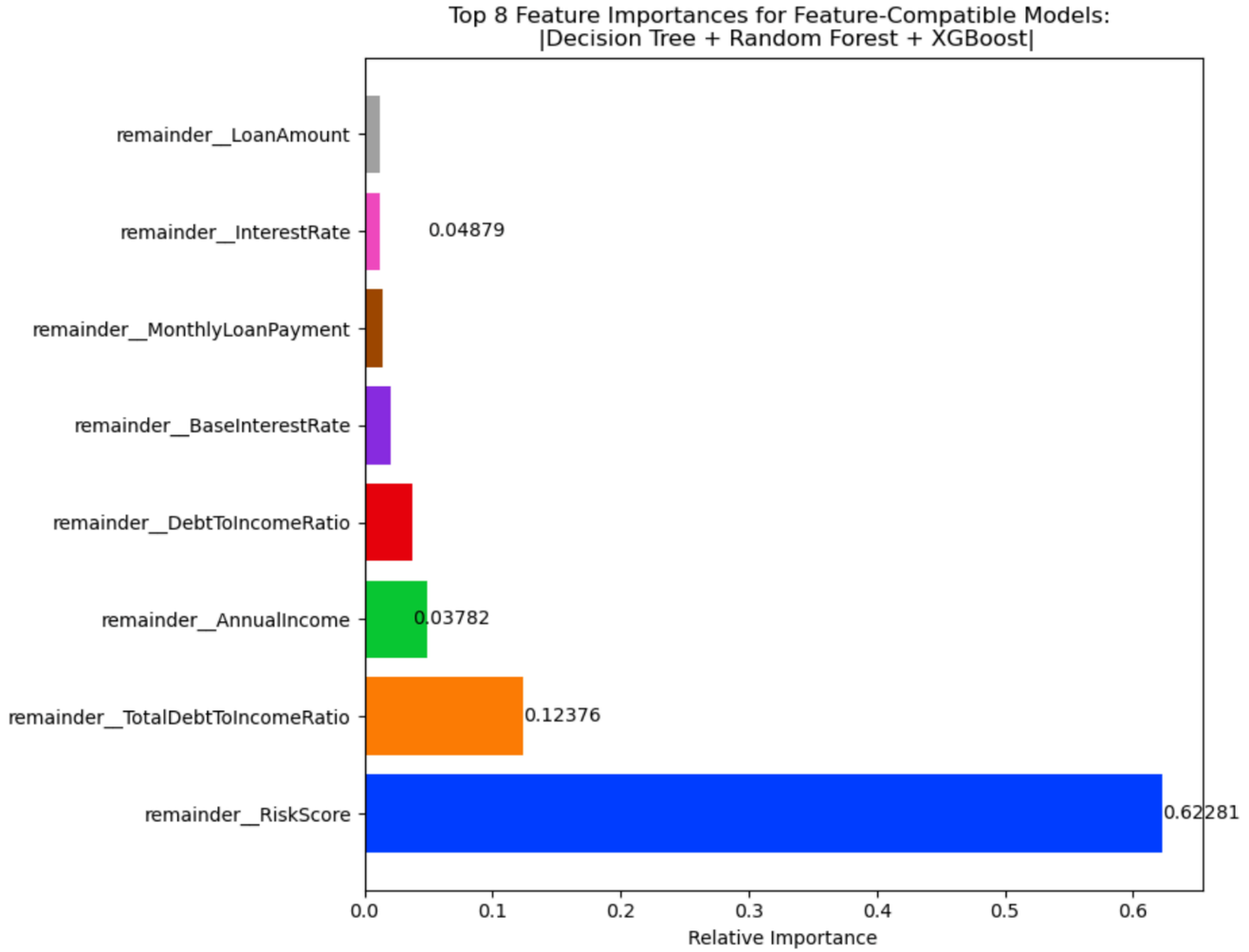
- Risk score overwhelming indicator of whether loan is approved.
- Other major factors include TotalDTI, DTI, Net Worth
- Lower income applicants with large debt payments have higher risk scores and are more likely to be rejected for a loan.



Modelling Results

Feature importances: |DT + RF + XGBoost|

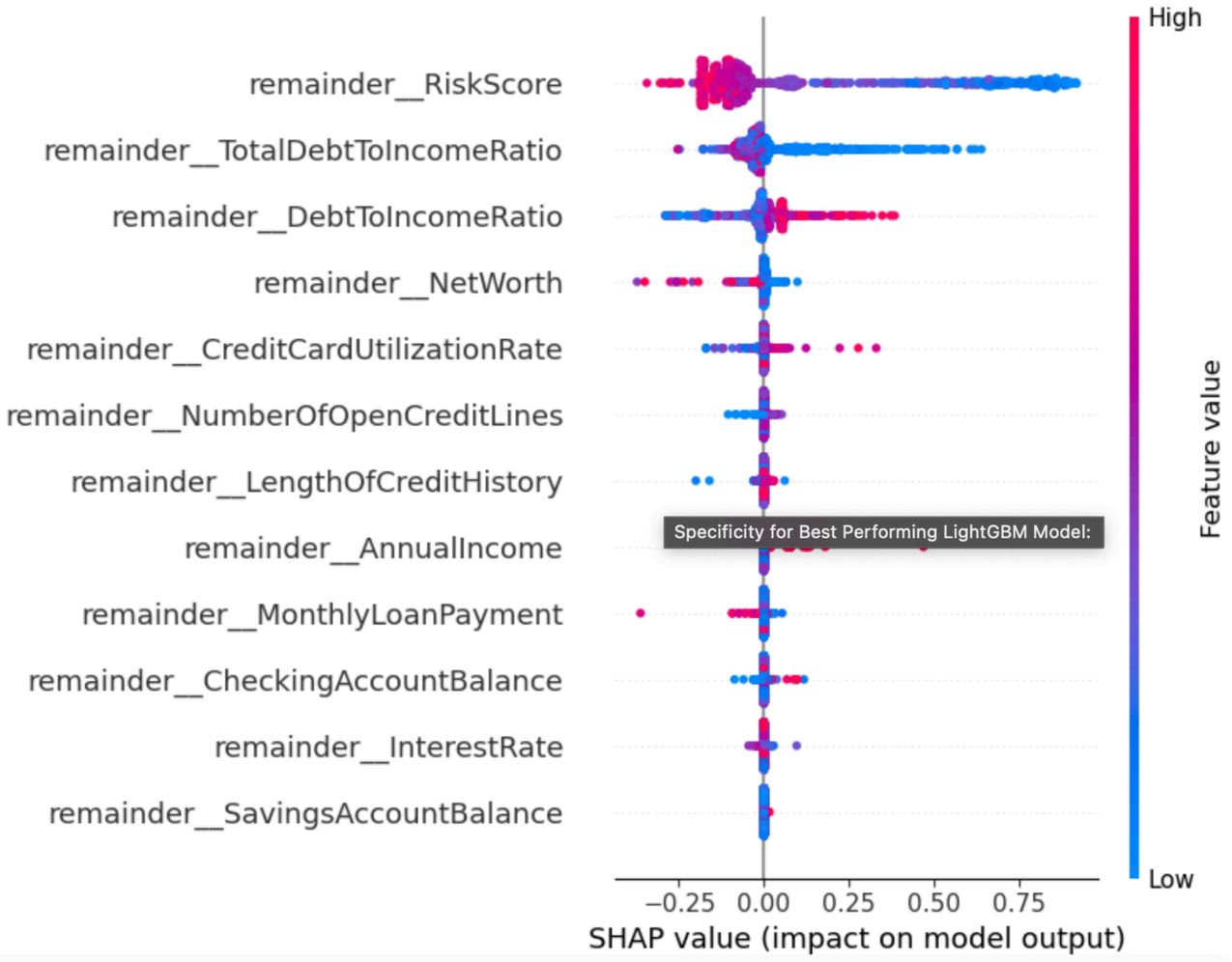
- Risk score biggest factor again.
- TotalDTI, Annual Income and DTI key factors in predicting loan approval.
- This matches the conclusions found in EDA: Higher incomes, lower debts, lower risk score -> loan more likely to be approved.



Modelling Results

SHAP analysis: Decision Tree model: Part 1

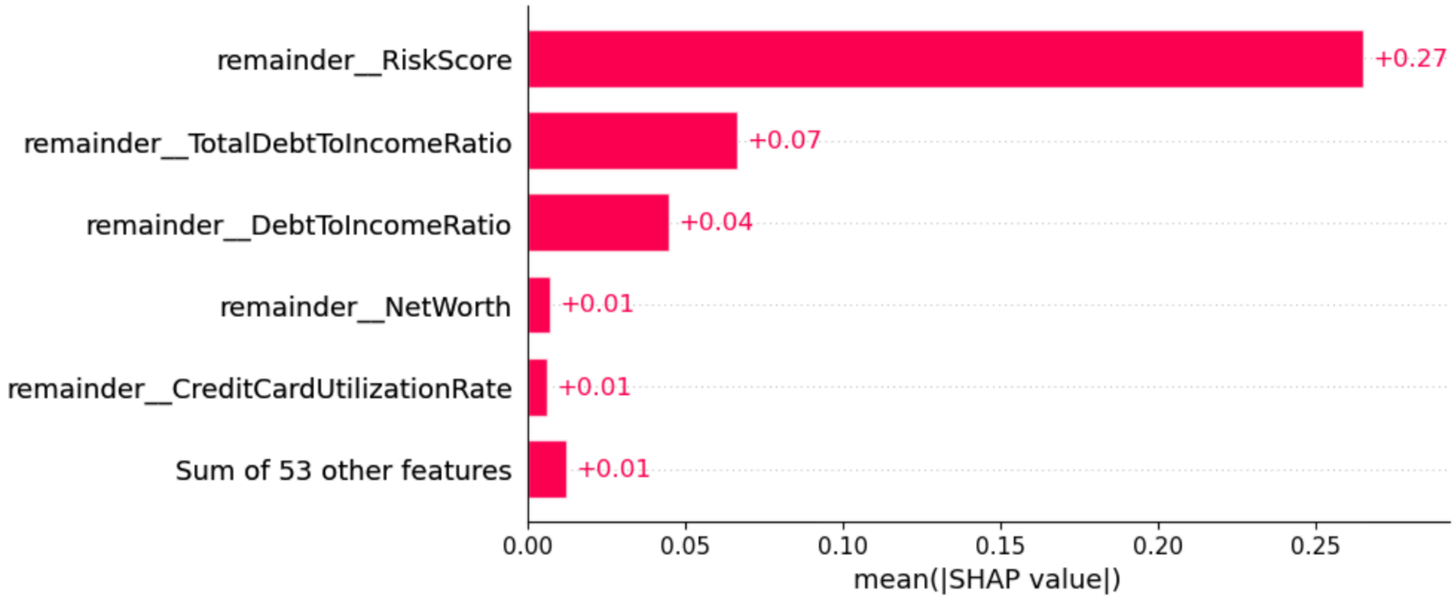
- High risk score: SHAP value is negative: Risk score predicts loan rejection. Most cases have a high risk score and are rejected (see dense red area in bee-swarm).
- Low TotalDTI: SHAP value is positive, Low TotalDTI predicts loan approval. Large spread of cases have low TotalDTI and are approved (see long blue area in bee-swarm).



Modelling Results

SHAP analysis: Decision Tree model: Part 2

- Biggest global factors that contribute to loan approval are Risk Score, TotalDTI, Net Worth.
- This matches the model-specific feature importance from earlier
- High debt, low income applicants seen as too risky to offer a loan and are thus rejected.



Business Impact

How much could the UK banking industry save annually?

- I created a mobile Streamlit app which can be used to calculate the annual savings to the UK banking sector using the precision specificity of a predictive ML model (like the ones in this study).
- Annual saving is approx £961 million with best model compared to not using a predictive model to classify loan applications.
- Based on average UK mortgage size in 2024, number of mortgages approved in Q1 of 2024 and average annual mortgage default rate.
- Link: https://mobileloancostapp-q4a9vpsebx2vffwlnly5dr.streamlit.app

Conclusions
Overall summary

- Key factors in predicting and classifying Loan Approval:
  - Risk Score: High risk score guarantees loan rejection.
  - Education: higher postgraduate educated applicants are more likely to be approved for a loan than undergraduates and high schoolers.
  - Annual Income: higher income applicants are very likely to be approved a loan and seen as low risk.
  - Size of loan: asking for a smaller loan and monthly loan repayments is seen as low risk and means you are more likely to be approved.
  - Debt-to-income ratio: having lower debt proportional to your income is seen as low risk and means higher chance of approval.

Next steps

Areas for improvement and further study

- Recommendations:
  - Use best predictive SVC model to implement classification of loan applications.
- Further study:
  - Use local SHAP analysis of best performing model to further validate conclusions (e.g. on RiskScore, Annual Income, etc).
  - Either improve the performance of feature-compatible models, or find a way to show feature analysis for the best performing SVC model.
  - Estimate business impact for a single bank: request and use a company dataset in a similar manner to this study.

Appendix
Extra bits

- Hyperparameters for best performing models:
  - kNN: (n_neighbors=101, algorithm = 'auto', weight = ‘uniform’).
  - SVC: (degree=2, kernel='poly', probability=True, random_state = 22).
  - Decision Tree: (ccp_alpha=0, criterion='entropy', max_depth=6, random_state=22).
  - Bagging: (DecisionTreeClassifier(max_depth=6), n_estimators=100, random_state = 22).
  - Pasting: BaggingClassifier(bootstrap=False, estimator=DecisionTreeClassifier(max_depth=8), n_estimators=50,random_state=22).
  - Random Forest: (ccp_alpha = 0, criterion = 'gini', max_depth = 12, min_samples_split = 3, n_estimators = 100, random_state = 22).
  - XGBoost: (ccp_alpha = 0, criterion = log_loss, max_depth = 17, min_samples_split = 2, random_state = 22).
  - Lightgbm does not take any hyper parameters