

Abstract geometric lines in the top-left corner of the slide, consisting of several thin black lines forming various polygons and intersecting each other.

PREDICTING LOAN DEFAULT

SHASHI BHUSHAN
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DSC 680

AGENDA

Introduction

Data Selection

Modeling and Methods Used

Interpretation of Analysis /

Model Results

Conclusion

An abstract geometric design featuring two thin, dark gray lines that intersect on a light gray background. One line is oriented diagonally from the top-left towards the bottom-right, while the other is oriented from the top-right towards the bottom-left. The intersection point is located in the upper-left quadrant of the image.

INTRODUCTION

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- In 3Q 2021, 64 million Americans had debt with collection agencies
- In 2008 financial crisis, mortgage default rates increased significantly



DATA SELECTION



KAGGLE

- Resource Link: <https://www.kaggle.com/datasets/yasserh/loan-default-dataset/data>
- Loan default noted as 0 or 1
- Data collected in 2022
- Both categorical and numerical data
- 148,670 rows

Features - ID, year, loan limit, gender, approved in advance, loan type, loan purpose, credit worthiness, open credit, business or commercial, loan amount, interest rate, upfront charges, loan term, negative amortization, lump sum payment, property value, construction type, occupancy type, secured by, total units, income, credit type, credit score, co-application credit type, age group, submission of application to institution or not, LTV, region, security type, Status, debt to income ratio.



MODELS AND METHODS USED

VISUALIZATIONS

Boxplots

1. Loan amount with categories positive loan default (1) and negative loan default (0)
2. Income with categories positive loan default (1) and negative loan default (0)
3. Credit Score with categories positive loan default (1) and negative loan default (0)

Bar charts

For positive default cases with below categorical variables:

- Gender
- Loan purpose
- Credit worthiness
- Age
- Region
- Security type

DATA PREPARATION

- Variables with > 10% missing values dropped
- Missing values imputed as noted below:
 - Categorical variables – mode
 - Numerical variables – KNN imputer using 5 neighbors
- Dummy variables created – one hot encoding

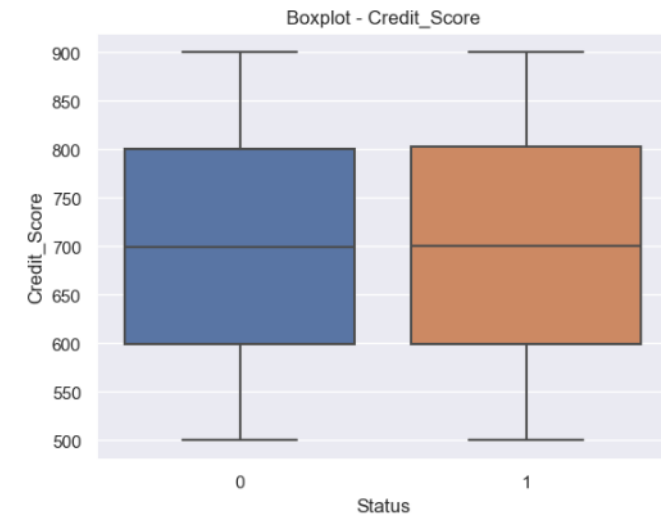
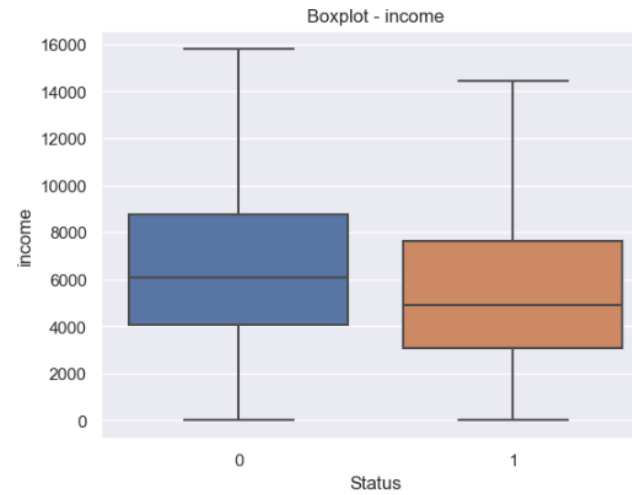
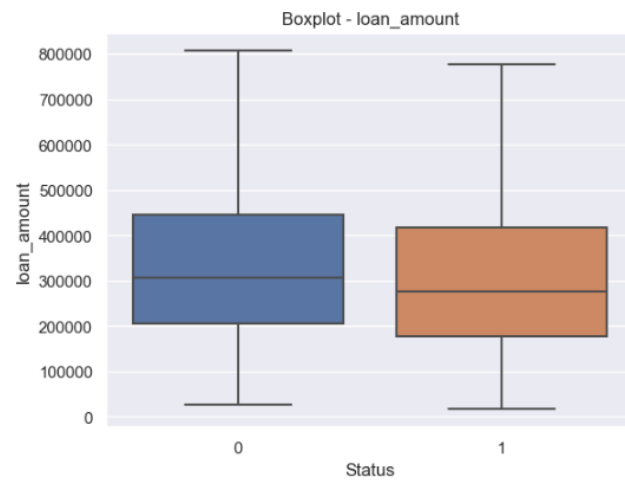
MODELING

- Target outcome – 1 or 0
- Created two models:
 - Random Forest
 - Naïve Bayes

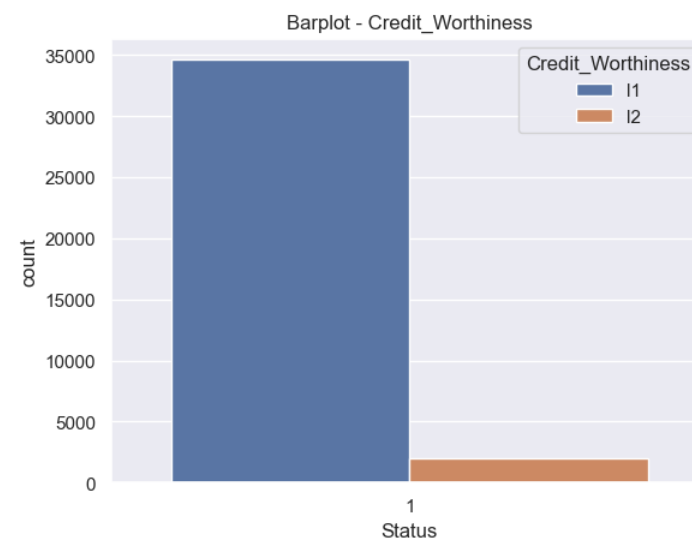
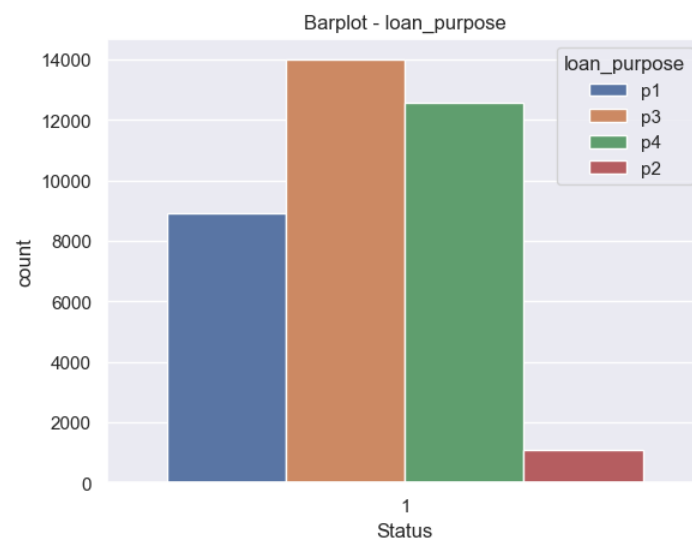
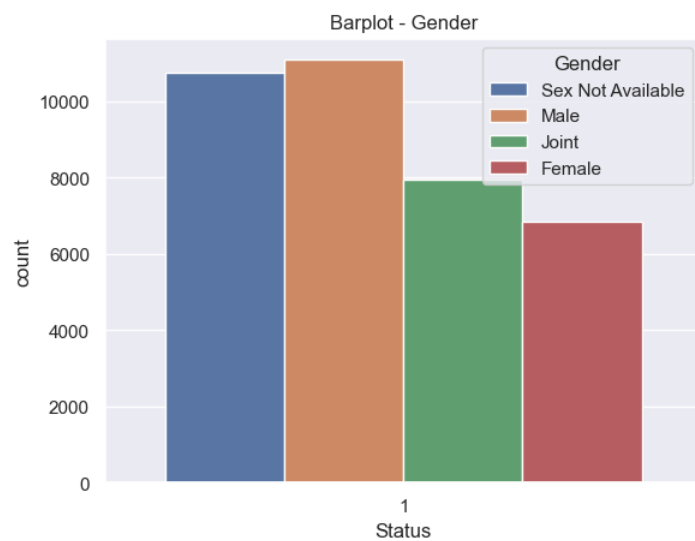


INTERPRETATION OF ANALYSIS / MODEL RESULTS

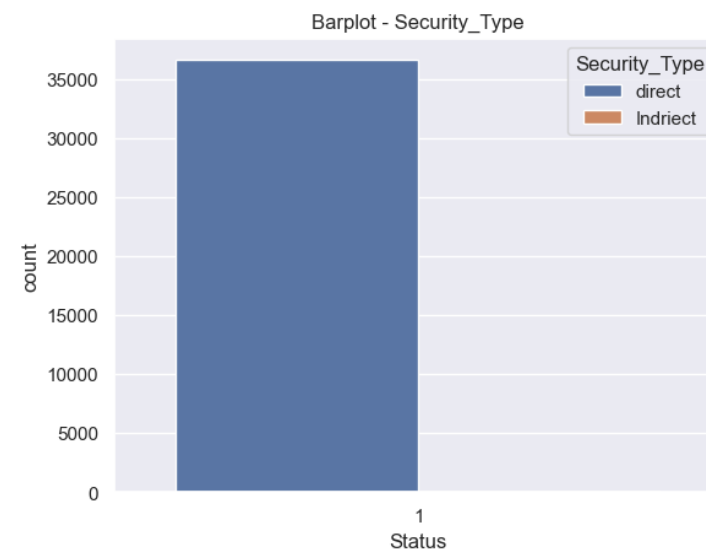
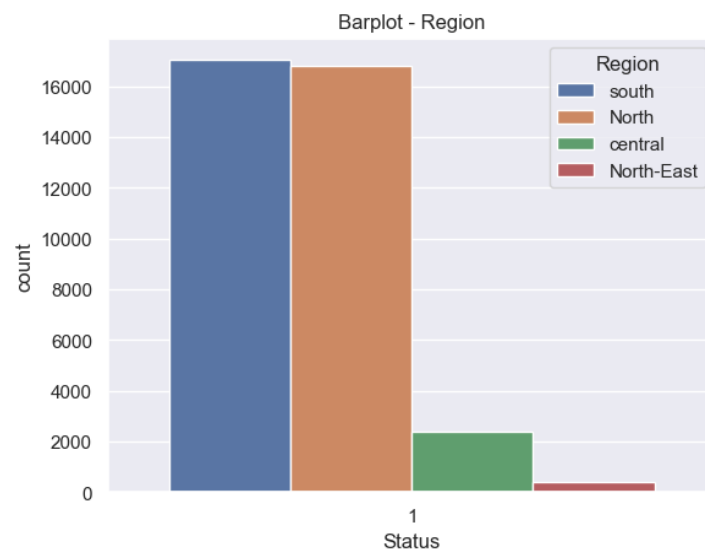
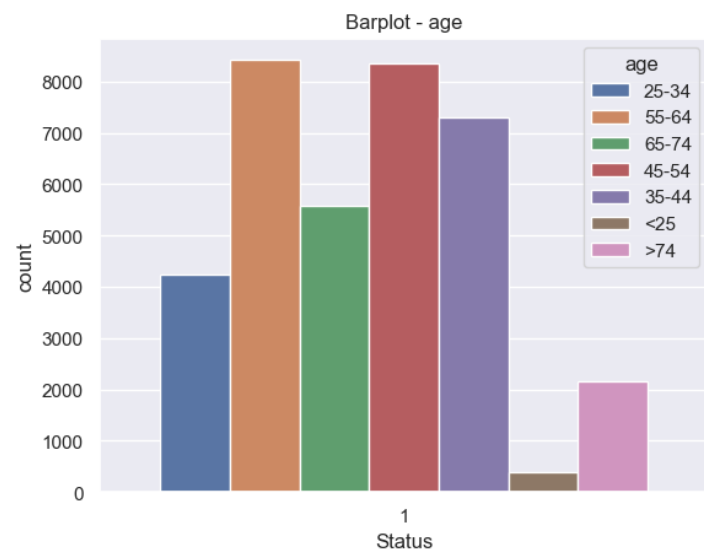
VISUALIZATIONS



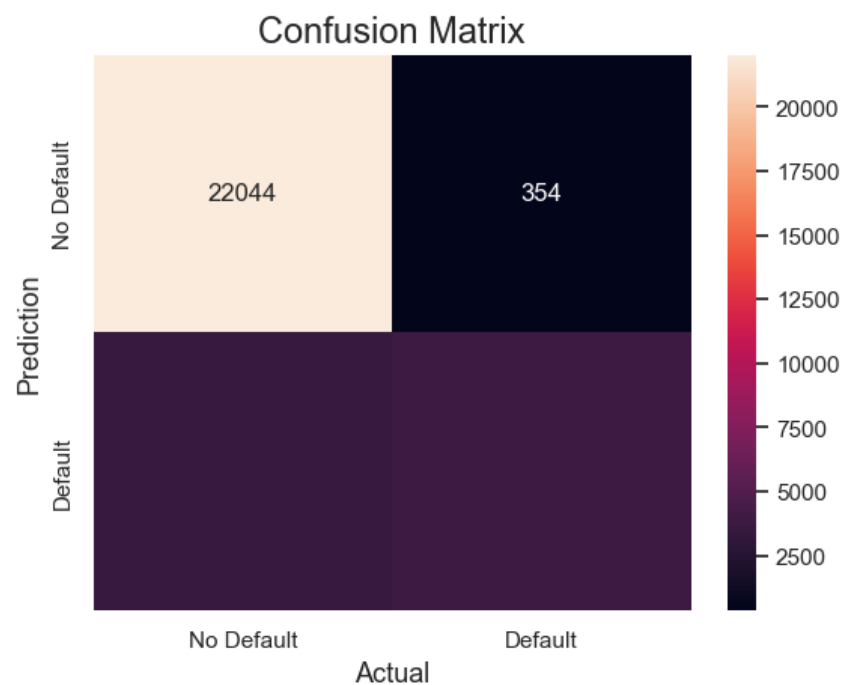
VISUALIZATIONS



VISUALIZATIONS

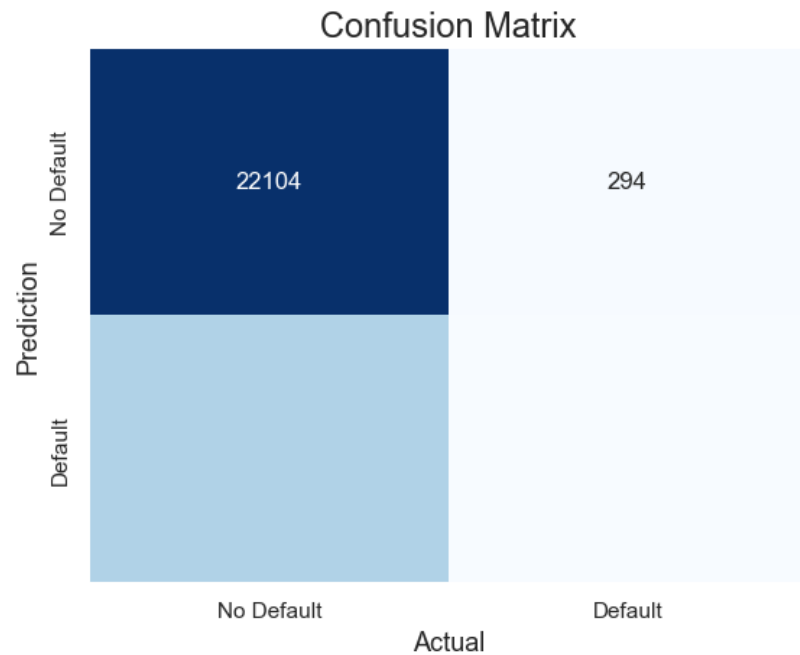


MODEL RESULT INTERPRETATION – RANDOM FOREST



	precision	recall	f1-score	support
0	0.86	0.98	0.92	22398
1	0.91	0.52	0.66	7336
accuracy			0.87	29734
macro avg	0.89	0.75	0.79	29734
weighted avg	0.88	0.87	0.86	29734

MODEL RESULT INTERPRETATION – NAÏVE BAYES



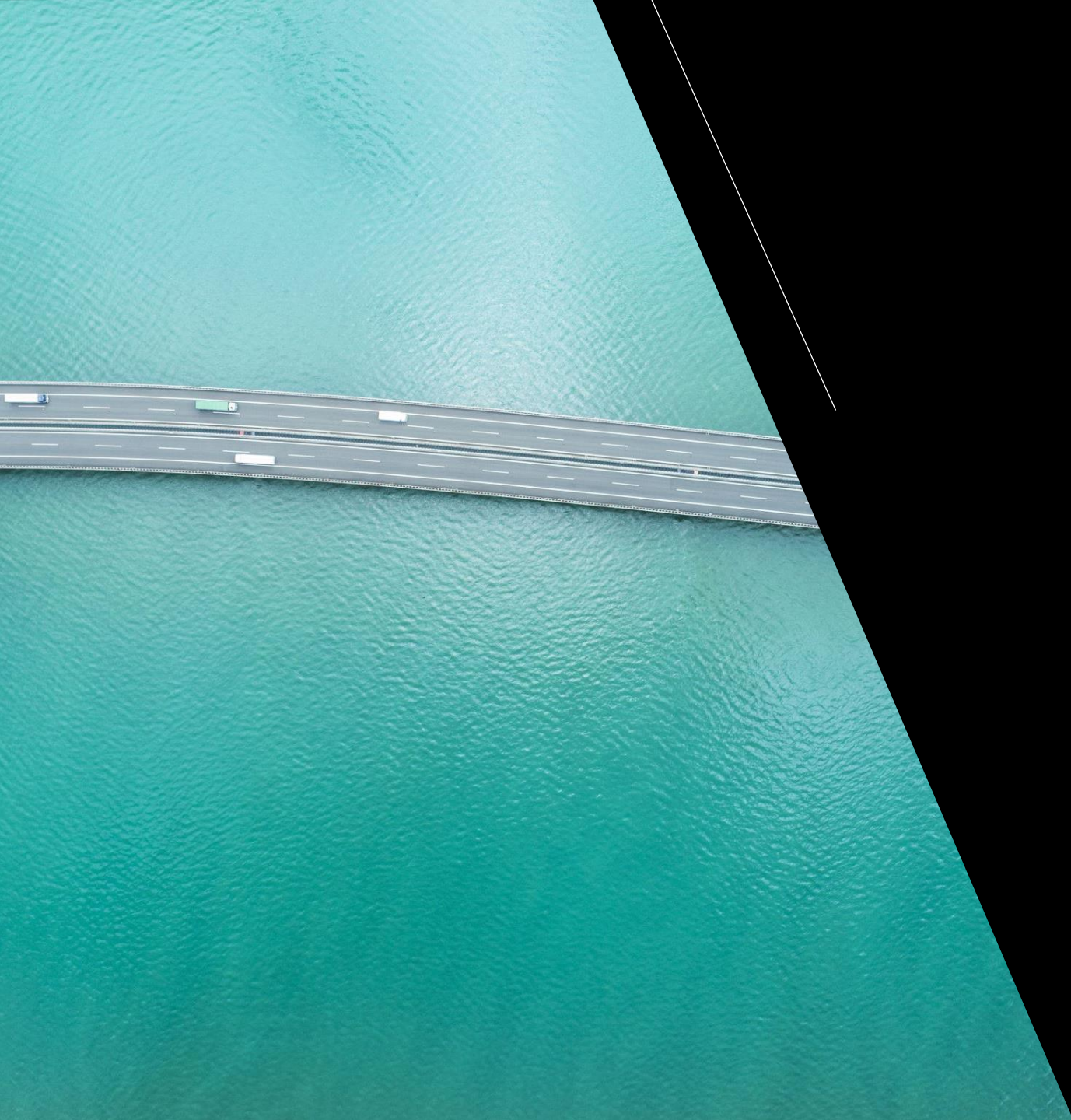
	precision	recall	f1-score	support
0	0.76	0.99	0.86	22398
1	0.37	0.02	0.05	7336
accuracy			0.75	29734
macro avg	0.56	0.51	0.45	29734
weighted avg	0.66	0.75	0.66	29734



CONCLUSION

Recommend Random Forest Model

- Higher accuracy for both 0 and 1
- High Precision, recall and f1 scores



THANK YOU