



BREIF

ANALYSIS

CONCLUSION

CREDIT SCORE FORECASTING

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01

DATA INTRODUCTION

Problem Statement and the dataset





We're working as a data scientists. Our dataset includes basic bank details with a lot of credit-related information. We're looking forward building an intelligent system that predict customers credit score based on the main features that effects it.

PROBLEM STATEMENT





CREDIT SCORE (TARGET)

Represents the bracket of credit score (Poor, Standard, Good). It's used to help the lender to decide either to lend the customer or not based on multiple features that affects the credit score.

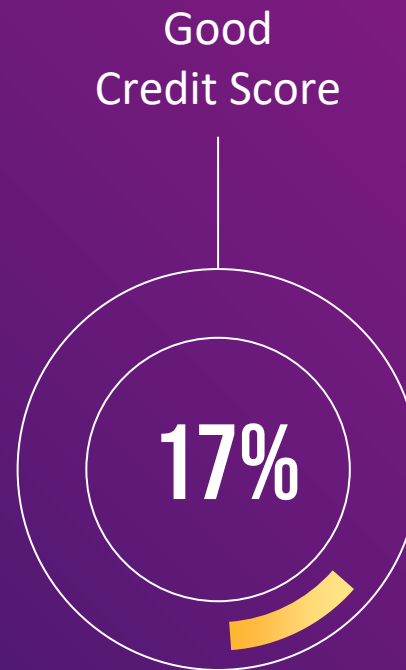




CREDIT SCORE DISTRIBUTION



Standard
Credit Score



Good
Credit Score



Poor Credit Score





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02

APPROACH OVERVIEW

Model Steps & Algorithms





MODEL STEPS:

READING THE DATA

Reading the Data After the Analysis.

01



02



SPLITTING

Splitting the Data to Train and Test.

04



03



STANDARDIZATION

Re-scaling the Data.

05



06

ENCODING

Get Dummies & Ordinal Encoder.

DROPPING & FEATURE SELECTION

Removing Irrelevant Columns and Selecting the Most Important Feature for the Model.

MODEL BUILDING

Training the Model & Fine Tuning Hyperparameter



MODEL STEPS:

READING THE DATA

Reading the Data After the Analysis.

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IN
8
MONTHS

12,500

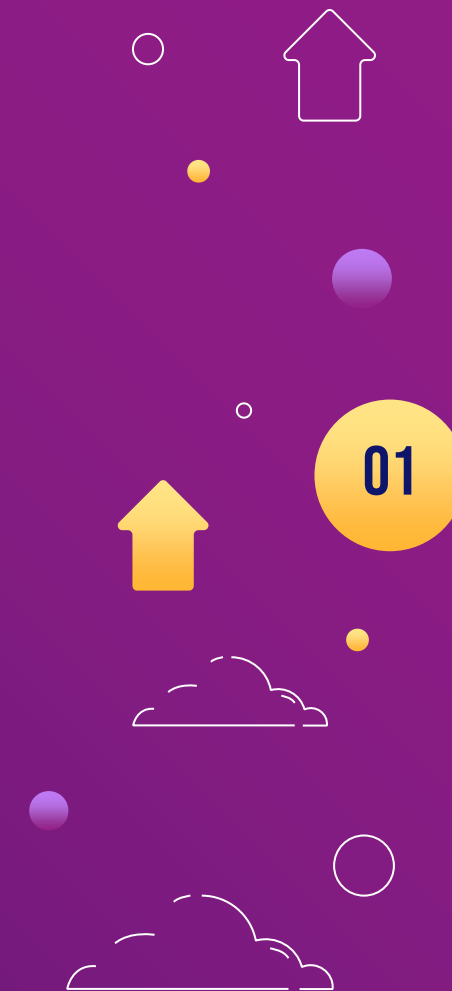
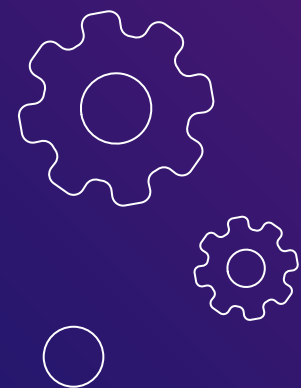
Number of Customers

100,000

Number of Rows

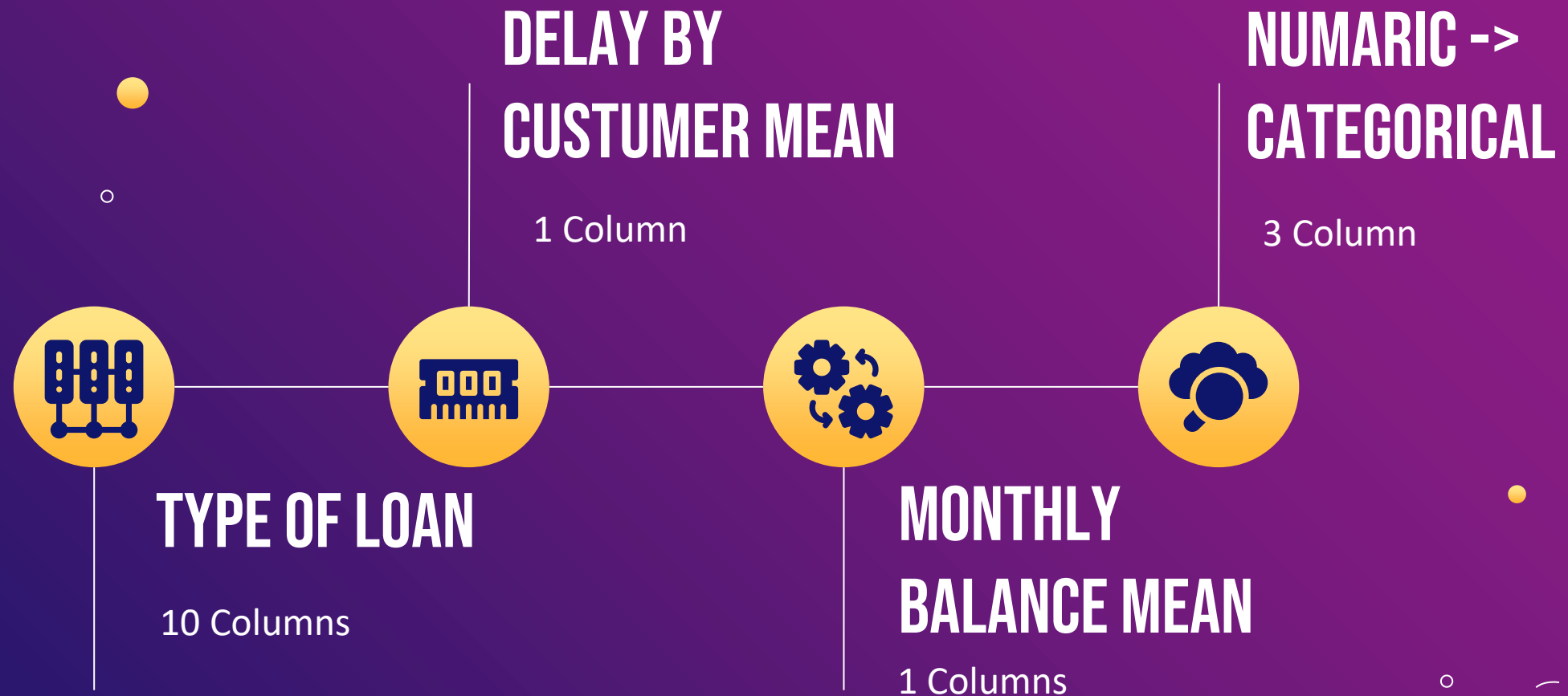
28 → 43

Number of Columns





COLUMNS DIGGER





02 ORDINAL ENCODING

CREDIT SCORE	MAPPINGS
Good	2
Standard	1
Poor	0

PAYMENT OF MIN AMOUNT	MAPPINGS
No	2
NM	1
Yes	0

CREDIT MIX	MAPPINGS
Good	2
Standard	1
Bad	0





GET DUMMIES ENCODING

OCCUPATION	ACCOUNTANT
Customer-1	1
Customer-2	1
Customer-3	0

PEYMENT BEHAVIOR	SMALL SPENT SMALL VALUE PAYMENT
Customer-1	0
Customer-2	1
Customer-3	0





03

COLUMN DROPPING

CUSTOMER ID

NAME

SSN

MONTHLY IN HAND SALARY

TYPE OF LOAN

ANNUAL CATEGORY

HISTORY AGE
CATEGORY

AGE CATEGORY



FEATURE SELECTION:



Before feature selection, we've chosen one month for our model.

After encoding for categorical features, we ended up with 49 columns and used 16 of them.

We used **SelectKBest** with **Mutual Information**.

Mutual information is a measure between two (possibly multi-dimensional) random variables X and Y , that quantifies the amount of information obtained about one random variable.

04

DATA SPLITTING

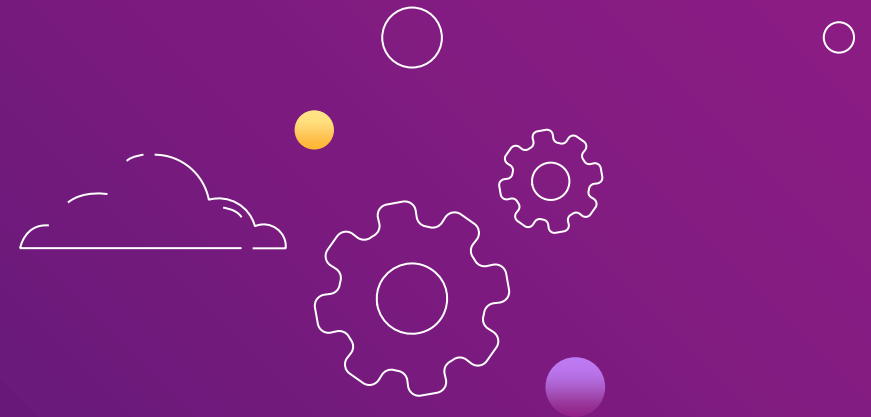
Training

80%

Testing

20%

Stratify Split to Ensure the Same
Distribution of Classes in Training and
Testing Data.





ALGORITHMS



XGBOOST CLASSIFIER

First: Accuracy -> 77%
Then: Accuracy -> 74%

VS

GRADIENT BOOST

Accuracy -> 77%





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CONCLUSION & RESULTS

Accuracy Before and After Fine Tunning





ACCURACIES



RESULTS

TEST ACCURACY

BEFORE FINE TUNNING 77%

AFTER FINE TUNNING 76%

TRAIN ACCURACY

BEFORE FINE TUNNING 79%

AFTER FINE TUNNING 82%





04

MODEL DEPLOYMENT

User Interface for the Credit Score Model.





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THANKS!

DO YOU HAVE ANY QUESTIONS?

Made with Lots of Love by the Most
Creative Clever People Ever.



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MAYAS MASALMEH

