DSCI-552 PROJECT

GROUP-6

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INTRODUCTION

Home Credit's Role and Vision

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- **Founded in 1997:** Home Credit is an established international consumer finance provider dedicated to responsible lending, particularly focusing on individuals with little or no credit history.
- **Commitment to Inclusion:** The company is committed to expanding financial inclusion and ensuring a positive, safe borrowing experience for the unbanked population.

The Challenge of Financial Inclusion

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- **Absence of Credit History:** Many individuals, especially younger ones or those preferring cash transactions, lack a traditional credit history, leading to frequent loan denials.
- **Critical Need for Accurate Data:** Effective loan repayment determination relies on robust data, which is often lacking for these underserved groups.

Technological Solution Through Data Science

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- **Innovation with Scorecards:** Consumer finance providers use advanced statistical and machine learning methods to develop predictive models, known as scorecards, for assessing loan risks.
- **Dynamic Adaptation Required:** The ever-changing behaviors of clients necessitate ongoing updates to these models to maintain their accuracy and relevance.

Balancing Stability with Performance

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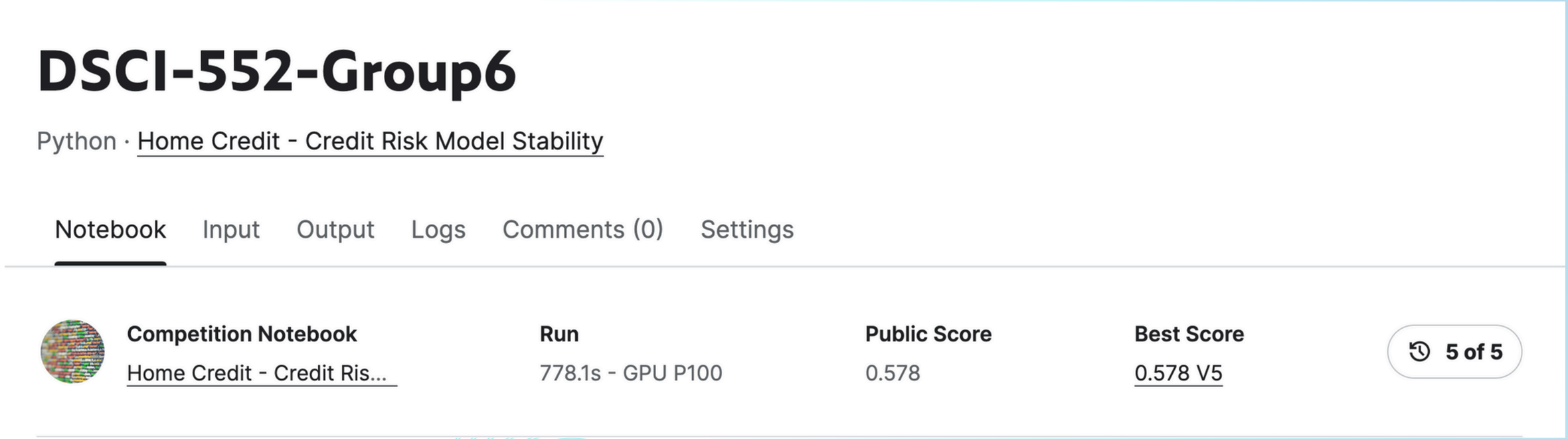
- **Importance of Model Stability:** Stability in predictive models ensures reliable risk assessments over time, which is essential to prevent an increase in loan defaults.
- **Achieving Optimal Performance:** The development and implementation of these models require a careful balance between their stability and performance to ensure effective deployment.

KEY ACCOMPLISHMENTS

Created a model to predict which clients are more likely to default on their loans with an accuracy of 57.8%.



DATASET DESCRIPTION

1 Base Tables and Dataset Composition

Fundamental Data:

- Base Tables: Store essential identifiers and basic information, which are fundamental for data linkage and preliminary analysis.
- Examples: train_base.csv, test_base.csv – these are pivotal for initiating all analyses.

Depth-Specific Data Layers:

- Static Data (Depth 0): Consists of non-time-variant data from both internal and external sources.
- Historical Data (Depth 1): Contains records detailing past interactions and behaviors.
- Detailed Historical Data (Depth 2): Provides granular insights into detailed historical behaviors.

2 Data Formats and Accessibility

File Formats:

- Available in both CSV and Parquet formats, enhancing accessibility and processing efficiency across different computing platforms.

Mirrored File Structure:

- The structure of the training and testing datasets mirrors each other, facilitating realistic testing environments and model validation.

3 Key Features and Data Transformations

Essential Columns:

- Identifiers and Metrics: Including case_id, date_decision, WEEK_NUM, MONTH, and target.
- Indexing for Depth: num_group1 and num_group2 are used for navigating through historical data layers.

Transformations Applied:

- Transformation Types: Days Past Due (P), categorical masking (M), amount adjustments (A), date transformations (D), Unspecified Transform(T) and Unspecified Transform(L).

4 Usage and Integration of Data for Predictive Analysis

Unique Identifier (case_id):

- Facilitates the seamless integration of data across various tables, ensuring coherent data merging for comprehensive analysis.

Data Layering:

- Utilizes **num_group1** and **num_group2** for aggregating historical data, enhancing the depth of analysis possible with the dataset.

Predictive Analysis Enhancement

- **Foundation for Modeling**: Base tables serve as the backbone for the entire predictive modeling process, underpinning the development of models that estimate default risks.
- **Comprehensive Data Utilization**: By integrating diverse data sources, the dataset allows for a holistic view of client profiles, crucial for accurate risk prediction.

DATA WRANGLING

Pipeline function - Data Preprocessing

drop_unnecessary_columns:

- Drops columns that are unnecessary for analysis to reduce complexity and improve model performance. (date columns)
- Drop columns with more than 70% missing values to reduce noise and improve data quality.
- Drop columns with only one unique value or more than 200 unique values which helps in reducing overfitting and improving model generalization.
- if (freq == 1) | (freq > 200)

AGGREGATOR CLASS - FEATURE ENGINEERING

1 Numerical Features

- Aggregates numerical features to extract useful information for statistical analysis and modeling.

2 Date Features

- Aggregates date features to extract temporal patterns and significant for time-based analysis and modeling.

3 String, Count, and Other Features

- Aggregates string features to extract textual patterns.
- Aggregates count features to summarize frequency.
- Aggregates other features to extract miscellaneous information.
- Aggregating these features for comprehensive analysis and modeling.

FEATURE ENGINEERING AND MEMORY OPTIMIZATION

Feature engineering process:

- Add month and weekday features based on "date_decision".
- Join additional depth DataFrames.
- Handle dates using the Pipeline method.

Memory optimization techniques:

- Reduce memory usage: Iterate through all columns of a dataframe and modify the datatype to reduce memory usage.

Importance of these functions in efficiently handling large datasets and optimizing memory usage

OUR APPROACH: CATBOOST CLASSIFIER

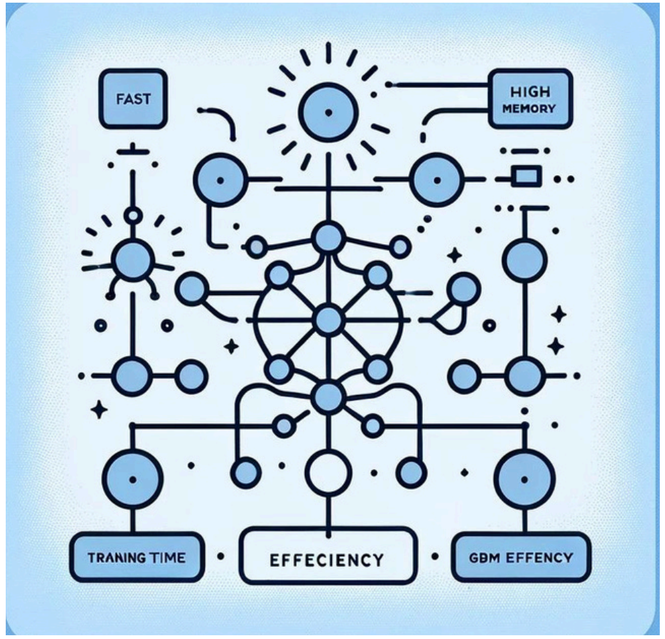
What is CatBoost?

- Open-source library for gradient boosting on decision trees
- Uses ordered boosting to optimize support of categorical features without the need for extensive preprocessing
- Builds symmetric tree architecture which serves as regularization and controls overfitting

OUR APPROACH: CHOOSING A MODEL

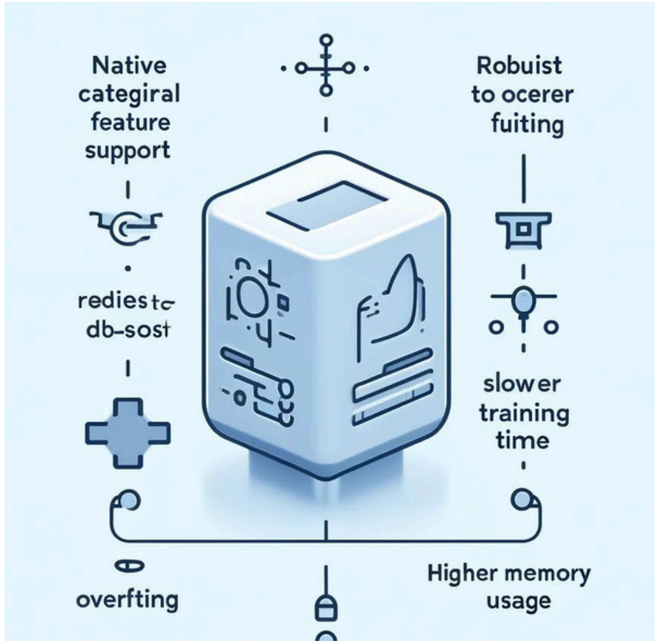
LIGHT GBM

- Requires extensive feature engineering
- Vulnerable to overfitting
- Fast training time
- High memory efficiency



CATBOOST

- Native categorical feature support
- Robust to overfitting
- Slower training time
- Higher memory usage



PREPROCESSING AND FEATURE SELECTION FOR TRAINING DATA

1 Data Loading and Preprocessing:

- Performing Feature Engineering on the dictionary that stores different dataframes generated from reading parquet files
- Using Pipeline for Data Preprocessing.
- Using Aggregator to extract features.

2 Handling Missing Values:

- Identifying columns with missing values and grouping them based on the number of missing values.
- Iterating through the grouped missing value columns and applying correlation-based grouping.

3 Feature Selection:

- Creating a list of selected features based on the grouping and selection criteria.
- Including categorical columns in the selected feature list.

PREPROCESSING AND FEATURE SELECTION FOR TEST DATA

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Data Loading and Preprocessing

Loading and preprocessing test data performing Feature Engineering.
Deleting unnecessary variables and garbage collecting to optimize memory usage

Feature Selection

Selecting features for the test data that are present in the training data.
Ensuring consistency between the features used in training and testing

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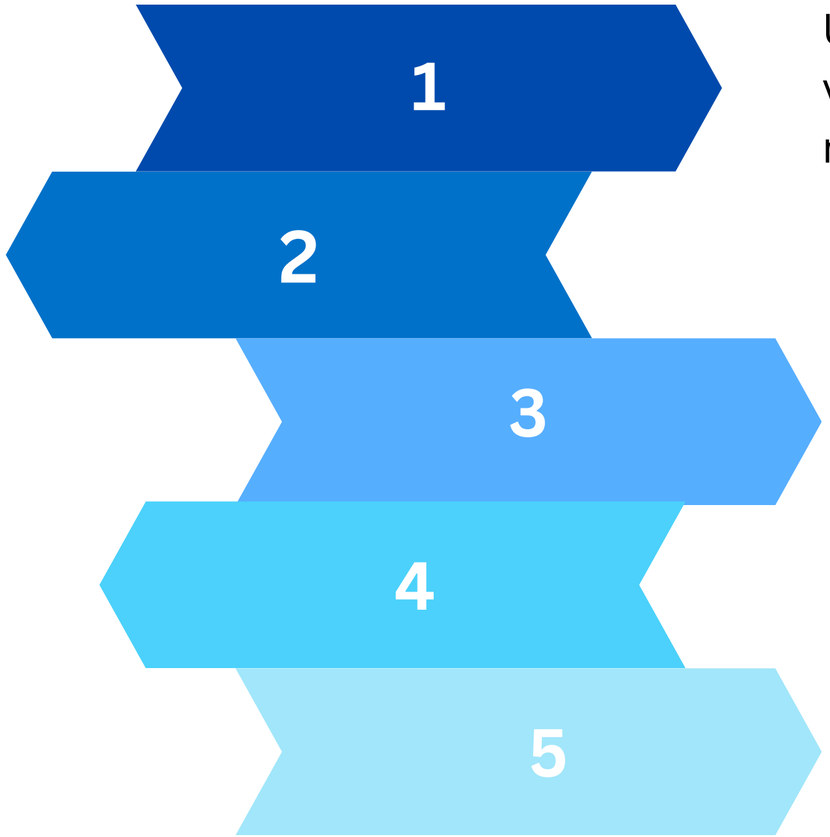
Memory Optimization

Converting the test data to pandas DataFrame format. Reducing memory usage of the test DataFrame. Performing garbage collection to release memory resources.

OUR APPROACH - CATBOOST CLASSIFIER

Dropping unnecessary columns such as "target", "case_id", and "WEEK_NUM" from the training data

Hyperparamter Tuning, Initializing and Training CatBoost Classifier



Using Stratified Group K-Fold cross-validation with 5 splits to evaluate the model's performance.

Converting categorical columns to string type to ensure compatibility with CatBoost's categorical feature handling.

Identifying the maximum AUC score achieved across all folds as the maximum CV AUC score.

OUR APPROACH - PARAMETERS USED

Evaluation Metrics used

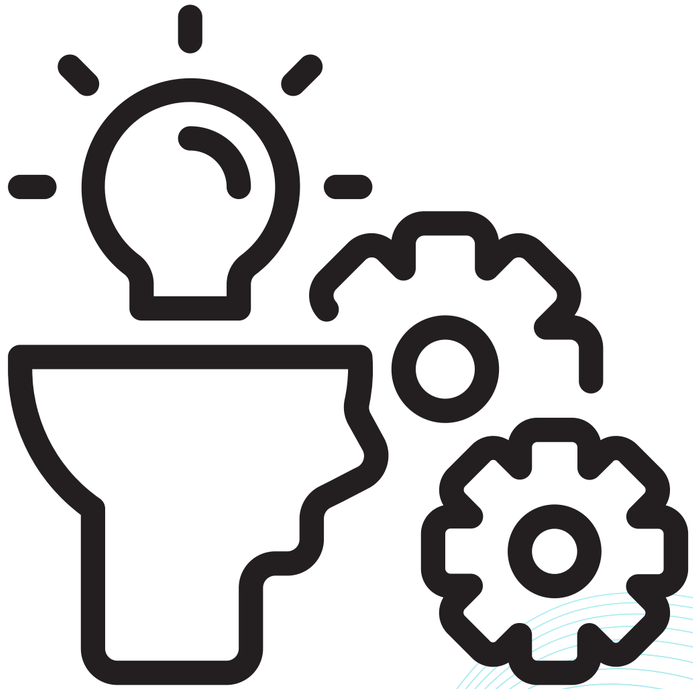
- Area Under the Receiver Operating Characteristic (ROC) Curve (AUC)

Learning Rate

- 0.03

AUC Score

- 0.82



OUR APPROACH - MODEL FITTING

1 Custom Voting Model Definition

- Capable of aggregating predictions from a list of base estimators

2 Model Initialization and Training

- Initializing the VotingModel with a list of fitted models (fitted_models), typically obtained from cross-validation or individual model training.

3 Prediction Generation

- Generating predictions (y_pred) using the custom VotingModel for the test data.

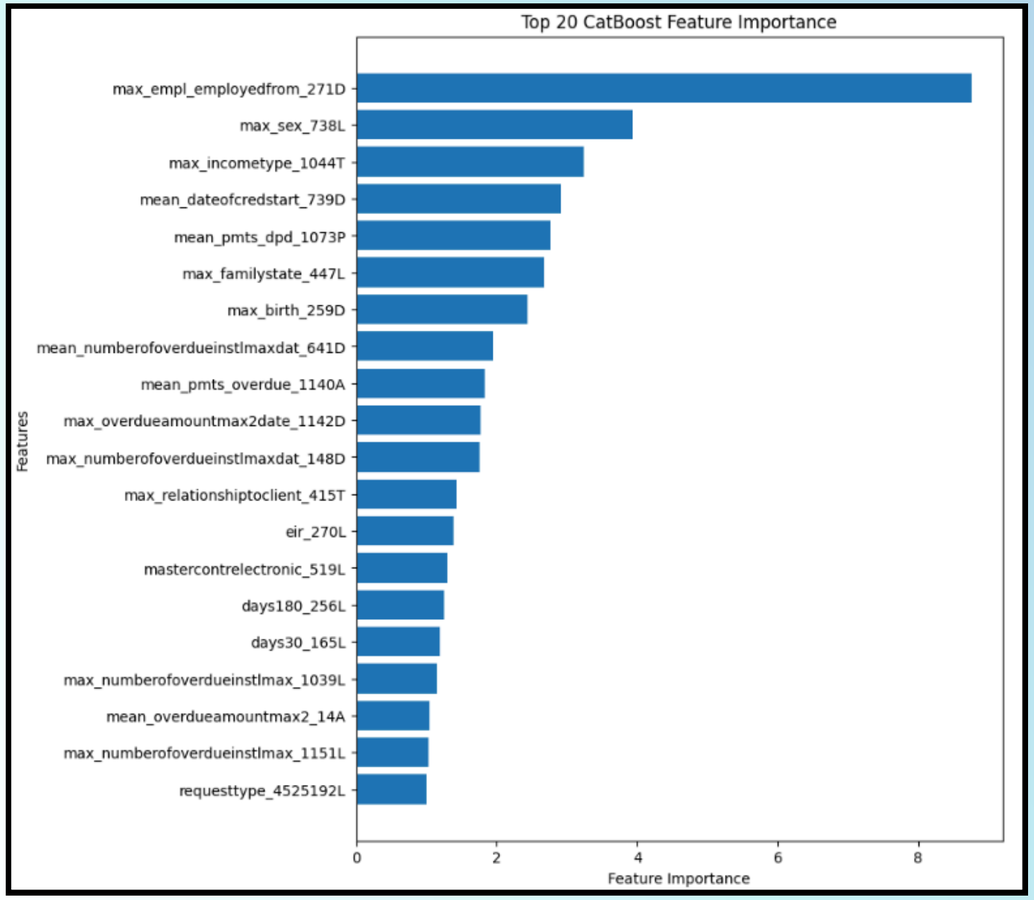
OUR APPROACH - ABLATION STUDIES

1 Feature Ablation

- Determined feature importance based on change in prediction values

2 Complexity Ablation

- Dropped unnecessary or excessively sparse columns
- Evaluated the impact of dropping columns with regards to overfitting and noise



Q & A

THANK YOU