# Predicting Home Credit Loan Default



**Group 3 - Navy Seals**

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# Outline

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# Background

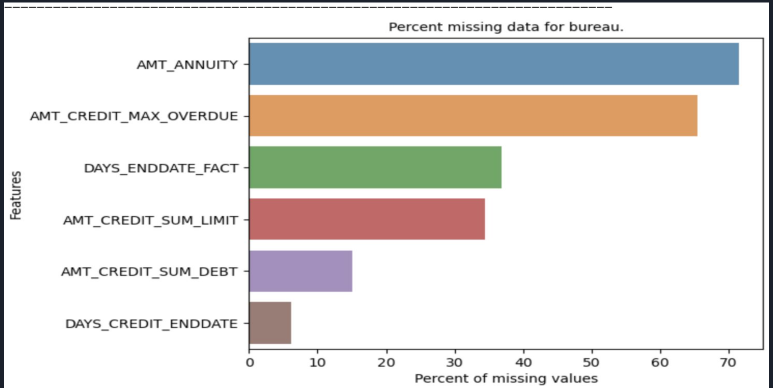
**High-Level Goal:** Build a machine learning model which can accurately predict whether the customer defaults on a loan or not.

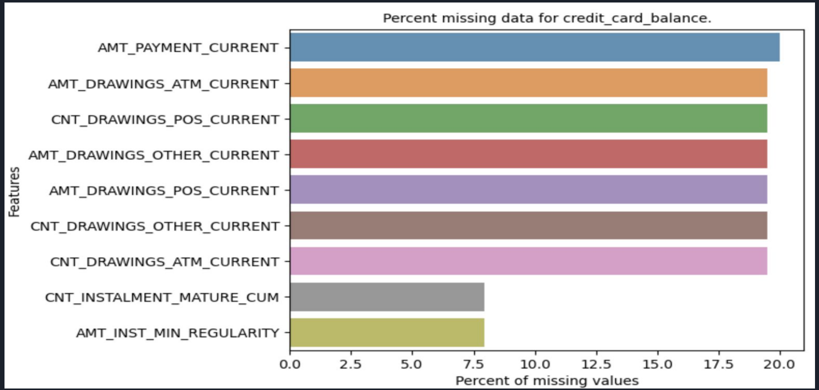
- **Phase 2 Objective:** compare six classification models' performance after hyperparameter tuning (along with additional feature engineering from Bureau dataset)

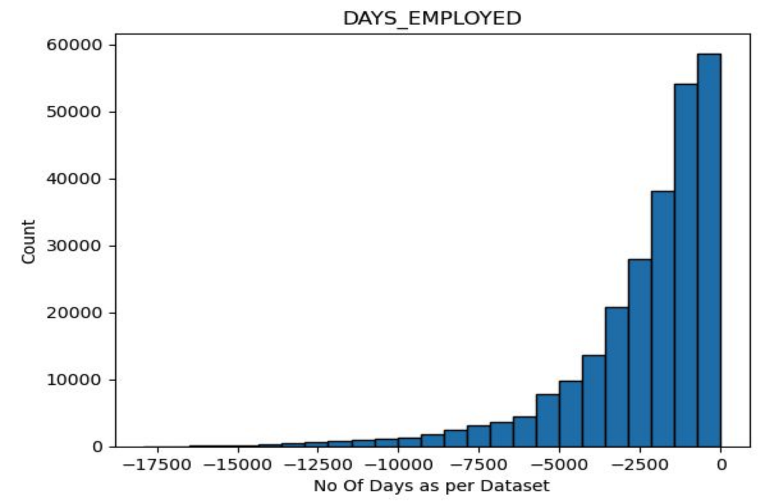
**Completed Activities:**

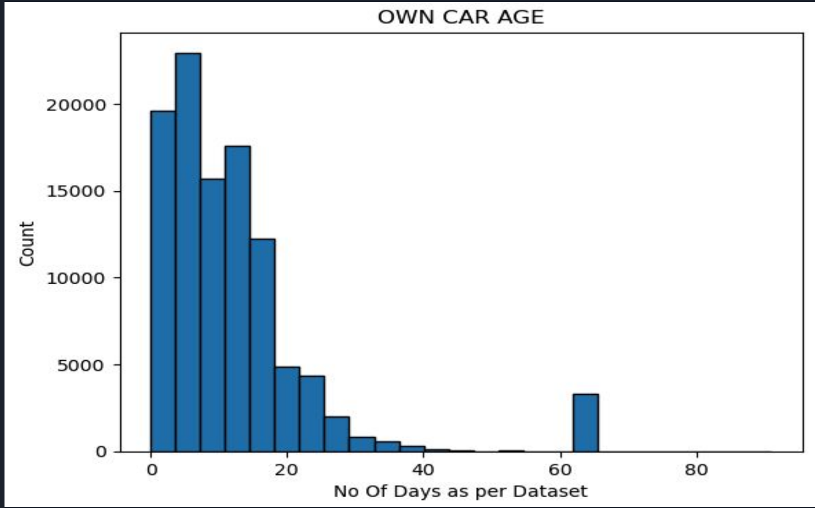
- Phase 0: Performed EDA on the datasets and  identified algorithms and evaluation metrics
- Phase 1: Implemented baseline model with Logistic Regression and fine-tuned parameters

# Additional EDA

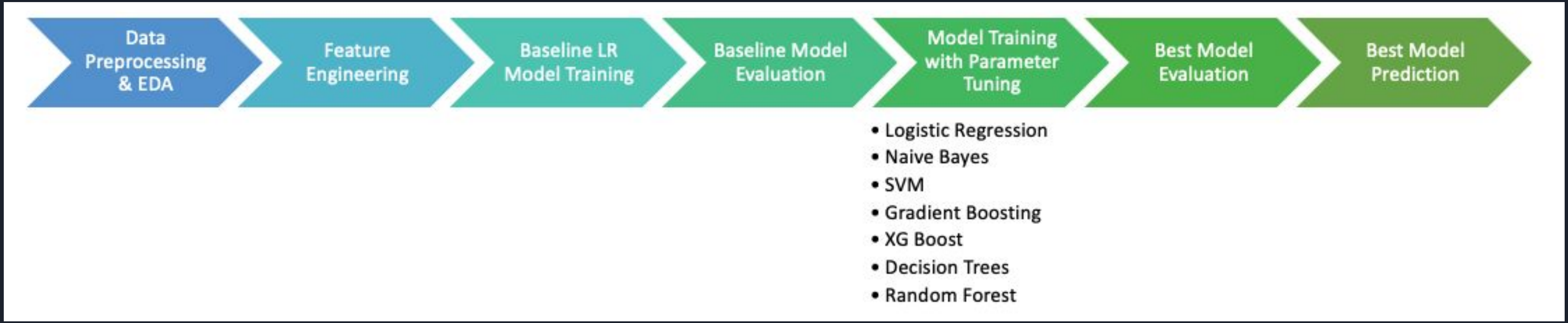


# Modeling Pipeline

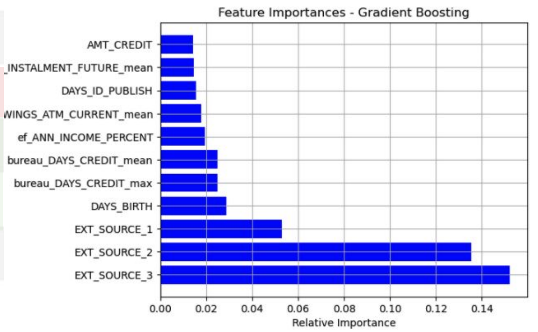



1. Data was downloaded, pre-processed , EDA, new features created, and data pipeline set-up with highly correlated numerical and categorical features
2. Implemented Grid Search to tune hyper-parameters with other classifier models
3. Grid search is performed on each classifier and generated evaluation metrics (accuracy score, AUC score, Log Loss, RMSE, MAE, and p-value), confusion matrix, and ROC curve plots.
4. Use above results to find the best performing model and submit to Kaggle.

# Results & Discussion

Final experiment results:

| | exp_name | Train Acc | Valid Acc | Test Acc | Train AUC | Valid AUC | Test AUC | Train Precision | Valid Precision | Test Precision | Train Recall | Valid Recall | Test Recall | Train Log Loss | Valid Log Loss | Test Log Loss | P Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Baseline_91_features | 0.9188 | 0.9191 | 0.9182 | 0.7615 | 0.7504 | 0.7567 | 0.4976 | 0.5600 | 0.3895 | 0.0206 | 0.0160 | 0.0148 | 2.7957 | 2.8187 | 2.8269 | 0.0000 |
| 1 | Logistic Regression | 0.9191 | 0.9188 | 0.9185 | 0.7589 | 0.7490 | 0.7561 | 0.5592 | 0.5000 | 0.4286 | 0.0172 | 0.0114 | 0.0132 | 2.7889 | 2.8107 | 2.8157 | 0.0477 |
| 2 | Naive Bayes | 0.1960 | 0.1929 | 0.1944 | 0.6583 | 0.6522 | 0.6489 | 0.0867 | 0.0861 | 0.0862 | 0.9340 | 0.9302 | 0.9303 | 27.8160 | 27.8216 | 27.8264 | 0.0000 |
| 3 | Gradient Boosting | 0.9235 | 0.9197 | 0.9185 | 0.8244 | 0.7582 | 0.7580 | 0.8198 | 0.5926 | 0.4636 | 0.0735 | 0.0366 | 0.0280 | 2.6279 | 2.8179 | 2.8157 | 0.0000 |
| 4 | XGBoost | 0.9230 | 0.9194 | 0.9190 | 0.8563 | 0.7592 | 0.7619 | 0.9132 | 0.6000 | 0.5200 | 0.0574 | 0.0240 | 0.0208 | 2.6005 | 2.8024 | 2.7989 | 0.0000 |
| 5 | DecisionTrees | 0.9188 | 0.9188 | 0.9188 | 0.7059 | 0.6966 | 0.6896 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 2.7960 | 2.8183 | 2.8034 | 0.8562 |
| 6 | RandomForest | 0.9193 | 0.9188 | 0.9188 | 0.8884 | 0.7454 | 0.7502 | 1.0000 | 0.0000 | 0.0000 | 0.0057 | 0.0000 | 0.0000 | 2.7792 | 2.8111 | 2.8034 | 0.0001 |




- Gradient Boosting and XGBoost - statistically significant improvement over baseline
- Naive Bayes was worst performing model, possible due to lack of proper feature weights
- No statistical significance achieved from Decision Tree; Random Forest same performance as baseline
- Phase 2 Kaggle score (0.74779) vs Phase 1 (0.74306)

| Name | Submitted | Wait time | Execution time | Score |
|---|---|---|---|---|
| submission_P2.csv | 38 minutes ago | 1 seconds | 1 seconds | 0.74779 |

Complete

# Conclusions & Next Steps

- Refined baseline model, engineered new features, and test against other classification models
- XGBoost and Gradient Boosting were best performing models

**Project Challenges:**

- Determine appropriate features to engineer and deal with missing data.
- **Memory issues** - needed to increase to 7 CPU's and 11GB memory in Docker to run the model. Running SVM crashed our kernels; also XGBoost kept running and hence couldn't submit for Kaggle.

**Next Steps:**

- For Phase 3, run PyTorch model in IU Red.
- Attempt SVM in new environment
- Examine feature engineering process