HOME CREDIT DEFAULT RISK

PROJECT PROPOSAL FIRST PRESENTATION

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Agenda

- Business problem
- Approach
- Data / Data wrangling
- Exploratory data analysis
- Predictive modeling
- Conclusion
- Future work

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Business Problem

Many people struggle to get loans due to insufficient or non-existent credit histories

This population is often taken advantage by untrustworthy lenders.

Home credit tries to include the unbanked population to support their economic needs.

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Goal

Identify if a new client shows a high risk for loan default

How can this help?

Reduce Uncertainty

Proportional Disbursement

Risk Reduction

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Data Set

The Data is taken from Kaggle's competition publicly available

application_train.csv

- 307511 Records, 122 Columns
- Imbalanced Target Labels.
- Source for training machine Learning models.
- Target Labels :
- 0's – 282686, 1's - 24825

application_test.csv

- 48744 Records, 121 Columns
- No Target Labels.
- Source for testing the performance of machine Learning models.
- Target Labels :
- None – need to predict.

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Understanding Data Set

There are 122 columns with different data types:

- 65 floating point numbers.
- 41 integer numbers – some are numerical categories.
- 16 Strings – Categories involved

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Data Clean

Cleaning steps can be many, relative to the approach taken & judgement calls.

Since the ML model can't inherently deal with text, the data must be converted to appropriate numbers. Any significant distortion/noise in the model must be removed as much as possible.

- Converting string categorical columns into numerical – Label encoding.
- Converting string categorical columns into numerical and adding new columns to indicate the presence of categorical variables – One hot encoding.
- Replacing illogical outliers with empty values (NAN values).
- Imputing empty cells with the median of the values. In some cases, imputation is approached with a certain grouping.
- Dealing with a few anomalies.
- Changing invalid entries into valid entries.

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Train Data Set Top 15 Columns with Missing values

	Missing Count	Missing Count Ratio	Missing Count %
COMMONAREA_MEDI	214865	0.698723	69.9
COMMONAREA_AVG	214865	0.698723	69.9
COMMONAREA_MODE	214865	0.698723	69.9
NONLIVINGAPARTMENTS_MODE	213514	0.694330	69.4
NONLIVINGAPARTMENTS_AVG	213514	0.694330	69.4
NONLIVINGAPARTMENTS_MEDI	213514	0.694330	69.4
FONDKAPREMONT_MODE	210295	0.683862	68.4
LIVINGAPARTMENTS_MODE	210199	0.683550	68.4
LIVINGAPARTMENTS_AVG	210199	0.683550	68.4
LIVINGAPARTMENTS_MEDI	210199	0.683550	68.4
FLOORSMIN_AVG	208642	0.678486	67.8
FLOORSMIN_MODE	208642	0.678486	67.8
FLOORSMIN_MEDI	208642	0.678486	67.8
YEARS_BUILD_MEDI	204488	0.664978	66.5
YEARS_BUILD_MODE	204488	0.664978	66.5

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Test Data Set Top 15 Columns with Missing values

	Missing Count	Missing Count Ratio	Missing Count %
COMMONAREA_AVG	33495	0.687161	68.7
COMMONAREA_MODE	33495	0.687161	68.7
COMMONAREA_MEDI	33495	0.687161	68.7
NONLIVINGAPARTMENTS_AVG	33347	0.684125	68.4
NONLIVINGAPARTMENTS_MODE	33347	0.684125	68.4
NONLIVINGAPARTMENTS_MEDI	33347	0.684125	68.4
FONDKAPREMONT_MODE	32797	0.672842	67.3
LIVINGAPARTMENTS_AVG	32780	0.672493	67.2
LIVINGAPARTMENTS_MODE	32780	0.672493	67.2
LIVINGAPARTMENTS_MEDI	32780	0.672493	67.2
FLOORSMIN_MEDI	32466	0.666051	66.6
FLOORSMIN_AVG	32466	0.666051	66.6
FLOORSMIN_MODE	32466	0.666051	66.6

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Different kinds of classes in every categorical column

	Categorical Column	Count
0	NAME_CONTRACT_TYPE	2
1	CODE_GENDER	3
2	FLAG_OWN_CAR	2
3	FLAG_OWN_REALTY	2
4	NAME_TYPE_SUITE	7
5	NAME_INCOME_TYPE	8
6	NAME_EDUCATION_TYPE	5
7	NAME_FAMILY_STATUS	6
8	NAME_HOUSING_TYPE	6
9	OCCUPATION_TYPE	18
10	WEEKDAY_APPR_PROCESS_START	7
11	ORGANIZATION_TYPE	58
12	FONDKAPREMONT_MODE	4
13	HOUSETYPE_MODE	3
14	WALLSMATERIAL_MODE	7
15	EMERGENCYSTATE_MODE	2

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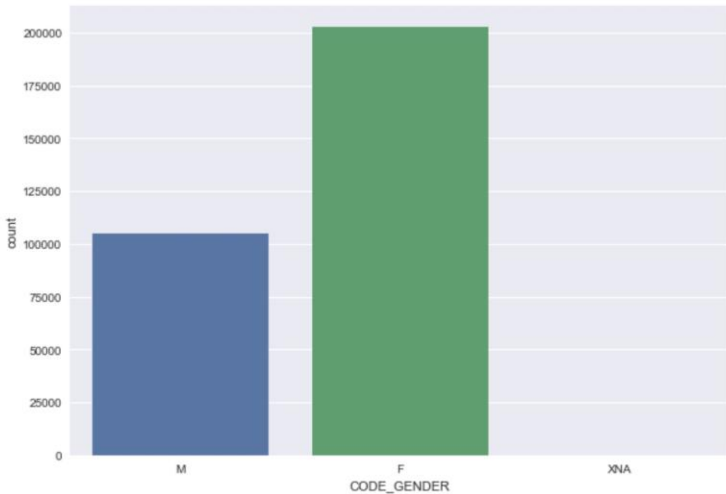
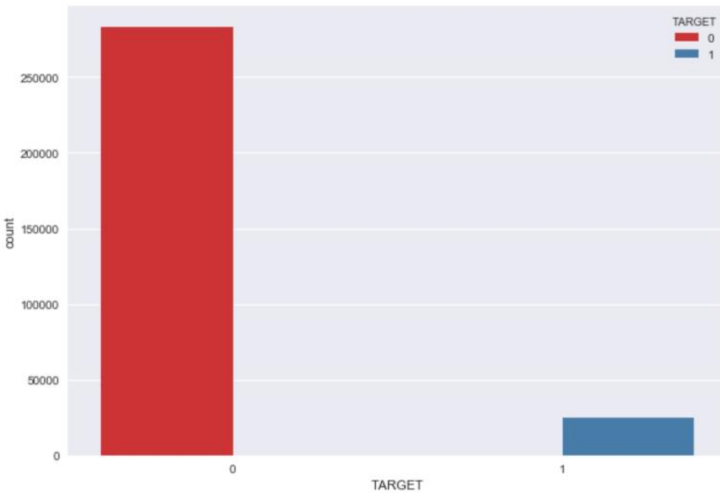
Target Column

EDA suggests that most people returned the money





Females are the highest borrowers with counts:
F - 202448
M - 105059
XNA - 4

Most people returned the borrowed money:
0 - 282686
1 - 24825

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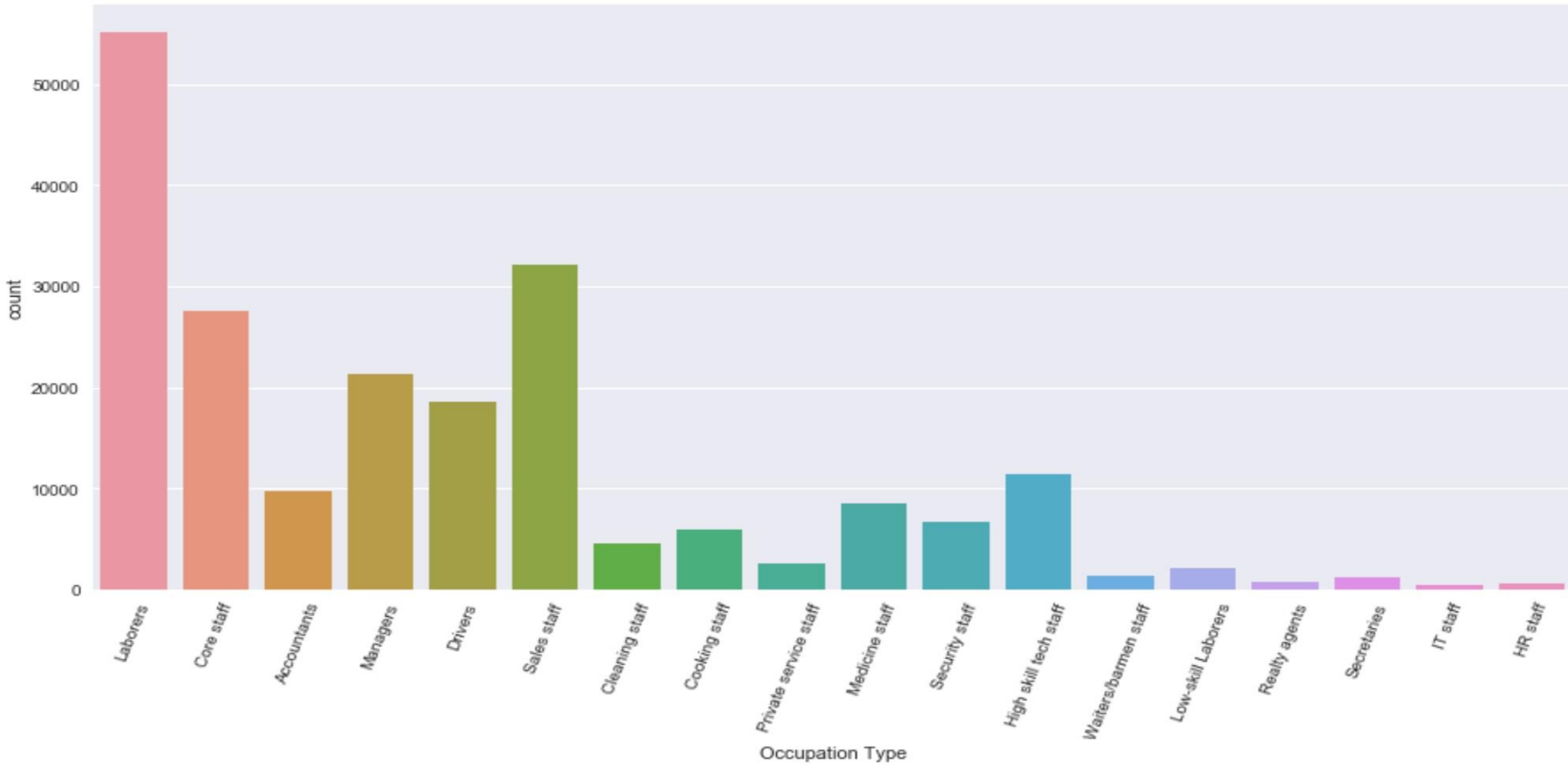
Occupation type vs Borrowers

Laborers - occupation type were the most borrowers.



Most of the clients are laborers and the least of the clients are IT Staff.

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ML Models

Predictive Modeling – Outcome of the model is expected to identify the potential that someone will default on a loan

Expected Target Outcome: 0 or 1, 0 – Not a defaulter, 1 – potential defaulter.

Performance Metrics : Accuracy.

ML Models : Logistic regression, Random forest, XGBoost, LightGBM, Naïve bayes, ensemble.

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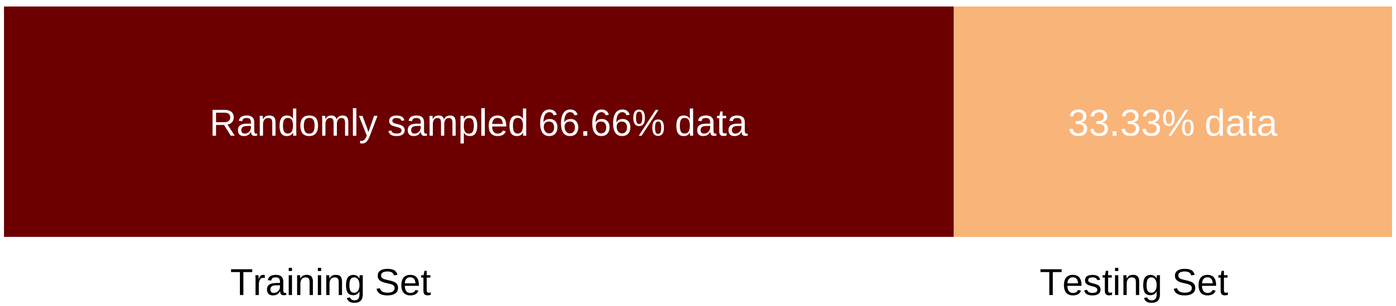
Data Partition and Preparation

Training and Testing datasets were subjected to the same feature engineering to evaluate the model.



- Out of the main training dataset, a certain percentage is kept untrained to test the model's performance.
- Training set and validation set are split in following percentages: 66.66% : 33.33%.
- On the testing set, the target labels are hidden, until the performance is evaluated.

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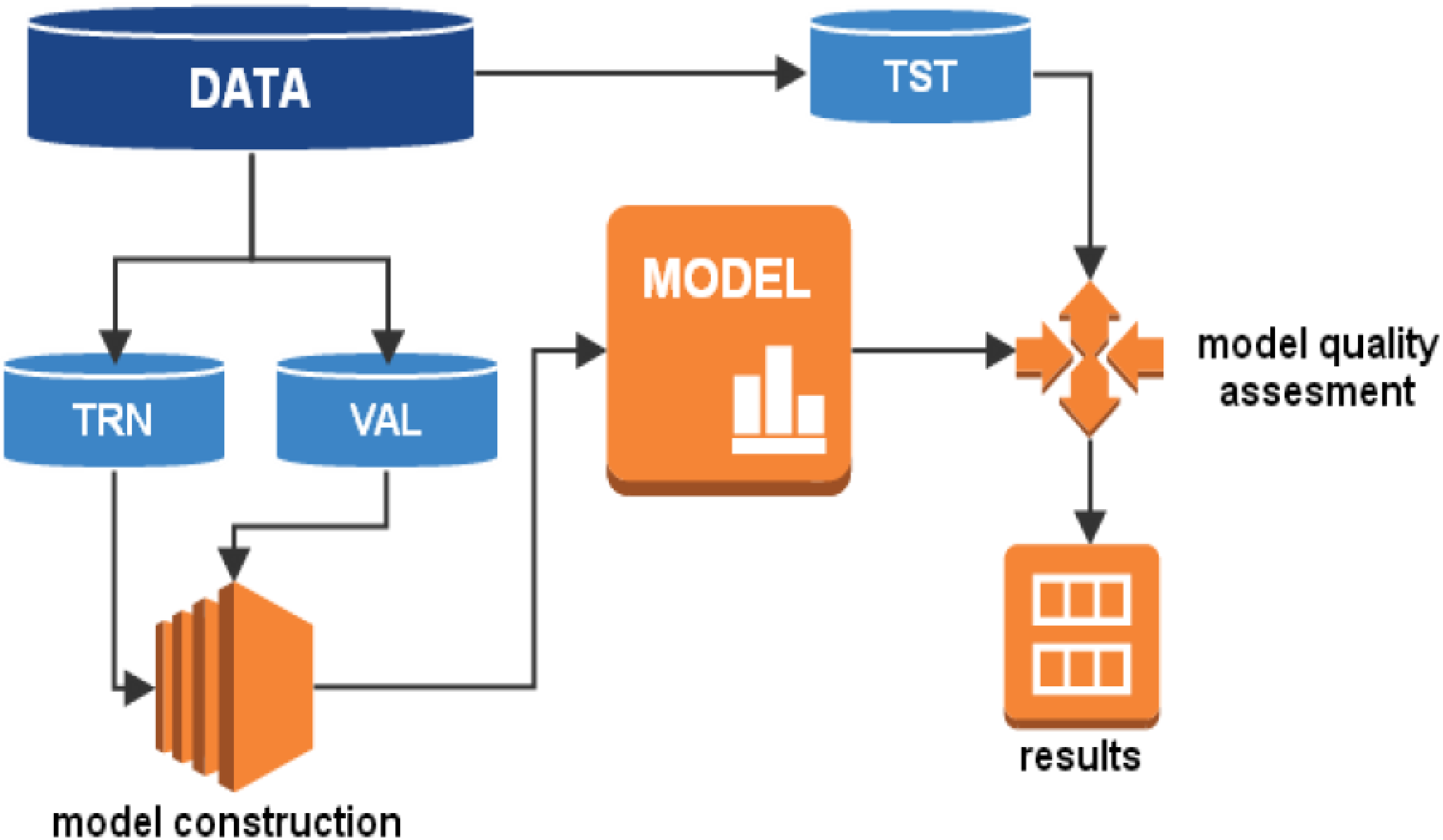
Data Partition and Preparation



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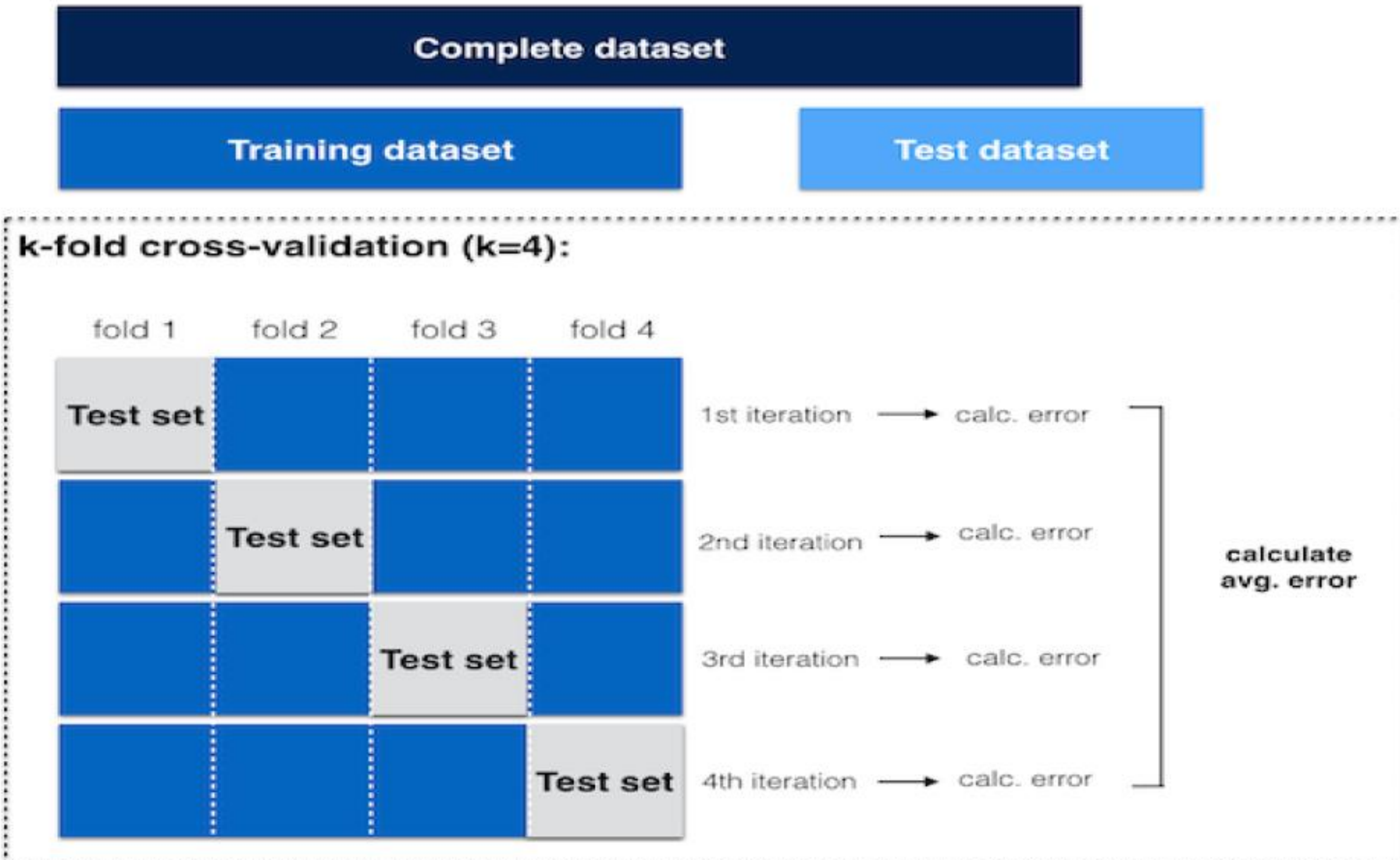
Cross Validation



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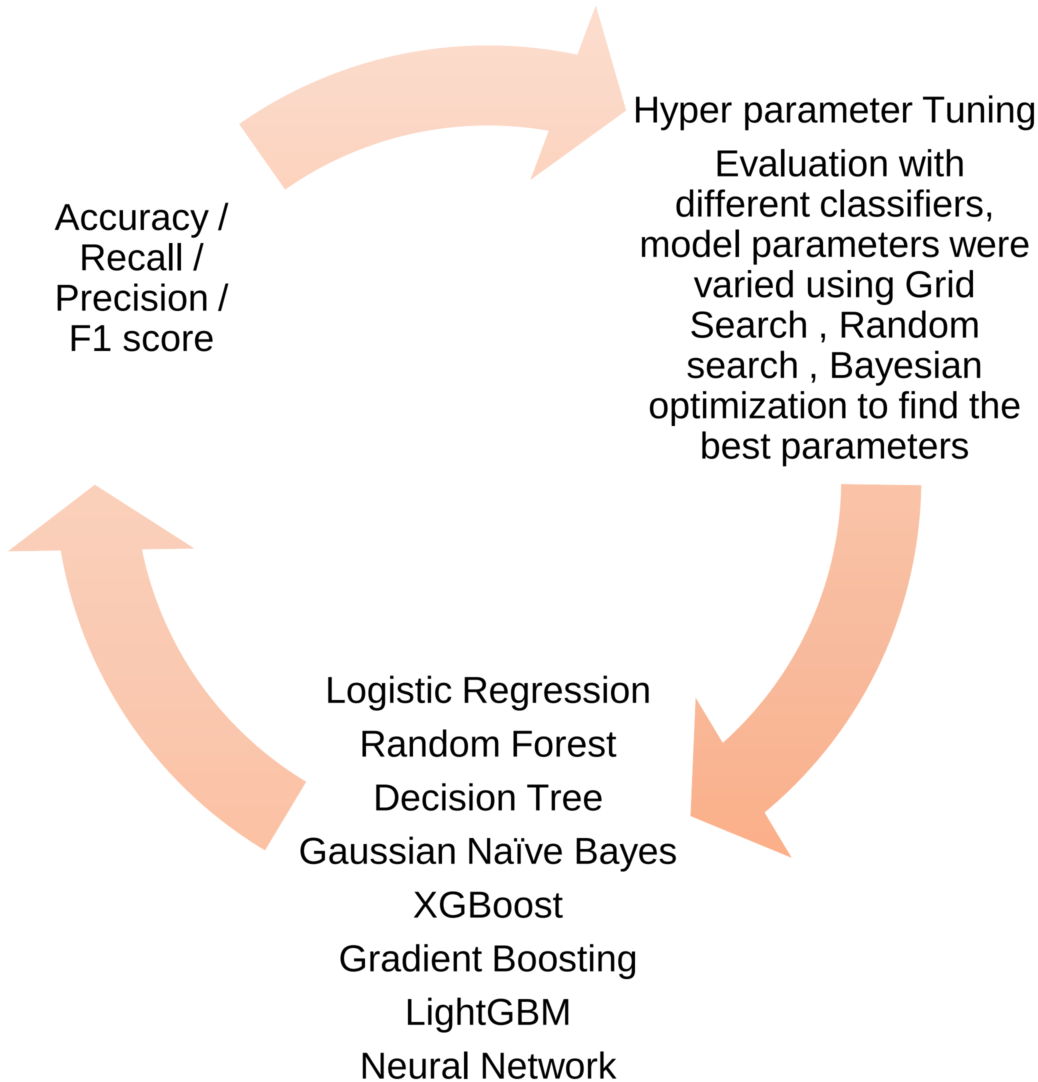
Technical Approach – ML Techniques



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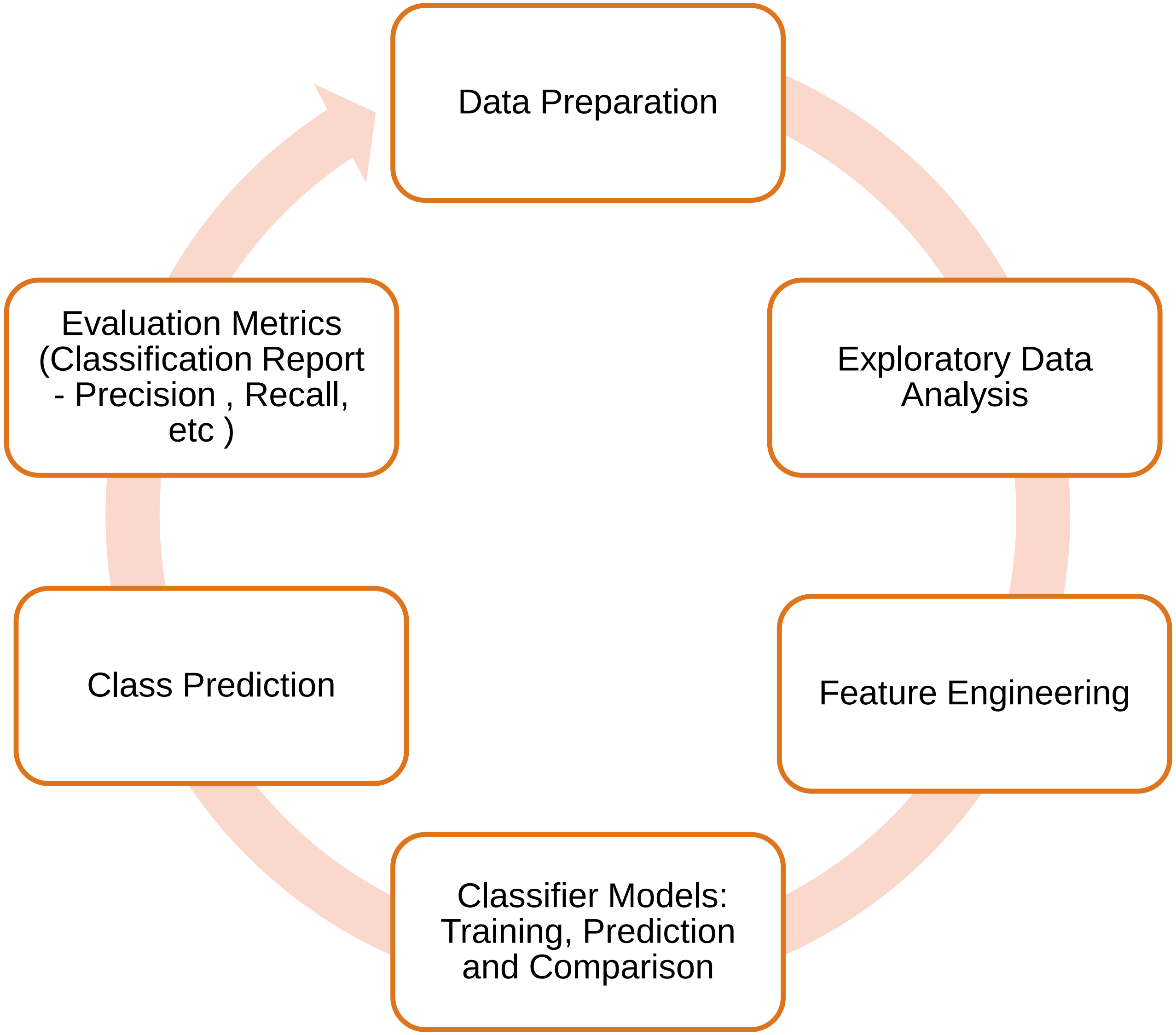
Project Scope



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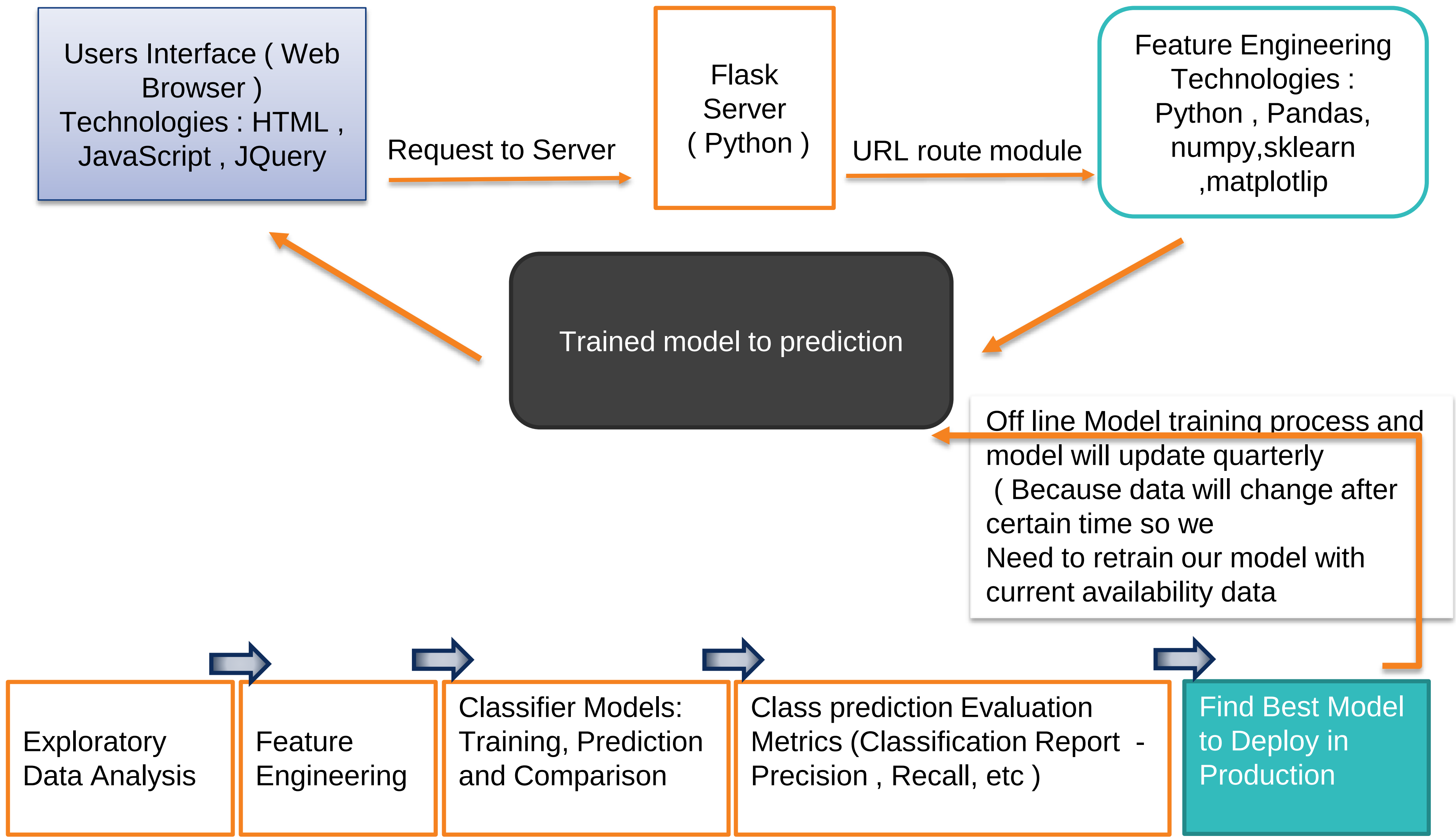
Technical Approach – System Design



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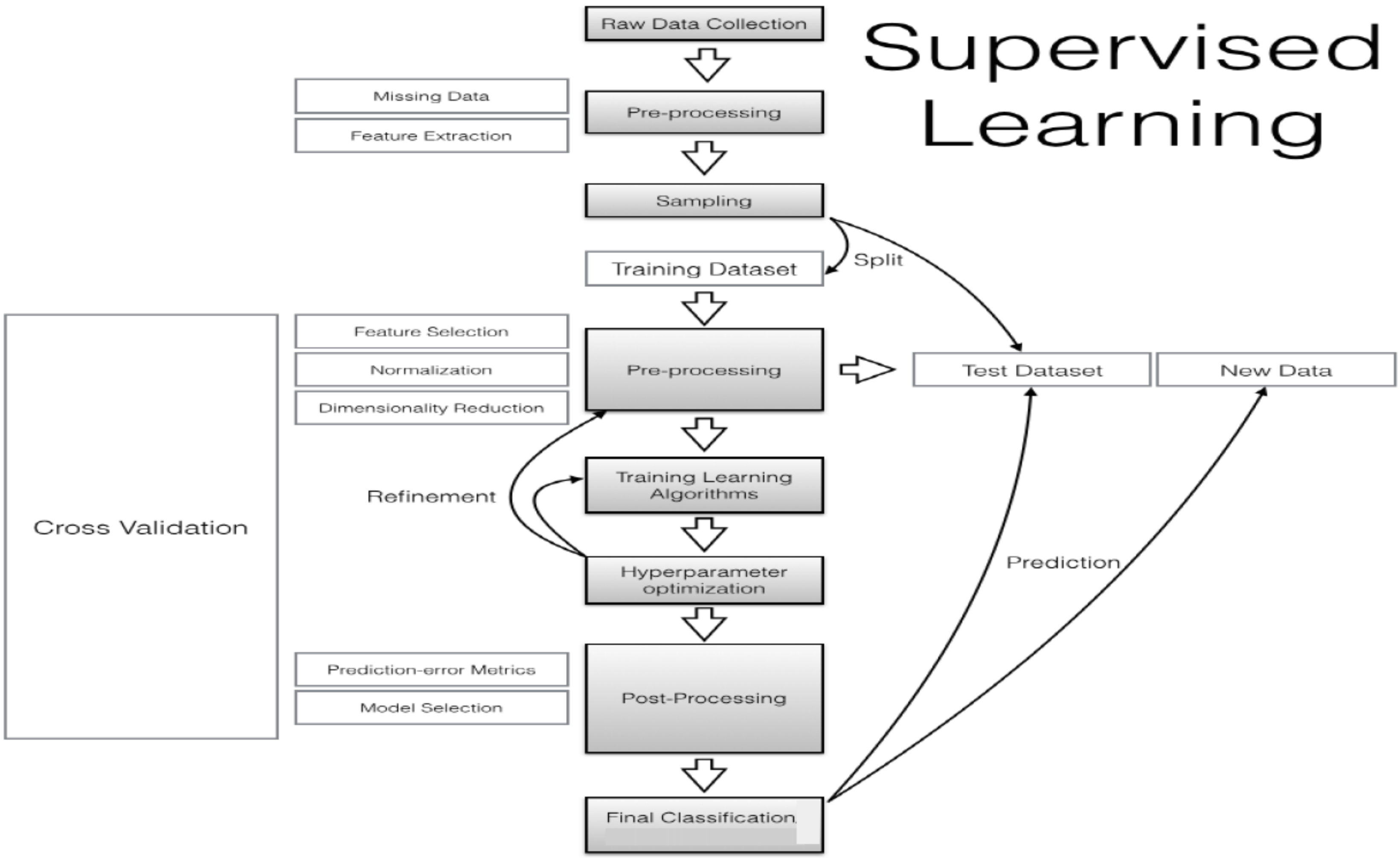
Supervised Learning Approach



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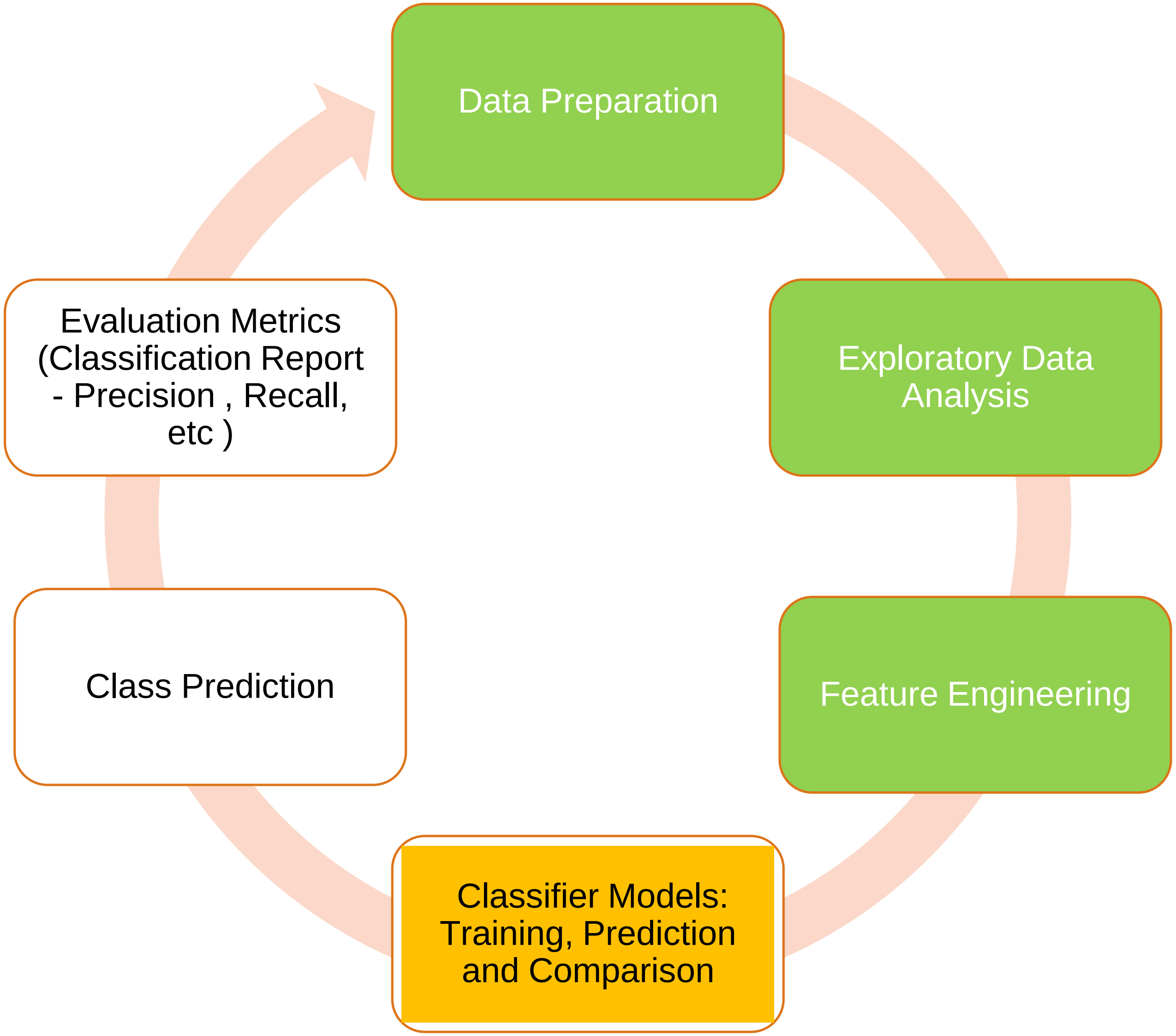
Status Update



Legend:

Completed
In progress

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Value add to this project

- Performed data wrangling / cleaning, setting up the data for analysis and model building.
- Dealt with data having anomalies.
- Added Interaction variables.
- Performed hyper parameters optimization.
- Incorporated Domain Feature engineering.
- Performed Exploratory Data Analysis.
- Discovered patterns in data.
- Built bagging based ensemble model.

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Q&A

Thank you for your attention.

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