Crypto Forecasting

CSE 523 Machine Learning
Prof Mehul Raval

END SEMESTER PRESENTATION

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BY CRYPTOPOLICE

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Where the Crypto Hype Is Taking Over



Share of respondents in selected countries who said that they used or owned cryptocurrencies



000-7,000 respondents (18-64 y/o) per country rveyed Jan-Aug 2019/Jan-Dec 2021 ource: Statista Global Consumer Survey





Introduction

"We have elected to put our money and faith in a mathematical framework that is free of politics and human error."

- Tyler Winklevoss

Cryptocurrencies are one of the most popular assets for speculation and investments but they are highly volatile. The fluctuating nature causes both hype and risk.

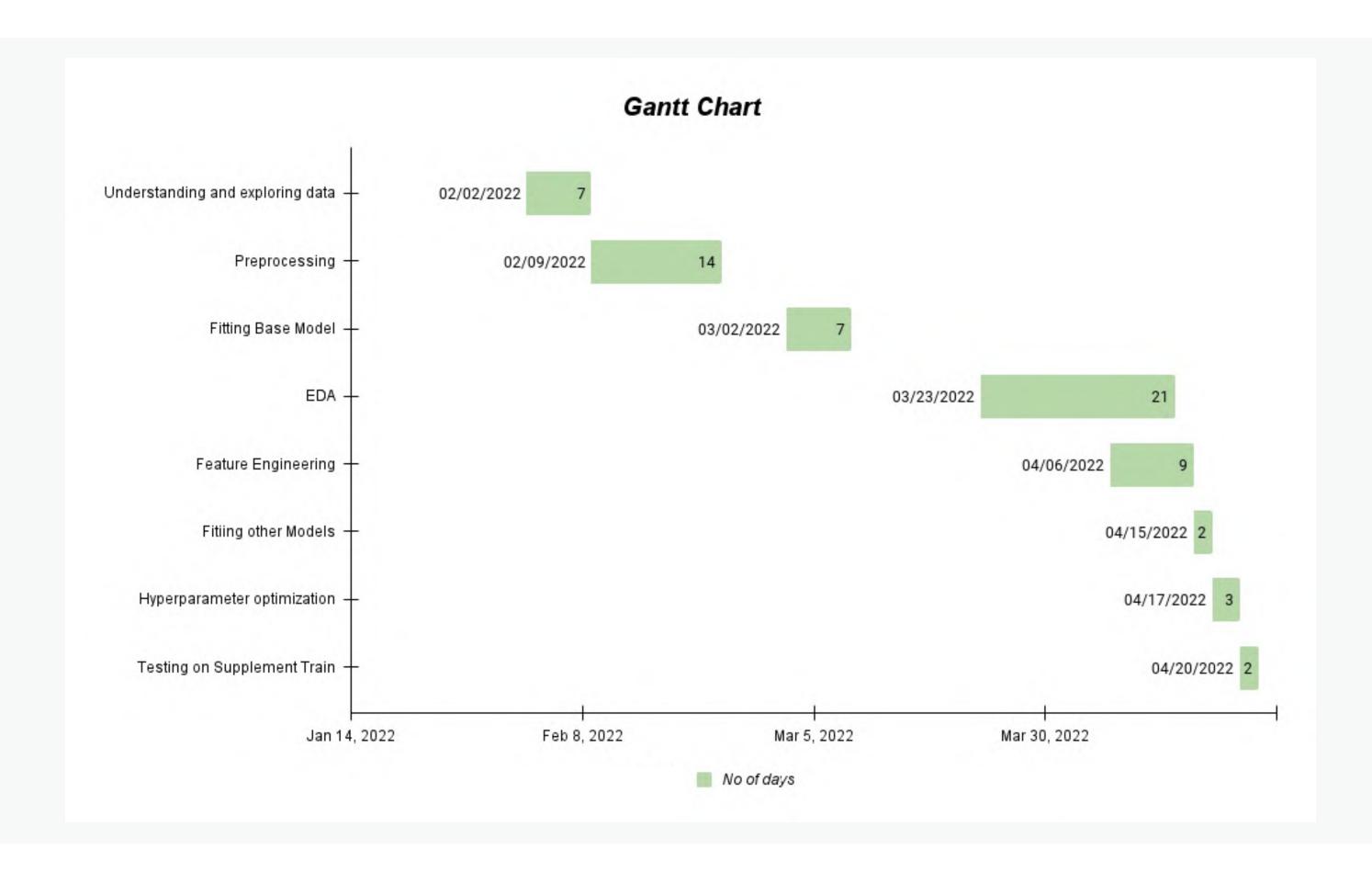
Crypto Forecasting is a process of utilizing the time-series data of given cypto currencies along with other features to predict the future value of these crypto currencies by analysing the past trends and data.

Through Crypto Forecasting, we intend to forecast short term return in 14 popular cryptocurencies using Machine Learning.

(?) Problem Statement

Given the time series data, the challenge is to predict the future returns of 14 cryptocurrencies using various regression and time-series models.

GANTT CHART SHOWING PROJECT PROGRESS



Existing Body of work

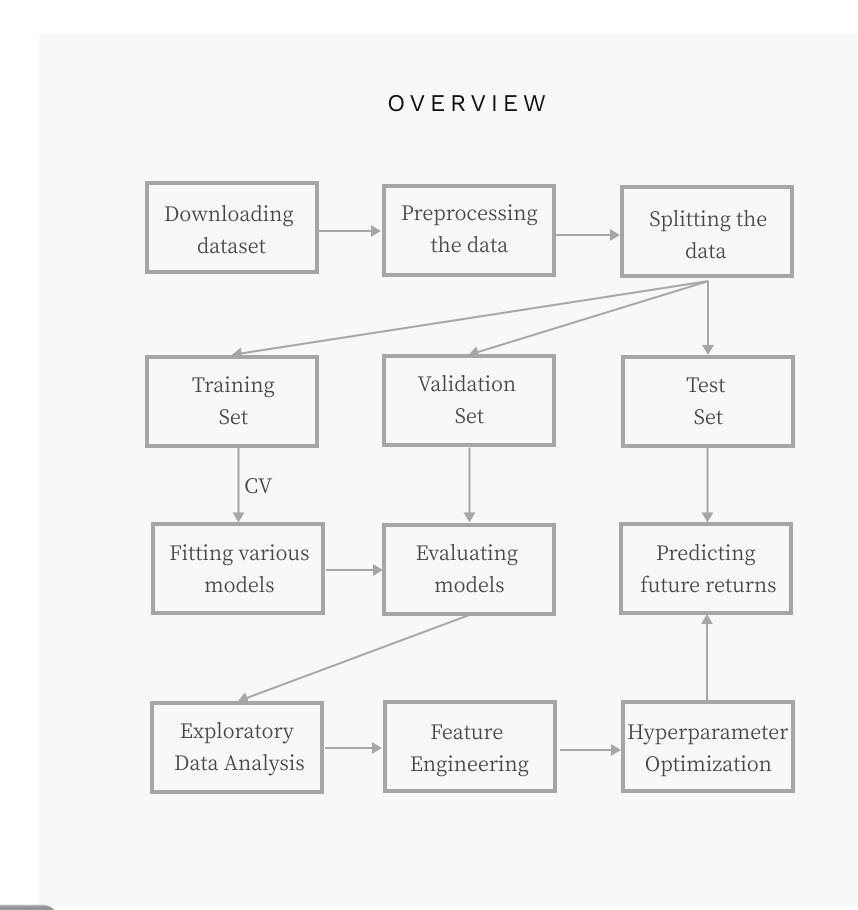
<u>Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach</u>

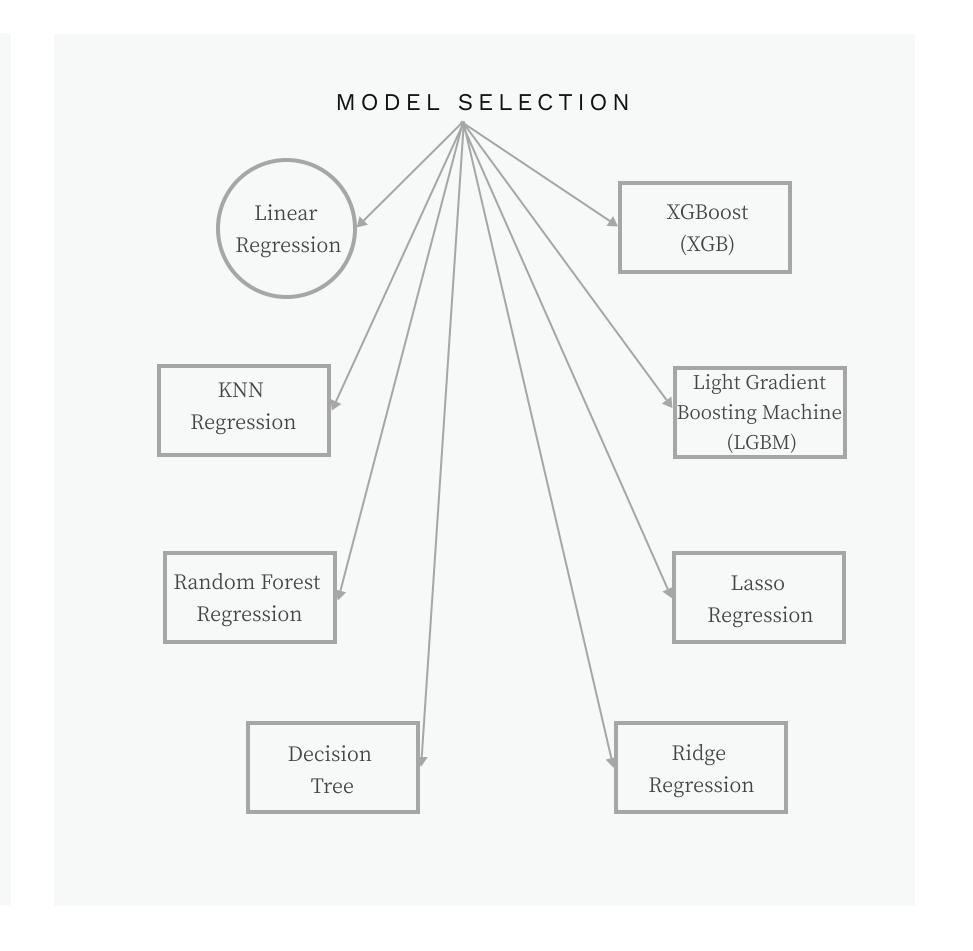
Forecasting and trading cryptocurrencies with machine learning under changing market conditions

<u>Cryptocurrency price prediction using traditional statistical and machine - learning techniques: A survey</u>

Machine Learning Strategies for Time Series Forecasting

APPROACH





APPROACH

DATA PREPROCESSING

- 1. Null value detection
- 2. Timestamp aggregation
- 3. Standardizing data

EXPLORATORY DATA ANALYSIS

- 1. Finding correlation between features
- 2. Detecting outliers
- 3. Plotting Feature vs Target graph
- 4. Seasonal trend
- 5. Lag features
- 6. Distribution of each feature

FEATURE ENGINEERING

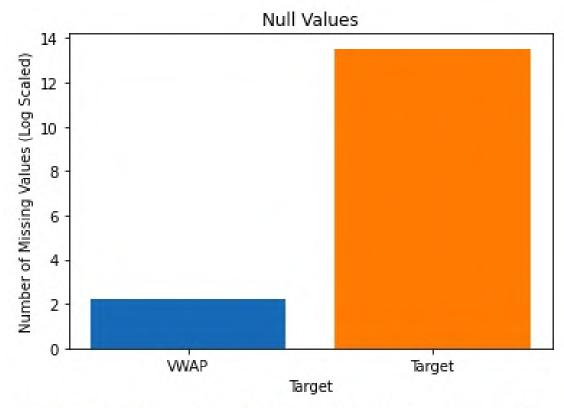
- 1. Removing features with high correlation.
- 2. Creating new features.

HYPERPARAMETER OPTIMIZATION

- 1. Grid Search
- 2. Optuna

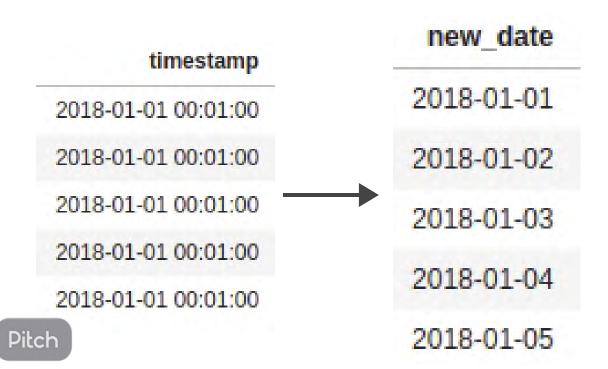


NULL VALUES



Features with null values: ['VWAP', 'Target']

TIMESTAMP AGGREGATION



RESULTS

DATA PRE-PROCESSING

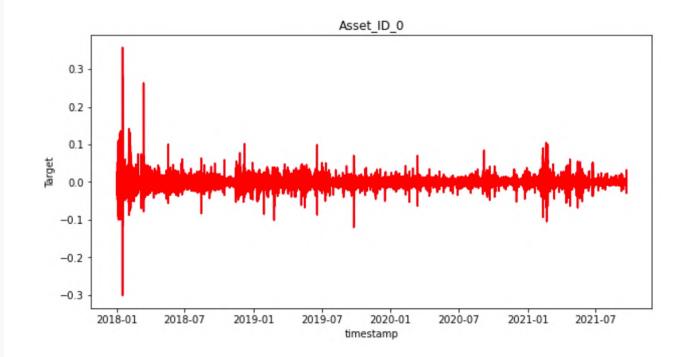
- 1. Null Values
- 2. Time stamp aggregartion

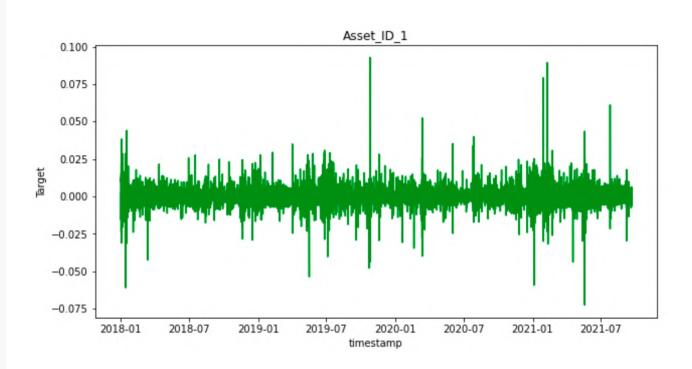
BASE MODEL - LINEAR REGRESSION

 $MSE = 3 \times 10^{-5}$

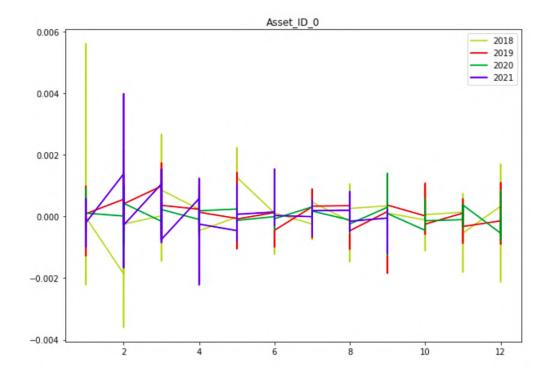
Conclusion - Can be a good fit.

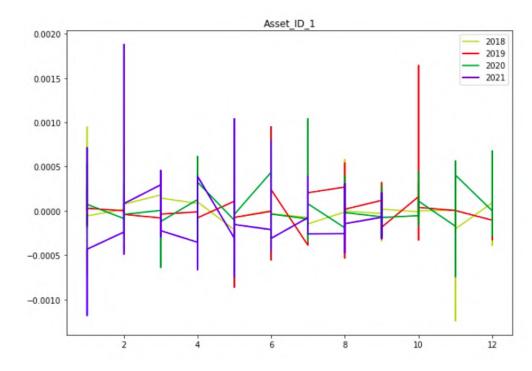
LINEAR REGRESSION TIMESTAMP VS TARGET





SEASONALITY GRAPH





RESULTS

EXPLORATORY DATA
ANALYSIS (EDA)

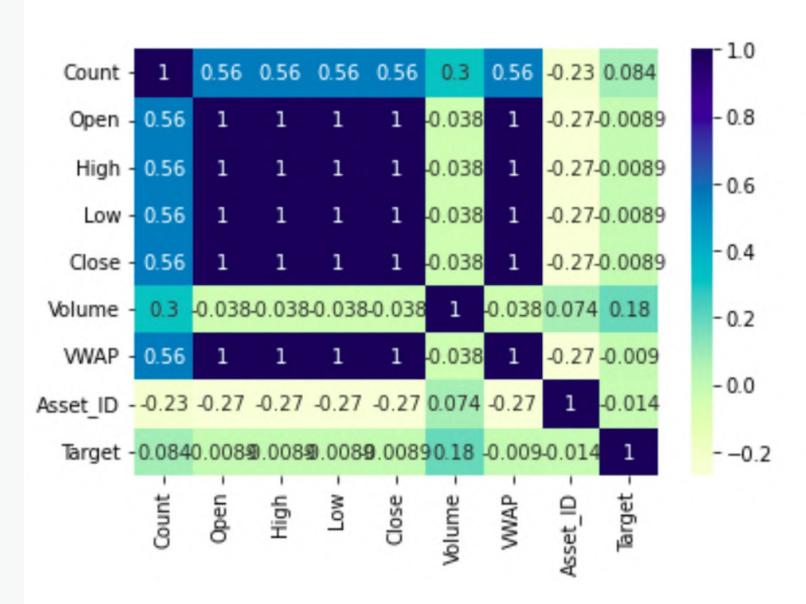
Seasonal Trends

'Target' vs 'Month' No strong seasonality

Correlation Graph

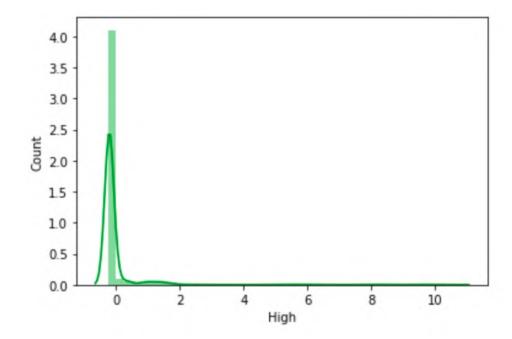
Conclusion - Removing features that are highly correlated

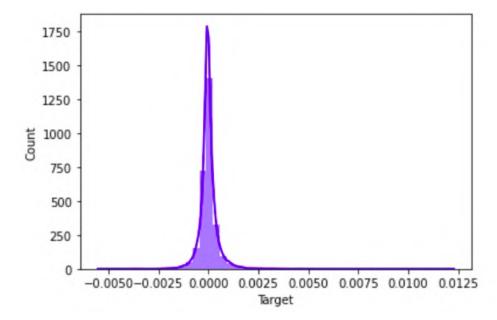
CORRELATION GRAPH FOR ALL ASSET ID





DISTRIBUTION OF FEATURES





RESULTS

EXPLORATORY DATA
ANALYSIS (EDA)

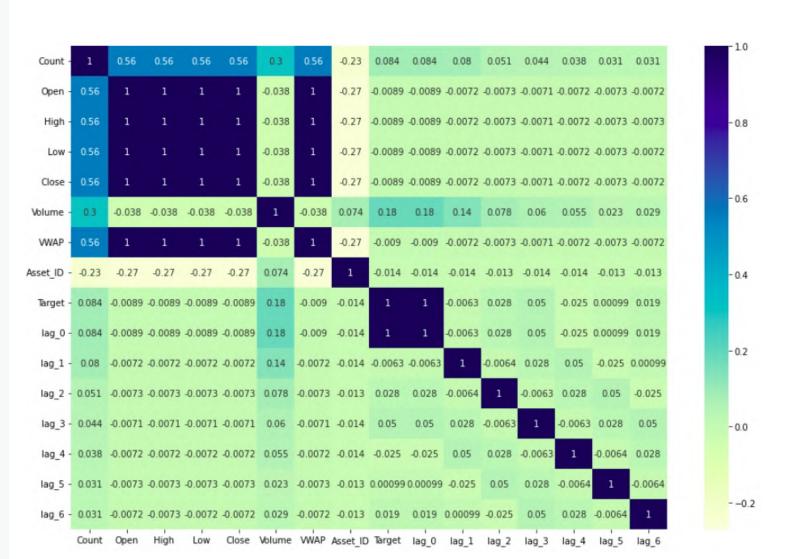
<u>Distribution of features</u>

- 1. Skewed Guassian distribution
 - 2. Mean near to 0
 - 3. Low variance
 - 4. High kurtosis

<u>Lag features</u>

The correlation is not strong with 'Target'.

FOR LAG FEATURES





FEATURES WITH

HIGH CORRELATION:

- 1. Open
- 2. Close
- 3. High
- 4. Low
- 5. VWAP

NEW FEATURES

Range_Close_Open	Range_High_Low
0.009311	-0.106561
0.009823	-0.106239
0.009775	-0.106443
0.010801	-0.105861
0.011829	-0.102587

RESULTS

FEATURE ENGINEERING

Dropping columns with high correlation

Adding new features
1) Open-Close range
2) High-Low range

MODEL FITTING

Performance metrics -Mean Sqaure Error

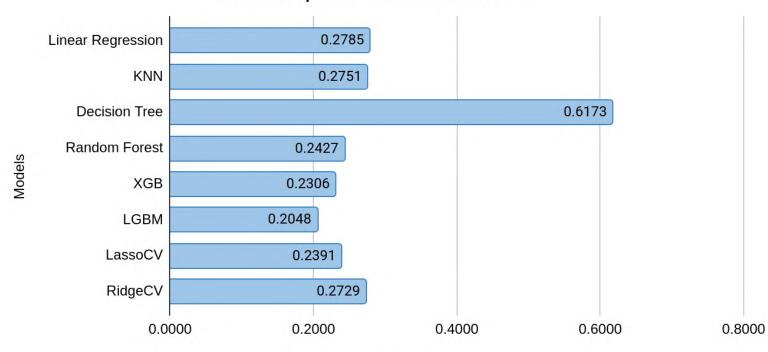
Top 3 Models:

- 1) LGBM
- 2) XGB
- 3) LassoCV

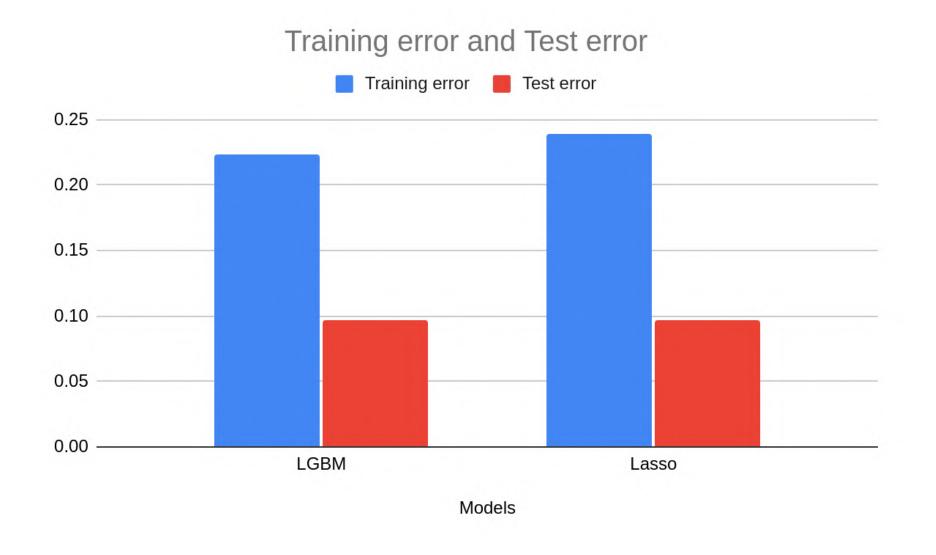


MODEL VS MSE

Mean square error vs. Models



Mean square error





HYPERPARAMETER TUNING

1) Optuna
2) Grid Search
The optimizer that gave better results was chosen.

Error for XGB model

Training error: 0.23056

Test error: 200

Conclusion - Overfitting

Generalization gap lower for LGBM

Conclusion - Final model is LGBM.

CONCLUSION

- Not all features of the dataset are needed to predict the returns
- Lasso and LGBM perform the best on Test Data Set
- There is a significant improvement from the base model.
- XGBoost overfits on Training Data Set
- The lowest Test Error achieved is 0.09 MSE

ROLE OF EACH MEMBER

Role	Name
Data Preprocessing	Khushi, Sameep, Kavya, Kashvi
Model Fitting	Khushi, Sameep Linear Regression, Lasso, KNN, XGBoost Kavya, Kashvi Random Forest, Decision Tree, LGBM, Ridge Regression
EDA , Feature Engineering	Khushi, Sameep, Kavya, Kashvi
Hyperparameter Optimization	Khushi, Kashvi Grid Search Sameep, Kavya Optuna

References:

- 1. A Comprehensive Guide to Time Series Analysis Analytics Vidhya
- 2. <u>Time-Series Forecasting with Spark ML: Part—1</u>
- 3. <u>G-Research Crypto Forecasting</u>
- 4. The Complete Guide to Time Series Analysis and Forecasting
- 5. <u>Learn Time Series Tutorials</u>
- ^{6.} How-To Guide on Exploratory Data Analysis for Time Series Data
- 7. Exploratory Data Analysis Kaggle Source
- 8. <u>Tuning Hyperparameter with Optuna</u>
- 9. Guide to LightGBM Hyperparameter Tuning with Optuna
- 10. Grid Search for Model Tuning
- ^{11.} Tune Hyperparameters with GridSearchCV

