GROUP - 5: PIED PIPERS

Crypto Price Forecasting

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INTRODUCTION

Cryptocurrencies amounting to billions of dollars are traded every day. These currencies are extremely volatile. So, in order to minimize financial risks while trading them, one needs an approach to quantify these uncertainties and predict their future prices with appreciable accuracy.

PROBLEM STATEMENT

To devise an approach to predict the short term *(15 mins)* return of crypto currencies using machine learning algorithms so that we can minimize the financial risk which occurs while trading them

Existing
Body of Work

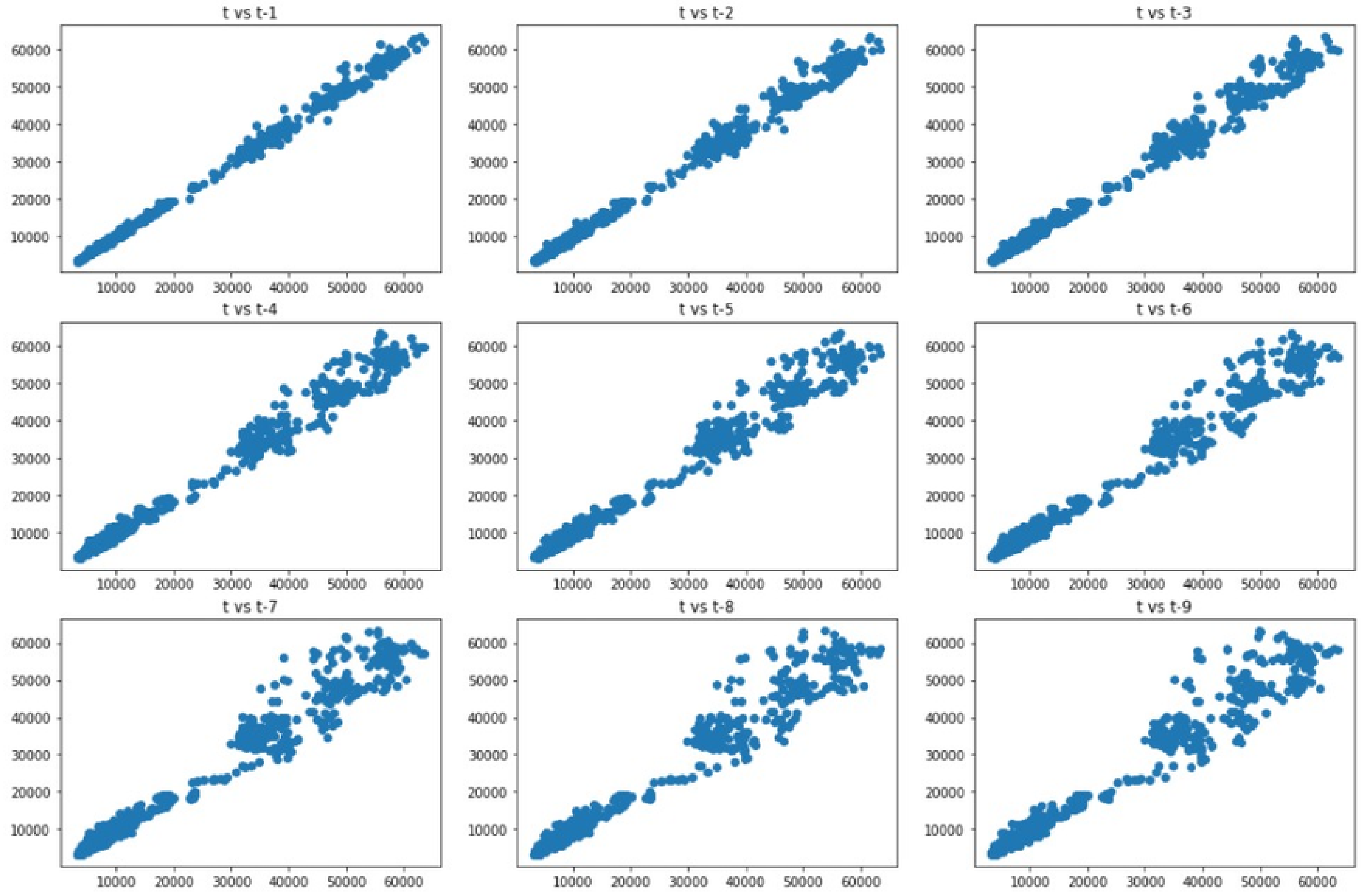
- *Bontempi G: [5]*
  - linear statistical models (ARIMA)
  - non-linear autoregressive models
  - decision trees, SVMs
  - ANNs
  - Role of ML in dealing with forecasting problems.
- *Velankar S: [3]*
  - how crypto assets are different from stocks and sales
- *Southern Methodist University: [4]*
  - using sentimental analysis of tweets
  - The research showed a high correlation of searches with cryptocurrency prices both when prices rise and when they fall, as are tweet volumes.

Our Approach

Dataset	G-Reserach's dataset providing features like opening price, closing price, timestamp, etc of 14 different crypto currencies
Data Preprocessing	Removing redundant data and handling missing and null values
Data Analysis	Various visualizations to build intutions about data
Feature Engineering	Transforming features(lag feature) to derive more information from the data
Model Selection	Testing various regressive algorithms to find optimal results
Parameters Tuning	Tune the hyperparameters of the model to improve accuracy

Exploratory Data Analysis

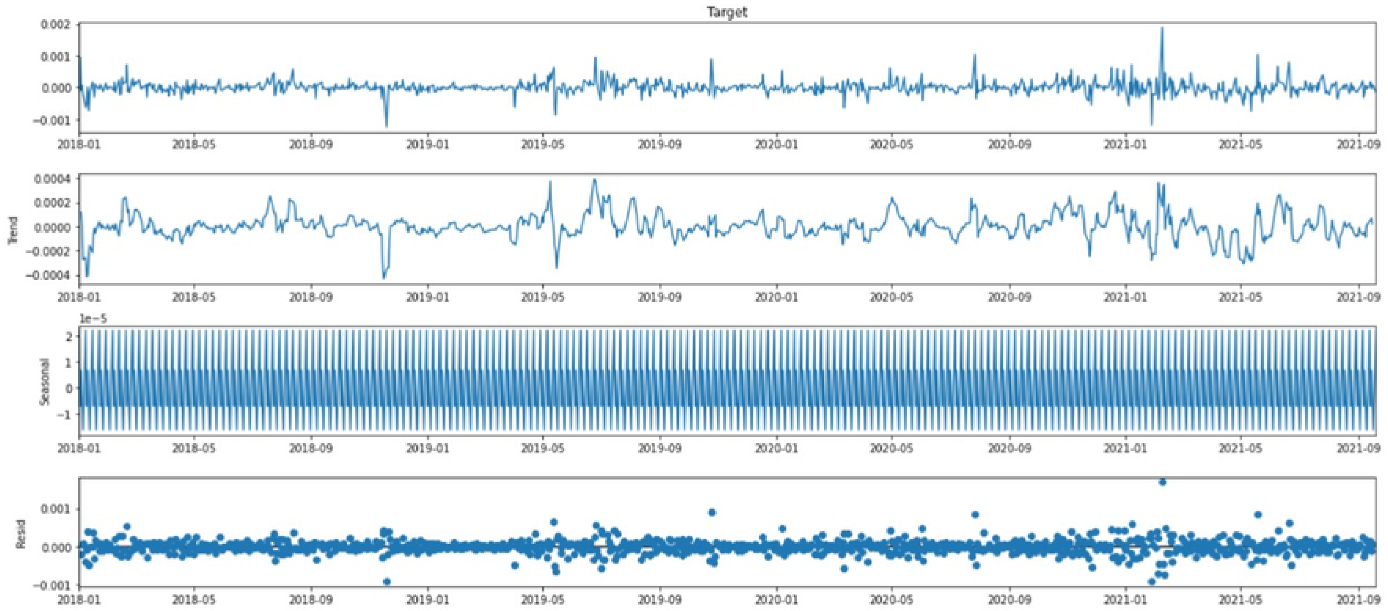
- **By plotting the closing price at time *t* against the closing price at time *t* + *k*, could observe that those are highly correlated**
- **It motivated us to take into account the data from past while predicting the current returns**



closing price at t vs *closing price at t* + k

Exploratory Data Analysis

BTC



Etehreum

series decomposition of closing price vs time

- **By performing the series decomposition of various cryptocurrencies we could observe that the time series data comprises of :**
  - **long term trends**
  - **seasonal patterns of fixed frequency**
  - **cyclical patterns of unfixed frequency**

Initial Results

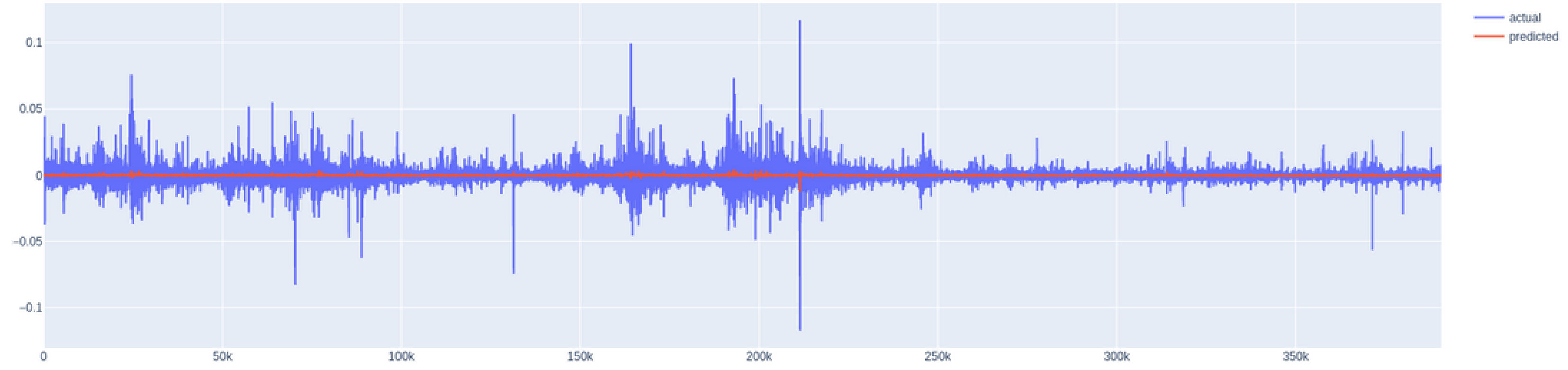
Cryptocurrency	ARIMA coefficients	Linear Regression coefficients
Binance Coin	0.203	0.0254
Bitcoin	0.194	0.0089
Bitcoin Cash	0.179	0.0080
Cardano	0.206	0.0248
Dogecoin	0.214	0.0025
EOS.IO	0.188	0.0038
Ethereum	0.204	0.0066
Ethereum Classic	0.233	-0.0197
IOTA	0.299	-0.0101
Litecoin	0.193	-0.0040

Initial Results

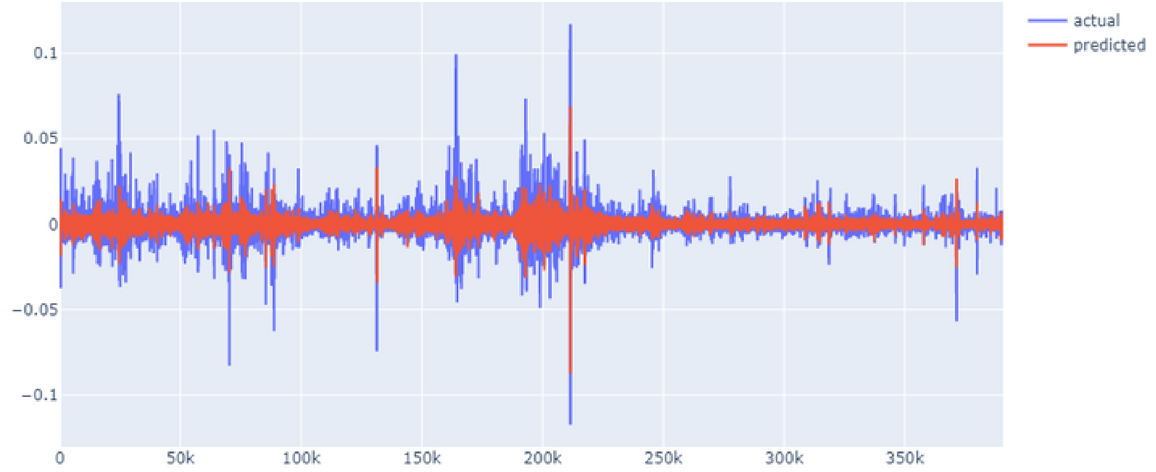
Linear Regression

ARIMA

Bitcoin Cash



target(returns) vs time plots



target(returns) vs time plots

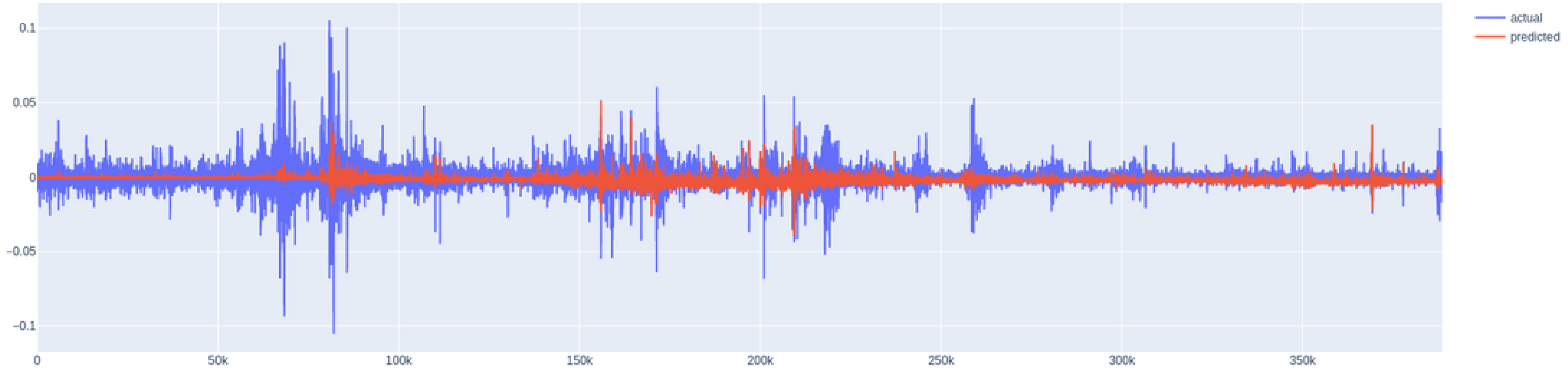
- For linear regression, we have used the input variables without using any feature transformation
- For the ARIMA model the hyperparameters are:
  - number of lag observations - P = 4
  - number of times data is differenced - D = 2
  - size of moving average window - Q = 0
- We can see that ARIMA is better able to capture the complexity of time series data

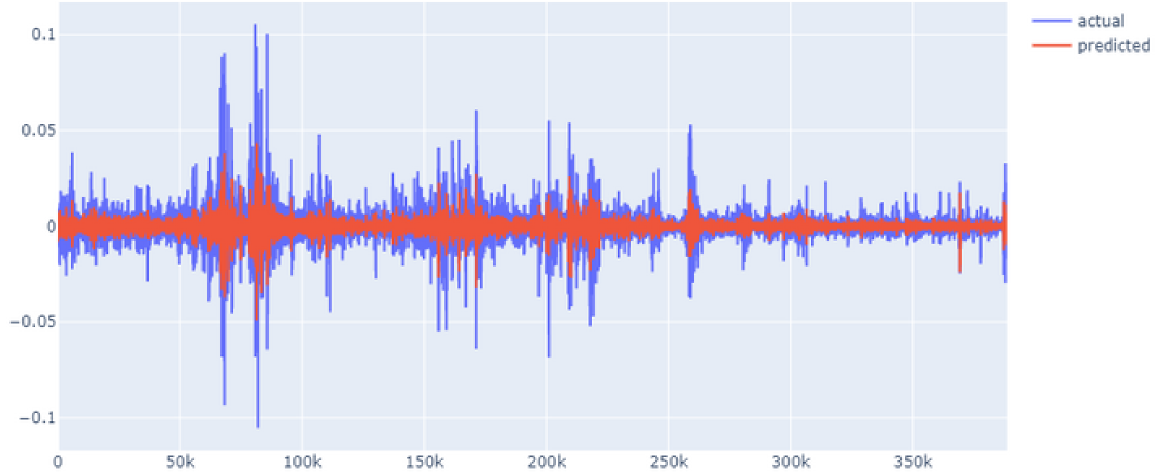
Initial Results

Linear Regression

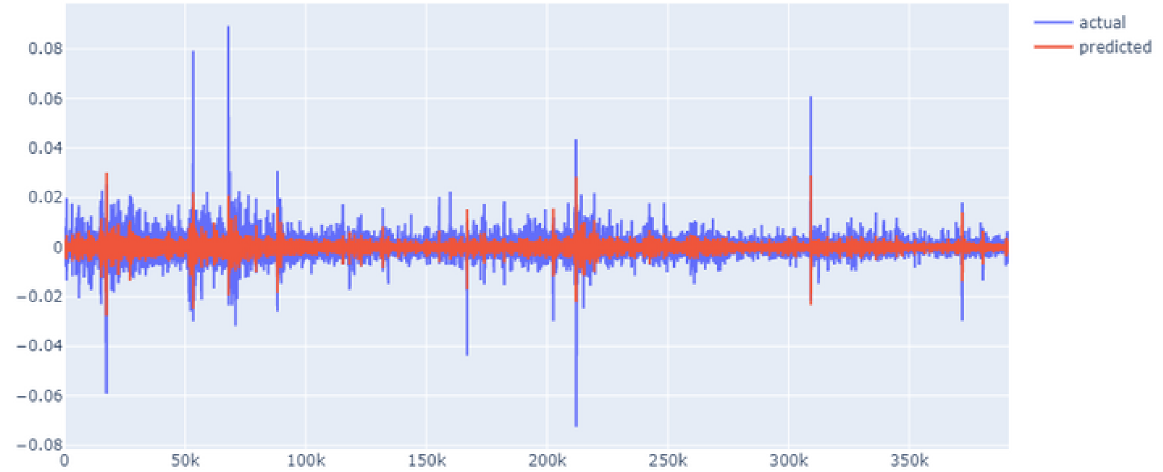
ARIMA

Binance Coin





Bitcoin



target(returns) vs time plots

target(returns) vs time plots

Role of each group member

	Exploratory Data Analysis	Data preprocessing	Linear Regression	Arima
Neel	✔	✔	✔	
Nipun		✔	✔	✔
Tirth	✔	✔		✔
Vinay	✔		✔	✔

Role of each group member

	EDA	Data preprocessing	Linear Regression	ARIMA
Neel	✔	✔	✔	
Nipun		✔	✔	✔
Tirth	✔		✔	✔
Vinay	✔	✔		✔

Future Work

We aim to improve our prediction further using:

FEATURE ENGINEERING

We can derive more information by the transformation of the feature vector. We will feed these additional features into our models to improve our accuracy

TIMER SERIES MODELS

Based on the performance of ARIMA, we have decided to implement and test other algorithms of the ARIMA family

TUNING PARAMETERS

We will fine-tune the hyper-parameters of the ARIMA model to better handle the complexity of the input data and improve our prediction

References

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[5] G. Bontempi, S. Ben Taieb, και Y.-A. Le Borgne, ‘Machine Learning Strategies for Time Series Forecasting’, τ. 138, 01 2013.

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