Crypto Forecasting App - Project Outline

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Outline

- Project Scope
- Project Workflow
- Process/Data Flow
- Backend Infrastructure
- App Design
- Data
- Models

Problem Definition

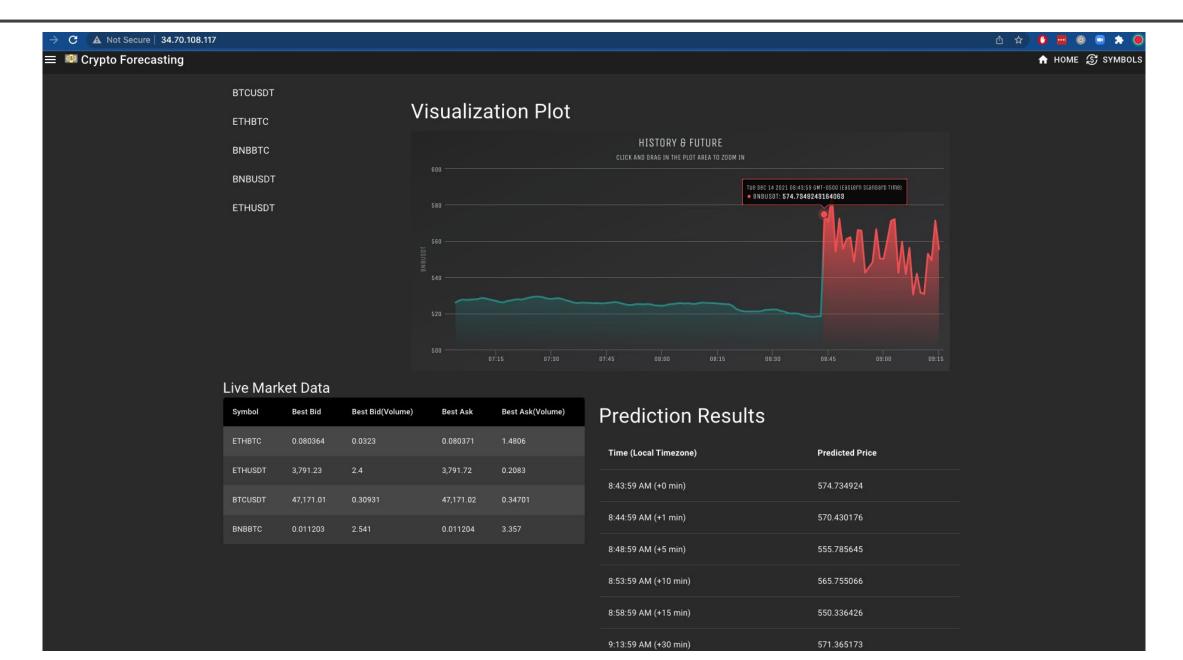
The current state of the crypto market is extremely volatile. Due to lack of experience/involvement from traditional actors, there is a lack of systematic investment strategies in the crypto environment; therefore, there is an opportunity to extract value from an accurate prediction of the price dynamics of pairs.

The scope of this project is to create a Proof of Concept to see if there is opportunity when using Deep Learning in crypto markets.

Objectives

- Bridging the lack of structure dealing with crypto exchanges in building a scalable and modular database architecture that will gather various features from different exchanges (starting with Binance) for 'pairs' (a 'pair' refers for instance to the dynamics of the market for BTC vs USDT)
- Building a predictive ML/DL model using real-time predictions that will enable us to gain insights as to how the market is evolving over time in order to inform trading decision making

Final Product



Project Scope

Proof Of Concept (POC)

- Setup database infrastructure, gathering both the historical data and the real-time data from Binance exchange
- Perform data exploration and data processing
- Experiment on some baseline models: last price, exponential smoothing
- Develop training pipeline for one specific pair (BTC-USDT)
- Benchmarking our model against baseline models

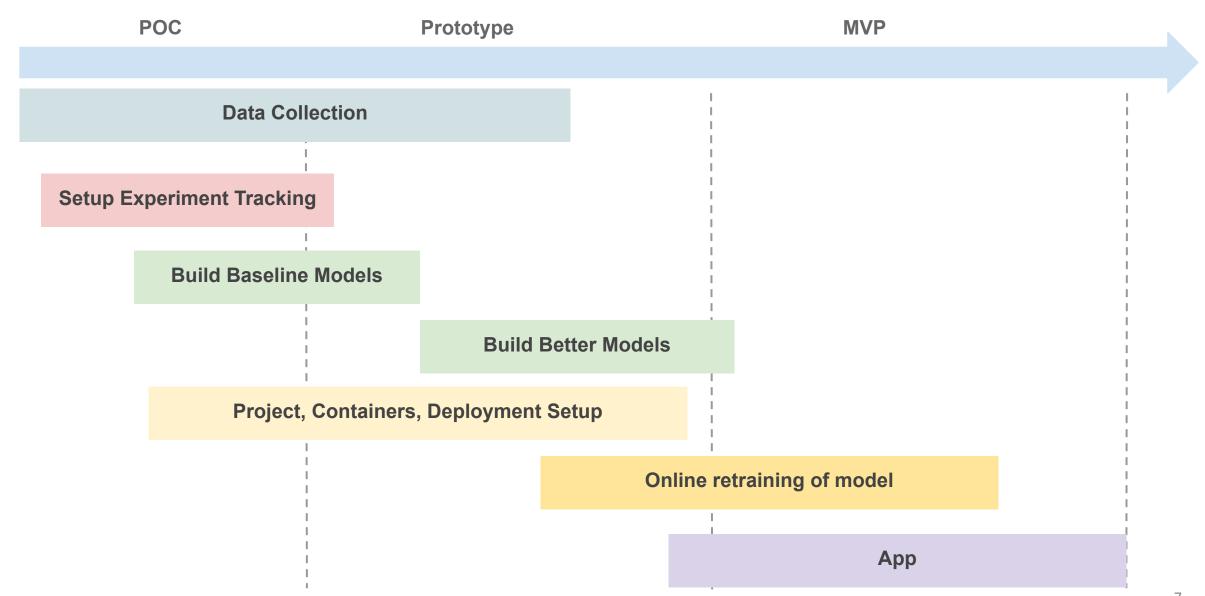
Prototype

- Develop a more advanced model, significantly improving over the different baselines
- Create a mockup of screens to see how the app will look
- Be able to launch the query of new pairs from the frontend side
- Perform regular data tests in order to verify the quality of the data
- Deploy models utilizing FastAPI to serve model predictions

Minimum Viable Product (MVP)

- Setup the front-end in order for users to interact with the API
- Provide real-time predictions using the deployed model
- Provide recommendations for user's investment
- Perform regular re-training of the deployed models

Project Workflow



Process (People)

Execution (Code)

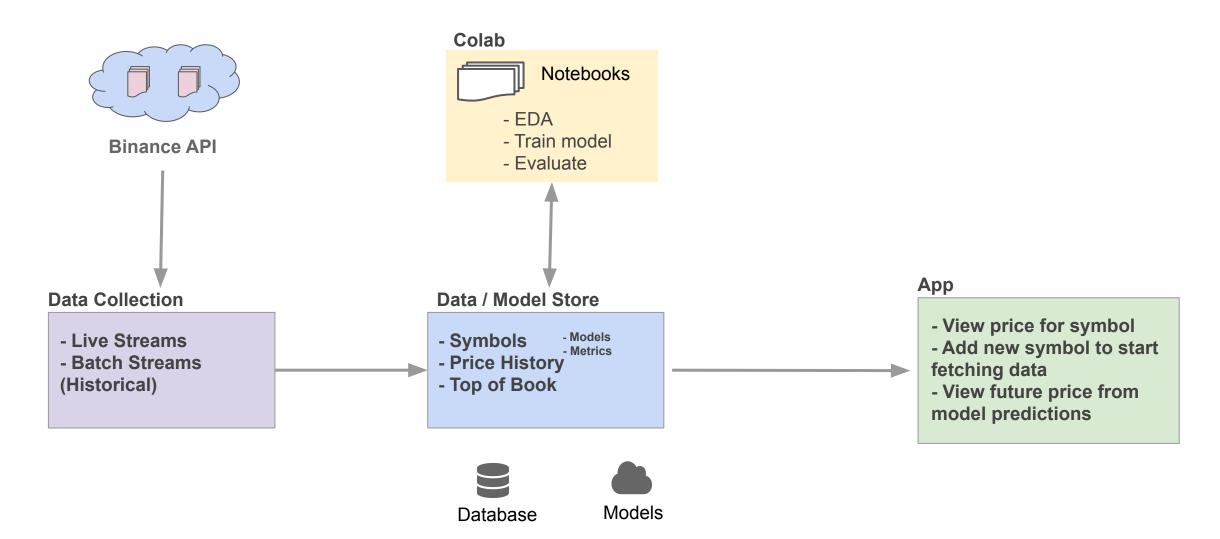
State (Source, Data, Models)

- Collect initial data from Binance API
- Keep querying real-time data
- EDA on initial data
- Time Series modeling (single/multiple prediction approach)
- User selects a certain pair to obtain historical data and predictions
- View prediction results

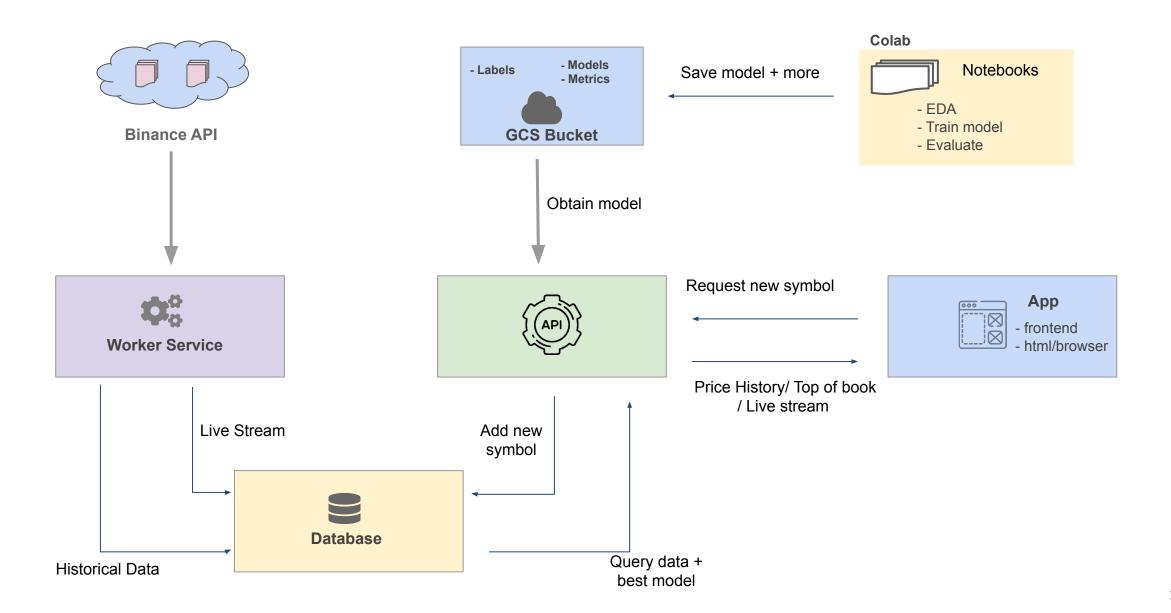
- Save data to a common store and keep updating
- Create tables and save in Postgres database
- Save model weights
- Information on pre processing

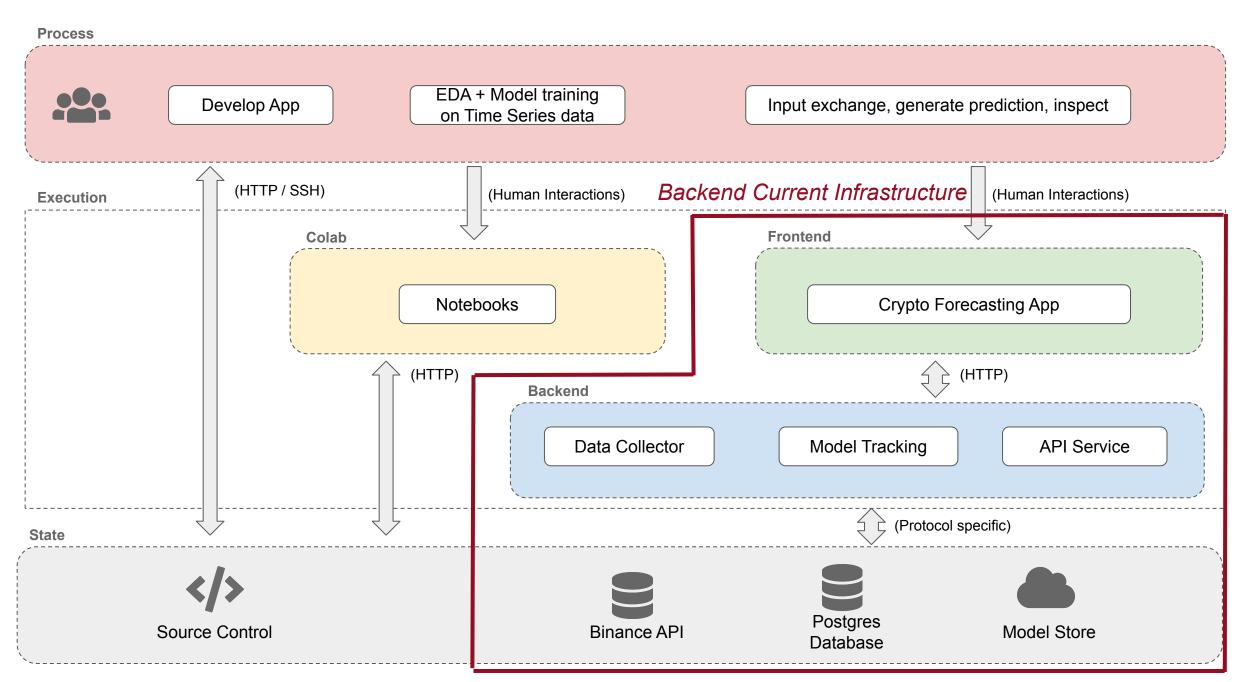
- Preprocess the initial data for both time-series and tabular modeling
- Use the best model to make prediction
- Return results to user as a minute-by-minute predictions over 24 hour period
- Track best model

Process Flow

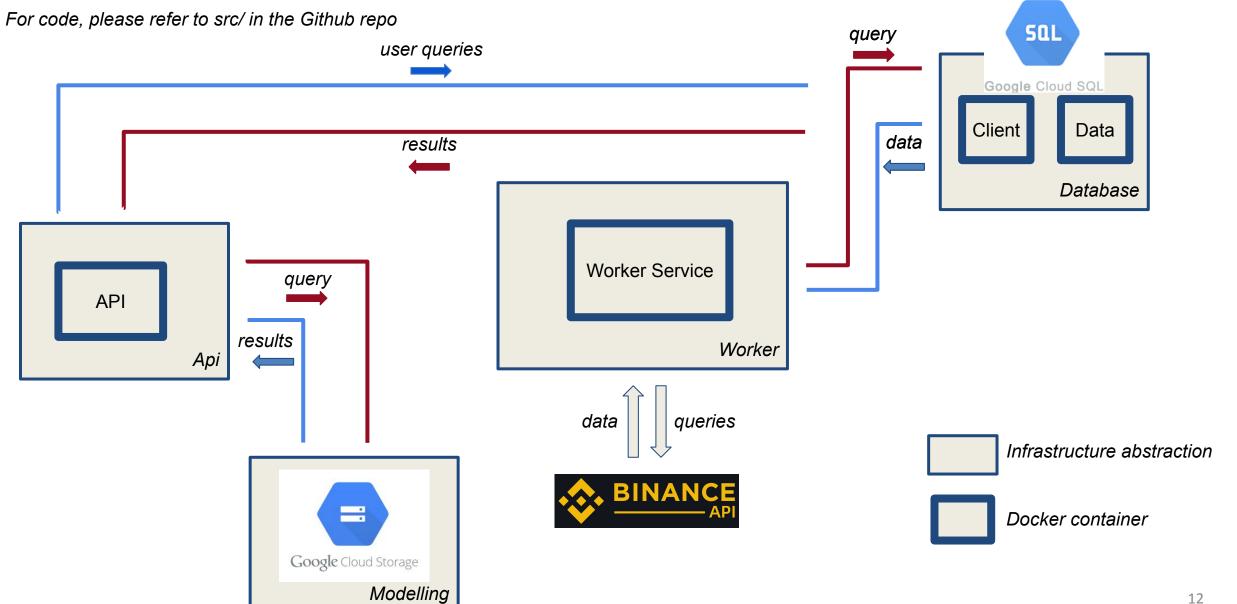


Data Flow





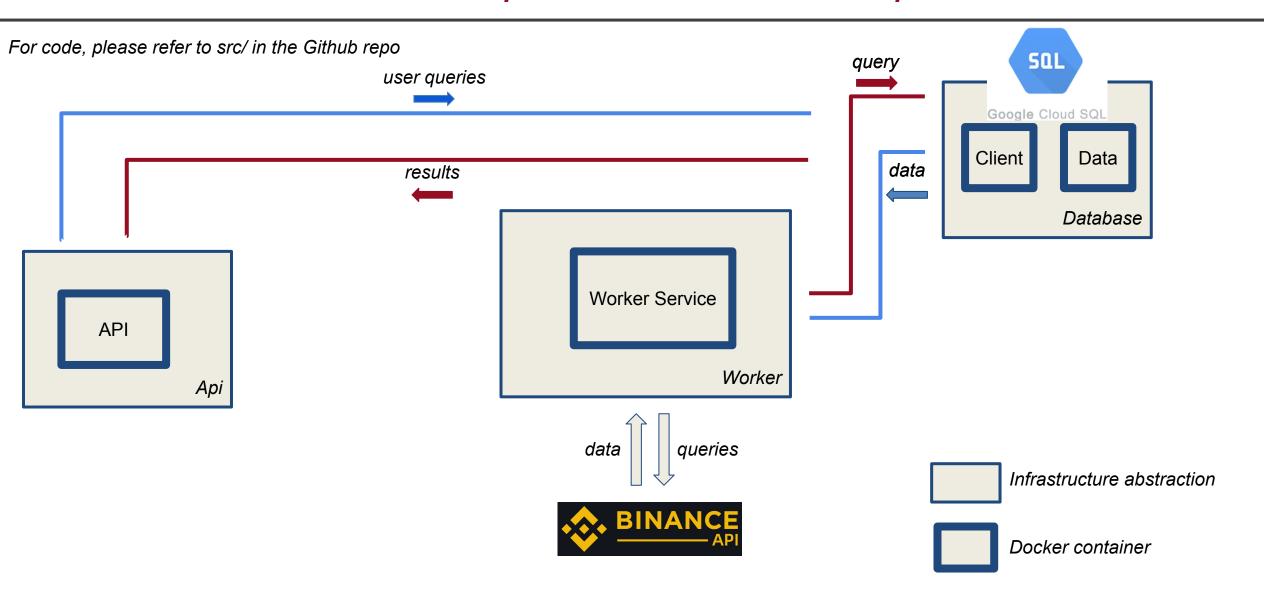
Backend Infrastructure



Backend Infrastructure: Update data with online streams

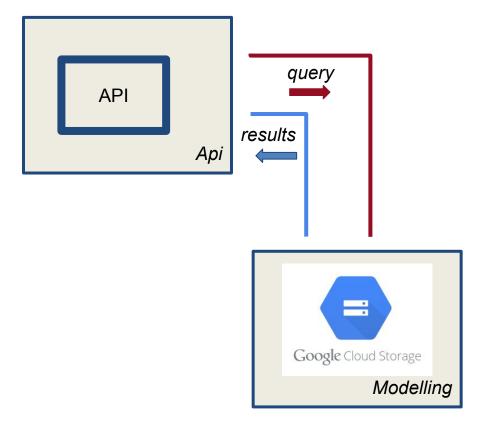
For code, please refer to src/ in the Github repo SQL query Google Cloud SQL Client Data data Database Worker Service Worker *Infrastructure abstraction* Docker container

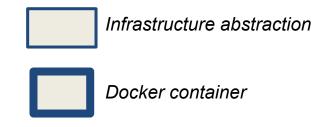
Backend Infrastructure: Update data with new pairs



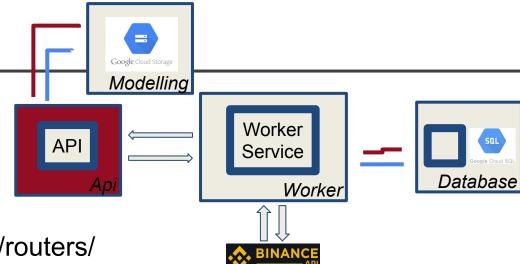
Backend Infrastructure: Get model predictions & retraining

For code, please refer to src/ in the Github repo



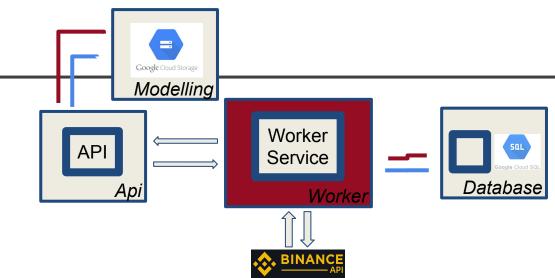


Current Infrastructure: API



- Use FastAPI implementation of REST API
 - Implementation of tasks in api/service.py and api/routers/
- Use <u>Uvicorn in order to host the server</u>
- Receives API call based on user input from the Frontend and either...
 - Adds symbol to symbols table if it's a new pair (e.g. BNBBTC)
 - Queries price history table and GCS bucket for model prediction
 - Queries price_history and top_of_book table from Postgres database (either on CloudSQL or container depending on deployment type) for real-time and/or historical data for visualization purposes

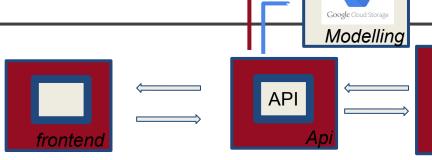
Current Infrastructure: Worker



- The worker is responsible for fetching the data from Binance and writing it in the Database
- Two types of data: Historical fetching and online streaming
- MultiProcessing:
 - One process constantly running in order to perform live streaming of the different pairs. This
 process uses an abstraction of a Threaded WebSocket Manager in order to be able to monitor
 1000 streams at the same time
 - Several processes idle when no historical fetching happens, and then when a user queries a symbol that is not yet in the database, these processes will fetch the historical data for these new symbols
- Data Backup: when spinning up the worker, fetches the data from the last updated timestamp to the current timestamp in order for the database to contain data for every timestamp, even when the VM goes down
- Worker monitors the database for api queries

Current Infrastructure:

Worker + API +Front-End



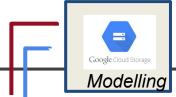


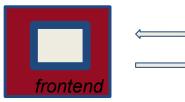
Worker Service

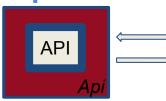
Worker

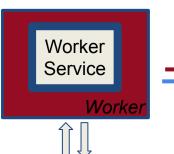
- Scenario: a user selects in the front-end side a symbol (e.g. BNBBTC)
- 2 possibilities
 - The symbol is already in the database → provide the appropriate data (top of book, candlestick) to the data
 - The symbol is not already in the database → the worker is going to fork a process that will fetch
 the historical data for this symbol. Once the historical fetching is done, this symbol will be added
 to the online streams for the 'online process' of worker service and the online data will be
 fetched for this symbol
- Communication between API and Worker is being done on the Database side: symbols table that contains all the important logs. The worker service is monitoring the symbols table and creates new processes based on changes on this data table

Current Infrastructure: Front-End













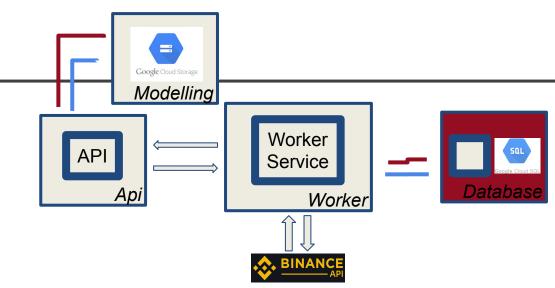
Frontend Components:

- React Javascript Library
- Material UI, High Charts Visualization
- Showing a live feed market data table for all symbols selected
- Showing a visualization plot for historical data and future prediction price
- Showing a prediction table with future prediction price

API Calls:

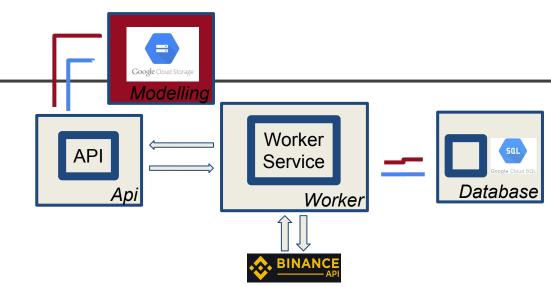
- Frontend will send selected symbol as a json dictionary to backend API service for model prediction
- Frontend will then make API calls and get back response data from console log
- Response data returned in json dictionary format consists of a designed interface with symbol, historic price, historical timestamp, future price, future timestamp (predicted from model) and live market data.
- Those response data are then used in frontend for displaying time series visualization plot, live market feed and prediction price table

Current Infrastructure: Database



- Use migration code in order to monitor the different tables
- The Database is a Postgresql database
- 3 major tables:
 - Symbols: contains all the meta-information about the symbols for which we are fetching data.
 This table also serves the purpose of communication between API and worker when a user queries a new symbol. It also serves the purpose of being able to get the data we missed while the worker was down
 - Price_history: contains the candle data for the different symbols. Historical data that is available for the different pairs, back until 08/17/2017
 - top_of_book: online data, will enable us to have non aggregated data on the market for visualization and backtesting purposes
- When spinning up the infrastructure for the first time, insert default symbols (the most frequent ones)
 in the symbols table in order for the worker to start fetching data without needing for a user querying
 new symbol
- Use of Google's CloudSQL to handle automatic scaling, backups, etc.

Current Infrastructure: Model



- Original models creation happens in a Google Colaboratory Notebook
- Models are uploaded to the GCS bucket
- From the GCS bucket, the API queries for the best model to use for real-time predictions
- The models are re-trained on new, incoming data on daily basis
- The raw data obtained from the GCS bucket goes to a preprocessing pipeline before being fed to the model (more information on the preprocessing pipeline on subsequent slides)
- The training architecture and the data preprocessing pipeline are common for all pairs. The only major difference is the raw data fed into the preprocessing pipeline.
- Future steps: automated model training pipeline utilizing VertexAI that independently initializes model training once a user enters a new symbol through the frontend API

Dataset(s)

For code, please refer to src/api_for_data_download in the Github repo

- Dataset(s):
 - Historical data queried from Binance API (dtype: candlesticks)
 - earliest timestamp for the BTC-USDT pair: 2017-08-17 04:00:00
 - Real time data updating from Binance API (dtype: candlesticks) using a websocket
- Dataset(s) size:
 - Number of datasets: 1,612 (one dataset per pair)
 - Size of dataset per pair (~0.3Gb)
 - Total dataset(s) size (~500Gb)
- For the EDA and the initial modelling phases focus on the BTC-USDT pair
- The modelling extended to 5 pairs for the final app (BTC-USDT, BNB-BTC, BNB-USDT, ETH-BTC, ETH-USDT)

Raw Dataset(s) Features

Candle Feature	Description			
Open Time Open High Low Close Volume Close Time Qupte Asset Volume Number of Trades Taker Buy Base Asset Volume Taker Buy Quote Asset Volume	Candle Open Time Open Price in Quote (Secondary) Asset Units High Price in Quote (Secondary) Asset Units Low Price in Quote (Secondary) Asset Units Close Price in Quote (Secondary) Asset Units Total Trade Volume in Base (Primary) Asset Units Candle Close Time Total Trade Volume in Quote (Secondary Asset Units Total Number of Trades Taker (Matching Existing Order) Buy Base Asset Volume Taker (Mathcing Existing Order) Buy Quote Asset Volume			
Ignore	Safe to Ignore			

Dataset(s) Quality

Data Types:

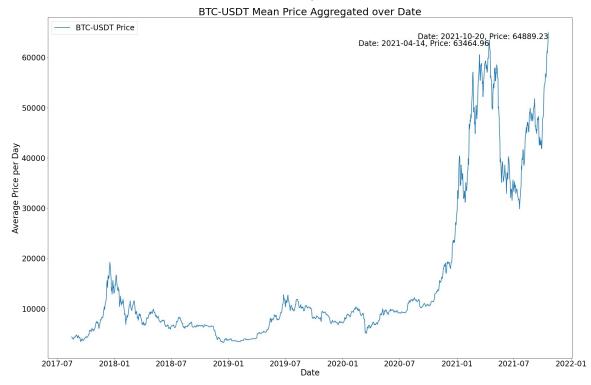
<pre><class 'pandas.core.frame.dataframe'=""></class></pre>						
Int64Index: 2188604 entries, 0 to 2188603						
Data columns (total 12 columns):						
# Column	Dtype					
0 Open Time	int64					
1 Open Price	float64					
2 High price	float64					
3 Low Price	float64					
4 Close Price	float64					
5 Volume Traded	float64					
6 Close Time	int64					
7 Quote asset Volume	float64					
8 Number of Trades int64						
9 Taker buy base asset volume float64						
10 Taker buy quote asset volume	float64					
11 NA	float64					
dtypes: float64(9), int64(3)						
memory usage: 217.1 MB						

Missing Values:

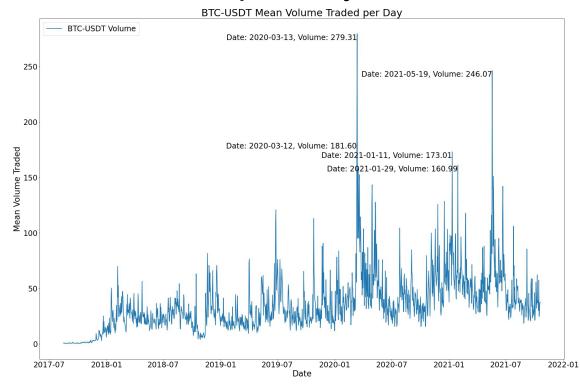
Open Time	0
Open Price	0
High price	0
Low Price	0
Close Price	0
Volume Traded	0
Close Time	0
Quote asset Volume	0
Number of Trades	0
Taker buy base asset volume	0
Taker buy quote asset volume	0
NA	0
dtype: int64	

EDA - Time Series Data

Mean Price per Day



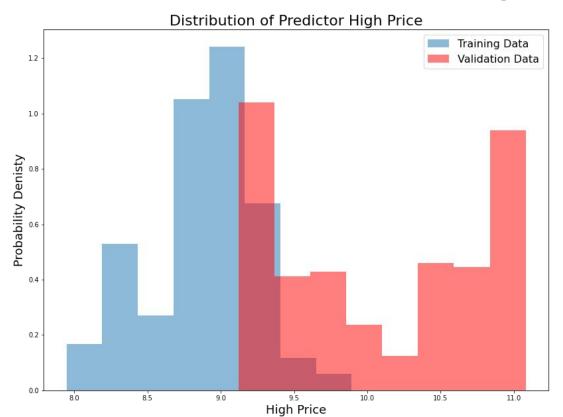
Mean Volume per Day

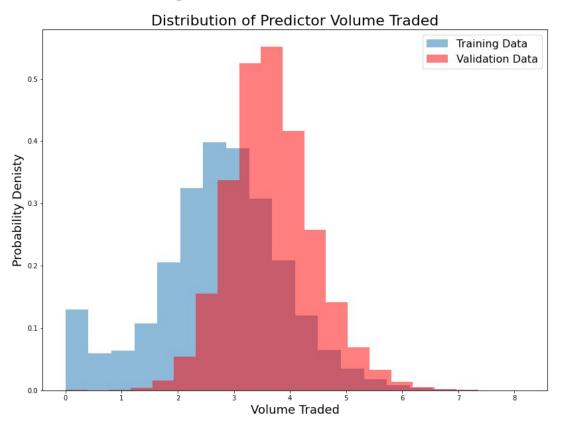


- The relative value of BTC-USDT increases rapidly due to COVID-19 pandemic
- The trading volume of BTC-USDT is fairly flat, with a few spikes due to COVID-19 pandemic

EDA - Out of Distribution Validation Data

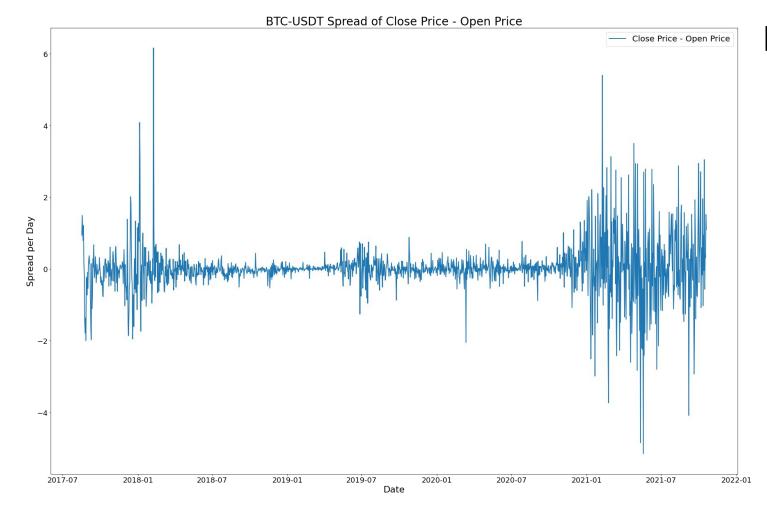
Covariate Shift between Training Data and Validation Data, Log-Normalized Data





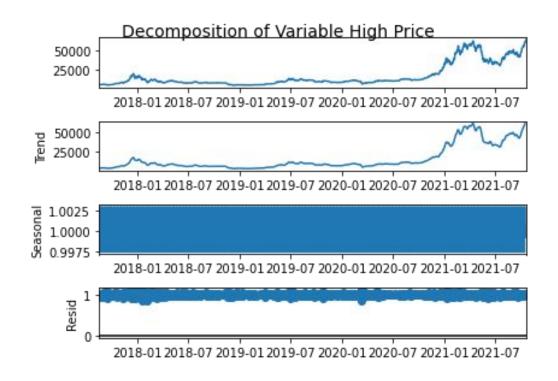
- Observable covariate shift in variable `High Price`
- Behavior hinted in the previous slide; validation data post COVID-19

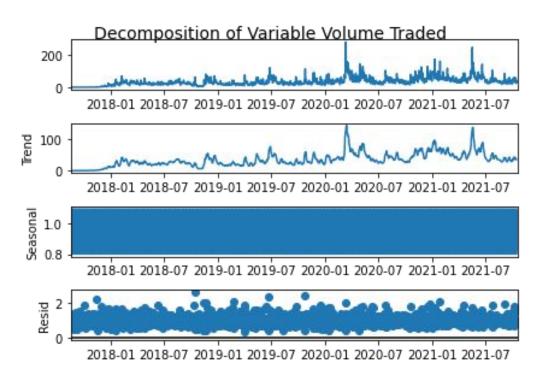
EDA - Response Variable(s)



- The spread of `Open Price` `Close Price` is fairly
 constant before COVID-19
 pandemic
- Since start of COVID-19 pandemic, significantly larger volatility
- This information should be taken into account during modelling/choosing response variable

EDA - Variable Decomposition





- Visible trend for variable `High Price`, as already hinted in previous EDA slides
- No clear trend for variable `Volume Traded`

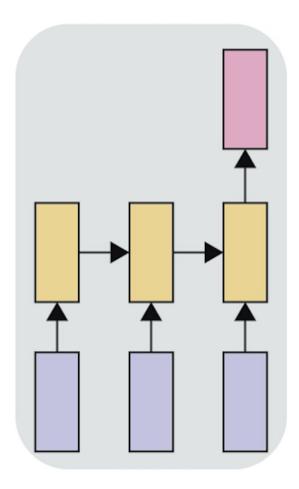
Modeling Decisions

- 80-10-10 train-validation-test split (HP tuning models)
- 100-0-0 train-validation-test split (Models pushed to GCS)
- Feature Engineering for Tensorflow Modeling:
 - Remove Close Time, Open Time, NA
 - Time-based features
 - Statistical features
 - Domain knowledge-based features
 - Log-transform data (numerical features)
 - Standardize data (whole dataset)
- Metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE)
- Predict: standardized `mid_true mid_baseline`

Modeling Approaches

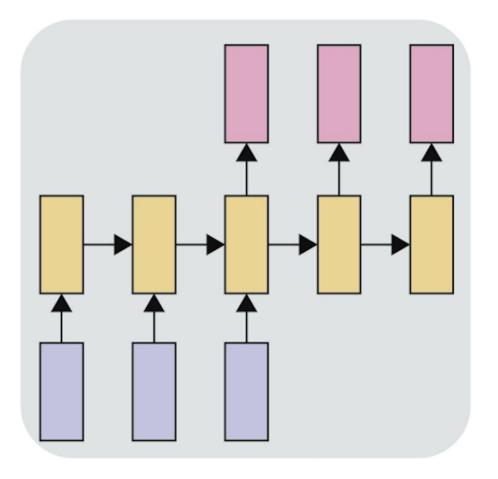
Previous: Multi-input, Single-output

given the current input, the model infers the value of the pre-defined pair, one time step in the future



Current: Multi-input, Multi-output

given the current input, the model infers the value of the pre-defined pair, X time steps in the future



Credit

Models

Baseline - Persistent Model

- For Multi-input, Single-output predicts the Close Price of the next time step to be the same as the Close Price of the current time step
- For Multi-input, Multi-output predicts the Close Price of the next X time steps to be the same as the Close Price of the current time step

Second Iteration - LSTM on Standardized Raw Features

- For Multi-input, Single-output predicts the Close Price of the next time step based on the input features of the previous X time steps
- For Multi-input, Single-output predicts the Close Price of the X next time steps based on the input features of the previous X time steps

Final Model - LSTM on Engineered Features

- Feature Engineering on input data: Log-transformed, Standardized, Time-based features, Statistical features, Domain knowledge-based features)
- Feature Engineering on output data: Transformed the output feature to standardized `mid true - mid baseline`

Models - Model Tuning Results TO ADD

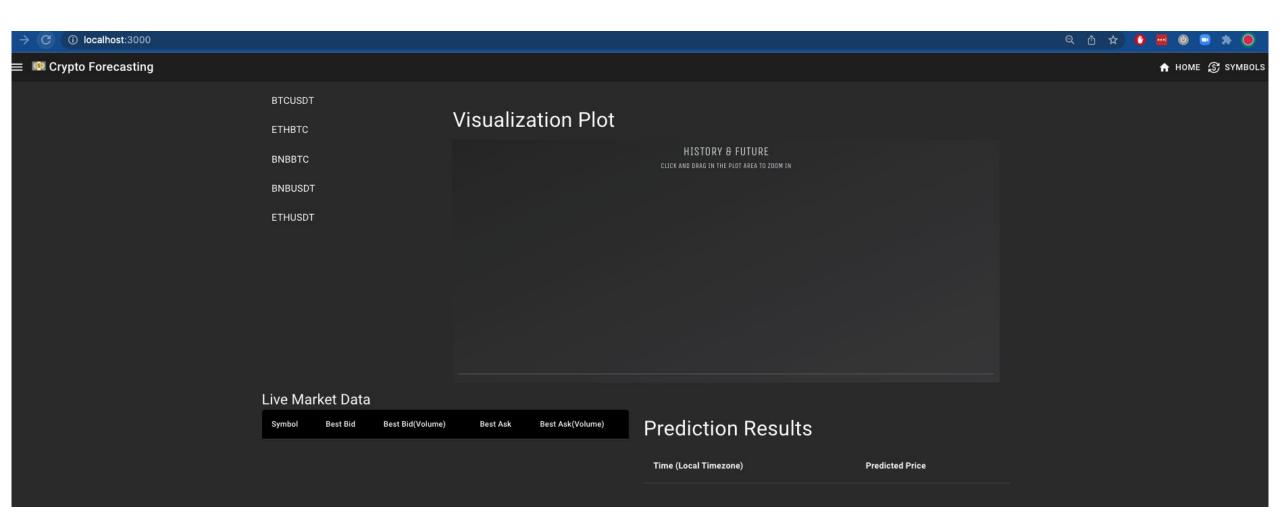
Models	Train MSE	Train MAE	Validation MSE	Validation MAE
Baseline - Single Output (SO) - /	2.8378e-6	0.0007	9.2235e-6	0.0020
Baseline - Multi Output (MO) - /	1	1	1	1
LSTM - Standardized Raw Features (SO) - input_seq_len = 32	1.0474e-5	0.0017	9.1504e-5	0.0044
LSTM - Standardized Raw Features (MO) - input_seq_len = 32	5.4911e-5	0.0035	1.6730e-4	0.0084
LSTM - Engineered Features (SO) - /	1	1	1	1
LSTM - Engineered Features (MO) - input_seq_len = 8	6.8703e-5	0.004	1.7115e-4	0.0091

Note: The models were trained on the BTC-USDT pair. It is important to bear in mind that the target variable for the Baseline (SO), LSTM - Standardized Raw Features (SO) and LSTM - Standardized Raw Features (MO) models was `Close Price`. However, for LSTM - Engineered Features (MO) the target variable was altered to 'mid_true - min_baseline`. Furthermore, for the LSTM - Standardized Raw Features (MO) we used `input_seq_len` = 32, while for the LSTM - Engineered Features (MO) we used `input_seq_len` = 8 due to compute resource limitations.*

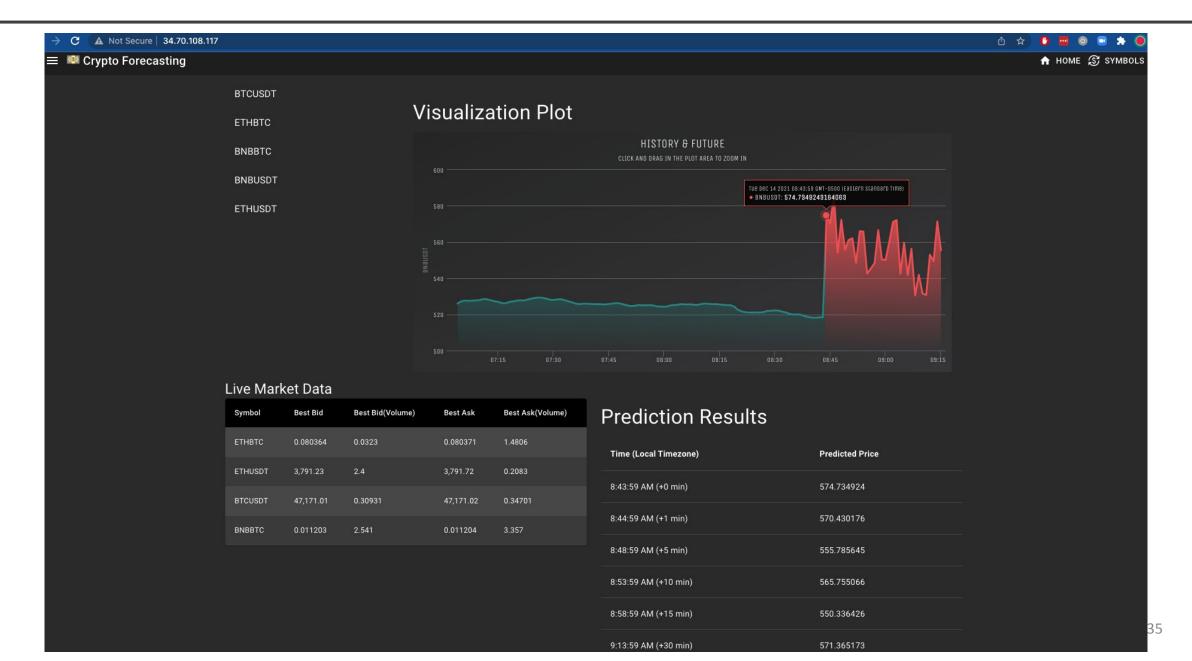
Frontend - React

- We used React javascript library to build our frontend UI
- Our UI consists of the following components
 - Time series plot with zoom in feature (highcharts)
 - Green color: Historic price
 - Red color: Future price prediction up to 32 minutes later
 - Allow user to zoom in and reset at any period of time
 - Selection of pair for prediction (material UI)
 - Prediction results table
 - Live market data table

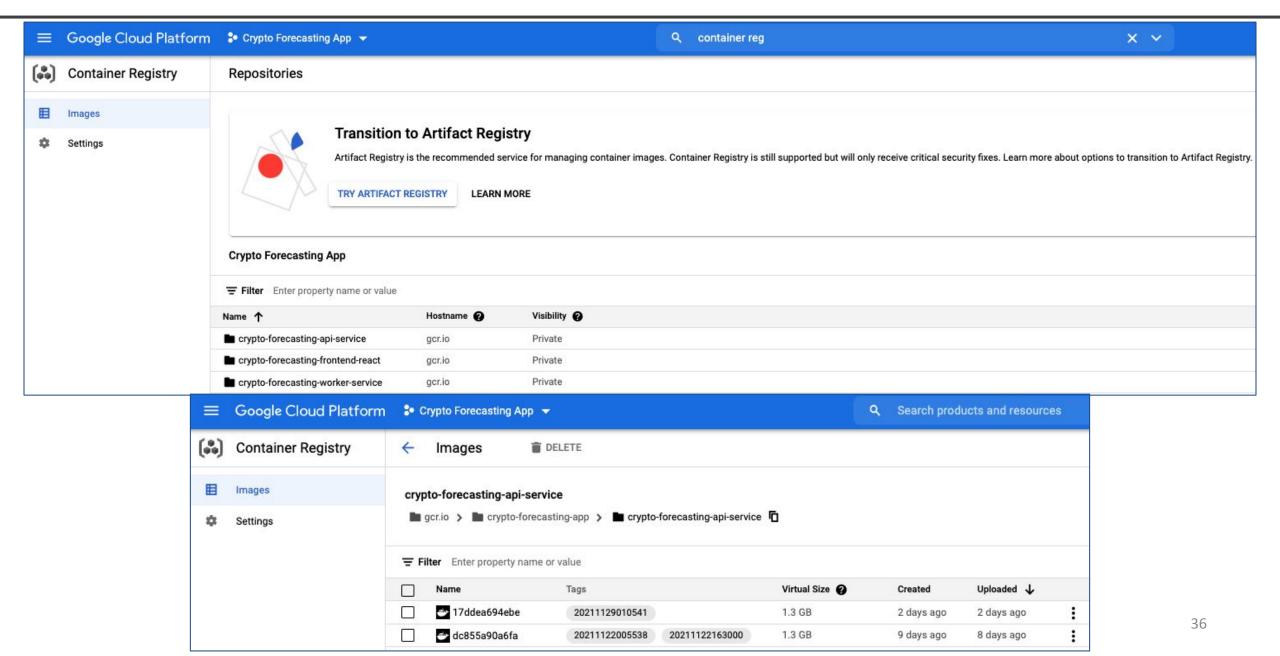
Frontend - Start-Up Screen



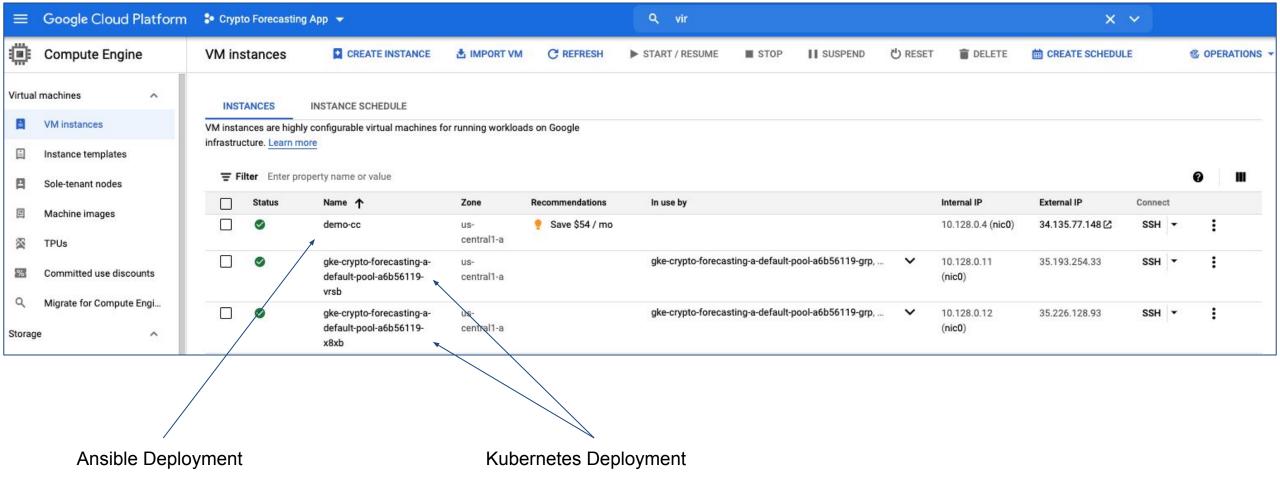
Frontend View



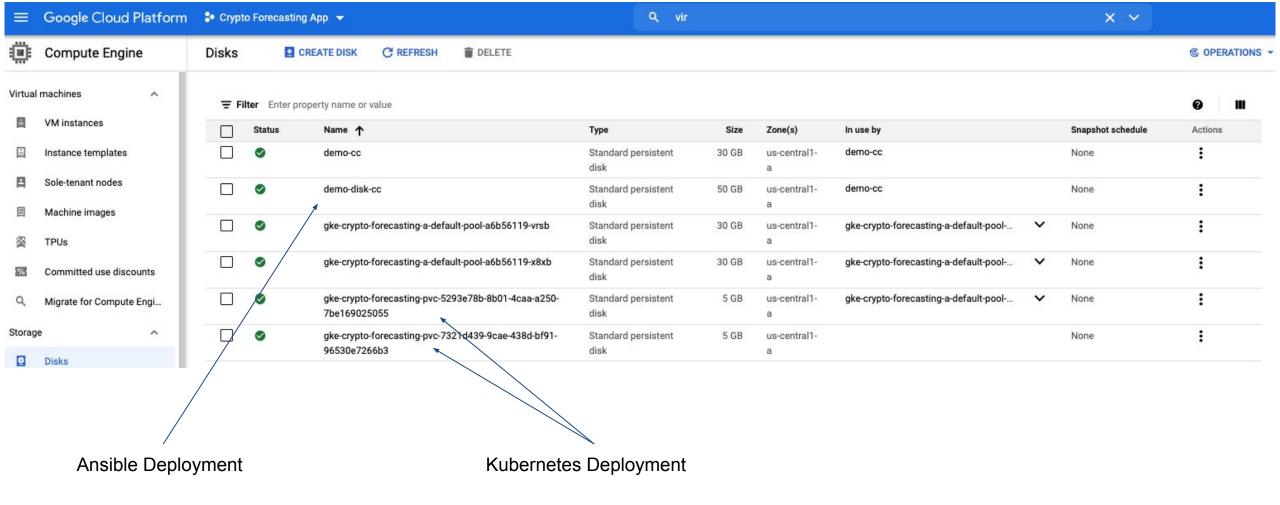
Deployment - Container Registry



Deployment - Compute Engine



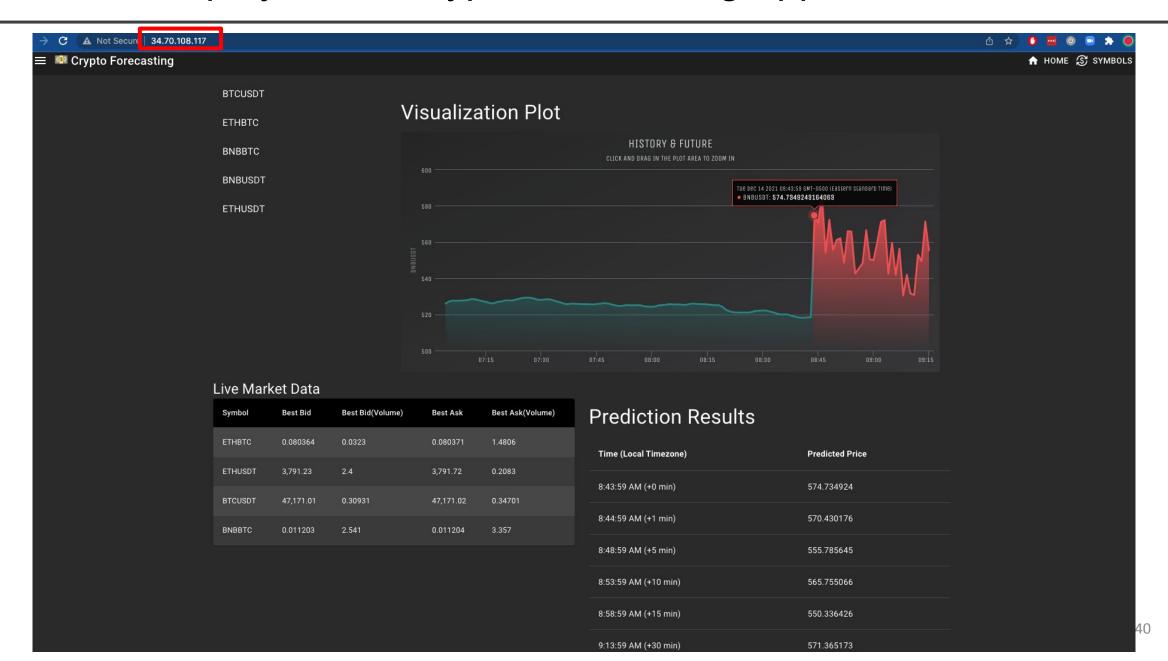
Deployment - Persistent Disk (Saving Postgres Database)



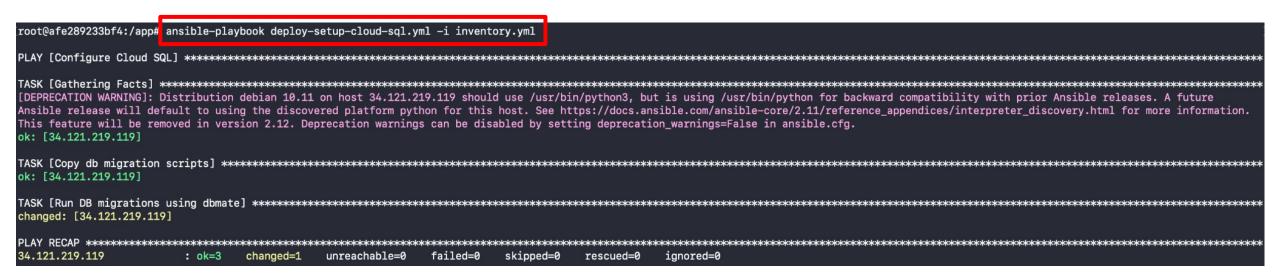
Standard Deployment - Virtual Machine SSH

Commondation	- g I Bado docker Image 15								
REPOSITORY		TAG	IMAGE ID	CREATED	SIZE				
gcr.io/crypto-forecasting-app/crypto-forecasting-worker-service		20211129010541	7998cf254ecb	37 hours ago	650MB				
gcr.io/crypto-forecasting-app/crypto-forecasting-api-service		20211129010541	e64b373aed92	37 hours ago	2.63GB				
gcr.io/crypto-forecasting-app/crypto-forecasting-frontend-react		20211129010541	edfc06298332	37 hours ago	162MB				
postgres		latest	577410342f45	12 days ago	374MB				
nginx		stable	aedf7f31bdab	13 days ago	141MB				
connorcapitolo	o g harvard edu@demo-cc:~\$ sudo docker container ls								
CONTAINER ID	IMAGE			COMMAND		CREATED	STATUS	PORTS	NAMES
7d2992b474fe	e nginx:stable			"/docker-entrype	oint"	37 hours ago	Up 37 hours	0.0.0.0:80->80/tcp, 0.0.0.0:443->443/tcp	nginx
7d5bc228417a	17a gcr.io/crypto-forecasting-app/crypto-forecasting-worker-service:20211129010541			"/bin/bash ./do	cker"	37 hours ago	Up 37 hours		worker-service
78cf76469a44	469a44 gcr.io/crypto-forecasting-app/crypto-forecasting-api-service:20211129010541			"/bin/bash ./docker"		37 hours ago	Up 37 hours	0.0.0.0:9600->9000/tcp	api-service
90b0a0ffbd4e postgres:latest				"docker-entrypoint.s"		37 hours ago	Up 37 hours	0.0.0.0:5432->5432/tcp	postgres
8ab2619b5094 gcr.io/crypto-forecasting-app/crypto-forecasting-frontend-react:20211129010541				"/docker-entrypoint"		37 hours ago	Up 37 hours	0.0.0.0:3000->80/tcp	frontend

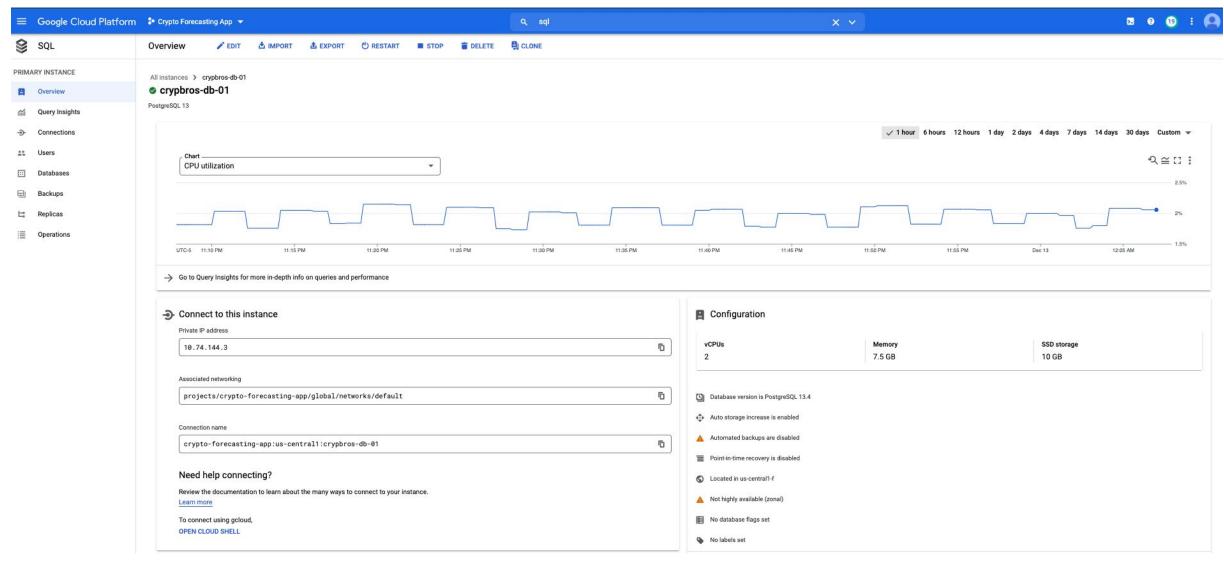
Standard Deployment - Crypto Forecasting App



Kubernetes Deployment - Cloud SQL Script



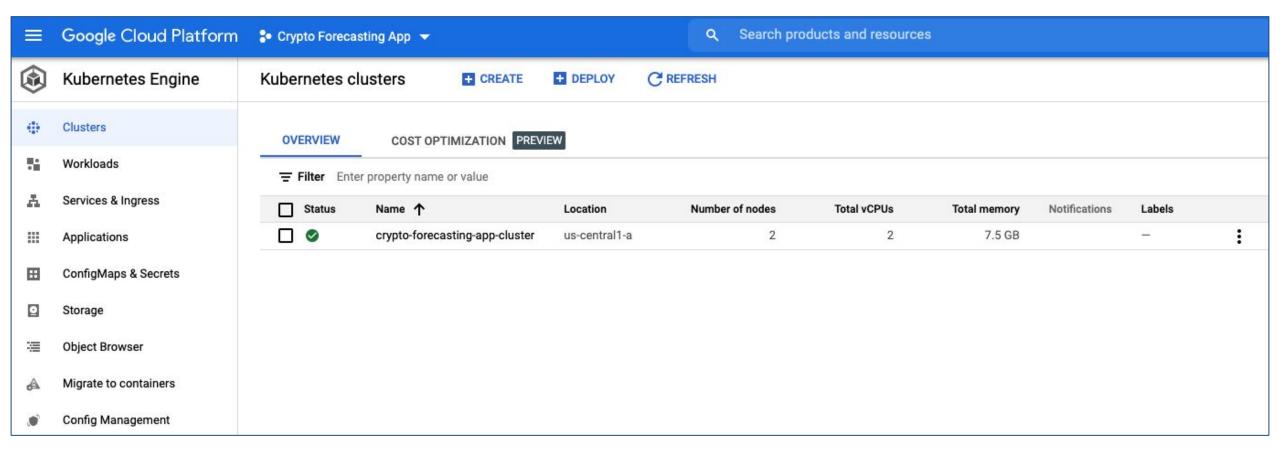
Kubernetes Deployment - Google Cloud SQL



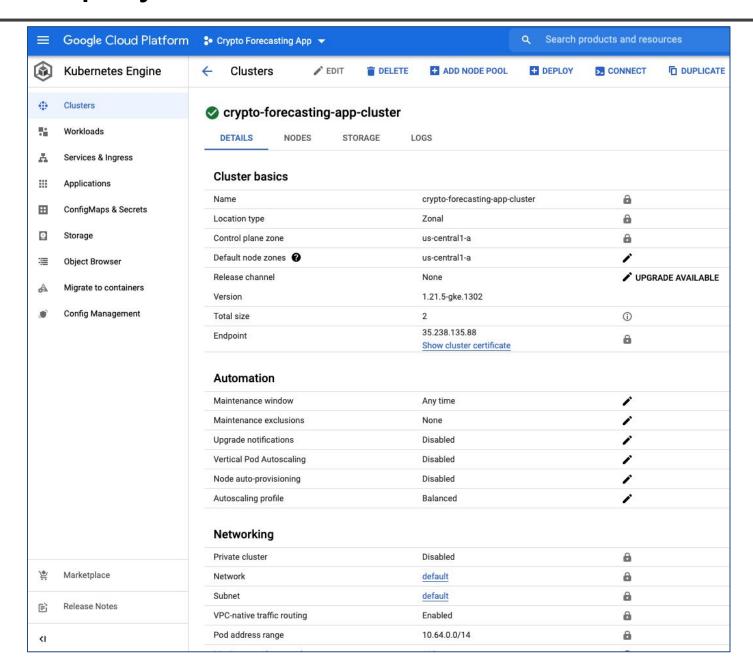
Kubernetes Deployment - Kubernetes Script (Partial View)

```
root@425fa92ea59f:/app# ansible-playbook deploy-k8s-cluster.yml -i inventory.yml --extra-vars cluster state=present
[DEPRECATION WARNING]: community.kubernetes.helm_repository has been deprecated. The community.kubernetes collection is being renamed to kube
rnetes.core. Please update your FQCNs to
kubernetes.core instead. This feature will be removed from community.kubernetes in version 3.0.0. Deprecation warnings can be disabled by set
ting deprecation warnings=False in ansible.cfg.
[DEPRECATION WARNING]: community.kubernetes.helm has been deprecated. The community.kubernetes collection is being renamed to kubernetes.core
. Please update your FQCNs to kubernetes.core
instead. This feature will be removed from community kubernetes in version 3.0.0. Deprecation warnings can be disabled by setting deprecation
warnings=False in ansible.cfg.
***************
*****************
changed: [localhost]
***************
changed: [localhost]
****************
changed: [localhost]
******************
changed: [localhost]
******************
ok: [localhost]
******************
changed: [localhost]
*******************
ok: [localhost]
```

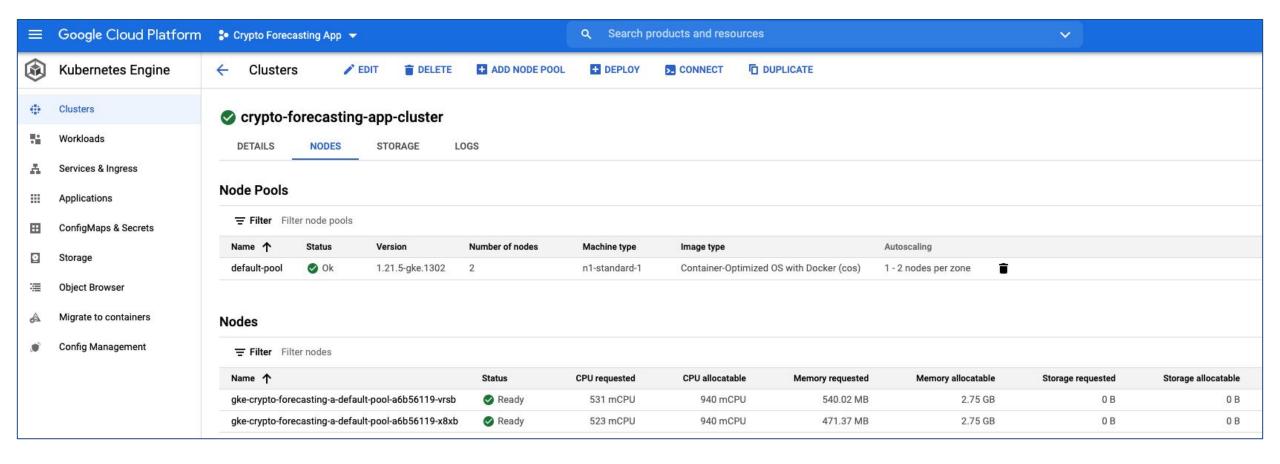
Kubernetes Deployment - Kubernetes Engine Homepage



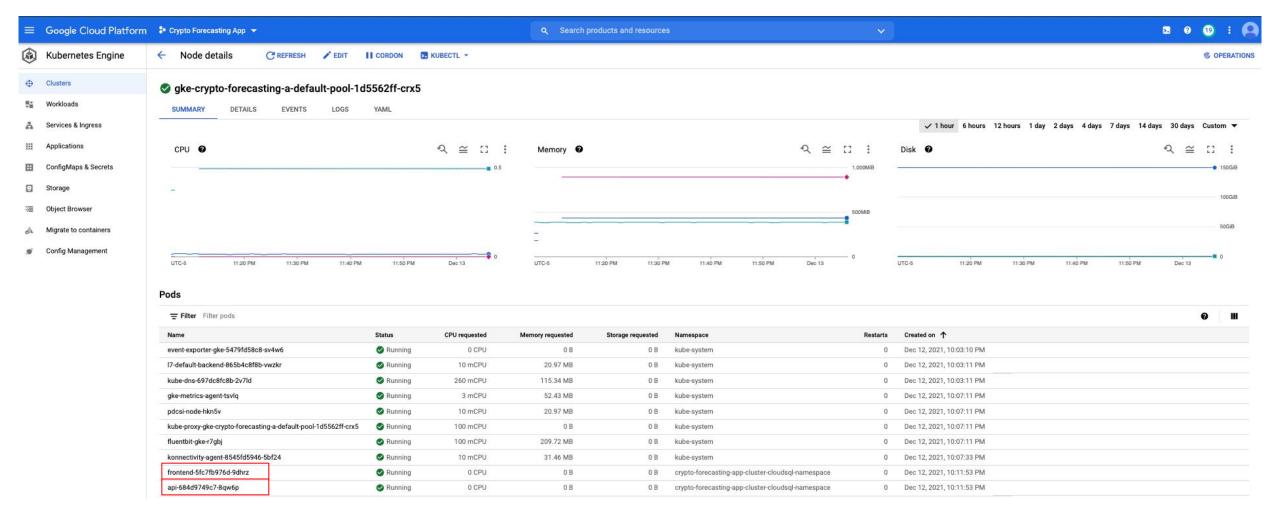
Kubernetes Deployment - Kubernetes Cluster



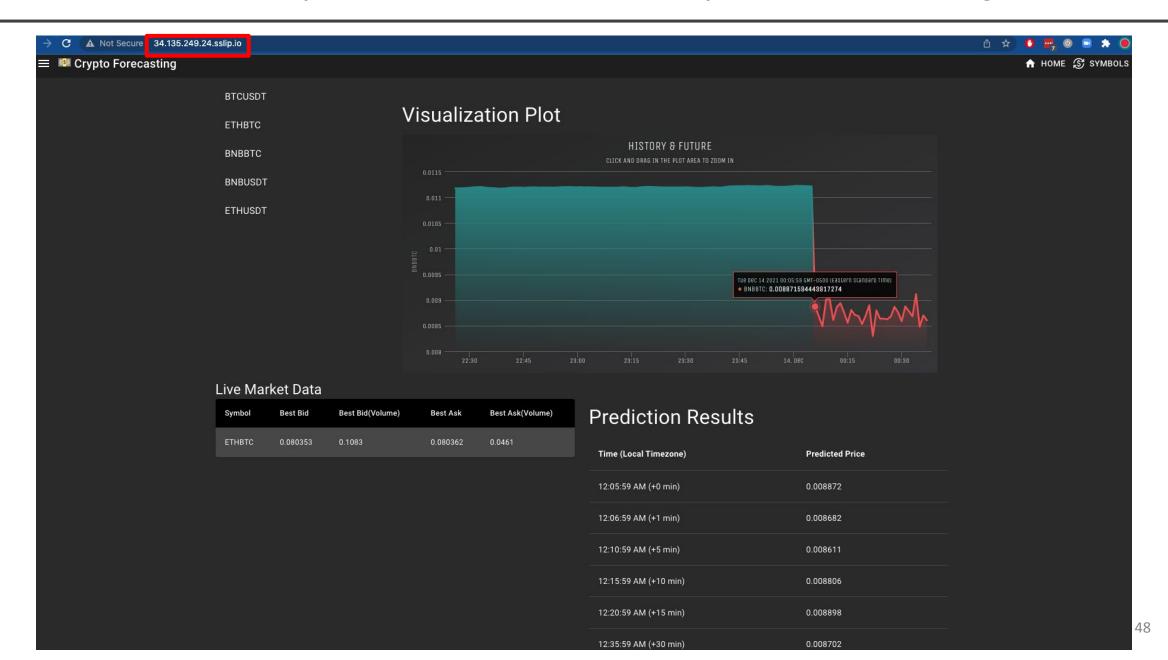
Kubernetes Deployment - Kubernetes Node Pool & Nodes



Kubernetes Deployment - Kubernetes Pod



Kubernetes Deployment - Kubernetes Crypto Forecasting App



Next Steps

- Work on latency issues on the API side when processing raw data, loading the best model and performing predictions
- Build an automated modeling and training pipeline using VertexAI in order to automatically train new models when a user inputs a new symbol
- Improve current performances of the models
- Fix issues on the worker service side (not yet robust to all edge cases)
- Perform data tests
- Update the front-end to support the dynamic addition of symbols
- Improve UI by providing more relevant features for different use cases (e.g. log-in accounts, news information, new symbols to track and query, trading platform)
- Setup the backtesting and trading API (longer term)