# Ocean Protocol :: ETH Prediction Challenge



## **Challenge description**

### Challenge

Contestants are requested to submit the following:

- Csv with the predictions for ETH price over a 24-hour period, with first prediction on from Mon Oct 17, 2022 at 1:00am UTC, and a prediction every hour on the hour after that, for 24 predictions total.
- A report of 10-30 slides describing your approach, and insights you gained in making the predictions. Think of this as a "conference presentation" for your work.
- Optional: add at least one slide presenting any challenges faced during the bounty and/or recommendations you may have.

#### **Evaluation Criteria**

- 80% of the competitor's score will be objectively measured, based on <u>Normalized Mean Square Error</u>(NMSE) of the predictions (1). The README shows the precise calculations.
- 20% of the competitor's score will be based on the slides (2), subjectively measured by a panel of judges. The criteria will be like those of a presentation in a technical conference.



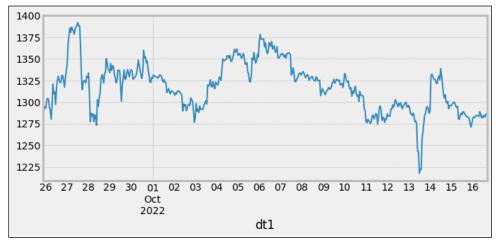
## **Input dataset**

You can download the dataset from here:

https://cexa.oceanprotocol.io/ohlc?exchange=binance&pair=ETH/USDT&period=1h

This data feed returns ETH/USDT ohlc history: {open, high, low, close} over time, drawn from Binance. It's over the most recent 500 hours: every hour, on the hour.

### ETH close price hourly plot:



### The last 3 rows from our dataset:

	open	high	low	close	volume	
dt1						
2022-10-16 14:00:00	1,284.65	1,285.60	1,280.19	1,283.12	8,268.21	
2022-10-16 15:00:00	1,283.13	1,287.79	1,282.97	1,286.35	8,622.73	
2022-10-16 16:00:00	1,286.36	1,287.71	1,285.48	1,286.44	2,257.71	

We converted the time to UTC+0 timezone as it is needed in the competition.

It is important to note that we have the holdout period – it is the number of hours to the first prediction.

In our case we have the latest data at 16:00 so we didn't see 8 data values to the first prediction point.

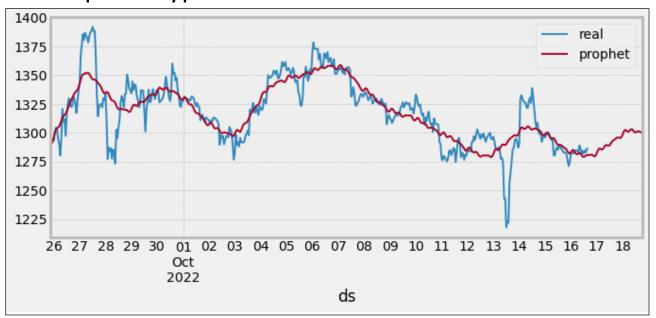


<sup>\*</sup>More details you can find in the following script: 1 get predictions.ipynb

# **Final predictions**

We have used the prophet model for getting the final predictions (<a href="https://facebook.github.io/prophet/">https://facebook.github.io/prophet/</a>). The parameters of the model is the following: m = Prophet(weekly\_seasonality=True, daily\_seasonality=True).

### ETH close price hourly predictions:

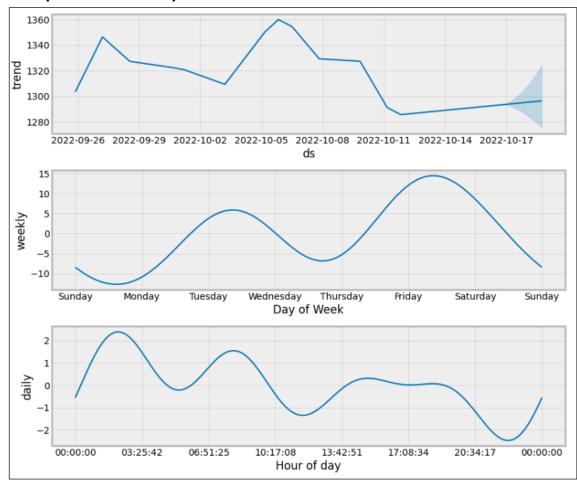


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# **Model description**

By running the command *m.plot\_components()* we can see the following description of the model. We have the trend, weekly and daily components of the model.

### **Prophet model components:**



<sup>\*</sup>More details you can find in the following script: 1\_get\_predictions.ipynb



# **Models testing**

We have tried to train 3 models:

- last available value prediction
- exponential smoothing
- prophet model

We have evaluated them by different metrics:

- nmse normalized mean squared error (main competition metric)
- mse mean squared error
- mae mean absolute error
- mape mean absolute percentage error

We have used one day for evaluation set (14,15 or 16 of October), the data before that day was used for training but with one more parameter *hours\_skip* – it is the number of last values to skip in the training set (holdout period – we will explore the dependencies of that parameter on the quality on the next slide).

### Prophet model is the best model for the most number of validation results:

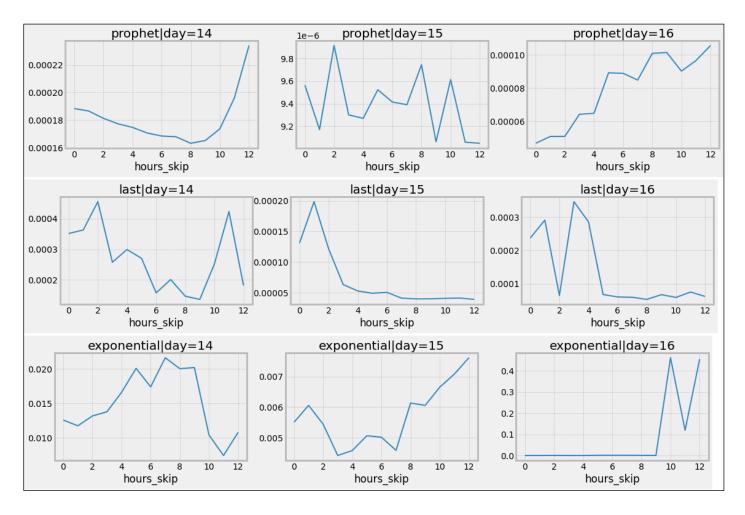
nmse			mse			mae			mape		
14	15	16	14	15	16	14	15	16	14	15	16
0.007419	0.004421	0.000128	12,851.449538	7,326.537462	212.199923	109.578713	85.345469	9.183035	0.083042	0.066305	0.007068
0.000136	0.000039	0.000054	236.441487	65.011750	89.075313	12.863750	6.647500	5.422917	0.009830	0.005156	0.004164
0.000163	0.000009	0.000047	282.473698	14.992973	77.421920	15.036990	2.346065	5.122902	0.011374	0.001828	0.003936
	0.007419	0.007419	14 15 16	14 15 16 14   0.007419 0.004421 0.000128 12,851.449538   0.000136 0.000039 0.000054 236,441487	14 15 16 14 15   0.007419 0.004421 0.000128 12,851.449538 7,326.537462   0.000136 0.000039 0.000054 236.441487 65.011750	14     15     16     14     15     16       0.007419     0.004421     0.000128     12,851.449538     7,326.537462     212.199923       0.000136     0.000039     0.000054     236.441487     65.011750     89.075313	14     15     16     14     15     16     14       0.007419     0.004421     0.000128     12,851.449538     7,326.537462     212.199923     109.578713       0.000136     0.000039     0.000054     236.441487     65.011750     89.075313     12.863750	14     15     16     14     15     16     14     15       0.007419     0.004421     0.000128     12,851.449538     7,326.537462     212.199923     109.578713     85.345469       0.000136     0.000039     0.000054     236.441487     65.011750     89.075313     12.863750     6.647500	14     15     16     14     15     16     14     15     16       0.007419     0.004421     0.000128     12,851.449538     7,326.537462     212.199923     109.578713     85.345469     9.183035       0.000136     0.000039     0.000054     236.441487     65.011750     89.075313     12.863750     6.647500     5.422917	14     15     16     14     15     16     14     15     16     14     15     16     14       0.007419     0.004421     0.000128     12,851.449538     7,326.537462     212.199923     109.578713     85.345469     9.183035     0.083042       0.000136     0.000039     0.000054     236.441487     65.011750     89.075313     12.863750     6.647500     5.422917     0.009830	14     15     16     14     15     16     14     15     16     14     15       0.007419     0.004421     0.000128     12,851.449538     7,326.537462     212.199923     109.578713     85.345469     9.183035     0.083042     0.066305       0.000136     0.000039     0.000054     236.441487     65.011750     89.075313     12.863750     6.647500     5.422917     0.009830     0.005156



<sup>\*</sup>More details you can find in the following script: 3\_models\_testing.ipynb

# The dependencies of hours\_skip parameter on the NMSE metric

As we can see on the picture below based on validations results that there is now a high drop in quality if we will use not fresh data (let's say 5-10 hours to the first prediction). In our case we didn't have a chance to have a fresh data and we have executed the forecasting scripts in 8 hours before the deadline.



<sup>\*</sup>More details you can find in the following script: 3 models testing.ipynb



### Recommendations & Ideas for the future work

#### **Results:**

- 1. We have tested 3 approaches on the validation sets: last value prediction, exponential smoothing and prophet model. And after that explorations we decided to use prophet model to generate the final predictions.
- 2. We have shown that there is now a high drop in quality if we will use not fresh data if we will have 5-10 hours of holdout period to the first prediction.

### The ideas how to improve the results:

- 1. Try to collect more data of ETH prices, maybe 500 points is not enough to get accurate predictions..
- 2. Based on extended dataset try to train Machine Learning models (Boosting, Random Forests..) that can use simple models predictions (prophet, exponential smoothing...) as features.
- 3. Based on extended dataset try to train multistep Recurrent Neural Networks (LSTM, GRU) with different architectures.

