

# Data Streaming project: Trading Data with Kafka

Yao Pacome KOUAME , Pierre LOVITON and Angie MÉNDEZ-LLANOS

MASTER DS IP-PARIS

January 16, 2022

# Overview

- 1 Goals
- 2 Data
- 3 Batch models
- 4 Online models
- 5 Application

# Goals

## Objectives

- Using online learning to predict the future value of a given cryptocurrency using Kafka to process the data.
- Comparing the result of the online learning models with a similar batch version.

# Data

One observation per minute, retrieved making a request from the **Binance API** by blocks. There are 13 features per observation:

## Features

'open time', 'open', 'high', 'low', 'volume', 'close time', 'quote asset volume', 'nb trades', 'Taker buy base asset volume', 'Taker buy quote asset volume', 'Ignore'

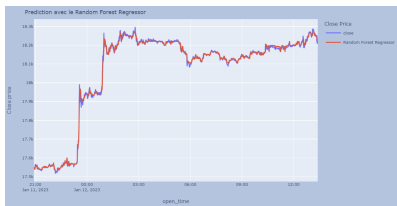
The models were built using the '**close**' variable as target.  
Chosen cryptocurrency: **BTCUSDT**.

# Batch Models

The data was split in **75-25 train-test** and evaluated on the test data for two different models:



Linear Regression



Random Forest

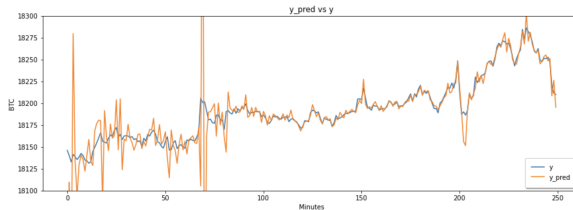
The performance was evaluated via the **RMSE** and **MAE**:

Model	Linear Regression	Random Forest
RMSE	7.99	9.73
MAE	5.50	7.60

# Online models

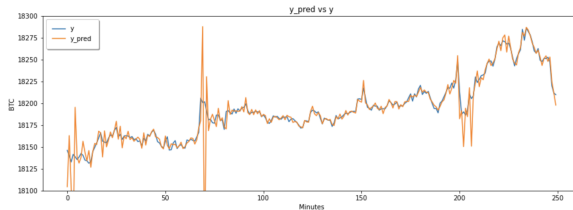
## 1. Linear Regression Classic

MAE: 3.055636519804319 ; SMAPE: 0.016764278383043646



## Tuned (intercept $l_r = 0.25$ )

MAE: 3.3712420839288093 ; SMAPE: 0.018501314848544396

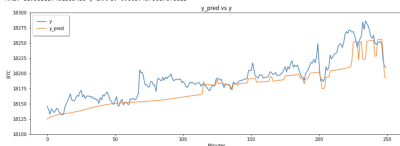


# Online models

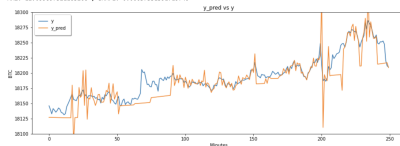
## 2. Hoeffding Tree Regressor

GP: grace period ; MSD: model selector decay

grace\_period: 18 ; model\_selector\_decay: 0.5  
MAE: 11.98537491365426 ; SMAPE: 0.86574973617678825

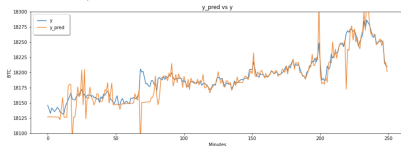


grace\_period: 100 ; model\_selector\_decay: 0.9  
MAE: 12.899887521185208 ; SMAPE: 0.8663733391719749



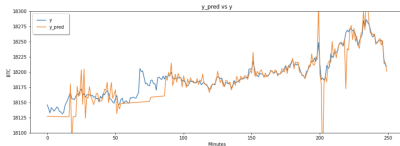
GP: 10 ; MSD: 0.5

grace\_period: 200 ; model\_selector\_decay: 0.5  
MAE: 6.199117941220793 ; SMAPE: 0.8348288062139668



GP: 100 ; MSD: 0.9

grace\_period: 200 ; model\_selector\_decay: 0.9  
MAE: 6.111248022371385 ; SMAPE: 0.833546381287892864



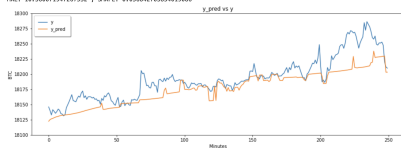
GP: 200 ; MSD: 0.5

GP: 200 ; MSD: 0.9

# Online models

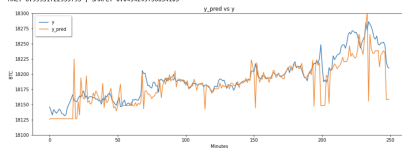
## 3. Hoeffding Adaptive Tree Regressor

grace\_period: 10 ; model\_selector\_decay: 0.1  
MAE: 18.360871947267532 ; SMAPE: 0.85684270354819806



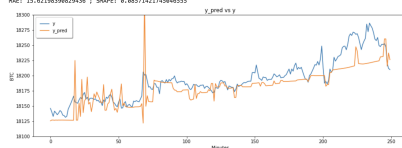
GP: 10 ; MSD: 0.1

grace\_period: 200 ; model\_selector\_decay: 0.5  
MAE: 8.99951722955793 ; SMAPE: 0.409424975654185



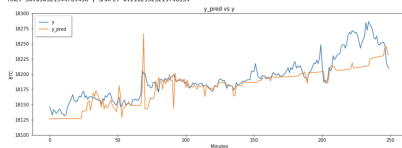
GP: 200 ; MSD: 0.5

grace\_period: 100 ; model\_selector\_decay: 0.5  
MAE: 15.62196398029436 ; SMAPE: 0.88571421745846555



GP: 100 ; MSD: 0.5

grace\_period: 200 ; model\_selector\_decay: 0.9  
MAE: 38.458321944769436 ; SMAPE: 0.21629525219746354



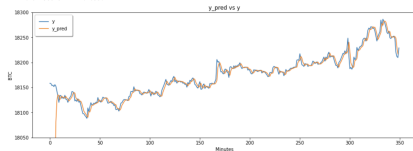
GP: 200 ; MSD: 0.9



# Online models

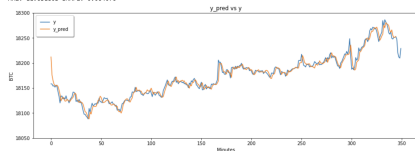
## 4. SNARIMAX horizon: 10 (horizon!= h)

h: 1 ; n\_iter: 349  
MAE: 6.912588 SMAPE: 0.838817



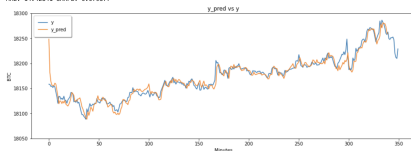
h: 1

h: 5 ; n\_iter: 345  
MAE: 11.051883 SMAPE: 0.864876



h: 5

h: 10 ; n\_iter: 348  
MAE: 14.42841 SMAPE: 0.879377



h: 10

# Kafka

The data was processed using Kafka.

## Topics

- Original data : **BTCUSDT-1m-raw**
- Clean data: **BTCUSDT-1m-clean**
- Model outputs
  - Linear model: **model-linear-BTCUSDT**
  - Hoeffding Tree Regressor: **model-HTreg-BTCUSDT**
  - Hoeffding Adaptive Tree Regressor:  
**model-HATReg-BTCUSDT**
  - SNARIMAX: **model-SNARIMAX-BTCUSDT**

# Python scripts

One script for retrieving real-time data, one for cleaning it and one for inouting the data to each model and saving the results.

## Data flow

- 1 Retrieving the data **ingest-data-BTCUSDT.py**
  - Kafka producer - *BTCUSDT-1m-raw*
- 2 Clean raw data **clean-data-BTCUSDT.py**
  - Kafka consumer - *BTCUSDT-1m-raw*
  - Kafka producer - *BTCUSDT-1m-clean*
- 3 Model clean data (identical for each model)  
**model-linear-BTCUSDT.py**
  - Kafka consumer - *BTCUSDT-1m-clean*
  - Kafka producer - *model-linear-BTCUSDT*