Final Project Assignment
DADS 6005 : Data Streaming and Real-Time Analytics

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Requirements

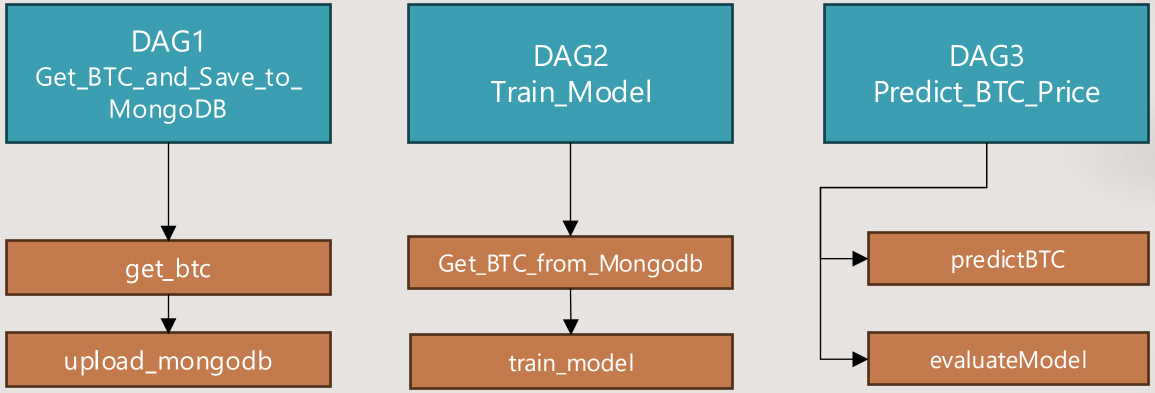
รันระบบ airflow สามวัน ดังนี้ วันที่ 21, 22, 23 ธค โดยในแต่ละวันจะกำหนดช่วงเวลาในการ predict BTC ตั้งแต่ 22:00 ~ 6:00 โมงเช้า โดย schedule ทุกๆ 5 นาที และคำนวณ mape ทุกๆ ชั่วโมง (หมายถึง len=12) โดย นศ จะส่ง mape.txt 3 files (ของช่วงวันเวลาที่ทดสอบ 3 วัน) + code 3 dags + requirement.txt และ files อื่นๆ ถ้ามีความแตกต่างจาก starter kit กำหนด

1.dataset ในการสร้าง train และ predict model จะมี column (X=closeTime) และ (Y=lastPrice)
2.นศ สามารถใช้ regression model ต่างๆ หรือ เทคนิคทางด้าน time series หรือ AI มาช่วยวิเคราะห์ได้

Airflow DAG Diagram

DAG

Task



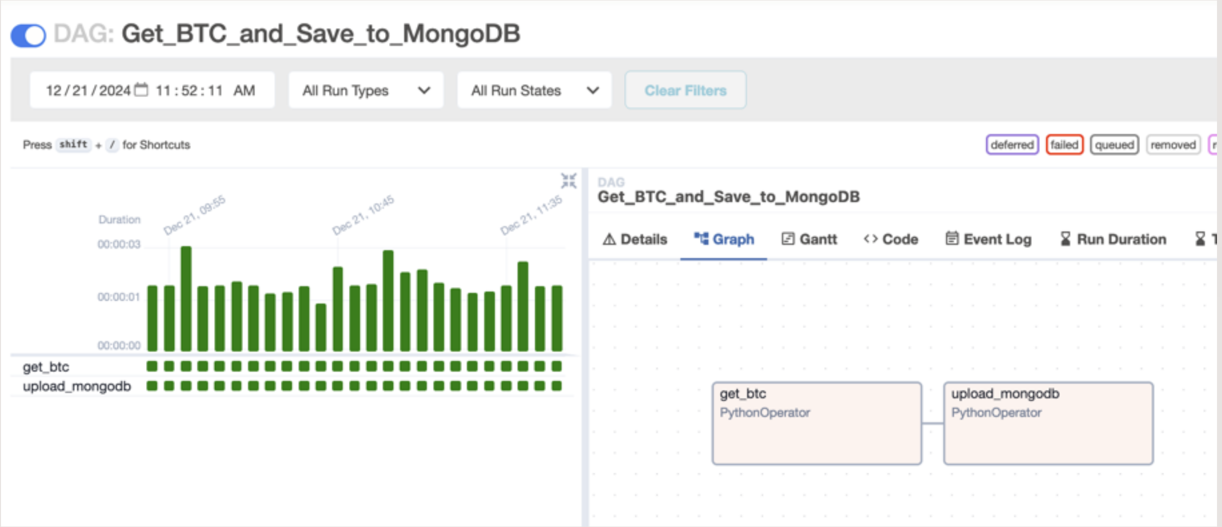
Schedule

Schedule : Every 5 minutes
Start 2024-12-21 00:00 UTC7
End 2024-12-24 06:00 UTC7

Schedule : Every hour at
minute 50
Start 2024-12-21 00:00 UTC7
End 2024-12-24 06:00 UTC7

Schedule : Every 5 minutes at
22:00 – 06:00 nextday from
December date 21-23
Start 2024-12-21 21:00 UTC7
End 2024-12-24 06:00 UTC7

DAG 1 : Get_BTC_and_Save_to_MongoDB



There are 2 task in DAG 1 as following :

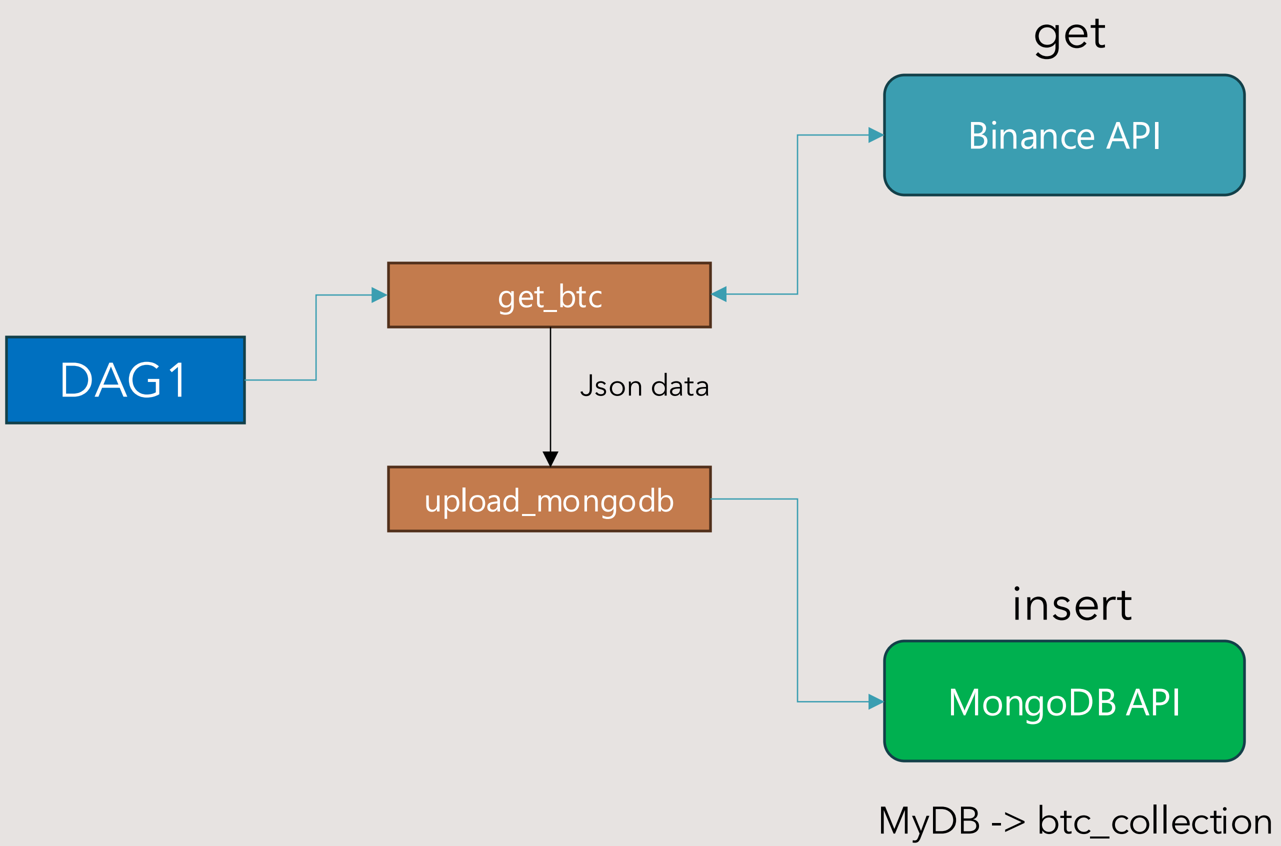
- **Get_btc** : This task use https requests to get current BTCUSDT price from Binance API with windows size of 1 hours (average last 1 hour metrics) which contain data ('_id', 'symbol', 'openPrice', 'highPrice', 'lowPrice', 'lastPrice','volume', 'quoteVolume', 'openTime', 'closeTime', 'firstId', 'lastId','count') in json format.

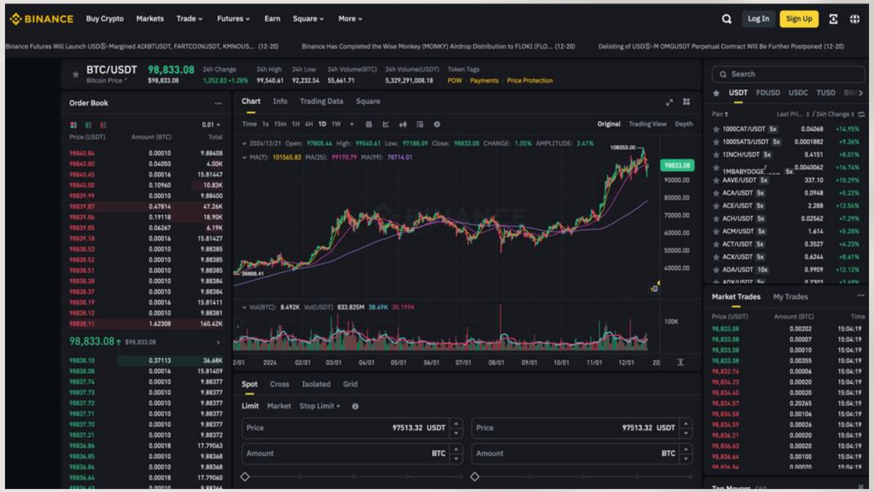
- **Upload_mongodb** : This task insert the json data output from above task to MongoDB cloud (MyDB->btc_collection)

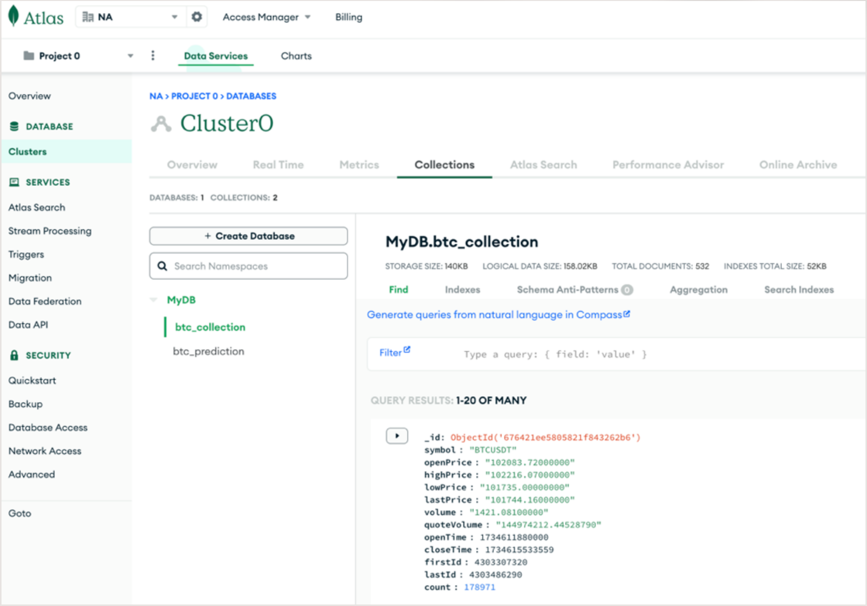
Schedule : Every 5 minutes. start 2024-12-21 00:00 utc7, end 2024-12-24 06:00 utc7

**More detail please check on code at dag1.py*

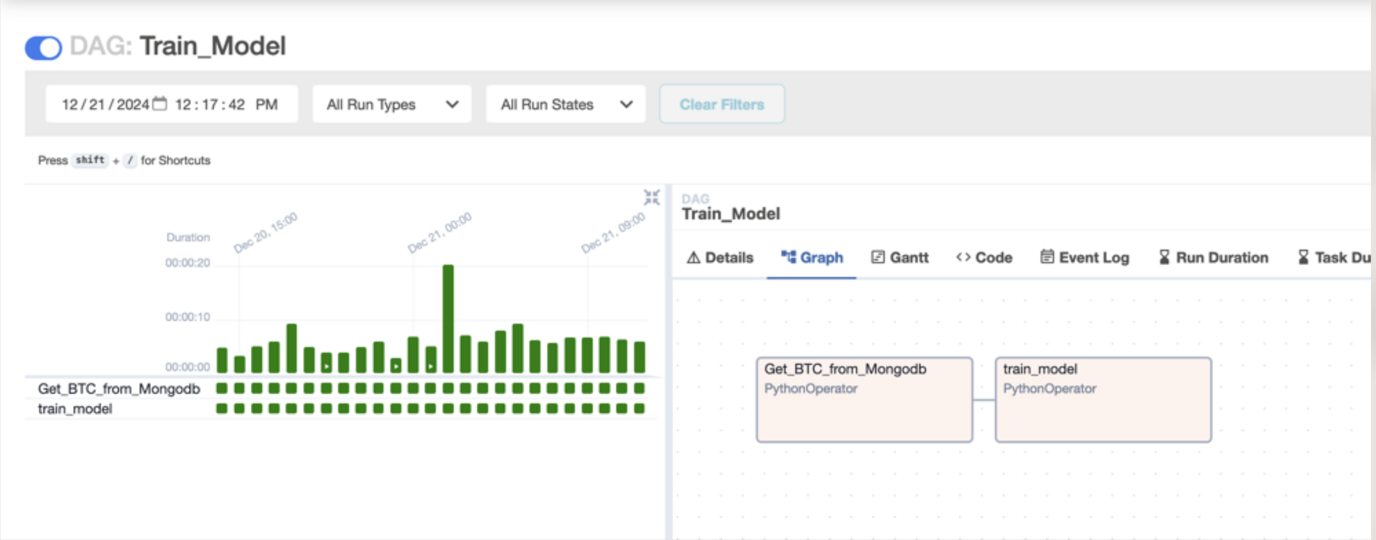
DAG 1 : Get_BTC_and_Save_to_MongoDB







DAG 2 : Train_Model



There are 2 task in DAG 2 as following :

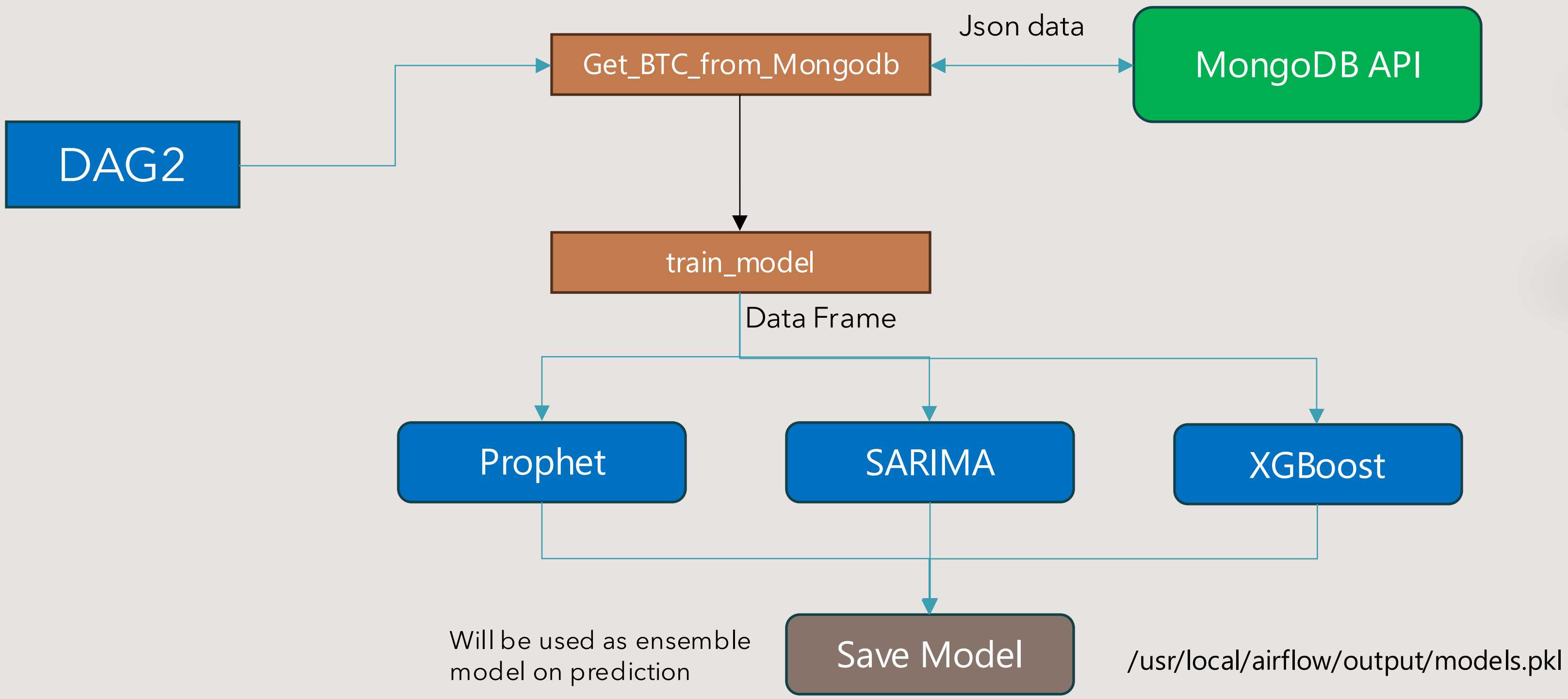
- **Get_BTC_from_Mongodb** : This task load data (last1day from current) from MongoDB cloud (MyDB->btc_collection).

- **Train_model** : use data output from above task (last 1day from current) with closeTime(X) and lastPrice(y) to train model.
  Then save model to "/usr/local/airflow/output/models.pkl"
  This project come with the idea of **ensemble model** of (Prophet, SARIMA and XGBoost) so we train all these 3 models in once.
  - **Prophet:** Suitable for handling seasonality and trend changes, modeled with multiplicative seasonality.
  - **SARIMA:** Incorporates both seasonal and non-seasonal components for autoregressive integrated moving average predictions.
  - **XGBoost:** A tree-based ensemble method optimized for regression tasks, trained with engineered time-series features.

Schedule : Every 1 hour at 50 minutes of each hour, e.g. 01:50, 02:50, 03:50 ... onward. start 2024-12-21 00:00 utc7, end 2024-12-24 06:00 utc7.

**More detail please check on code at dag2.py*

DAG 2 : Train_Model




```python
# Save all models
import pickle
models = {
    'prophet': model,
    'sarima': sarima_results,
    'xgb': xgb_model,
    'features': features,
    'last_timestamp': df['datetime'].max(),
    'last_prices': df['lastPrice'].tail(6).tolist()  # Save last 6 prices for lag features
}

modelFile = '/usr/local/airflow/output/models.pkl'
with open(modelFile, 'wb') as f:
    pickle.dump(models, f)
```

DAG 2 : Train_Model

Prep Data

Load past 1 day to current data (288 reccords)

```
data = ti.xcom_pull(
    task_ids="Get_BTC_from_Mongodb",
    key="data"
)
df = pd.DataFrame(json.loads(data))

# prep data
df['datetime'] = pd.to_datetime(df['closeTime'], unit='ms')
df = df[~df['datetime'].duplicated(keep='first')]
df.set_index('datetime', inplace=True, drop=False)
df = df.sort_index()
df['lastPrice'] = pd.to_numeric(df['lastPrice'], errors='coerce')
df['lastPrice'] = df['lastPrice'].ffill() # Forward fill
```

Assign index from datetime and sort by index.

As requirement :
X = closedTime only
Y = lastPrice

Prophet

datetime = closeTime

```
from prophet import Prophet
# Prepare data for Prophet
prophet_df = pd.DataFrame()
prophet_df['ds'] = df['datetime']
prophet_df['y'] = df['lastPrice']

model = Prophet(
    changepoint_prior_scale=0.001,
    seasonality_prior_scale=0.1,
    seasonality_mode='additive',
    daily_seasonality=True,
    weekly_seasonality=True
)
model.fit(prophet_df)
```

SARIMA

Use index as datetime

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
# Fit SARIMA model
sarima_model = SARIMAX(
    df['lastPrice'],
    order=(0, 1, 3),  # ARIMA parameters (p,d,q)
    seasonal_order=(0, 1, 1, 24),  # Seasonal parameters (P,D,Q,s)
)
sarima_results = sarima_model.fit()
```

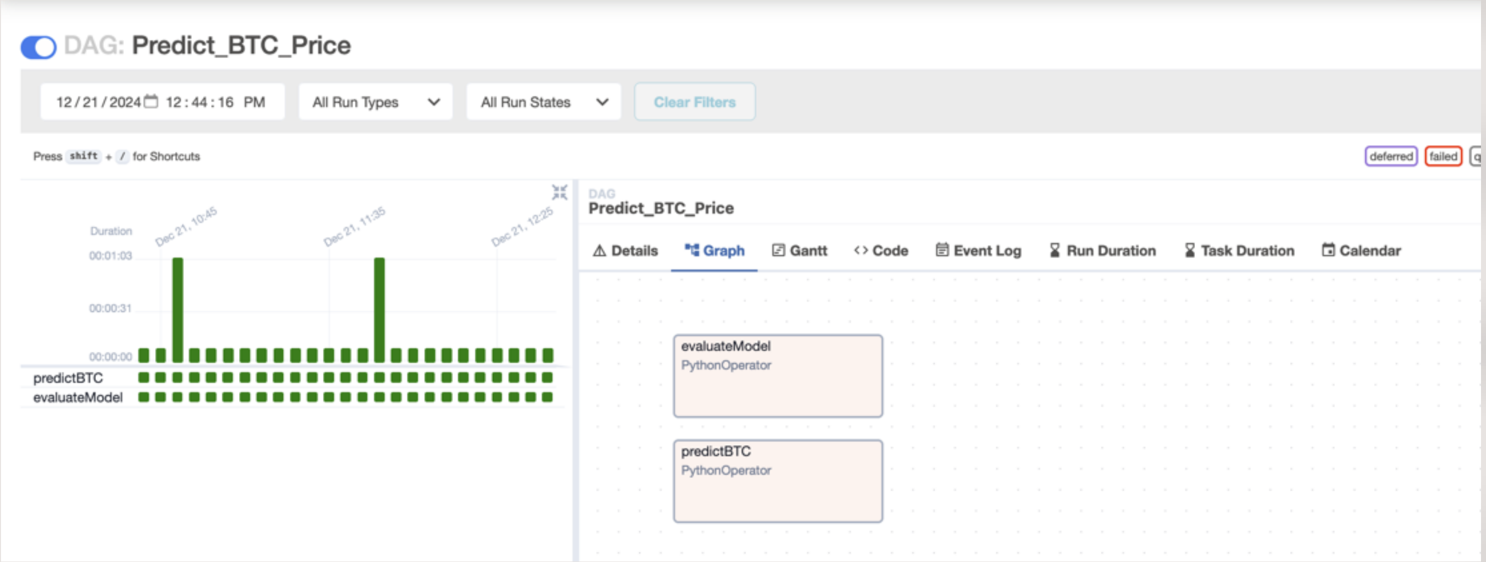
XGBoost

Feature Engineering for XGBoost

```
# Feature Engineering for Time Series
df['lag1'] = df['lastPrice'].shift(1) # previous 1 price as featur
df['lag2'] = df['lastPrice'].shift(2) # previous 2 price as featur
df['lag3'] = df['lastPrice'].shift(3) # previous 3 price as featur
df['rolling_mean_6'] = df['lastPrice'].rolling(window=6).mean() #
df['rolling_std_6'] = df['lastPrice'].rolling(window=6).std() # mo
```

```
# Features and Target
features = ['closeTime', 'lag1', 'lag2', 'lag3', 'rolling_mean_6', 'rolling_std_6']
X = df[features].dropna()
y = df['lastPrice'].loc[X.index]

# Train-test split
split_index = int(0.8 * len(X))
X_train = X[:split_index]
X_test = X[split_index:]
y_train = y[:split_index]
y_test = y[split_index:]

print(f"Training set size: {X_train.shape}, Test set size: {X_test.shape}")

# XGBoost parameters
params = {
    'objective': 'reg:squarederror',
    'learning_rate': 0.01,
    'max_depth': 5,
    'subsample': 0.8,
    'colsample_bytree': 0.8,
    'reg_alpha': 1.0,
    'reg_lambda': 2.0,
    'min_child_weight': 1,
    'eval_metric': 'rmse'
}

# Create DMatrix objects
dtrain = xgb.DMatrix(X_train, label=y_train)
dtest = xgb.DMatrix(X_test, label=y_test)

# Set up evaluation list
evallist = [(dtrain, 'train'), (dtest, 'eval')]

# Train with early stopping
xgb_model = xgb.train(
    params,
    dtrain,
    num_boost_round=1000,
    evals=evallist,
    early_stopping_rounds=50,
    verbose_eval=True
)
```

DAG 3 : Predict_BTC_Price



There are 2 independent task in DAG 3 as following :

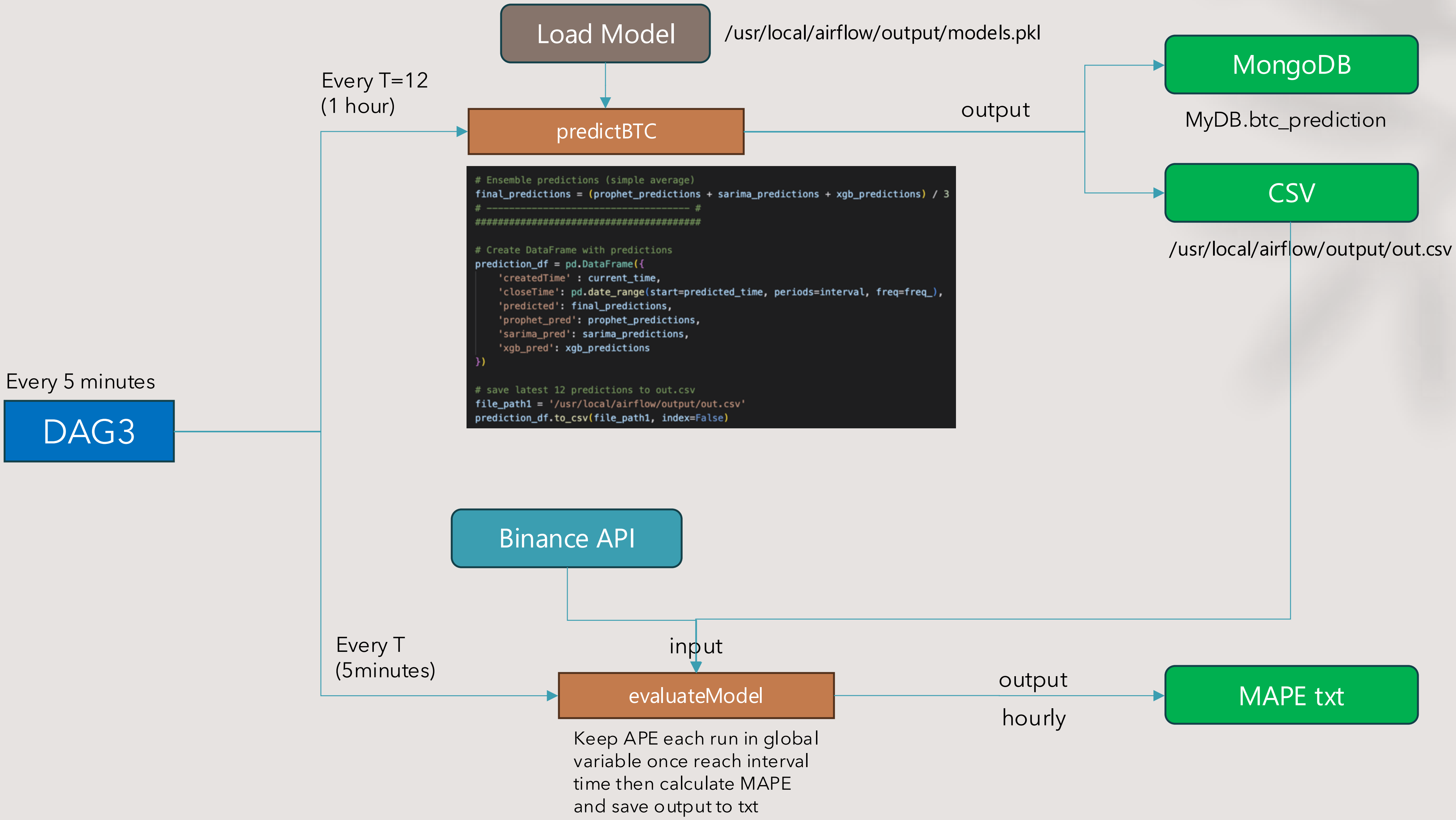
- **predictBTC** : This task execute only every interval (in this case interval = 12 runs) has been met. So, each run in every 5 minutes means 12 * 5minutes = 1hour. It predicts using the saved model from dag2 output and **forecast BTC price in next 12-time interval**, e.g. if task executed at 10:55 then it will forecast BTC price for 11:00, 11:05, 11:10,… 11:55 and then save(overwrite) the latest output to **"/usr/local/airflow/output/out.csv"** as well as append it to the historical to **/usr/local/airflow/output/prediction_history.csv** for later analysis.

- **EvaluateModel** : use data output from above task "/usr/local/airflow/output/out.csv" (use ensemble predicted result) to calculate MAPE with actual prices.
  - Every run (5 minutes) it will load current lastPrice from Binance API as y-actual and compare error with y-hat (ensemble predicted result) and add into global variable list.
  - Every interval has been met (12 runs) it will calculate MAPE(Mean Absolute Percentage Error) from last 12 absolute error percentage and save to f'/usr/local/airflow/output/mape_{str_date}.txt'

Schedule : Every 5 minutes from 22:00-06:00 between december21-24. start 2024-12-21 00:00 utc7, end 2024-12-24 06:00 utc7

**More detail please check on code at dag3.py*

DAG 3 : Predict_BTC_Price




```python
# Ensemble predictions (simple average)
final_predictions = (prophet_predictions + sarima_predictions + xgb_predictions) / 3
# ------------------------------------ #
########################################

# Create DataFrame with predictions
prediction_df = pd.DataFrame({
    'createdTime' : current_time,
    'closeTime': pd.date_range(start=predicted_time, periods=interval, freq=freq_),
    'predicted': final_predictions,
    'prophet_pred': prophet_predictions,
    'sarima_pred': sarima_predictions,
    'xgb_pred': xgb_predictions
})

# save latest 12 predictions to out.csv
file_path1 = '/usr/local/airflow/output/out.csv'
prediction_df.to_csv(file_path1, index=False)
```

Example of Output

out.csv

- write every 1 hour

createdTime	closeTime	predicted	prophet_pred	sarima_pred	xgb_pred
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:05:02.328255+07:00	95480.67276	95219.5978	95462.08454	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:10:02.328255+07:00	95507.3187	95236.55105	95525.06911	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:15:02.328255+07:00	95468.04296	95253.84045	95389.95248	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:20:02.328255+07:00	95549.81703	95271.32149	95617.79367	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:25:02.328255+07:00	95497.2787	95288.84884	95442.65131	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:30:02.328255+07:00	95512.43296	95306.27737	95470.68559	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:35:02.328255+07:00	95529.39509	95323.46316	95504.38619	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:40:02.328255+07:00	95495.47118	95340.26451	95385.81309	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:45:02.328255+07:00	95481.42088	95356.5429	95327.3838	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:50:02.328255+07:00	95485.46549	95372.16391	95323.89661	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 06:55:02.328255+07:00	95481.93737	95386.99816	95298.478	95760.336
2024-12-23 06:00:01.328255+07:00	2024-12-23 07:00:02.328255+07:00	95379.66291	95400.92213	94977.73066	95760.336

Use as predicted price each T(5 minutes) to calculate APE and then MAPE at the end of T(12)
Remark: predicted =(prophet_pred+sarima_pred+xgb_pred)/3

mape_yyyy-mm-dd.txt

- append every 1 hour

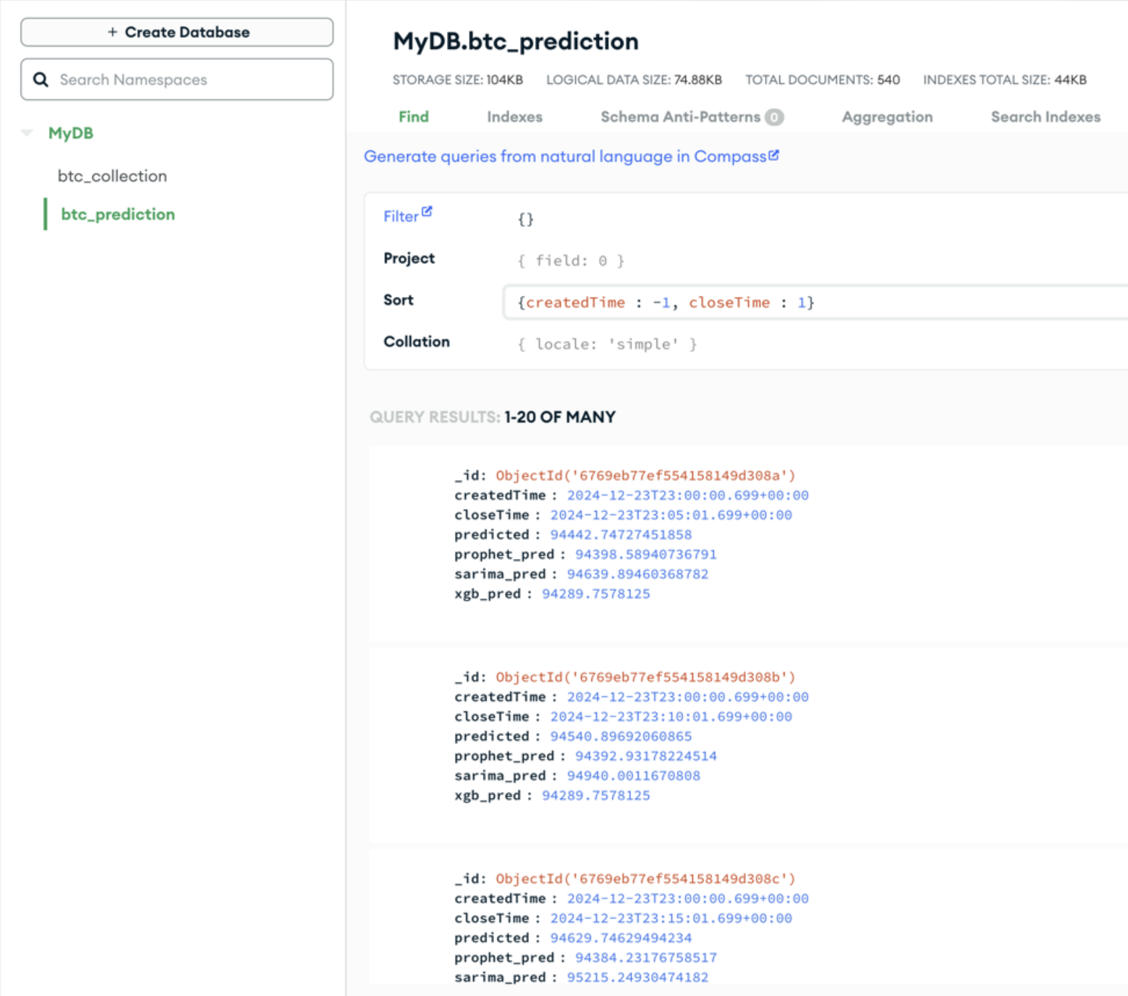
mape_2024-12-23.txt

```
time, mape
2024-12-23 23:00:01.508251+07:00, 0.8757151772568086
2024-12-24 00:00:00.501407+07:00, 0.6924791788102762
2024-12-24 01:00:00.993524+07:00, 0.38809660191634643
2024-12-24 02:00:00.942024+07:00, 0.5397986858375143
2024-12-24 03:00:00.768641+07:00, 0.21193403650303966
2024-12-24 04:00:00.834085+07:00, 0.8157276056855576
2024-12-24 05:00:01.524880+07:00, 0.7295407806492584
2024-12-24 06:00:00.869186+07:00, 0.834218185192831
```

Use for calculate MAPE(mean absolute percentage error) from APE of each 5 minutes past hour (12T, 5 minutes each)

Mongodb btc_prediction

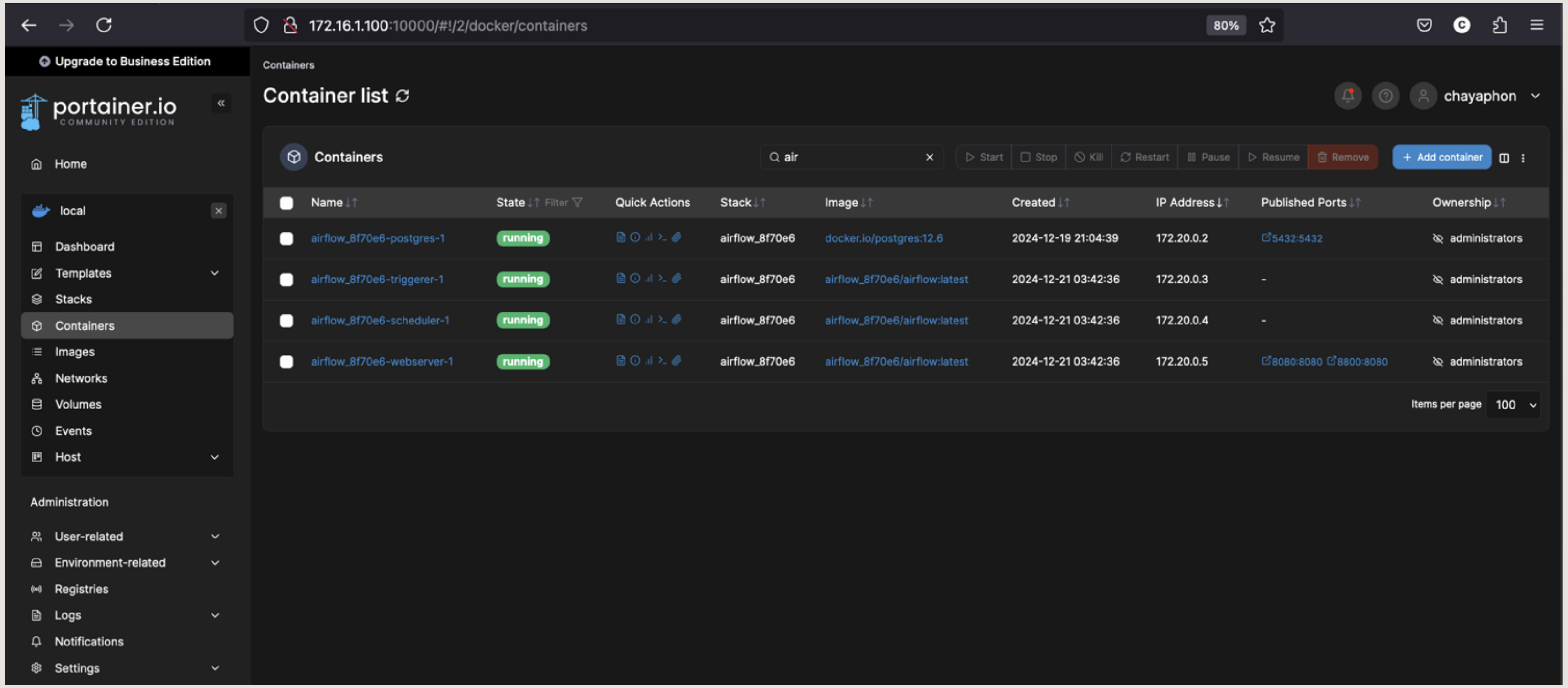
- Insert the prediction of every 1 hours in advance into mongo for later analysis.



Appendix

Docker

In this project we use docker technology to help us running airflow and related services.



docker-compose.override.yml

Orverride the standard config of astro docker

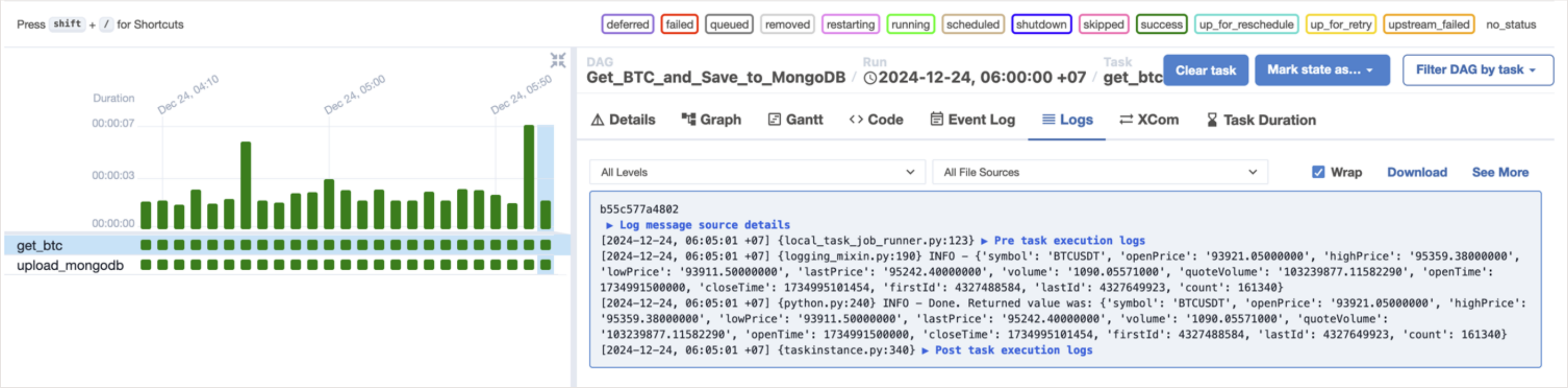
```yaml
version: '3'
services:
  scheduler:
    volumes:
      - ./output:/usr/local/airflow/output
  webserver:
    # Map host port 8800 to container port 8080,Because my docker server has already used port 8080 for other service.
    ports:
      - "8800:8080"
    # below command allow me to access it from client pc (I hosted docker in server and access it from client)
    command: >
      airflow webserver --port 8080 --host 0.0.0.0
```

I have created local directory "**output**" which map to docker airflow "**usr/local/airflow/output**" where I use to dump output of task inside docker to persistent in local machine.

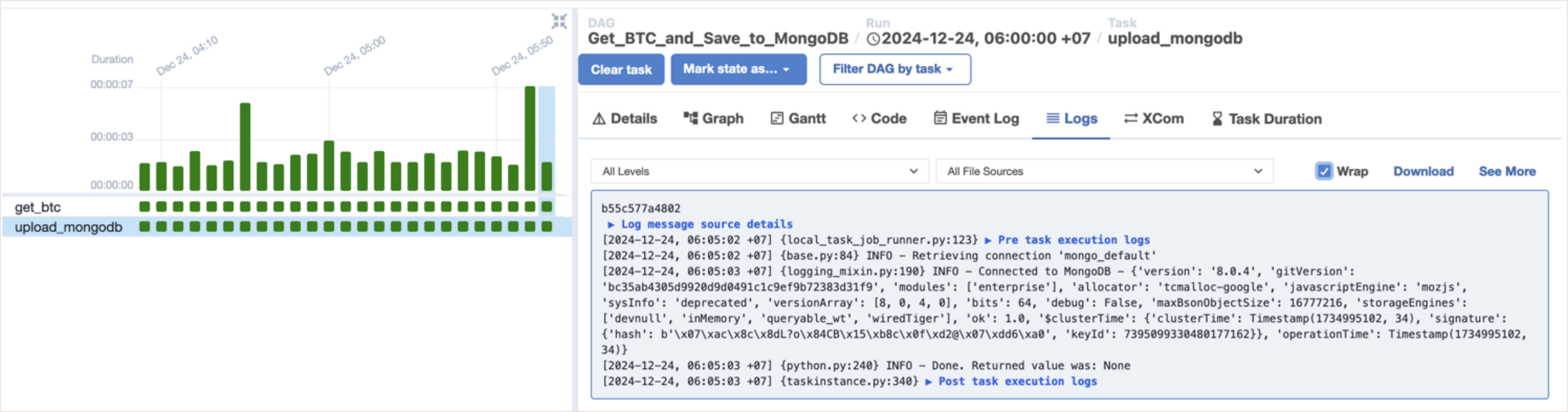
Some of Task Output Screen Shot

Get_BTC_and_Save_to_MongoDB

get_btc



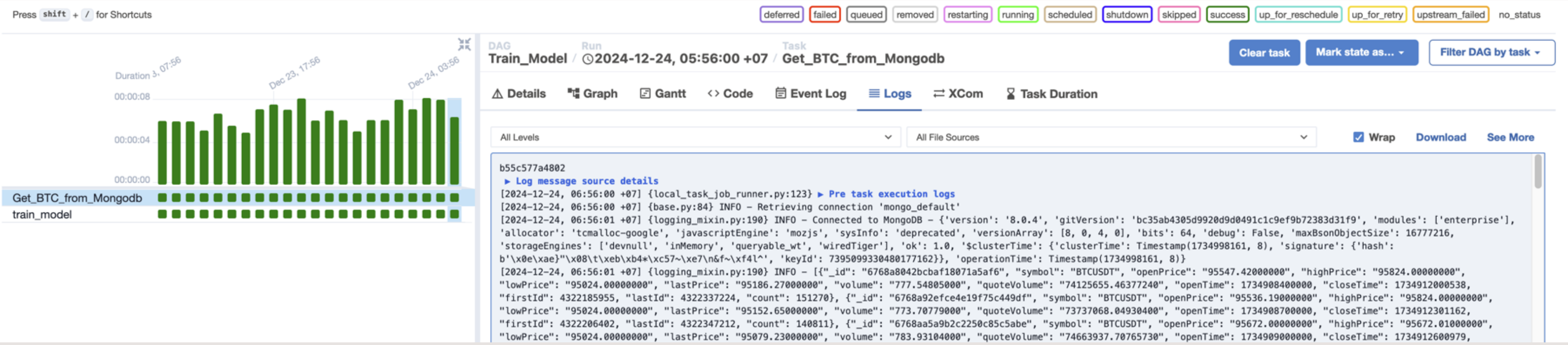
upload_mongodb



Some of Task Output Screen Shot

Tran_Model

Get_BTC_from_Mongodb. (last 1 day data 288 records)

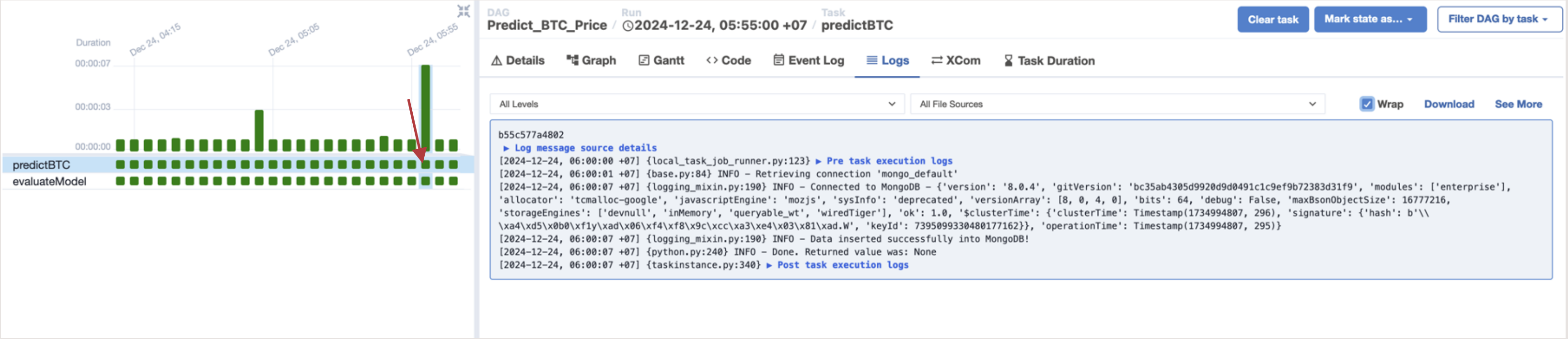


Train_model

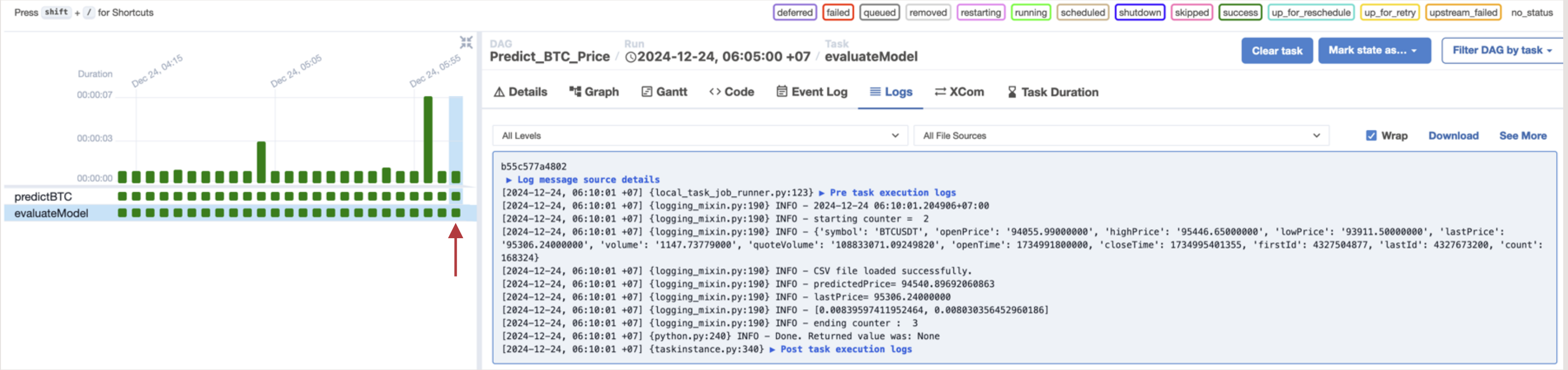
Some of Task Output Screen Shot

Tran_Model

predictBTC : write predicted price in next 12T (5 minutes each) to out.csv and insert data to MongoDB

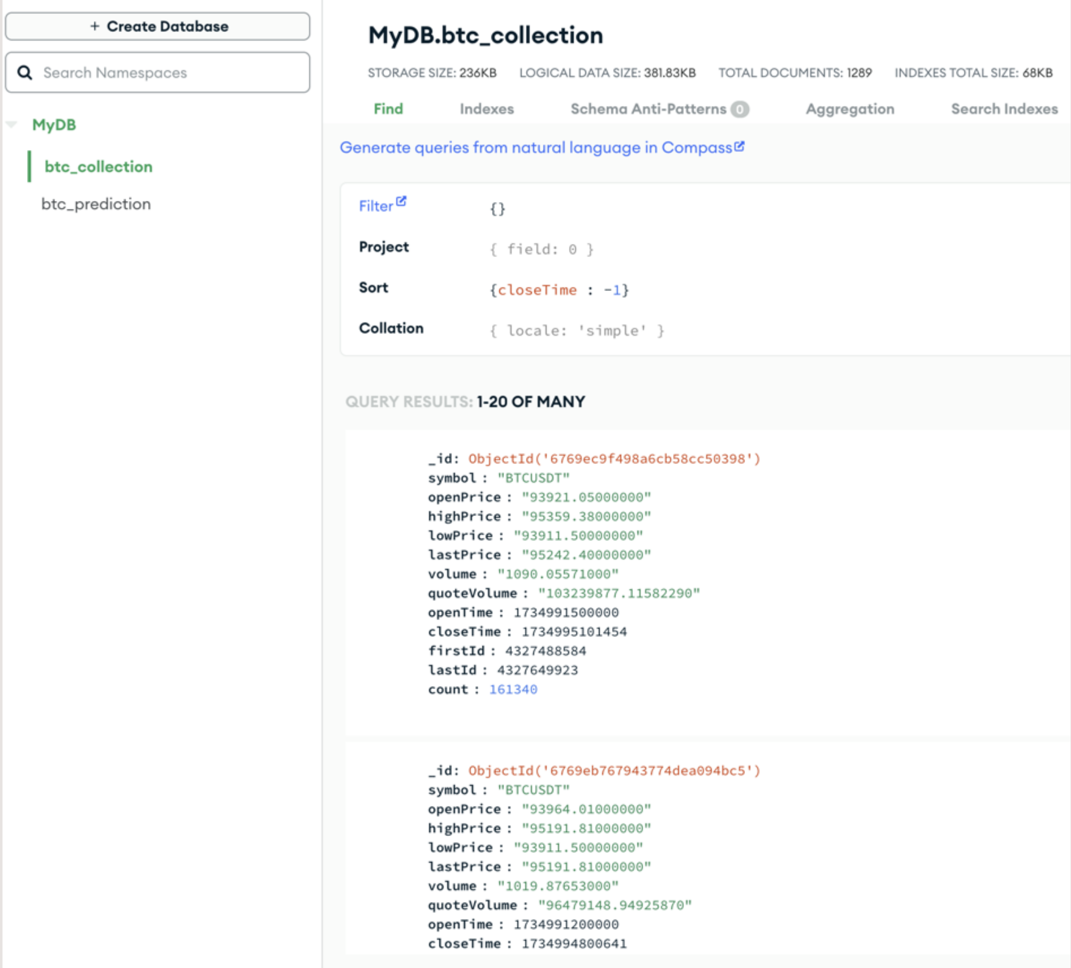


evaluateModel : calculate error (predict-actual)/actual for each T (5 minutes)

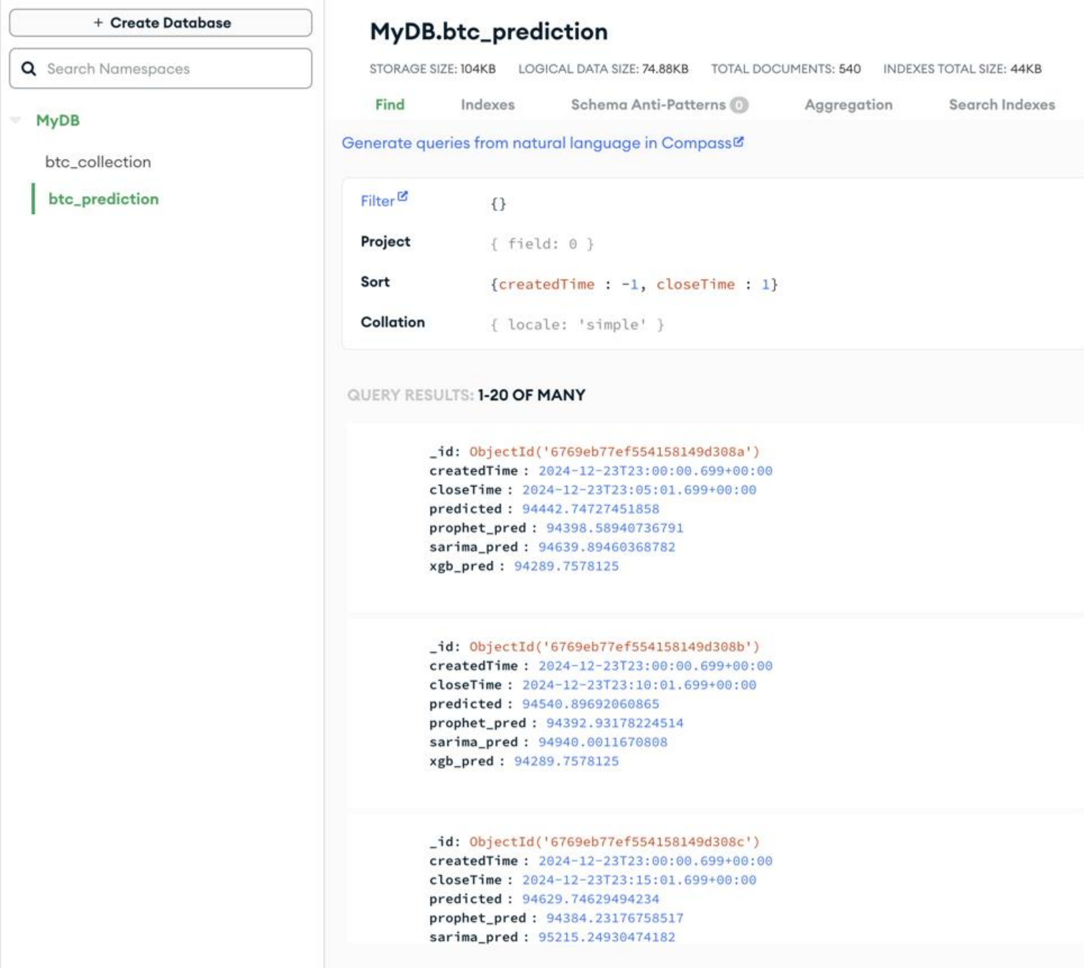


Mongo DB

btc_collection



btc_prediction



Code Reference

https://github.com/chayaphon/realtime_airflow-btcPrediction