Anomaly Detection Service : Hands On I

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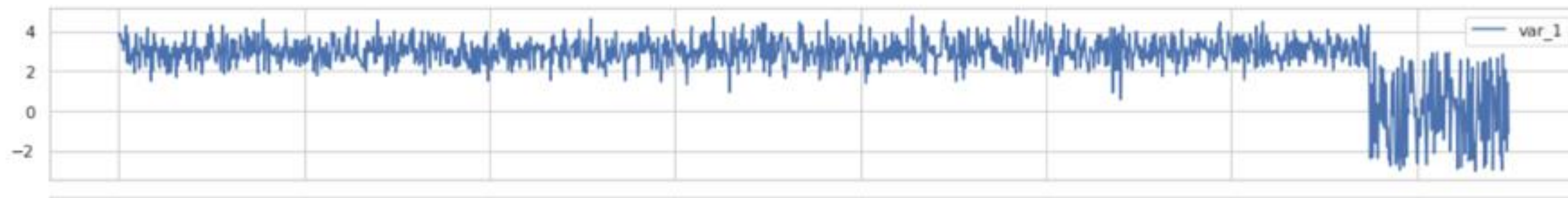
Outline

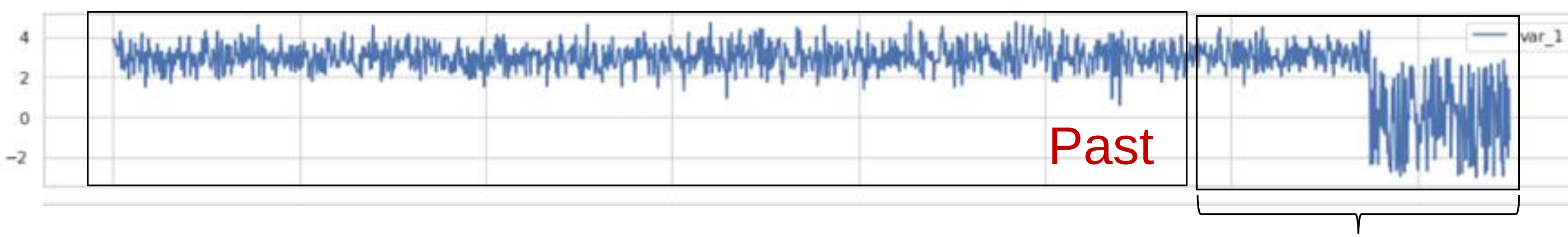
- ❑Unsupervised AD in Univariate Time Series
- ❑Unsupervised AD in Multivariate Time Series
- ❑Regression-Model based AD
- ❑Semi-supervised AD
- ❑Mixture-Model based AD

Unsupervised Anomaly Detection Scenario

- ***Batch/Entire*** : Detect Anomaly in Given time series

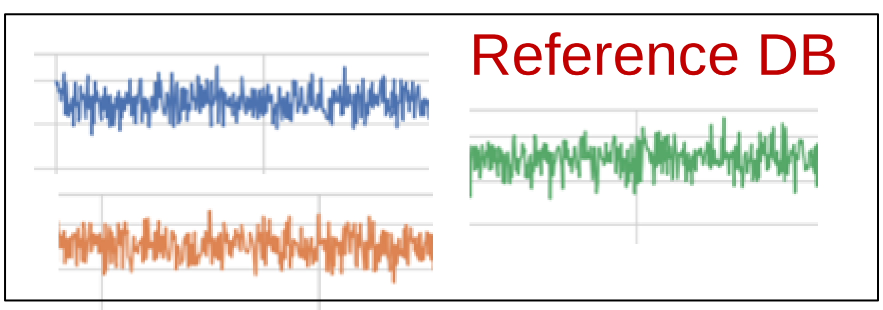


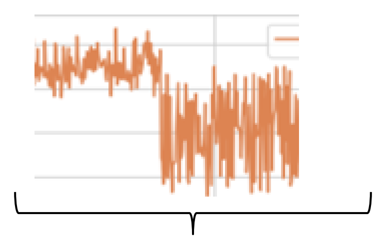
- ***Stream/Recent*** : Use Past time series to detect anomaly in recent input



Detect Anomaly Here

- ***Across*** : Use other time series to detect anomaly in given time series





Detect Anomaly Here

Unsupervised Anomaly Detection API

API end points

https://developer.ibm.com/apis/catalog/ai4industry--anomaly-detection-product/api/API--ai4industry--anomaly-detection-api#batch_uni

Overview
- Introduction
- Getting Started

</> Anomaly Detection API
- Connection Check
- Get Result
- Submit an Anomaly Detection Job
  - Detect anomalies on multivariate time series
  - **Detect anomalies on univariate time series**
  - Discover anomaly model using semi-supervised approach
  - Discover mixture model based anomaly
  - Discover regression based anomaly model

</> Code snippet

Detect anomalies on univariate time series

cURL | Ruby | Python | PHP | Java | Node | Go | Swift

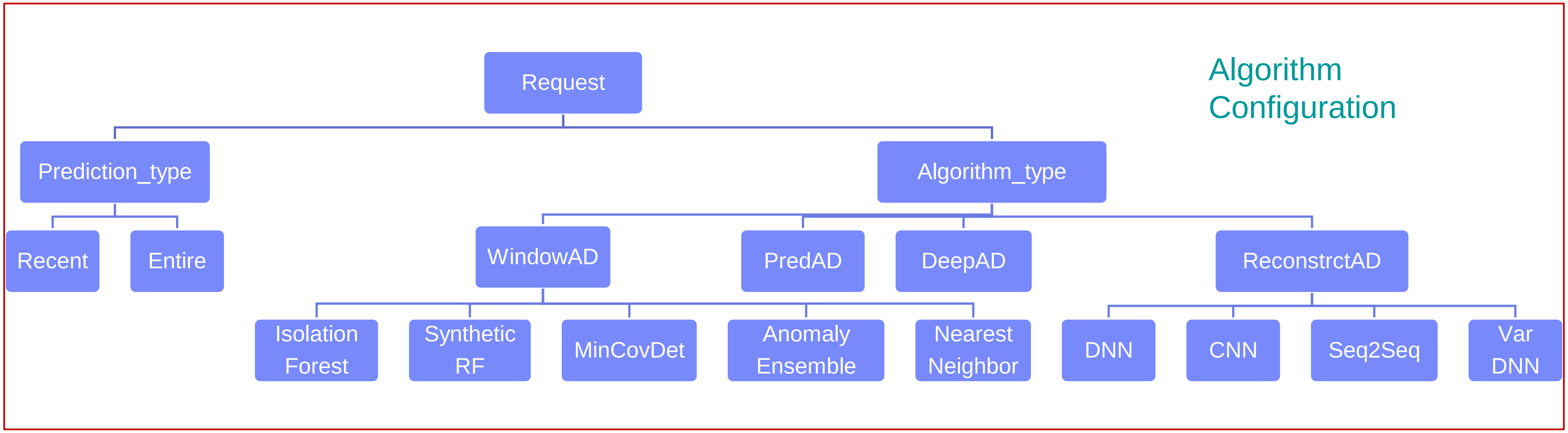
```
curl --request POST \
  --url https://api.ibm.com/ai4industry/run/anomaly-detection/timeseries/univariate/batch \
  --header 'X-IBM-Client-Id: REPLACE_THIS_KEY' \
  --header 'X-IBM-Client-Secret: REPLACE_THIS_KEY' \
  --header 'accept: application/json' \
  --header 'content-type: multipart/form-data' \
  --form data_file=REPLACE_THIS_VALUE \
  --form time_column=REPLACE_THIS_VALUE \
  --form time_format=REPLACE_THIS_VALUE \
  --form target_column=REPLACE_THIS_VALUE \
  --form prediction_type=REPLACE_THIS_VALUE \
  --form recent_data=REPLACE_THIS_VALUE \
  --form algorithm_type=REPLACE_THIS_VALUE \
  --form anomaly_estimator=REPLACE_THIS_VALUE \
  --form lookback_window=REPLACE_THIS_VALUE \
  --form observation_window=REPLACE_THIS_VALUE \
  --form labeling_method=REPLACE_THIS_VALUE \
  --form labeling_threshold=REPLACE_THIS_VALUE
```

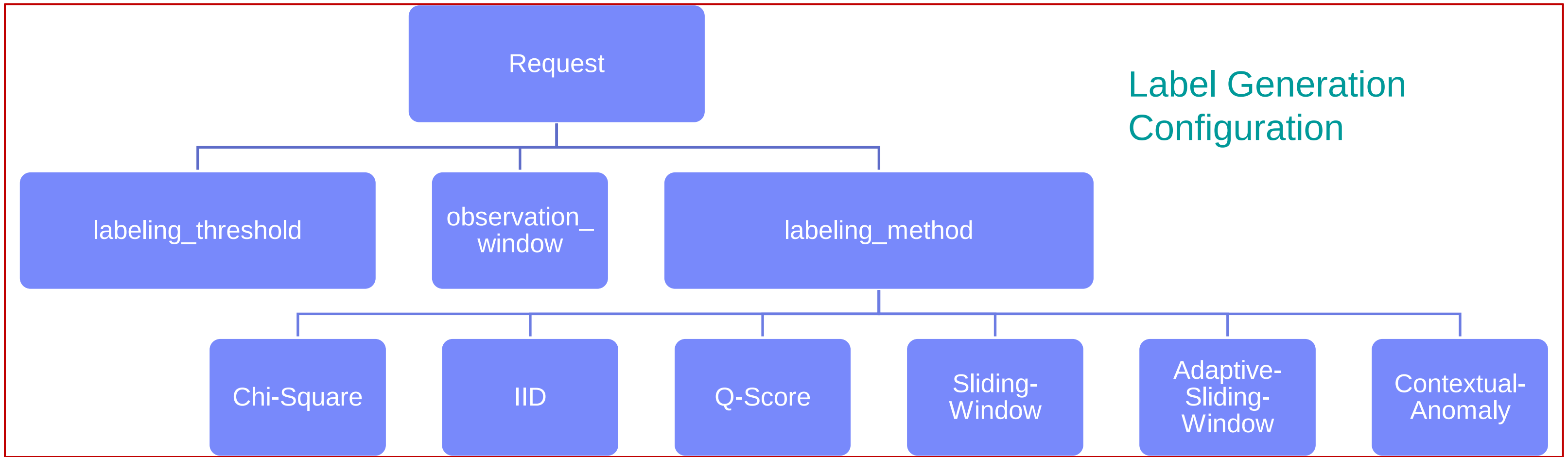
OpenAPI doc

Try this API

Unsupervised Anomaly Detection API

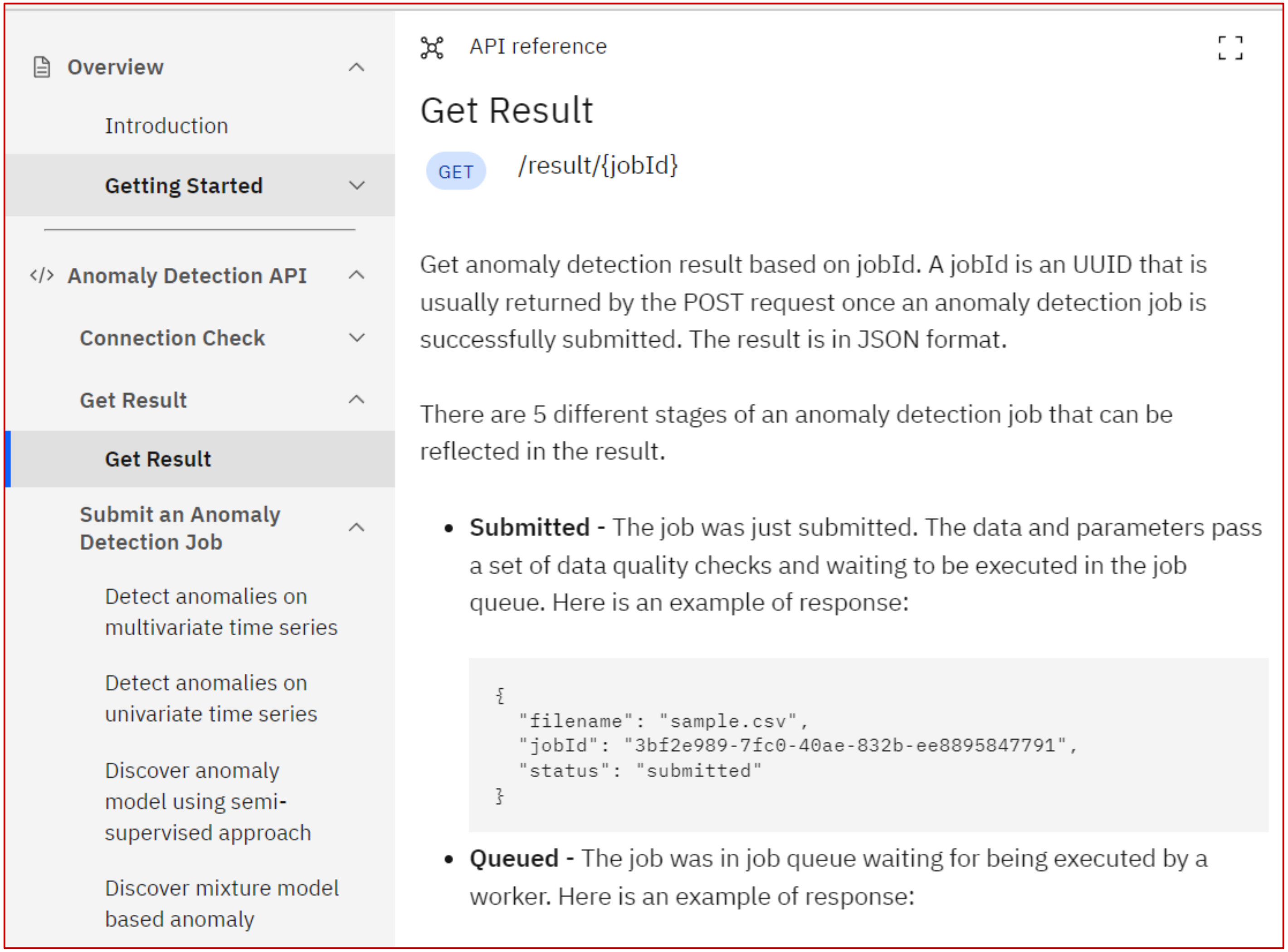
- API arguments are categorized into four configuration
  – Meta Data : target column, feature column, time column and format, etc
  – Algorithm Configuration : Which algorithm to run
  – Evaluation Setting : Instance size, evaluation metric, etc
  – Anomaly Label Generation : How to generate anomaly label (+1/-1)





Unsupervised Anomaly Detection Execution

- On submitting a user request, AD service return a “Job ID”
- End user can use : https://developer.ibm.com/apis/catalog/ai4industry--anomaly-detection-product/api/API--ai4industry--anomaly-detection-api#get_result_by_id



Overview

Introduction

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Get Result

Submit an Anomaly Detection Job

Detect anomalies on multivariate time series

Detect anomalies on univariate time series

Discover anomaly model using semi-supervised approach

Discover mixture model based anomaly

API reference

Get Result

GET /result/{jobId}

Get anomaly detection result based on jobId. A jobId is an UUID that is usually returned by the POST request once an anomaly detection job is successfully submitted. The result is in JSON format.

There are 5 different stages of an anomaly detection job that can be reflected in the result.

- **Submitted -** The job was just submitted. The data and parameters pass a set of data quality checks and waiting to be executed in the job queue. Here is an example of response:

```
{
  "filename": "sample.csv",
  "jobId": "3bf2e989-7fc0-40ae-832b-ee8895847791",
  "status": "submitted"
}
```

- **Queued -** The job was in job queue waiting for being executed by a worker. Here is an example of response:

Unsupervised Anomaly Detection Execution

- Each Job in processed by Celery Work
- Celery worker submit job to Code Engine (Serverless Computing Capability)
- Code Engine run an Anomaly Workflow for each request

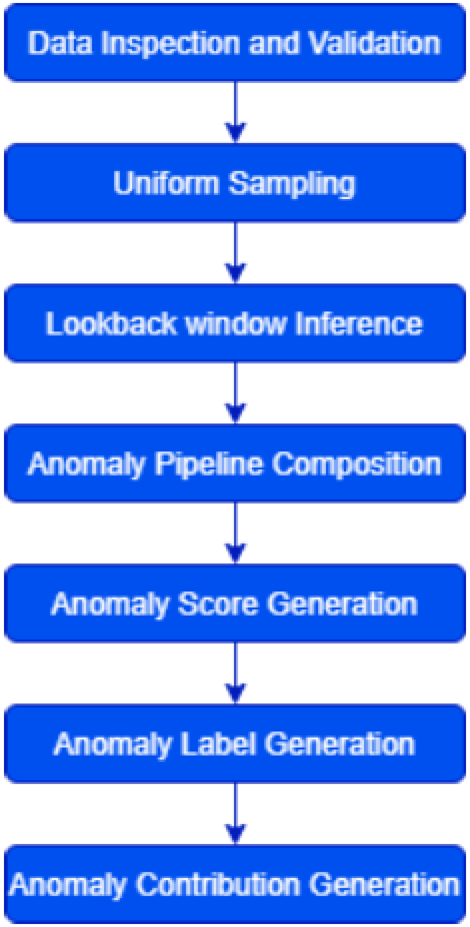

Figure 2: Anomaly Workflow

Unsupervised Anomaly Detection Execution

- Anomaly Score and Anomaly Label are two important outcome

```
result = []
result_header = ['timestamp', 'anomaly_score', 'anomaly_label']

for item in json_data['summary']['result']:
    result.append([item['timestamp'], item['value']['anomaly_scor

result = pd.DataFrame(result)
result.columns = result_header
result.tail(10)
```

	timestamp	anomaly_score	anomaly_label
990	2017-01-04 10:30:00	0.000154	1.0
991	2017-01-04 10:35:00	0.009484	1.0
992	2017-01-04 10:40:00	0.013656	1.0
993	2017-01-04 10:45:00	0.020583	1.0
994	2017-01-04 10:50:00	0.540153	1.0
995	2017-01-04 10:55:00	0.594477	1.0
996	2017-01-04 11:00:00	0.438216	1.0
997	2017-01-04 11:05:00	1.541768	1.0
998	2017-01-04 11:10:00	-0.000458	1.0
999	2017-01-04 11:15:00	0.372137	1.0

Demo 1

- Clone repo :

https://github.com/IBM/anomaly-detection-code-pattern

- Run Notebook (Expected execution time ~ 1 minutes) –

https://github.com/IBM/anomaly-detection-code-pattern/blob/main/notebooks/Univariate_AD_service_sample_data.ipynb

```
file_path = './datasets/univariate/sample_data/' + datafile_name
files = {'data_file': (datafile_name, open(file_path, 'rb'))}

data = {
    'target_column': value,
    'time_column': timestamp,
    'time_format': time_format,
    'prediction_type': 'entire',
    'algorithm_type': 'DeepAD',
    'lookback_window': 'auto',
    'observation_window': 10,
    'labeling_method': 'Chi-Square',
    'labeling_threshold': 10,
    'anomaly_estimator': 'Default',
}

headers = {
    'X-IBM-Client-Id': Client_ID,
    'X-IBM-Client-Secret': Client_Secret,
    'accept': "application/json",
    }

import requests
post_response = requests.post("https://api.ibm.com/ai4industry/run/anomaly-detection/timeseries/univariate/batch",
                              data=data,
                              files=files,
                              headers=headers)
```

```
--------------------------------------------------------------------------------------------------------------------
---------------------------------------------------------
lookback_window             33
model_summary               [('SkipTransformer',NoOp()),('NormalizedFlatten',NormalizedFlatten(feature_columns=[1],lookback_win=33,t
arget_columns=[1])),('LinearSVR',LinearSVR(random_state=0)),]
num_pipelines_explored      75
total_execution_time (sec)  54.34661364555359
```

Demo 2

- Clone repo :

https://github.com/IBM/anomaly-detection-code-pattern

- Run Notebook with Modification (Expected execution time ~ 1 minutes) –

https://github.com/IBM/anomaly-detection-code-pattern/blob/main/notebooks/Univariate_AD_service_sample_data.ipynb

Algorithm Type	Anomaly Estimator	Execution Time	Observations
WindowAD	MinCovDet	46 Sec	??
WindowAD	IsolationForest	21 Sec	
WindowAD	AnomalyEnsembler	23 Sec	
ReconstructAD	CNN_AutoEncoder	28 Sec	
ReconstructAD	Seq2seq_AutoEncoder	40 Sec	

!!! Look at the Anomaly Score
!!! Look at the Model Summary
!!! Vary Labelling Method

Demo 3

- Clone repo :

  https://github.com/IBM/anomaly-detection-code-pattern

- Run Other Notebook

  https://github.com/IBM/anomaly-detection-code-pattern/blob/main/notebooks/Univariate_AD_service_public_data.ipynb

Dataset	Num of Records	Algorithm Used
ec2_network_in_5abac7	4718	ReconstructAD
Twitter_volume_AAPL	150902	DeepAD
Bitcoin price	30066	PredAD

Testing Support for Long Time Series

Unsupervised Anomaly Detection in Multivariate Time Series

IBM

- Build anomaly model using multiple time series as input
- API end points
  https://developer.ibm.com/apis/catalog/ai4industry--anomaly-detection-product/api/API--ai4industry--anomaly-detection-api#batch_uni

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Detect anomalies on univariate time series

Discover anomaly model using semi-supervised approach

</> Code snippet

Detect anomalies on multivariate time series

cURL | Ruby | Python | PHP | Java | Node | Go | Swift

```
curl --request POST \
  --url https://api.ibm.com/ai4industry/run/anomaly-detection/timeseries/multivariate/batch \
  --header 'X-IBM-Client-Id: REPLACE_THIS_KEY' \
  --header 'X-IBM-Client-Secret: REPLACE_THIS_KEY' \
  --header 'accept: application/json' \
  --header 'content-type: multipart/form-data' \
  --form data_file=REPLACE_THIS_VALUE \
  --form time_column=REPLACE_THIS_VALUE \
  --form time_format=REPLACE_THIS_VALUE \
  --form target_columns=REPLACE_THIS_VALUE \
  --form prediction_type=REPLACE_THIS_VALUE \
  --form recent_data=REPLACE_THIS_VALUE \
  --form algorithm_type=REPLACE_THIS_VALUE \
  --form anomaly_estimator=REPLACE_THIS_VALUE \
  --form lookback_window=REPLACE_THIS_VALUE \
  --form observation_window=REPLACE_THIS_VALUE \
  --form labeling_method=REPLACE_THIS_VALUE \
  --form labeling_threshold=REPLACE_THIS_VALUE
```

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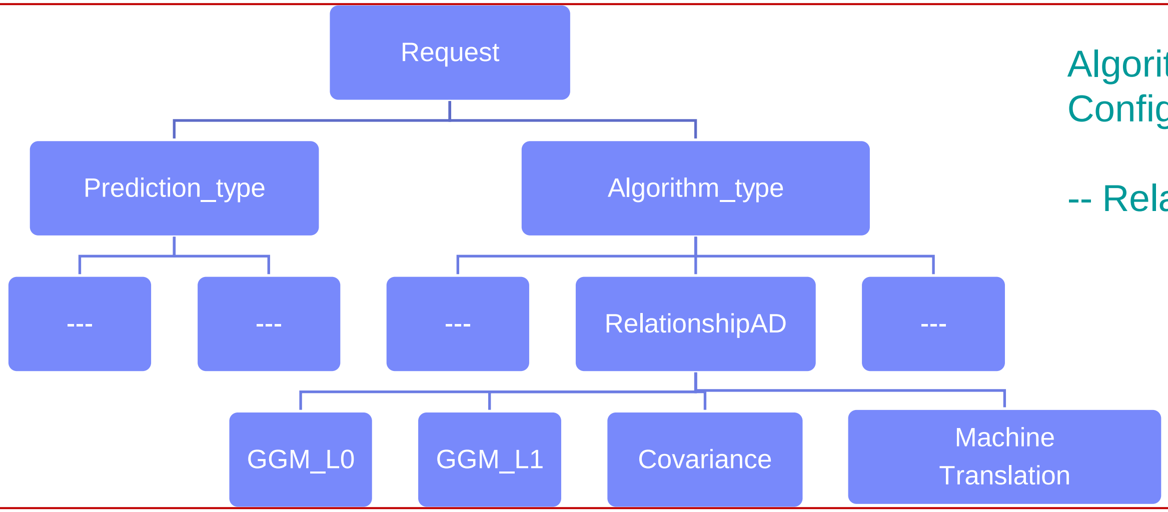
  – Anomaly Label Generation : How to generate anomaly label (+1/-1)

- Algorithm Configuration : All that we discussed for Univariates and then ***RelationshipAD***



Algorithm Configuration

-- RelationshipAD

Demo 4

- Clone repo :

  https://github.com/IBM/anomaly-detection-code-pattern

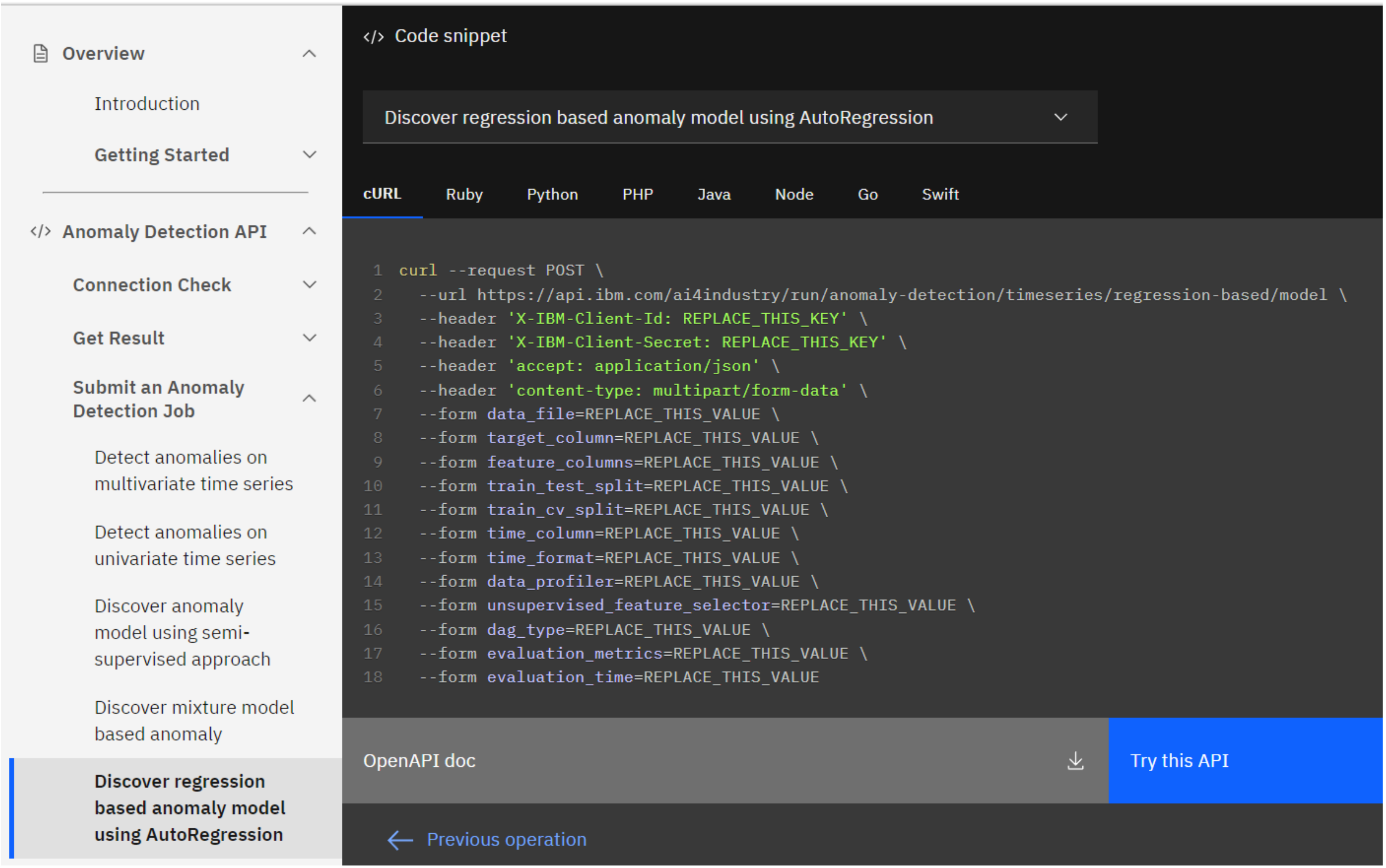
- Run Other Notebook

  https://github.com/IBM/anomaly-detection-code-pattern/blob/main/notebooks/Multivariate_AD_service_sample_data.ipynb

Regression-aware Anomaly Detection API

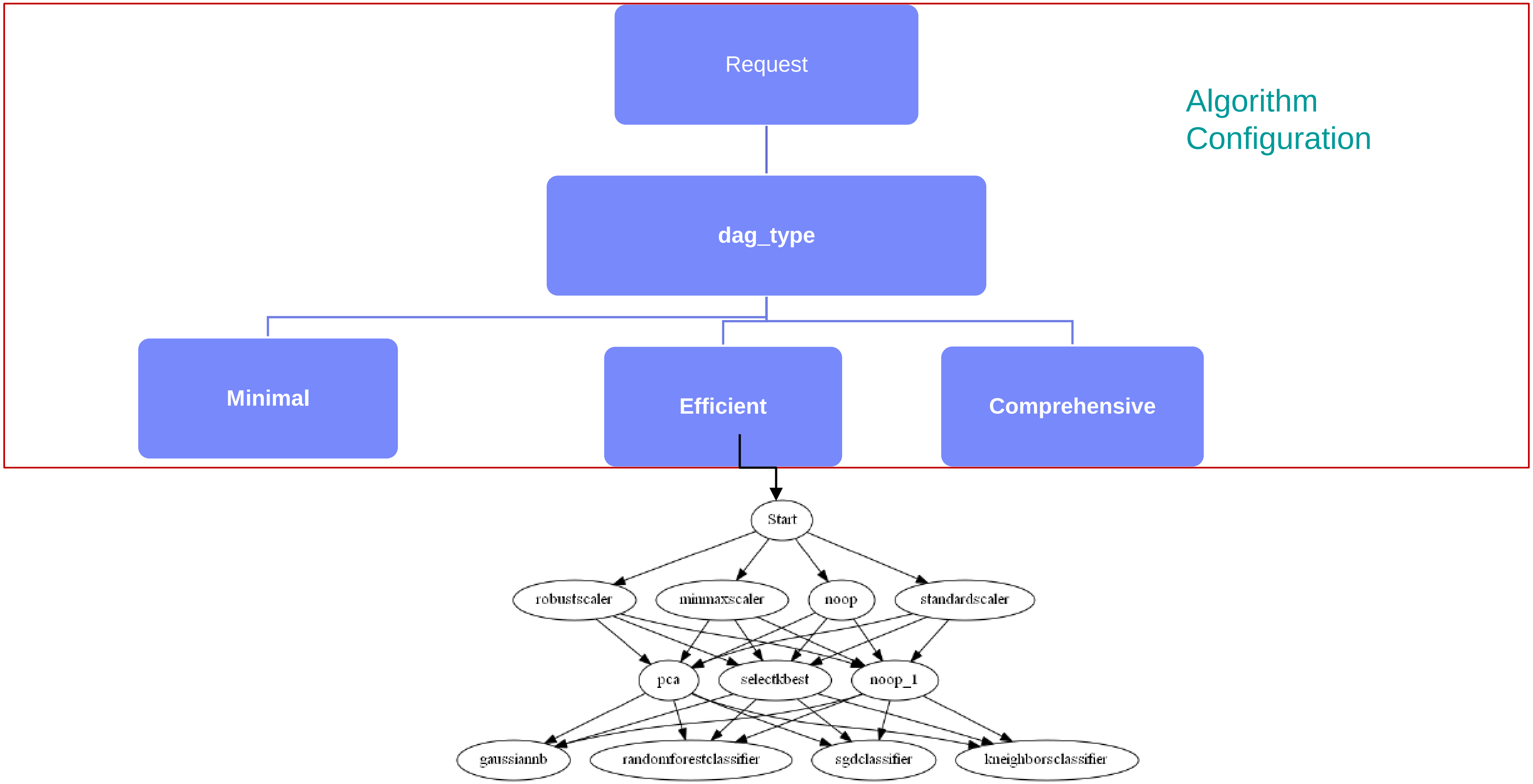
API end points

https://developer.ibm.com/apis/catalog/ai4industry--anomaly-detection-product/api/API--ai4industry--anomaly-detection-api#model_regression_based



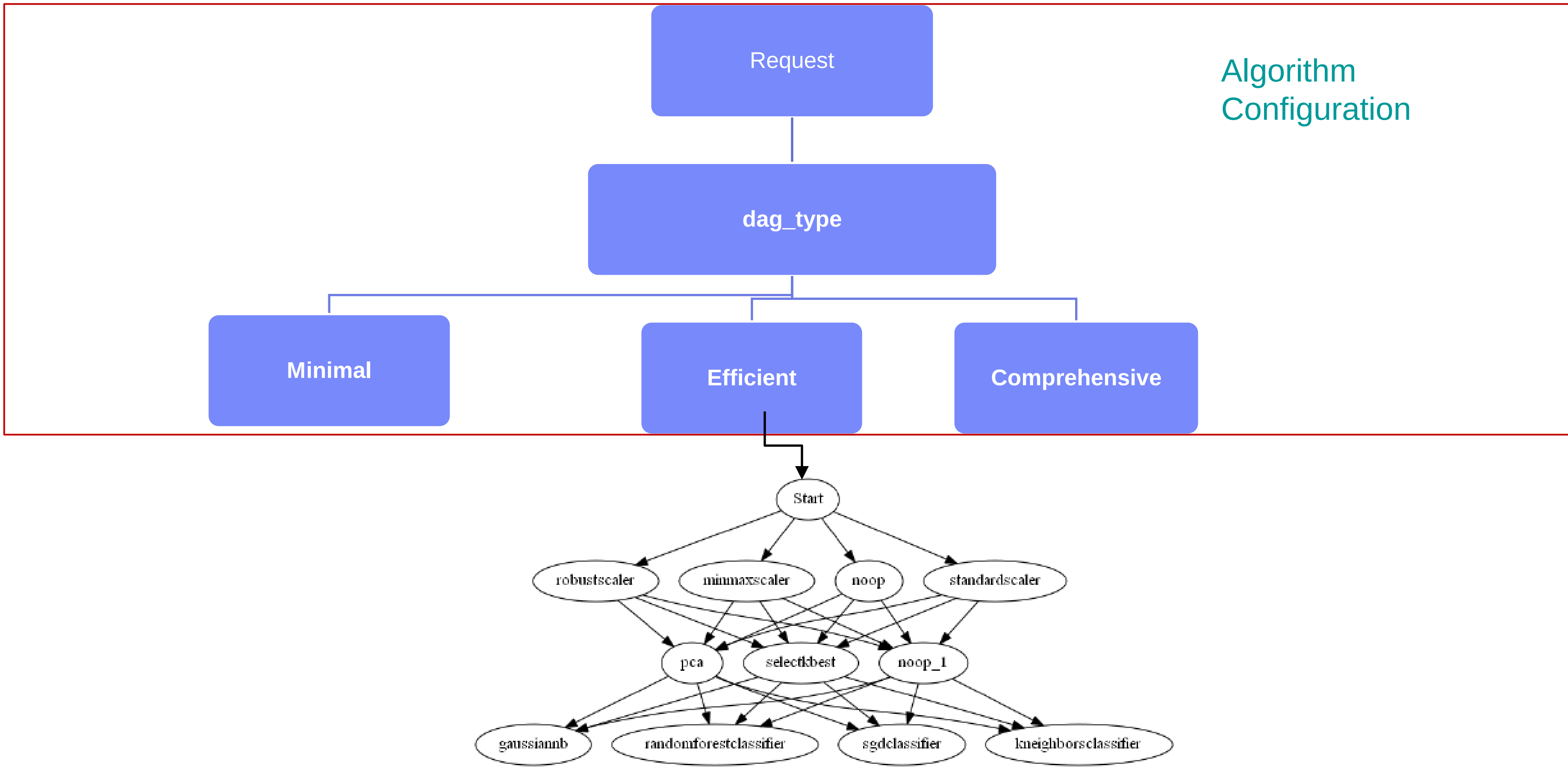
Regression-aware Anomaly Detection API

- Important API arguments
  - target column
  - feature column
  - Directed Acyclic Graph based ***AutoRegression***



Regression-aware Anomaly Detection API

- Important API arguments
  - Model Selection Process
  - **train_test_split -** partition a data into train and test. train dataset is used for model ranking. Test dataset is used for hold out evaluation and prediction output
  - **train_cv_split** – model ranking



Demo 5

- Clone repo :

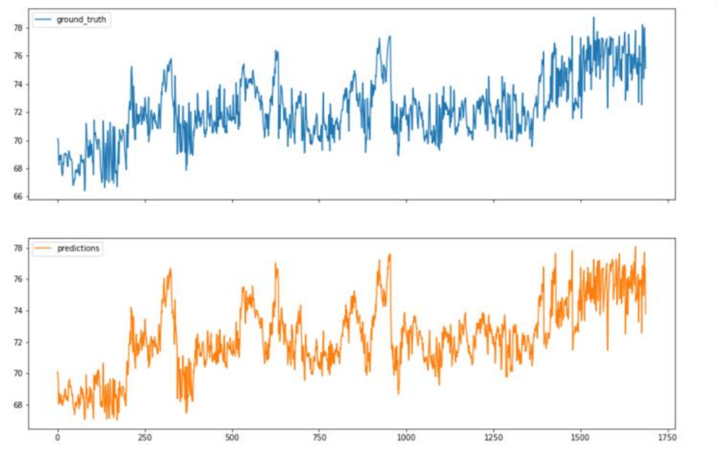
  https://github.com/IBM/anomaly-detection-code-pattern

- Run Other Notebook

  https://github.com/IBM/anomaly-detection-code-pattern/blob/main/notebooks/Regression-aware_AD_service_sample_data.ipynb

In [36]:
```
import numpy as np

time_column = "Date_time"
feature_columns = ['Gost_avg', 'Git_avg', 'Rs_avg', 'Ws_avg', 'Wa_avg']
target_columns = 'Gb1t_avg'
time_format="%Y-%m-%d %H:%M:%S"
```



Unsupervised Feature Selection

- A Boolean argument in many Anomaly Detection APIs
- The feature selection is motivated from many IoT applications that monitors the same process/asset using redundant set of the sensor variable
  - Data driven discovery of the process
- Apply ensemble of three feature selectors
  - Variance based
  - Influence Factor
  - Correlation based
- If more than two feature Selector tag an input columns
  - We drop the column from further analysis
- Speed-up related optimization
  - We have embedded the optimization related to the size of data and number of records on increasing the speed on the feature related task

Obtain IBM Cloud Access

- https://www.ibm.com/cloud/object-storage/faq