CLOUD DATA MANAGEMENT PROJECT REPORT

Anishka Chauhan
AP19110010518
CSE-C

Abstract:

Microsoft Azure: Microsoft Azure is a public cloud platform with more than 200 products and services accessible over the public internet. Like other public cloud vendors, Azure manages and maintains hardware, infrastructure, and resources that can be accessed for free or pay-per-use basis.

Anomaly detector is one of the azure cognitive services, it is an AI Powered API This API helps users to easily detect and figure out abnormal points in Time series data without any pre-trained machine learning model.
It can be applied into various practical use cases like system performance or behavior abnormal detection or monitoring, fraud detection, etc…

Objective: Create an Anomaly detector to figure out abnormal points in a time series data.

Motivation: Anomaly detectors can help customers to easily detect any abnormal activities in their realtime business use cases which can notify the users if detected any while monitoring, this service does not require any pre-trained ML model to be developed by users to use it.

Tools Required: Azure Anomaly detector API, Alpha vantage API, Python3, Jupyter notebook, Bokeh.JS, Pandas, Matplotlib.

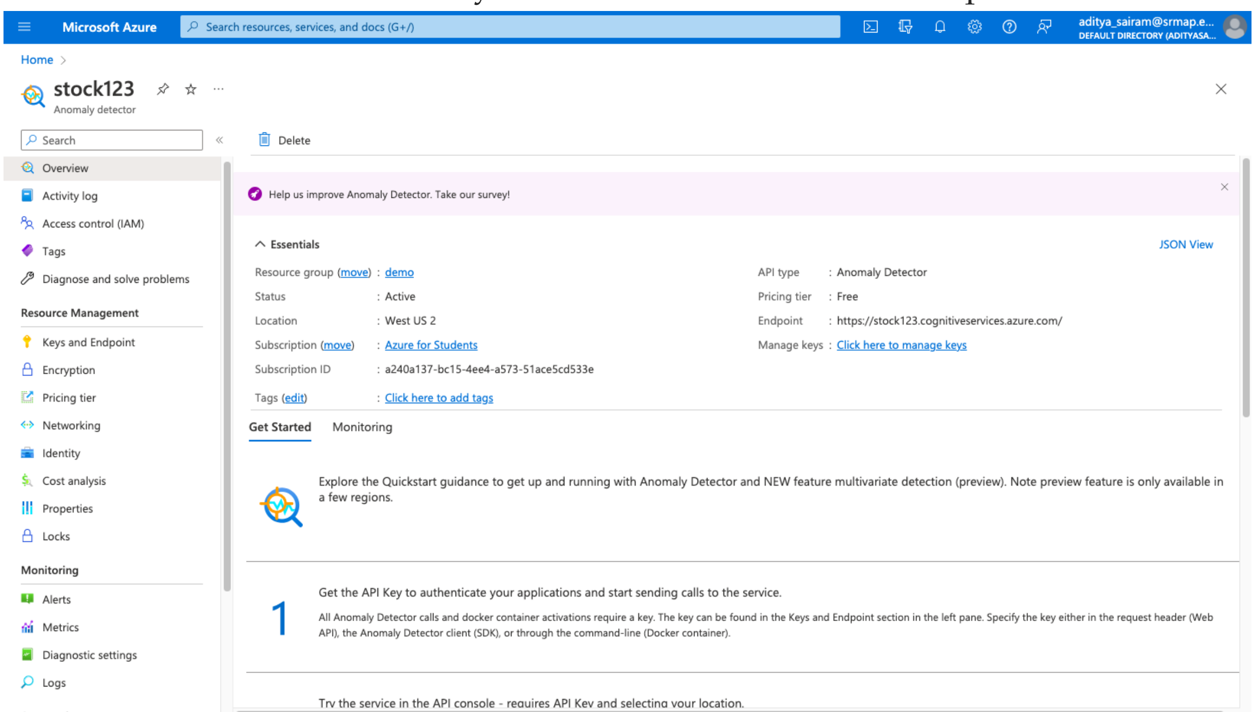
Process:

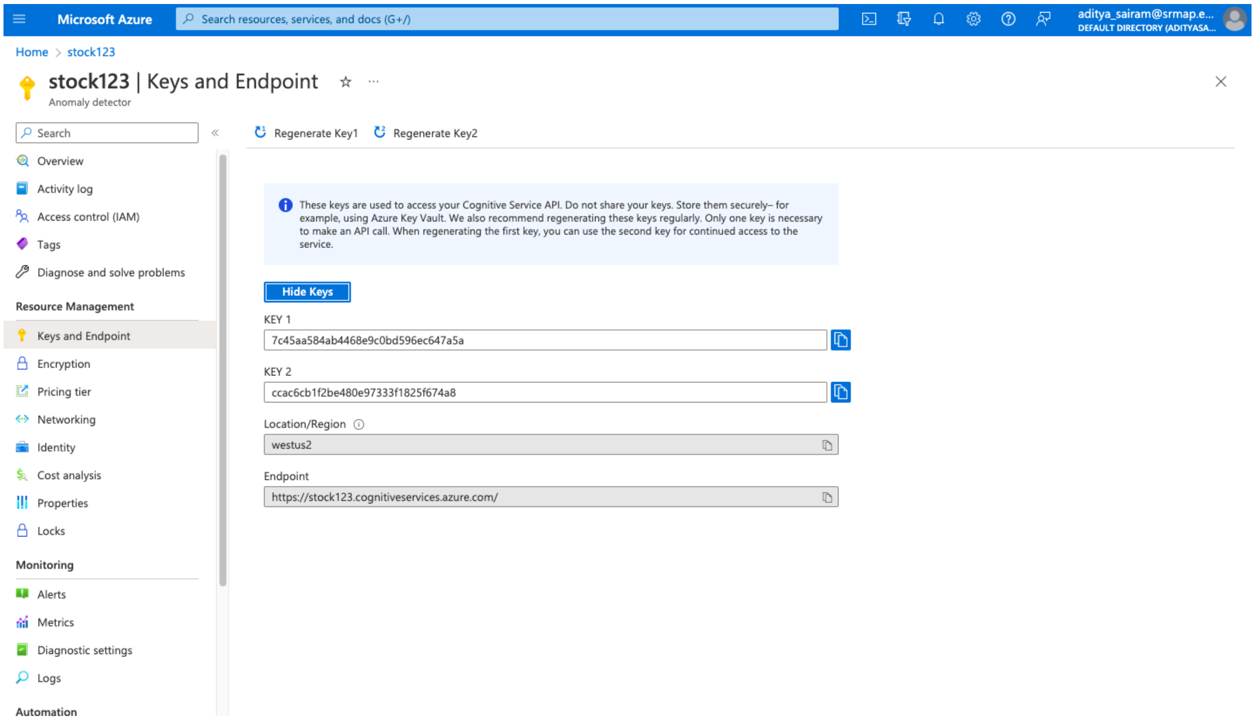
In this project we will obtain US stock performance data from Alpha Vantage API. Alpha Vantage API is supported minutely, hourly, daily, weekly and monthly stock time series data call. Azure anomaly detector API also supports yearly time series calls as well.

STEP-1: Obtain and Prepare stock data from alpha vantage API to feed azure anomaly detector API.

1. Installing alpha vantage package
2. Dropping unnecessary dataframes
3. Finally loading into a .json file stockdatafromav.json

STEP-2: Create a stock anomaly detector resource in the azure portal





STEP-3: Load the json file to Azure Anomaly Detector API to Analyze Stock Performance Data.

- To start sending requests to the Anomaly Detector API, we should paste the subscription key received after creating the Anomaly Detector resource. '
- Use the endpoint received from overview section of the Anomaly Detector resource we created
- Import necessary packages
  - requests
  - json
  - pandas
  - numpy
  - matplotlib
  - BokehJS
- Defining API Function call

  def detect(endpoint, subscription_key, request_data):

      headers = {'Content-Type': 'application/json', 'Ocp-Apim-Subscription-Key': subscription_key}

```
    response = requests.post(endpoint, data=json.dumps(request_data),
headers=headers)
    if response.status_code == 200:
        return json.loads(response.content.decode("utf-8"))
    else:
        print(response.status_code)
        raise Exception(response.text)
```

- Define API response handling function

```
def build_figure(sample_data, sensitivity):
    sample_data['sensitivity'] = sensitivity
    result = detect(endpoint, subscription_key, sample_data)
    columns = {'expectedValues': result['expectedValues'], 'isAnomaly':
result['isAnomaly'], 'isNegativeAnomaly': result['isNegativeAnomaly'],
          'isPositiveAnomaly': result['isPositiveAnomaly'], 'upperMargins':
result['upperMargins'], 'lowerMargins': result['lowerMargins'],
          'timestamp': [parser.parse(x['timestamp']) for x in
sample_data['series']],
          'value': [x['value'] for x in sample_data['series']]}
    response = pd.DataFrame(data=columns)
    values = response['value']
    label = response['timestamp']
    anomalies = []
    anomaly_labels = []
    index = 0
    anomaly_indexes = []
    p = figure(x_axis_type='datetime', title="Batch Anomaly Detection ({0}
Sensitvity)".format(sensitivity), width=800, height=600)
    for anom in response['isAnomaly']:
        if anom == True and (values[index] >
response.iloc[index]['expectedValues'] +
response.iloc[index]['upperMargins'] or
                        values[index] < response.iloc[index]['expectedValues'] -
response.iloc[index]['lowerMargins']):
```

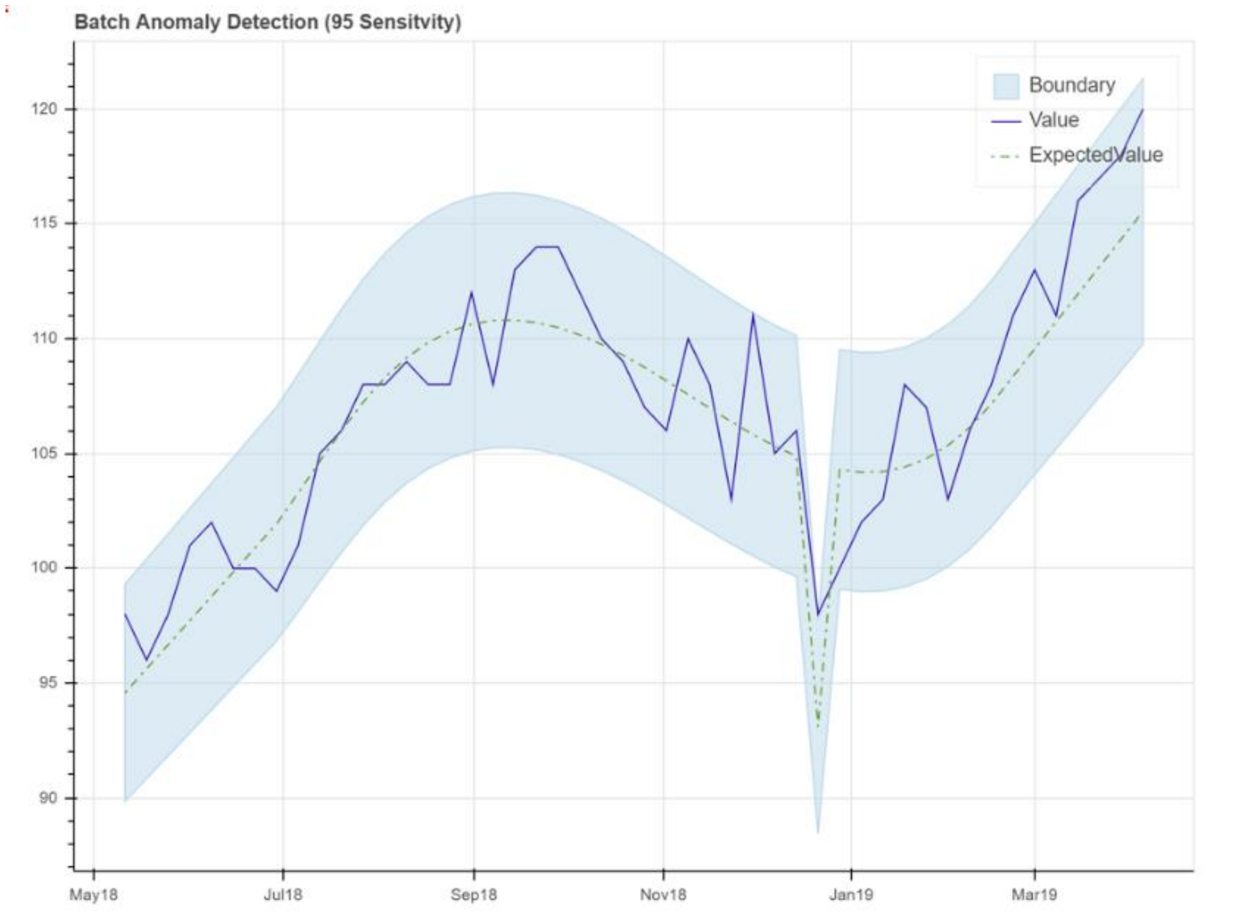
```
            anomalies.append(values[index])
            anomaly_labels.append(label[index])
            anomaly_indexes.append(index)
        index = index+1
    upperband = response['expectedValues'] + response['upperMargins']
    lowerband = response['expectedValues'] -response['lowerMargins']
    band_x = np.append(label, label[::-1])
        #band_x = np.append(label, label[::-1])
    band_y = np.append(lowerband, upperband[::-1])
        #band_y = np.append(lowerband, upperband[::-1])
    boundary = p.patch(band_x, band_y, color=Blues4[2], fill_alpha=0.5,
line_width=1, legend='Boundary')
    p.line(label, values, legend='Value', color="#2222aa", line_width=1)
    p.line(label, response['expectedValues'], legend='ExpectedValue',
line_width=1, line_dash="dotdash", line_color='olivedrab')
    anom_source = ColumnDataSource(dict(x=anomaly_labels,
y=anomalies))
    anoms = p.circle('x', 'y', size=5, color='tomato', source=anom_source)
    p.legend.border_line_width = 1
    p.legend.background_fill_alpha  = 0.1
    show(p, notebook_handle=True)
```

- Load prepared stock performance data from Alpha Vantage API

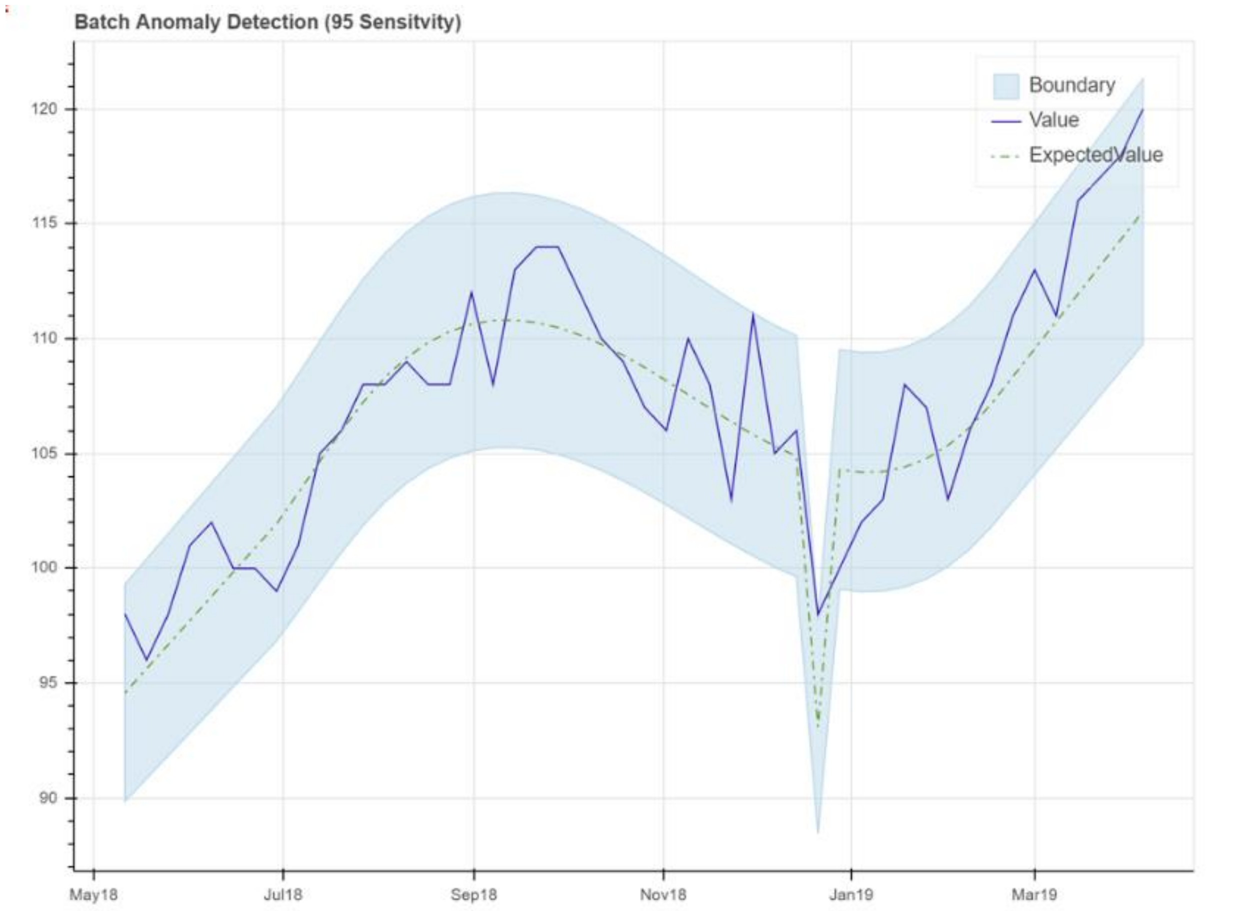
```
import json
stock_data_from_av = json.load(open('stockdatafromav.json'))
print(stock_data_from_av)
```

- Batch Anomaly Detection with 95% sensitivity

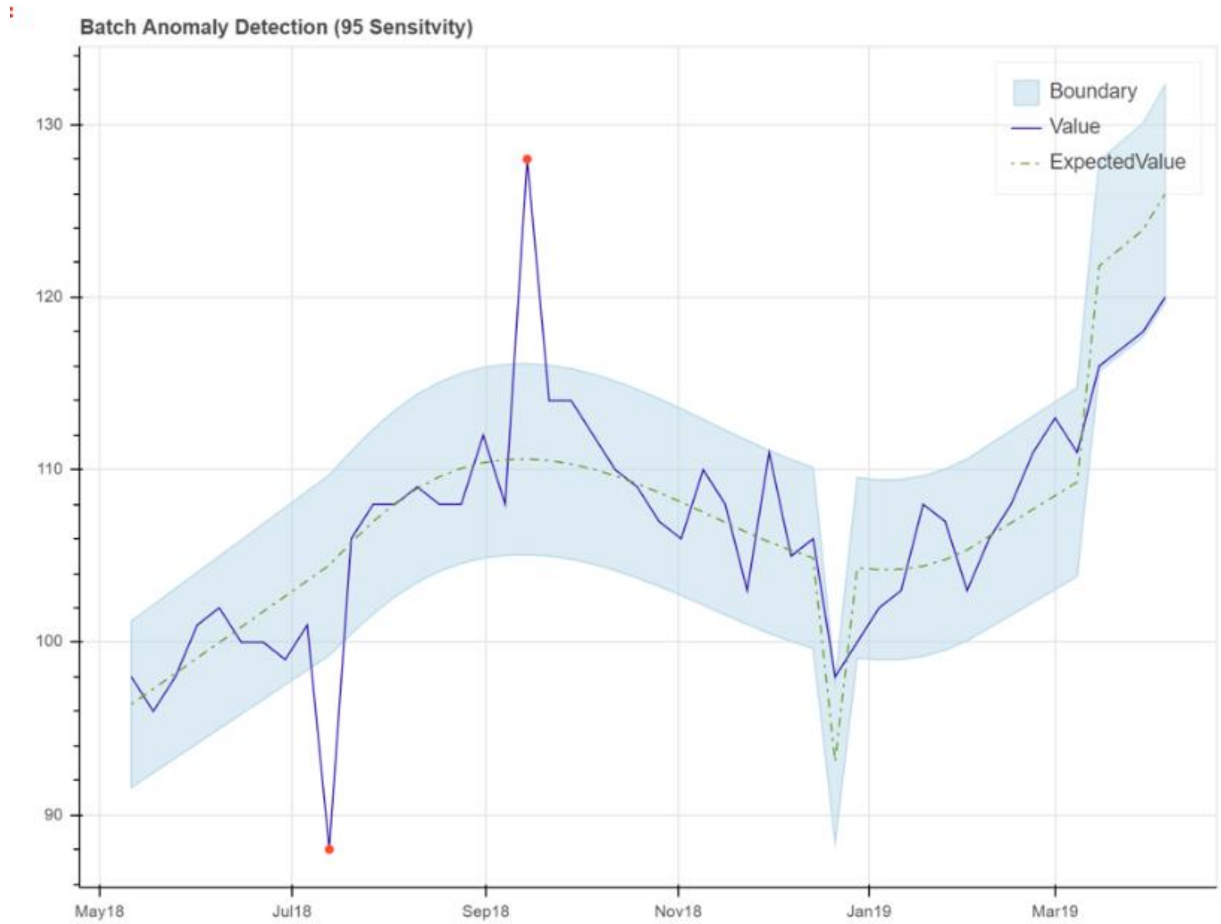
```
# weekly sample
sample_data = json.load(open('stockdatafromav.json'))
sample_data['granularity'] = 'weekly'
# 95 sensitivity
build_figure(sample_data,95)
```



- Batch Anomaly Detection with 90% sensitivity
  # weekly sample
  sample_data = json.load(open('stockdatafromav.json'))
  sample_data['granularity'] = 'weekly'
  # 90 sensitivity
  build_figure(sample_data,90)



- Batch Anomaly Detection with 95% sensitivity
  # weekly sample
  sample_data = json.load(open('stockdatafromav_modified.json'))
  sample_data['granularity'] = 'weekly'
  # 95 sensitivity
  build_figure(sample_data,95)



From the above result we can see the azure anomaly detector API is able to find and pinpoint the abnormal spikes in the time series data.

Result: We can now leverage Azure Anomaly Detector API to figure out abnormal points easily without building any machine learning model or algorithms (e.g. linear regression).