

## Lab Center – Hands-On Lab – Part THREE

### Forecasting with SARIMAX

Session 1239 - IBM Think2020 IoT Lab

## Hyper-Local Weather and Crop prediction using Watson: Analysing Weather Data using Jupyter Notebook

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20200501



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# 1 Objective

In this part of the LAB we will set up a WatsonStudio Instance with a Jupyter Notebook to forecast Rainy and Dry days. We will create some queries which we trigger from Node-RED and display on the Node-RED Dashboard.

**Note:** We will walk through Part Three together first before you start.

## 1.1 Pre-Requirement

Please sign up for a free WatsonStudio/IBM Cloud account [Register for WatsonStudio](https://dataplatform.cloud.ibm.com/registration/stepone)  
<https://dataplatform.cloud.ibm.com/registration/stepone>

Download the github to your VM/Desktop  
<https://github.com/markusvankempen/ThinkLab1239>

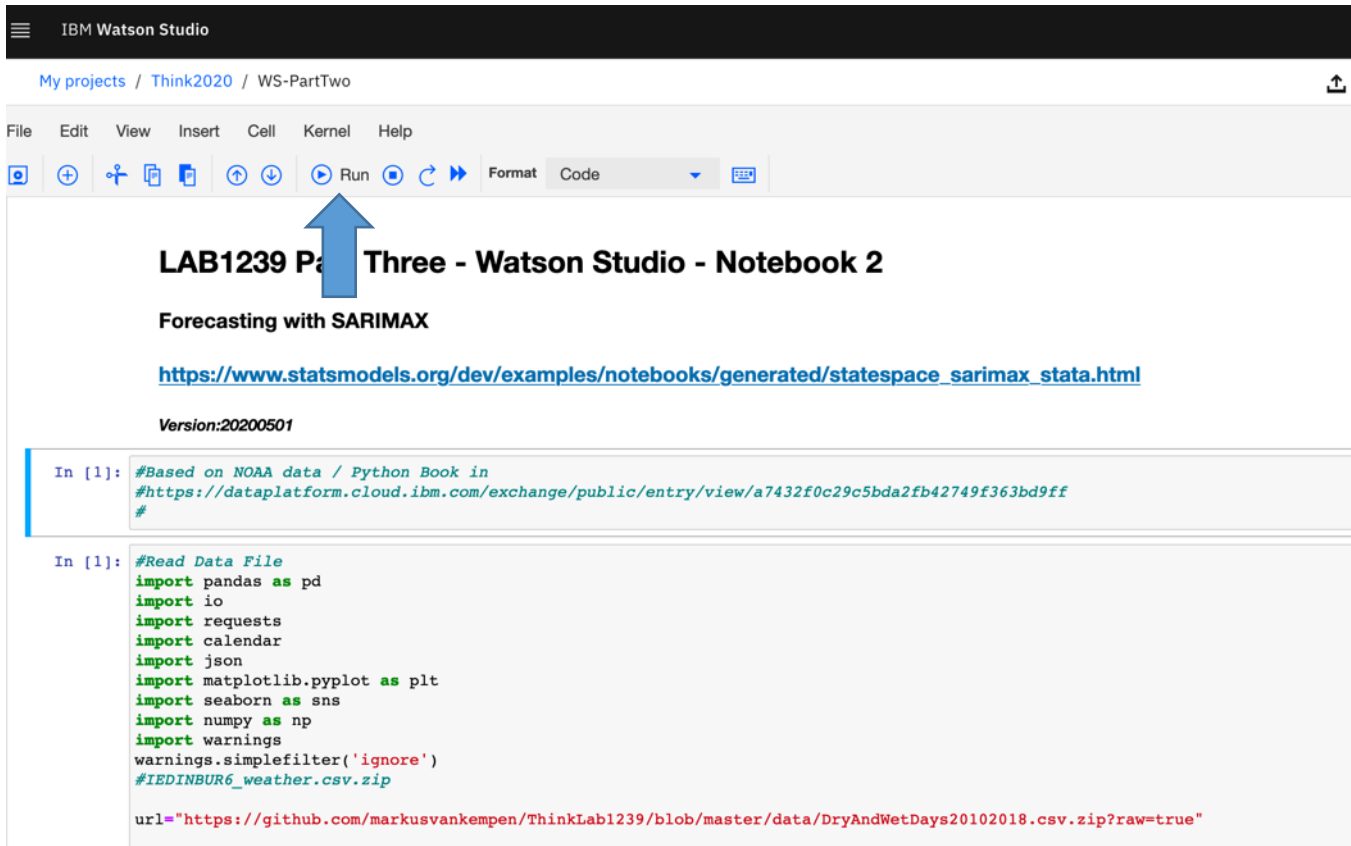
## 1.2 Setup WatsonStudio

If you worked through the LAB Part One already you should have Watson Studio already set up and can skip this step and just import the Python notebook (LabPart Three / Notebook #2 ).  
If you have not set up your WatsonStudio instance yet follow the instruction for LAB Part two 1<sup>st</sup>.

**Tip:** use WatsonStudio with FireFox and Node-RED / LAB instructions in Chrome so you can switch back and forth between the environments easier.

## 1.3 Forecasting using a Python Notebook

Once you have imported the Notebook you should see the following screen



The notebook will read the cleaned monthly weather data file from the previous LAB from the github. See

<https://github.com/markusvankempen/ThinkLab1239/blob/master/data/DryAndWetDays20102018.csv.zip>

Put the notebook into Edit mode and step thru it via the Run button.

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File Edit View Insert Cell Kernel Help

Run

Out[2]:

date	Dry	Wet	year	month_name	temp_c_max	rain_inc	rain_hours	day
2010-01-31	29.0	2.0	2010	Jan	8.08	0.85	6.0	2010-01-31
2010-02-28	22.0	6.0	2010	Feb	2.27	1.52	13.0	2010-02-28
2010-03-31	24.0	7.0	2010	Mar	9.56	2.33	16.0	2010-03-31
2010-04-30	26.0	4.0	2010	Apr	10.95	1.46	8.0	2010-04-30
2010-05-31	28.0	3.0	2010	May	16.06	0.90	6.0	2010-05-31

```
In [3]: ### Exercise consistency data check -do we have data elements for everything...any outliers
print(dataM["2010":"2010"]["month_name"])
dataM["2010":"2010"]["Dry"].plot()
```

When you have parsed the data, you can display/plot some of the data elements to make sure we have no outliers or odd data spikes.



This looks ok. Less rainy days in the summer? Try the “Dry” data element.

## 1.4 Forecasting via SARIMAX

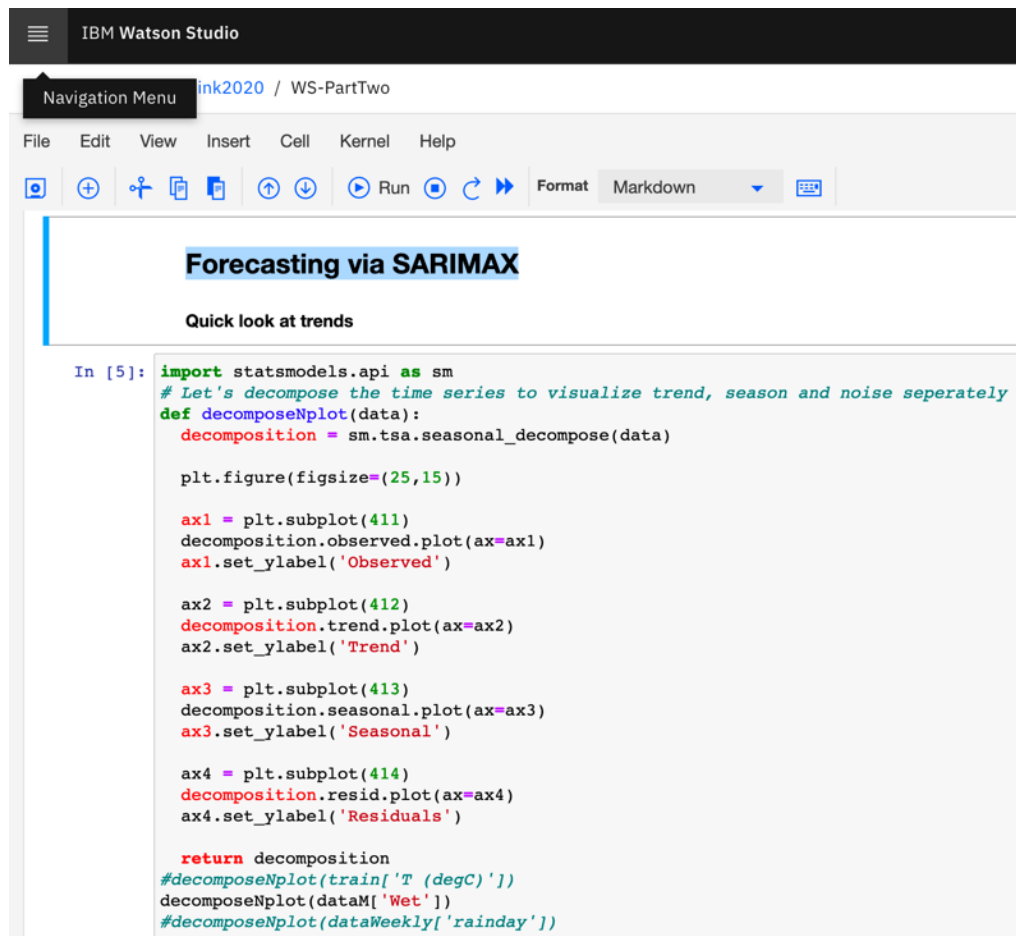
For forecasting we using a SARIMAX as a model for our seasonal data to predict the Dry weather days. You can read up on the ARIMA and SARIMAX here — lots of math ;)

[https://www.statsmodels.org/dev/examples/notebooks/generated/statespace\\_sarimax\\_stata.html](https://www.statsmodels.org/dev/examples/notebooks/generated/statespace_sarimax_stata.html)

In the LAB we will not go through the details of modeling. There are lot of other model approaches especially for the time series data set, but for the simplicity we just use ARIMA / SARIMAX in this LAB. You can use Watson AI as well create a model which can deployed and called via APIs. See here <https://dataplatform.cloud.ibm.com/docs/content/wsj/analyze-data/autoai-overview.html>

Check also the instruction folder form more excerise around AutoAI for extra credit. In this LAB we kept the approach simple and generic so it can be used in different Python Runtime environments.

The 1<sup>st</sup> step to create a model is to check if we have a trend and consistency and to see if we have seasonal data.



```
In [5]: import statsmodels.api as sm
# Let's decompose the time series to visualize trend, season and noise seperately
def decomposeNplot(data):
    decomposition = sm.tsa.seasonal_decompose(data)

    plt.figure(figsize=(25,15))

    ax1 = plt.subplot(411)
    decomposition.observed.plot(ax=ax1)
    ax1.set_ylabel('Observed')

    ax2 = plt.subplot(412)
    decomposition.trend.plot(ax=ax2)
    ax2.set_ylabel('Trend')

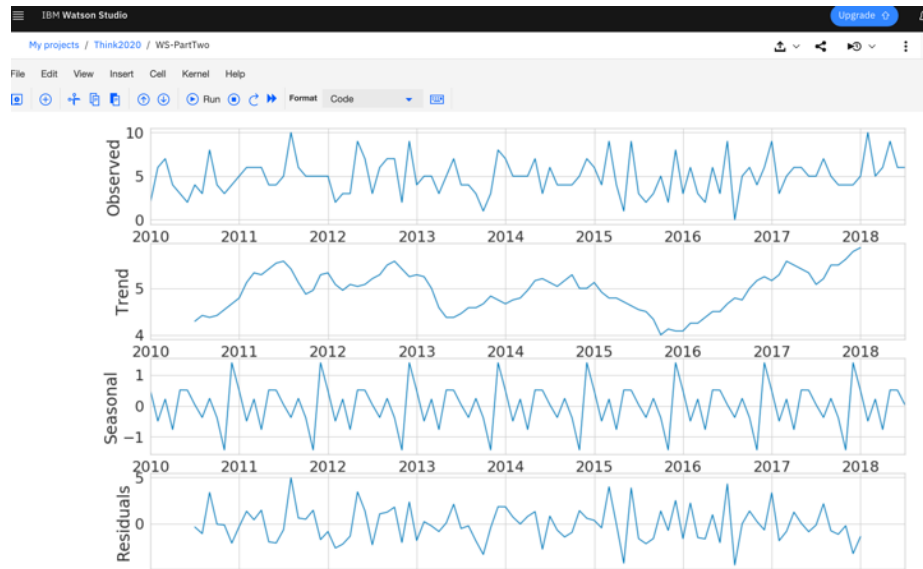
    ax3 = plt.subplot(413)
    decomposition.seasonal.plot(ax=ax3)
    ax3.set_ylabel('Seasonal')

    ax4 = plt.subplot(414)
    decomposition.resid.plot(ax=ax4)
    ax4.set_ylabel('Residuals')

    return decomposition
#decomposeNplot(train['T (degC)'])
decomposeNplot(dataM['Wet'])
#decomposeNplot(dataWeekly['rainday'])
```

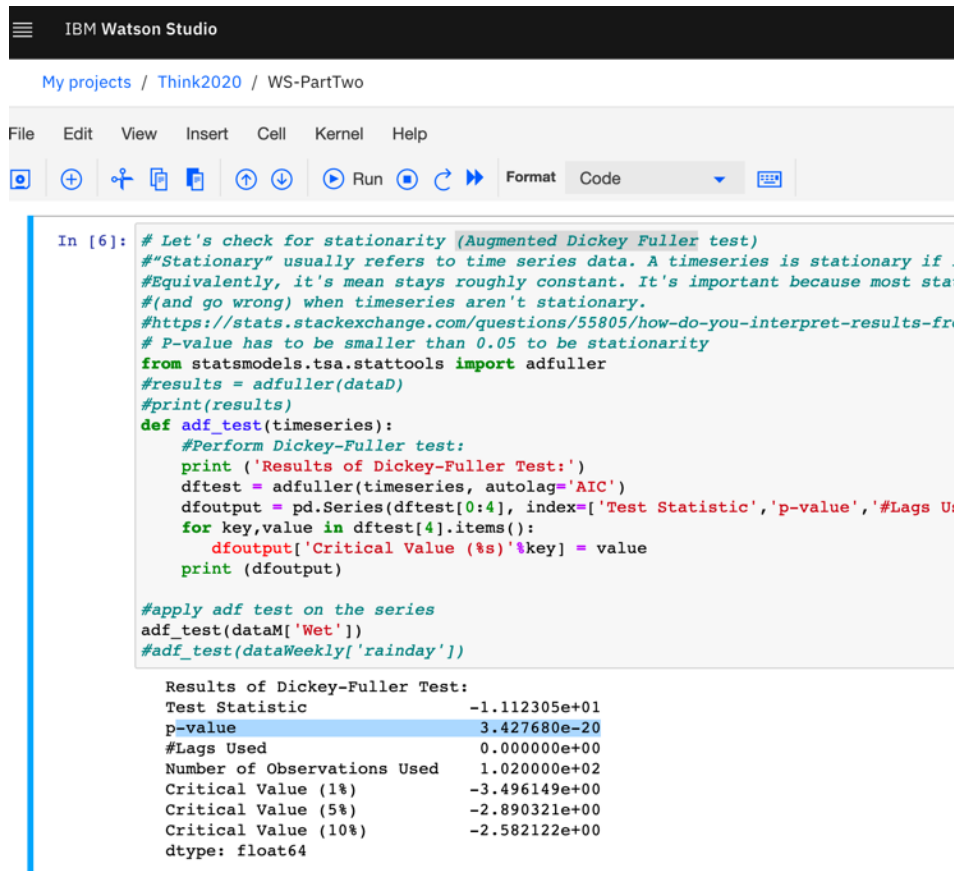


Based on the plot below and of course based on our previous data analyzing exercise we can see that the data is seasonal.



We know can further test the data to see if it is “stationarity”. We using a Augmented Dickey Fuller test. [https://en.wikipedia.org/wiki/Augmented\\_Dickey%E2%80%93Fuller\\_test](https://en.wikipedia.org/wiki/Augmented_Dickey%E2%80%93Fuller_test)

Again, a lot of math there but the key thing for us is that the p-value is smaller than 0.05



IBM Watson Studio

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Run

```
In [6]: # Let's check for stationarity (Augmented Dickey Fuller test)
# "Stationary" usually refers to time series data. A timeseries is stationary if .
# Equivalently, it's mean stays roughly constant. It's important because most sta
# (and go wrong) when timeseries aren't stationary.
# https://stats.stackexchange.com/questions/55805/how-do-you-interpret-results-fr
# P-value has to be smaller than 0.05 to be stationarity
from statsmodels.tsa.stattools import adfuller
# results = adfuller(dataD)
# print(results)
def adf_test(timeseries):
    # Perform Dickey-Fuller test:
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', '#Lags Us
    for key,value in dfoutput[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)

# apply adf test on the series
adf_test(dataM['Wet'])
# adf_test(dataWeekly['rainday'])

Results of Dickey-Fuller Test:
Test Statistic      -1.112305e+01
p-value              3.427680e-20
#Lags Used           0.000000e+00
Number of Observations Used  1.020000e+02
Critical Value (1%)    -3.496149e+00
Critical Value (5%)    -2.890321e+00
Critical Value (10%)   -2.582122e+00
dtype: float64
```

## 1.5 Creating the “Model”

Next we create the Model to predict the Dry weather days. We will divide the data up in Training and Test data and then execute the modeling function. There is a lot of information as a result.

```
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e Edit View Insert Cell Kernel Help
] [ Run Format Code

Create SARIMAX Model

In [7]: ## Resampling the data to monthly and averaging out the temperature & we will predict the month
train = dataM['2016']
test = dataM['2016']
alldata=dataM['2018-03']['Dry']
#alldata=dataM['2017-07']['Dry']
ftraindata = train['Dry']
ftestdata = test['Dry']

#dataWeekly['rainday']
#train = dataWeekly['2015':'2016']
#test = dataWeekly['2016']
#alldata=dataM['dataWeekly']
#alldata=dataWeekly['2015':'2018-04']['rainday']
#ftraindata = train['rainday']
#ftestdata = test['rainday']

from statsmodels.tsa.statespace.sarimax import SARIMAX
#endog.index = endog.datetime
#
#endog = endog.drop(['T (degC)'])

#exog.index = exog.dates
#exog = exog.drop(['dates'], axis = 1)
#Weekly
#model = SARIMAX(alldata,order=(2,0,2),seasonal_order=(1,1,0,52),trend='ct', freq='W')#,endog
#Monthly
#model = SARIMAX(alldata,order=(1, 0, 1),seasonal_order=(1, 1, 0, 12),trend='n', freq='M',en
#model = SARIMAX(dataM['Dry'],order=(2,0,2),trend='n',freq='M',enforce_stationarity=True)
#(2, 0, 2)xh(1, 1, 0, 52)
results = model.fit()

print(np.mean(np.abs(results.resid)))

results.summary()

5.011193571004436
```

Out[7]:

```
5.011193571004436
```

Out[7]:

Statespace Model Results

Dep. Variable:	Dry			No. Observations:	99
Model:	SARIMAX(1, 0, 1)x(1, 1, 0, 12)			Log Likelihood	-206.418
Date:	Fri, 01 May 2020			AIC	420.836
Time:	03:41:29			BIC	430.700
Sample:	01-31-2010			HQIC	424.808
- 03-31-2018					
Covariance Type:	opg				
	coef	std err	z	P> z	[0.025 0.975]
ar.L1	0.8886	0.117	7.587	0.000	0.659 1.118
ma.L1	-0.9998	7.527	-0.133	0.894	-15.752 13.752
ar.S.L12	-0.5579	0.121	-4.626	0.000	-0.794 -0.322
sigma2	6.2280	46.795	0.133	0.894	-85.488 97.944
Ljung-Box (Q):	29.65	Jarque-Bera (JB):	0.57		
Prob(Q):	0.88	Prob(JB):	0.75		
Heteroskedasticity (H):	1.14	Skew:	-0.12		
Prob(H) (two-sided):	0.72	Kurtosis:	2.69		

Again lots of math which you can learn more about here (<https://www.machinelearningplus.com/time-series/arima-model-time-series-forecasting-python/>) . The interesting value we looking for is MAE  
The Mean Absolute Error (MAE) see here for more information  
<https://medium.com/@ewuramaminka/mean-absolute-error-mae-machine-learning-ml-b9b4afc63077>

The MEA basically tells us how good our model is. In our case the prediction could be 5days off ☹

Reason for this is that we used monthly data if we get more data for example using weekly or daily data and work with the SARIMAX / ARIMA parameters more we would get much better results. See the Reference Section for more information

## 1.6 Visualizing the Model

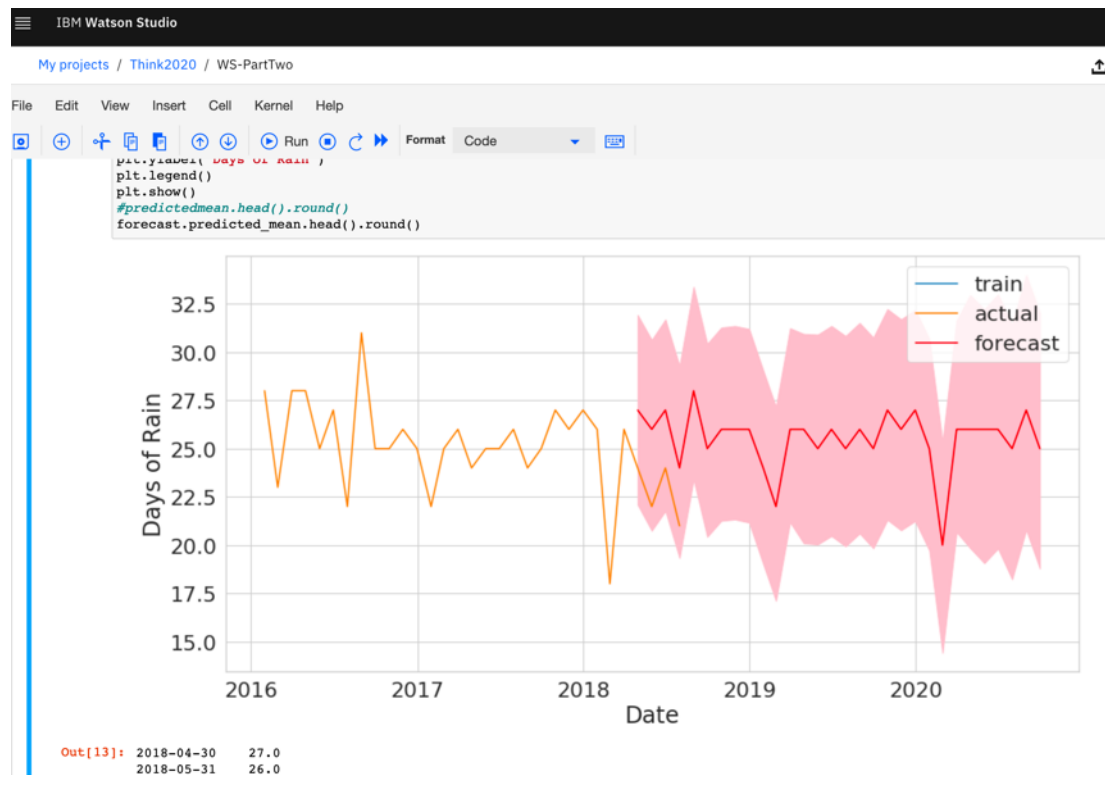
Once create the model and execute the prediction functions like:

#STEPS = Month ex., 2 years

```
forecast = results.get_forecast(steps=30) #len(ftestdata))
forecast.predicted_mean.head(10).round()
```

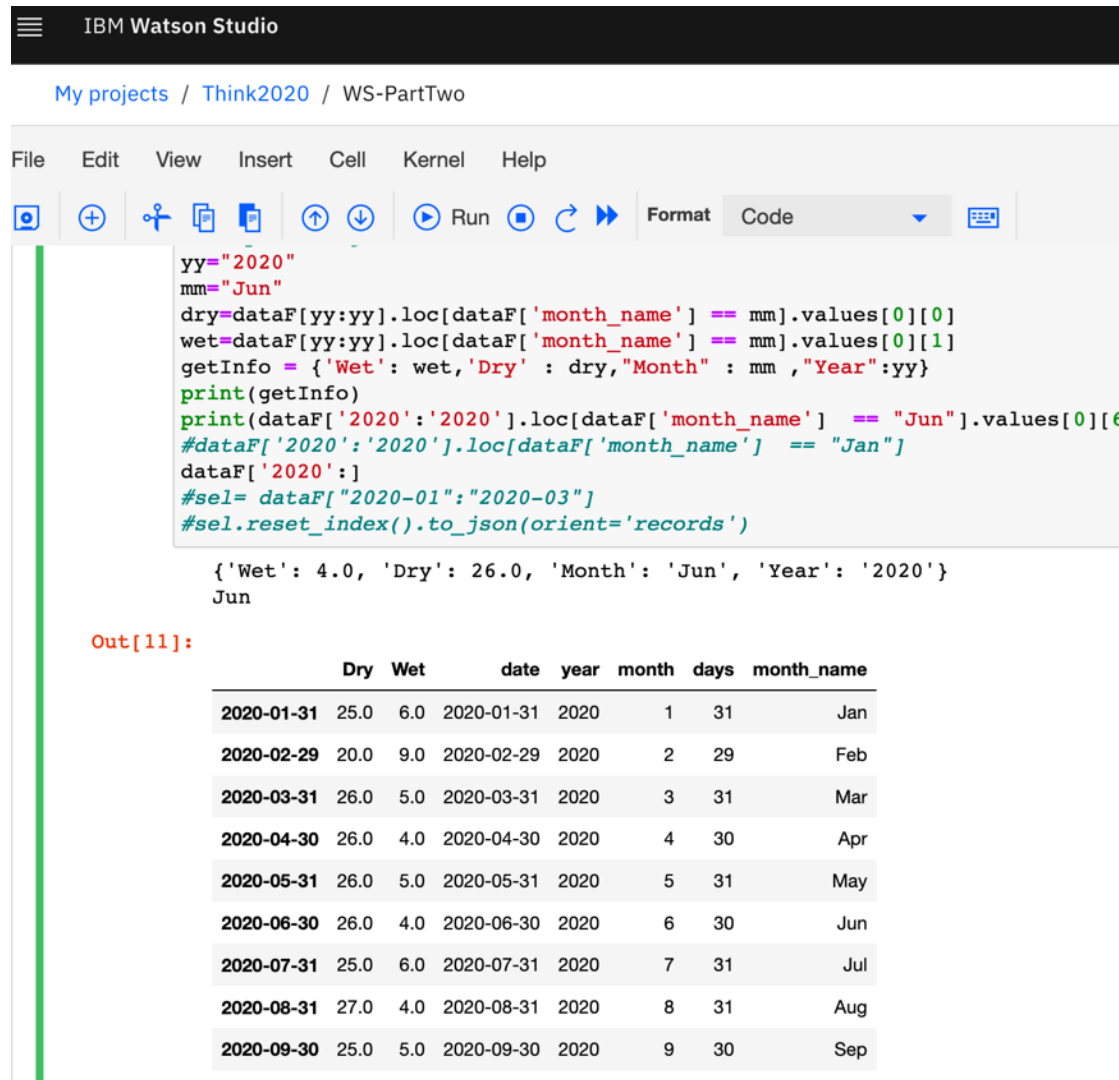
We can use our Test, Training and forecast data to visualize the result. See below.

**#Exercise:** Try using different date ranges for the plot, such as 2018



## 1.7 Merging Forecast with the History data

Once we have the forecast data, we merge the data with some of the history and calculate the Rainy days.



The screenshot shows the IBM Watson Studio interface. At the top, there's a header with the IBM logo and 'IBM Watson Studio'. Below it, a breadcrumb trail reads 'My projects / Think2020 / WS-PartTwo'. The main area is a Jupyter Notebook with a menu bar (File, Edit, View, Insert, Cell, Kernel, Help) and a toolbar with icons for running, saving, and other actions. The code cell contains the following Python code:

```
yy="2020"
mm="Jun"
dry=dataF[yy:yy].loc[dataF['month_name'] == mm].values[0][0]
wet=dataF[yy:yy].loc[dataF['month_name'] == mm].values[0][1]
getInfo = {'Wet': wet, 'Dry' : dry, "Month" : mm , "Year":yy}
print(getInfo)
print(dataF['2020':'2020'].loc[dataF['month_name'] == "Jun"].values[0][0])
#dataF['2020':'2020'].loc[dataF['month_name'] == "Jan"]
dataF['2020:']
#sel= dataF["2020-01":"2020-03"]
#sel.reset_index().to_json(orient='records')
```

The output of the code is displayed below the code cell:

```
{'Wet': 4.0, 'Dry': 26.0, 'Month': 'Jun', 'Year': '2020'}
Jun
```

Below the output, there's a table labeled 'Out[11]:' showing a summary of the data for the year 2020. The table has columns: Dry, Wet, date, year, month, days, and month\_name. The rows represent the months from January to September.

	Dry	Wet	date	year	month	days	month_name
2020-01-31	25.0	6.0	2020-01-31	2020	1	31	Jan
2020-02-29	20.0	9.0	2020-02-29	2020	2	29	Feb
2020-03-31	26.0	5.0	2020-03-31	2020	3	31	Mar
2020-04-30	26.0	4.0	2020-04-30	2020	4	30	Apr
2020-05-31	26.0	5.0	2020-05-31	2020	5	31	May
2020-06-30	26.0	4.0	2020-06-30	2020	6	30	Jun
2020-07-31	25.0	6.0	2020-07-31	2020	7	31	Jul
2020-08-31	27.0	4.0	2020-08-31	2020	8	31	Aug
2020-09-30	25.0	5.0	2020-09-30	2020	9	30	Sep

Note: That we have 2 dataset dataM (historic data) and dataF (forecast) .

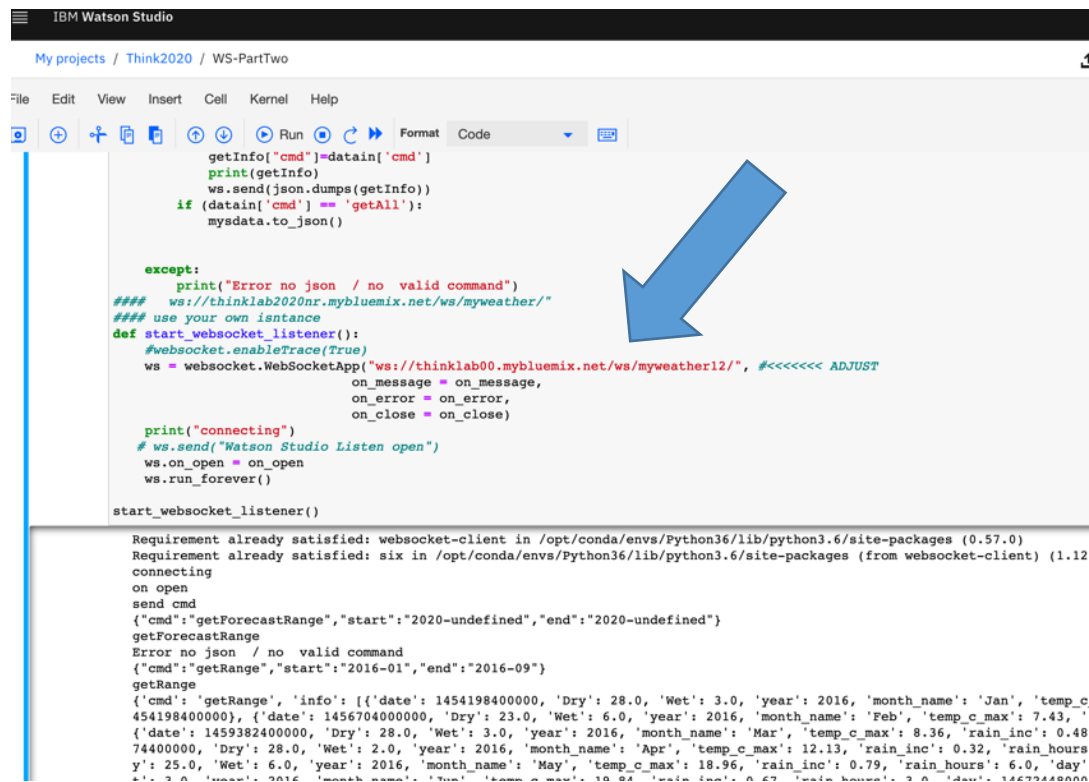
In the previous LAB where we analyzed the data and created queries for Node-RED and we will do the same here. Simply go through the different cells and explore the different queries, Feel free to add/change data elements.



**Note:** Make sure to execute each cell in the Notebook.

## 1.9 Python <-> Node-Red connection

As before, now we need to connect our python notebook to your Node-RED instance.



```

IBM Watson Studio

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File Edit View Insert Cell Kernel Help

getInfo["cmd"]=datain['cmd']
print(getInfo)
ws.send(json.dumps(getInfo))
if (datain['cmd'] == 'getAll'):
    mysdata.to_json()

except:
    print("Error no json / no valid command")
### ws://thinklab2020nr.mybluemix.net/ws/myweather/"
### use your own instance
def start_websocket_listener():
    #websocket.enableTrace(True)
    ws = websocket.WebSocketApp("ws://thinklab00.mybluemix.net/ws/myweather12/", #<----- ADJUST
                                on_message = on_message,
                                on_error = on_error,
                                on_close = on_close)

    print("connecting")
    # ws.send("Watson Studio Listen open")
    ws.on_open = on_open
    ws.run_forever()

start_websocket_listener()

Requirement already satisfied: websocket-client in /opt/conda/envs/Python36/lib/python3.6/site-packages (0.57.0)
Requirement already satisfied: six in /opt/conda/envs/Python36/lib/python3.6/site-packages (from websocket-client) (1.12)
connecting
on open
send cmd
{"cmd":"getForecastRange","start":"2020-undefined","end":"2020-undefined"}
getForecastRange
Error no json / no valid command
{"cmd":"getRange","start":"2016-01","end":"2016-09"}
getRange
{'cmd': 'getRange', 'info': [{'date': 1454198400000, 'Dry': 28.0, 'Wet': 3.0, 'year': 2016, 'month_name': 'Jan', 'temp_c': 454198400000}, {'date': 1456704000000, 'Dry': 23.0, 'Wet': 6.0, 'year': 2016, 'month_name': 'Feb', 'temp_c_max': 7.43, 'date': 1459382400000, 'Dry': 28.0, 'Wet': 3.0, 'year': 2016, 'month_name': 'Mar', 'temp_c_max': 8.36, 'rain_inc': 0.48, 'Dry': 28.0, 'Wet': 2.0, 'year': 2016, 'month_name': 'Apr', 'temp_c_max': 12.13, 'rain_inc': 0.32, 'rain_hours': 74400000, 'Dry': 28.0, 'Wet': 2.0, 'year': 2016, 'month_name': 'May', 'temp_c_max': 18.96, 'rain_inc': 0.79, 'rain_hours': 6.0, 'day': 3.0, 'year': 2016, 'month_name': 'Jun', 'temp_c_max': 18.84, 'rain_inc': 0.67, 'rain_hours': 3.0, 'day': 1467744000000}]}

```

Make sure to adjust the websock URL with your instance/LABID number. You may also need to check the websocket path which is defined in Node-RED. Ex., `/ws/myweather12/`. Execute the cell and you should see something like:

```

ws.on_open = on_open
ws.run_forever()

start_websocket_listener()

Collecting websocket-client
  Downloading https://files.pythonhosted.org/packages/4c/5f/f61b42014/
  |████████████████████| 204kB 7.8MB/s eta 0:00:01
Requirement already satisfied: six in /opt/conda/envs/Python36/lib/python3.6/site-packages (from websocket-client) (1.12)
Installing collected packages: websocket-client
Successfully installed websocket-client-0.57.0
connecting
on open
send cmd

31]: print("Hello")

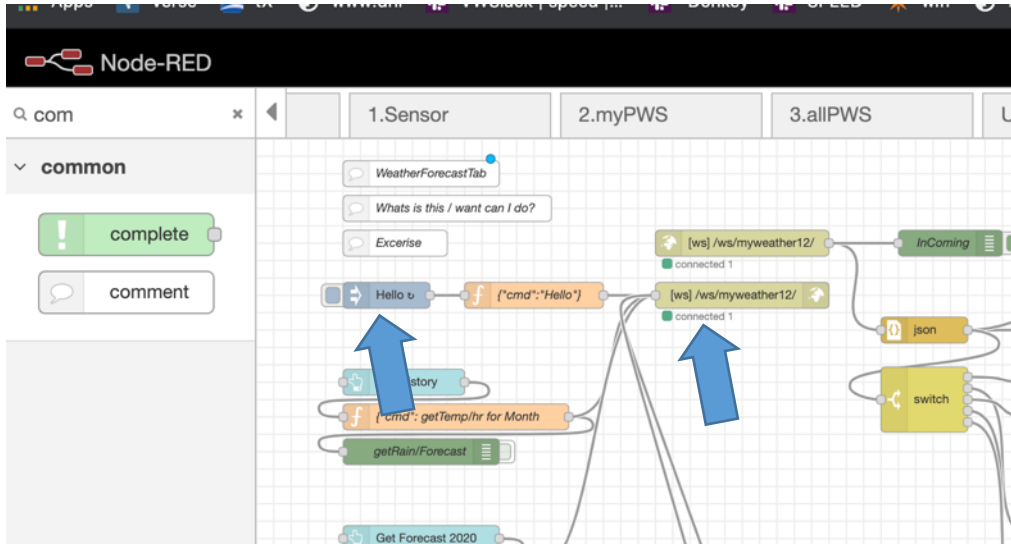
Hello

```

This means the connection is working. If you run into issues make sure you Node-RED host name is correct and the WebSocket url also check the **troubleshoot section**.

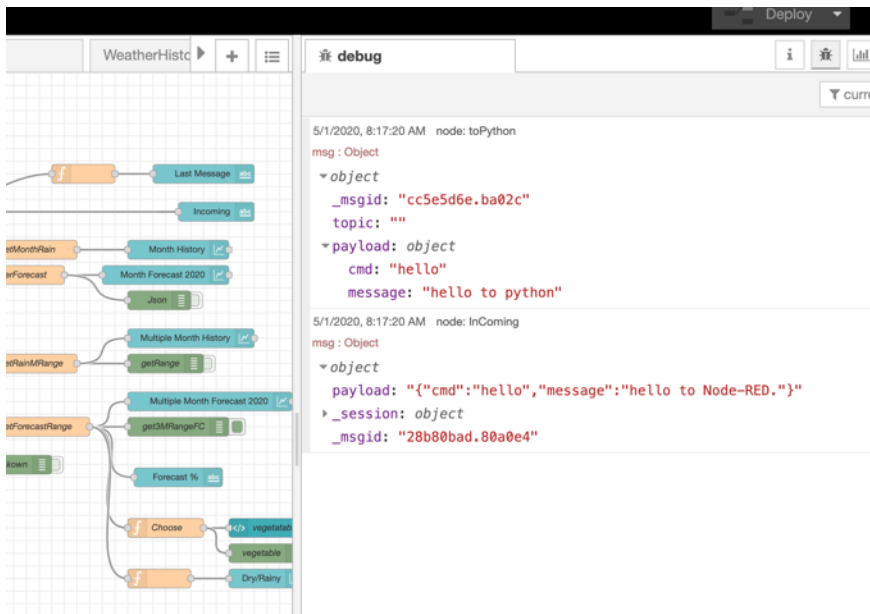
## 1.10 Querying Python from Node-RED

Switch back to your Node-RED instance and look at the WeatherForecast Tab. You should see 2 green icons under the WebSocket and debug messages, like Heartbeats from your Notebook.



Send a hello message from Node-RED to python and check in the Python Notebook if you see the messages.

Sending a Hello back and forth—see below





```
start_websocket_listener()
```

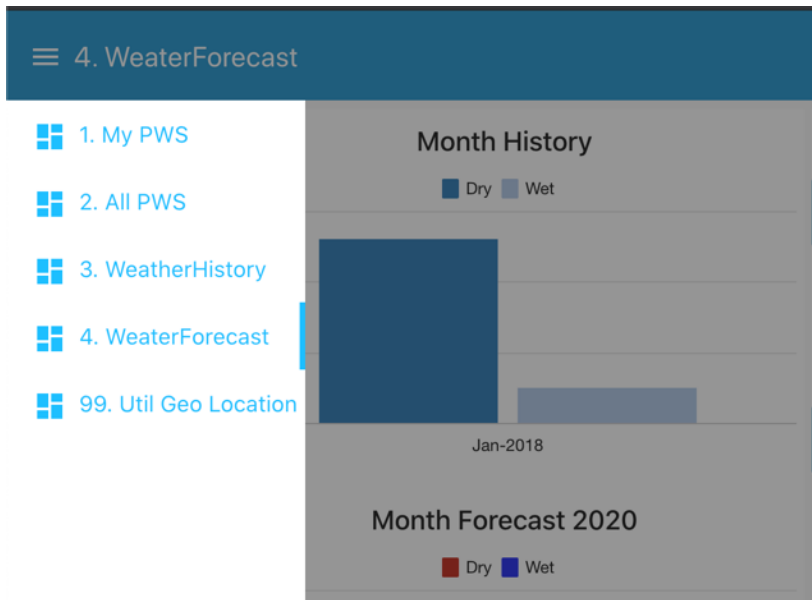
```
Requirement already satisfied: websocket-client in /opt/conda/envs/Py
Requirement already satisfied: six in /opt/conda/envs/Python36/lib/py
connecting
on open
send cmd
{"cmd":"hello","message":"hello to python"}
hello
{"cmd":"hello","message":"hello to Node-RED."}
{"cmd":"hello","message":"hello to python"}
hello
{"cmd":"hello","message":"hello to Node-RED."}
```

```
[*]: print("Hello")
```

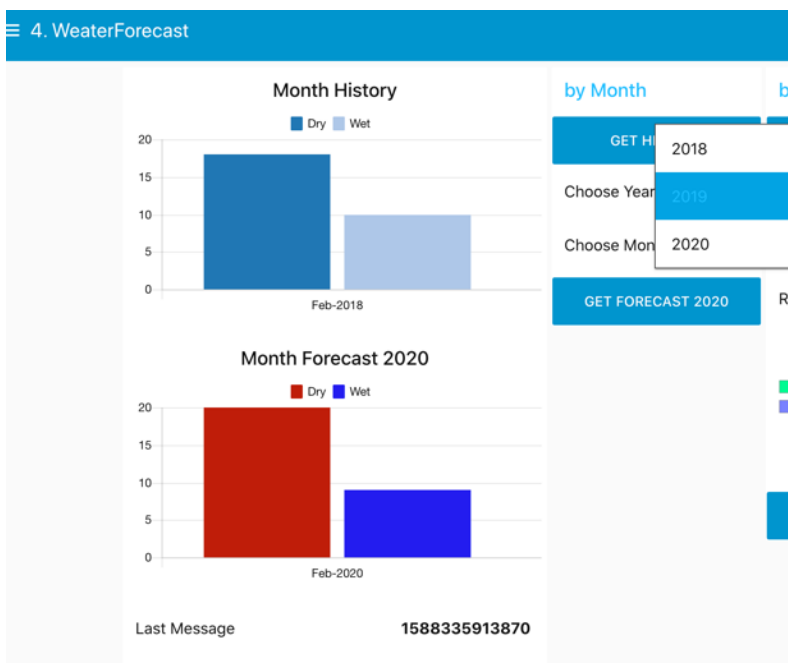
## 2 Forecasting

### 2.1 Using the Forecasting Dashboards

Open your Node-RED your instance.mybluemix.net/ui dashboard and select menu # 4. You should see a screen below

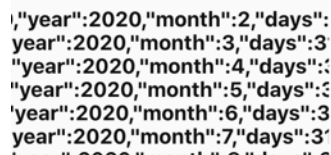


Try to get data for Feb 2018 and Feb 2020, in the Month Section:



### #Exercise Add the Missing Month and years (2010-2017)

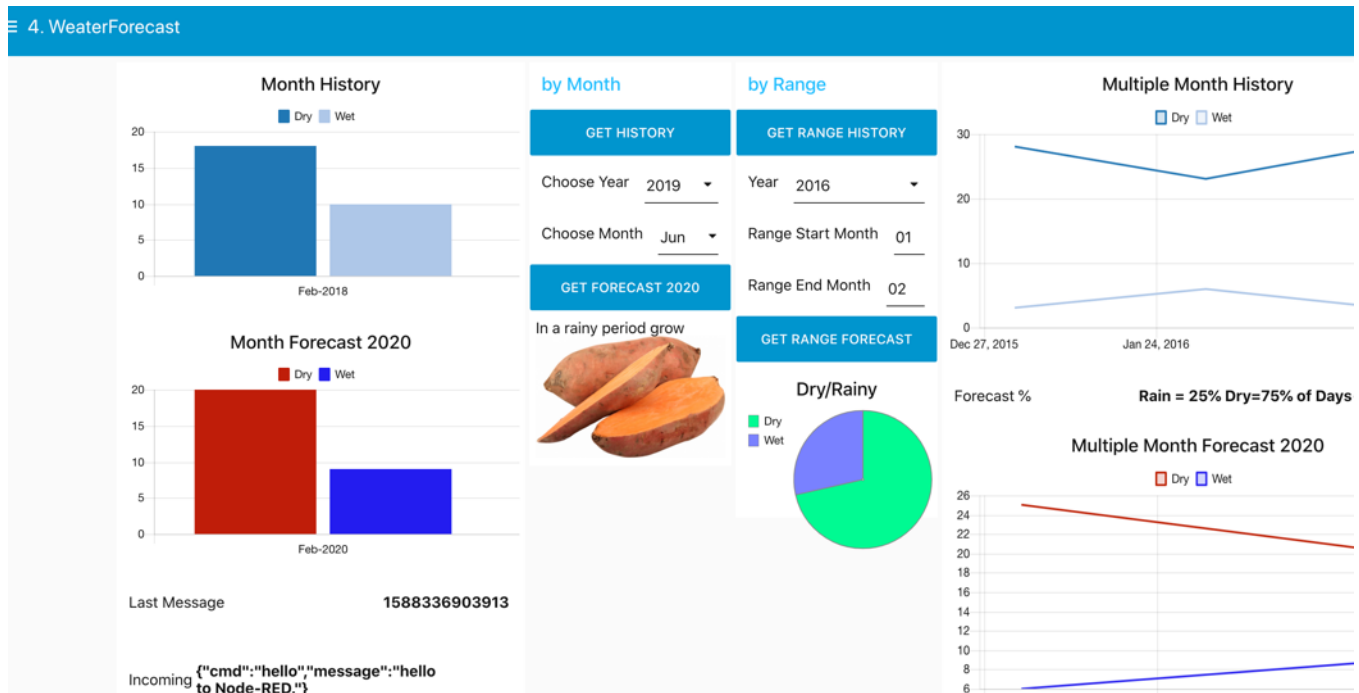
The Range section on the Right will let you query multiple month. Try to query Feb-Sep etc.



Again the forecast year is hard coded to 2020. Add the missing years in the Node-RED

## 2.3 Vegetable choice

The dashboard as some hidden functionality like displaying the vegetable which one can grow based on Dry/Rainy days. Try to discover and enable the function and display images.



Feel free change the flow/code.

**THE END !**

## 3 Trouble shooting

### 3.1 WebSocket connection

Make sure install the websocket client in the cell via **!pip install websocket-client**

There are 2 parts to connecting

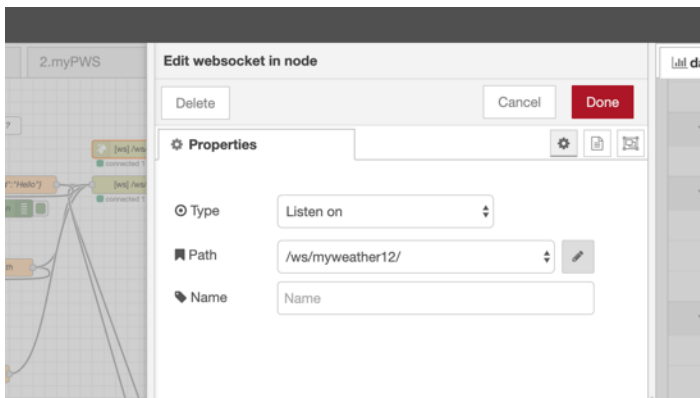
1. Make sure the the url in the the Python Notebook is correct.

Like

**ws://thinklab??mybluemix.net/ws/myweather12**

where ??? is you LabID / Node-RED hostname

2. Make sure Node-RED code is deployed and the websocket path is the same e.g **/ws/myweather12**



Sometimes it helps if you change the path on bth ends .. like to **/ws/myweather99** or so

### 3.2 WebSocket is stuck

Sometimes you cannot tell if the socket works from the Python notebook. Than you the Stop button in the notebook to stop the cell and start a gain ... try to execute a different cell 1<sup>st</sup> before starting the notebook again like the hello work once. If you cannot get any reaction form the Notebook try to reload the whole notebook and execute each cell again.

### 3.3 Queries not working / No data coming into Node-RED

Sometime the queries are not working. You can see that Node-RED send a command like:

```
ws.run_forever()  
  
start_websocket_listener()  
  
Requirement already satisfied: websocket-client in /opt/conda/envs/Python36/lib/p  
Requirement already satisfied: six in /opt/conda/envs/Python36/lib/python3.6/site  
connecting  
on open  
send cmd  
{"cmd": "getForecastMonth", "month": "Jun", "year": "2020"}  
getForecastMonth  
Error no json / no valid command
```

In that case a dataset is most likely not initialize like dataF or so ... make sure to stop the notebook than and go thru the query section of the notebook again.

**4 3**

## 5 References and Information

<https://datapatform.cloud.ibm.com/exchange/public/entry/view/a7432f0c29c5bda2fb42749f363bd9ff>  
<https://machinelearningmastery.com/sarima-for-time-series-forecasting-in-python/>  
[https://www.statsmodels.org/dev/examples/notebooks/generated/statespace\\_sarimax\\_stata.html](https://www.statsmodels.org/dev/examples/notebooks/generated/statespace_sarimax_stata.html)  
<https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/>  
<https://www.kaggle.com/poiupoiu/how-to-use-sarimax>  
<https://www.kaggle.com/amar09/time-series-delhi-weather-forecasting-arima>

### Get the instructions for LAB here

<https://github.com/markusvankempen/ThinkLab1239/tree/master/instructions>

For more details got to the github

<https://github.com/markusvankempen/ThinkLab1239>

Cheers

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