COURSE CODE: SWE2020

COURSE NAME: SOFTWARE METRICS

J-COMPONENT

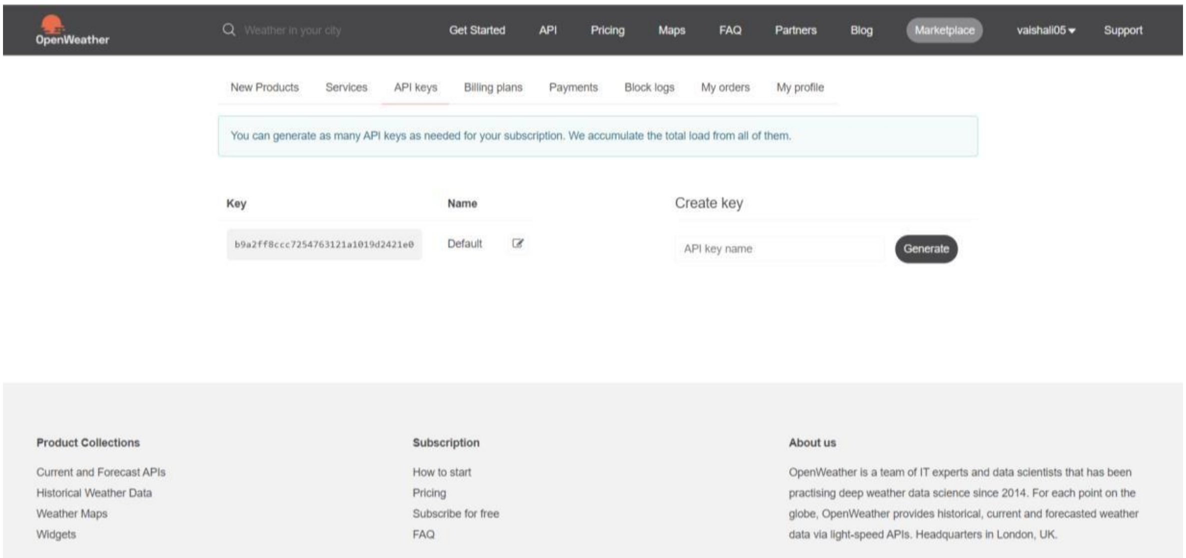
METRICS ANALYSIS IN CURRENT WEATHER PREDICTION

BY:

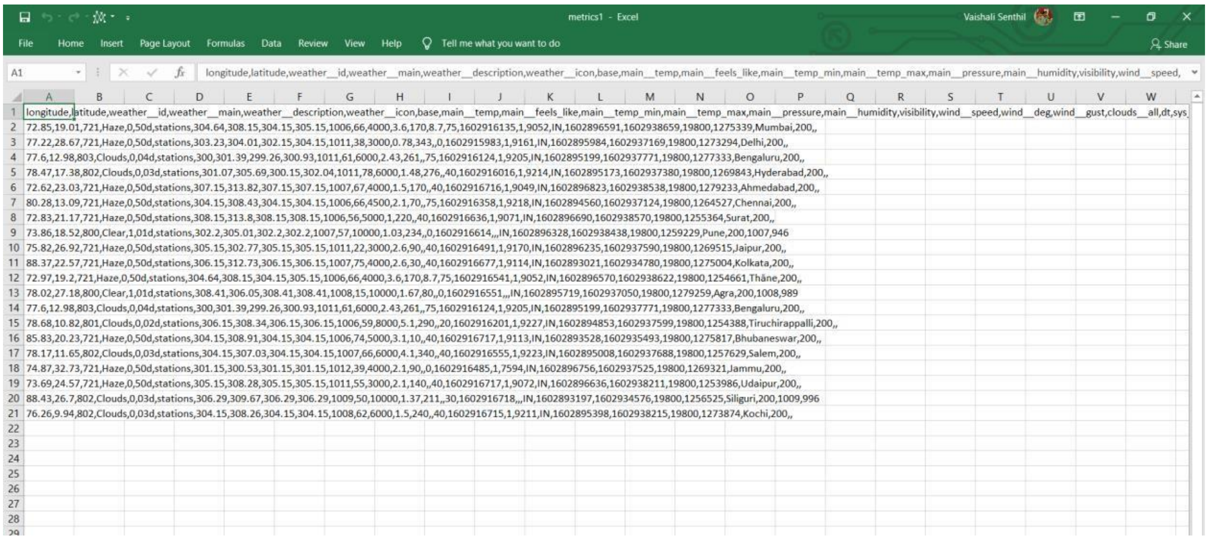
VAISHALI.S - 18MIS0082

FRAMEWORK:

The main focus of the project is to predict the accuracy of weather with the current data from openweather website within india . Then the data is retrieved using python and API key.



About 20 different cities are referred and the data is obtained.



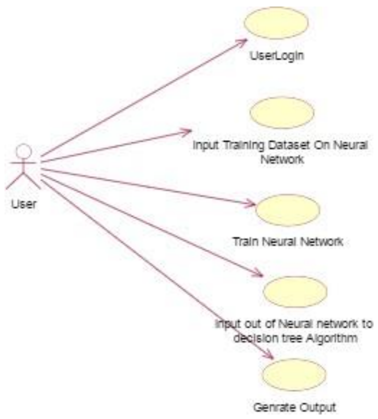

```
longitude,latitude,weather__id,weather__main,weather__description,weather__icon,base,main__temp,main__feels_like,main__temp_min,main__temp_max,main__pressure,main__humidity,visibility,wind__speed,wind__deg,wind__gust,clouds__all,dt,sys
72.85,19.01,721,Haze,0,50d,stations,304.64,308.15,304.15,305.15,1006,66,4000,3.6,170,8.7,75,1602916135,1,9052,IN,1602896591,1602938659,19800,1275339,Mumbai,200,,
77.22,28.67,721,Haze,0,50d,stations,303.23,304.01,302.15,304.15,1011,38,3000,0.78,343,,0,1602915983,1,9161,IN,1602895984,1602937169,19800,1273294,Delhi,200,,
77.6,12.98,803,Clouds,0,04d,stations,300,301.39,299.26,300.93,1011,61,6000,2.43,261,,75,1602916124,1,9205,IN,1602895199,1602937771,19800,1277333,Bengaluru,200,,
78.47,17.38,802,Clouds,0,03d,stations,301.07,305.69,300.15,302.04,1011,78,6000,1.48,276,,40,1602916016,1,9214,IN,1602895173,1602937380,19800,1269843,Hyderabad,200,,
72.62,23.03,721,Haze,0,50d,stations,307.15,313.82,307.15,307.15,1007,67,4000,1.5,170,,40,1602916716,1,9049,IN,1602896823,1602938538,19800,1279233,Ahmedabad,200,,
80.28,13.09,721,Haze,0,50d,stations,304.15,308.43,304.15,304.15,1006,66,4500,2.1,70,,75,1602916358,1,9218,IN,1602894560,1602937124,19800,1264527,Chennai,200,,
72.83,21.17,721,Haze,0,50d,stations,308.15,313.8,308.15,308.15,1006,56,5000,1,220,,40,1602916636,1,9071,IN,1602896690,1602938570,19800,1255364,Surat,200,,
73.86,18.52,800,Clear,1,01d,stations,302.2,305.01,302.2,302.2,1007,57,10000,1.03,234,,0,1602916614,,,IN,1602896328,1602938438,19800,1259229,Pune,200,1007,946
75.82,26.92,721,Haze,0,50d,stations,305.15,302.77,305.15,305.15,1011,22,3000,2.6,90,,40,1602916491,1,9170,IN,1602896235,1602937590,19800,1269515,Jaipur,200,,
88.37,22.57,721,Haze,0,50d,stations,306.15,312.73,306.15,306.15,1007,75,4000,2.6,30,,40,1602916677,1,9114,IN,1602893021,1602934780,19800,1275004,Kolkata,200,,
72.97,19.2,721,Haze,0,50d,stations,304.64,308.15,304.15,305.15,1006,66,4000,3.6,170,8.7,75,1602916541,1,9052,IN,1602896570,1602938622,19800,1254661,Thāne,200,,
78.02,27.18,800,Clear,1,01d,stations,308.41,306.05,308.41,308.41,1008,15,10000,1.67,80,,0,1602916551,,,IN,1602895719,1602937050,19800,1279259,Agra,200,1008,989
77.6,12.98,803,Clouds,0,04d,stations,300,301.39,299.26,300.93,1011,61,6000,2.43,261,,75,1602916124,1,9205,IN,1602895199,1602937771,19800,1277333,Bengaluru,200,,
78.68,10.82,801,Clouds,0,02d,stations,306.15,308.34,306.15,306.15,1006,59,8000,5.1,290,,20,1602916201,1,9227,IN,1602894853,1602937599,19800,1254388,Tiruchirappalli,200,,
85.83,20.23,721,Haze,0,50d,stations,304.15,308.91,304.15,304.15,1006,74,5000,3.1,10,,40,1602916717,1,9113,IN,1602893528,1602935493,19800,1275817,Bhubaneswar,200,,
78.17,11.65,802,Clouds,0,03d,stations,304.15,307.03,304.15,304.15,1007,66,6000,4.1,340,,40,1602916555,1,9223,IN,1602895008,1602937688,19800,1257629,Salem,200,,
74.87,32.73,721,Haze,0,50d,stations,301.15,300.53,301.15,301.15,1012,39,4000,2.1,90,,0,1602916485,1,7594,IN,1602896756,1602937525,19800,1269321,Jammu,200,,
73.69,24.57,721,Haze,0,50d,stations,305.15,308.28,305.15,305.15,1011,55,3000,2.1,140,,40,1602916717,1,9072,IN,1602896636,1602938211,19800,1253986,Udaipur,200,,
88.43,26.7,802,Clouds,0,03d,stations,306.29,309.67,306.29,306.29,1009,50,10000,1.37,211,,30,1602916718,,,IN,1602893197,1602934576,19800,1256525,Siliguri,200,1009,996
76.26,9.94,802,Clouds,0,03d,stations,304.15,308.26,304.15,304.15,1008,62,6000,1.5,240,,40,1602916715,1,9211,IN,1602895398,1602938215,19800,1273874,Kochi,200,,
```

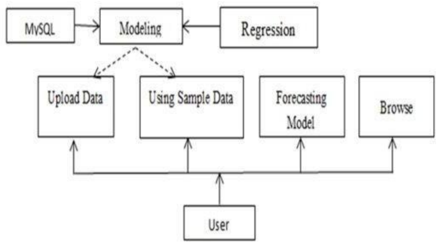
Then the datsets are trained and tested with the activation function and the accuracy is obtained after 10 epochs.

In order to get pictorial representation of the datasets in various ways it is represented in pie charts, line graph ,histogram and scatter plot with colorbar.

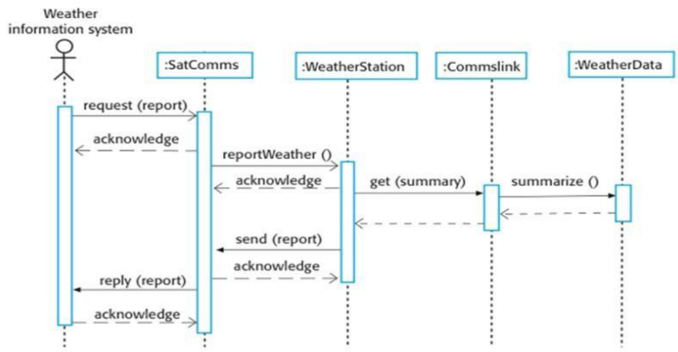
The developed network and resluts are analysed with codacy which works with the module radon itself and the results are obtained.

ARCHITECTURE DIAGRAM:





USE CASE DIAGRAM



SEQUENCE DIAGRAM

CODE FOR WEATHER PREDICTION:

```
In [4]: !pip install requests

Requirement already satisfied: requests in c:\programdata\anaconda3\lib\site-packages (2.24.0)
Requirement already satisfied: idna<3,>=2.5 in c:\programdata\anaconda3\lib\site-packages (from requests) (2.10)
Requirement already satisfied: certifi>=2017.4.17 in c:\programdata\anaconda3\lib\site-packages (from requests) (2020.6.20)
Requirement already satisfied: chardet<4,>=3.0.2 in c:\programdata\anaconda3\lib\site-packages (from requests) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in c:\programdata\anaconda3\lib\site-packages (from requ
ests) (1.25.9)

In [5]: import requests

In [6]: api_address='http://api.openweathermap.org/data/2.5/weather?appid=b9a2ff8ccc7254763121a1019d2421e0&q='
city1,city2,city3,city4,city5,city6,city7,city8,city9,city10,city11,city12,city13,city14,city15,city16,city17,city18,city19,city
20=input("City name:").split()

City name:Mumbai delhi bangalore hyderabad ahmedabad chennai surat pune jaipur kolkata thane agra madurai Tiruchirappalli Bhuba
neswar Salem jammu udaipur Siliguri Kochi

In [7]: url1 = api_address + city1
url2 = api_address + city2
url3 = api_address + city3
url4 = api_address + city4
url5 = api_address + city5
url6 = api_address + city6
url7 = api_address + city7
url8 = api_address + city8
url9 = api_address + city9
url10 = api_address + city10
url11 = api_address + city11
url12 = api_address + city12
url13 = api_address + city13
url14 = api_address + city14
url15 = api_address + city15
url16 = api_address + city16
url17 = api_address + city17
url18 = api_address + city18
url19 = api_address + city19
url20 = api_address + city20
```

```
In [8]: json_data1 = requests.get(url1).json()
formatted_data = json_data1['weather'][0]['description']
print(formatted_data)
json_data2 = requests.get(url2).json()
formatted_data = json_data2['weather'][0]['description']
print(formatted_data)
json_data3 = requests.get(url3).json()
formatted_data = json_data3['weather'][0]['description']
print(formatted_data)
json_data4 = requests.get(url4).json()
formatted_data = json_data4['weather'][0]['description']
print(formatted_data)
json_data5 = requests.get(url5).json()
formatted_data = json_data5['weather'][0]['description']
print(formatted_data)
json_data6 = requests.get(url6).json()
formatted_data = json_data6['weather'][0]['description']
print(formatted_data)
json_data7 = requests.get(url7).json()
formatted_data = json_data7['weather'][0]['description']
print(formatted_data)
json_data8 = requests.get(url8).json()
formatted_data = json_data8['weather'][0]['description']
print(formatted_data)
json_data9 = requests.get(url9).json()
formatted_data = json_data9['weather'][0]['description']
print(formatted_data)
json_data10 = requests.get(url10).json()
formatted_data = json_data10['weather'][0]['description']
print(formatted_data)
json_data11 = requests.get(url11).json()
formatted_data = json_data11['weather'][0]['description']
print(formatted_data)
json_data12 = requests.get(url12).json()
formatted_data = json_data12['weather'][0]['description']
print(formatted_data)
json_data13 = requests.get(url3).json()
formatted_data = json_data13['weather'][0]['description']
print(formatted_data)
json_data14 = requests.get(url14).json()
formatted_data = json_data14['weather'][0]['description']
print(formatted_data)
json_data15 = requests.get(url15).json()
```

```
json_data16 = requests.get(url16).json()
formatted_data = json_data16['weather'][0]['description']
print(formatted_data)
json_data17 = requests.get(url17).json()
formatted_data = json_data17['weather'][0]['description']
print(formatted_data)
json_data18 = requests.get(url18).json()
formatted_data = json_data18['weather'][0]['description']
print(formatted_data)
json_data19 = requests.get(url19).json()
formatted_data = json_data19['weather'][0]['description']
print(formatted_data)
json_data20 = requests.get(url20).json()
formatted_data = json_data20['weather'][0]['description']
print(formatted_data)

haze
haze
broken clouds
scattered clouds
haze
haze
haze
clear sky
haze
haze
haze
clear sky
broken clouds
few clouds
haze
scattered clouds
haze
haze
scattered clouds
scattered clouds

In [9]: print(json_data1)
print(json_data2)
print(json_data3)
print(json_data4)
print(json_data5)
print(json_data6)
```

```
print(json_data7)
print(json_data8)
print(json_data9)
print(json_data10)
print(json_data11)
print(json_data12)
print(json_data13)
print(json_data14)
print(json_data15)
print(json_data16)
print(json_data17)
print(json_data18)
print(json_data19)
print(json_data20)
```

{'coord': {'lon': 72.85, 'lat': 19.01}, 'weather': [{'id': 721, 'main': 'Haze', 'description': 'haze', 'icon': '50d'}], 'base': 'stations', 'main': {'temp': 304.64, 'feels_like': 308.15, 'temp_min': 304.15, 'temp_max': 305.15, 'pressure': 1006, 'humidity': 66}, 'visibility': 4000, 'wind': {'speed': 3.6, 'deg': 170, 'gust': 8.7}, 'clouds': {'all': 75}, 'dt': 1602916135, 'sys': {'type': 1, 'id': 9052, 'country': 'IN', 'sunrise': 1602896591, 'sunset': 1602938659}, 'timezone': 19800, 'id': 1275339, 'name': 'Mumbai', 'cod': 200}
{'coord': {'lon': 77.22, 'lat': 28.67}, 'weather': [{'id': 721, 'main': 'Haze', 'description': 'haze', 'icon': '50d'}], 'base': 'stations', 'main': {'temp': 303.23, 'feels_like': 304.01, 'temp_min': 302.15, 'temp_max': 304.15, 'pressure': 1011, 'humidity': 38}, 'visibility': 3000, 'wind': {'speed': 0.78, 'deg': 343}, 'clouds': {'all': 0}, 'dt': 1602915983, 'sys': {'type': 1, 'id': 9161, 'country': 'IN', 'sunrise': 1602895984, 'sunset': 1602937169}, 'timezone': 19800, 'id': 1273294, 'name': 'Delhi', 'cod': 200}
{'coord': {'lon': 77.6, 'lat': 12.98}, 'weather': [{'id': 803, 'main': 'Clouds', 'description': 'broken clouds', 'icon': '04d'}], 'base': 'stations', 'main': {'temp': 300, 'feels_like': 301.39, 'temp_min': 299.26, 'temp_max': 300.93, 'pressure': 1011, 'humidity': 61}, 'visibility': 6000, 'wind': {'speed': 2.43, 'deg': 261}, 'clouds': {'all': 75}, 'dt': 1602916124, 'sys': {'type': 1, 'id': 9205, 'country': 'IN', 'sunrise': 1602895199, 'sunset': 1602937771}, 'timezone': 19800, 'id': 1277333, 'name': 'Bengaluru', 'cod': 200}
{'coord': {'lon': 78.47, 'lat': 17.38}, 'weather': [{'id': 802, 'main': 'Clouds', 'description': 'scattered clouds', 'icon': '03d'}], 'base': 'stations', 'main': {'temp': 301.07, 'feels_like': 305.69, 'temp_min': 300.15, 'temp_max': 302.04, 'pressure': 1011, 'humidity': 78}, 'visibility': 6000, 'wind': {'speed': 1.48, 'deg': 276}, 'clouds': {'all': 40}, 'dt': 1602916016, 'sys': {'type': 1, 'id': 9214, 'country': 'IN', 'sunrise': 1602895173, 'sunset': 1602937380}, 'timezone': 19800, 'id': 1269843, 'name': 'Hyderabad', 'cod': 200}
{'coord': {'lon': 72.62, 'lat': 23.03}, 'weather': [{'id': 721, 'main': 'Haze', 'description': 'haze', 'icon': '50d'}], 'base': 'stations', 'main': {'temp': 307.15, 'feels_like': 313.82, 'temp_min': 307.15, 'temp_max': 307.15, 'pressure': 1007, 'humidity': 67}, 'visibility': 4000, 'wind': {'speed': 1.5, 'deg': 170}, 'clouds': {'all': 40}, 'dt': 1602916716, 'sys': {'type': 1, 'id': 9049, 'country': 'IN', 'sunrise': 1602896823, 'sunset': 1602938538}, 'timezone': 19800, 'id': 1279233, 'name': 'Ahmedabad', 'cod': 200}
{'coord': {'lon': 80.28, 'lat': 13.09}, 'weather': [{'id': 721, 'main': 'Haze', 'description': 'haze', 'icon': '50d'}], 'base': 'stations', 'main': {'temp': 304.15, 'feels_like': 308.43, 'temp_min': 304.15, 'temp_max': 304.15, 'pressure': 1006, 'humidity': 66}, 'visibility': 4500, 'wind': {'speed': 2.1, 'deg': 70}, 'clouds': {'all': 75}, 'dt': 1602916358, 'sys': {'type': 1, 'i

In [25]:
```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Flatten, Dense
```

In [26]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
```

In [40]:
```
dataset = pd.read_csv('metrics1.csv')
```

In [41]:
```
dataset.head(20)
```

Out[41]:

	coord__lon	coord__lat	weather__id	weather__main	weather__description	weather__icon	base	main__temp	main__feels_like	main__temp_min	...	sys
0	72.85	19.01	721	Haze	0	50d	stations	304.64	308.15	304.15	...	90
1	77.22	28.67	721	Haze	0	50d	stations	303.23	304.01	302.15	...	91
2	77.60	12.98	803	Clouds	0	04d	stations	300.00	301.39	299.26	...	92
3	78.47	17.38	802	Clouds	0	03d	stations	301.07	305.69	300.15	...	92
4	72.62	23.03	721	Haze	0	50d	stations	307.15	313.82	307.15	...	90
5	80.28	13.09	721	Haze	0	50d	stations	304.15	308.43	304.15	...	92
6	72.83	21.17	721	Haze	0	50d	stations	308.15	313.80	308.15	...	90
7	73.86	18.52	800	Clear	1	01d	stations	302.20	305.01	302.20	...	
8	75.82	26.92	721	Haze	0	50d	stations	305.15	302.77	305.15	...	91
9	88.37	22.57	721	Haze	0	50d	stations	306.15	312.73	306.15	...	91
10	72.97	19.20	721	Haze	0	50d	stations	304.64	308.15	304.15	...	90
11	78.02	27.18	800	Clear	1	01d	stations	308.41	306.05	308.41	...	
12	77.60	12.98	803	Clouds	0	04d	stations	300.00	301.39	299.26	...	92
13	78.68	10.82	801	Clouds	0	02d	stations	306.15	308.34	306.15	...	92
14	85.83	20.23	721	Haze	0	50d	stations	304.15	308.91	304.15	...	91
15	78.17	11.65	802	Clouds	0	03d	stations	304.15	307.03	304.15	...	92

20 rows × 30 columns

In [43]:
```
X = dataset.drop(labels=['weather__icon','base','sys__id','sys__country','name','main__sea_level','main__grnd_level','wind__gust','sys__type','timezone','cod'],axis = 1)
Y = dataset['weather__description']
```

In [44]:
```
from sklearn.preprocessing import LabelEncoder
```

In [45]:
```
label1 = LabelEncoder()
X['weather__main'] = label1.fit_transform(X['weather__main'])
```

In [46]:
```
X.head(15)
```

Out[46]:

	coord__lon	coord__lat	weather__id	weather__main	weather__description	main__temp	main__feels_like	main__temp_min	main__temp_max	main__pressu
0	72.85	19.01	721	2	0	304.64	308.15	304.15	305.15	10
1	77.22	28.67	721	2	0	303.23	304.01	302.15	304.15	10
2	77.60	12.98	803	1	0	300.00	301.39	299.26	300.93	10
3	78.47	17.38	802	1	0	301.07	305.69	300.15	302.04	10
4	72.62	23.03	721	2	0	307.15	313.82	307.15	307.15	10
5	80.28	13.09	721	2	0	304.15	308.43	304.15	304.15	10
6	72.83	21.17	721	2	0	308.15	313.80	308.15	308.15	10
7	73.86	18.52	800	0	1	302.20	305.01	302.20	302.20	10
8	75.82	26.92	721	2	0	305.15	302.77	305.15	305.15	10
9	88.37	22.57	721	2	0	306.15	312.73	306.15	306.15	10
10	72.97	19.20	721	2	0	304.64	308.15	304.15	305.15	10
11	78.02	27.18	800	0	1	308.41	306.05	308.41	308.41	10
12	77.60	12.98	803	1	0	300.00	301.39	299.26	300.93	10
13	78.68	10.82	801	1	0	306.15	308.34	306.15	306.15	10
14	85.83	20.23	721	2	0	304.15	308.91	304.15	304.15	10

```
In [47]: X = pd.get_dummies(X, drop_first=True, columns =['weather__main'])
         X.head()
```

Out[47]:

	coord__lon	coord__lat	weather__id	weather__description	main__temp	main__feels_like	main__temp_min	main__temp_max	main__pressure	main__humidi
0	72.85	19.01	721	0	304.64	308.15	304.15	305.15	1006	
1	77.22	28.67	721	0	303.23	304.01	302.15	304.15	1011	
2	77.60	12.98	803	0	300.00	301.39	299.26	300.93	1011	
3	78.47	17.38	802	0	301.07	305.69	300.15	302.04	1011	
4	72.62	23.03	721	0	307.15	313.82	307.15	307.15	1007	

```
In [48]: from sklearn.preprocessing import StandardScaler

In [49]: X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size = 0.2, random_state = 0, stratify = Y)

In [50]: scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X_test = scaler.transform(X_test)

In [51]: X_train

Out[51]: array([[ 2.36441150e+00,  3.50356041e-01, -1.13367221e+00,
                 -3.77964473e-01,  7.09688355e-01,  1.43295909e+00,
                  7.33213408e-01,  6.74644411e-01, -7.67365737e-01,
                  1.19456892e+00, -8.31185826e-01,  3.38572376e-01,
                 -1.93549477e+00,  2.11200495e-01,  9.03767848e-01,
                 -2.23683184e+00, -2.31769700e+00,  7.95042267e-01,
                 -8.81917104e-01,  1.13389342e+00],
                [ 8.96973630e-02,  1.01846001e+00,  8.40104198e-01,
                  2.64575131e+00,  1.55495617e+00, -1.78516789e-01,
                  1.50551160e+00,  1.60932418e+00, -2.95140668e-01,
                 -2.30173036e+00,  1.74280899e+00, -4.59836017e-01,
                 -1.38758401e+00, -1.37901500e+00,  4.09332032e-01,
                  1.88251839e-01, -3.50995559e-01,  1.25273663e+00,
                 -8.81917104e-01, -8.81917104e-01],
                [ 1.88597978e-01, -4.01804394e-01,  8.90073221e-01,
```

```
                 -2.79147535e-01,  2.73670404e-01,  1.04556405e+00,
                  1.13389342e+00, -8.81917104e-01]])

In [52]: model = Sequential()
         model.add(Dense(X.shape[1], activation='relu', input_dim = X.shape[1]))
         model.add(Dense(128, activation='relu'))
         model.add(Dense(1, activation='sigmoid'))

In [53]: X.shape[1]

Out[53]: 20

In [54]: model.compile(optimizer='adam', loss='binary_crossentropy', metrics = ['accuracy'])

In [55]: model.fit(X_train, Y_train.to_numpy(), batch_size = 10,epochs = 10, verbose = 1)

         Epoch 1/10
         2/2 [==============================] - 0s 2ms/step - loss: 0.6483 - accuracy: 0.6250
         Epoch 2/10
         2/2 [==============================] - 0s 998us/step - loss: 0.6054 - accuracy: 0.8125
         Epoch 3/10
         2/2 [==============================] - 0s 1ms/step - loss: 0.5616 - accuracy: 0.8750
         Epoch 4/10
         2/2 [==============================] - 0s 2ms/step - loss: 0.5262 - accuracy: 0.8750
         Epoch 5/10
         2/2 [==============================] - 0s 998us/step - loss: 0.4943 - accuracy: 0.8750
         Epoch 6/10
         2/2 [==============================] - 0s 1ms/step - loss: 0.4648 - accuracy: 0.8750
         Epoch 7/10
         2/2 [==============================] - 0s 1ms/step - loss: 0.4398 - accuracy: 0.8750
         Epoch 8/10
         2/2 [==============================] - 0s 2ms/step - loss: 0.4132 - accuracy: 0.8750
         Epoch 9/10
         2/2 [==============================] - 0s 2ms/step - loss: 0.3908 - accuracy: 0.8750
         Epoch 10/10
         2/2 [==============================] - 0s 1ms/step - loss: 0.3708 - accuracy: 0.8750

Out[55]: <tensorflow.python.keras.callbacks.History at 0x1e6e5f6ec40>

In [56]: Y_pred = model.predict_classes(X_test)
```

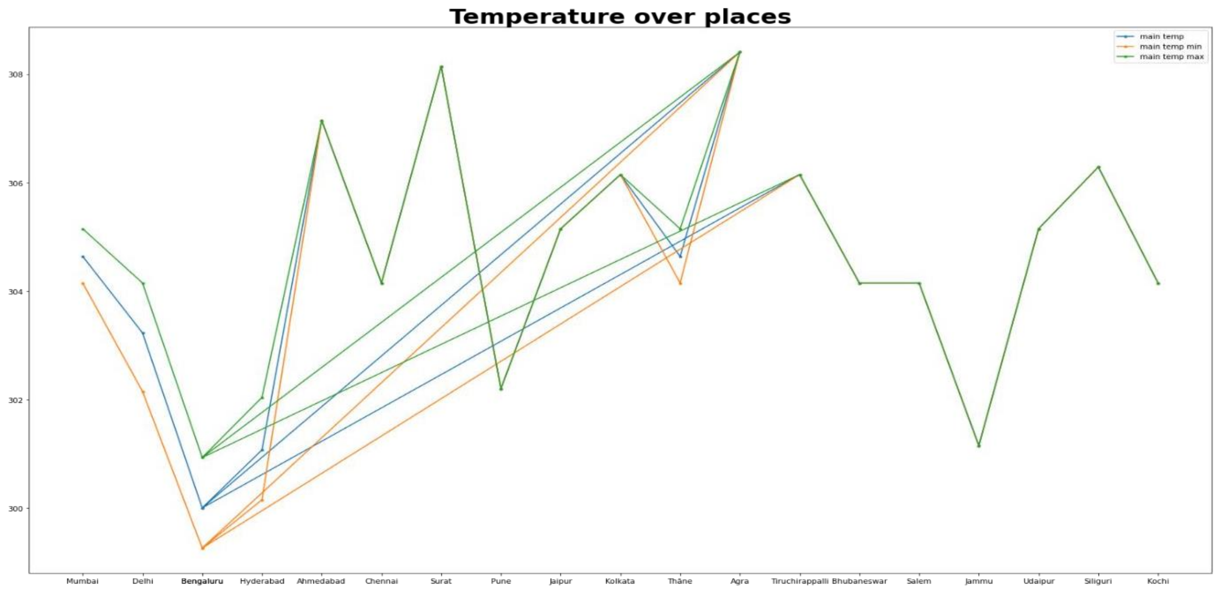
```
In [56]: Y_pred = model.predict_classes(X_test)

         WARNING:tensorflow:From <ipython-input-56-67856f0c4cd2>:1: Sequential.predict_classes (from tensorflow.python.keras.engine.sequ
         ential) is deprecated and will be removed after 2021-01-01.
         Instructions for updating:
         Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if your model does multi-class classification   (e.g. if it uses
         a `softmax` last-layer activation).* `(model.predict(x) > 0.5).astype("int32")`,   if your model does binary classification
         (e.g. if it uses a `sigmoid` last-layer activation).

In [57]: Y_pred

Out[57]: array([[0],
                [0],
                [0],
                [0]])

In [58]: Y_test

Out[58]: 5     0
         17    0
         0     0
         14    0
         Name: weather__description, dtype: int64

In [59]: model.evaluate(X_test, Y_test.to_numpy())

         1/1 [==============================] - 0s 2ms/step - loss: 0.2421 - accuracy: 1.0000

Out[59]: [0.24211816489696503, 1.0]

In [60]: from sklearn.metrics import confusion_matrix, accuracy_score

In [61]: confusion_matrix(Y_test, Y_pred)

Out[61]: array([[4]], dtype=int64)

In [62]: accuracy_score(Y_test,Y_pred)

Out[62]: 1.0
```

jupyter metrics3 Last Checkpoint: Last Saturday at 10:56 PM (autosaved)

File Edit View Insert Cell Kernel Widgets Help

In [29]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

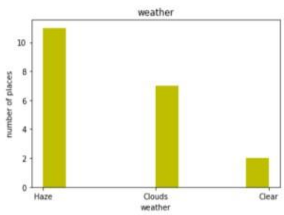
In [56]:
```
metrics =pd.read_csv('metrics1.csv')

plt.figure(figsize=(26,15))

plt.title('Temperature over places',fontdict={'fontweight': 'bold','fontsize':30})

plt.plot(metrics.name, metrics.main__temp, label= 'main temp',marker='.')
plt.plot(metrics.name, metrics.main__temp_min, label='main temp min',marker='.')
plt.plot(metrics.name, metrics.main__temp_max, label='main temp max',marker='.')

plt.xticks(metrics.name)

plt.legend()


plt.show()
```



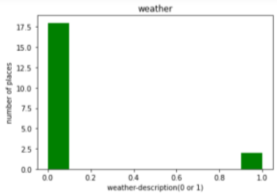
In [40]:
```
metrics1= pd.read_csv('metrics1.csv')
```

In [59]:
```
plt.hist(metrics1.weather__main,color='y')
plt.xlabel('weather')
plt.ylabel('number of places')
plt.title('weather')
plt.show
```

Out[59]: <function matplotlib.pyplot.show(*args, **kw)>

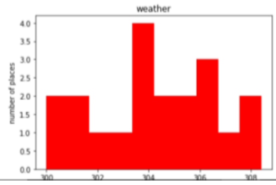


In [58]:
```
plt.hist(metrics1.weather__description,color='g')
plt.xlabel('weather-description(0 or 1)')
plt.ylabel('number of places')
plt.title('weather')
plt.show
```



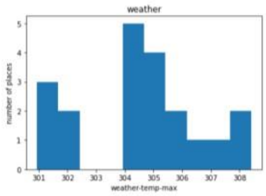

```
In [57]: plt.hist(metrics1.main__temp,color='r')
         plt.xlabel('weather-main-temp')
         plt.ylabel('number of places')
         plt.title('weather')
         plt.show
```

```
Out[57]: <function matplotlib.pyplot.show(*args, **kw)>
```

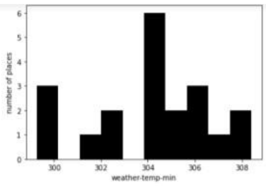



```
In [54]: plt.hist(metrics1.main__temp_max)
         plt.xlabel('weather-temp-max')
         plt.ylabel('number of places')
         plt.title('weather')
         plt.show
```

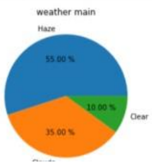
```
Out[54]: <function matplotlib.pyplot.show(*args, **kw)>
```



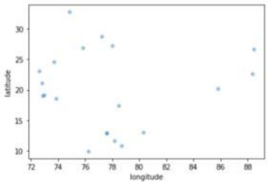

```
In [60]: plt.hist(metrics1.main__temp_min,color='black')
         plt.xlabel('weather-temp-min')
         plt.ylabel('number of places')
         plt.title('weather')
         plt.show
```




```
In [66]: Haze=metrics1.loc[metrics1['weather__main']=='Haze'].count()[0]
         Clouds=metrics1.loc[metrics1['weather__main']=='Clouds'].count()[0]
         Clear=metrics1.loc[metrics1['weather__main']=='Clear'].count()[0]

         labels =['Haze','Clouds','Clear']
         plt.pie([Haze,Clouds,Clear], labels=labels,autopct='%.2f %%')

         plt.title('weather main')

         plt.show()
```

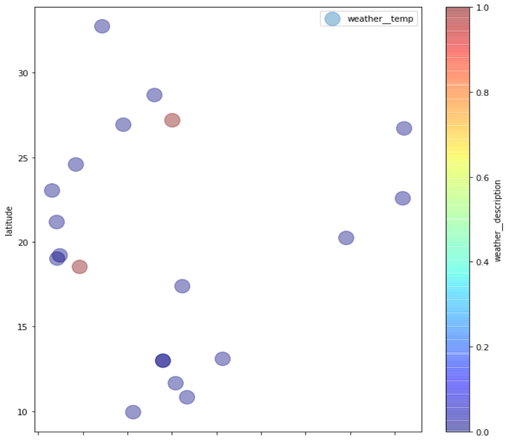


In [100]:
```
import matplotlib.pyplot as plt
metrics3 =pd.read_csv(r'C:\Users\Vaishali\Desktop\metrics12.csv')
metrics3.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4)
plt.show()
```

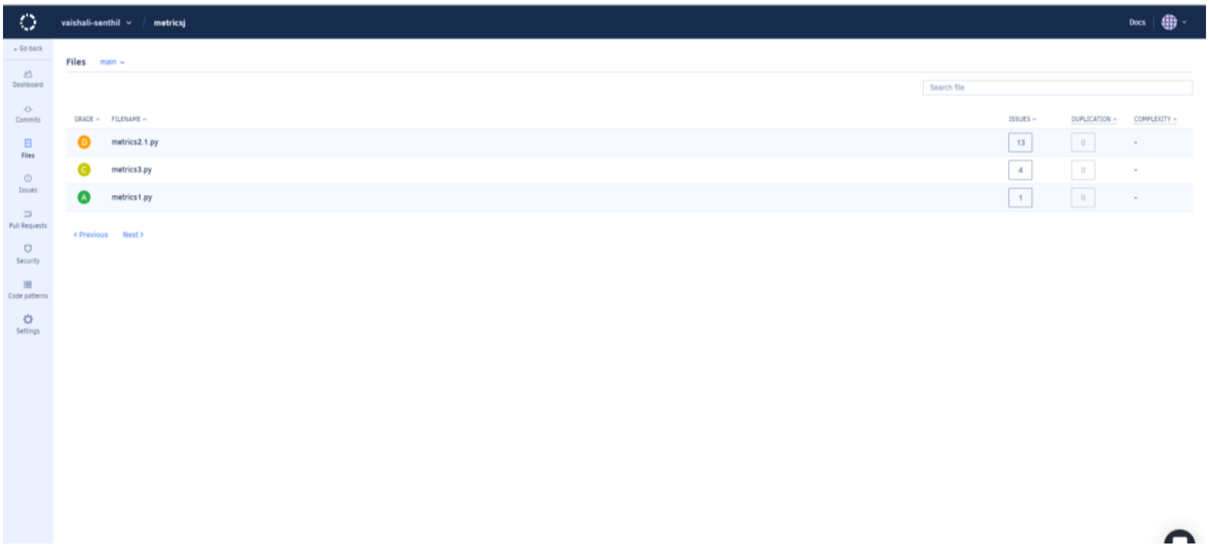


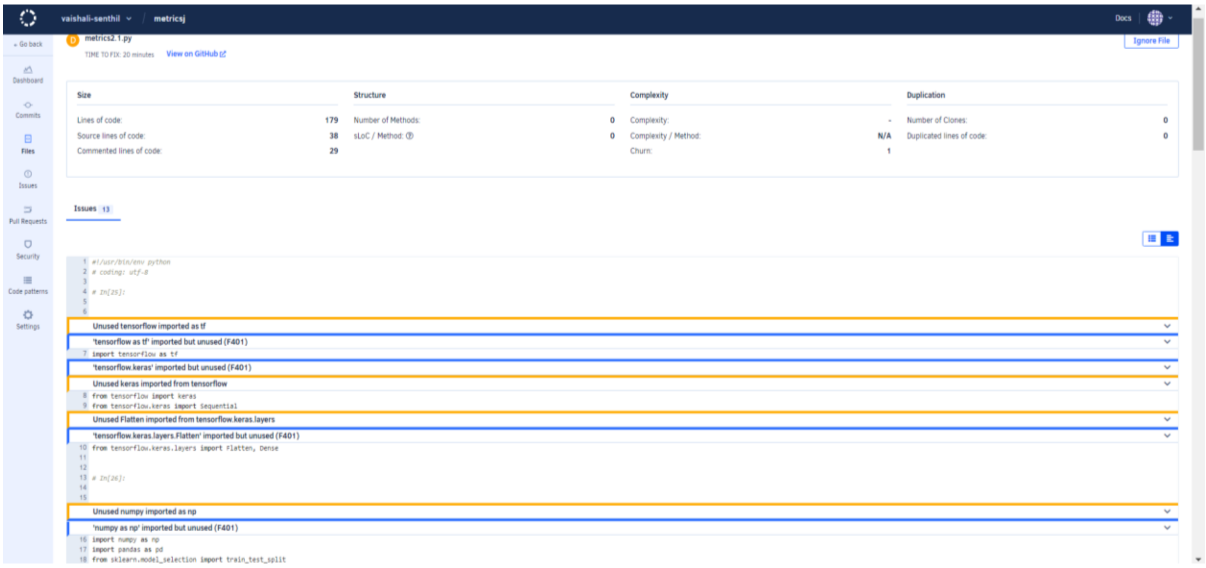
In [105]:
```
metrics4 =pd.read_csv('metrics1.csv')
```

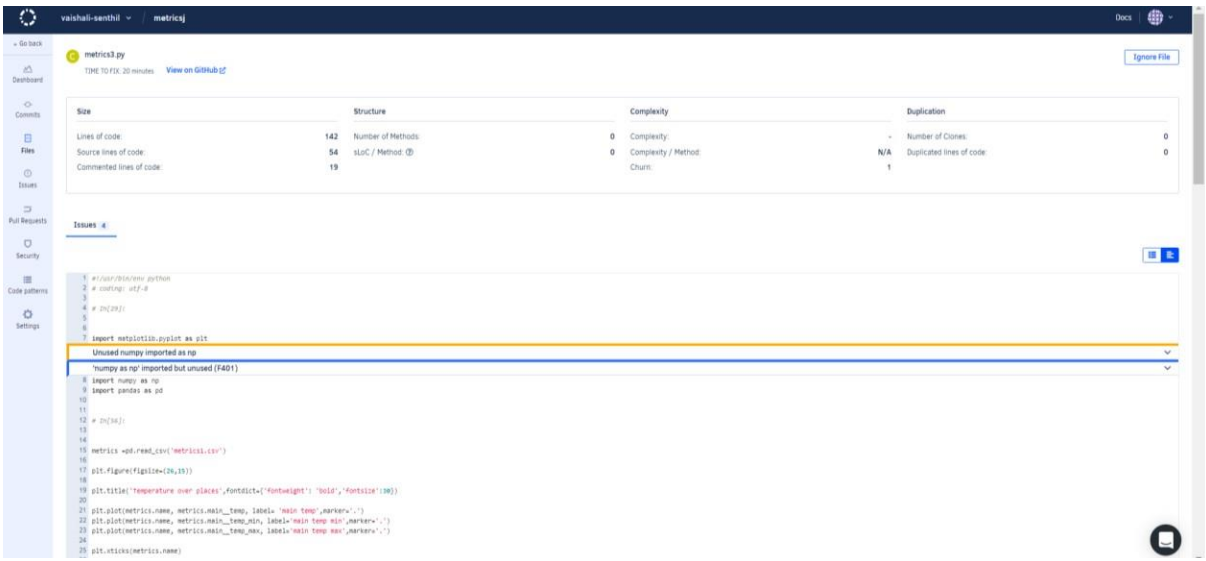
In [112]:
```
metrics4.plot(kind="scatter", x="longitude", y="latitude",s=metrics4['main__temp'], label="weather__temp", c="weather__descripti
plt.legend()
plt.show()
```

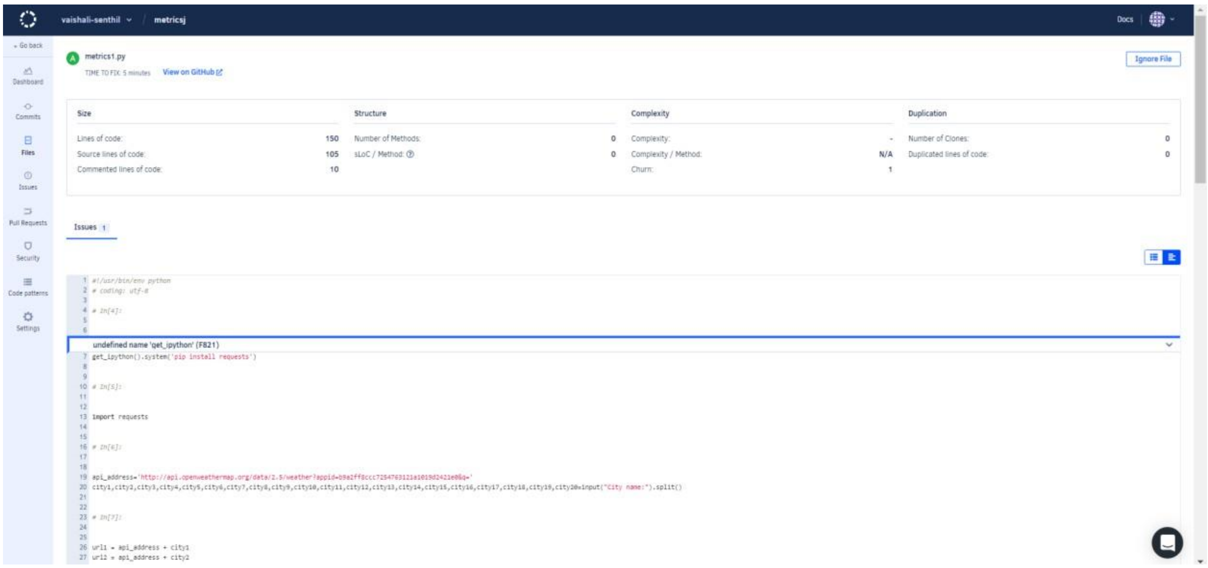


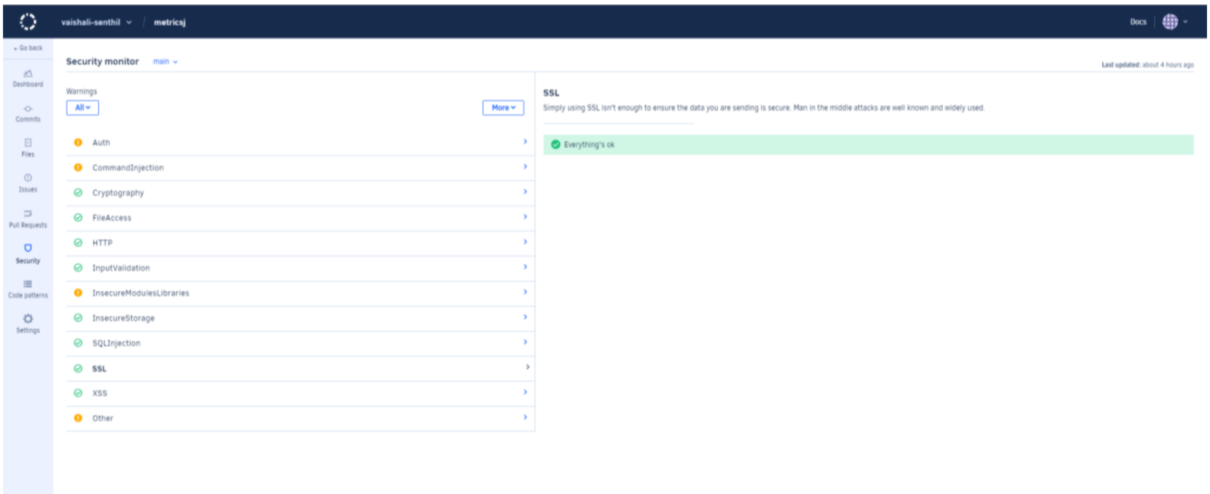
METRICS ANAYSIS OF THE CODE:








vaishali-senthil
metricsj
Docs
Go back
Dashboard
Commits
Files
Issues
Pull Requests
Security
Code patterns
Settings
metrics1.py
TIME TO FIX: 5 minutes
View on GitHub
Ignore File
Size
Lines of code: 150
Source lines of code: 105
Commented lines of code: 10
Structure
Number of Methods: 0
sLoC / Method: 0
Complexity
Complexity: -
Complexity / Method: N/A
Churn: 1
Duplication
Number of Clones: 0
Duplicated lines of code: 0
Issues 1
#!/usr/bin/env python
coding: utf-8
In[4]:
undefined name 'get_ipython' (F821)
get_ipython().system('pip install requests')
# In[5]:
import requests
# In[6]:
city1,city2,city3,city4,city5,city6,city7,city8,city9,city10,city11,city12,city13,city14,city15,city16,city17,city18,city19,city20=input("City name:").split()
# In[7]:
url1 = api_address + city1
url2 = api_address + city2


vaishali-senthil
metricsj
Docs
Go back
Dashboard
Commits
Files
Issues
Pull Requests
Security
Code patterns
Settings
Security monitor
main
Last updated: about 4 hours ago
Warnings
All
More
Auth
CommandInjection
Cryptography
FileAccess
HTTP
InputValidation
InsecureModulesLibraries
InsecureStorage
SQLInjection
SSL
XSS
Other
SSL
Simply using SSL isn't enough to ensure the data you are sending is secure. Man in the middle attacks are well known and widely used.
Everything's ok

1) Quality of Weather Forecasts Review and recommendations Authors: Pascal J. Mailier Ian T. Jolliffe David B. Stephenson

An important lesson learned from this project is that the absence of a way of community between weather outlook suppliers and between forecast users. This fragmented state - and therefore the lack of constructive dialogue that results - represent a major obstacle to establishing a ordinarily united strategy for higher quality standards within the business. basic changes of disposition and angle are required. The role of forecast suppliers ought to reach from the mere distribution of product to the delivery of a real service that has the availability of user- familiarized forecast quality assessments and therefore the necessary user education. data on forecast performance ought to be seen as a necessary a part of a User Guide that helps users to form wise use of the product they get. Uncertainty within the forecasts and within the metric estimates ought to be treated as valuable data rather than content. sadly, the present background of more and more aggressive competition within the marketplace doesn't favour openness on forecast performance at a time once additional transparency is required. It is hoped that the commission planned to the Society in section six.3 can foster a additional cooperative and participative culture among the business. the matter of assessing the standard of weather forecasts from a user stand is far additional complicated than the standard forecaster-oriented verification as a result of it must take the user s own necessities under consideration. several of the already existing techniques are often simply applied to assess forecast quality for users. If needed, new, straightforward strategies and metrics may be designed to answer specific questions from a user on forecast performance. However, there are necessary aspects of the standard of service offered by weather outlook suppliers that can't be assessed by straightforward objective metrics, for instance the approach the forecasts are presented to the user, or the availability of subjective forecast steerage by a meteorologist. Moreover, the case studies during this project have checked out forecast quality from the attitude of commercial, agricultural or money call manufacturers who use weather forecasts to mitigate (optimise) weather-related losses (profits). The principal reason for this choice is solely that it's been primarily users from this class WHO have felt the survey. A definition of forecast quality for the media offers most likely additional weight to the efficaciousness of the graphics and attention getters whereas giving less weight to accuracy. even so, a standard checklist containing the necessary basic queries that suppliers ought to be asked could be a helpful aid for several users no matter their profile, and therefore the drawing of such a list might be a future task for the committee planned in section 6.3. Specific recommendations on that metrics to use are created in section 6.2. These recommendations do no purport to confine forecast quality assessment to a rigid set of prescribed metrics. Considering the increasing kind of weather forecast product and therefore the growing range of applications, quality assessment techniques are guaranteed to become additional complicated and distributed. In section 2.2, some consulted stakeholders expressed the would like to envision additional cooperative work involving suppliers and users. there's little doubt that the triple-crown development of future user-specific quality assessment strategies and metrics can require additional synergism between each ends of the statement line. Associate in Nursing approach to forecast quality assessment supported symbolic logic was in short discussed in section three.1. once adopting a fuzzy quality assessment strategy, forecasts that are on the point of the observations don't seem to be therefore unhealthy as forecasts that are faraway, and thus they're doubtless additional helpful. This approach is very appealing for sensible applications as a result of it offers the user considerable flexibility to specify objectively or subjectively the structure of the membership functions that outline the goodness or badness of the forecasts. This avenue of analysis is also value following, however ultimately it's the demand arising from sensible user applications that has got to provide the directions for future advances within the development of user-oriented methodologies and metrics.

2) Performance Metrics for Climate Models: WDAC advancements towards routine modeling benchmarks(Peter Gleckler* Program for Climate Model Diagnosis and Intercomparison (PCMDI) LLNL, USA)

obs4MIPs and alternative efforts attempt to advance the association between knowledge experts and model analysts

• Transparency is crucial:

- Knowing the information came from the suitable supply (ideally the information experts)
- correct info regarding the information product version
- Documentation on the information product that's relevant for model analysts

• Quantifying empirical uncertainty remains a key challenge:

- for a few fields, model errors stay >> than empirical uncertainty, however not thus in several cases
- though inadequate, the common path is to characterize obs uncertainty by mistreatment multiple product
- progressively, model analysts expect helpful quantification of uncertainties
- New observation ensembles, exploring the impact of process decisions, are of tremendous interest

PCMDI

14

Possible advancements for a community-based effort to establish routine benchmarks for climate models

• The WGNE/WGCM metrics panel is functioning to develop associate degree analysis package to be shared with all leading modelling teams. this may embrace straightforward analysis routines, empirical knowledge, and a info of metrics results from all on the market climate models. this may alter modelling teams to match the results from other models at intervals their model development method.

• The model knowledge conventions applied to CMIP5 still remodel however model evaluation is completed within the analysis community. In essence, all scientists ar mistreatment the same knowledge, that is structured equally for every model with tightly outlined metadata conventions. This disclose the chance for next-generation steps towards a shared setting for model analysis tools. Careful incorporation of empirical knowledge into this framework are crucial, and obs4MIPs and alternative projects are paving the course

3) Application of Data Mining Techniques in Weather Prediction and Climate Change Studies(Adesesan Barnabas Adeyemo University of Ibadan, Ibadan, Nigeria)

In this work the C5 call tree classification algorithm was wont to generate call trees and rules for classifying weather parameters like most temperature, minimum temperature, rainfall, evaporation and wind speed in terms of the month and year. the information used was for urban center metropolis obtained from the earth science station between 2000 and 2009. The results show however these parameters have influenced the weather determined in these months over the study period. Given enough knowledge the determined trend over time could be studied and vital deviations that show changes in climatical patterns known. Artificial Neural Networks will observe the relationships between the input variables and generate outputs supported the determined patterns inherent within the data with none want for programming or developing complex equations to model these relationships. Hence given enough knowledge ANN's will observe the relationships between weather parameter and use these to predict future climate. each TLFN neural networks and perennial network architectures were wont to developed prognosticative ANN models for the prediction of future values of Wind speed, Evaporation, Radiation, Minimum Temperature, most Temperature and Rainfall given the Month and Year. Among the perennial neural network architectures used the perennial TLFD network that used the TDNN memory element gave a more robust coaching and testing result and this higher than the most effective TLFD network that used a Gamma memory element. The results obtained were evaluated with the check knowledge set ready along with the coaching knowledge and were found to be acceptable considering the tiny size of the information available for coaching and testing. to possess a more robust result a larger knowledge set which is able to comprise of information collected over several decades are going to be required. In future analysis works neuro-fuzzy models are going to be used for the weather prediction method. This work is very important to climatical change studies as a result of the variation in weather conditions in term of temperature, precipitation and wind speed are often studied victimisation these data processing techniques.

4) Weather forecast prediction: a data mining application(Ms. Ashwini Mandale, Mrs. Jadhawar B.A.)

Weather forecasting is a crucial application in meteorology and has been one amongst the foremost scientifically and technologically difficult issues round the world. during this paper, we have a tendency to analyse the employment of information mining techniques in statement weather. this may be administrated mistreatment Artificial Neural Network and call tree Algorithms and meteoric information collected in specific time. The performance of those algorithms was compared mistreatment normal performance metrics, and also the algorithmic rule that gave the best results wont to generate classification rules for the mean weather variables. The results show that given enough case information mining techniques will be used for forecasting. Data suggests that assortment of data. info suggests that organized assortment of information. information warehouse suggests that that provides enterprise with memory. information Mining- it's extraction of attention-grabbing (non-trivial, implicit, antecedently unknown and doubtless useful) information or patterns from large quantity data} .It is a noteworthy technique that may be enforced in numerous areas to come up with useful info from the present massive volumes of information. data processing has so far been with success enforced to bring success in business applications. a number of the applications of information mining embody discovery of attention-grabbing patterns, bunch of information based mostly on parameters and prediction of results by mistreatment the present information. There square measure various techniques and algorithms out there in information mining that may be enforced for numerous applications. This paper proposes associate economical data processing technique for weather outlook. Knowledge Discovery in Databases (KDD) is that the whole method of finding helpful info and patterns in information. Typical information mining design is as shown In this the C5 call tree classification algorithmic rule was wont to generate call trees and rules for classifying weather parameters such as most temperature, minimum temperature, rainfall, evaporation and wind speed in terms of the month and years. Given enough information the ascertained trend over time can be studied and vital deviations that show changes in climatical patterns will be identified. Artificial Neural Networks will observe the relationships between the input variables and generate outputs supported the observed patterns inherent within the information with none would like for programming or developing advanced equations to model these relationships. therefore given enough information ANN's will observe the relationships between weather parameter and use these to predict future weather conditions this is often vital to climatical modification studies as a result of the variation in climate in term of temperature, rainfall and wind speed will be studied mistreatment these data processing techniques.

5)A Unified modeling approach to climate system prediction by james hurrell, gerald a . meehl, david bader, thomas l. delworth, ben kirtman, and bruce wielicki

Strategies for a more unified approach to climate system prediction currently embrace the following: i) mistreatment Inter government Panel on temperature change (IPCC) category coupled climate models for predictions on time scales from days to decades; ii) mistreatment compass point P category models for seasonal-to-decadal prediction, when modification to properly account for dynamic radiative forcing; and iii) developing terribly high-resolution models with mesoscale processes expressly resolved, either globally or by nesting high-resolution regional models within international climate models. There area unit different rising approaches still, like the idea of starting integrations with higher resolutions to satisfy weather forecast necessities, and so cascading down to lower-resolution versions of the model with consistent physical parameterization schemes for longer time-scale predictions. All of those approaches attempt to take away the excellence between weather and climate by taking advantage of the processes and mechanisms that characterize the climate system at all time and area scales. Questions area unit being raised as to whether or not model development efforts ought to be focused on rising AOGCMs before trying ESMs , with their supplemental complexities of coupled carbon and chemical element cycles, chemistry, aerosols, dynamic vegetation, and different parts . With a unified modelling approach, the common processes is addressed in each categories of models and progress will be created on each fronts. There area unit different potential benefit s o f mistreatment similar models for predictions on different time scales; among the m are talent improvement in each weather and climate forecasts, stronger collaboration and shared knowledge e Egyptian deity g those e in the weather and climate "communities " performing on physical parameterization schemes, knowledge assimilation schemes and initialisation methods , and shared infrastructure and technical capabilities. in addition, current and future efforts with ESMs will give a lot of complete assessments of the physics of temperature change by together with further parts and processes that don't seem to be essential to the shorter time scales. The process burden of the ESMs can check the possible limits of the specific resolution of multiscale interactions and a lot of regional discrimination of temperature change impacts. Moreover, given comparatively giant systematic errors, the extra feedbacks from a lot of interactive parts of ESMs clearly increase the uncertainty within the magnitude and nature of the climate changes projected in future state of affairs simulations. The time-evolving ingredients needed for future state of affairs integrations with ESMs conjointly still should be calculable as a range of attainable outcomes primarily based, to an outsized extent, on the unpredictable nature of human actions. These, along with empirical knowledge wants, supply problems related to coupling ways and matched initialisation, and therefore the scientific queries associated with the myriad of at liberty and poorly understood feedbacks, are important aspects of those rising ESMs that will still stretch each process and human resources for the predictable future. However, activities that have already begun indicate that we tend to area unit moving into a brand new and exciting era of climate system prediction that may, naturally of the convergency interests, modelling tools, and methodologies, produce greater interactions among antecedent separate communities, and thereby offer higher predictions of the climate system in the slightest degree time and area scales.

6) Data Mining Techniques for Weather Prediction: A Review(Divya Chauhan, Jawahar Thakur)

Data mining may be a method that finds helpful patterns from large amount of information. data processing may also be outlined because the process of extracting implicit, antecedently unknown and helpful information and information from giant quantities of clanging, ambiguous, random, incomplete information for utilisation. It is a robust new technology with nice potential to assist companies target the foremost necessary data in their databases. It uses machine learning, applied mathematics and visual image technique to get and predict information in a very kind that is understandable to the user. Prediction is that the most vital technique of information mining that employs a group of pre-classified examples to develop a model which will classify the info and discover relationship between freelance and dependent information. Weather prediction is that the application of science and technologyto predict the state of the atmosphere for a given location. It is becoming progressively important for scientists, agriculturists, farmers, international food security, disaster management and connected organizations to grasp the natural phenomena to set up and be ready for the longer term.The art of weather prediction began with early civilizations victimization reoccurring astronomical and meteorologic events to assist them monitor seasonal changes within the weather. Throughout the centuries, attempts are created to supply forecasts supported weather changes and private observations. Many This paper presents a survey that victimization data processing techniques for weather prediction yields sensible results and might be considered as another to ancient scientific discipline approaches. The study describes the capabilities of assorted algorithms in predicting many weather phenomena like temperature, thunderstorms, precipitation and over that major techniques like call trees, lazy learning, artificial neural networks, cluster and regression algorithms area unit appropriate to predict weather phenomena. A comparison is created during this paper, that shows that call trees and k-mean cluster are best suited data processing technique for this application. With the increase in size of coaching set, the accuracy is initial increased then again reduced when a precise limit.

7) Application of Data Mining Techniques in Weather Prediction and Climate Change Studies(Folorunsho Olaiya Department of Computer & Information Systems, Achievers University, Owo, Nigeria)

the C5 call tree classification algorithm was wont to generate call trees and rules for classifying weather parameters like most temperature, minimum temperature, rainfall, evaporation and wind speed in terms of the month and year. the information used was for city metropolis obtained from the meteoric station between 2000 and 2009. The results show however these parameters have influenced the weather discovered in these months over the study period. Given enough information the discovered trend over time Application of knowledge Mining Techniques in Weather Prediction and global climate change Studies fifty nine Copyright © 2012 MECS I.J. info Engineering and Electronic Business, 2012, 1, 51-59 could be studied and vital deviations that show changes in environmental condition patterns known. Artificial Neural Networks will find the relationships between the input variables and generate outputs supported the discovered patterns inherent within the data with none would like for programming or developing complex equations to model these relationships. Hence given enough information ANN's will find the relationships between weather parameter and use these to predict future climatic conditions. each TLFN neural networks

and continual network architectures were wont to developed prophetic ANN models for the prediction of future values of Wind speed, Evaporation, Radiation, Minimum Temperature, most Temperature and Rainfall given the Month and Year.Among the continual neural network architectures used the continual TLFD network that used the TDNN memory part gave a higher coaching and testing result and this higher than the simplest TLFD network that used a Gamma memory part. The results obtained were evaluated with the check information set ready along with the coaching information and were found to be acceptable considering the tiny size of the information available for coaching and testing. to possess a higher result a larger information set which is able to comprise of knowledge collected over several decades are going to be required. In future analysis works neuro-fuzzy models are going to be used for the weather prediction method. This work is very important to environmental condition change studies as a result of the variation in weather conditions in term of temperature, downfall and wind speed will be studied mistreatment these data processing techniques.

8) Assimilation of Satellite Cloud and Precipitation Observations in Numerical Weather Prediction Models: Introduction to the JAS Special Collection RONALD M. ERRICO, GEORGE OHRING, PETER BAUER, BRAD FERRIER, JEAN-FRANÇOIS MAHFOUF, & JOE TURK, AND FUZHONG WENG

As a results of higher numerical weather prediction (NWP) models, additional powerful computers, new satellite observations, and additional economical and effective information assimilation systems, the forecast talent of midtropospheric synoptic flow patterns has steady improved over the past few decades. Today's 4-day forecasts of these patterns area unit as correct as 3-day predictions were simply a decade agone and as a pair of-day forecasts were 2 decades agone. Forecasts for the hemisphere, wherever satellites offer the majority of observations, area unit currently virtually as correct as those for the hemisphere.

However, the progress in prediction weather components that area unit of explicit public interest, like clouds, quantitative precipitation, and precipitation kind, has been less dramatic. To date, the assimilation of satellite measurements has targeted on the clear atmosphere. however satellite observations within the visible, infrared, and microwave offer an excellent deal of knowledge on clouds and precipitation. the difficulty is a way to use this data to enhance the formatting of clouds and precipitation in models. Since clouds and precipitation usually occur in sensitive regions for forecast impacts, such enhancements area unit doubtless necessary for continued to accumulate vital gains in foretelling.

To accelerate progress within the field, the Joint Center for Satellite information Assimilation (JCSDA), a joint activity of the National Oceanic and part Administration (NOAA), National physical science and house Administration (NASA), and Department of Defense (DoD), sponsored a global workshop in could 2005. Participants enclosed specialists within the multiple scientific disciplines involved—satellite observations of clouds and precipitation, radiative transfer (RT), modeling clouds and precipitation in NWP, and information assimilation.

The diverse set of models and associated parts needed for information assimilation have varied degrees of responsibleness. part dynamics at horizontal scales larger than one hundred metric linear unit around area unit generally handled quite well each in terms of study and short-run forecast talent. Moreover, operational NWP models area unit able to predict the situation in house and time of clouds related to large-scale organized systems, however their talent degrades because the strength of synoptic forcing or the degree of larger-scale organization decreases.

Large uncertainties stay in several of the physical parameterizations utilized in each forecast models and in relating observations to analysis fields. Modeling of some diabatic processes, significantly those related to damp convection and therefore the radiative effects of clouds, area unit still unreliable. spatial distributions of clouds, significantly over hotter oceans, will vary considerably once totally different mixtures of well-tested physical parameterizations area unit used. Even in regions wherever robust dynamics tend to get vital precipitation and clouds that area unit well diagrammatical, quantitative responsibleness remains lacking. Arguably the most important issue among NWP remains the right illustration of subgrid-scale causative convection among coarser-resolution models. alternative schemes needing enhancements embrace the parameterization of the results of shallow convective clouds related to the planetary physical phenomenon, microphysics of cloud formation (especially the initiation of ice-phase processes), exchanges between the atmosphere and therefore the surface (this includes the myriad of land surface processes and more and more sophisticated coupling with the ocean), and overlap of multiple cloud layers for radiative calculations. Finally, rising the coupling between physical processes by exchanging additional data among physical parameterizations is changing into even as vital, complicating each the model code and interpretations of results.

Even schemes apparently supported elementary physics, like "explicit microphysical precipitation schemes," area unit in truth extremely parameterized with abundant incidental to uncertainty. Also, details like ice cloud particle form and size distributions, that area unit important for estimating radiative effects, area unit rather inexpertly delineate even in these schemes. The assimilation of satellite radiances in cloudy regions necessitates that the model counterparts area unit moderately well delineate. As a consequence, damp physical processes in NWP models ought to have enough realism, as well as data on hydrometeor properties to supply moderately smart representations of discovered radiances. Useful, linearized versions of those models area unit required for variational information assimilation schemes (to expeditiously solve the optimisation problem).

Specific workshop recommendations for rising the utility of the varied models needed for information assimilation embrace 1) constructing many strong empiric or simulated cloud-resolving model datasets for corroboratory method models and parts, like those used for corroboratory single-column models; 2) developing damp convective schemes that area unit additional compatible with information assimilation applications, requiring the prediction of hydrometeor characteristics that area unit directly associated with observations (e.g., particle characteristics that govern radiative scattering) and validation ways that use extra metrics (e.g., not simply time-mean surface precipitation rates); and 3) developing cooperative programs involving the varied subdisciplines among the part community having the experience needed for prosperous cloud and precipitation assimilation.

9) Long-Term Performance Metrics for National Weather Service Tornado Warnings

tornado warnings square measure one amongst the foremost necessary product issued by the National Weather Service (NWS). they supply doubtless rescue data in things that involve decision-making underneath uncertainty with short times to create selections and with the potential for excellent prices related to errors. As such, the performance has been studied inside a spread of contexts, like error analysis (e.g., Brotzge and Erickson 2009, 2010; Brotzge et al. 2011), prices and advantages of warnings (Simmons and Sutter 2005, 2008; Sutter and Erickson 2010), and inside a theoretical call analysis framework (Brooks 2004). Changes in official definitions have taken place, most notably the amendment from questionable county-based warnings to storm-based warnings that happened in October 2007, that conjointly enclosed changes in analysis methodology. No changes within the analysis methodology happened once the initial changes with the start of the storm-based era.

The NWS reports official statistics for tornado warnings underneath the mandate of the govt. Performance and coverage Act (GPRA; Ralph et al. 2013), that sets goals for the chance of detection, warning quantitative relation, and time interval for warnings. the problem of however those quantities square measure outlined are going to be mentioned later. The interrelationships between the GPRA metrics and different performance measures square measure complicated. we'll examine the performance over the amount from 1986 to 2016, the complete record of warning performance offered from the NWS Performance Management web site .

Given the changes within the ways in which tornadoes are reported and warnings are created (county-based or storm-based warnings, software, etc.), also as official analysis metrics, it's difficult to seem at the warnings in a very consistent manner. we'll specialize in data that's offered throughout the 1986–2016 amount with a similar definitions for metrics throughout the amount in spite of the official definitions in use at the time. this can permit America to spot changes in warning philosophy and see once important changes occurred. it's necessary to notice that we tend to square measure trying neither at individual warning decision-making nor specializing in the transition to storm-based warnings. Instead, we'll use what we tend to decision AN archeologic approach to spot what the “culture” of the NWS implicitly values. Describing the sector of anthropology, eating apple

(1986) cites A. H. Pitt-Rivers's read that "it is that the study of the standard everyday things that helps America to reconstruct the past, much more therefore than rare, valuable objects that were uncommon even in their own time and place." The culture depends on official policy, also as operational follow for discretionary activities inside the official policy. As AN example, a political candidate policy would possibly inflict higher and lower limits on the period of warnings, however operational follow could lead on to the particular limits utilized by forecasters being smaller than the official bounds. The constraints on however tornado warnings square measure structured (e.g., space coated, duration) square measure comparatively loose and permit for native offices to tailor product to the perceived desires of their native areas or things at hand. By staring at the warning product created over the years across the country, we are able to learn one thing regarding what has been thought-about necessary in numerous eras. though it's on the far side the scope of this paper, the methodology delineate may well be wont to look into changes in area or kind of warning state of affairs. we tend to follow that by staring at the complete assortment of warnings over thirty one years, instead of specific cases. As can become clear, major changes in warning structure and performance square measure disclosed by this approach. above all, the connection between chance of detection and false alarms because it has evolved in follow are often seen and the way these factors may well be evaluated collectively, instead of individually, are often thought-about. As a result, additionally to our interest within the performance of the tornado warning system, we tend to have an interest within the additional general drawback of a way to develop techniques which will permit the community to observe and find changes in performance over time. The tornado warning system is a perfect candidate to contemplate such techniques.

10) Precipitation and Temperature Forecast Performance at the Weather Prediction Center

David R. Novak; Christopher Bailey; Keith F. Brill;Patrick Burke;Wallace A. Hogsett;Robert Rausch;Michael Schichtel

Analyses of multiyear verification of short-range precipitation forecasts and medium-range most temperature forecasts from the Weather Prediction Center (WPC) square measure compared to machine-controlled NWP steerage. Results show that human-generated forecasts improve over raw settled model steerage once verified victimization each ancient ways moreover as modern ways. However, maybe the additional compelling result's that on the idea of a applied mathematics analysis of 2 recent years, human-generated forecasts did not outstrip the foremost skillful downscaled, bias-corrected ensemble steerage for precipitation and most temperature out there close to a similar time because the human-modified forecasts.

Specifically, historical verification results show that the human-generated WPC QPFs improve upon settled raw model steerage, which the % improvement has been comparatively constant over the past twenty years (e.g., Fig. 4a). Medium-range most temperature forecasts conjointly exhibit improvement over MOS. the advance has been increasing throughout the 2005–12 amount. the standard extra by humans for forecasts of high-impact events varies by part and forecast projection, with typically giant enhancements once the soothsayer makes changes ≥8°F (4.4°C) to MOS temperatures within the medium-range forecast. Human improvement for extreme rain events [3 in. (24 h)−1] relies on forecast projection, affirmative larger human enhancements within the short-range forecast. modern verification confirms that the human soothsayer makes little, however statistically vital enhancements over competitive settled model steerage for precipitation and most temperature.

However, human-generated forecasts did not outstrip the foremost skillful downscaled, bias-corrected ensemble steerage for precipitation and most temperature out there close to a similar time because the human-modified forecasts. Such downscaled, bias-corrected ensemble steerage represents the foremost skillful operational benchmark. Thus, it's premature to say superiority by the human soothsayer till such forecasts square measure statistically considerably higher than the foremost skillful steerage. In fact, these results raise the question of whether or not human-generated forecast superiority has concluded.

Indeed, as pc resources advance, models can expressly simulate additional processes, and additional and higher observations are employed by improved information assimilation systems. These advances can cause improved NWP steerage. in addition, additional refined postprocessing of raw model steerage, together with bias correction and downscaling, can improve machine-controlled forecasts of smart weather components. Roebber et al. (2004) cite the human ability to interpret Associate in Nursingd measure info as an inherent advantage over recursive machine-controlled processes. However, AI algorithms still try to simulate such human choices, as an example, developing ways to modify selective agreement of ensemble members (e.g., Etherton 2007), or applying artificial neural network and biological process programming approaches that "learn" through time (e.g., Bakhshaii and Stull 2009; Roebber 2010). Given this future atmosphere, it's tough to visualize the human soothsayer adding quality in terms of forecast accuracy.

11) Performance metrics for climate models

Climate model "metrics," as delineate here, square measure scalar quantities designed to determine model performance. outlined for this purpose, metrics may be contrasted with "diagnostics," which can take several forms (e.g., maps, statistic, power spectra) and should typically reveal additional regarding the causes of model errors and therefore the processes liable for those errors. There is, for a spread of reasons, growing interest at intervals the climate analysis community in establishing a customary suite of metrics that characterize model performance. Metrics square measure sometimes designed to quantify however simulations disagree from observations, and that they square measure usually wont to characterize however well models compare with one another. in contrast to numerical weather prediction, there's presently no wide accepted suite of metrics for evaluating climate model performance. the best challenge in choosing metrics for mensuration climate model performance is determinant what phenomena square measure vital to simulate accurately, and so what the metrics have to be compelled to live. It remains for the most part unknown what aspects of discovered climate should be properly simulated so as to create reliable predictions of temperature change.

The metrics used here indicate that models don't seem to be all equally skillful in simulating the annual cycle meteorology and therefore the variance of monthly anomalies. the data provided by our metrics makes it doable for anyone to draw inferences regarding the relative performance of various models, however here we have a tendency to signifies some obvious generalizations. First, the "mean model" and "median model" exhibit clear superiority in simulating the annual cycle meteorology. This conclusion is strong across variables, regions (tropics and extra-tropics) and therefore the part thought of (e.g., deviations from the annual mean, annual mean, deviations from the zonal mean). Second there square measure some models that in several respects stand out as superior. within the extra-tropics, for instance, we discover we discover, UKMO-HadGEM1, GFDL-CM2.1, MICROC3.2 (hires), and MPI-ECHAM5 errors square measure smaller than those found within the "typical" model by quite 100%. Relative to the foremost poorly acting models, these errors square measure lower by up to 30%–40%. within the tropics, the UKMO-HadCM3, MPI-ECHAM5, CCCMA-CGCM-1 (at each resolutions), and each GFDL model versions, every have overall errors on the order of fifty but the standard error, and on the order of half-hour less than the foremost poorly acting models. whereas quantitative, these conclusions square measure drawn by trying conjointly at a number of variables having a large vary of experimental uncertainty. Moreover, even for these "better" acting models we have a tendency to should retell the very fact that the vary of performance across variables is substantial, and a minimum of within the tropics there's very little indication that relative mean climate performance interprets to however well models simulated basic characteristics of variability.

12) Performance Metrics for Soil Moisture Retrievals and Application Requirements

Dara Entekhabi; Rolf H. Reichle; Randal D. Koster; Wade T. Crow

RMSE and correlation area unit 2 usually used quadratic metrics that capture the degree of pair between retrievals and also the true values of the measured variables. The RMSE metric is extremely sensitive to biases in each mean and amplitude of fluctuations (such as a bias in commonplace deviation). In distinction, the correlation live is indifferent to any bias in mean or amplitude of variations.

The correspondence of the retrieval estimates and also the true values area unit evaluated otherwise by the RMSE and correlation statistics. Analysis of (5) and (6) shows that a target RMSE price (RMSEtarget) can't be achieved if its magnitude lies below that of the bias in either the mean or the quality deviation. moreover, the assignment of meteorology can trivially satisfy the accuracy target (in RMSE terms) if the quality deviation of the soil wetness being measured (σtrue) lies below RMSEtarget, provided actuality mean is understood. In distinction, no matter the worth the worth, alittle however correlational statistics would imply that the retrievals do contain probably helpful data within the context of amendment and/or anomaly detection.

It is assumed in abundant of our discussion that bias within the mean is understood and off from the RMSE calculations (i.e., we frequently specialise in ubRMSE instead of RMSE itself). this could or might not be possible; abundant depends on the standard and amount of obtainable standardisation and validation knowledge. In any case, this drawback relates to the RMSE metric only; any existing semipermanent biases within the mean or variance don't have an effect on the correlation (r) metric.

In this study we tend to conjointly introduce a nontraditional approach to process soil wetness needs. it's engineered round the concept that a user will outline specific needs for a given application's amount which these needs, once combined with data of the connection between the applications amount and soil wetness and with data of the soil wetness PDF, will be reworked into the a lot of ancient RMSE and r soil wetness metrics once process specific mission validation needs. sensible issues persist, especially the requirement for correct estimates of the soil wetness PDF and of the connection between soil wetness and also the amount of connection for the appliance. whereas these issues could limit the immediate application of the approach, {they area unit|they're} not insurmountable and are left for future analysis. we tend to envision that an extra development of the framework will facilitate the interpretation and/or specification of mensuration and validation needs for SMAP and different future soil wetness satellite missions.

13) Antarctic Verification of the Australian Numerical Weather Prediction Model

Benjamin J. E. Schroeter

The Australian Community Climate ANd Earth-System Simulator-Global (ACCESS-G) options an atmosphere-only numerical weather prediction (NWP) suite used operationally by the Australian Bureau of Meteorology to forecast atmospheric condition for the Antarctic. this operational version of the forecast model, the Australian Parallel Suite v2 (APS2), has been used operationally since early 2016. To date, the performance of the model has been mostly unproved for the Antarctic and anecdotal reports counsel challenges for model performance within the region. This study investigates the performance of ACCESS-G south of 50°S over 2017 and finds that model performance degrades toward the poles and in proportion to forecast horizon against a variety of performance metrics. The model exhibits persistent negative surface and mean water level pressure biases round the Adelie penguin Land coast, that is joined to the underrepresentation of model winds to the west, and driven by positive screen temperature biases that inhibit sculpturesque katabatic outflow. These results counsel that AN improved illustration of physical phenomenon parameterization might be enforced to boost model performance within the region.

the performance of ACCESS-G NWP over the high southern latitudes wherever the performance of the model was found to degrade toward the poles, at a rate proportional to forecast horizon. This behavior was diagnosed by many performance metrics. analysis of model error each spatially and vertically counsel physical phenomenon parameterization, initial conditions and associated physical processes is also causative factors within the error behavior of the region, as might the abnormal surface pressure and temperature behavior determined in 2017 (Clem et al. 2018). several of those biases square measure interconnected, coalescing into regional biases like the mixture of heat surface biases, weak model winds and positive surface pressure biases that inadequately represent cyclonic activity round the Adelie penguin Land coast.The biases examined during this paper might be self-addressed through AN improved illustration of the physical processes governing model low-level formatting and physical phenomenon parameterization over the distinctive Antarctic region (see Tastula and Vihma 2011; Powers et al. 2003), that are shown to be sensitive to initial conditions over frozen surfaces (Hines et al. 2011). rising model performance within the region would doubtless yield improved model forecast steering to those in operation within the region. However, this can be mostly speculative and more model experimentation is needed. As such, future ACCESS-G development ought to target higher illustration of Antarctic processes to boost overall model performance.Additional observations created offered for knowledge assimilation would additionally doubtless yield enhancements to the model initial conditions, as could enlarged model resolution. Given the supplying and money challenges of putting in and maintaining in place observant systems, this needs modelers to create bigger use of remotely perceived and satellite observations for knowledge assimilation and verification functions (Casati et al. 2017).

We acknowledge the restrictions of this study, specifically the utilization of model analysis as a reference dataset for verification and also the use of one year of information. Given the event schedules of the ACCESS family of models, knowledge from 2017 were the foremost consistent and complete, across a full twelvemonth. Ideally, a extended statistic further|and extra} experimental knowledge would supply additional context around model performance, as would a seasonally centered study.

14) Object-Based Evaluation of a Numerical Weather Prediction Model's Performance through Forecast Storm Characteristic Analysis

Huaqing Cai

Object-based forecast analysis tools like MODE will diagnose forecast performance, therefore providing additional perceptive data than is also gleaned from ancient pixel-versus-pixel contingency-table verification. supported the MODE analysis of storm properties throughout a 3-week amount of the HRRR model convective storm forecasts within the summer of 2010 over the jap common fraction of the contiguous u. s., it's found that the HRRR model satisfactorily forecasted storm property characteristics—storm variety, size, intensity, orientation, ratio, and complexity—as a operate of either storm size or time of day. However, vital bias and/or interruption did exist certainly storm characteristics. Specifically, the model attended underforecast the whole variety and total space of convective storms, and its capability to forecast new storm initiation was terribly totally different for the 2 subregions examined, particularly at longer forecast lead times. as an example, though the HRRR apparently had bother initiating normal thunderstorms within the Southeast once afternoon diurnal heating is that the major forcing mechanism, it did very well in prognostication new storms within the higher ara|geographic area|geographical region|geographic region} wherever storms are additional generally driven by synoptic-scale frontal boundaries.

Another fascinating MODE designation considerations the HRRR's capability to handle giant MCS features: HRRR made comparably sized MCSs compared with observations for the 4-h forecast however didn't maintain them, leading to a lot of smaller storms for the 8- and 12-h forecasts.The combined forecast analysis of CSI scores along side MODE analysis confirmed the hypothesis that the diurnal CSI score variation was for the most part a results of storm size variation through the diurnal cycle. {the fact|the terribly fact|the actual fact} that each MODE analysis and CSI scores came to constant conclusion—forecasts with shorter lead times outperformed those with longer lead times—suggests that even very tiny CSI score variations may probably be trustworthy , as long as that tiny distinction is consistent and has pregnant physical explanations.

The focus of this paper has been on designation model performance problems. the foremost vital contribution toward aiding the modelers' efforts in up their model is that the diagnostic data on the convective initiation difficulties within the Southeast and therefore the overall downside with maintaining giant storms. In fact, shut collaborations between NOAA/GSD, NCAR's analysis Applications Laboratory, and MIT–Lincoln Laboratory throughout the course of this analysis ensured that the analysis of the 2010 HRRR model junction rectifier to any enhancements in later versions of the HRRR.

Future work can valuate model forecasts for matched objects victimisation MODE. an easy score like CSI supported matched or unmatched objects may well be calculated and used as a live for forecast performance. additionally to object-based CSI scores, variety of matched-object attributes may even be analyzed, of that the foremost necessary one would be the centre of mass distance. The matched object's centre of mass distance can offer a quantitative estimate of forecast displacement error—a parameter that a conventional pixel-versus-pixel verification cannot offer however that has necessary implications on a way to use the model storm forecast most effectively, particularly for aviation and severe weather applications of the HRRR.

15) Probabilistic Weather Prediction with an Analog Ensemble

analog ensemble (AnEn), a 21-member system generated victimization the past forecasts and substantiating observations of settled 15-km world Environmental Multiscale (GEM) model runs, to a state-of-the-science numerical weather prediction (NWP) ensemble, the surroundings North American nation Regional Ensemble Prediction System (REPS) that consists of twenty one runs of a 33-km version of GEM. For truthful comparison, the direct output from REPS is label to supply ensemble model output statistics (EMOS) forecasts victimization an equivalent historical knowledge accessible to AnEn. A fourth system, supply regression (LR), generates probabilistic forecasts from the 15-km GEM to supply another truthful comparison with AnEn. a very important distinction between previous implementations of analog-based ensemble strategies (e.g., HW06) and also the AnEn methodology planned here is that whereas the previous area unit postprocessing procedures of a NWP ensemble, the latter produces associate degree ensemble from a NWP settled run (as are often finished LR with its extended formulation; Wilks 2009). Another key distinction is that in AnEn the analog search is absolutely localized in area.

All four forecast systems area unit tested for 0–48-h probabilistic predictions initialized at 1200 UTC of 10-m wind speed and 2-m temperature at 550 METAR stations over the contiguous u. s. for the twenty three April–31 July 2011 amount. The coaching set for AnEn, EMOS, and LR includes all knowledge from one could 2010 up to the day the forecast would are issued, as if the forecasts were made in real time.The AnEn and LR appear to be additional economical than EMOS, as shown in Fig. thirteen wherever AnEn and LR area unit generated employing a single member of REPS (i.e., at of the process value of EMOS) and exhibit solely alittle decrease in performance with relevancy EMOS. the final selection then is to run the members of a period NWP ensemble that additionally needs activity victimization historical knowledge, or to get probabilistic forecasts from one NWP forecast (allowing for smaller grid increments than any on the NWP ensemble members) victimization an equivalent historical dataset that might be wont to calibrate the NWP ensemble. The latter could also be the popular selection for applications wherever predictions area unit necessary at specific locations (e.g., renewable energy), however additional studies (see below) area unit necessary to see the relative advantage of the 2 choices for applications wherever two- or three-dimensional fields area unit required.

The bigger potency of AnEn than EMOS are often explained by the subsequent issues. Grid spacing (i.e., model resolution) is a very important consider the standard of region prediction. In formulating associate degree estimate of the forecast likelihood density operate (PDF), associate degree ensemble simulates uncertainty info solely concerning region phenomena on scales resolved by the NWP model. Potential errors of unresolved scales should then be incorporated by widening the forecast PDF via activity. Increasing model resolution permits for direct simulation of smaller scales and enhanced resolution (and value) of the probabilistic forecasts. so a key advantage of AnEn is that the use of a 15-km model grid versus the EMOS use of a 33-km model grid. scrutiny these 2 ensembles could seem unfair initially, however the purpose to think about is that the resources needed to run any n-member NWP ensemble may well be place toward manufacturing one NWP run at a far higher resolution, that the analog methodology will then offer reliable forecast uncertainty info, maybe leading to additional worth for higher cognitive process by the tip user.

This study's finding of bigger potency by AnEn in manufacturing skillful probabilistic forecasts is encouraging and motivates additional investigations. Testing ought to be expanded from prediction of 10-m wind speed and 2-m temperature to different forecast variables (e.g., ratio, pressure, precipitation), from prediction at observation locations at the surface to upper-air forecasts over a three-dimensional grid, and additionally to incorporate completely different and longer verification regions and periods. analysis is additionally required on the sensitivity of AnEn performance to key aspects of its formulation like the amount of members to use, aspects of the analog search (e.g., the set of predictors enclosed, their weights, and also the formulation of the analog-quality metric), and also the length of the coaching dataset. As shown in Fig. 14, AnEn and LR greatly enjoy enhanced coaching, with AnEn maybe benefiting the foremost from such extension, which can result to the distinct variations in AnEn style mentioned on top of. Testing may even be performed on a hybrid ensemble approach that mixes each the analog and NWP ensemble by finding multiple analogs for every member of the NWP ensemble, which can calibrate the NWP ensemble members whereas generating a additional totally sampled forecast.

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