## Project 3 : Spatiotemporal Analysis with Spark

A report by Adarsh and Ayush

1. **Climate Chart**: We first read the data from the sample files on Orion, into a dataframe. We are using predefined python functions to compute geohash based on latitude and longitude as input parameters. We are converting the time into the month of the year. We are then reading features such as temperature and precipitation.

The below image shows 12 month data, for a given geohash 'dnd'.

	1_time	max(temperature_surface)	min(temperature_surface)	avg(total_precipitation_surface_3_hour_accumulation)	avg(temperature_surface)
0	1430341200000	296.62330	293.87330	0.000000	294.977467
1	1445396400000	280.52850	278.65350	0.000000	279.307346
2	1447038000000	282.31354	274.06354	0.000000	276.626040
3	1443236400000	290.90260	289.52760	1.442308	290.075677
4	1442026800000	291.46582	286.59082	0.005682	290.227184
5	1442847600000	298.00000	296.00000	0.000000	297.178571
6	1431874800000	302.32275	298.07275	0.116071	300.215607
7	1430924400000	301.92456	295.92456	0.000000	299.538196
8	1444467600000	287.68700	283.06200	0.237500	285.387000
9	1427749200000	292.63990	290.63990	0.000000	291.814900
10	1437987600000	295.24365	293.49365	0.041667	294.843650
11	1433257200000	294.03955	290.16455	0.062500	291.557407
12	1444402800000	299.62524	294.62524	0.125000	298.316416

2. **Travel Startup**: We are calculating the comfort Index based on three features from the dataset. They are temperature\_surface, relative\_humidity and pressure\_surface. We have considered ideal temperature range to be (294 - 304), ideal humidity range (5 - 25) and ideal pressure range (101000 - 102000). To calculate the comfort index we are considering, how much the values deviate from the means of these ranges and then computing the average of those deviations. A lower value of comfort index means more comfortable in our case.

Initially, we filter out the data which doesn't lie in these ranges. Then, from the remaining, we compute the top 5 locations, according to the best comfort index, which we recommend as a part of our travel startup.

Below image, shows the top 5 geohashes and the time of the year, we got on running our program.

	5_hash	1_time	temperature_surface	relative_humidity_zerodegc_isotherm	pressure_surface	c_idx
0	d7b	01	298.348927	16.909580	101501.593649	1.2840521994996514
1	9vp	10	298.301239	23.413302	101478.392518	10.107340817496015
2	95x	11	298.109089	19.937802	101474.337802	10.23636284003633
3	d6v	03	300.360270	5.042528	101518.578263	10.298668363849922
4	9s0	02	296.744381	18.621229	101526.536313	10.471053765362091

3. **Solar Wind**: We have found the locations of solar farms based on the feature temperature\_surface and wind farms based on pressure\_maximum\_wind. The ideal temperature we have considered lies between 308 and 338. The ideal pressure\_maximum\_wind we have considered is more than 20000.

The top 3 locations for solar farms, based on temperature surface are as below:

	5_hash	1_time	pressure_maximum_wind	temperature_surface
0	9tbq	07	21111.943557	311.928496
1	9tbm	07	21408.059874	311.491012
2	9tbq	08	20832.068599	311.478068

The top 3 locations for wind farms, based on wind pressure are as below:

	5_hash	1_time	pressure_maximum_wind	temperature_surface
0	f6b6	05	33926.435958	270.893060
1	cdyh	04	33784.938600	256.736114
2	f4fu	04	33710.226613	258.950405

The top 3 locations for solar and wind farms, combining both features are as below:

	5_hash	1_time	pressure_maximum_wind	temperature_surface
0	9se5	06	24738.138428	308.946569
1	9sdu	06	24571.477879	308.757447
2	9se3	06	24040.346235	308.524853

4. **Climate Change**: We calculated the geohashes from latitude and longitude values of the dataset. Based on the geohashes, we calculated the average temperature over the period of 5 years.

	5_hash	2014	2015	2016	2017	2018	2019
0	f2	273.6225	310.83887	null	null	312.14615	310.55997
1	c0	285.7475	317.34937	null	null	311.72736	309.67
2	f6	254.6225	305.88745	null	null	304.06995	306.63
3	сс	267.8725	312.84448	null	null	317.43997	315.60962
4	bc	281.9975	290.5183	null	null	290.585	291.3078

We then found, in which of these cases, is the temperature increasing.

	5_hash	2014	2015	2016	2017	2018	2019	is_increasing
0	bc	281.9975	290.5183	null	null	290.585	291.3078	true
1	9u	297.9975	323.3811	null	null	325.96997	326.4664	true
2	9x	274.3725	319.81274	null	null	321.16968	321.41	true
3	9s	299.1225	328.09082	null	null	331.566	331.61	true
4	9e	301.9975	326.83325	null	null	328.0671	328.85913	true
5	9p	288.6225	318.38745	null	null	318.41995	318.43	true
6	dp	278.2475	312.4287	null	null	314.58997	316.2473	true
7	bf	281.8725	304.7229	null	null	305.4071	308.69943	true
8	f0	277.3725	310.5537	null	null	312.83	314.73734	true
9	8y	290.9975	296.68628	null	null	296.84616	298.83997	true

Then, from these cases, where temperature is increasing, we found the correlation with humidity.

	5_hash	1_time	relative_humidity_zerodegc_isotherm	temperature_surface
0	8y	2019	44.216567	298.83997
1	9e	2015	50.282616	326.83325
2	bf	2015	77.759759	304.7229
3	9u	2015	41.340677	323.3811
4	9u	2017	35.508914	null
5	8y	2017	47.083304	null
6	9e	2014	21.146939	301.9975
7	9s	2017	39.180013	null
8	9s	2018	43.306710	331.566
9	bc	2014	74.665127	281.9975
10	9p	2019	51.262530	318.43

```
|geohash|temp humidity correlation|
     8y
           -0.46113040974179764
           0.014012919025987024
     9e
            -0.4509179772252986
     90
              0.4328976712939623
     9s
     9u
            0.03709686305438359
     9x
             0.2750060043533481
           -0.7771805988932008
     bc
     bf
            0.14249577226255644
     dp
             0.31984315570757504
     fol
           0.06425264460115487
```

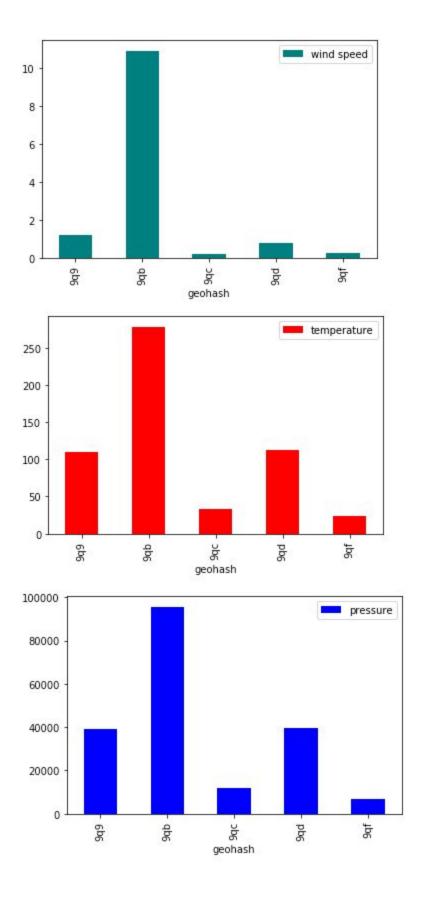
5. **Weather Station**: We made a load\_file.py code for streaming the data from the files. The data was received in form of rdd and calculating the mean with the new values coming in. Following shows the similar data for temperature.

```
{'geohash': '9qd', 'temperature': 107.60127945767196, 'M2': 85847.90365122746}
{'geohash': '9qf', 'temperature': 15.995929740441708, 'M2': 69596.57696703213}
{'geohash': '9q9', 'temperature': 104.92814299903847, 'M2': 84828.38001964623}
{'geohash': '9qb', 'temperature': 278.1117893055556, 'M2': 15.046257003863454}
{'geohash': '9qc', 'temperature': 25.399975841081275, 'M2': 70967.46500002636}

Time: 2020-12-09 23:08:12

{'geohash': '9qd', 'temperature': 112.7402131822264, 'M2': 122978.45124568781}
{'geohash': '9qf', 'temperature': 23.26814274374341, 'M2': 147972.26843974067}
{'geohash': '9q9', 'temperature': 110.24001105182127, 'M2': 124499.99476715154}
{'geohash': '9qb', 'temperature': 278.5114676207086, 'M2': 227.8236074677496}
{'geohash': '9qc', 'temperature': 33.776791623791354, 'M2': 149699.3748616972}
```

We have also uploaded a video of our weather station in action on github. We have shown bar graphs for each feature and each geohash.



6. **Anomaly Detector**: We are considering a feature to be anomaly, if the new value exceeds 120% of the previous mean value. The previous mean value is considered for the previous 10 values. We are using a function called deviate checker for this. We are using the streaming data, same as the previous task.

```
def deviateChecker(mean, new):
    true means anomaly, i.e more than 120% of prev value
    return mean*1.2 < new
def computeVal(new, old):
    for i in range(6):
        if len(old[i][0]) == 10:
            mean = calculateMean(old[i][0])
            is anomaly = deviateChecker(mean, new[i][0][0])
            if not is anomaly:
                old[i][0].pop(0)
                old[i][0].append(new[i][0][0])
            else:
                old[i][1] = True
        else:
            old[i][0].append(new[i][0][0])
    return old
```

We are then showing, which of the data points in the streaming data are Anomaly and Not Anomaly and showing it by printing it.

The idea for taking the previous 10 values is to take into consideration, that the features could change eventually but there shouldn't be a sudden change.

```
['9hs | ', 'surface_temp : Not Anomaly ', 'pressure : Not Anomaly ', 'humidity : Anomaly ', 'precipitation : Anomaly ', 'v
isibility: Not Anomaly ', 'wind_speed: Anomaly ']
['f0q | ', 'surface temp: Not Anomaly ', 'pressure: Not Anomaly ', 'humidity: Anomaly ', 'precipitation: Not Anomaly
  'visibility: Not Anomaly', 'wind_speed: Anomaly']
['cl0 | ', 'surface_temp : Not Anomaly ', 'pressure : Not Anomaly ', 'humidity : Anomaly ', 'precipitation : Anomaly ', 'v
isibility: Not Anomaly ', 'wind_speed: Anomaly ']
['cbh | ', 'surface_temp : Not Anomaly ', 'pressure : Not Anomaly ', 'humidity : Anomaly ', 'precipitation : Not Anomaly
', 'visibility : Anomaly ', 'wind_speed : Anomaly ']
['dqt | ', 'surface_temp : Not Anomaly ', 'pressure : Not Anomaly ', 'humidity : Anomaly ', 'precipitation : Anomaly ', 'v
isibility: Anomaly', 'wind_speed: Anomaly']
['9vh | ', 'surface_temp: Not Anomaly ', 'pressure: Not Anomaly ', 'humidity: Anomaly ', 'precipitation: Anomaly ', 'v
isibility: Anomaly', 'wind_speed: Anomaly']
['bc9 | ', 'surface_temp: Not Anomaly ', 'pressure: Not Anomaly ', 'humidity: Anomaly ', 'precipitation: Anomaly ', 'v
isibility: Anomaly', 'wind_speed: Anomaly']
['f8j | ', 'surface_temp: Not Anomaly ', 'pressure: Not Anomaly ', 'humidity: Anomaly ', 'precipitation: Not Anomaly
  'visibility : Anomaly ', 'wind_speed : Anomaly ']
['dp2 | ', 'surface temp: Not Anomaly ', 'pressure: Not Anomaly ', 'humidity: Anomaly ', 'precipitation: Anomaly ', 'v
isibility: Anomaly ', 'wind_speed: Anomaly ']
['cb8 | ', 'surface_temp : Not Anomaly ', 'pressure : Not Anomaly ', 'humidity : Anomaly ', 'precipitation : Anomaly ', 'v
isibility: Not Anomaly ', 'wind_speed: Anomaly ']
```

7. **Prediction (Travel Startup)**: We are considering our Travel Startup task, for ML analysis and predicting the comfort index based on past statistics, using linear regression.

We first calculate the comfort Index and geohashes, same as the previous task, in part 2.

	5_hash	1_time	temperature_surface	relative_humidity_zerodegc_isotherm	pressure_surface	label
0	9kts	12	293.521624	20.829932	101738.396786	82.901695
1	d5de	12	301.269737	24.305921	101600.328526	37.634727
2	95ys	12	295.523142	20.266667	101838.426671	115.390068
3	9k94	12	293.576559	19.700000	101964.923307	158.015579
4	9krm	12	295.818871	18.223837	101607.346228	37.583733

We are considering the data from 2014 - 18 as the training data and the 2019 data as test data to check our prediction.

predictio	features	label	pressure_surface	relative_humidity_zerodegc_isotherm	emperature_surface
111.9270239209399	[296.220634694533	142.05672	101923.21336977495	16.177419354838708	296.22063469453377
94.0418759649419	[296.719555471014	119.2216	101853.76842753626	12.384057971014492	296.71955547101464
58.45931986315008	[298.463292621359	5.049218	101505.2668867314	24.41747572815534	298.46329262135924
69.8251792789633	[297.641601943462	35.549282	101599.75398939928	21.5354609929078	297.64160194346294
87.9369762033529	[297.174849831081	71.16052	101705.24762500002	22.408783783783782	297.1748498310811
56.9880193862300	[296.890108885017	2.3898225	101500.0001358885	21.05944055944056	296.8901088850174
16.6190597112399	[299.549408185840	67.12158	101303.93688053089	18.75221238938053	299.54940818584066
42.04068503064263	[297.972160894568]	5.5898848	101483.77256230034	15.514376996805112	297.9721608945686
102.1036777803947	[294.8797725,14.0	118.08346	101850.22715298507	14.097014925373134	294.8797725
126.822072947328	[294.921826116504	143.86455	101920.59958899676	22.915857605177994	294.9218261165048
64.4787981270183	[298.112082371541	14.388734	101533.08573913043	24.968379446640316	298.1120823715414
35.0432167854087	[298.280508416666	39.62212	101386.69748749999	20.28333333333333	298.2805084166667
108.6922135105614	[295.523142190476	115.39007	101838.42667142859	20.2666666666666	295.5231421904762
32.9933982690217	[298.874585472636]	54.134167	101347.05915422887	23.587064676616915	298.87458547263685
74.8864955047429	[296.353952807571	49.787468	101644.40405047315	18.312302839116718	296.353952807571
30.86979623806291	[296.191488425925	80.54533	101269.21573148147	24.04320987654321	296.19148842592597
27.9846074548258	[301.055458014440	51.340878	101357.75485198559	23.72202166064982	301.05545801444043
122.4101965606896	[295.681796935484	161.48352	101980.63557096773	16.496774193548386	295.681796935484
140.0886290983071	[294.452655940594	169.29019	101995.82816171617	23.495049504950494	294.4526559405941
53.3896653816773	[296.716850265486	21.81499	101562.35124336283	13.189427312775331	296.71685026548687

only showing top 20 rows

We are considering the output of prediction as the new comfort indexes for these locations. Based on comfort Index, we are better able to suggest the travel locations, thus improving our travel startup.

The lower the comfort index, the better place it would be for travel.

8. **Final Project Update**: We are starting with our analysis on stackoverflow data for our final project, which we complete later using Google cloud platform.

Starting with the Users.xml file from our dataset, we try to read the xml files and convert them into rdd. We first filter our data and then extract userid and usernames from the data.

ld	username
1	Community
2	Confi Dalgag
3	Geoff Dalgas  Jarrod Dixon
1	4 N. C.
3	txwikinger  Nathan Osman
5	
5 7	Emmett  Helix
8	100 to 10
9	mechanical_meat  Andrew
10	DLH
11	hannes.koller
12	
13	
14	
16	
17	
18	excid3
20	
21	GeoD
22	Alan Featherston

We are also extracting the data related to postld and the text based on the comments.xml file.

userId	creationDate	text	score	postId
10	2010-07-28T19:36:	Using /opt helps	0	23
10	2010-07-28T19:38:	but popping in a	0	18
50	2010-07-28T19:39:	That will revert	0	27
12	2010-07-28T19:41:	I think you meant	0	31
63	2010-07-28T19:41:	@DLH apparently n	0	18
96	2010-07-28T19:46:	"ssh -X <server></server>	2	12
10	2010-07-28T19:48:	@Suppressingfire:	0	12
56	2010-07-28T19:48:	Can you please re	0	50
5	2010-07-28T19:49:	It probably shoul	0	27
5	2010-07-28T19:50:	Do you mean the c	0	58
4	2010-07-28T19:50:	Have you checked	0	47
104	2010-07-28T19:51:	Might be related	1	47
4	2010-07-28T19:51:	Do you use Gnome	0	58
66	2010-07-28T19:52:	This causes data	0	60
4	2010-07-28T19:53:	no the live CD do	0	18
35	2010-07-28T19:55:	Does this let the	0	52
4	2010-07-28T19:56:	LDAP and nfs are	2	56
27	2010-07-28T19:56:	Can I use it on a	0	10
45	2010-07-28T19:56:	That's a good tip	1	70
86	2010-07-28T19:58:	That is probably	0	70

only showing top 20 rows

We are also doing some analysis combining these two, using joins, which will be helpful in the final project.

userId	creationDate	text	score	postId	username		id
964	2010-10-13T21:37:	I can confirm thi	0	4602	Brummermann	Hendrik	964
964	2012-04-28T06:17:	They took it in d	0	118087	Brummermann	Hendrik	964
964	2015-08-03T13:26:	I have the same i	0	638027	Brummermann	Hendrik	964
1677	2011-12-03T21:56:	@fossfreedom i do	0	84949	eslambasha		1677
1697	2010-12-08T22:36:	@Marco, I know, I	0	16683	Frxstrem		1697
1697	2010-12-09T19:05:	This seems to be	0	16784	Frxstrem		1697
1697	2010-12-10T22:26:	I only want to di	1	16886	Frxstrem		1697
1697	2010-12-10T22:28:	This is not an ac	1	16892	Frxstrem		1697
1697	2010-12-11T19:22:	Have you tried bu	0	16988	Frxstrem		1697
1697	2010-12-14T23:14:	@Stefano fixed it	0	17471	Frxstrem		1697
1697	2010-12-17T13:50:	My guess is that	0	17892	Frxstrem		1697
1697	2010-12-18T17:53:	-1 It's too uncle	0	18014	Frxstrem		1697
1697	2010-12-22T17:48:	You did replace `	0	18273	Frxstrem		1697
1697	2011-10-15T22:18:	Firstly, I have a	0	67121	Frxstrem	50 50	1697
1697	2012-03-01T00:30:	You should use `t	0	108944	Frxstrem		1697
1697	2014-04-23T07:29:	Daily builds can	2	453415	Frxstrem		1697
1697	2015-08-26T16:36:	@user2662639 Simp	0	223442	Frxstrem		1697
1697	2015-08-26T16:37:	@user2662639 (I t	0	223442	Frxstrem		1697
1697	2016-03-25T12:21:	@Fiksdal I don't	2	17650	Frxstrem		1697
1697	2017-04-01T13:36:	@DavidFoerster Th	0	899129	Frxstrem		1697

only showing top 20 rows