In [ ]:
```
# Project 3: Spatiotemporal Analysis with Spark (v 1.0)
```

In [11]:
```
from pyspark.sql.functions import udf
df = spark.read.load('hdfs://orion11:11001/Project3/part-*-8aab2773-5596-
                        , format='csv', sep='\t'
                        , inferSchema='true'
                        , header='true')
```

In [12]:
```
import pygeohash as pgh
import pyspark.sql.functions as F
geohashEncodeUDF = F.udf(lambda x, y: pgh.encode(x, y))

df = df.withColumnRenamed('1_time', 'time').withColumnRenamed('2_lat', 'l
df = df.withColumn('geohash', geohashEncodeUDF(df['lat'], df['lon']))
df.take(3)
```

Out[12]:
```
[Row(time=1542186000000, lat=26.960126220715807, lon=-89.7937412174380
8, albedo_surface=6.0, precipitable_water_entire_atmosphere_single_laye
r=42.71665, pressure_maximum_wind=21520.148, pressure_surface=102031.26
6, pressure_tropopause=9503.021, relative_humidity_zerodegc_isotherm=9
7.0, snow_depth_surface=0.0, temperature_surface=300.1487, temperature_
tropopause=199.29172, total_cloud_cover_entire_atmosphere_single_layer=
100.0, total_precipitation_surface_3_hour_accumulation=1.125, vegetatio
n_surface=0.0, visibility_surface=24100.0, wilting_point_surface=0.0, w
ind_speed_gust_surface=16.018291, geohash='dhb1keynn5v9'),
 Row(time=1542186000000, lat=32.309655275902315, lon=-113.5378774164521
2, albedo_surface=28.0, precipitable_water_entire_atmosphere_single_lay
er=4.716647, pressure_maximum_wind=18924.95, pressure_surface=99181.66
4, pressure_tropopause=16783.822, relative_humidity_zerodegc_isotherm=
7.0, snow_depth_surface=0.0, temperature_surface=277.7687, temperature_
tropopause=206.5917, total_cloud_cover_entire_atmosphere_single_layer=
0.0, total_precipitation_surface_3_hour_accumulation=0.0, vegetation_su
rface=2.0, visibility_surface=24100.0, wilting_point_surface=0.047, win
d_speed_gust_surface=6.8182907, geohash='9mxrb3u1rsq9'),
 Row(time=1542186000000, lat=27.48415658524732, lon=-115.9057550351125
2, albedo_surface=6.0, precipitable_water_entire_atmosphere_single_laye
r=8.416647, pressure_maximum_wind=16712.95, pressure_surface=102164.06,
pressure_tropopause=15536.622, relative_humidity_zerodegc_isotherm=5.0,
snow_depth_surface=0.0, temperature_surface=294.37872, temperature_trop
opause=205.4917, total_cloud_cover_entire_atmosphere_single_layer=0.0,
total_precipitation_surface_3_hour_accumulation=0.0, vegetation_surface
=0.0, visibility_surface=24100.0, wilting_point_surface=0.0, wind_speed
_gust_surface=13.0182905, geohash='9kvs6e24b4hu')]
```

In [13]:
```
df.createOrReplaceTempView("df_temp")
```

```
In [7]:  #Strangely Snowy: Find a location that contains snow while its surroundin
         #high mountain peak in a desert?
         snow_covered_locations = spark.sql("select distinct(geohash) from df_temp

         # for row in snow_covered_locations:
         #     print(row.geohash)
```

```
In [15]: for row in snow_covered_locations:
             snowy = False
             length = len(row.geohash)
             substring = row.geohash[0: 2]
             query = "SELECT DISTINCT(geohash) FROM df_temp WHERE geohash LIKE '"
             neighbor_locations = spark.sql(query).collect()

             neighbor = False
             for neighbor in neighbor_locations:
                 neighbor = True
                 query = "SELECT count(*) FROM df_temp WHERE geohash = '" + neighb
                 count = spark.sql(query).collect()

                 if(len(count) > 0):
                     snowy = True
                     break


             if (snowy == False and neighbor == True):
                 print("strangely snowy place found")
                 print("cold place " + row.geohash)
                 break;
```

```
[Stage 139:=====================================================>  (21 +
1) / 22]

strangely snowy place found
cold place f2r487vvgzuf
```

```
In [8]:  details_of_location = spark.sql("select * from df_temp where geohash ='f2
         # print(details_of_location)
```

TimeTaken to execute query: 1hr 23 mins The point is around Eagle Lake, ME, hence it is snowy. Eagle Lake is located in northern Maine, which experiences cold winters with significant snowfall. The region's climate is classified as a continental climate, characterized by cold winters and warm summers. The average snowfall in this area can vary.

In [19]:

```
#Climate Chart: Given a Geohash prefix as an input, build a function that
#This includes high, low, and average temperatures, as well as monthly av
#(poor quality) script that will generate this for you, but you should pr
#scale, etc. are all presented in a readable fashion.

# '9q8y' San Francisco
climatechart = spark.sql( "SELECT  \
                            MONTH(FROM_UNIXTIME(time/1000)) as month, \
                            min(temperature_surface) as mintemperature, \
                            max(temperature_surface) as maxtemperature, \
                            avg(temperature_surface) as windspeed, \
                            avg(precipitable_water_entire_atmosphere_sing
                        FROM df_temp \
                        WHERE \
                            geohash like '9q8y%' \
                        GROUP BY \
                            MONTH(FROM_UNIXTIME(time/1000)) order by mont
```

In [20]:

```
for row in climatechart:
    print(f"{row.month} {row.maxtemperature} {row.mintemperature} {row.av
```

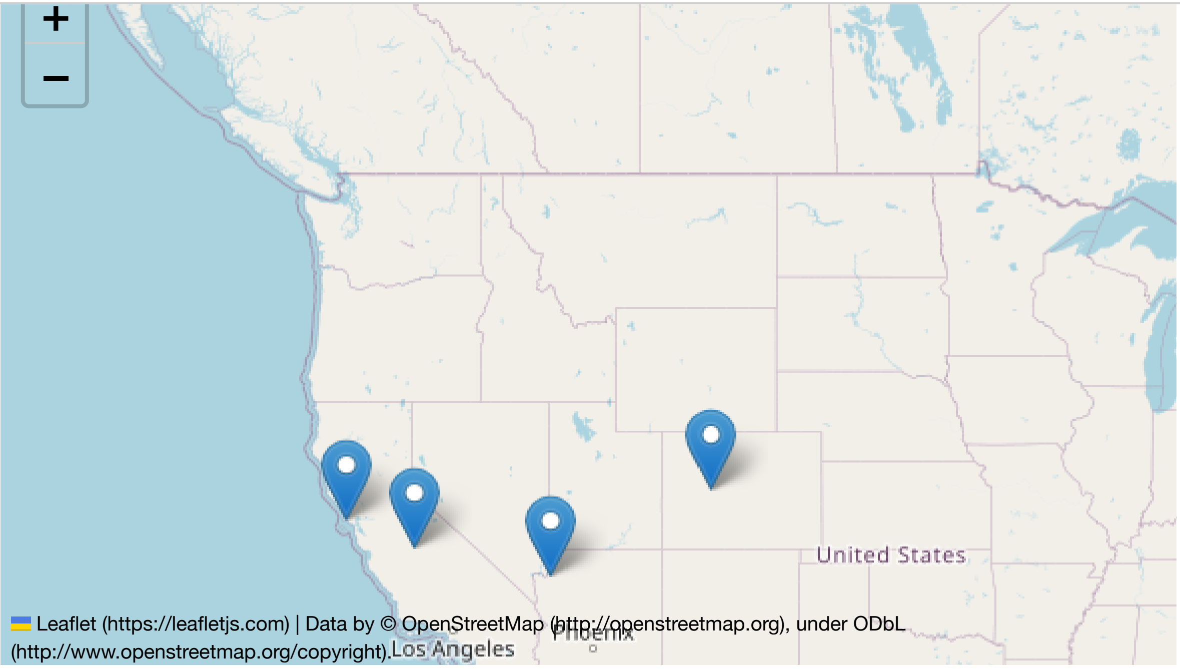
```
1 287.31268 280.58478 18.122153010869567 286.09792543478255
2 294.08905 279.73398 10.51255908181818 285.0857968181818
3 298.1007 280.39893 13.227399359183677 285.6007559183673
4 288.70123 283.14417 14.7388813106383 286.1134661702128
5 299.49 284.91513 18.91990586065574 287.0655240983607
6 293.3207 285.35416 14.831884346938775 287.5678455102041
7 302.7684 286.11072 22.12117175510204 289.31127775510197
8 301.43997 286.58633 17.377214108695654 289.50044565217394
9 298.28876 285.82037 14.924881104545454 288.94066181818175
10 297.72638 285.5869 18.479864312765958 289.39579106382973
11 294.27374 282.37433 15.484264729268292 288.22323902439024
12 288.9798 279.8313 16.559842177777774 286.841882
```

In [14]:

```
# Travel Startup: After graduating from USF, you found a startup that aim
# using big data analysis. Given your own personal preferences, build a p
# Or, in other words: pick 5 regions. What is the best time of year to vi
# Part of this involves determining the comfort index for a region. You c
# not too cold, dry, humid, windy, etc. There are several different ways
# could also analyze how well your own metrics do.
# Another part of this involves presentation. You have to convince your p
# is better than something they could come up with themselves with a litt
# about local points of interest, etc.

relative_humidity_zerodegc_isotherm = 45
temperature_surface = 299
total_cloud_cover_entire_atmosphere = 60
# Grand canyon 9qrhf6btbt3jevhn
# Panhandle san francisco 9q8yvs4t
# New york dr5regw2z6y
# Fresno 9qd23ynghrrz
# Colorado 9x58

traveldata = spark.sql( "SELECT  \
                            substring(geohash, 0, 4) as region, \
                            MONTH(FROM_UNIXTIME(time/1000)) as month, \
                            AVG(temperature_surface) as temperature, \
                            AVG(relative_humidity_zerodegc_isotherm) as hu
                            AVG(wind_speed_gust_surface) as windspeed, \
                            AVG(total_cloud_cover_entire_atmosphere_singl
                        FROM df_temp \
                        WHERE \
                            Geohash like '9qd2%' or \
                            Geohash like 'dr5r%' or \
                            Geohash like '9q8y%' or \
                            Geohash like '9qrh%' or  \
                            Geohash like '9x58%'  \
                        GROUP BY \
                            MONTH(FROM_UNIXTIME(time/1000)), \
                            substring(geohash, 0, 4)").collect()
```

In [15]:

```
import folium
from pygeohash import decode
relative_humidity_zerodegc_isotherm = 45
temperature_surface = 299
total_cloud_cover_entire_atmosphere = 60
region = set()
for row in traveldata:
    isgood = True
    if(row.temperature < (temperature_surface - (temperature_surface * .1
       row.temperature > (temperature_surface + (temperature_surface * .1
        isgood = False
    if(row.humdity < (relative_humidity_zerodegc_isotherm - (relative_hum
       row.humdity > (relative_humidity_zerodegc_isotherm + (relative_hum
        isgood = False
    if(row.cloudcover < (total_cloud_cover_entire_atmosphere - (total_clo
       row.cloudcover > (total_cloud_cover_entire_atmosphere + (total_clo
        isgood = False
    if(isgood == True) and len(region) <= 5 :
        print(f"{row.region} {row.month} ")
        region.add(row.region)

t = folium.Map(location=[37.0902, -95.7129], zoom_start=4)


for g in region:
    # Extract the latitude and longitude from the geohash
    lat, lon = decode(g)
    # Add a marker to the map at the geohash location
    folium.Marker(location=[lat, lon], popup=g).add_to(t)
t
```


+
−
United States
Phoenix
Los Angeles
🇺🇦 Leaflet (https://leafletjs.com) | Data by © OpenStreetMap (http://openstreetmap.org), under ODbL (http://www.openstreetmap.org/copyright).

In [ ]:

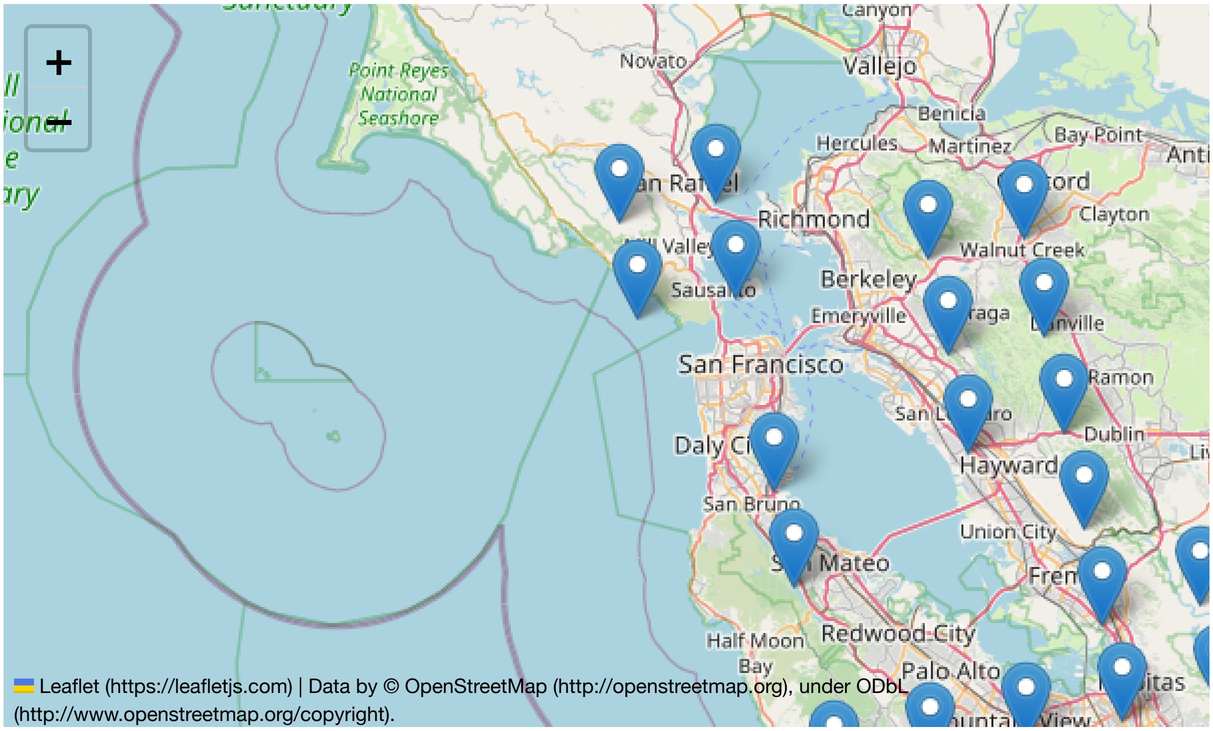
```
# We use five specific locations (Arizona, San Francisco, New York, Fresn
# prediction parameters include temperature, cloud cover, and humidity. W
# parameters in each region using the first four characters of their geoh
# average values with predefined criteria. The temperature should fall wi
# specified value, and cloud cover within 50% of our value. Based on thes
# the locations for travel according to the given criteria.

# Grand canyon Arizona(9qrh) - December, January, March
# Panhandle san francisco(9q8y) - November, December, May, April, March,
# New york (dr5r) - May, October, August, June
# Fresno (9qd2) - December, January, March
# Colorado (9x58) - September
```

In [17]:

```
# Escaping the fog: After becoming rich from your startup, you are lookin
# Area mansion with unobstructed views. Find the locations that are the l
from IPython.display import display, HTML
from pygeohash import decode
import folium


fogResult = spark.sql("SELECT geohash, \
                                AVG(visibility_surface) as visSurface, \
                                AVG(albedo_surface) as avgSurface, \
                                wilting_point_surface \
                       FROM df_temp \
                       WHERE (geohash LIKE '9q8y%' \
                          OR geohash LIKE '9q8z%' \
                          OR geohash LIKE '9q9h%' \
                          OR geohash LIKE '9q9k%' \
                          OR geohash LIKE '9q9m%' \
                          OR geohash LIKE '9q9p%' \
                          OR geohash LIKE '9q8v%' \
                          OR geohash LIKE '9q9n%') \
                          AND (wilting_point_surface > 0.0) \
                       GROUP BY geohash, wilting_point_surface \
                       ORDER BY avgSurface desc, visSurface desc").collec

cordinates_list = []
i = 0

for x in fogResult:
#     print(fogResult[i][0]," ",fogResult[i][1]," " ,fogResult[i][2]," ",
    cordinates_list.append(decode(fogResult[i][0]))
    i += 1
print(cordinates_list)



m = folium.Map(location=[37.491989, -121.952673], zoom_start=10)

# Add markers for each set of coordinates
for coord in cordinates_list:
    folium.Marker(coord).add_to(m)

# Display the map
m
```

```
[Stage 52:=====================================================>  (21 +
1) / 22]

[(37.491989, -121.952673), (37.513057, -121.820522), (37.323334, -122.3
21857), (37.344703, -122.189984), (37.365968, -122.058057), (37.408186,
-121.794052), (37.42914, -121.661969), (37.596798, -121.979318), (37.38
7129, -121.92608), (37.534022, -121.688315), (37.701559, -122.006016),
(37.303266, -121.767633), (37.80627, -122.032765), (37.282221, -121.899
539), (37.910929, -122.059566), (37.680363, -122.138363), (37.889711, -
122.192162), (37.785063, -122.165236), (37.951537, -122.484425), (37.92
9995, -122.616986), (37.825431, -122.589635), (37.846961, -122.457198),
(37.63766, -122.402903), (37.532933, -122.375835)]
```

Out[17]:



Leaflet (https://leafletjs.com) | Data by © OpenStreetMap (http://openstreetmap.org), under ODbL (http://www.openstreetmap.org/copyright).

In [34]:

```
# SolarWind, Inc.: After getting rich from your travel startup you get bo
#     help power companies plan out the locations of solar and wind farms
#     for solar and wind farms, as well as a combination of both (solar +
#     Geohashes as well as their relevant attributes (for example, cloud
solarFarms = spark.sql("SELECT \
                            SUBSTRING(geohash,1,6) as prefix, \
                            AVG(CAST(total_cloud_cover_entire_atmosphere_
                            wilting_point_surface \
                        FROM df_temp \
                        WHERE (geohash LIKE 'c%' or geohash LIKE '9%') an
                        GROUP BY prefix, wilting_point_surface \
                        ORDER BY cloudCover").collect()

print("Top three solar farms")
print("Geohash:" + str(solarFarms[0][0]) + ", Avg total_cloud_cover_entir
print("Geohash:" + str(solarFarms[1][0]) + ", Avg total_cloud_cover_entir
print("Geohash:" + str(solarFarms[2][0]) + ", Avg total_cloud_cover_entir



windFarms = spark.sql("SELECT \
                            SUBSTRING(geohash,1,6) as prefix, \
                            AVG(wind_speed_gust_surface) as avgWind, \
                            wilting_point_surface \
                        FROM df_temp \
                        WHERE (geohash LIKE 'c%' or geohash LIKE '9%') an
                        GROUP BY prefix, wilting_point_surface \
                        ORDER BY avgWind desc").collect()

print("Top three wind farms")
print("Geohash:" + str(windFarms[0][0]) + ", Avg wind_speed_gust_surface:
print("Geohash:" + str(windFarms[1][0]) + ", Avg wind_speed_gust_surface:
print("Geohash:" + str(windFarms[2][0]) + ", Avg wind_speed_gust_surface:

maxWindSpeed = spark.sql("SELECT MAX(wind_speed_gust_surface) FROM df_tem

windAndSolarFarms = spark.sql(f"SELECT \
                                     SUBSTRING(geohash,1,6) as prefix, \
                                     AVG(wind_speed_gust_surface) as avgW
                                     AVG(CAST(total_cloud_cover_entire_at
                                     wilting_point_surface \
                                 FROM df_temp \
                                 WHERE (geohash LIKE 'c%' or geohash LIKE
                                 GROUP BY prefix, wilting_point_surface \
                                 ORDER BY ((avgWind/ {maxWindSpeed[0][0]}

first = windAndSolarFarms[0]
second = windAndSolarFarms[1]
third = windAndSolarFarms[2]

print("Top three wind and solar farms")
print("Geohash:" + str(first[0]) + ", Score:", str(first[1]/maxWindSpeed[
print("Geohash:" + str(second[0]) + ", Score:", str(second[1]/maxWindSpee
print("Geohash:" + str(third[0]) + ", Score:", str(third[1]/maxWindSpeed[
```

```
Top three solar farms
Geohash:9mtzhd, Avg total_cloud_cover_entire_atmosphere_single_layer:
4.973684
Geohash:9mv6vz, Avg total_cloud_cover_entire_atmosphere_single_layer:
5.635659
Geohash:9mwh9p, Avg total_cloud_cover_entire_atmosphere_single_layer:
5.769231



Top three wind farms
Geohash:9xkzng, Avg wind_speed_gust_surface: 10.506980859999999
Geohash:9xsc6w, Avg wind_speed_gust_surface: 10.409824772481203
Geohash:9xmnd4, Avg wind_speed_gust_surface: 10.40498561470588



Top three wind and solar farms
Geohash:c19ewq, Score: 1180.430376615631
Geohash:c196jz, Score: 1166.7002720722528
Geohash:c1c1pw, Score: 1155.0288341570981
```

In [ ]:

```
# Weather Station: Write a multi-threaded server (outside of Spark) that
# thread – and then streams them out on a socket for a Spark streaming co
# files have to be opened at once! :-)). The program should produce recor
# faster than real time. Using Spark, consume the streams and then:

# Choose five geographical locations to aggregate. You will filter out an
# Build an online summary of surface temperature, pressure, humidity, pre
# geographical locations you selected.Produce a visual overview of these
# however you'd like, but the idea here is to give the viewer a high-leve
# and how it is changing in real time (well, actually faster than real ti
# show each metric separately on a 5-by-6 grid. Your visualization should
# as data arrives, or you can build a video by exporting each frame of th
# them.Turn in a video of your weather station in action.
```

In [ ]:

```
# We created server.go and tried to connect to the spark streaming but di
```

In [45]:

```
# Prediction/Classification: Revisit any of the problems above and enhanc
# MLlib. You will need to explain:
# The feature you will predict/classify
# Features used to train the model
# How you partitioned your data
# How the prediction/classification improves your analysis

from pyspark.ml.feature import VectorAssembler

def prepare_data(dframe, predictors, target):
    assembler = VectorAssembler(inputCols=predictors, outputCol="features
    output = assembler.transform(dframe)
    return output.select("features", target).withColumnRenamed(target, "l


prepped = prepare_data(df,
    [
     "albedo_surface",
     "vegetation_surface",
     "relative_humidity_zerodegc_isotherm",
     "total_precipitation_surface_3_hour_accumulation",
     "temperature_surface"
    ],
    "snow_depth_surface")

prepped.show()
(trainingData, testData) = prepped.randomSplit([0.8, 0.2])
```

```
+--------------------+------+
|            features| label|
+--------------------+------+
|[19.3,1.0,17.0,0....|   0.0|
|[17.0,13.0,40.0,0...|4.0E-5|
|[20.3,26.9,13.0,0...|   0.0|
|[6.0,0.0,23.0,0.0...|   0.0|
|[16.0,18.4,14.0,0...|   0.0|
|[13.9,28.2,18.0,0...|   0.0|
|[17.3,25.1,12.0,0...|   0.0|
|[18.3,31.0,35.0,0...|   0.0|
|[19.6,28.1,22.0,0...|   0.0|
|[6.0,0.0,10.0,0.0...|   0.0|
|[18.7,26.0,24.0,0...|   0.0|
|[17.6,17.9,14.0,0...|   0.0|
|[17.0,6.0,39.0,0....|   0.0|
|[6.0,0.0,19.0,0.0...|   0.0|
|[25.5,8.1,55.0,0....|   0.0|
|[6.0,0.0,5.0,0.0,...|   0.0|
|[17.0,1.0,29.0,0....|   0.0|
|[22.7,1.0,14.0,0....|   0.0|
|[23.9,15.0,30.0,0...|   0.0|
|[17.0,9.0,34.0,0....|   0.0|
+--------------------+------+
only showing top 20 rows
```

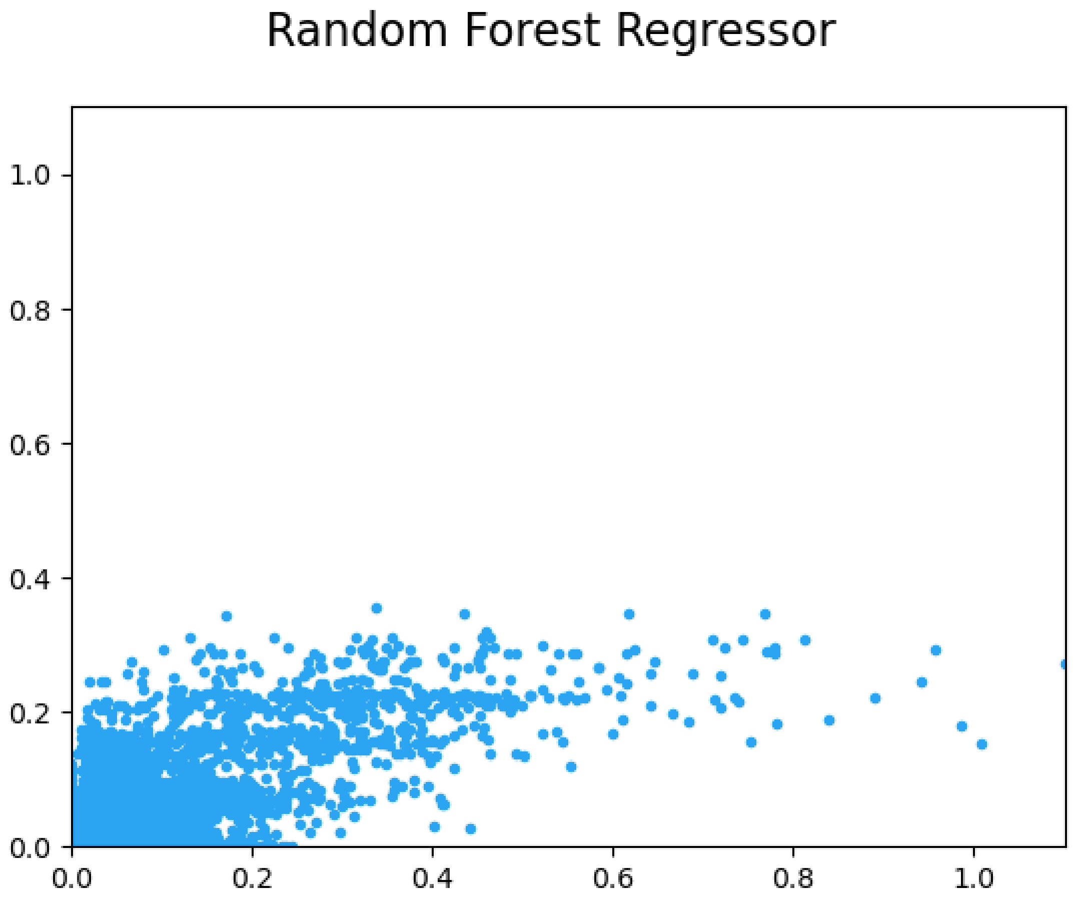
In [46]:

```
from pyspark.ml.regression import RandomForestRegressor
from pyspark.ml.evaluation import RegressionEvaluator

rf = RandomForestRegressor(numTrees=100, maxDepth=5, maxBins=32)
model = rf.fit(trainingData)
predictions = model.transform(testData)

evaluator = RegressionEvaluator(
    labelCol="label", predictionCol="prediction", metricName="rmse")
rmse = evaluator.evaluate(predictions)
print("Root Mean Squared Error (RMSE) on test data = %g" % rmse)
```

```
WARNING: An illegal reflective access operation has occurred
WARNING: Illegal reflective access by org.apache.spark.util.SizeEstimat
or$ (file:/bigdata/spark-3.3.2-bin-hadoop3/jars/spark-core_2.12-3.3.2.j
ar) to field java.nio.charset.Charset.name
WARNING: Please consider reporting this to the maintainers of org.apach
e.spark.util.SizeEstimator$
WARNING: Use --illegal-access=warn to enable warnings of further illega
l reflective access operations
WARNING: All illegal access operations will be denied in a future relea
se
[Stage 322:====================================================>  (21 +
1) / 22]

Root Mean Squared Error (RMSE) on test data = 0.0170701
```

In [47]:

```
import matplotlib.pyplot as plt

p_df = predictions.select("label", "prediction").toPandas()

plt.suptitle('Random Forest Regressor', fontsize=16)

minval = p_df[['label', 'prediction']].min().min()
maxval = p_df[['label', 'prediction']].max().max()
plt.axis([minval, maxval, minval, maxval])

plt.plot(p_df['label'], p_df['prediction'], '.', color='#2ba5f1')
plt.plot(range(int(minval), int(maxval)), range(int(minval), int(maxval))
plt.show()
```



In [ ]:

```
# Q.) The feature you will predict/classify: "snow_depth_surface"
# Q.) Features used to train the model: "albedo_surface"
#                                       "vegetation_surface"
#                                       "relative_humidity_zerodegc_isoth
#                                       "total_precipitation_surface_3_ho
#                                       "temperature_surface"
# Q.) How you partitioned your data: 80% for training and 20% for testing
# Q.) How the prediction/classification improves your analysis: Based on
#     which yielded a root mean square error (RMSE) of 0.0170701, we have
#     the snow depth for any new incoming point.
```