2.SparkSQLDataFrameOperations

October 11, 2018

In [1]:
```
#Initialize and load weather dataframe

from pyspark import SparkContext
sc = SparkContext(master="local[4]")
#sc.version

import os
import sys

from pyspark import SparkContext
from pyspark.sql import SQLContext
from pyspark.sql.types import Row, StructField, StructType, StringType, IntegerType
%pylab inline

# Just like using Spark requires having a SparkContext, using SQL requires an SQLConte
sqlContext = SQLContext(sc)

from os.path import split,join,exists
from os import mkdir,getcwd,remove
from glob import glob

# create directory if needed

notebook_dir=getcwd()
data_dir=join(split(split(notebook_dir)[0])[0],'Data')
weather_dir=join(data_dir,'Weather')

if exists(weather_dir):
    print('directory',weather_dir,'already exists')
else:
    print('making',weather_dir)
    mkdir(weather_dir)

file_index='NY'
zip_file='%s.tgz'%(file_index) #the .csv extension is a mistake, this is a pickle file
old_files='%s/%s*'%(weather_dir,zip_file[:-3])
for f in glob(old_files):
```

```
            print('removing',f)
            !rm -rf {f}

        command="wget https://mas-dse-open.s3.amazonaws.com/Weather/by_state/%s -P %s "%(zip_fi
        print(command)
        !$command
        !ls -lh $weather_dir/$zip_file

        #extracting the parquet file
        !tar zxvf {weather_dir}/{zip_file} -C {weather_dir}

        weather_parquet = join(weather_dir,zip_file[:-3]+'parquet')
        print(weather_parquet)
        df = sqlContext.read.load(weather_parquet)
        df.show(1)
```

```
Populating the interactive namespace from numpy and matplotlib
directory /home/jovyan/work/Sections/Data/Weather already exists
removing /home/jovyan/work/Sections/Data/Weather/NY.parquet
removing /home/jovyan/work/Sections/Data/Weather/NY.tgz
wget https://mas-dse-open.s3.amazonaws.com/Weather/by_state/NY.tgz -P /home/jovyan/work/Sectio
--2018-04-09 01:16:40--  https://mas-dse-open.s3.amazonaws.com/Weather/by_state/NY.tgz
Resolving mas-dse-open.s3.amazonaws.com (mas-dse-open.s3.amazonaws.com)... 52.218.196.178
Connecting to mas-dse-open.s3.amazonaws.com (mas-dse-open.s3.amazonaws.com)|52.218.196.178|:44
HTTP request sent, awaiting response... 200 OK
Length: 23182008 (22M) [application/x-tar]
Saving to: /home/jovyan/work/Sections/Data/Weather/NY.tgz

NY.tgz              100%[===================>]  22.11M   279KB/s    in 65s

2018-04-09 01:17:46 (347 KB/s) - /home/jovyan/work/Sections/Data/Weather/NY.tgz saved [2318200

-rwxrwxrwx 1 jovyan staff 23M Mar 16 20:25 /home/jovyan/work/Sections/Data/Weather/NY.tgz
NY.parquet/
NY.parquet/_SUCCESS
NY.parquet/part-00000-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00001-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00002-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00003-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00004-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00005-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00006-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00007-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00008-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00009-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00010-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00011-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
NY.parquet/part-00012-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
```

```
NY.parquet/part-00013-8342bcf4-7fc2-4183-8e11-aefdb4915fbb-c000.snappy.parquet
/home/jovyan/work/Sections/Data/Weather/NY.parquet
+-----------+-----------+----+--------------------+-----+
|    Station|Measurement|Year|              Values|State|
+-----------+-----------+----+--------------------+-----+
|USC00303452|       PRCP|1903|[00 7E 00 7E 00 7...|   NY|
+-----------+-----------+----+--------------------+-----+
only showing top 1 row
```

0.1 Dataframe operations

Spark DataFrames allow operations similar to pandas Dataframes. We demonstrate some of those. For more, see the official guide and this article

```
In [2]: df.printSchema()
```

```
root
 |-- Station: string (nullable = true)
 |-- Measurement: string (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Values: binary (nullable = true)
 |-- State: string (nullable = true)
```

```
In [3]: print(df.count())
        df.show(1)
```

```
84199
+-----------+-----------+----+--------------------+-----+
|    Station|Measurement|Year|              Values|State|
+-----------+-----------+----+--------------------+-----+
|USC00303452|       PRCP|1903|[00 7E 00 7E 00 7...|   NY|
+-----------+-----------+----+--------------------+-----+
only showing top 1 row
```

0.1.1 .describe()

The method `df.describe()` computes five statistics for each column of the dataframe `df`. The statistics are: **count, mean, std, min,max**
You get the following man page using the command `df.describe?`

```
Signature: df.describe(*cols)
Docstring:
Computes statistics for numeric and string columns.
```

```
This include count, mean, stddev, min, and max. If no columns are
given, this function computes statistics for all numerical or string columns.

.. note:: This function is meant for exploratory data analysis, as we make no
    guarantee about the backward compatibility of the schema of the resulting DataFrame.

>>> df.describe(['age']).show()
+-------+------------------+
|summary|               age|
+-------+------------------+
|  count|                 2|
|   mean|               3.5|
| stddev|2.1213203435596424|
|    min|                 2|
|    max|                 5|
+-------+------------------+
>>> df.describe().show()
+-------+------------------+-----+
|summary|               age| name|
+-------+------------------+-----+
|  count|                 2|    2|
|   mean|               3.5| null|
| stddev|2.1213203435596424| null|
|    min|                 2|Alice|
|    max|                 5|  Bob|
+-------+------------------+-----+

.. versionadded:: 1.3.1
File:      ~/spark-2.2.1-bin-hadoop2.7/python/pyspark/sql/dataframe.py
Type:      method
```

```
In [4]: df.describe().select('station','measurement').show()
```

```
+-----------+-----------+
|    station|measurement|
+-----------+-----------+
|      84199|      84199|
|       null|       null|
|       null|       null|
|USC00300015|       PRCP|
|USW00094794|       TOBS|
+-----------+-----------+
```

groupby and agg The method `.groupby(col)` groups rows according the value of the column `col`.

The method .agg(spec) computes a summary for each group as specified in spec

```
In [5]: df.groupby('measurement').agg({'year': 'min', 'station':'count'}).show()
```

```
+-----------+---------+--------------+
|measurement|min(year)|count(station)|
+-----------+---------+--------------+
|       TMIN|     1873|         13442|
|       TOBS|     1876|         10956|
|       TMAX|     1873|         13437|
|       SNOW|     1884|         15629|
|       SNWD|     1888|         14617|
|       PRCP|     1871|         16118|
+-----------+---------+--------------+
```

```
In [6]: # THis command will load the python module that defines the SQL functions
        #%load ls ~/spark-latest/python/pyspark/sql/functions.py
```

0.1.2 Using SQL queries on DataFrames

There are two main ways to manipulate DataFrames:

Imperative manipulation Using python methods such as .select and .groupby. * Advantage: order of operations is specified. * Disrdavantage : You need to describe both **what** is the result you want and **how** to get it.

Declarative Manipulation (SQL)

- Advantage: You need to describe only **what** is the result you want.
- Disadvantage: SQL does not have primitives for common analysis operations such as **covariance**

0.1.3 Using sql commands on a dataframe

Spark supports a subset of the Hive SQL query language.
For example, You can use Hive select syntax to select a subset of the rows in a dataframe.
To use sql on a dataframe you need to first register it as a TempTable.
for variety, we are using here a small dataframe loaded from a JSON file.

```
In [7]: # when loading json files you can specify either a single file or a directory containi
        path = "../../Data/people.json"

        # Create a DataFrame from the file(s) pointed to by path
        people = sqlContext.read.json(path)
        #print('people is a',type(people))
        # The inferred schema can be visualized using the printSchema() method.
        people.show()
```

```
+----+-------+
| age|   name|
+----+-------+
|null|Michael|
|  30|   Andy|
|  19| Justin|
+----+-------+
```

```
In [8]: people.printSchema()
```

```
root
 |-- age: long (nullable = true)
 |-- name: string (nullable = true)
```

```
In [9]: # Register this DataFrame as a table.
        people.registerTempTable("people")

        # SQL statements can be run by using the sql methods provided by sqlContext
        teenagers = sqlContext.sql("SELECT name FROM people WHERE age >= 13 AND age <= 19")
        for each in teenagers.collect():
            print(each[0])
```

```
Justin
```

Counting the number of occurances of each measurement, imparatively

```
In [10]: L=df.groupBy('measurement').count().collect()
         #L is a list (collected DataFrame)

In [11]: D=[(e.measurement,e['count']) for e in L]
         sorted(D,key=lambda x:x[1], reverse=False)[:6]

Out[11]: [('TOBS', 10956),
          ('TMAX', 13437),
          ('TMIN', 13442),
          ('SNWD', 14617),
          ('SNOW', 15629),
          ('PRCP', 16118)]
```

Counting the number of occurances of each measurement, declaratively.

```
In [12]: sqlContext.registerDataFrameAsTable(df,'weather') #using older sqlContext instead of
```

```
In [13]: query="""
         SELECT measurement,COUNT(measurement) AS count,
                            MIN(year) AS MinYear
         FROM weather
         GROUP BY measurement
         ORDER BY count
         """
         print(query)
         sqlContext.sql(query).show()
```

```
SELECT measurement,COUNT(measurement) AS count,
                   MIN(year) AS MinYear
FROM weather
GROUP BY measurement
ORDER BY count

+-----------+-----+-------+
|measurement|count|MinYear|
+-----------+-----+-------+
|       TOBS|10956|   1876|
|       TMAX|13437|   1873|
|       TMIN|13442|   1873|
|       SNWD|14617|   1888|
|       SNOW|15629|   1884|
|       PRCP|16118|   1871|
+-----------+-----+-------+
```

Performing a map command

- In order to perform a `map` on a dataframe, you first need to transform it into an RDD.
- **Not** the recommended way. Better way is to use built-in sparkSQL functions.
- Or register new ones (Advanced).

```
In [14]: def find_century(row):
             if row.Year < 1900:
                 return '19th'
             elif row.Year <2000:
                 return '20th'
             elif row.Year <2010:
                 return '21st'
             else:
                 return 'possibly_bad_data'
```

```
In [15]: df.rdd.map(find_century).take(5)

Out[15]: ['20th', '20th', '20th', '20th', '20th']
```

Aggregations

- **Aggregation** can be used, in combination with built-in sparkSQL functions to compute statistics of a dataframe.
- computation will be fast thanks to combined optimzations with database operations.
- A partial list : `count(), approx_count_distinct(), avg(), max(), min()`
- Of these, the interesting one is `approx_count_distinct()` which uses sampling to get an approximate count fast.
- The gory details

```
In [16]: import pyspark.sql.functions as F # used here just for show.
```

```
In [17]: df.agg({'station':'approx_count_distinct'}).show()
```

```
+------------------------------+
|approx_count_distinct(station)|
+------------------------------+
|                           339|
+------------------------------+
```

Approximate Quantile

- Suppose we want to partition the years into 10 ranges
- such that in each range we have approximately the same number of records.
- The method `.approxQuantile` will use a sample to do this for us.

```
In [18]: print('with accuracy 0.1: ',df.approxQuantile('year', [0.1*i for i in range(1,10)], 0
         print('with accuracy 0.01: ',df.approxQuantile('year', [0.1*i for i in range(1,10)], 
```

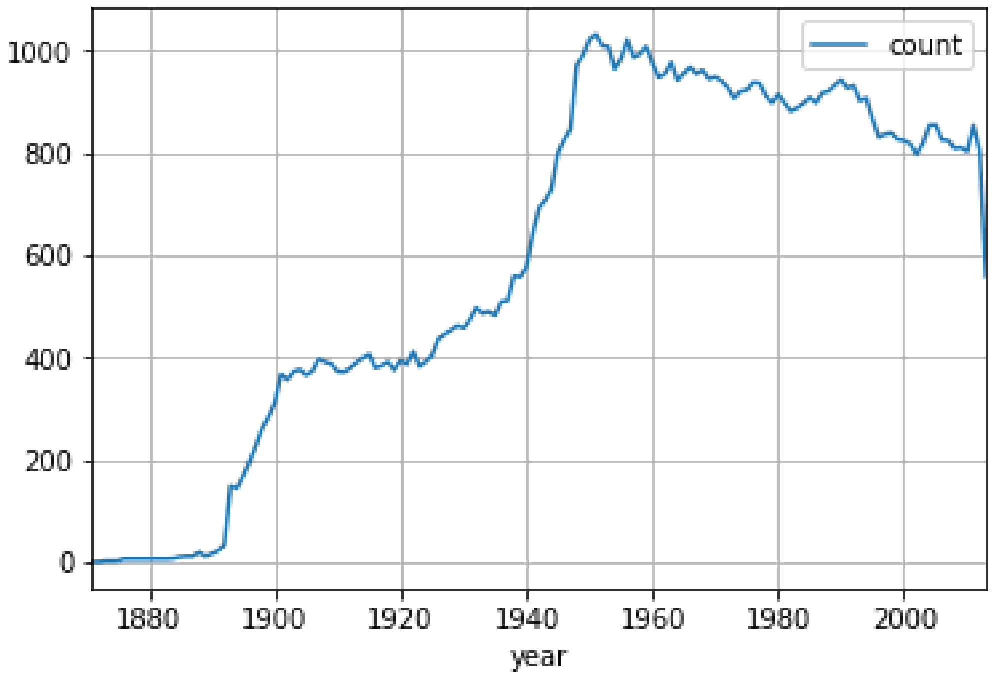
```
with accuracy 0.1:  [1871.0, 1945.0, 1949.0, 1965.0, 1972.0, 1978.0, 1984.0, 1988.0, 2013.0]
with accuracy 0.01:  [1917.0, 1936.0, 1949.0, 1957.0, 1966.0, 1975.0, 1984.0, 1993.0, 2003.0]
```

Lets collect the exact number of rows for each year This will take much longer than ApproxQuantile on a large file

```
In [19]: # Lets collect the exact number of rows for each year ()
         query='SELECT year,COUNT(year) AS count FROM weather GROUP BY year ORDER BY year'
         print(query)
         counts=sqlContext.sql(query)
         print('counts is ',counts)
```

```
SELECT year,COUNT(year) AS count FROM weather GROUP BY year ORDER BY year
counts is  DataFrame[year: int, count: bigint]
```

In [20]:
```
import pandas as pd
A=counts.toPandas() # Transform a spark Dataframe to a Pandas Dataframe
A.plot.line('year','count')
grid()
```



0.1.4 Reading rows selectively

Suppose we are only interested in snow measurements. We can apply an SQL query directly to the parquet files. As the data is organized in columnar structure, we can do the selection efficiently without loading the whole file to memory.

Here the file is small, but in real applications it can consist of hundreds of millions of records. In such cases loading the data first to memory and then filtering it is very wasteful.

In [21]:
```
data_dir='../../Data'
query="""SELECT station,measurement,year
FROM parquet.`%s.parquet`
WHERE measurement=\"SNOW\" """%(weather_dir+'/'+zip_file[:-4])
print(query)
df2 = sqlContext.sql(query)
print(df2.count(),df2.columns)
df2.show(5)
```

```
SELECT station,measurement,year
FROM parquet.`/home/jovyan/work/Sections/Data/Weather/NY.parquet`
WHERE measurement="SNOW"
```

```
15629 ['station', 'measurement', 'year']
+-----------+-----------+----+
|    station|measurement|year|
+-----------+-----------+----+
|USC00303452|       SNOW|1903|
|USC00303452|       SNOW|1904|
|USC00303452|       SNOW|1905|
|USC00303452|       SNOW|1906|
|USC00303452|       SNOW|1907|
+-----------+-----------+----+
only showing top 5 rows
```

0.2 Summary

- Dataframes can be manipulated decleratively, which allows for more optimization.
- Dataframes can be stored and retrieved from Parquet files.
- It is possible to refer directly to a parquet file in an SQL query.
- See you next time!

0.3 References

- For an introduction to Spark SQL and Dataframes see: Spark SQL, DataFrames
- Also spark-dataframe-and-operations from analyticsvidhya.com

For complete API reference see * SQL programming guide For Java, Scala and Python (Implementation is first in Scala and Python, later pyspark) * pyspark API for the DataFrame class * pyspark API for the pyspark.sql module