SDSC Summer Institute
Scalable Machine Learning

SDSC SAN DIEGO SUPERCOMPUTER CENTER

UC San Diego

PySpark Hands-On

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Overview

- **Weather station measurements**
- **Data Exploration**
  - Load into Spark DataFrame
  - Describe schema
  - Show summary statistics
  - Calculate correlation between features
- **Cluster to identify different weather patterns**
  - Spark k-means
  - Parallel plots

Get Latest from Github Repo

- **If haven't cloned Summer Institute repo**
  - git clone <URL>
- **If already cloned Summer Institute repo**
  - git pull <URL>
- **<URL>**

https://github.com/sdsc/sdsc-summer-institute-2019

Server Setup

- **Go to pyspark directory**

  cd <SI2019_dir>/datasci3_scalable_machine_learning/spark/pyspark

- **Request compute node**
  - *sbatch --res=SI2019DAY4 spark.slrm*

Dataset Description

- **Measurements from weather station on Mt. Woodson, San Diego**
- **Air temperature, humidity, wind speed, wind direction, etc.**
- **Three years of data: Sep. 2011 - Sep. 2014**
- ***minute_weather.csv***
  - measurement every minute
- ***daily_weather.csv***
  - aggregated measurements

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  - aggregated measurements

Clustering

Data Exploration

Server Setup (cont.)

- **Check queue**
  - *squeue –u $USER*
  - Note compute node name (e.g., comet-14-43)
    - 18223060 compute spark <user> R 1:19 2 comet-14-[43-49]
- **Check that Jupyter Notebook has started**
  - ls –l spark*.out

-rw-r--r-- 1 <user> sds148 840 Aug 4 09:32 spark.18317995.comet-14-43.out

Should be > 0

  - tail spark*.out
  - Copy token
    - *Copy/paste this URL into your browser when you connect for the first time, to login with a token:*

      http://localhost:8888/?token=395fe3d456cb951e34ef125adf27e6a62

Browser Setup

- **In browser, type:**
  - comet-xx-xx.sdsc.edu:8888
  - Paste token

comet-14-43.sdsc.edu:8888/login?next=%2Ftree%3F

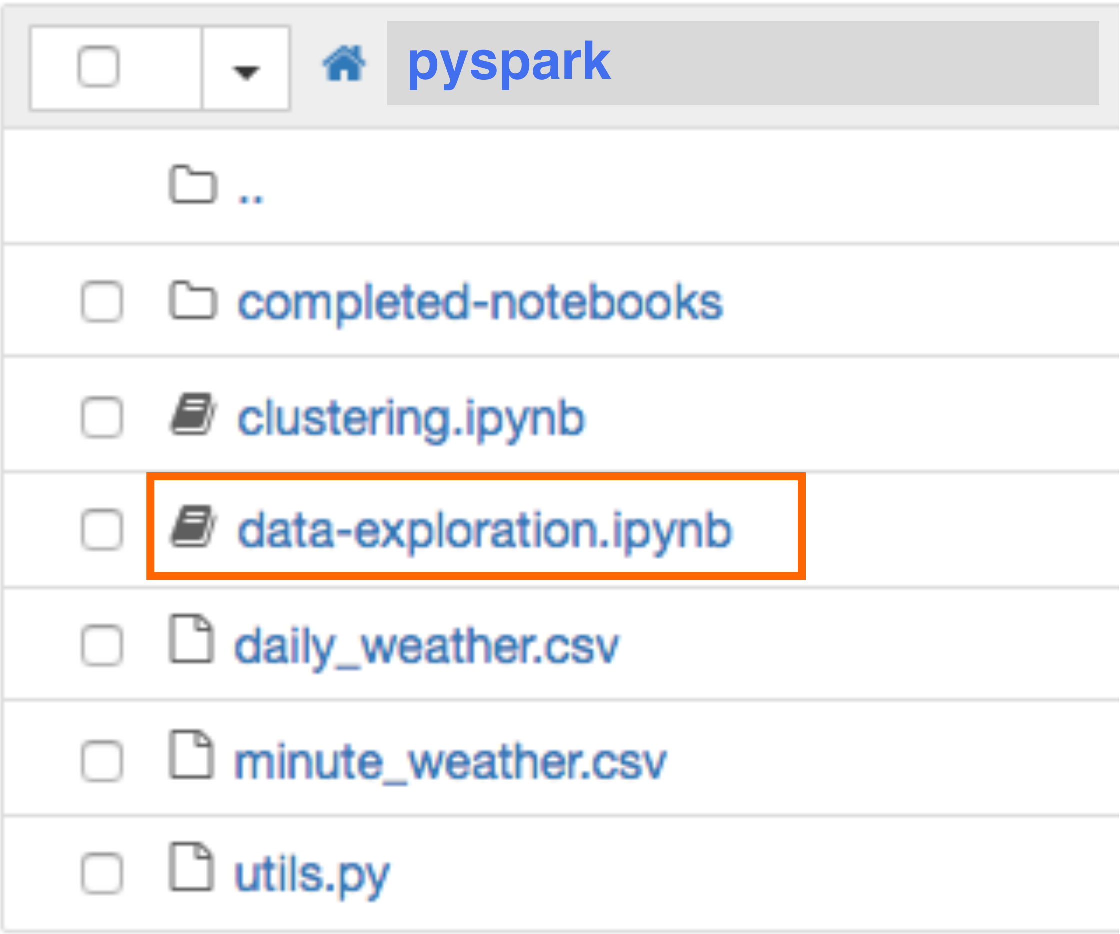
jupyter

Password or token: •• Log in

Token authentication is enabled

If no password has been configured, you need to open the notebook server with its login token in the URL, or paste it above. This requirement will be lifted if you enable a password.

Open Data Exploration Notebook



Load Data into Spark DataFrame

- Start the Spark session
- Read the daily weather data into a Spark DataFrame

```
# Load data into Spark dataframe

inputfile = <<FILL-IN>>
df = spark.read.load(inputfile, format="csv", inferSchema="true", header="true")
```

- Replace with data filename (with quotes):
  “daily_weather.csv”

Examine Schema

df.printSchema()

```
root
 |-- number: integer (nullable = true)
 |-- air_pressure_9am: double (nullable = true)
 |-- air_temp_9am: double (nullable = true)
 |-- avg_wind_direction_9am: double (nullable = true)
 |-- avg_wind_speed_9am: double (nullable = true)
 |-- max_wind_direction_9am: double (nullable = true)
 |-- max_wind_speed_9am: double (nullable = true)
 |-- rain_accumulation_9am: double (nullable = true)
 |-- rain_duration_9am: double (nullable = true)
 |-- relative_humidity_9am: double (nullable = true)
 |-- relative_humidity_3pm: double (nullable = true)
```

Show Summary Statistics

df.describe().toPandas().transpose()

	0	1	2	3	4
summary	count	mean	stddev	min	max
number	1095	547.0	316.24357700987383	0	1094
air_pressure_9am	1092	918.8825513138094	3.184161180386833	907.9900000000024	929.3200000000012
air_temp_9am	1090	64.93300141287072	11.175514003175877	36.752000000000685	98.90599999999992
avg_wind_direction_9am	1091	142.2355107005759	69.13785928889189	15.500000000000046	343.4
avg_wind_speed_9am	1092	5.50828424225493	4.5528134655317185	0.69345139999974	23.554978199999763
max_wind_direction_9am	1092	148.95351796516923	67.23801294602953	28.89999999999991	312.19999999999993
max_wind_speed_9am	1091	7.019513529175272	5.598209170780958	1.1855782000000479	29.84077959999996
rain_accumulation_9am	1089	0.20307895225211126	1.5939521253574893	0.0	24.01999999999907
rain_duration_9am	1092	294.1080522756142	1598.0787786601481	0.0	17704.0
relative_humidity_9am	1095	34.24140205923536	25.472066802250055	6.090000000001012	92.6200000000002
relative_humidity_3pm	1095	35.34472714825898	22.524079453587273	5.3000000000006855	92.2500000000003

Number of Rows

df.count()

1095

First Two Rows

df.show(2)

```
+------+----------------+----------------+---------------------+------------------+---------------------+------------------+--------------------+----------------+--------------------+--------------------+
|number|    air_pressure_9am|    air_temp_9am|avg_wind_direction_9am|avg_wind_speed_9am|max_wind_direction_9am|max_wind_speed_9am|rain_accumulation_9am|rain_duration_9am|relative_humidity_9am|relative_humidity_3pm|
+------+----------------+----------------+---------------------+------------------+---------------------+------------------+--------------------+----------------+--------------------+--------------------+
|     0|918.0600000000087|74.82200000000041|               271.1|2.080354199999768|    295.39999999999986|2.863283199999908|                 0.0|             0.0|    42.42000000000046|   36.160000000000494|
|     1|917.3476881177097|71.40384263106537|    101.93517935618371|2.443009215734023|    140.47154847112498|3.5333236016106238|                 0.0|             0.0|   24.328697291802207|     19.4265967985621|
+------+----------------+----------------+---------------------+------------------+---------------------+------------------+--------------------+----------------+--------------------+--------------------+
only showing top 2 rows
```

Number and Names of Columns

df.columns

['number', 'air_pressure_9am', 'air_temp_9am', 'avg_wind_direction_9am', 'avg_wind_speed_9am', 'max_wind_direction_9am', 'max_wind_speed_9am', 'rain_accumulation_9am', 'rain_duration_9am', 'relative_humidity_9am', 'relative_humidity_3pm’]

len(df.columns)

11

Correlation Between Air Temperature and Relative Humidity

df.stat.corr("air_temp_9am", "relative_humidity_9am")

-0.536670…

Show Plots in Notebook

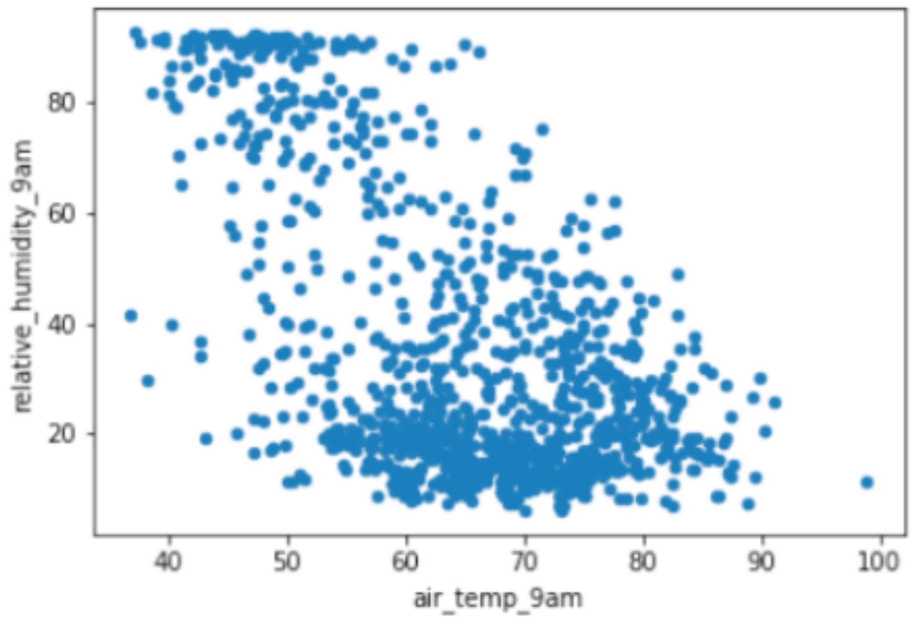
%matplotlib inline

Scatter Plot of Air Temperature vs Humidity

df.select('air_temp_9am', 'relative_humidity_9am')

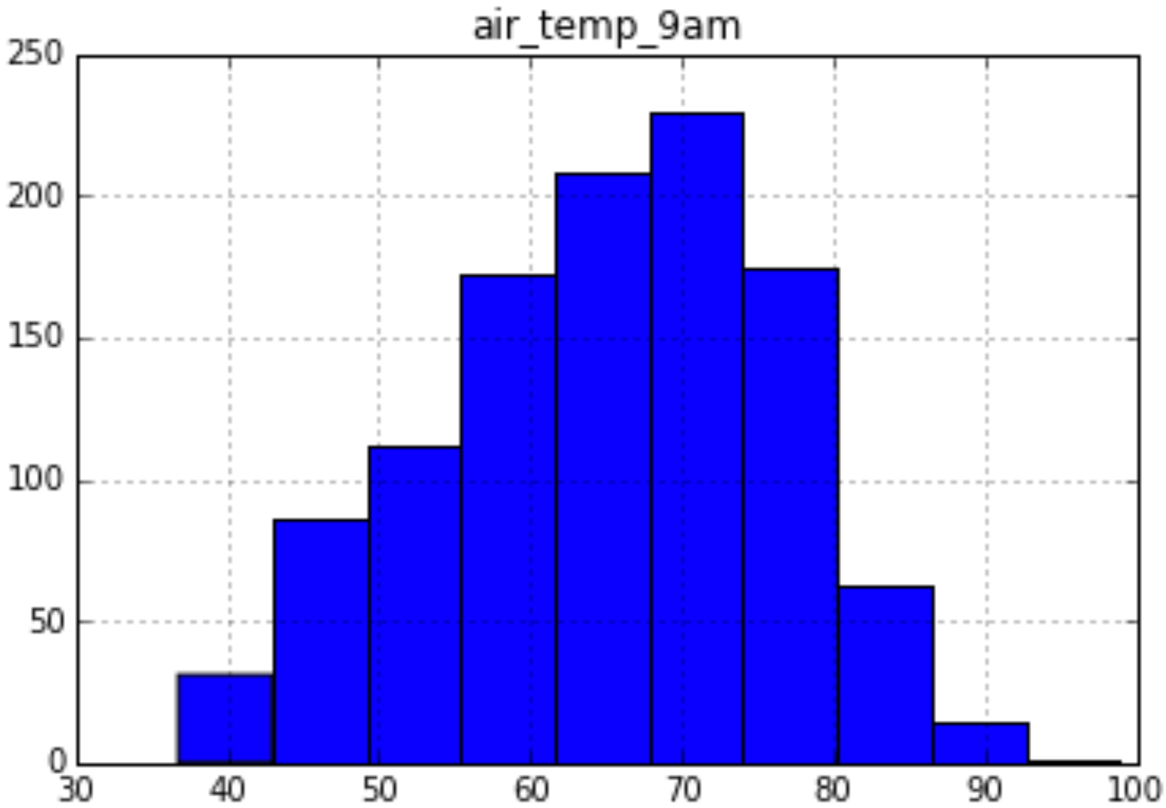
.toPandas()

.plot (kind='scatter', x='air_temp_9am',
y='relative_humidity_9am')



Histogram of Air Temperature

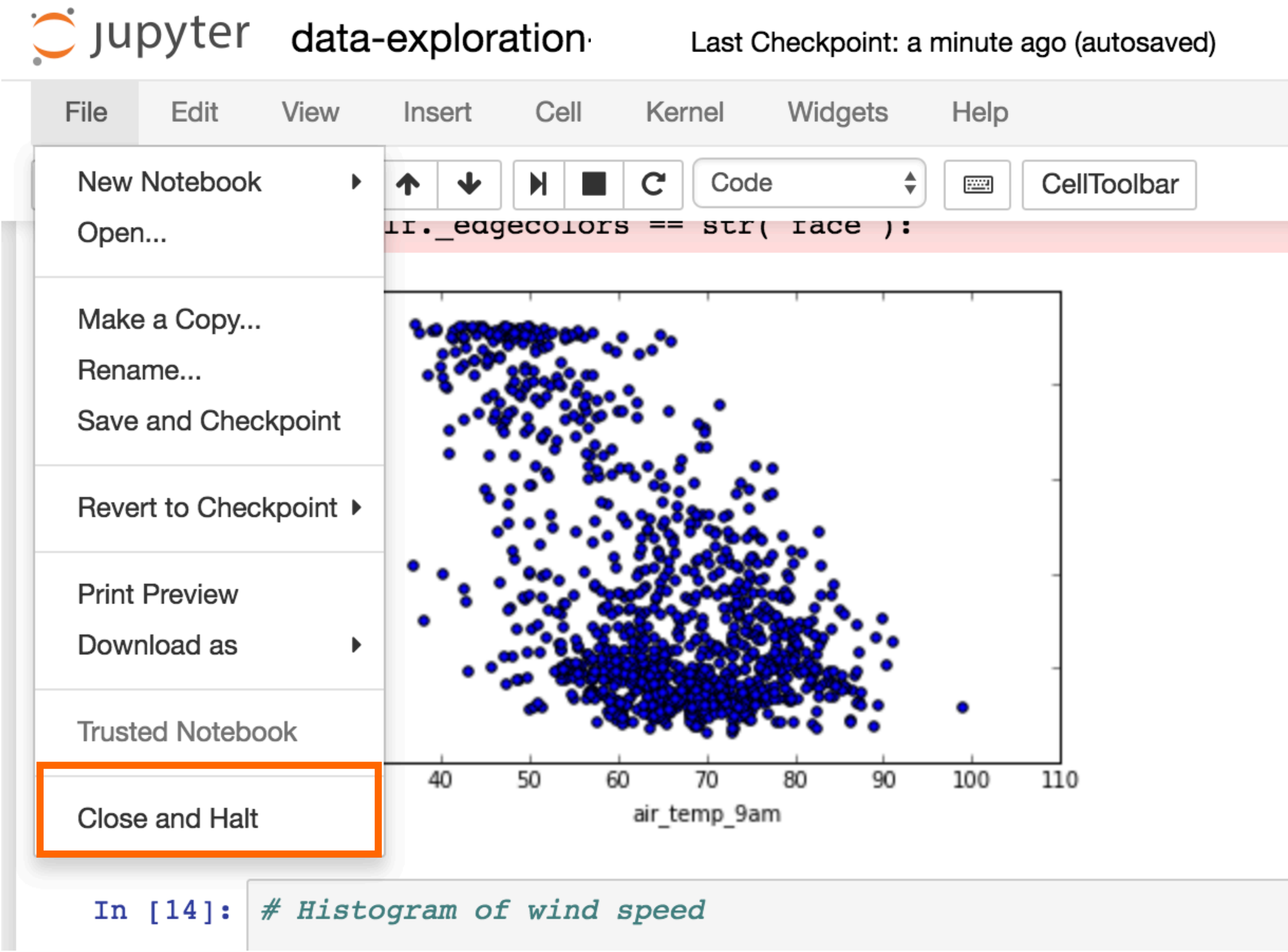
df.select('air_temp_9am').toPandas().hist()



Stop Spark Session

spark.stop()

Save and Exit Notebook



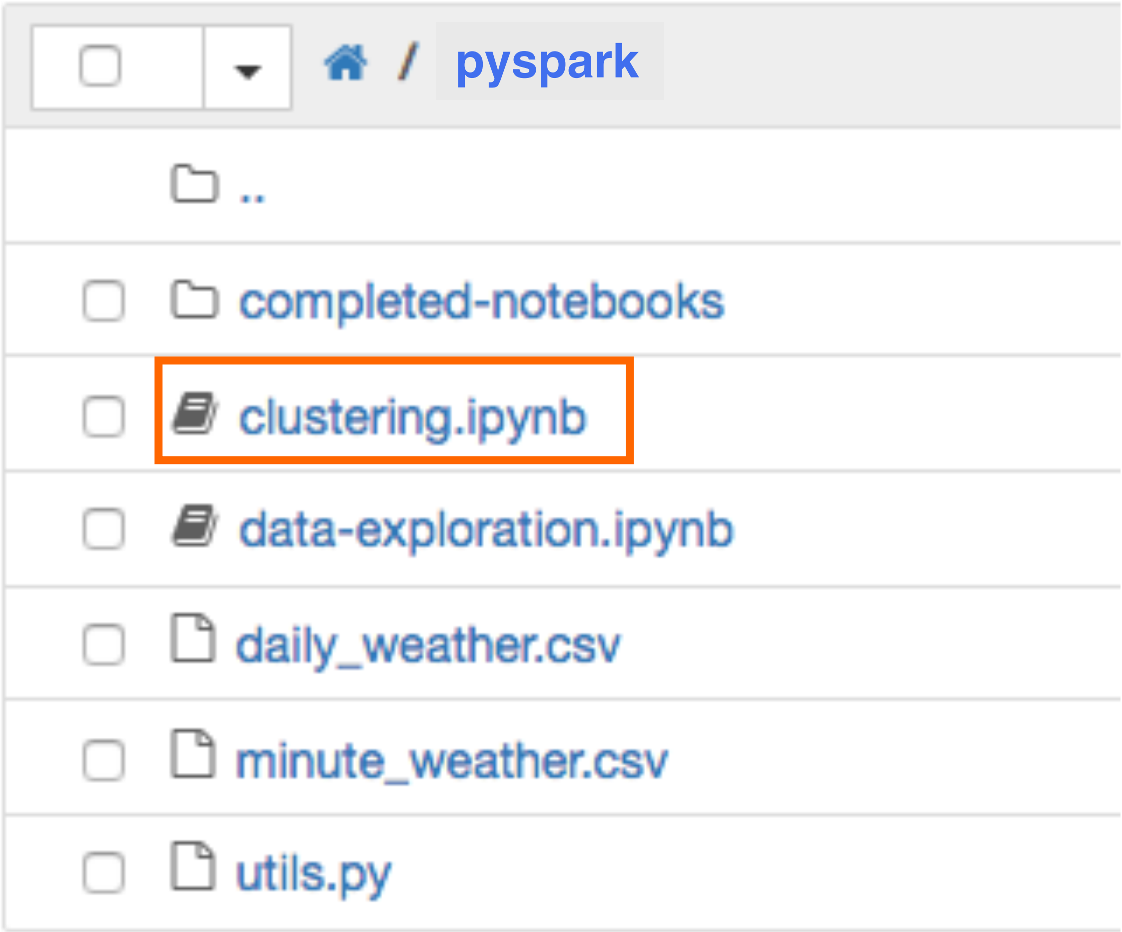
Clustering to Identify Santa Ana Conditions

- **Strong, dry winds in Southern California**
  - wind speed > 30mph
  - wind direction between 10 & 110 degrees (from east)
  - relative humidity < 10%
- **Extreme fire danger**
  - May 2014, swarm of 14 wildfires in San Diego County
  - 2008, Witch Fire, ~200,000 acres
  - 2003, Cedar Fire, ~280,000 acres

Data

- **In terminal**
  - cd /home/<user>/<SI2019>/datasci3_scalable_machine_learning/spark/pyspark
  - gunzip minute_weather.csv.gz

Open Clustering Notebook



Import Modules & Start Spark Session

```
# Import modules

import pyspark
from pyspark.ml.clustering import KMeans
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.feature import StandardScaler
import utils
%matplotlib inline
```

```
# Start Spark session

from pyspark.sql import SparkSession

spark = SparkSession.builder.getOrCreate()
```

Load Modules & Minute Weather Data

```
# Load minute weather data

inputfile = <FILL-IN>>
df = spark.read.load (inputfile, format="csv", inferSchema="true", header="true")
```

- Replace with data filename (with quotes):
  - “minute_weather.csv”

Examine Schema

df.printSchema()

```
root
 |-- rowID: integer (nullable = true)
 |-- hpwren_timestamp: timestamp (nullable = true)
 |-- air_pressure: double (nullable = true)
 |-- air_temp: double (nullable = true)
 |-- avg_wind_direction: double (nullable = true)
 |-- avg_wind_speed: double (nullable = true)
 |-- max_wind_direction: double (nullable = true)
 |-- max_wind_speed: double (nullable = true)
 |-- min_wind_direction: double (nullable = true)
 |-- min_wind_speed: double (nullable = true)
 |-- rain_accumulation: double (nullable = true)
 |-- rain_duration: double (nullable = true)
 |-- relative_humidity: double (nullable = true)
```

Count Rows and Filter Data

- **Count rows**

  df.count()

  = 1587257

Filter data

filteredDF = df.filter((df.rowID % 100) == 0)

filteredDF.count()

= 15873

Show Summary Statistics

filteredDF.describe().toPandas().transpose()

	0	1	2	3	4
summary	count	mean	stddev	min	max
rowID	15873	793600.0	458228.4746717515	0	1587200
air_pressure	15873	916.8291627291587	3.0517222151797943	905.1	929.4
air_temp	15873	61.854689094688936	11.83541379082148	32.36	96.44
avg_wind_direction	15870	161.2875236294896	95.3131612965649	0.0	359.0
avg_wind_speed	15870	2.7928040327662296	2.0705061984600173	0.1	20.1
max_wind_direction	15870	162.70094517958412	92.26960112663167	0.0	359.0
max_wind_speed	15870	3.41462507876495	2.428906406812135	0.1	20.9
min_wind_direction	15870	166.64429741650915	97.82483630682509	0.0	359.0
min_wind_speed	15870	2.1522684310018896	1.7581135042599596	0.0	19.5

Drop Samples with Null Values

workingDF = filteredDF.na.drop()
workingDF.count()

= 15869

Create Feature Vector

```
featuresUsed = ['air_pressure', 'air_temp', 'avg_wind_direction', 'avg_wind_speed',
        'max_wind_speed','relative_humidity']
assembler = VectorAssembler(inputCols=featuresUsed, outputCol="features_unscaled")
assembled = assembler.transform(workingDF)
```

Scale Data

```
scaler = StandardScaler(inputCol="features_unscaled", outputCol="features", withStd=True,
scalerModel = scaler.fit(assembled)
scaledData = scalerModel.transform(assembled)
```

Use One-third Data for Elbow Plot

```
# Use one-third data for elbow plot

scaledData = scaledData.select("features", "rowID")

elbowset = scaledData.filter((scaledData.rowID % 3) == 0).select("features")
elbowset.persist()
elbowset.count()
```

```
5289
```

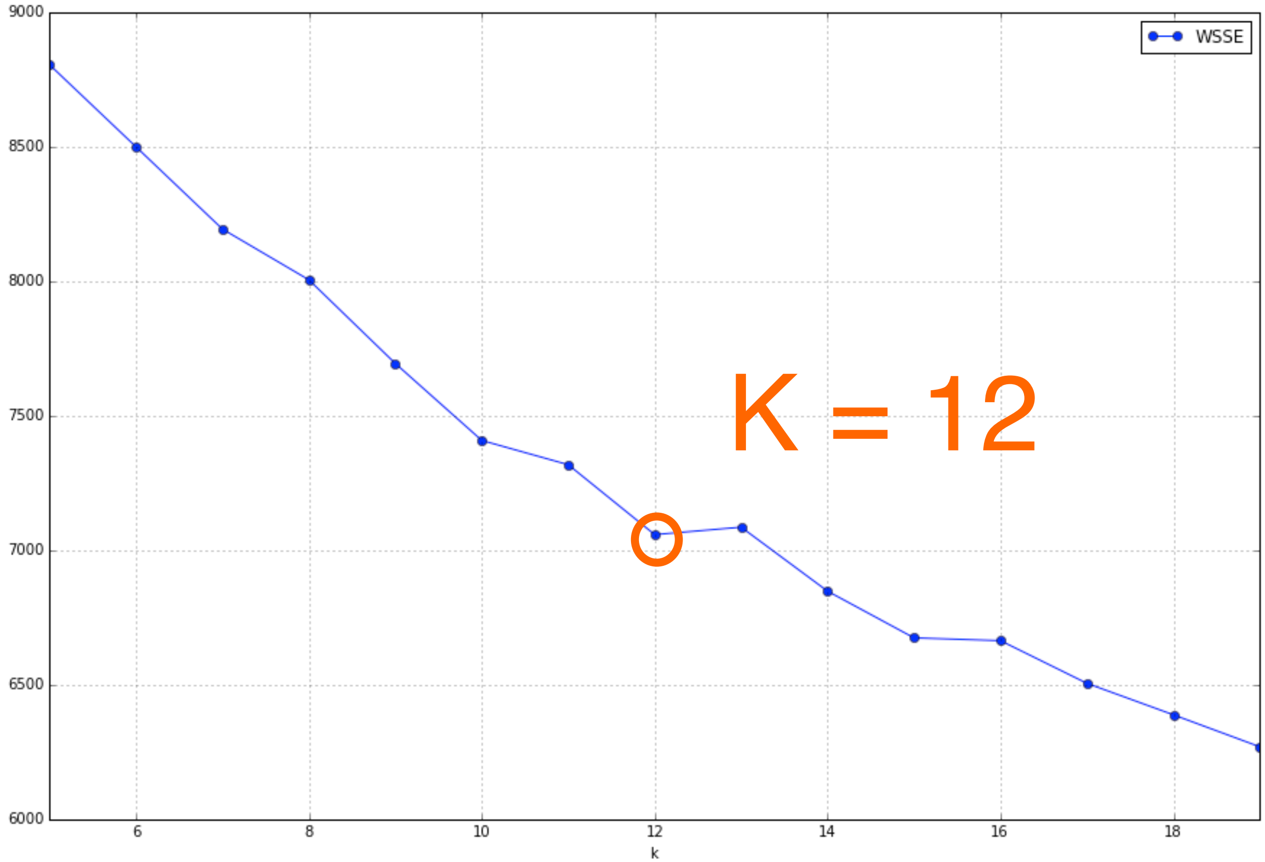
Generate Clusters for Elbow Plot

clusters = range(5, 20)
wsseList = utils.elbow(elbowset, clusters)

```
Training for cluster size 5
......................WSSE = 8804.118354684928
Training for cluster size 6
......................WSSE = 8525.400895523859
Training for cluster size 7
......................WSSE = 8123.225352699479
Training for cluster size 8
......................WSSE = 7876.960906428347
Training for cluster size 9
......................WSSE = 7887.3819888393555
Training for cluster size 10
......................WSSE = 7554.953661841033
Training for cluster size 11
......................WSSE = 7294.20690385911
Training for cluster size 12
```

Show Elbow Plot

utils.elbow_plot(wsseList, clusters)



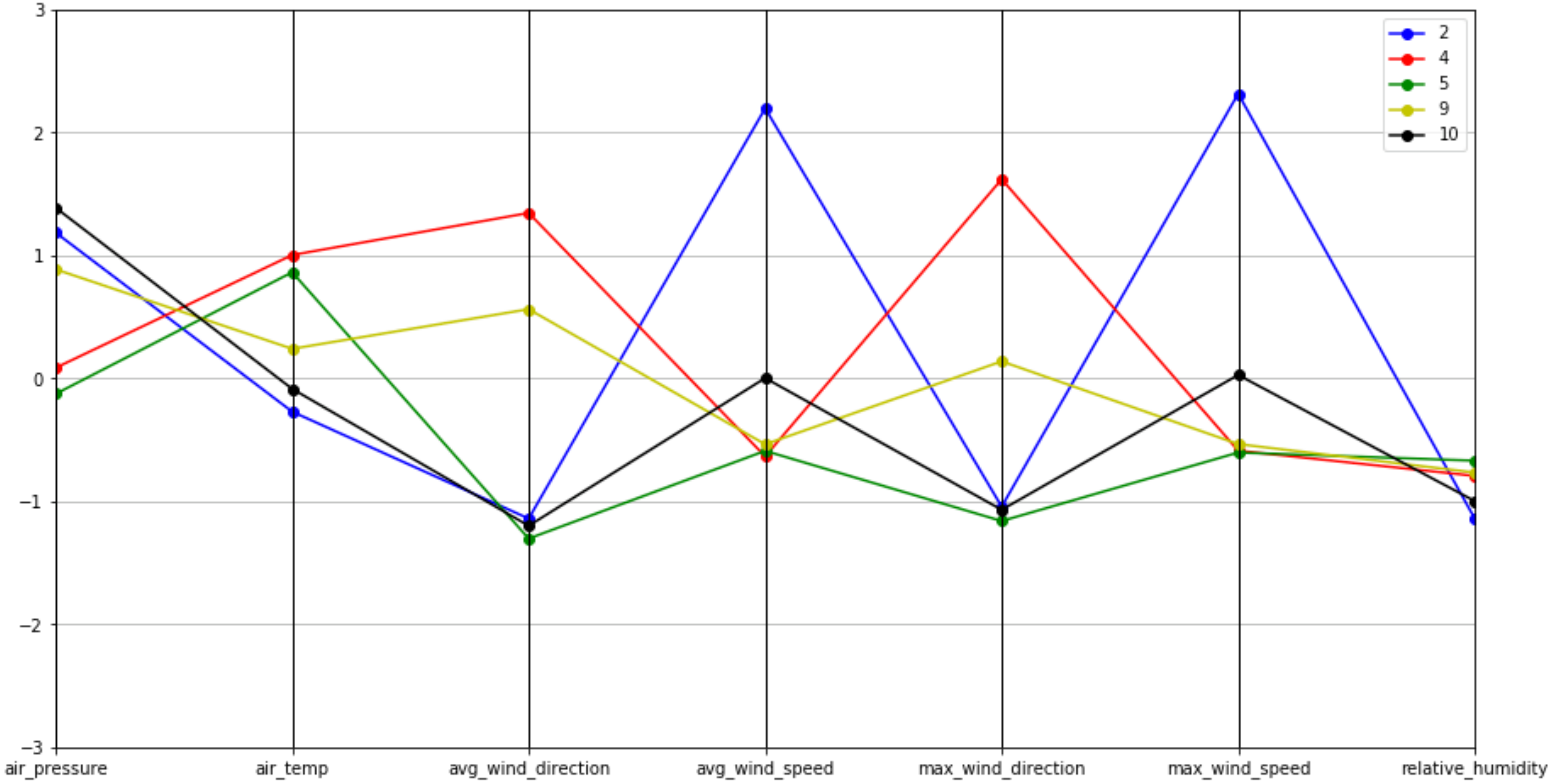
Run KMeans for k = 12 and Extract Cluster Centers

```
# Run KMeans for k = 12

scaledDataFeat = scaledData.select("features")
scaledDataFeat.persist()

kmeans = KMeans(k=12, seed=1)
model = kmeans.fit(scaledDataFeat)
transformed = model.transform(scaledDataFeat)
```

```
# Compute cluster centers

centers = model.clusterCenters()
P = utils.pd_centers(featuresUsed, centers)
centers
```

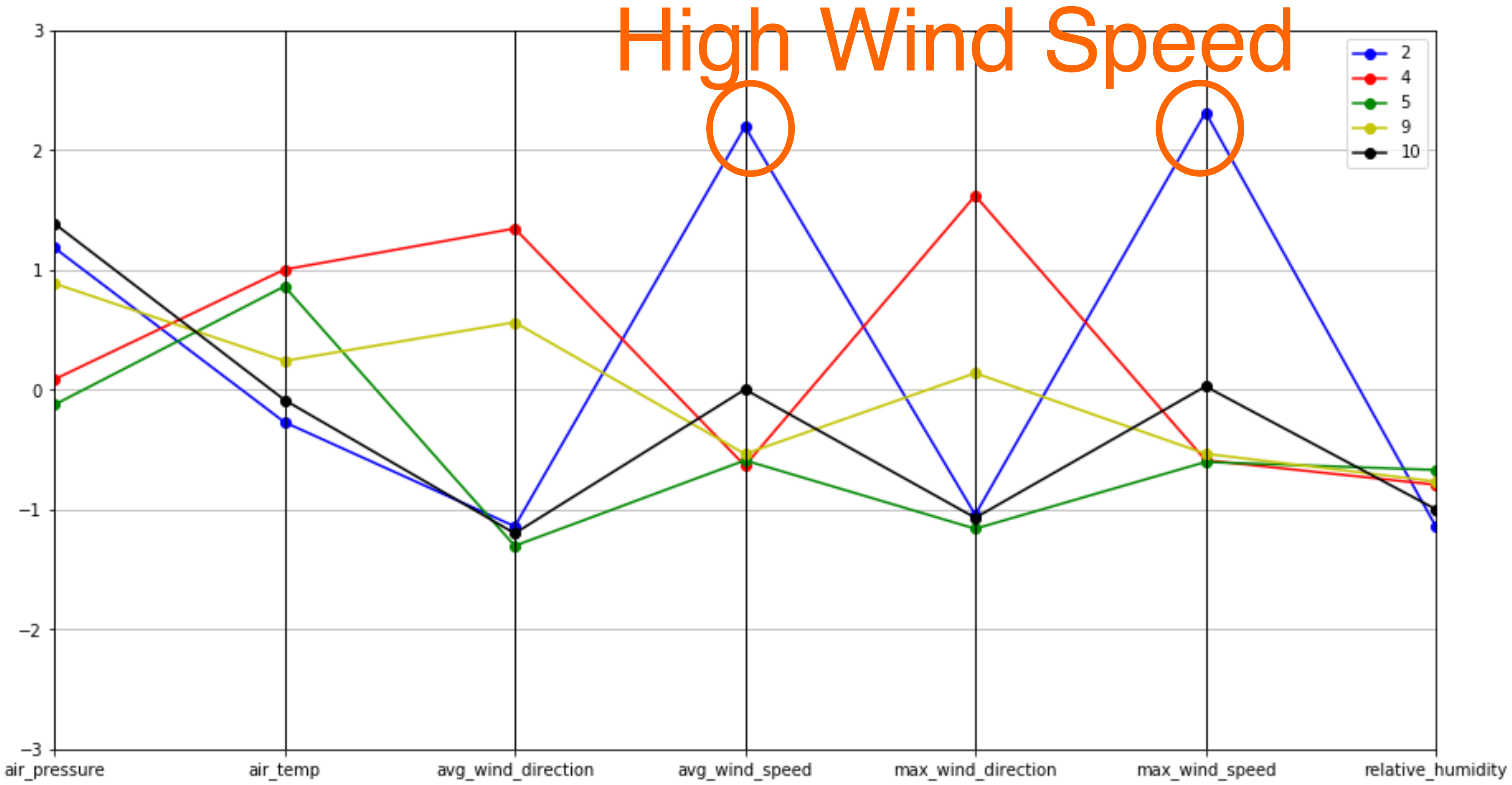
Parallel Plot: Dry Days

utils.parallel_plot(P[P['relative_humidity'] < -0.5], P)



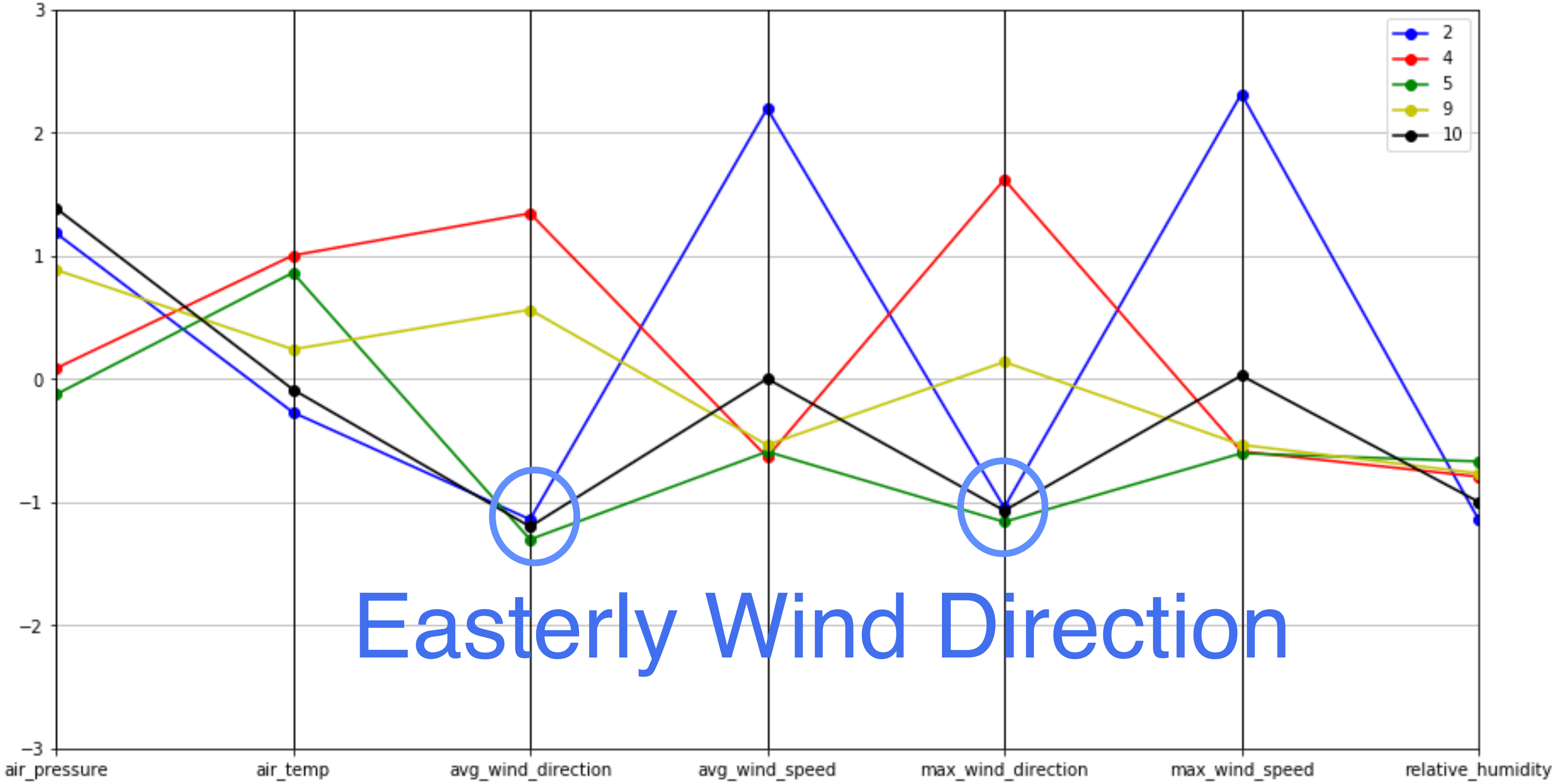
Parallel Plot: Dry Days

utils.parallel_plot(P[P['relative_humidity'] < -0.5], P)



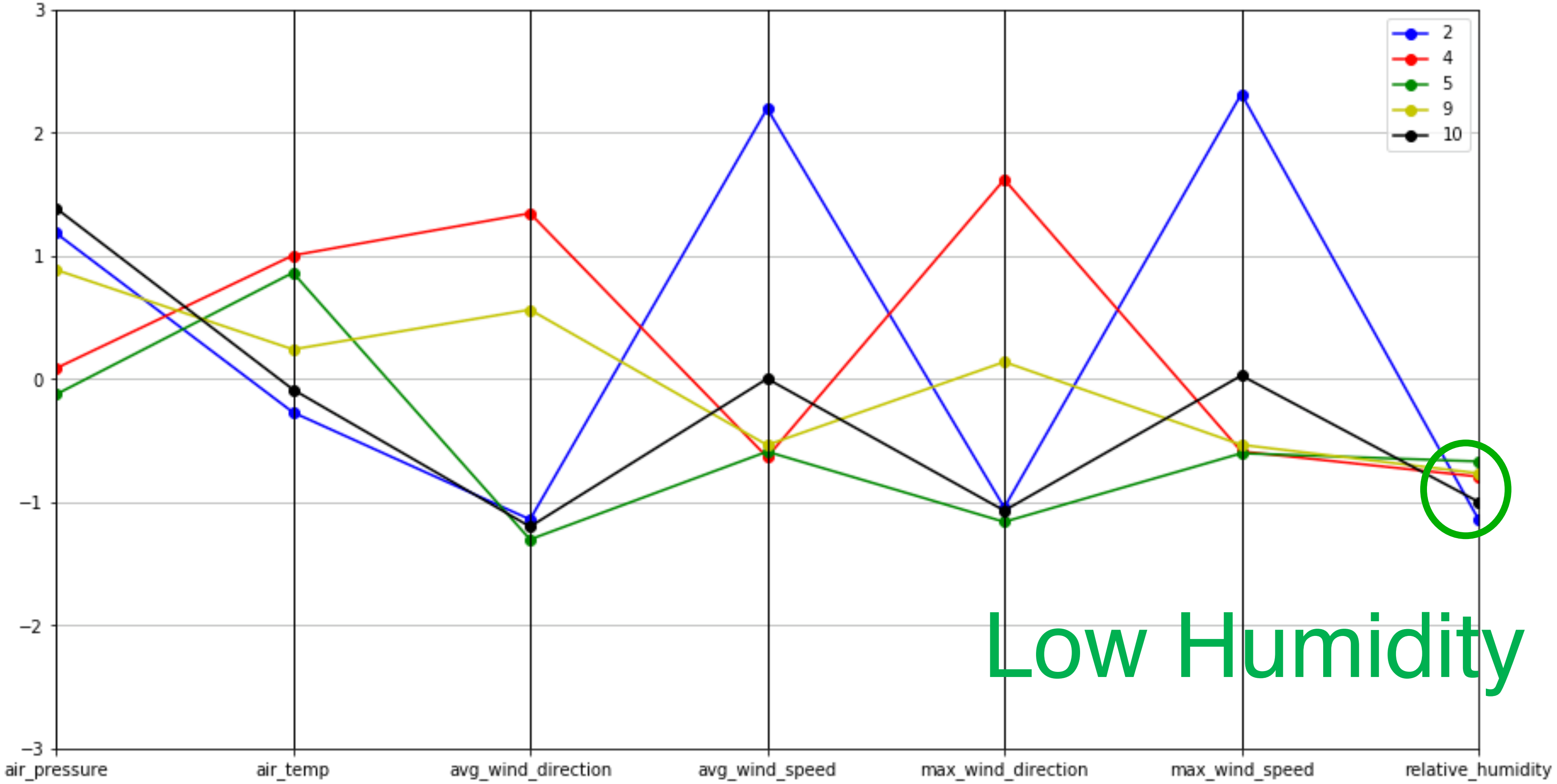
Parallel Plot: Dry Days

utils.parallel_plot(P[P['relative_humidity'] < -0.5], P)



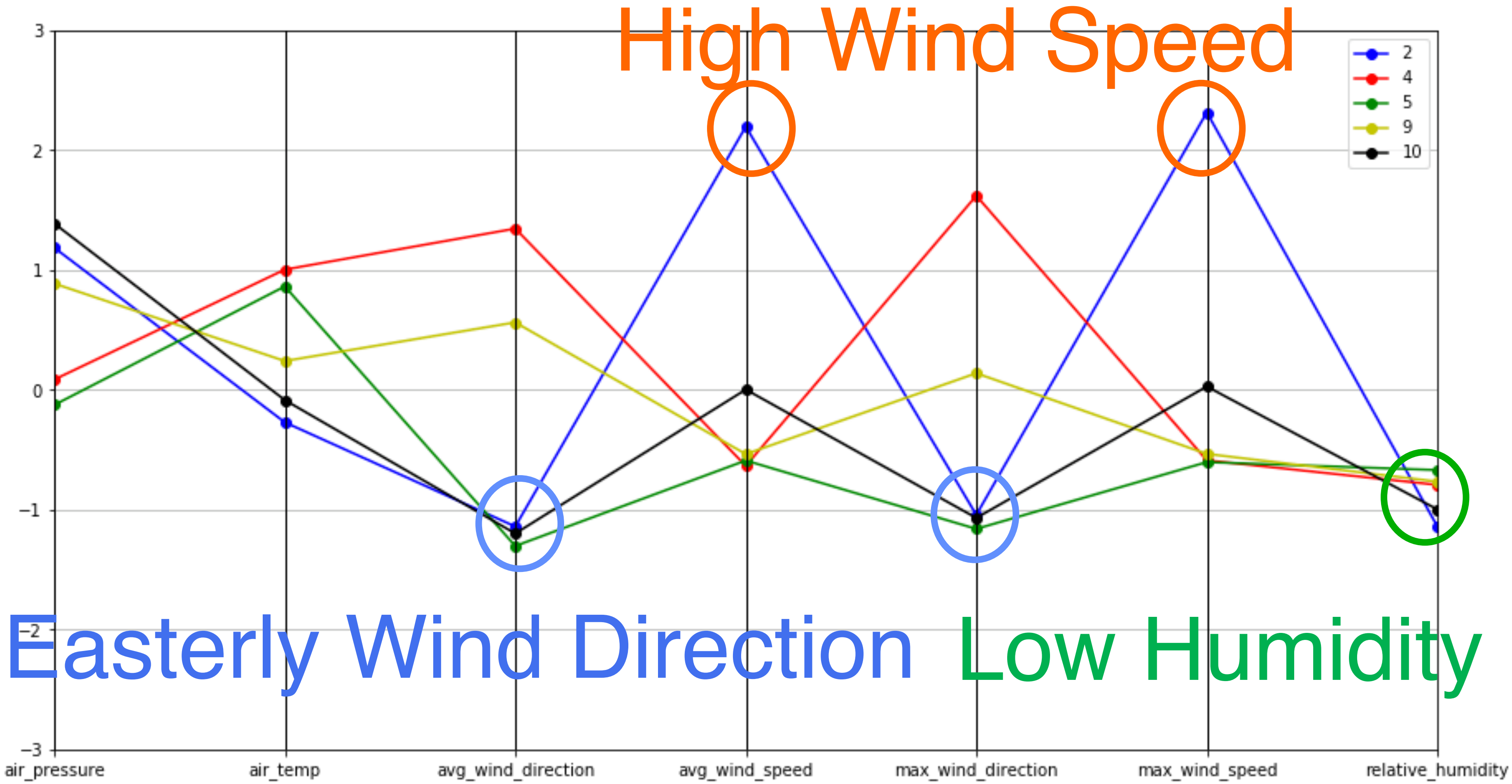
Parallel Plot: Dry Days

utils.parallel_plot(P[P['relative_humidity'] < -0.5], P)



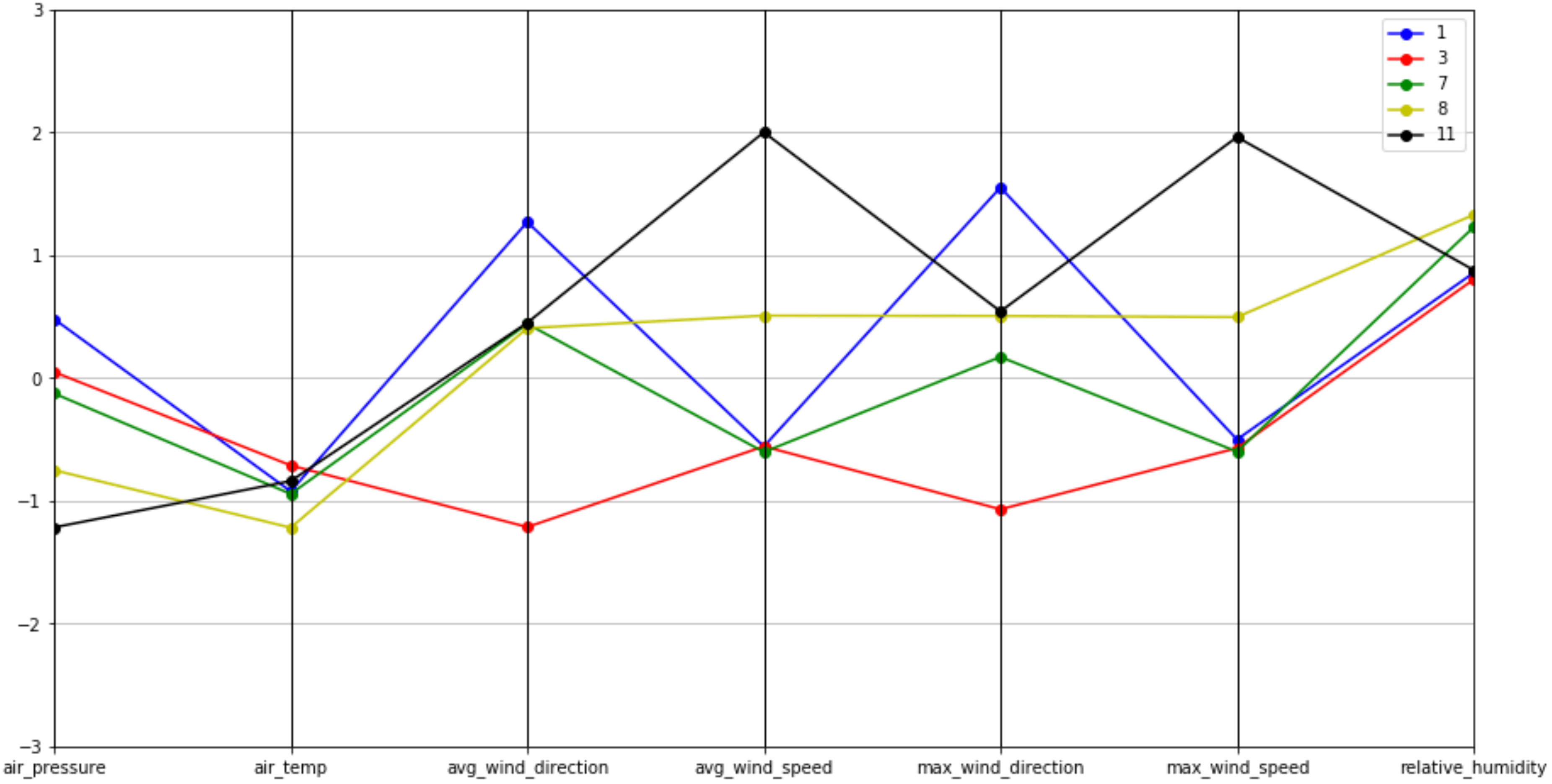
Parallel Plot: Dry Days

utils.parallel_plot(P[P['relative_humidity'] < -0.5], P)



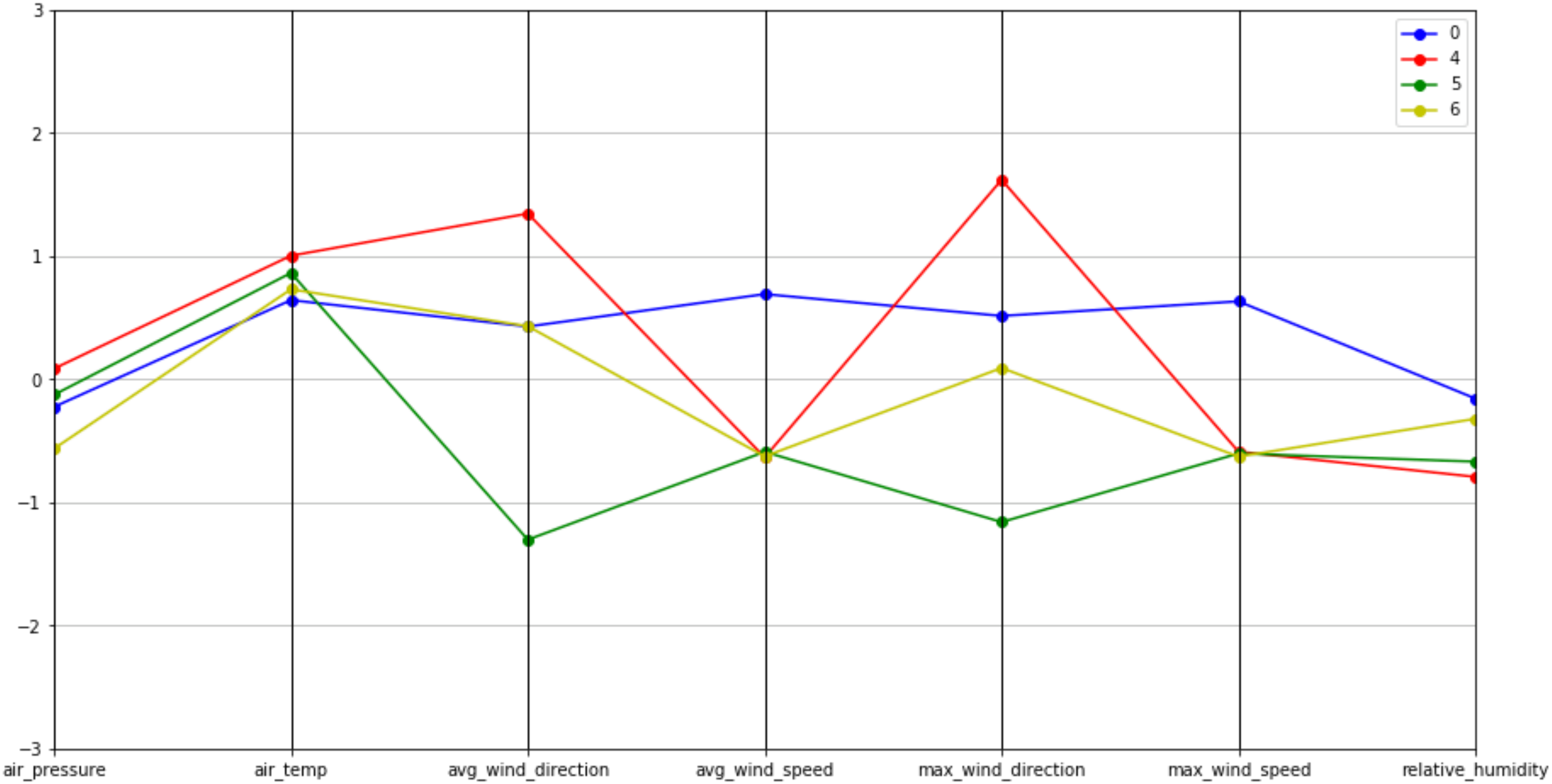
Parallel Plot: Humid Days

utils.parallel_plot(P[P['relative_humidity'] > 0.5], P)



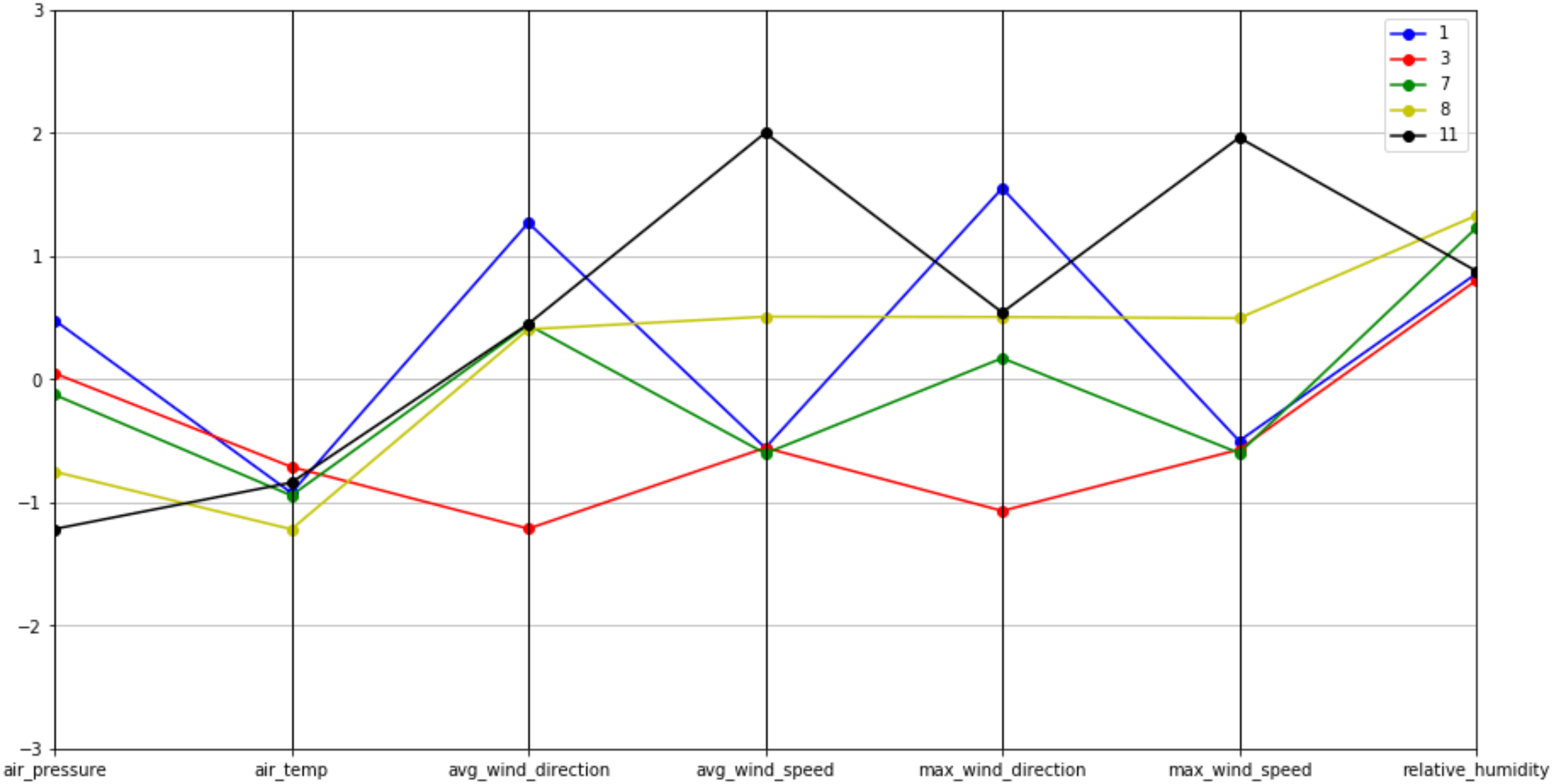
Parallel Plot: Hot Days

utils.parallel_plot(P[P[air_temp'] > 0.5], P)



Parallel Plot: Cool Days

utils.parallel_plot(P[P[air_temp'] > 0.5], P)



Stop Spark Session

spark.stop()

Clean Up

- **Exit notebook**
  - File -> Close and Halt

- **Exit Jupyter Notebook**
  - Click on ‘Logout’

Questions?