CIML Summer Institute 2022
Spark Hands-On Exercises

Spark Hands-On

Mai H. Nguyen, Ph.D.

Setup

- **Login to Expanse**
  - Open terminal window on local machine
  - ssh login.expanse.sdsc.edu -l <xdtr_account>
- **Pull latest from repo**
  - git pull
  - URL: https://github.com/ciml-org/ciml-summer-institute-2022

Server Setup for PySpark - Command Line

- **In terminal window**
  - jupyter_shared_spark
    - Alias for: galyleo launch --account ${CIML_ACCOUNT} --reservation ${CIML_RESERVATION_CPU} --partition shared --cpus 4 --memory 16 --time-limit 04:00:00 --env-modules singularitypro --sif /cm/shared/apps/containers/singularity/ciml/2022/pyspark-latest.sif --bind /expanse,/scratch,/cm --quiet

- **To check queue**
  - squeue -u $USER

Data Setup

- **In terminal window in Jupyter Lab, do the following**
- **Go to your home directory**

  cd
- **Link to data directory**

  ln -s /cm/shared/examples/sdsc/ciml/2022 data
- **Check contents of data directory**

  ls data

  Should see

    BookReviews_5M.txt

    minute_weather.csv

    (among other files)

PySpark Scaling Hands-On

- **Data**
  - BookReviews_5M.txt
    - Source : https://jmcauley.ucsd.edu/data/amazon/
- **Notebook**
  - pyspark_demo.ipynb
- **To do**
  - Change number of cores: 1, 2, 4
  - Note difference in execution times

GETTING EXECUTION TIMES

- In notebook, execution time is printed out in cell before Spark session is stopped (next to last cell)
- Need to <u>restart the kernel</u> and run all cells without stopping to get accurate execution time:
  - Run -> Restart Kernel and Run All Cells
- Find mean and standard deviation of execution times over 3 runs for
  - 1 core, 2 cores, and 4 cores

```
import pyspark
from pyspark.sql import SparkSession

conf = pyspark.SparkConf().setAll([
         ('spark.master’,   'local[2]'),
         ('spark.app.name', 'PySpark Demo)])
spark = SparkSession.builder.config(conf=conf).getOrCreate()
```

Specify number of cores.
‘*’ uses all available cores

SPARK SESSION

Use * to use all available cores, or integer value to specify number of cores to use

```
import pyspark
from pyspark.sql import SparkSession,SparkConf

conf = SparkConf().setAll([
         ('spark.master',    'local[*]'),
         ('spark.app.name', 'PySpark Demo')])

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

Configuration parameters for Spark session

Get existing Spark session or create new one

SPARK PROGRAM STRUCTURE

- **Start Spark session**
  - spark = SparkSession.builder.config(conf=conf).getOrCreate()
- **Create distributed dataset**
  - df = spark.read.csv(“data.csv”,header=”True”)
- **Apply transformations**
  - new_df = df.filter(col(“dept”) == “Sales”)
- **Perform actions**
  - df.collect()
- **Stop Spark session**
  - spark.stop()

START SPARK SESSION

```
import pyspark
from pyspark.sql import SparkSession,SparkConf

conf = SparkConf().setAll([
         ('spark.master’,   'local[*]'),
         ('spark.app.name', 'PySpark Demo')])

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

Use * to use all available cores, or integer value to specify number of cores to use

Configuration parameters for Spark session

Get existing Spark session or create new one

LOAD DATA

```
df = spark.read.text("file.txt")

df = spark.read.csv("file.csv",
                    header=True
                    inferSchema=True).cache()
```

Indicates whether column headers exist

Automatically infer data types of columns

Cache data

DROP ROWS WITH NULLS

- **Drop rows with null values**

```
df.dropna()
df.dropna(how='any')
df.dropna(how='all')
```

- **Check number of rows before and after dropping rows**

```
df.count()
```

CREATE FEATURE VECTOR COLUMN

- **Create feature vector column**
  - Combines given list of columns into single vector column
  - To feed data to machine learning models

```
from pyspark.ml.feature import VectorAssembler

features  = ['air_temp','relative_humidity']
assembler = VectorAssembler(inputCols=features,
                            outputCol='featureVector')
features_df = assembler.transform(df)
features_df.show()
```

New column appended to features_df

```
air_temp|relative_humidity
62.96   | 63.9
```

```
air_temp|relative_humidity|featureVector
62.96   | 63.9            |[62.96, 63.9]
```

PARTITION DATA

- **Partition available data into train and test data sets**

```
train_df,test_df = df.randomSplit(0.8,0.2),seed=<seed>)
```

Percentage of samples for train dataset

Percentage of samples for test dataset

SCALE DATA

- **Scale input data values**
  - Standardize values to have zero mean and unit standard deviation
  - Each feature is scaled separately
  - Create scale transformer using train data, then apply to train/test data

```
from pyspark.ml.feature import StandardScaler
scaler = StandardScaler(inputCol="features_unscaled",
                        outputCol="features_scaled",
                        withStd=True, withMean=True)
scalerModel = scaler.fit(train_df)

train_df = scalerModel.transform(train_df)
test_df  = scalerModel.transform(test_df)
```

BUILD MODEL

- **Build decision tree classifier**
  - Create model
  - Use fit() to train model

```
from pyspark.ml.classification import DecisionTreeClassifier

dt = DecisionTreeClassifier(
        featuresCol='featureVector',
        labelCol='label',
        predictionCol='prediction')

dt_model = dt.fit(<train>)
```

Can specify name of columns for features, labels, and predictions

APPLY MODEL

- **Apply trained model**
  - Use transform()

```
predictions = <model>.transform(<data>)
```

Will have <data> and new ‘prediction’ column appended at the end

Trained model

Input data

EVALUATE CLASSIFICATION MODEL

- **Evaluator for classification model**
  - Calculates F1, precision, recall, accuracy

```
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

mc_evaluator = MulticlassClassificationEvaluator(
   predictionCol='prediction',
   labelCol='label',
   metricName='f1')

mc_evaluator.evaluate(<predictions>)
```

Column with predictions

Column with labels

Evaluation metric

Contains predictions and labels

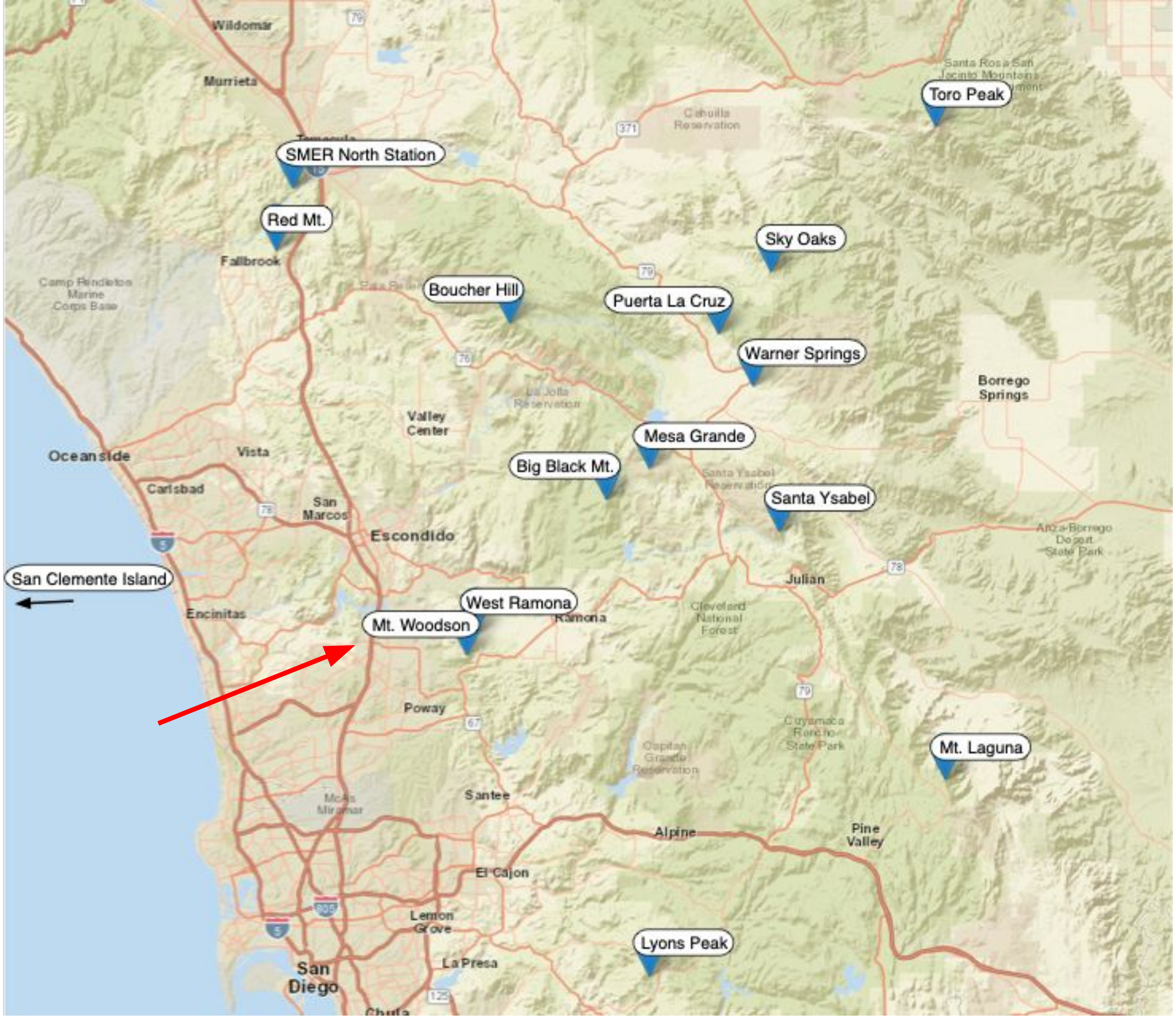
PySpark Cluster Analysis Hands-On

- **Data**
  - Weather station measurements
- **Task**
  - Perform cluster analysis to identify different weather patterns
- **Approach**
  - Spark k-means
- **Notebook**
  - pyspark-clustering.ipynb

Dataset Description

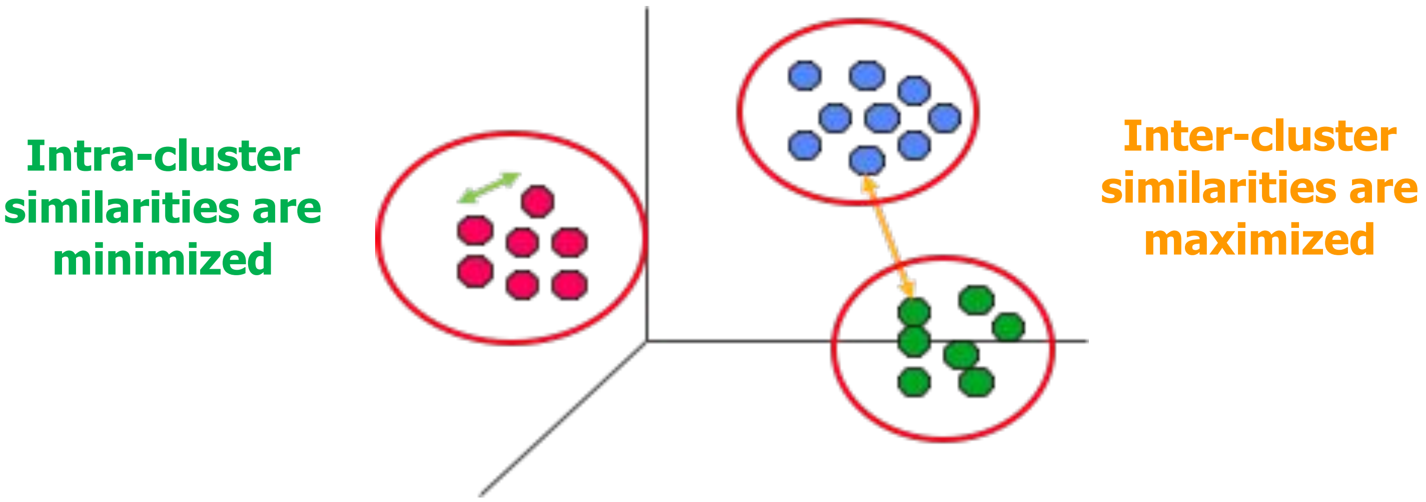
- **Measurements from weather station on Mt. Woodson, San Diego**
- **Air temperature, humidity, wind speed, wind direction, etc.**
- **Three years of data: Sep. 2011 - Sep. 2014**
  - minute_weather.csv: measurement every minute
- **Source**
  - http://hpwren.ucsd.edu

Map of HPWREN Weather Stations



Cluster Analysis

- **Cluster analysis divides data into groups**
  - Grouping is based on some similarity measure.
  - Samples within a cluster are more similar to each other than to samples in other clusters.



http://www-users.cs.umn.edu/~kumar/dmbook/index.php

k-Means Clustering

- **Partitional**
  - Clusters are divided into non-overlapping subsets
- **Centroid-Based**
  - Cluster represented by central vector
- **Simple, classic clustering technique**
  - Data points are grouped into *k* clusters
  - Cluster defined by cluster mean
- **Algorithm**

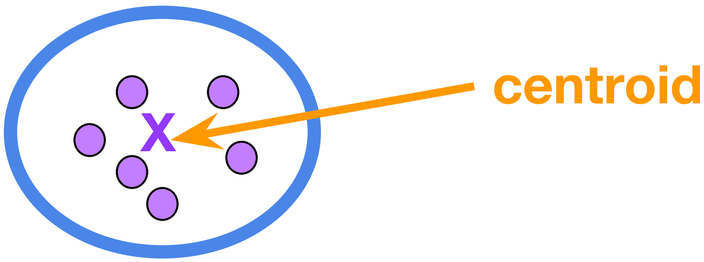
Select *k* initial *centroids* (cluster centers)

Repeat

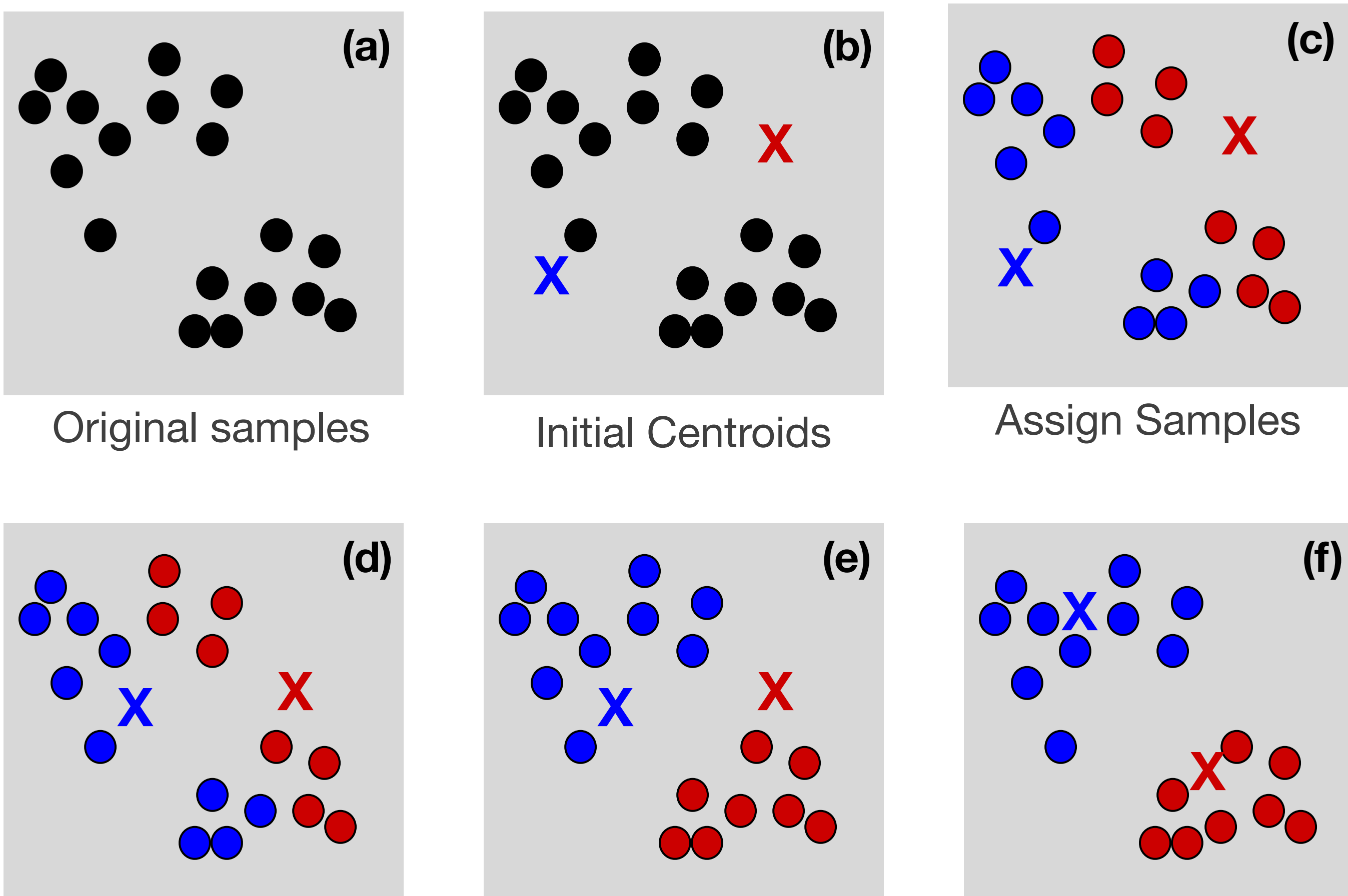
    Assign each sample to closest centroid

    Calculate mean of cluster to determine new centroid

Until some stopping criterion is reached



k-Means Clustering Illustration

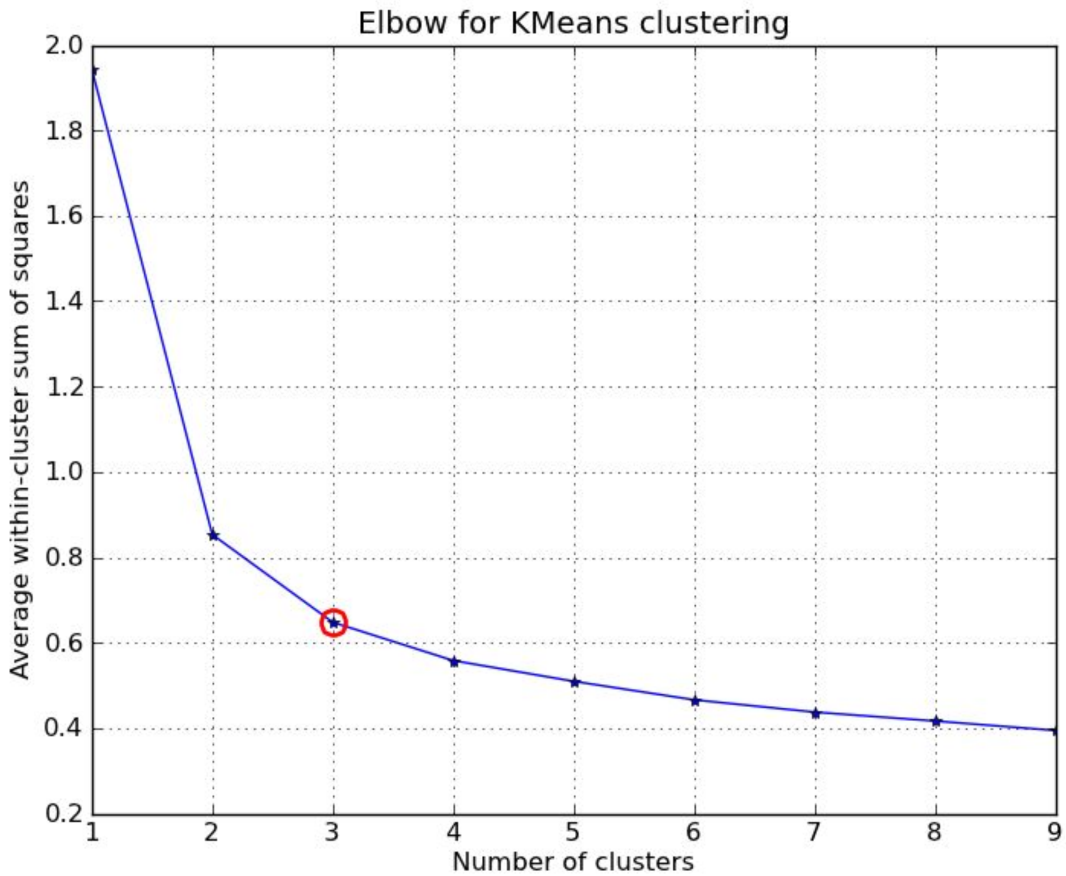


Original samples | Initial Centroids | Assign Samples

Re-calculate Centroids | Assign Samples | Re-calculate Centroids

Choosing Number of Clusters (*k*)

- **Elbow method**
  - Plot cluster evaluation metric (e.g., WSSE) vs. different values for k
  - "Elbow" in plot suggests value(s) for *k*



http://stackoverflow.com/questions/6645895/calculating-the-percentage-of-variance-measure-for-k-means

Evaluating Clustering Results

- **Within-Cluster Sum of Squared Error (WSSE)**
- For each sample, error is distance to centroid. Then, **WSSE** is computed as:

$$WSSE = \sum_{i=1}^{K} \sum_{x \in C_i} \| x - m_i \|^2$$

x: data sample in cluster $\boldsymbol{C}_i$

$\boldsymbol{m}_i$: cluster centroid (i.e., mean of cluster)

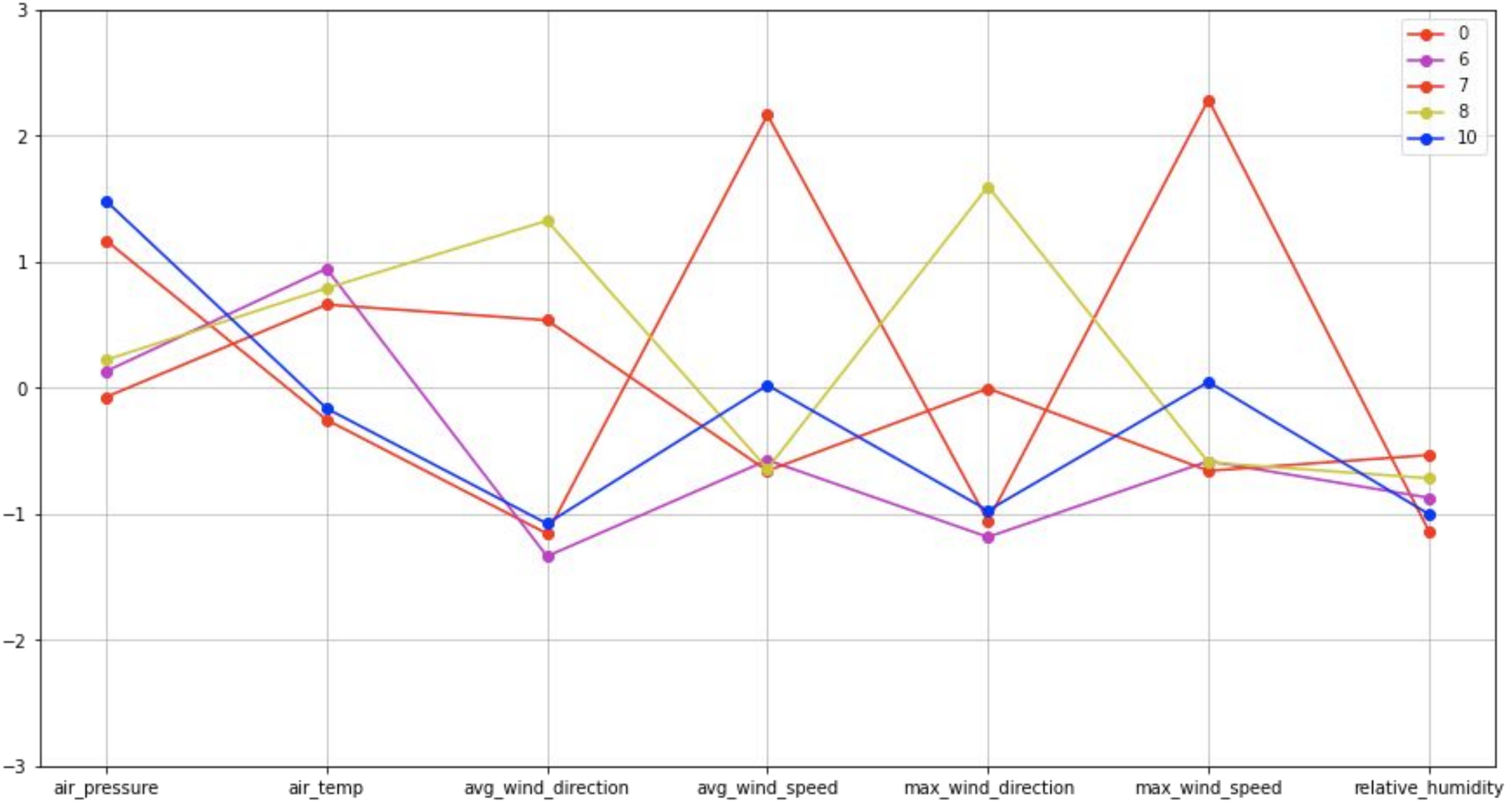
$\|x - m_i\|^2$: Euclidean distance between $\boldsymbol{m}_i$ and $\boldsymbol{x}$

Clustering Hands-On Overview

- **Setup**
  - Start Spark
  - Load modules
- **Load data**
  - Specify schema
  - Read in data from "minute_weather.csv"
- **Explore data**
  - Look at schema, number of rows, summary statistics
- **Prepare data**
  - Drop nulls
  - Create feature vector
- **Perform k-means cluster analysis**
  - Use elbow plot to determine k
  - Build k-means model
- **Evaluate clusters**
  - Plot cluster profiles
- **Stop Spark session**

Cluster Profile: Parallel Plots

utils.parallel_plot(centersNamed[centersNamed['relative_humidity'] < -0.5], numClusters, colors=colors_used);



PySpark Cluster Analysis Hands-On

- **Code**
  - **pyspark-clustering.ipynb**
    - Notebook for hands-on
    - Add your code where indicated
      - # ==> YOUR CODE HERE
  - **pyspark-clustering-wOutput.ipynb**
    - Has cell outputs
  - **utils.py**
    - Has utility functions
- **Resources**
  - Apache Spark
  - PySpark Documentation — PySpark Documentation
  - Spark SQL and DataFrames Guide
  - Python for Data Science Cheat Sheet (pdf)

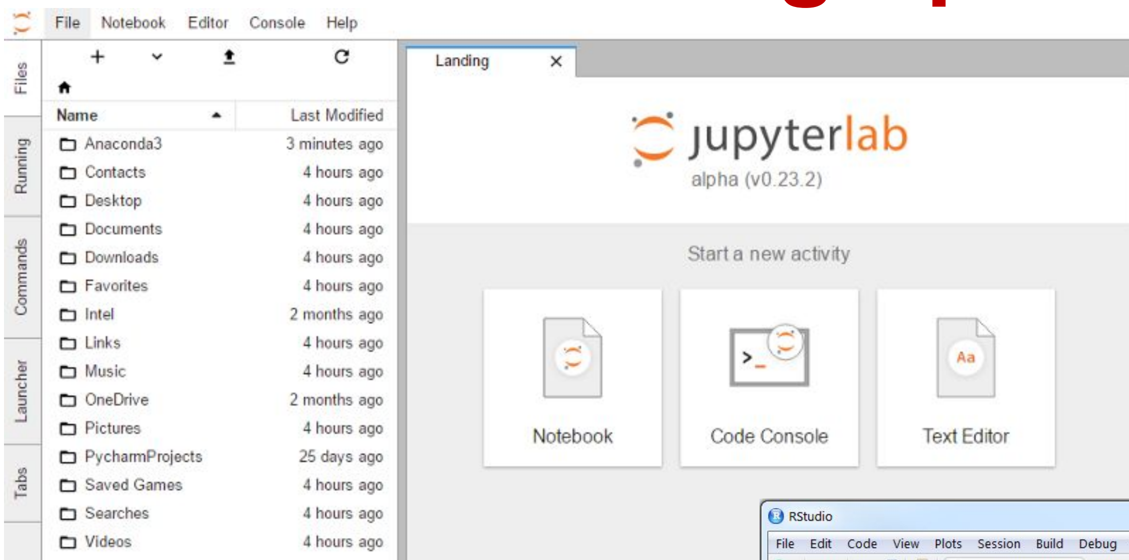
SparkR

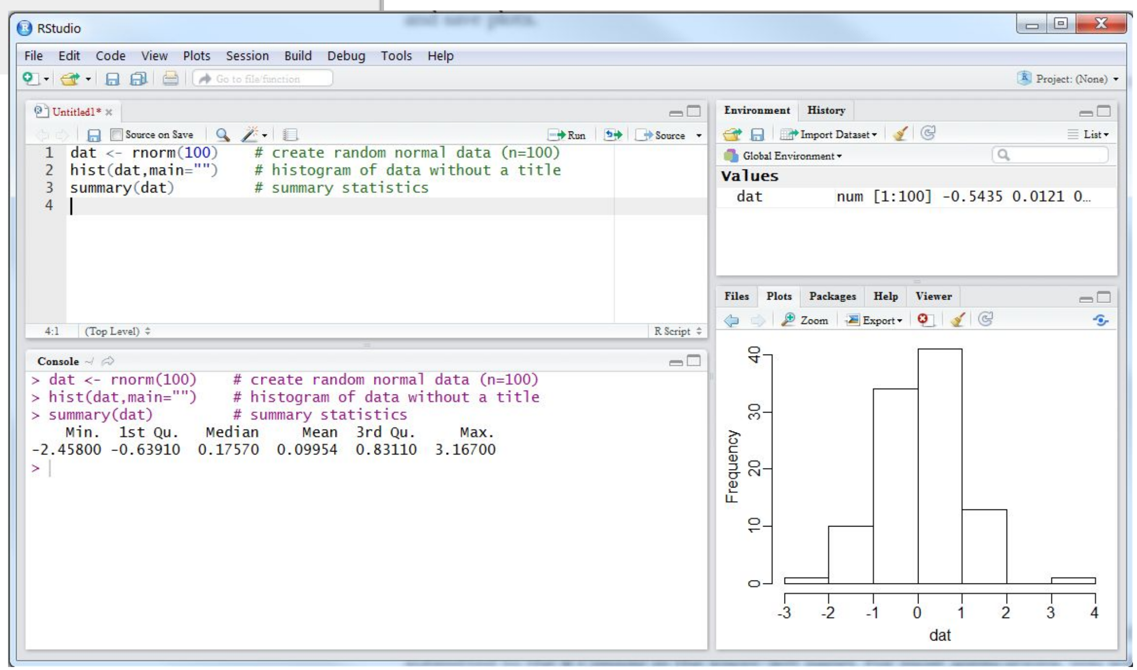
- R package that provides frontend to use Spark from R
- Supports distributed machine learning using R API
- Allows R script to connect to Spark cluster
- Can use with R shell or RStudio or other R IDEs.

SparkR

- **Uses MLlib for machine learning functionality**
- **Familiar R syntax:**
  - Read contents of file into a Spark dataframe
    - newdata <- read.df (“data.txt”, source=“csv”)
  - R formula operators for model fitting:
    - model <- spark.randomForest(training, label ~ features, "classification", numTrees = 10)
  - Get summary of fitted model
    - summary(model)
  - Apply model to make predictions
    - predictions <- predict(model, testDF)
  - Save model
    - write.ml (model, “mymodel”)

Running SparkR Code





sparklyr

- **R interface for Spark**
- **R Legacy**
  - From Rstudio
  - Available on CRAN
- **Spark backend to dplyr and SQL**
  - Interactively manipulate Spark data using dplyr and SQL
- **Access to Spark functionality**
  - Interface to Spark MLlib algorithms
- **Connect to Spark clusters**

sparklyr

- **Setup**
  - install.packages(“sparklyr”)
  - library(sparklyr)
  - spark_install ()
- **Connect to Spark**
  - sc <- spark_connect (master=“local”)
- **Using dplyr**
  - flights_sdf %>% group_by(tailnum)
    %>% filter(count > 20)
- **Machine Learning**
  - model <- ml_random_forest (
    train_sdf, quality ~ ., type=“classification”)

sparklyr Functions

- **Spark Operations**
  - Manage Spark connections (e.g., spark_config())
- **Spark Data Manipulation**
  - Read data in Spark DataFrame and perform operations (e.g., spark_read_csv(), tbl_cache())
- **Feature Transformers**
  - Transform data (e.g., ml_pca(), ft_bucketizer())
- **Distributed Machine Learning**
  - Access Spark Mllib algorithms (e.g., ml_kmeans())
- **Streaming**
  - Support streaming data operations (e.g., stream_read_json())
- **Extensions**
  - Interface to platforms for big data analysis, graph analytics, production

Machine Learning Algorithms in SparkR

Machine Learning

Algorithms

SparkR supports the following machine learning algorithms currently:

Classification

- `spark.logit`: Logistic Regression
- `spark.mlp`: Multilayer Perceptron (MLP)
- `spark.naiveBayes`: Naive Bayes
- `spark.svmLinear`: Linear Support Vector Machine

Regression

- `spark.survreg`: Accelerated Failure Time (AFT) Survival Model
- `spark.glm` or `glm`: Generalized Linear Model (GLM)
- `spark.isoreg`: Isotonic Regression

Tree

- `spark.gbt`: Gradient Boosted Trees for Regression and Classification
- `spark.randomForest`: Random Forest for Regression and Classification

Clustering

- `spark.bisectingKmeans`: Bisecting k-means
- `spark.gaussianMixture`: Gaussian Mixture Model (GMM)
- `spark.kmeans`: K-Means
- `spark.lda`: Latent Dirichlet Allocation (LDA)

Collaborative Filtering

- `spark.als`: Alternating Least Squares (ALS)

Frequent Pattern Mining

- `spark.fpGrowth` : FP-growth

Statistics

- `spark.kstest`: Kolmogorov-Smirnov Test

Resources

- Spark
  - https://spark.apache.org/
- PySpark API
  - https://spark.apache.org/docs/latest/api/python/index.html
- Spark DataFrame
  - https://spark.apache.org/docs/latest/sql-programming-guide.html
- MLlib
  - https://spark.apache.org/mllib/
- SparkR
  - https://spark.apache.org/docs/latest/sparkr.html
- SparkR API
  - https://spark.apache.org/docs/latest/api/R/
- sparklyr
  - https://spark.rstudio.com/