



# Scalable Machine Learning Agenda

```
8:00 - 8:20 -- Machine Learning Overview
8:20 - 9:00 -- R on HPC
9:00 - 9:15 -- Break
9:15 - 10:15 -- Spark
10:15 - 10:45 -- Spark Hands-On
```

# Spark Hands-On

Mai H. Nguyen, Ph.D.



## 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

```
Use * to use all
                                                     available cores, or
                                                     integer value to
import pyspark
                                                     specify number of
from pyspark.sql import SparkSession
                                                     cores to use
conf = pyspark.SparkConf().setAll([
           ('spark.master', 'local[*]'),
           ('spark.app.name', 'PySpark Demo')])
spark = SparkSession.builder.config(conf=conf).getOrCreate()
                          Configuration
                                                    Get existing Spark
                          parameters for
                                                    session or create
                          Spark session
                                                    new one
```



## LOAD DATA

Loading data from local file system

Loading data from HDFS

column headers exist

Cache data

## **CHAINING**

Chaining: Making multiple method calls on same object

**RDD Wordcount** 



## **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()
```



## FILL IN MISSING VALUES

Replace null values with empty string

```
df.na.fill(' ')
```

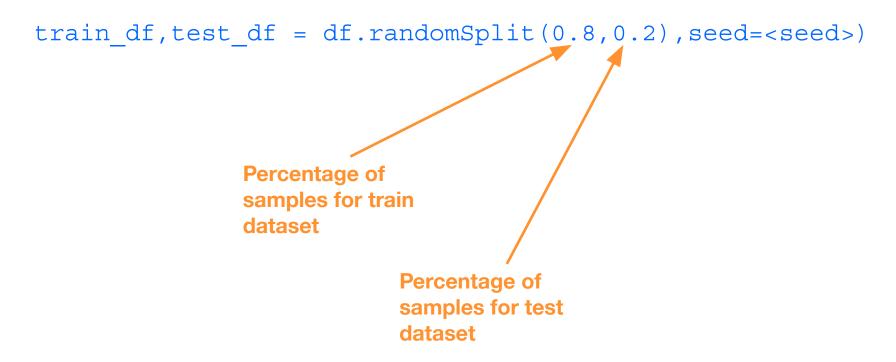
 Count number of rows with nulls before and after filling nulls

```
df.count()
```



#### PARTITION DATA

Partition available data into train and test data sets



## 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
air temp|relative humidity
                                                 appended to
                                                 features df
          63.9
62.96
air temp|relative_humidity|featureVector
                           [62.96, 63.9]
          63.9
62.96
```



## **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

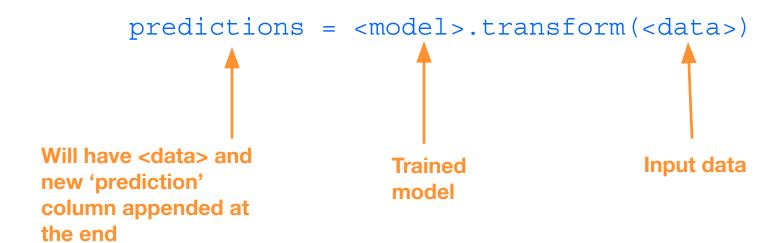


#### **BUILD MODEL**

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

## **APPLY MODEL**

- Apply trained model
  - Use transform()



#### **EVALUATE CLASSIFICATION MODEL**

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



# PySpark Cluster Analysis Hands-On

#### Data

Weather station measurements

#### Task

Perform cluster analysis to identify different weather patterns

## Approach

Spark k-means

#### Notebook

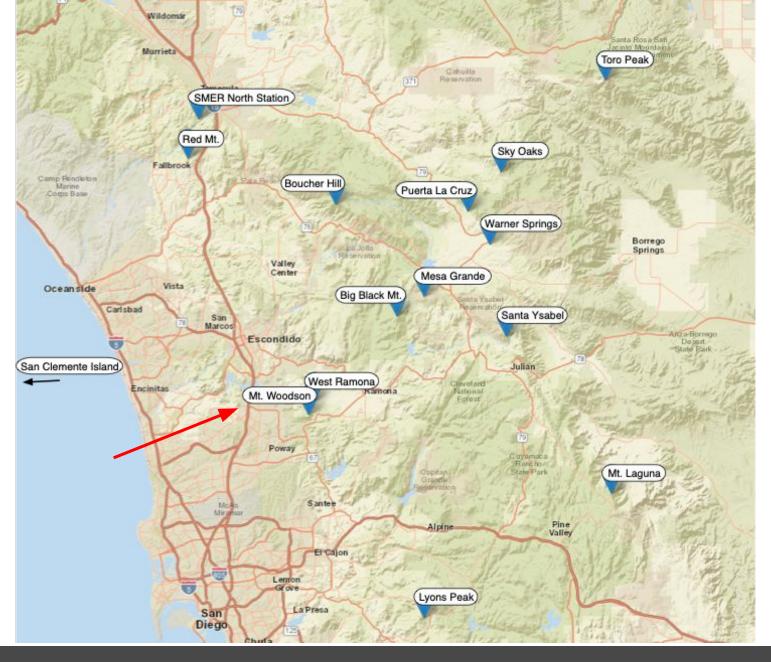
pyspark-clustering.ipynb

## **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



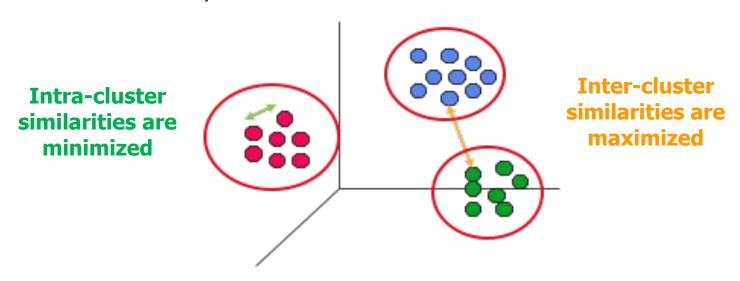
# Map of HPWREN Weather Stations





# **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

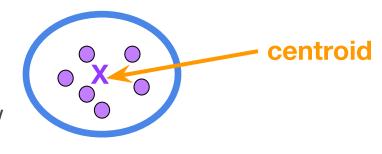
- Data points are grouped into k clusters
- Cluster defined by cluster mean

#### Algorithm

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

Repeat

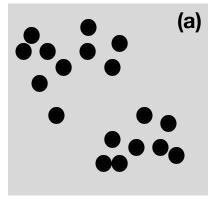
Assign each sample to closest centroid Calculate mean of cluster to determine new centroid



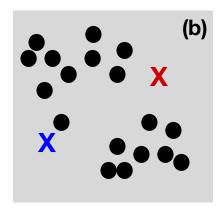
Until some stopping criterion is reached



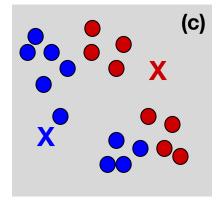
# k-Means Clustering Illustration



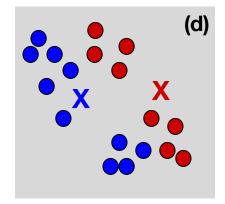
Original samples



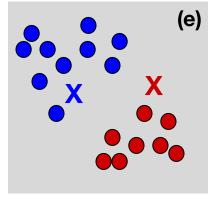
**Initial Centroids** 



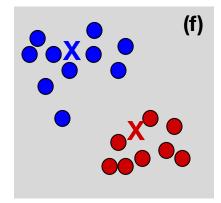
Assign Samples



Re-calculate Centroids



Assign Samples



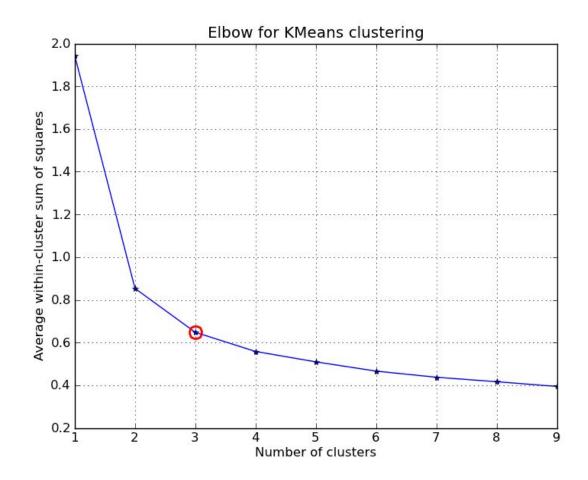
Re-calculate Centroids



# 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  $C_i$   $m_i$ : cluster centroid (i.e., mean of cluster)  $||x - m_i||^2$ : Euclidean distance between  $m_i$  and 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

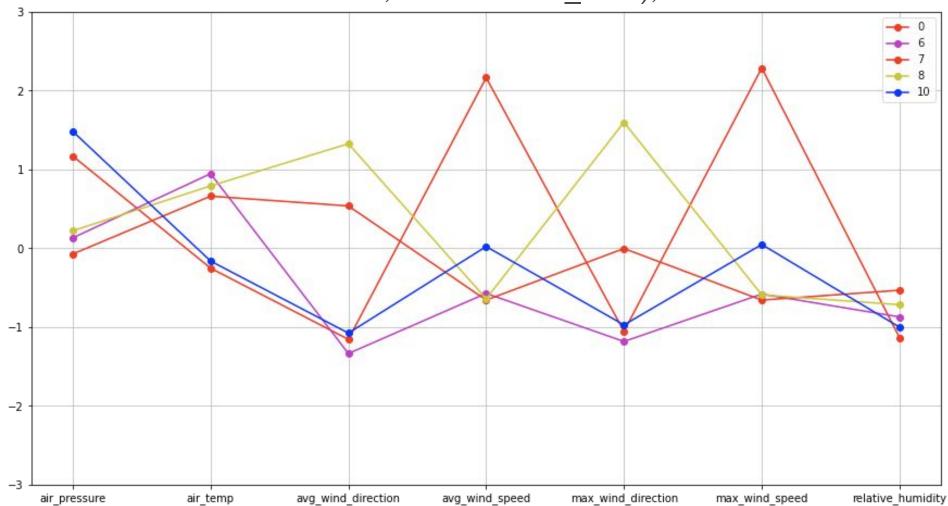
#### Evaluate clusters

- Plot cluster profiles
- Stop Spark session



## **Cluster Profile: Parallel Plots**

utils.parallel\_plot(centersNamed[centersNamed['relative\_humidity'] < -0.5], numClusters, colors=colors\_used);





## Setup

#### Login to Expanse

- Open terminal window on local machine
- ssh xdtrXXX@login.expanse.sdsc.edu

## Pull latest from repo

- cd <your-SI-repo>
- git pull
- URL: <a href="https://github.com/sdsc/sdsc-summer-institute-2021">https://github.com/sdsc/sdsc-summer-institute-2021</a>

# Server Setup for PySpark - Portal

#### Expanse Portal

- https://portal.expanse.sdsc.edu
- Use trainXXX account
- Interactive Apps -> Jupyter

#### Parameters

- Account: crl155
- Partition: shared
- Time limit (min): 60
- Number of cores: 2
- Memory required per node: 8 GB
- GPUs: 0
- Singularity image: /cm/shared/apps/containers/singularity/ciml/2021/pyspark-latest.sif
- Environment module: singularitypro
- Reservation: SI2021RES
- Type: JupyterLab



## Server Setup for PySpark - Command Line

- In terminal window
  - cd 3.1b\_Scalable\_Machine\_Learning
  - start-spark
    - Alias for:
    - export PATH="/cm/shared/apps/sdsc/galyleo:\${PATH}";
    - galyleo launch --account crl155 --reservation SI2021RES

       --partition shared --cpus-per-task 2 --memory-per-node 8
       --time-limit 01:00:00 --env-modules singularitypro --sif
      /cm/shared/apps/containers/singularity/ciml/2021/pyspark-latest.
      sif --bind /expanse,/scratch,/cvmfs --quiet"
  - Copy & paste URL in web browser
- To check queue
  - squeue -u \$USER



# PySpark Cluster Analysis Hands-On

#### Code

- pyspark-cluster.ipynb
  - Notebook for hands-on
  - Replace <<FILL-IN>> with code
- pyspark-cluster-w-outputs.ipynb
  - Has cell outputs
- utils.py
  - Has utility functions

#### Resources

- Apache Spark<sup>™</sup> Unified Analytics Engine for Big Data
- PySpark Documentation PySpark 3.1.2 documentation
- Spark SQL and DataFrames Spark 3.1.2 Documentation
- Python for Data Science Cheat Sheet (pdf)

