Business 4720 - Class 20

Analytics at Industrial Scale – Big Data Analytics

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This Class

What You Will Learn:

- Distributed data storage
  - Hadoop HDFS
- Distributed computation
  - Hadoop Map-Reduce
  - Spark
    - Dataframe operations
    - Spark SQL
    - Spark MLLib

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Further Reading

Hrishikesh V. Karambelkar (2018) *Apache Hadoop 3 Quick Start Guide*. Packt Publishing. Birmingham, UK.

Tom White (2012) *Hadoop – The Definitive Guide*. 3rd edition. O'Reilly Media. Sebastopol, California, US.

Bill Chambers and Matei Zaharia (2018) *Spark – The Definitive Guide*. O'Reilly Media. Sebastopol, California, US.

Jules Damji et al. (2020) *Learning Spark – Lightning-Fast Data Analytics*. 2nd edition. O'Reilly Media. Sebastopol, California, US.

Big Data

Characterized by any one or more of:

- Large volume
- Large ”velocity” (volume per time)
- Large variety (of data types and sources)

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Big Data Example – CERN

”Conseil Europeenne pour la Recherche Nucleaire”

`https://www.home.cern/science/computing/data-centre`[1]

Servers	≈ 12000	
CPU Cores	≈ 330000	
Disks	≈ 220000	
Total Disk Space	≈ 950000	TB
DB Transactions per second	≈ 20000	
File Transfer Throughput	≈ 500000	Gb/s

[1] Accessed Feb 23, 2024

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Distributed Data and Distributed Computation

Hadoop

- Initial release 2006
- Maintained by the Apache Foundation
- Inspired by Google File System (GFS) (2003) and Google MapReduce (2004) for large data management
- Early use cases by Yahoo (2009) and Facebook (2012) drove adoption
- Distributes data storage and computation across a cluster of computers
- *Data locality* means moving computation to data, not data to computation

Hadoop Benefits

- **Reliability**: Hardware and software failure tolerance through replication and automatic recovery
- **Scalability**: Dynamically adding and removing storage nodes and cluster re-balancing (more than 10,000 nodes in Hadoop 3)
- **Cost effective**: Open source, runs on commodity hardware, can use heterogenous nodes
- **Cloud support**: Vendors offering turn-key Hadoop systems

Main Hadoop Components

- **HDFS**: Hadoop Distributed File System
- **MapReduce**: Software framework for processing large data volumes
- **YARN**: Yet Another Resource Negotiator (cluster and compute job manager)

https://commons.wikimedia.org/wiki/File:Apache_Hadoop.png

HDFS Principles

- **Streaming data access**: Data is written and read linearly, processed one item at a time
- **Large datasets**: Multiple gigabytes or terabytes, hundreds of computers per clusters, millions of files per node
- **Write once**: Files once written are only read or appended to
- **Moving computation is cheaper than moving data**: Move compute applications to the server that stores the data

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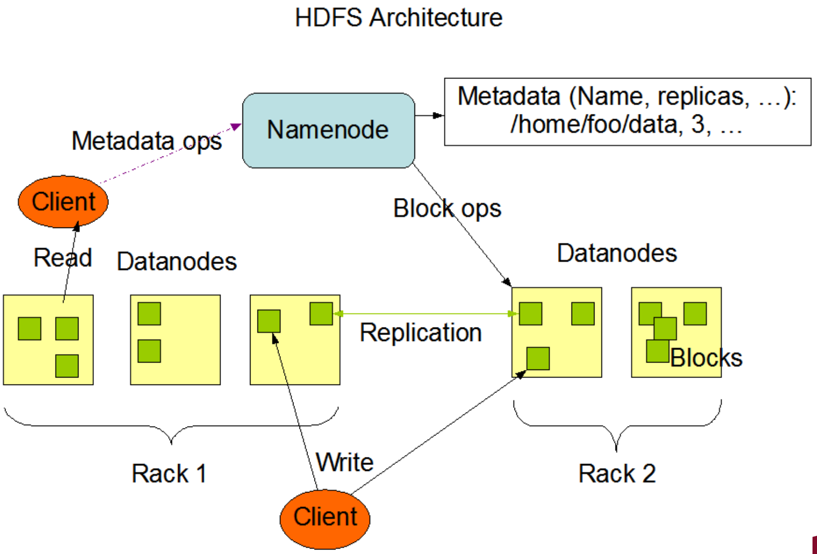

Source: Apache Foundation (`https://hadoop.apache.org/docs/`)

HDFS Architecture

NameNode

- One NameNode per cluster (plus sercondary/backup)
- Manages file namespace (sub-directories, file names, etc.)
- Regulates access to files
- Provides file operations such as opening, closing, renaming, etc.

DataNode

- Files are split into blocks stored on DataNodes
- DataNodes handle read and write requests of clients
- DataNodes perform block operations for file operations by NameNode

Working with HDFS

Use the `hdfs dfs` command to insteract with the distributed file system. The commands are similar to the regular Linux commands to interact with files.

hdfs dfs -cat	Print a file to standard output
hdfs dfs -cp	Copy a file or directory
hdfs dfs -df	Display free space
hdfs dfs -du	Display disk usage
hdfs dfs -get	Copy files to the local file system
hdfs dfs -head	Print the first kilobyte of a file
hdfs dfs -ls	List files and directories

Continued . . .

hdfs dfs -mkdir	Make a directory
hdfs dfs -mv	Move a file or directory
hdfs dfs -put	Copy files from the local file system
hdfs dfs -rm	Remove files or directories
hdfs dfs -rmdir	Removes a directory
hdfs dfs -tail	Print the last kilobyt of a file
hdfs dfs -concat	Concatenate existing files into a target file

Working with HDFS – Examples

Start the Hadoop cluster NameNode, DataNode, and YARN service:

```
sudo systemctl start hadoop.service
```

Download an event log file:

```
wget https://evermann.ca/busi4720/eventlog.short.log
```

Put the event log on to the Hadoop Distributed File System:

```
hdfs dfs -put eventlog.short.log
```

Display the start and end of it:

```
hdfs dfs -head eventlog.short.log
hdfs dfs -tail eventlog.short.log
```

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Working with HDFS – Examples [cont'd]

Show disk usage and disk free space:

```
hdfs dfs -du
hdfs dfs -df
```

Copy the event log:

```
hdfs dfs -cp eventlog.short.log eventlog.copy.log
```

List all files:

```
hdfs dfs -ls
```

Web Interface

- NameNode overview at `http://localhost:9870`
- HDFS explorer at `http://localhost:9870/explorer.html#/`

MapReduce

What is it?

- Programming model for parallel processing of data
- Move computation to data nodes

Strengths

- Massively parallelizable
- Conceptually simple: Only 2 types of functions

Drawbacks

- Disk limited: Intermediate results are written to disk
- Stateless functions only
- Non-iterative, acyclic dataflow programs only

MapReduce – Basic Steps

1. Map
   - Reads key–value pairs of input[2]
   - For each input key and value, outputs a list of key–value pairs

$$\mathit{Map}: \quad (\mathit{key}1, \mathit{value}1) \rightarrow \mathit{list}(\mathit{key}2, \mathit{value}2)$$

2. Shuffle
   - Distributes data based on keys produced by *map*
   - All values for the same key are sent to the same reducer
3. Reduce
   - Processes all values for a given key
   - For each input key and its values, outputs a list of key–value pairs

$$\mathit{Reduce}: \quad (\mathit{key}2, \mathit{list}(\mathit{value}2)) \rightarrow \mathit{list}(\mathit{key}3, \mathit{value}3)$$

[2] By default, for text input, each line is a key–value pair, separated by the first tab character

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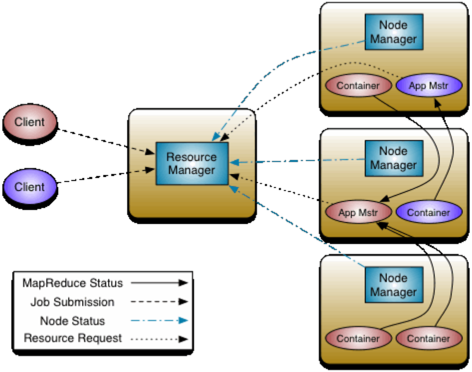
MapReduce on Hadoop – YARN cluster manager

- Submit an application (set of jobs) to **Resource Manager**
- **Application Master** tracks status of jobs and tasks
- Tasks distributed to nodes
- **Node Managers** manage local resources



https://hadoop.apache.org/docs/current/hadoop-yarn/hadoop-yarn-site/yarn_architecture.gif

MapReduce on Hadoop

- Specify input directory
  - Data in multiple data files
  - Data files are stored in blocks distributed across cluster
- One *map job* is executed for each input block
  - *Map* jobs are executed on node where input block is located
  - Necessary program files are sent to each node if necessary
  - Map output is moved to nodes for *reduce* job (”shuffle”)
- Execute a *reduce job* on every node for maximum parallelization

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MapReduce Example – Word Count

- *Hadoop MapReduce* is programmed in Java
- *Hadoop Streaming* allows mappers and reducers as executable programs (e.g. in Python)

The Mapper:

```
#!/usr/bin/env python
import sys

for line in sys.stdin:
    line = line.strip()
    words = line.split()
    for word in words:
        print ('{}\t{}'.format(word, 1))
```

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MapReduce Example – Word Count [cont'd]

The Reducer:

```
#!/usr/bin/env python
import sys

word_counts = dict()

for line in sys.stdin:
    word, count = line.split('\t', 1)
    count = int(count)

    if word not in word_counts:
       word_counts[word] = count
    else:
      word_counts[word] = word_counts[word] + count

for word, count in word_counts.items():
    print('{}\t{}'.format(word, count))
```

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MapReduce Example – Word Count [cont'd]

Try it locally:

```
wget https://evermann.ca/busi4720/map.py
wget https://evermann.ca/busi4720/reduce.py
wget https://evermann.ca/busi4720/hamlet.txt
chmod +x *.py
```

Run the mapper and view its output:

```
cat hamlet.txt | ./map.py > map.out
less map.out
```

Run the reducer and view its output:

```
cat map.out | ./reduce.py > reduce.out
sort -k2 -rn reduce.out | less
```

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MapReduce Example – Word Count [cont'd]

Put the text file on the HDFS:

```
hdfs dfs -mkdir hamlet
hdfs dfs -put hamlet.txt hamlet
hdfs dfs -ls hamlet
```

Run the MapReduce job on the Hadoop cluster:

```
mapred streaming \
  -input hamlet -output hamlet.out \
  -mapper map.py -reducer reduce.py \
  -file map.py -file reduce.py
```

Examine the results:

```
hdfs dfs -ls hamlet.out
hdfs dfs -get hamlet.out/part-*
cat part-* | sort -k2 -rn | less
```

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MapReduce Use Case – Scalable Process Discovery

1. α-Miner
   - 2 MapReduce phases
2. Flexible Heuristic Miner
   - 5 MapReduce phases

- Random process, 47 activity types
- 5 million traces, 80GB event logs
- Three cluster sizes:
  1. Single node cluster, 2 CPUs
  2. 10-Node cluster, 2 CPUs each
  3. 10-Node cluster, 10 CPUs each

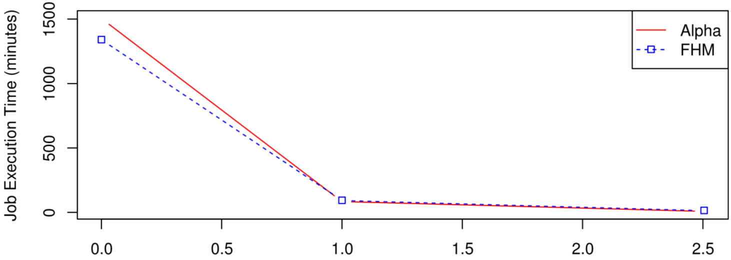
Source: Evermann, J. (2016) Scalable Process Discovery using Map-Reduce. *IEEE TSC*, 9 (3), 469-481.
`https://doi.org/10.1109/TSC.2014.2367525`

Example – Flexible Heuristic Miner MapReduce Pipeline

- Keys and values can be complex
- Define a comparison function to shuffle

$$
\begin{aligned}
\text{map1:}&(\mathit{Int}, \mathit{Text}) \rightarrow \mathit{set}(\mathit{CaseID}, (\mathit{Event}, \mathit{TimeStamp}))\\
\text{shuffle1:}&\mathit{set}(\mathit{caseID}, (\mathit{Event}, \mathit{TimeStamp})) \rightarrow (\mathit{CaseID}, \mathit{set}(\mathit{Event}, \mathit{TimeStamp}))\\
\text{reduce1:}&(\mathit{CaseID}, \mathit{set}(\mathit{Event}, \mathit{TimeStamp})) \rightarrow \mathit{set}((\mathit{Event}, \mathit{Event}), (\mathit{Int}, \mathit{Bool}, \mathit{Int}))\\
\text{combine2:}&\mathit{set}((\mathit{Event}, \mathit{Event}), (\mathit{Int}, \mathit{Bool}, \mathit{Int})) \rightarrow \mathit{set}((\mathit{Event}, \mathit{Event}, (\mathit{Int}, \mathit{Bool}, \mathit{Int}))\\
\text{reduce2:}&((\mathit{Event}, \mathit{Event}), \mathit{set}(\mathit{Int}, \mathit{Bool}, \mathit{Int})) \rightarrow \mathit{set}(c, (\mathit{Event}, \mathit{Event}, \mathit{Int}, \mathit{Float}))\\
\text{reduce3:}&\mathit{set}(c, (\mathit{Event}, \mathit{Event}), \mathit{set}(\mathit{Int}, \mathit{Float})) \rightarrow \mathit{set}(c, (\mathit{Event}, \mathit{Event}))\\
\text{map4:}&(\mathit{Int}, \mathit{Text}) \rightarrow \mathit{set}(\mathit{CaseID}, (\mathit{Event}, \mathit{TimeStamp}))\\
\text{shuffle4:}&\mathit{set}(\mathit{CaseID}, (\mathit{Event}, \mathit{TimeStamp})) \rightarrow (\mathit{CaseID}, \mathit{set}(\mathit{Event}, \mathit{TimeStamp}))\\
\text{reduce4:}&(\mathit{CaseID}, \mathit{set}(\mathit{Event}, \mathit{TimeStamp})) \rightarrow \mathit{set}((\mathit{Event}, \mathit{set}(\mathit{Event}), \mathit{Bool}), \mathit{Int})\\
\text{reduce5:}&((\mathit{Event}, \mathit{set}(\mathit{Event}), \mathit{Bool}), \mathit{set}(\mathit{Int})) \rightarrow ((\mathit{Event}, \mathit{set}(\mathit{Event}), \mathit{Bool}), \mathit{Int})
\end{aligned}
$$

MapReduce Use Case – Results



Source: Evermann, J. (2016) Scalable Process Discovery using Map-Reduce. *IEEE TSC*, 9 (3), 469-481. `https://doi.org/10.1109/TSC.2014.2367525`

α Algorithm

Single node	25:00 hours
Medium cluster	1:24 hours
Large cluster	0:08 hours

FHM

Single node	22:21 hours
Medium cluster	2:01 hours
Large cluster	0:17 hours

Apache Pig

Apache Pig

https://en.wikipedia.org/wiki/File:Apache_Pig_Logo.svg

- High-level programming
- Pig Latin language
- Pig Latin programs run as MapReduce jobs on Hadoop
- Procedural, not declarative (SQL)

https://pig.apache.org/docs/latest/basic.html

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Apache Pig Latin Example – Word Count

```
input_lines = LOAD 'hamlet.txt' AS (line:chararray);
-- Extract words from each line and put them into
-- a pig bag datatype, then flatten the bag to get
-- one word on each row
words = FOREACH input_lines \
   GENERATE FLATTEN(TOKENIZE(line)) AS word;
-- create a group for each word
word_groups = GROUP words BY word;
-- count the entries in each group
word_count = FOREACH word_groups  \
   GENERATE COUNT(words) AS count, group AS word;
-- order the records by count
ordered_word_count = ORDER word_count BY count DESC;
STORE ordered_word_count INTO 'hamlet.out';
```

Source: `https://en.wikipedia.org/wiki/Apache_Pig`

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Apache Pig Latin – Relational Operators

LOAD	STORE	DUMP
FILTER	DISTINCT	FOREACH . . . GENERATE
SAMPLE	JOIN	GROUP
CROSS	ORDER	LIMIT
UNION	SPLIT	

Apache Hive

https://commons.wikimedia.org/wiki/File:Apache_Hive_logo.svg

- Data warehouse
- HiveQL similar to SQL
- Translate HiveQL to run as MapReduce jobs on Hadoop

https://cwiki.apache.org/confluence/display/Hive/LanguageManual

HiveQL Example – Word Count

```
DROP TABLE IF EXISTS docs;
CREATE TABLE docs (line STRING);
LOAD DATA INPATH 'hamlet.txt'
  OVERWRITE INTO TABLE docs;

CREATE TABLE word_counts AS
SELECT word, count(1) AS count FROM
  (SELECT explode(split(line, '\s'))
    AS word FROM docs) temp
GROUP BY word
ORDER BY word;
```

Source: `https://en.wikipedia.org/wiki/Apache_Hive`

Apache Spark

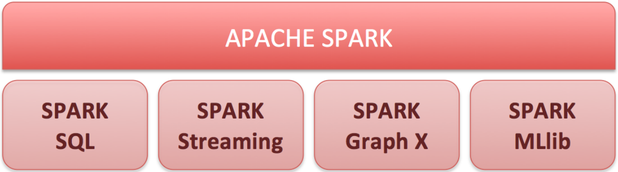
https://commons.wikimedia.org/wiki/File:Apache_Spark_logo.svg

- Origin at UC Berkeley in 2009
- Donated to Apache Software Foundation in 2013
- Quickly adopted due to performance advantages over MapReduce
- Builds on Hadoop HDFS and YARN
- Can use other file storage (S3, Azure, etc.) and cluster managers (Mesos, Kubernetes, etc.)

Apache Spark – Characteristics

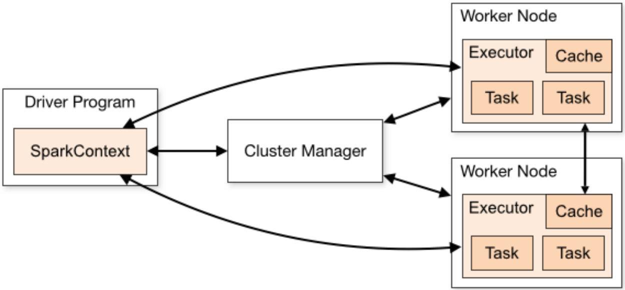
- **In-Memory Processing** with spill-over to disk
- **Efficiency** and much faster processing speed compared to MapReduce.
- **Integration** with Hadoop and its components
- **Unified Engine** for batch processing, real-time streaming, machine learning, and graph processing
- **Advanced Analytics** for machine learning, graph processing, SQL and structured data processing
- **Language Support** for Java, Scala, Python, and R
- **Scalability** from a single server to thousands of nodes.
- **Fault Tolerance** through execution engine that provides ”lineage” information to recompute lost data
- **Ease of Use** allows quicker development than Hadoop’s MapReduce.

Apache spark – Main Components



https://commons.wikimedia.org/wiki/File:Sch%C3%A9ma_d%C3%A9tail_outils_spark.png

Apache Spark – Cluster Overview



https://spark.apache.org/docs/latest/img/cluster-overview.png

Apache Spark – Spark on Hadoop

- YARN manages resources for Spark applications
- Spark RDD partitions correspond to HDFS blocks
- Spark is location aware, schedules job execution on nodes close to data
- Two layers of fault tolerance: HDFS replication and Spark RDD lineage

Apache Spark – Data Abstractions

1. RDD ("Resilient Distributed Dataset")
   - Dependencies: Data "lineage" information; how the RDD is computed; may be used to reconstruct an RDD
   - Partitions: Split data among executors; parallelize computation, with location info
   - Low-level programming interface focused on MapReduce
   - Procedural, no query optimization
2. DataFrame
   - Inspired by Pandas and R data frames
   - Builds on RDD
   - Named columns with data types
   - High-level programming interface
   - Immutable
   - Declarative, query optimization ("Catalyst" query optimizer)
3. Dataset
   - Strongly typed variant of DataFrame for Java and Scala

Apache Spark – Execution Principles

Transformations

- Transform a DataFrame into another DataFrame without altering the original (immutability)
- Examples: `map()`, `select()`, `filter()`, `groupBy()`, `orderBy()`, `join()`
- Recorded in data lineage
- **Lazy evaluation**: Delay execution until **action** is invoked; allows query optimization

Actions

- Returns a result or writes result to storage
- Does not produce another DataFrame
- Examples: `collect()`, `count()`, `show()`, `take()`
- Triggers execution of transformations

Start the local Hadoop cluster (if not already running) and the PySpark console:

```
sudo systemctl start hadoop.service
pyspark --master yarn
```

Read a file from HDFS and get some statistics:

```
textFile = spark.read.text( \
    'hdfs://localhost:9000/user/busi4720/hamlet.txt')
# Number of lines
textFile.count()
# First row
textFile.first()
# How many lines contain the word Hamlet?
textFile \
    .filter(textFile.value.contains("Hamlet")) \
    .count()
```

Word count example in Pyspark:

```
# Import useful functions from Spark SQL:
from pyspark.sql import functions as sf

wordCounts = textFile \
    .select(sf.explode(sf.split(textFile.value, "\s+")) \
        .alias("word")) \
    .groupBy("word") \
    .count() \
    .orderBy("count")
wordCounts.collect()
```

Apache Spark – Basic Transformations and Actions

Transformations (PySpark)

select()	filter()	where()
withColumn()	groupBy()	sort()
distinct()	drop()	cov()
orderBy()	withColumnRenamed()	union()
join()		

Actions (PySpark)

show()	collect()	take()
count()	head()	tail()
write.csv()	toPandas()	

Apache Spark – Schemas and DataFrames

Schema describes the columns of data frames and their types.

- No need for Spark to infer types
- No need for Spark to read data to infer schema
- Error detection when reading data

Define a schema using Spark schema DDL:

```
logSchema = \
    'caseID STRING, \
     activity STRING, \
     ts TIMESTAMP'
```

Spark DDL Data Types

STRING	TINYINT	SMALLINT	INT
BIGINT	BOOLEAN	FLOAT	DOUBLE
DATE	DECIMAL	TIMESTAMP	BINARY
STRUCT	ARRAY	MAP	

Apache Spark – Schemas and DataFrames

Read the data from HDFS into a data frame:

```
fname='hdfs://localhost:9000/user/busi4720/\
eventlog.short.log'

data = spark.read \
     .format('csv') \
     .option('delimiter', '\t') \
     .option('header', 'false') \
     .schema(logSchema) \
     .load(fname)
```

Query the schema, count rows, show 5 rows, and a summary:

```
data.printSchema()
data.count()
data.show(5)
data.summary().show()
```

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Register a data frame as a temporary SQL table (”view”):

```
data.createOrReplaceTempView('log')
```

Alternatively, create a permanent SQL table:

```
data.write.saveAsTable('log_table')
```

Query the SQL table, will return a data frame:

```
result_df = spark.sql('select * from log limit 5')
result_df.show()
```

Apache Spark – SQL

Create a Directly-Follows-Graph (DFG) from a log. Define the SQL Query:

```
sql_query = \
'SELECT COUNT(*), l1.activity AS activity1, \
 l2.activity AS activity2, AVG(l2.ts - l1.ts) AS dtime \
  FROM log AS l1 JOIN log AS l2 ON l1.caseid=l2.caseid \
   WHERE l2.ts = (SELECT MIN(ts) FROM log l3 \
    WHERE l3.caseid=l1.caseid AND l3.ts > l1.ts) \
     GROUP BY GROUPING SETS((l1.activity, l2.activity))'
```

Run the query, show the results and explain the query plan:

```
dfg = spark.sql(sql_query)
dfg.count()
dfg.show()

dfg.explain(mode='formatted')
dfg.explain(True)
```

Apache Spark – SQL

Run as self-contained application:

```
# Download file
wget https://evermann.ca/busi4720/spark_dfg.py
# Submit to Spark/Hadoop cluster
spark-submit --master yarn spark_dfg.py \
 hdfs://localhost:9000/user/busi4720/eventlog.short.log
```

Result will be written to HDFS.

Job Tracker

Use Hadoop Job Tracker at `https://localhost:8088` to track status of nodes and progress of jobs.

Apache Spark – Compare to PostgreSQL

```
psql
```

Create table and read data from CSV file:

```
CREATE TABLE log(
  caseId VARCHAR(20),
  activity VARCHAR(10),
  ts TIMESTAMP);
\COPY log FROM 'eventlog.short.log'
  WITH DELIMITER E'\t';
```

Execute query:

```
SELECT COUNT(*), l1.activity, l2.activity,
 AVG(l2.ts - l1.ts) AS dtime
  FROM log AS l1 JOIN log AS l2 ON l1.caseid=l2.caseid
   WHERE l2.ts = (SELECT MIN(ts) FROM log l3
    WHERE l3.caseid=l1.caseid AND l3.ts > l1.ts)
     GROUP BY (l1.activity, l2.activity);
```

Apache Spark – ML

Spark ML Frameworks

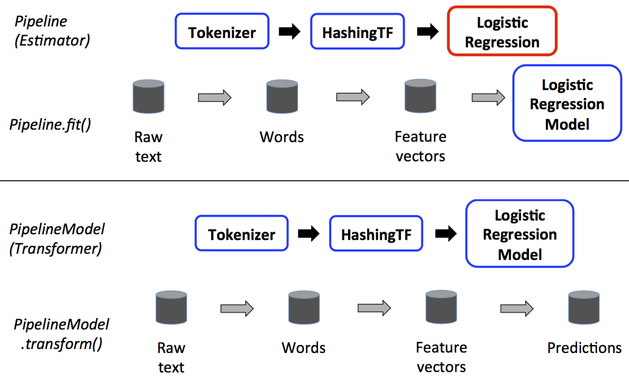
- **Spark.mllib**: RDD focused, maintenance only
- **Spark.ml**: Dataframe focused, actively developed

Spark ML Techniques

- **Supervised**: Classification, Regression
- **Unsupervised**: Clustering, Principal Component Analysis, etc.

Apache Spark – ML Pipelines

- **Transformers**: Accept a dataframe, execute `transform()` method, return a dataframe
- **Estimators**: Accept a dataframe, execute `fit()` method, return a transformer



https://spark.apache.org/docs/latest/ml-pipeline.html

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Apache Spark – Selection of available ML Models

Classification

Logistic regression, Decision trees, Random forests, Gradient-boosted trees, Multilayer perceptron, Support vector machines, Naive bayes

Regression

Linear regression, Generalized linear regression, Decision tree regression, Random forest regression, GBT regression, Survival regression

Unsupervised

K-means clustering, Principal components

Apache Spark – ML Example

Full example at

`https://evermann.ca/busi4720/spark_ml.py`

Run as self-contained application:

```
# Download file
wget https://evermann.ca/busi4720/spark_ml.py
# Submit to Spark/Hadoop cluster
spark-submit --master yarn spark_ml.py \
    hdfs://localhost:9000/user/busi4720/mushrooms.csv
```

Job Tracker

Use Hadoop Job Tracker at `https://localhost:8088` to track status of nodes and progress of jobs.

Apache Spark – ML Example

Get the dataset:

```
wget https://evermann.ca/busi4720/mushrooms.csv
hdfs dfs -put mushrooms.csv
```

https://archive.ics.uci.edu/dataset/848/secondary+mushroom+dataset

Define the schema:

```
the_schema = 'class STRING, `cap-diameter` DOUBLE, \
    `cap-shape` STRING, `cap-surface` STRING, \
    `cap-color` STRING, `does-bruise-or-bleed` STRING, \
    `gill-attachment` STRING, `gill-spacing` STRING, \
    `gill-color` STRING, `stem-height` DOUBLE, \
    `stem-width` DOUBLE, `stem-root` STRING, \
    `stem-surface` STRING, `stem-color` STRING, \
    `veil-type` STRING, `veil-color` STRING, \
    `has-ring` STRING, `ring-type` STRING, \
    `spore-print-color` STRING, habitat STRING, \
    season STRING'
```

Apache Spark – ML Example

Load data:

```
fname='hdfs://localhost:9000/user/busi4720/\
mushrooms.csv'

data = spark.read \
     .format('csv') \
     .option('delimiter', ',') \
     .option('header', 'true') \
     .schema(the_schema) \
     .load(fname)
data = data.drop('veil-type')
data = data.fillna('NULL')
```

Apache Spark – ML Example

Import all required pieces:

```
from pyspark.ml import Pipeline
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.feature import StandardScaler, \
    StringIndexer, OneHotEncoder, VectorAssembler
from pyspark.ml.evaluation \
    import BinaryClassificationEvaluator
from pyspark.ml import PipelineModel
```

Create the necessary **transformers** for the pipeline. Collect all numerical features:

```
numFeatures = VectorAssembler(
    inputCols = ['cap-diameter', 'stem-width',
                 'stem-height'],
    outputCol = 'numFeatures')

scaler = StandardScaler(inputCol='numFeatures',
                        outputCol='numFeaturesS')
```

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Apache Spark – ML Example

Encode categorical variables as one-hot (dummy variables):

```
categoricalCols = \
    [name for (name, dtype) in data.dtypes \
        if dtype=='string']
indexOutputCols = \
    [x + 'index' for x in categoricalCols]
oheOutputCols = \
    [x + 'ohe' for x in categoricalCols]

stringIndexer = StringIndexer(
    inputCols = categoricalCols,
    outputCols = indexOutputCols,
    handleInvalid='skip')

oheEncoder = OneHotEncoder(
    inputCols = indexOutputCols,
    outputCols = oheOutputCols)
```

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Apache Spark – ML Example

Assemble all features into a feature vector:

```
vecAssembler = VectorAssembler(
    inputCols = oheOutputCols+['numFeaturesS'],
    outputCol = 'feature_vec')
```

Encode the target classes as numbers:

```
stringIndexTarget = StringIndexer(
    inputCols = ['class'],
    outputCols = ['classIndex'],
    handleInvalid='skip')
```

Create the classification **estimator**:

```
logReg = LogisticRegression(
    featuresCol = 'feature_vec',
    labelCol = 'classIndex')
```

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Apache Spark – ML Example

Put all components into the **pipeline**:

```
pipeline = Pipeline(stages=[
    numFeatures,
    scaler,
    stringIndexer,
    oheEncoder,
    vecAssembler,
    stringIndexTarget,
    logReg])
```

Apache Spark – ML Example

Create train/test data split:

```
train_data, test_data = \
    data.randomSplit([.66, .33], seed=1)
```

Fit the model to the training data:

```
pipelineModel = pipeline.fit(train_data)
```

Summary of the training data:

```
summary = pipelineModel.stages[-1].summary
summary.accuracy
summary.areaUnderROC
summary.fMeasureByThreshold.show()
summary.precisionByLabel
summary.recallByLabel
summary.roc.show()
```

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Apache Spark – ML Example

Fitted estimators (including whole pipelines) become transformers. Predict for both training and testing data:

```
trainPred = pipelineModel.transform(train_data)
testPred = pipelineModel.transform(test_data)
```

Evaluate the model using AUC:

```
evaluator = BinaryClassificationEvaluator(
    labelCol='classIndex')
evaluator.evaluate(trainPred)
evaluator.evaluate(testPred)
```

Save the fitted model for later re-use:

```
pipelineModel.write().overwrite().save('myFirstModel')
```

Load a saved model:

```
savedModel = PipelineModel.load('myFirstModel')
```

Stream Analytics

- Network ("directed acyclic graph") of nodes
- Ingest records, process records, emit records
- Record-by-record processing
- Low latencies
- Resource intensive

Example Use Cases

- Customer click-stream analysis for real-time pricing
- Machine sensor data for failure warnings/alarms
- Financial/payments transaction fraud monitoring
- Market data anlytics, news monitoring
- Activity records for process compliance monitoring
- ...

Process Discovery with Streaming Data

- Flexible Heuristics Miner
- Activity completion records
- Record-by-record processing
- 57,000 – 160,000 traces per min
- 2,000,000 – 5,500,000 events per min
- 5 16-core, 32GB nodes

Source: Evermann, J., Rehse, J.-R., and Fettke, P.: Process Discovery from Event Stream Data in the Cloud - A Scalable, Distributed Implementation of the Flexible Heuristics Miner on the Amazon Kinesis Cloud Infrastructure. *CloudBPM Workshop on Business Process Monitoring and Performance Analysis in the Cloud at the 8th IEEE International Conference on Cloud Computing Technologies and Science (CloudCom 2016)* .

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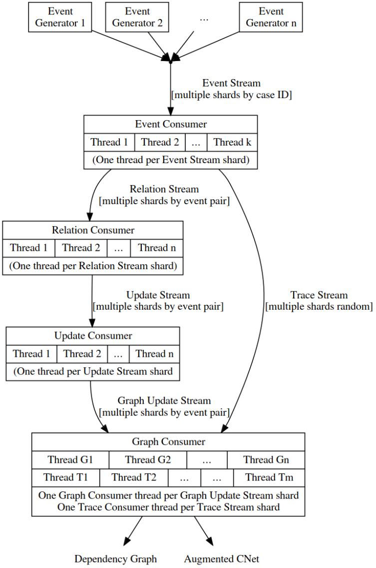
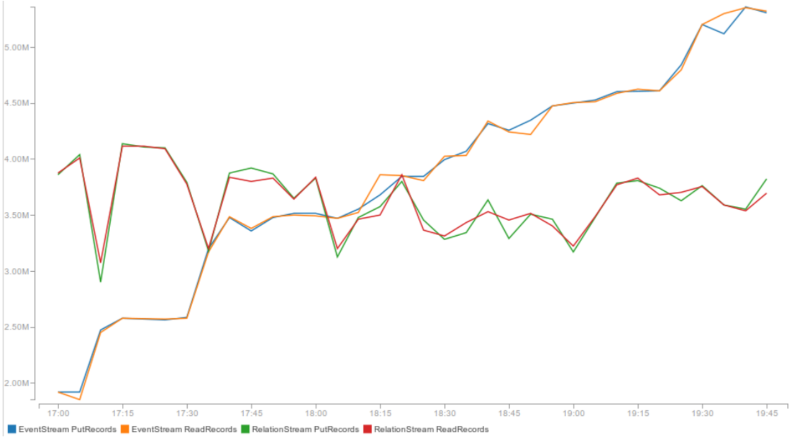
Process Discovery with Streaming Data



- Implemented on AWS Kinesis
- Directed acyclic graph (DAG)
- Multiple event generators
- Multiple record streams
- Stream is queue with ”Put” and ”Read” operations
- Streams contain multiple ”shards” (same keys)
- Multiple threads/executors per shard (key)

Performance Results:



Apache Spark – Stream Analytics

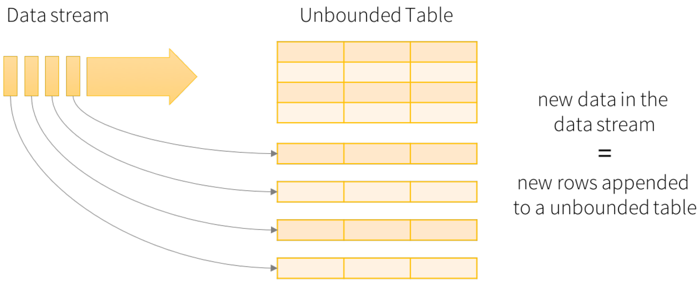
Principles

- Micro-batches
- Data stream as unbounded dataframe/table
- Unified programming model for batch and stream processing
- Support for time windows
- Wide range of input sources and output destinations
- Optimized stateful stream transformations and aggregations

https://spark.apache.org/docs/latest/img/streaming-arch.png

https://spark.apache.org/docs/latest/img/streaming-flow.png

Apache Spark – Stream Analytics



Data stream as an unbounded table

`https://spark.apache.org/docs/latest/img/structured-streaming-stream-as-a-table.png`

Triggering

- Micro-batch (process next batch when prior batch completed)
- Time trigger
- Once
- Continuous

Output Modes

- Append: Assume older output remains valid
- Update: Change parts of older output (requires appropriate output destination, e.g. PostgreSQL, but not HDFS)
- Complete: Replace/overwrite older output

Import all necessary functions and get a Spark Session:

```
from pyspark.sql.functions import \
    explode, split, col, desc, \
    window, current_timestamp
```

Create the stream reader to read from a network socket:

```
lines = spark.readStream \
            .format('socket') \
            .option('host', 'localhost') \
            .option('port', 9999) \
            .load()
```

`lines` is a DStream.

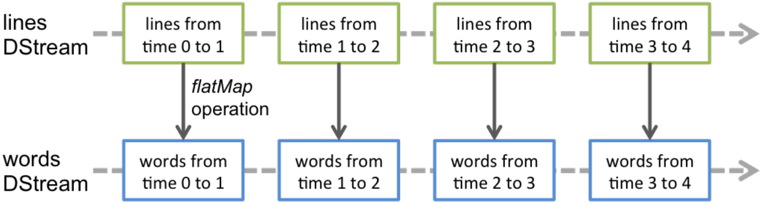
The stream reader opens a *client* socket, i.e. the socket must already be opened for writing.

Apache Spark – Stream Analytics

Define processing of lines:

```
words = lines.select(explode(split(col('value'), \
    '\\s')).alias('word'))
```

`words` is another DStream, connected to `lines`



https://spark.apache.org/docs/latest/img/streaming-dstream-ops.png

Define processing of words:

```
counts = words.groupBy('word') \
              .count() \
              .sort(desc('count'))
```

`counts` is another Dstream, connected to `words`

Define the output writer with output mode and processing trigger:

```
writer = counts.writeStream \
            .format('console') \
            .outputMode('complete') \
            .trigger(processingTime='5 second') \
            .option('checkpointLocation', \
                'hdfs://localhost:9000/user/busi4720/')
```

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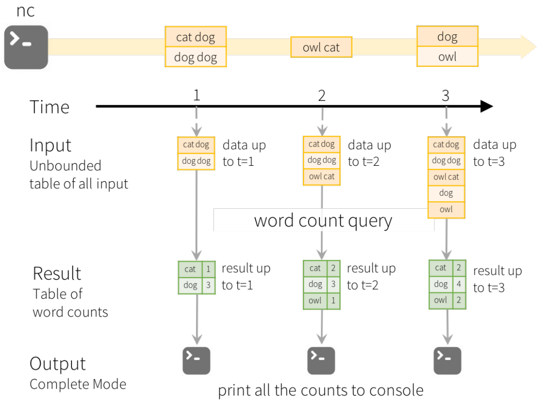


Model of the Quick Example

https://spark.apache.org/docs/latest/img/structured-streaming-example-model.png

First, open a server socket from the shell using `nc`:

```
nc -kl 9999
```

Start the processing by starting the writer. This returns a streaming query object that provides progress information. "`start()`" is a non-blocking operation:

```
streamingQuery = writer.start()
```

Get progress information through the `lastProgress` attribute of the query:

```
print(streamingQuery.lastProgress)
```

Stop the processing by calling `stop()` on the query object:

```
streamingQuery.stop()
```

Fault Tolerance

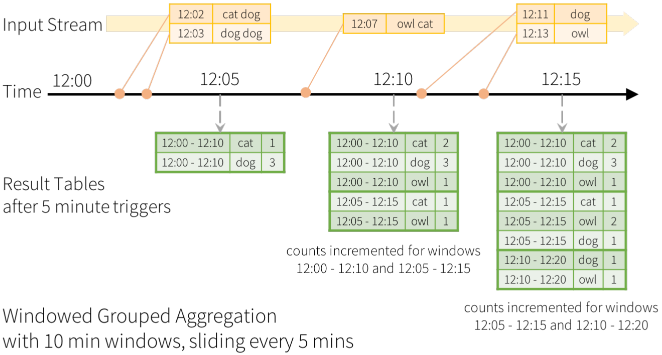
- Checkpointing of state
- ”End-to-end exactly-once” guarantees
  - Replayable sources
  - Deterministic computations
  - Destination that can identify duplicates

Time Windowing

```
words = lines.select(explode(split(col('value'), \
    '\\s')).alias('word')) \
    .withColumn('eventTime', current_timestamp())

counts = words \
    .groupBy('word', \
        window('eventTime', '1 minute', '30 second')) \
    .count() \
    .sort(desc('count'))
```

Apache Spark – Stream Analytics



https://spark.apache.org/docs/latest/img/structured-streaming-window.png

1. Streaming ML Learning
   - Streaming Linear Regression
   - Streaming Logistic Regression
   - Streaming KMeans
2. Streaming ML Prediction
   - From off-line trained models

Apache Spark – Further Reading

Quick Start

https://spark.apache.org/docs/latest/quick-start.html

SQL, DataFrames and Datasets

https://spark.apache.org/docs/latest/sql-programming-guide.html

Structured Streaming

https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html

Machine Learning

https://spark.apache.org/docs/latest/ml-guide.html

Last accessed on March 8, 2024

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