# Real-Life Use-Case Examples for Apache Spark Libraries



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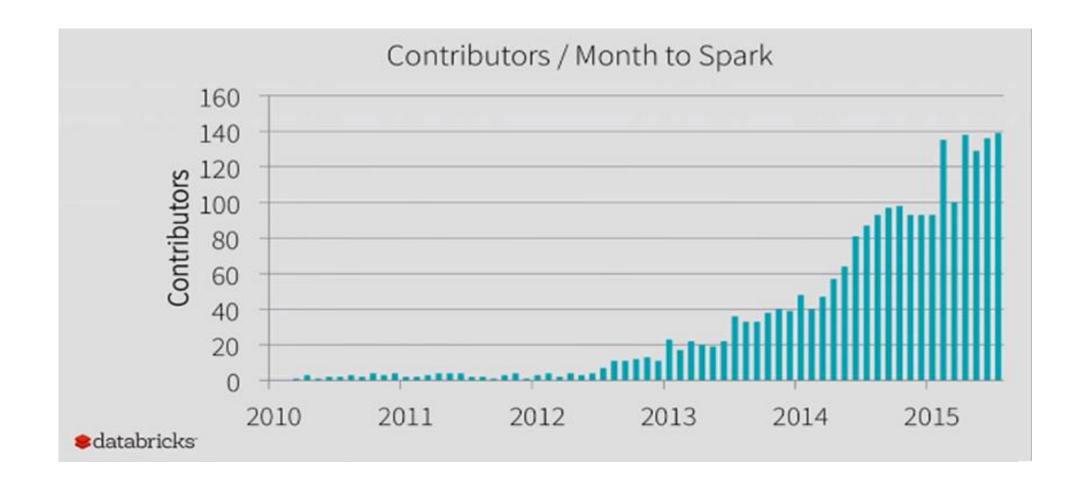




- Hadoop: Distributed data infrastructure
  - Storage component: Hadoop Distributed File System (HDFS)
  - Processing component: MapReduce
- MapReduce for batch processing
- Most ML algorithms run iteratively
- Apache Spark: General framework for processing and analysis of big data











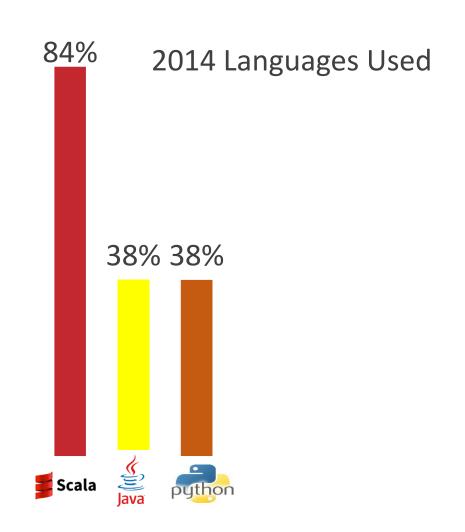


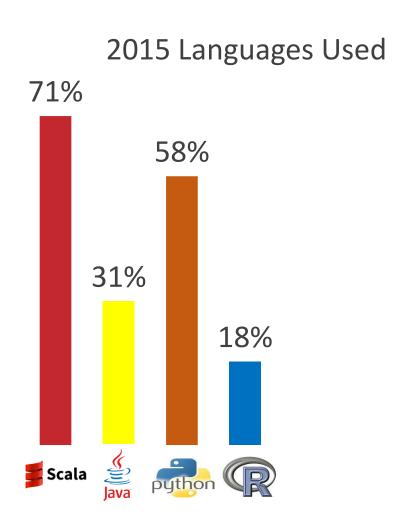
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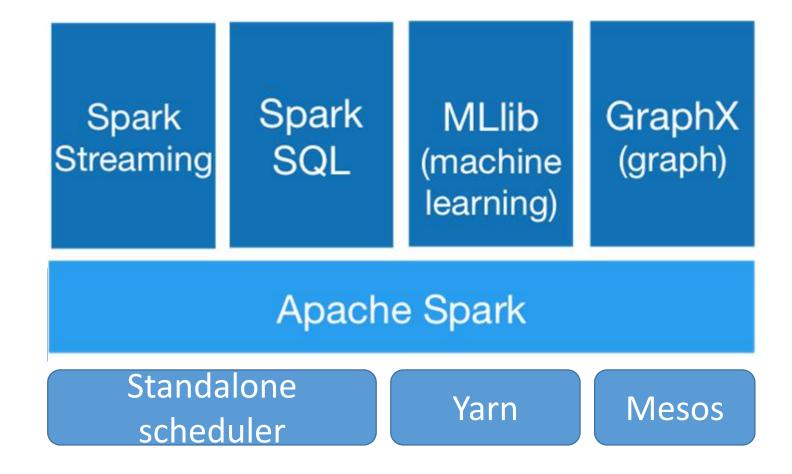






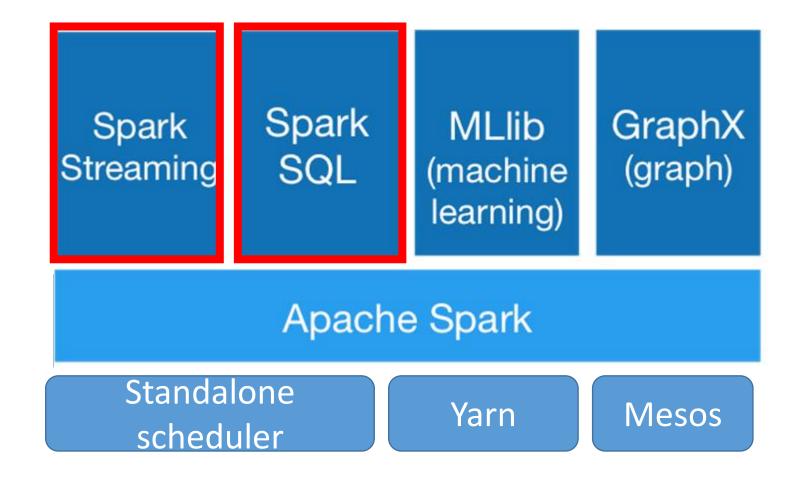






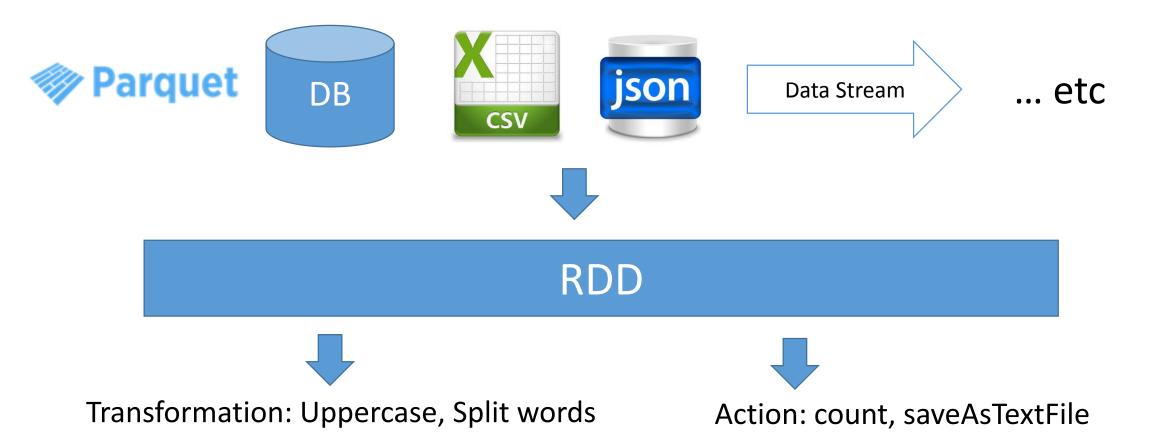








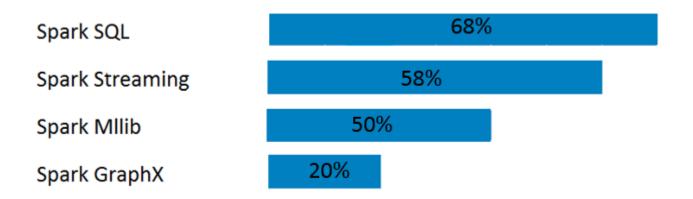
# **RDD: Resilient Distributed Dataset**







Which libraries do people use?



75% of users use more than one component



# **Spark Streaming**

Ingest and manipulate real-time data streams
Process data in near real-time







Use high level SQL language to query data

- Structured data
- Semi-structured data

Compatible with various file formats and data stores

Compatible with Hive

• Can read and write to Hive tables including ORC, Parquet, and SequenceFiles





### **DataFrames**

Distributed collections of data organized into named columns Equivalent to tables in relational databases







MLlib is Spark's Machine Learning library

It has the implementation of scalable Machine Learning algorithms

Good for integration with Spark SQL, Spark Streaming and Spark GraphX

- Spark SQL + MLlib → used to easily extract and analyze data from existing Apache
  Hive
- Spark Streaming + MLlib → used for analyzing streaming data in near-real-time

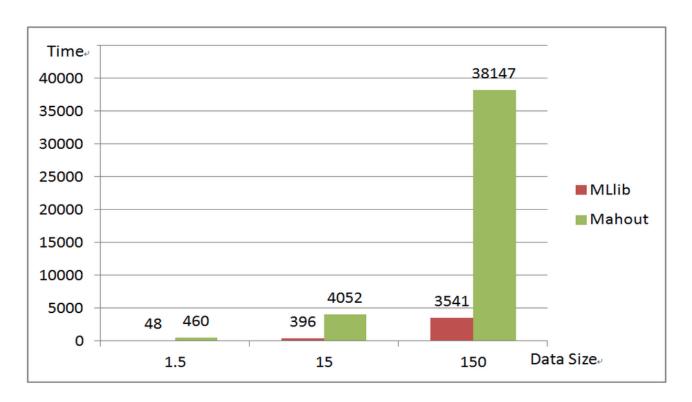
Spark MLlib



# **Spark MLlib**

### Spark MLlib is the replacement for Mahout

Machine Learning algorithms implemented based on Map-Reduce concept





Running times for different data sizes (GB)



# **Spark MLlib**

- Available algorithms on MLlib
  - Classification: logistic regression, linear SVM, naïve Bayes, least squares, classification tree
  - Regression: generalized linear models (GLMs), regression tree
  - Collaborative filtering: alternating least squares (ALS), non-negative matrix factorization (NMF)
  - Clustering: k-means
  - Decomposition: SVD, PCA
  - Optimization: stochastic gradient descent, L-BFGS





#### **Applications:**

- Classification of products, prediction of users' behaviour or interest
- Grouping similar entities, e.g. Twitter dataset for topic detection
- Recommender systems: make the appropriate personalized recommendation for different customers





A new component for Graph-parallel computation Advantages of using Spark GraphX:

- Growing set of algorithms and builders
- Parallel processing of graph operations
- Full integration with Spark RDD and DataFrame API

#### Application:

- Page Rank (importance of a node in a Graph e.g. Google Search)
- Shortest Distance





# **Spark Streaming**

# **Section Topics**



- DStreams
- Transformations
- Window Operations
- Output Operations













- **Count tweets**
- **Track most frequent words**
- Save tweets to file



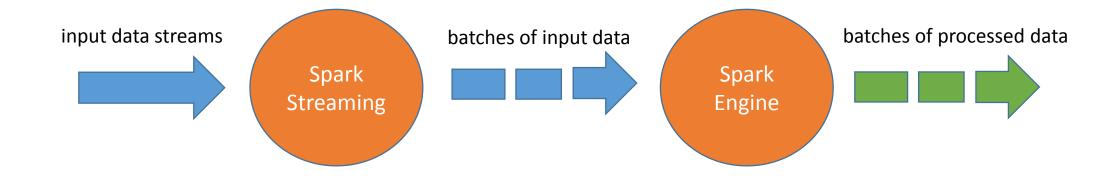


# DStream - Discretized Stream



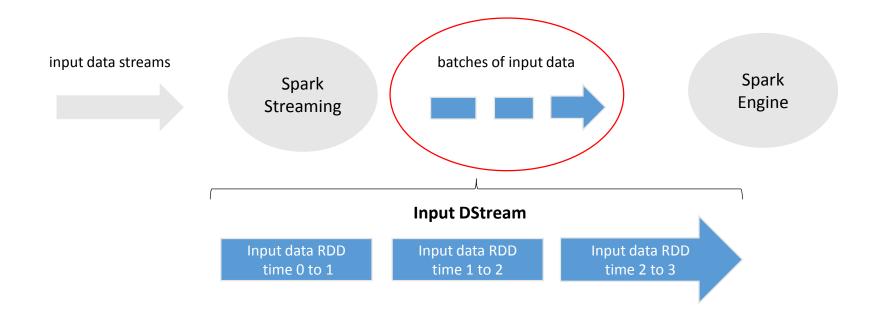
# **DStreams**







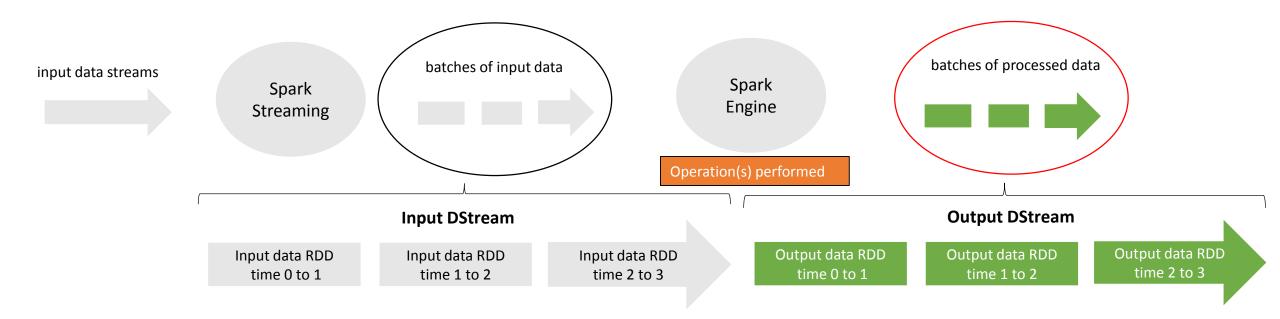




batches of processed data





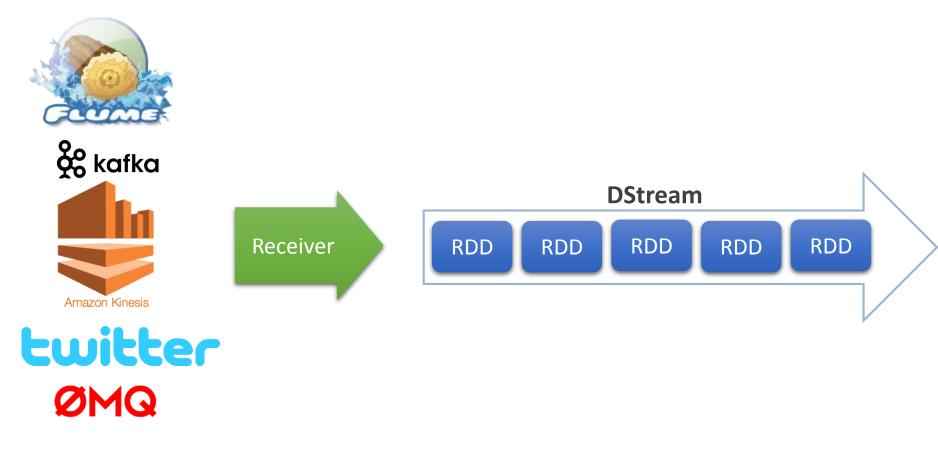




# **Input DStreams**

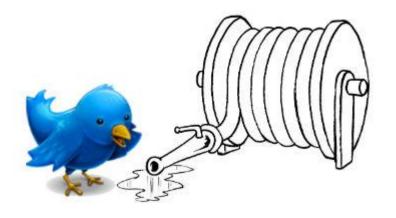
MQT

etc



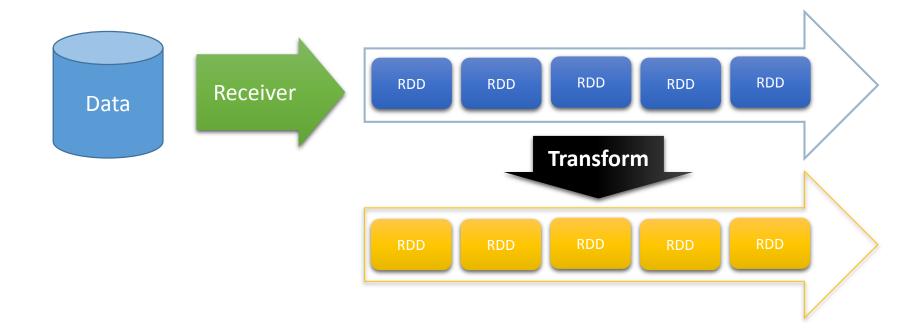






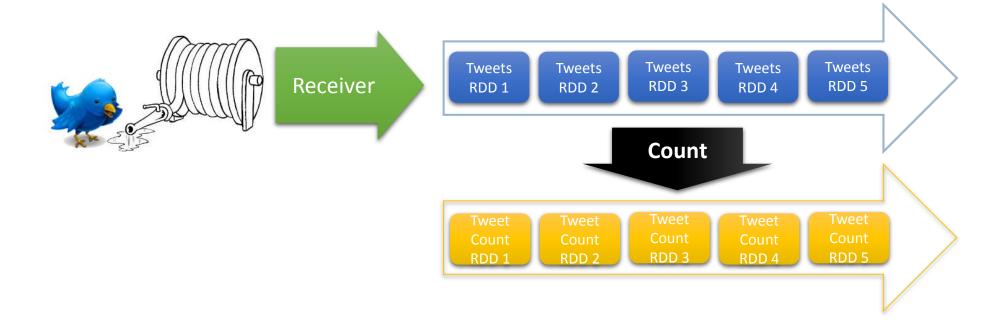












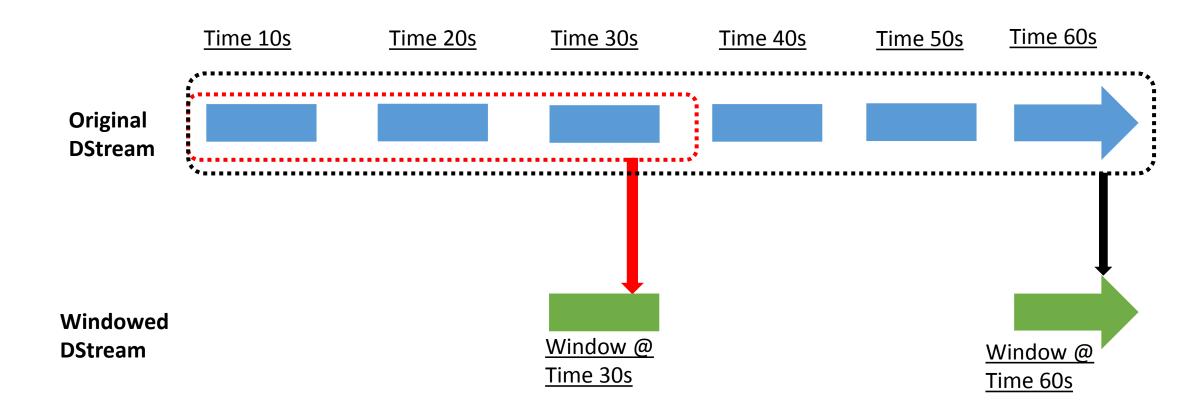




```
spark-submit --class academy.adastra.streamingexample.TwitterStream Document...
.TwitterStream Documents\NetBeansProjects\StreamingExample\target\StreamingExamp ^
le-1.0-SNAPSHOT.jar
15/08/11 16:18:04 WARN NativeCodeLoader: Unable to load native-hadoop library fo
 your platform... using builtin-java classes where applicable
Block #1 received 0 tweets.
Block #2 received 373 tweets.
Block #3 received 427 tweets.
Block #4 received 450 tweets.
Block #5 received 429 tweets.
Block #6 received 405 tweets.
Block #7 received 404 tweets.
Block #8 received 427 tweets.
Block #9 recei∪ed 471 tweets.
Block #10 received 439 tweets.
Block #11 received 420 tweets.
Block #12 recei∪ed 396 tweets.
Block #13 received 425 tweets.
Block #14 received 430 tweets.
Block #15 received 442 tweets.
Block #16 received 498 tweets.
Block #17 received 426 tweets.
Block #18 received 471 tweets.
Block #19 recei∪ed 437 tweets.
Block #20 recei∪ed 447 tweets.
```







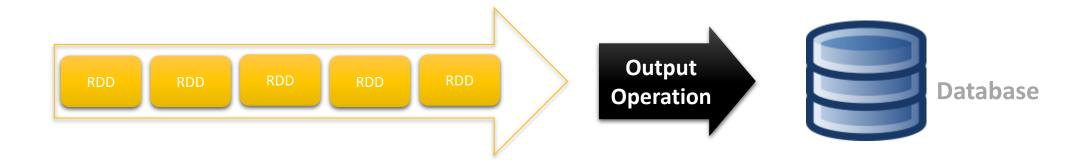


# **Tweet and Word Count**

```
Command Prompt
C:1.
Block #1 received 475 tweets.
Block #2 received 502 tweets.
Block #3 received 480 tweets.
The most frequent keywords in last 60 sec:
 this(28) will(23) just(20) powerball(18) back(18) that(18) have(16) what(15) nu
mbers(15) when(15)
Stopword list contains 1 words: this
Block #4 received 475 tweets.
Block #5 received 502 tweets.
Block #6 received 390 tweets.
The most frequent keywords in last 60 sec:
108> disconnected(107> year!(106> wrapped(106>
Stopword list contains 2 words:
                             this your
Block #7 received 367 tweets.
Block #8 received 371 tweets.
```

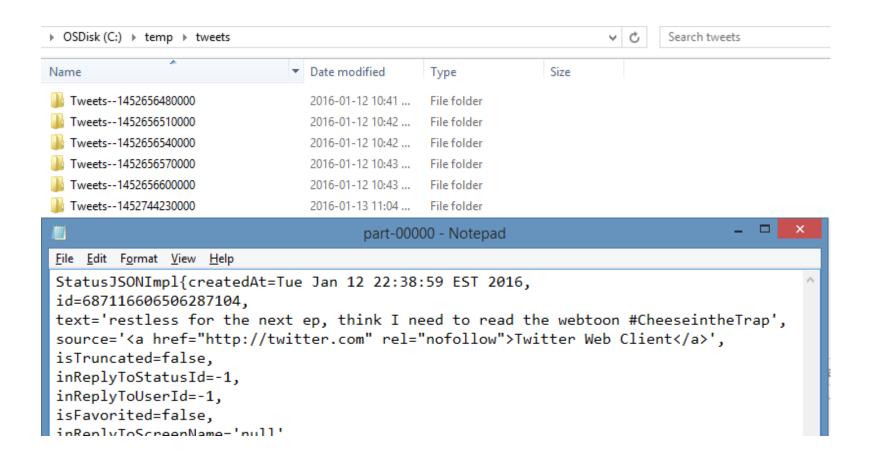








# **Output Data**







```
C:\WINDOWS\system32\cmd.exe - spark-submit --class academy.adastra.streamin...
[Stage 49:==========>
[Stage 49:-----> (41 + 1) / 42]
Block #10 received 582 tweets.
Block #11 received 610 tweets.
Block #12 received 588 tweets.
The most frequent keywords in last 60 sec:
#mtvhottest(45) that(43) when(32) just(31) more(28) love(27) para(26) #????????
???(23) follow(23) will(23)
Stopword list contains 4 words: this your with #mtvhottest
[Stage 69:======>
[Stage 69:=======>
[Stage 69:=======>
[Stage 69:======>>
[Stage 69:=======>>
[Stage 69:========>
[Stage 69:========>>
                                                      70 + 3) / 86°
                                                     (76 + 3) / 86°
                                                     (82 + 3) / 861
```



# Spark SQL





- SparkSQL is a component of Spark
- Distributed analysis framework on structured and semi-structured data
  - Data organized in rows, columns, columns can contain embedded data structures, arrays, or maps
- Uses high level SQL language to query data
- Read/write compatible with various file formats and data stores









- SQLContext object which supports SQL functionality in Spark
  - Created automatically when Spark Shell starts
    - Spark SQL is available out-of-the-box
    - No special configuration actions are necessary
  - Hive functionality with Spark speed and scalability
    - common tasks were reported performing ~10x faster than in native Hive running on Hadoop/YARN cluster







hiveContext.tableNames

table.printSchema

SQL

**SHOW TABLES** 

**DESCRIBE** table



#### Start data exploration with SQLContext

- Show tables available in Hive metastore:

Scala API: SQL:

sqlContext.tableNames.foreach(println)

C:\WINDOWS\system32\cmd.exe - spar... 

scala> sqlContext.tableNames.foreach(println) 
cr\_card\_dim
merch\_cat\_dim
merch\_dim
transaction
tweets

scala> 

...

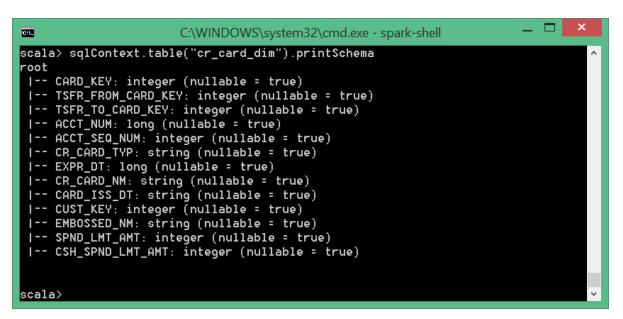
sqlContext.sql("SHOW TABLES").show





#### Scala API:

sqlContext.table("cr\_card\_dim").printSchema



#### SQL:

sqlContext.sql("DESCRIBE cr\_card\_dim").show

```
C:\WINDOWS\system32\cmd.exe - spark-shell
scala> sqlContext.sql("DESCRIBE cr_card_dim").show
           col_name|data_type|comment|
           CARD_KEY!
                           intl
|TSFR_FROM_CARD_KEY|
                           intl
   TSFR TO CARD KEY!
                           intl
                       bigint
           ACCT NUMI
       ACCT_SEQ_NUM|
                           intl
        CR_CARD_TYP!
                        stringl
            EXPR_DT |
                       bigint
         CR_CARD_NMI
                        stringl
        CARD_ISS_DT|
                       string
           CUST_KEY!
                           intl
        EMBOSSED NMI
                       string
       SPND_LMT_AMT|
                           intl
   CSH_SPND_LMT_AMT|
                           intl
```





table.show

table.select("column"...)

SQL

SELECT \* FROM table

SELECT column... FROM table





Scala API: sqlContext.table("merch\_dim").show

SQL: sqlContext.sql("SELECT \* FROM merch\_dim").show

```
C:\WINDOWS\system32\cmd.exe - spark-shell
[MERCH_KEY]
                          MERCH NM| MERCH ACCT NUMIMERCH CAT KEY|
          1|Francis Garza Cas...|5871773318452673|
          2|BitVision
                               ... | 9551426714760194 |
                                                                   41
                                                                   11
          3 | LPL
                               . . . | 3832410296436075 |
          4|James Williams
                               ... | 8005714589058633 |
                                                                   11
          5|Uincent Buchanan ...|7179991882545131|
                                                                   11
          6|Albos
                                                                   11
                               ... | 9258191614317116 |
          7|Avartis
                               . . . | 8851720442551984
                                                                   41
          8|Novional
                                                                   11
                               . . . | 9584819689622677 |
          9|Artia
                               . . . 14132201451908995
                                                                   11
                                                                   11
        10|ObjectWorks
        11 I GJJ
                                                                   11
        12|Illumos
        13|XQU Health Care
                               . . . 18372669659144557
                                                                   11
        14|Escentis
                               ...|1378449196210869|
                                                                   11
        15|TNF Stock Exchang...|3342709748470650|
                                                                   11
                                                                   41
        16|Albexis
                               ...|3557611478088378|
        17|Pentagon
                                                                   51
                               ... | 2572703956292519 |
        18|Ronald Barr
                                                                   41
                               . . . | 4253910480804024 |
        19|ClickStation
                                                                   11
                               ... [1851150018123793]
        20 | Cepheon
                                                                   11
only showing top 20 rows
```





Scala API: sqlContext.table("cr\_card\_dim").select("EMBOSSED\_NM","SPND\_LMT\_AMT").show

SQL: sqlContext.sql("SELECT EMBOSSED\_NM, SPND\_LMT\_AMT FROM cr\_card\_dim").show

C: L	C:\WINDOWS\system32\cmd.exe - spark-shell	X
+	+	^
EMBOSSED_NM SPN		
Chris Harmon LP	13418	
Robin Yates		
NanoForge Inc.		
Procum		
Procum	226991	
Alberta Cannon	3716	
Daniel Hicks	23957	
Jennifer Long	1492	
Dorothy Holmes	7482	
CZN Motors	21460	
CZN Motors	21460	
Claudia Bennett		
l Teresa Lyonsl	11320	
Clarissa Mills	23555	
Clarissa Mills	23555	
Robert Espinoza	14630	
	15967	
Jason Dixon	58761	
Manuel Allen	1701	
Manuel Allen	1701	
++		
only showing top 20 rows		





table.select(...).where(condition)

Condition example: \$"YEAR" > 2016

# SQL

SELECT \* FROM table WHERE condition

Condition example: YEAR > 2016





Scala API: sqlContext.table("cr\_card\_dim").select(\$"EMBOSSED\_NM",\$"SPND\_LMT\_AMT" as "LIMIT").

where(\$"LIMIT" > 24900).show

SQL: sqlContext.sql("SELECT EMBOSSED\_NM, SPND\_LMT\_AMT AS LIMIT FROM cr\_card\_dim WHERE SPND\_LMT\_AMT > 24900").show

```
C:\WINDOWS\system32\cmd.exe - spark-shell
scala> sqlContext.table("cr_card_dim").select($"EMBOSSED_NM",$"SPND_LMT_AMT" as
"LIMIT").where($"LIMIT" > 24900).show
    EMBOSSED_NM|LIMIT|
 Kenneth Davis|24956|
|Dorothy Morgan|24980|
     Jorge Hall|24947|
  Theresa Scott | 24907 |
    Nancy Craft | 24972 |
     June Scott | 24984 |
     June Scott1249841
    Lena Campos | 24932 |
   Brandon Cole | 24929 |
      Ross Knox | 24998 |
    Ellen Klein | 24972 |
  Gregory Smith | 24974 |
```





table.groupBy(cols).agg(exps)

Expression examples: count(\$"ID") sum(\$"PRICE")

# SQL

SELECT expr FROM table GROUP BY cols

Expression examples:
COUNT(\*)
SUM(PRICE)



#### **Grouping and aggregations**

Scala API: sqlContext.table("transaction").groupBy(\$"MERCH\_CAT\_KEY" as "CATEGORY").

agg(count(\$"TXN KEY") as "COUNT", sum(\$"TXN AMT") as "TOTAL").show

SQL: sqlContext.sql("SELECT MERCH\_CAT\_KEY AS CATEGORY, COUNT(TXN\_KEY) AS COUNT,
SUM(TXN\_AMT) AS TOTAL FROM transaction GROUP BY MERCH\_CAT\_KEY").show

```
C:\WINDOWS\system32\cmd.exe - spark-shell — X

| C:\WINDOWS\system32\cmd.exe - spark-shell — X
| C:\WINDOWS\system32\cmd.exe - spark-shell — X
| C:\WINDOWS\system32\cmd.exe - spark-shell — X
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| C:\WINDOWS\system32\squ
```





table.join(other, expr)

table.orderBy(columns)

Columns examples: \$"YEAR" \$"PRICE".desc

# SQL

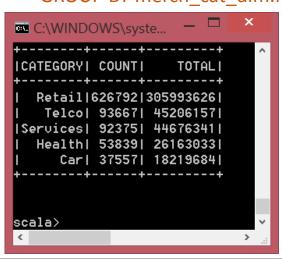
SELECT \* FROM table JOIN other ON expr

SELECT \* FROM table ORDER BY columns

Columns examples:
YEAR
PRICE DESC







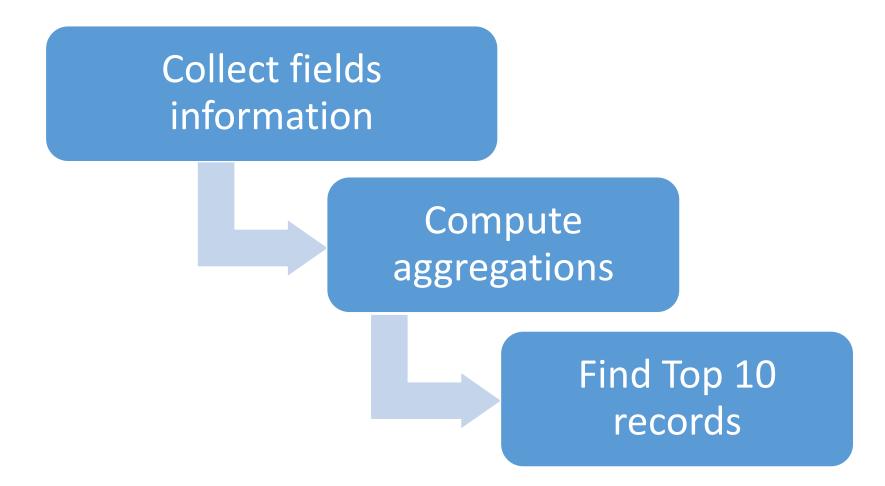


## **Example: Data profiling application**

- Extract interesting information from large sets of fuzzy data
- Look for various issues in data
- Task:
  - Compute and show field-by-field statistics
    - count, count distinct, count null, count not null all supported types
    - average, minimum, maximum numeric types only
    - first, last numeric and string types
    - top 10 values









## **Example dataset profile highlights**

10 min of the Twitter firehose sample data collected by the Twitter Streaming example application

25,217 total statuses

149 columns

24,425 distinct users

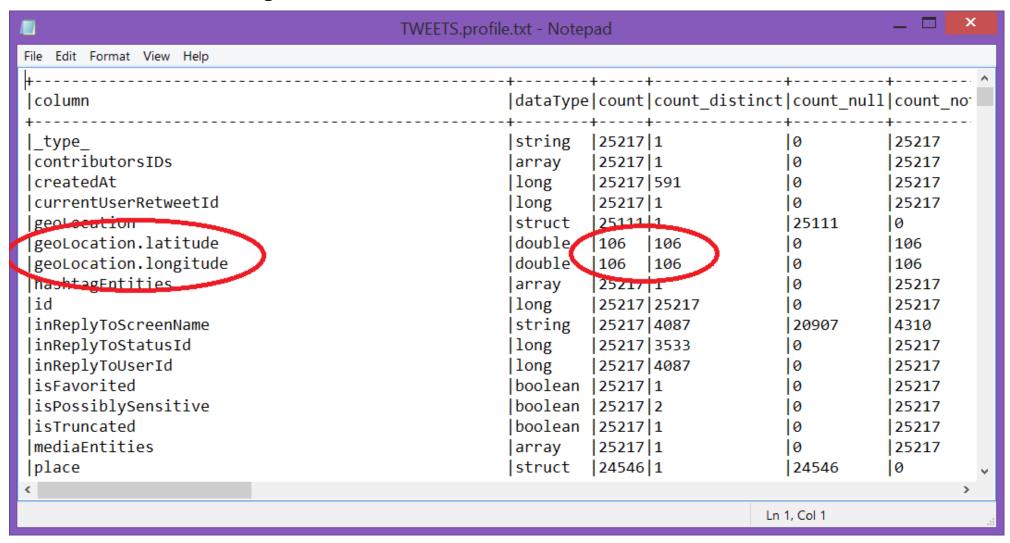
106 locations

49 languages

228 possibly sensitive statuses



#### Weakness – sparse data





#### **Extracted information from the data**



#### **Related Courses**



- Adastra Academy courses on Apache Spark include:
  - Introduction to Apache Spark for Developers and Engineers
  - Scala in Practice
  - Advanced Apache Spark for Data Scientists and Developers
- Go to our website: <a href="www.adastra.academy">www.adastra.academy</a>
- Use coupon code: TASM127
- Email us: <a href="mailto:info@adastra.academy">info@adastra.academy</a>



# Thank you!