Atom Smashing using Machine Learning at CERN

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About Me

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Evaluation of Apache Spark as Analytics Framework for CERN's Big Data Analytics

- Thanks to my mentors
  - Valentin Kuznetsov, Cornell University
  - Tony Wildish, Princeton University
  - Manuel Martin Marquez, CERN
  - Antonio Romero Marin, CERN

Project Scope

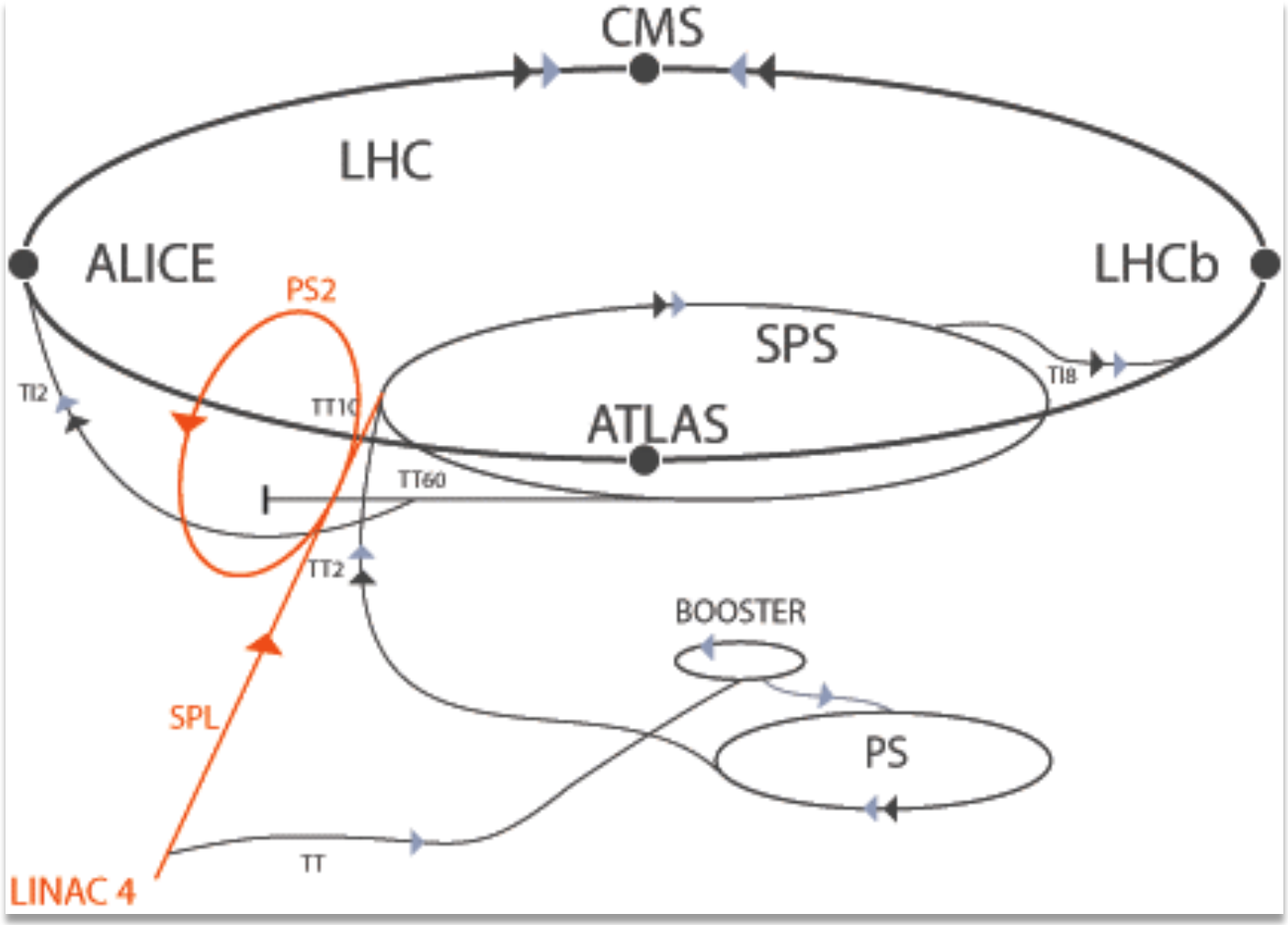
- Understanding CMS BIG data
  - Static + Streaming
- Exploring Apache Spark
  - Potential framework for big data analysis
  - Predict popular datasets in near real time
  - Facilitate Dynamic Data Placement
  - Efficient resource utilization

Outline

- CERN
- Understanding CMS Data
- Evaluation of Apache Spark
- Results and Conclusion

European Organization for Nuclear Research

LHC@CERN



Source: Manuel Martin Marquez, CERN

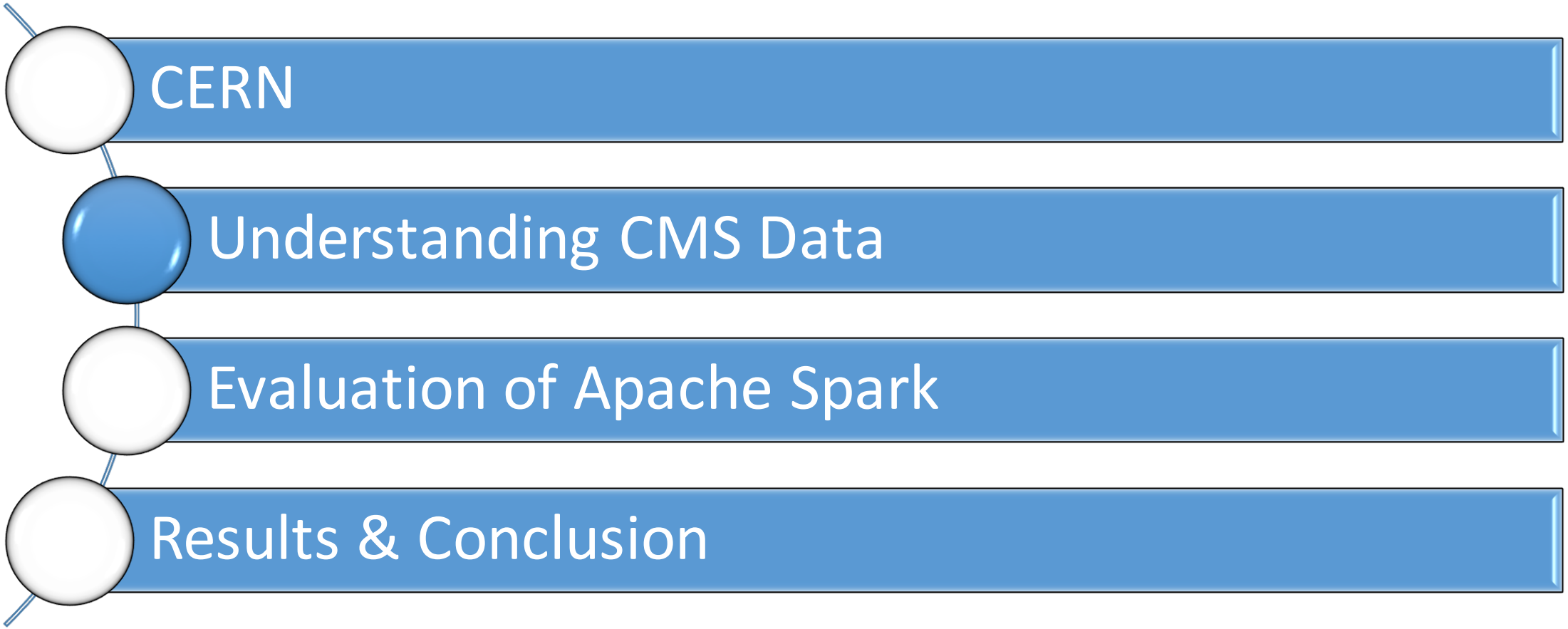
European Organization for Nuclear Research

LHC@CERN

Atom Smashing at CERN

- Compact Muon Solenoid(CMS) hunts for Higgs boson particles and clues to the nature of dark matter
- Beams of protons collide with energy of 13 TeV
  - Visualized in 3 dimensions
  - Digital summary of collisions
- Peta Byte (PB) -order data obtained, post filtering

Outline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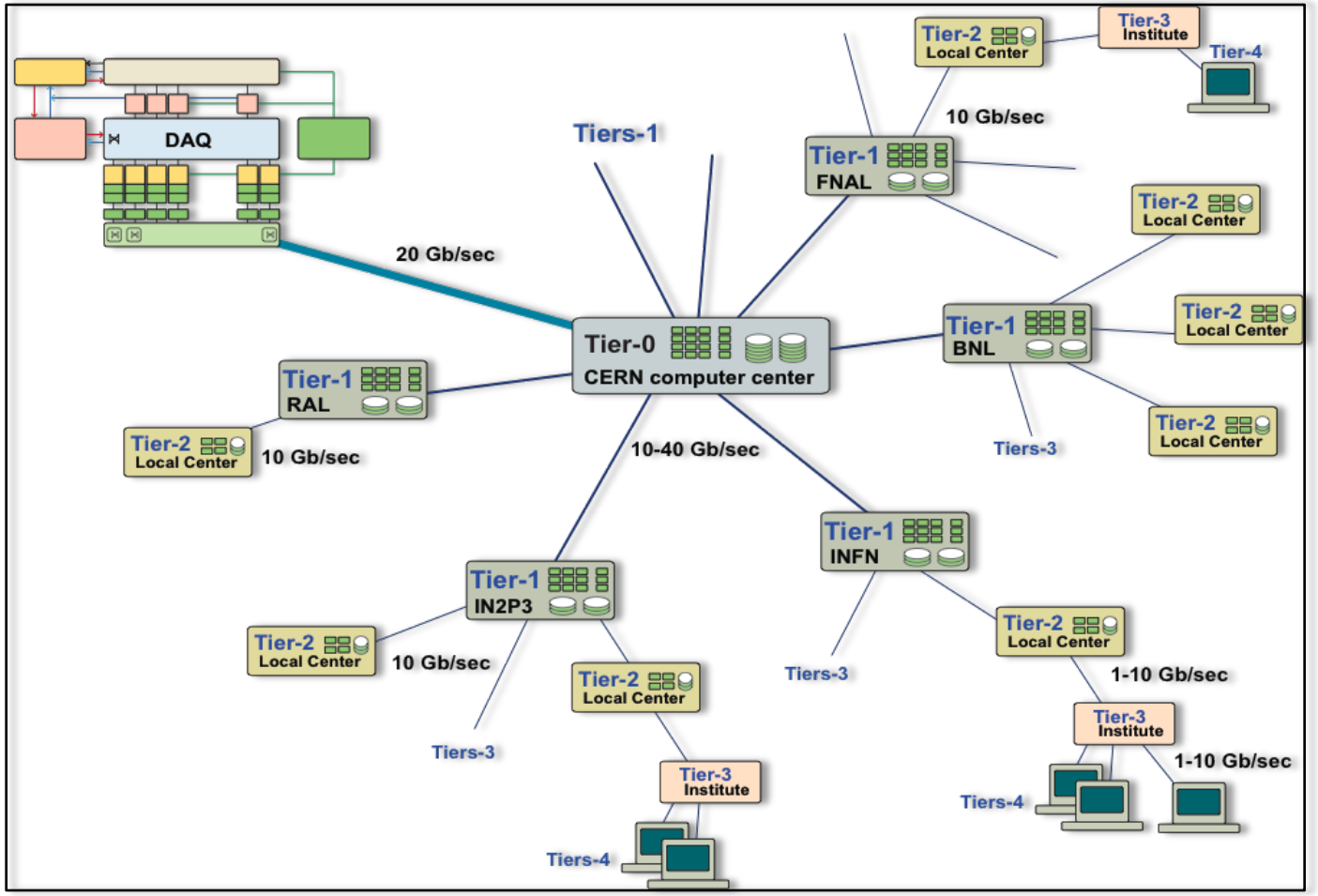
CERN Computing Grid

CERN

- Recording
- Reconstruction
- Distribution



Source: Manuel Martin Marquez, CERN

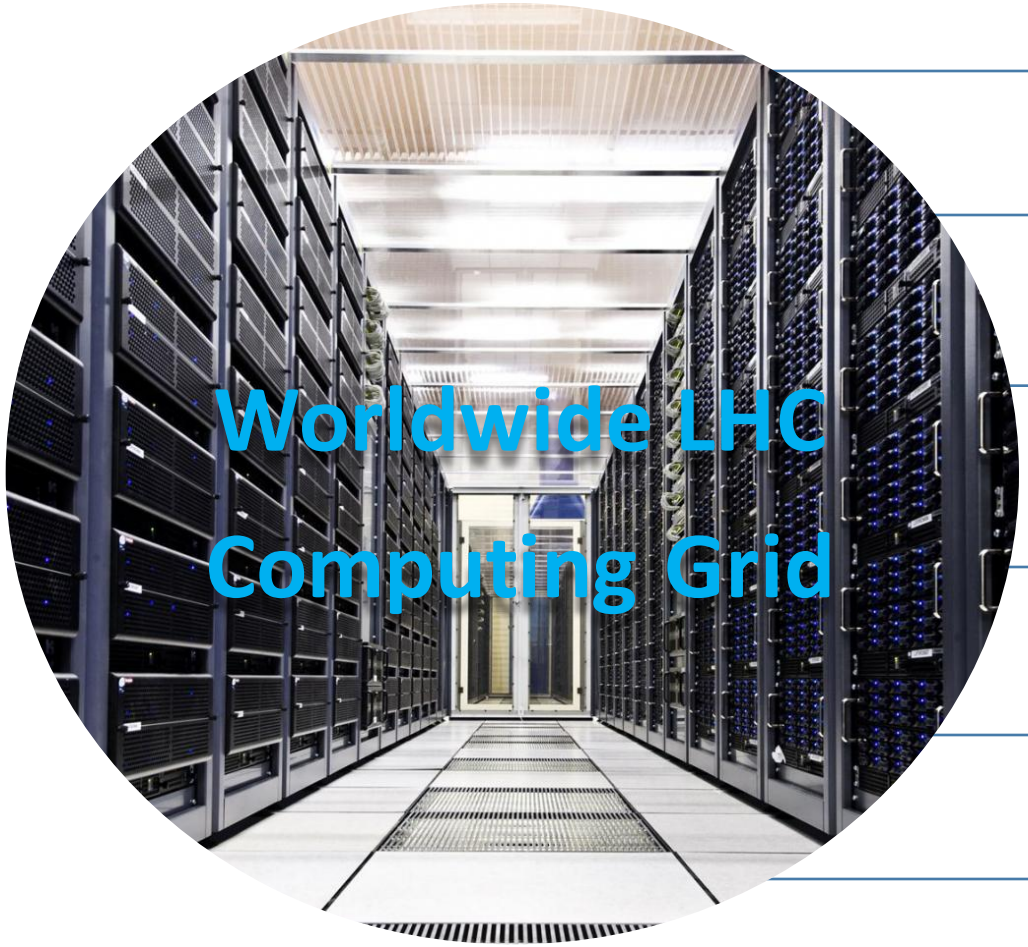
Physics Workflow and Data Analytics

- Physics data
  - Different streaming data scenario
  - The new data is of course interesting!
  - Old data is all the more interesting!!
    - Re-processed old data with signals and background check influences the importance of new data

Big Data Approach

Volume	Velocity	Variety	Veracity
• Number of collisions in the LHC • 15 PB order post filtering	• 300 Mb/s production rate • Quick availability of results • Real time feedback is NOT required	• Irregular data • Different kinds data sets	• Uncertain • Limited data integrity

Data Acquisition – Structured sources



PhEDEx: Physics Experiment Data Export

CMS Data Management System

CMS Workload Management System

PopDB

SiteDB

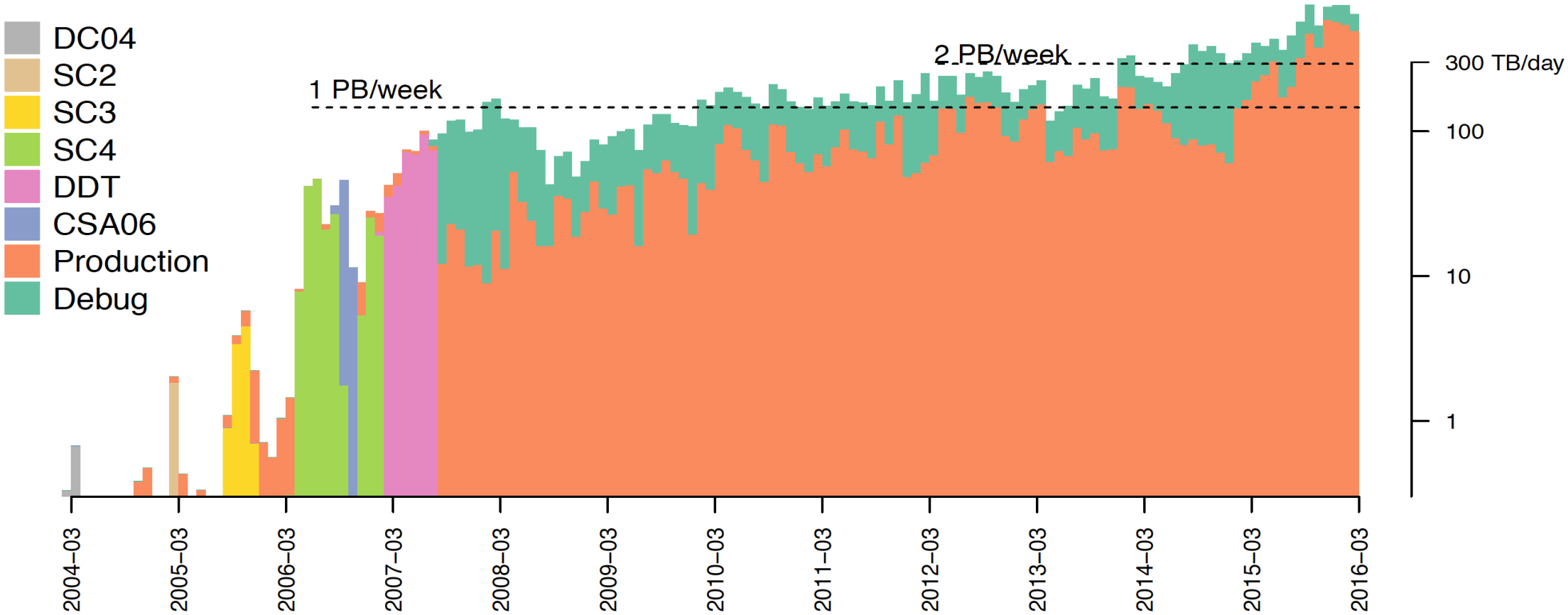
Dashboard

Data Acquisition – Unstructured sources

- CERN Indico
- CERN Zenodo
- CERN Vidyo

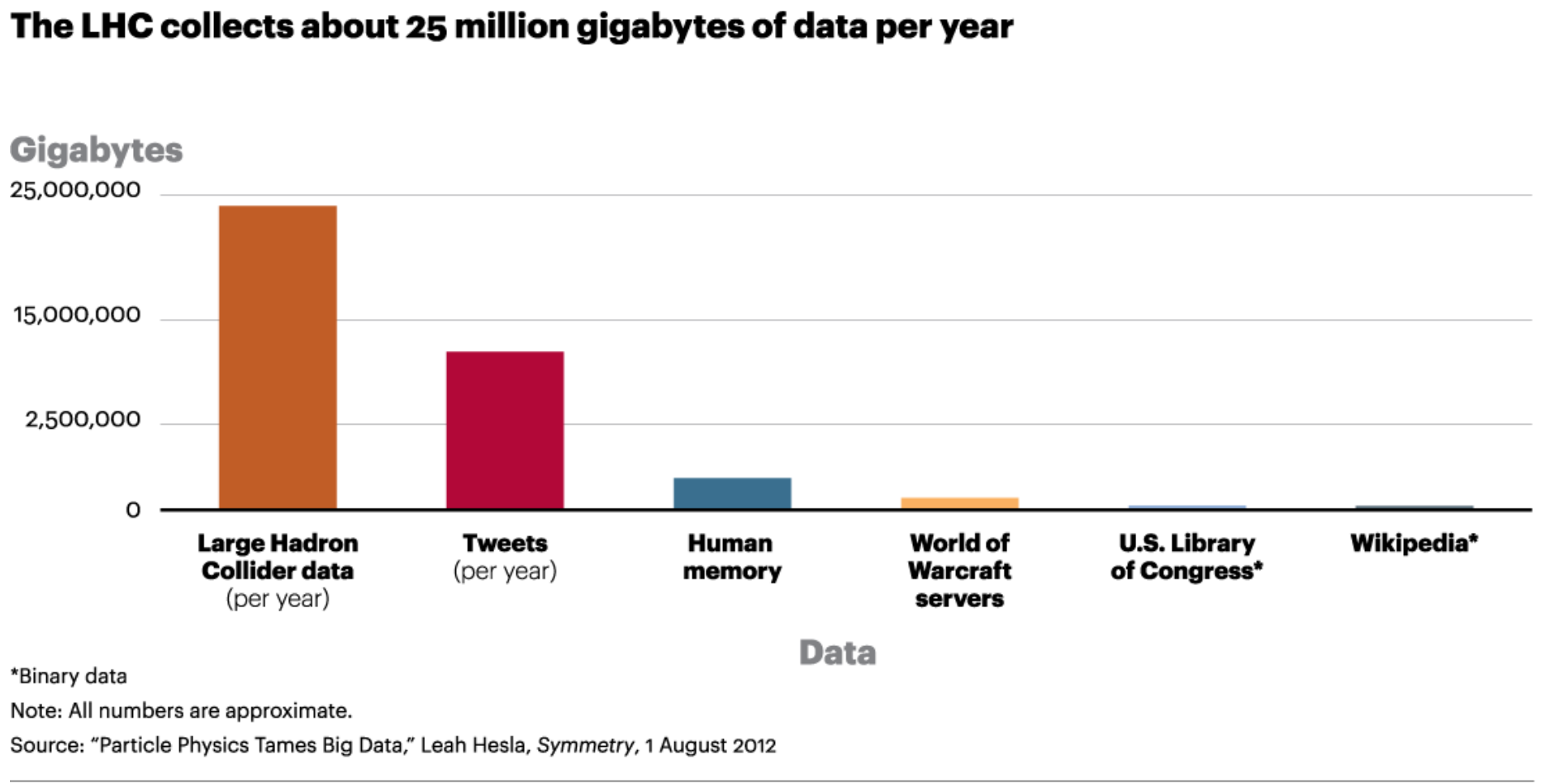
Data is important

Data is really important

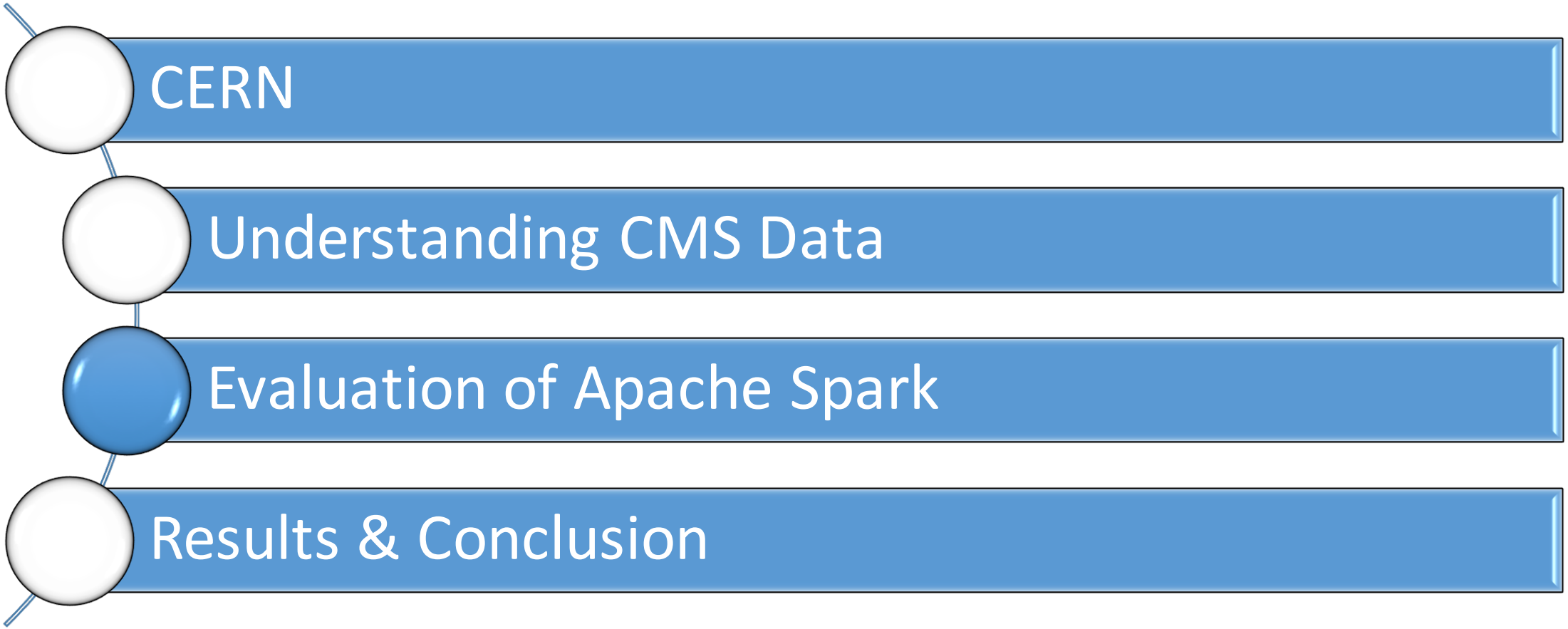


Source: Tony Wildish, Princeton University

Data is indeed important



Outline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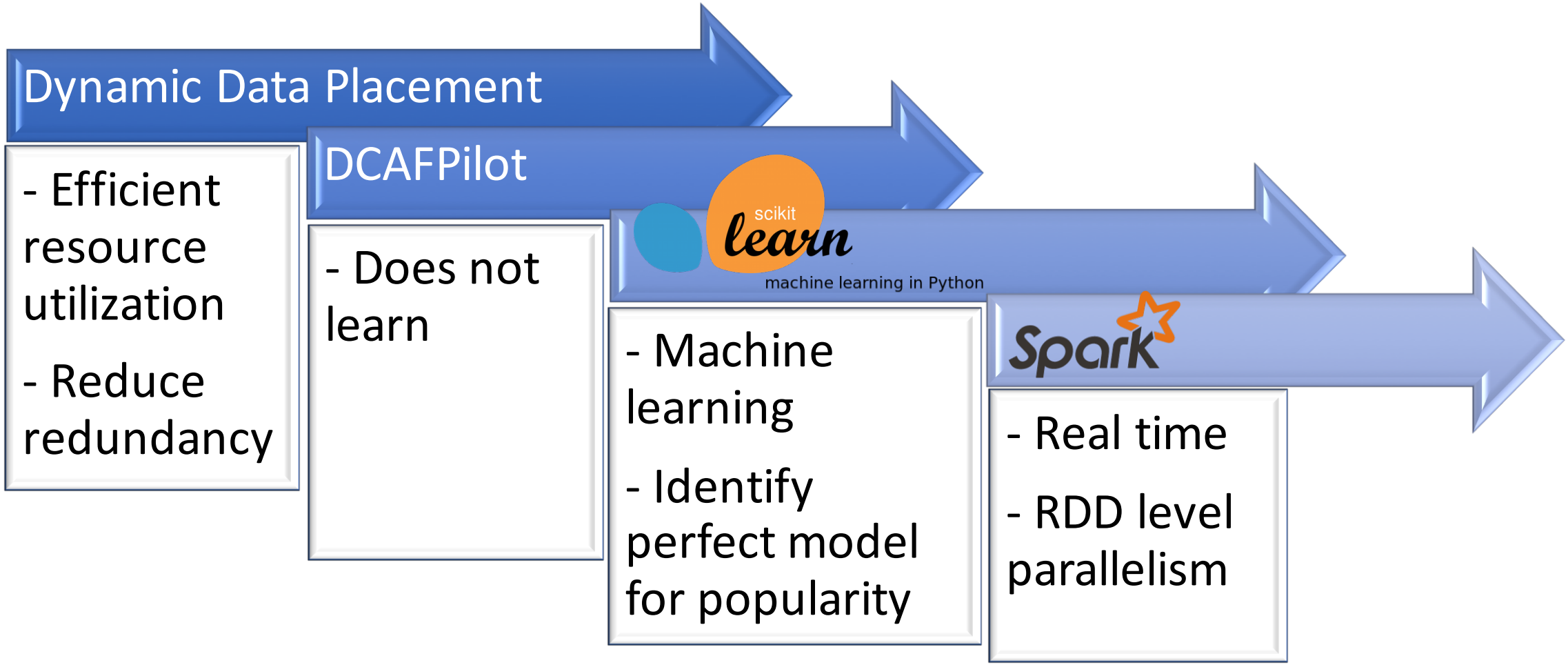
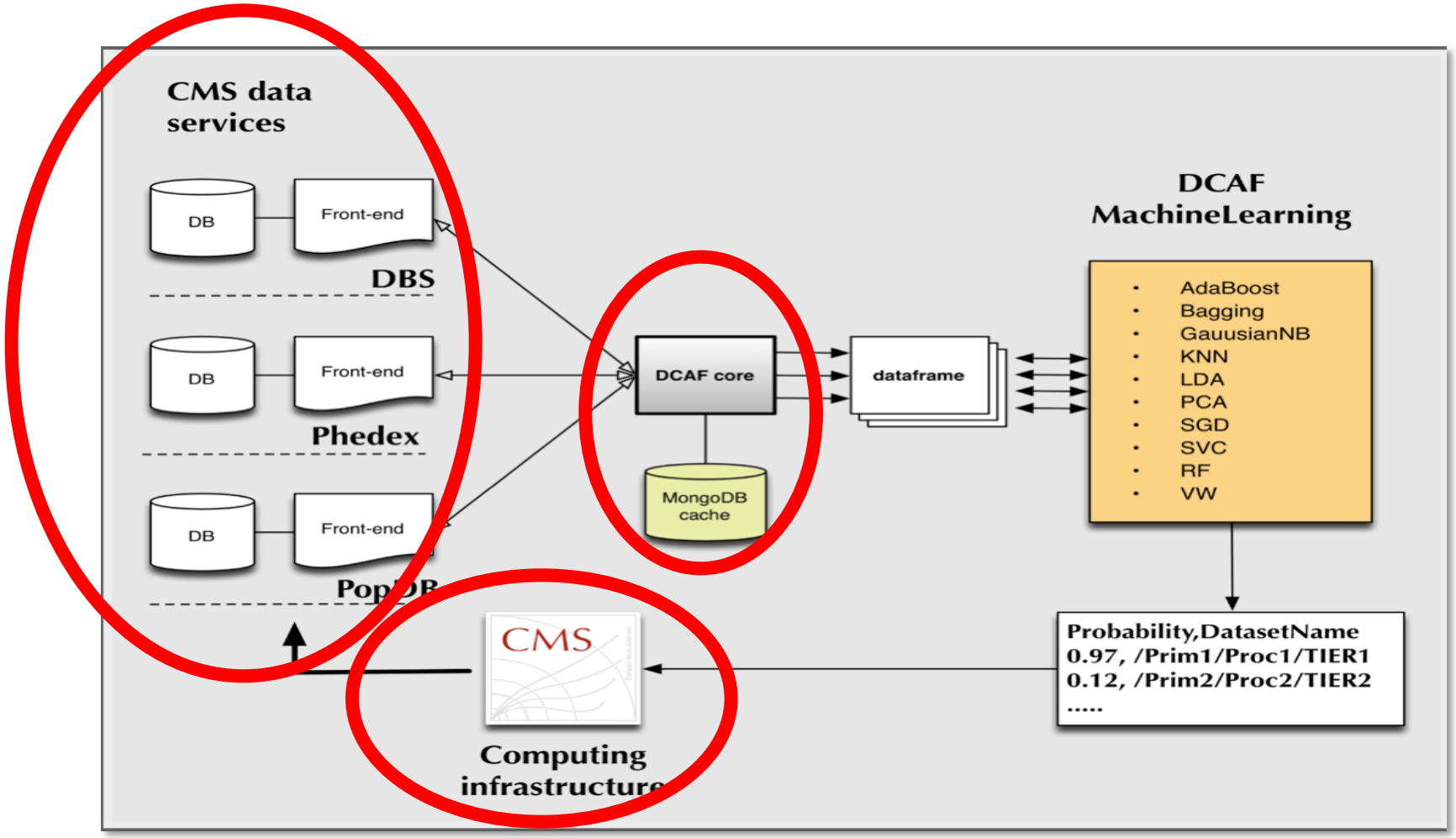
Timeline


Dynamic Data Placement
- Efficient resource utilization
- Reduce redundancy
DCAFPilot
- Does not learn
scikit
learn
machine learning in Python
- Machine learning
- Identify perfect model for popularity
Spark
- Real time
- RDD level parallelism

Data and Computing Analysis Framework



Source: https://github.com/dmwm/DMWMAnalytics/blob/master/Popularity/DCAFPilot/doc/talks/Pilot1/images/DCAFPilot_flow.png

1K popular

&

10K unpopular

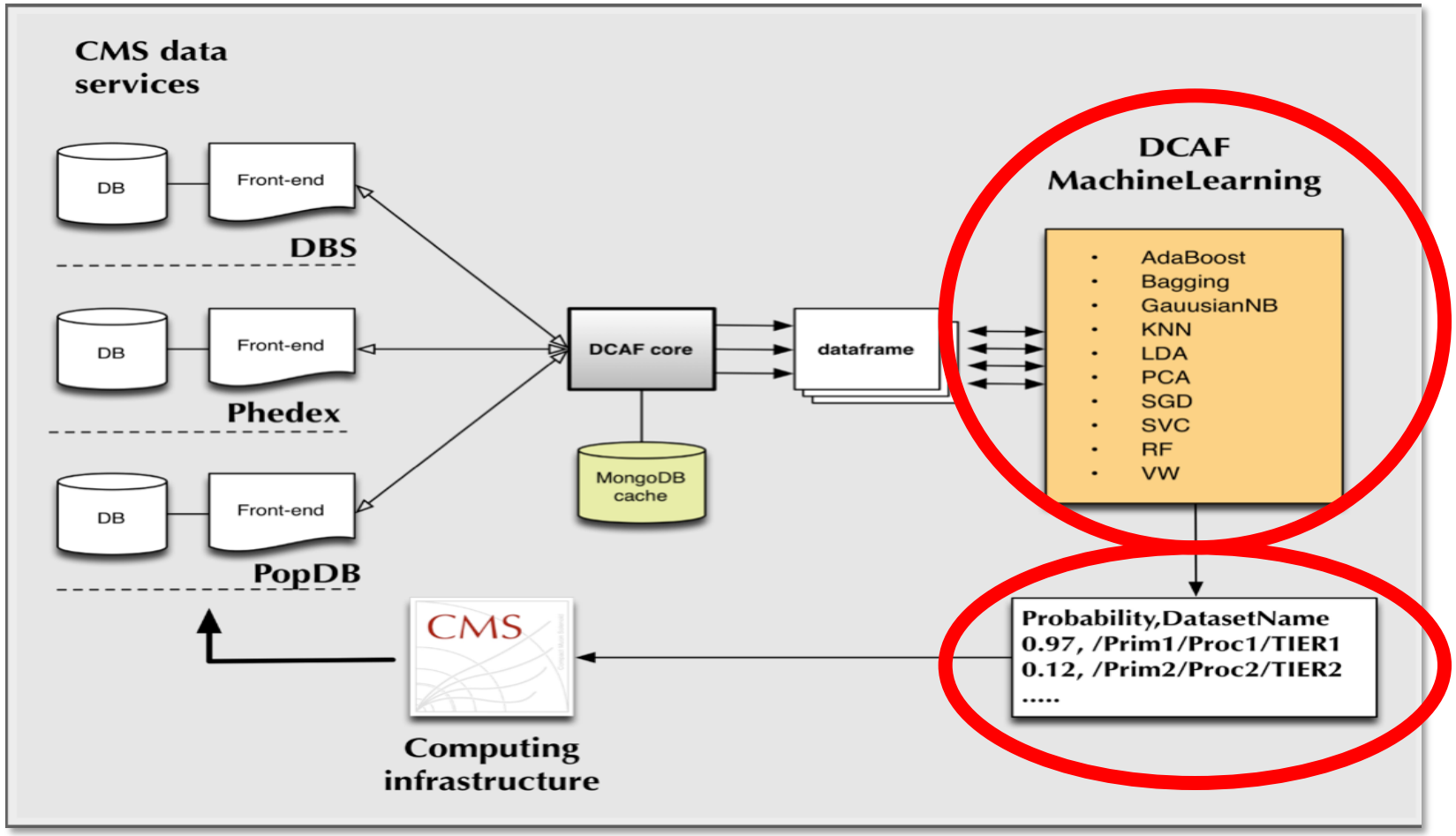
78 features

25 relevant features

Feature Extraction

id	cpu	nlumis	nfiles	nblk
creator	tier	nevt	proc_evts	nusers
wct	size	rnaccess	primds	nsites
totcpu	rtotcpu	rnusers	parent	nrel
naccess	era	dtype	dbs	dataset

Data and Computing Analysis Framework



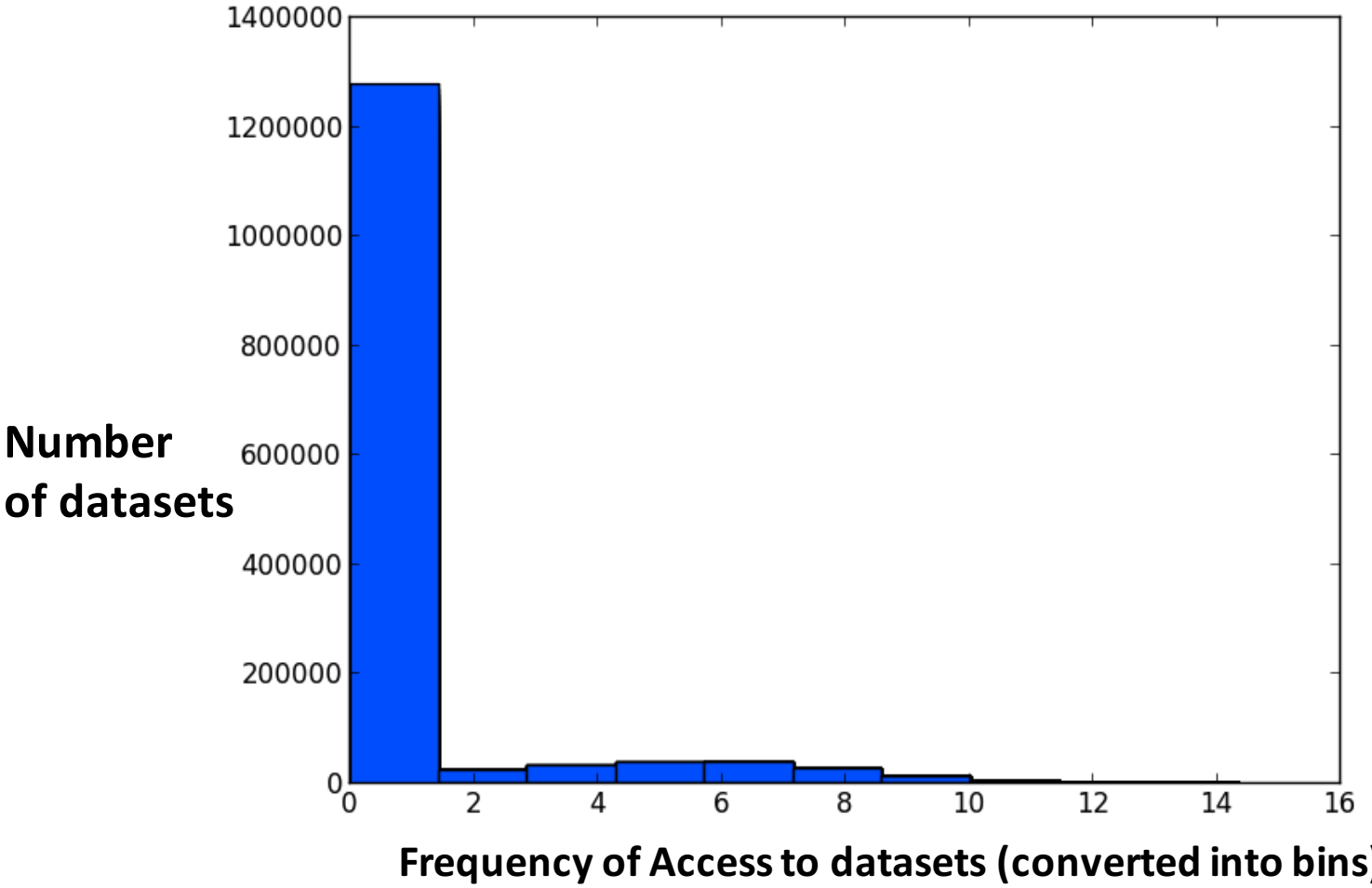
Source: https://github.com/dmwm/DMWMAnalytics/blob/master/Popularity/DCAFPilot/doc/talks/Pilot1/images/DCAFPilot_flow.png

Transforming to classification problem

- Classification problem
  - Target column is 1(popular) when naccess is greater than 10 and nusers is greater than 5

```
def convert(df):
    threshold_naccess = 10
    threshold_nusers = 5
    return df['naccess'] > threshold_naccess and
df['nusers'] > threshold_nusers
```

Frequency of Accesses



Naccess cut found by plotting the entire 2014 dataset against frequency of access

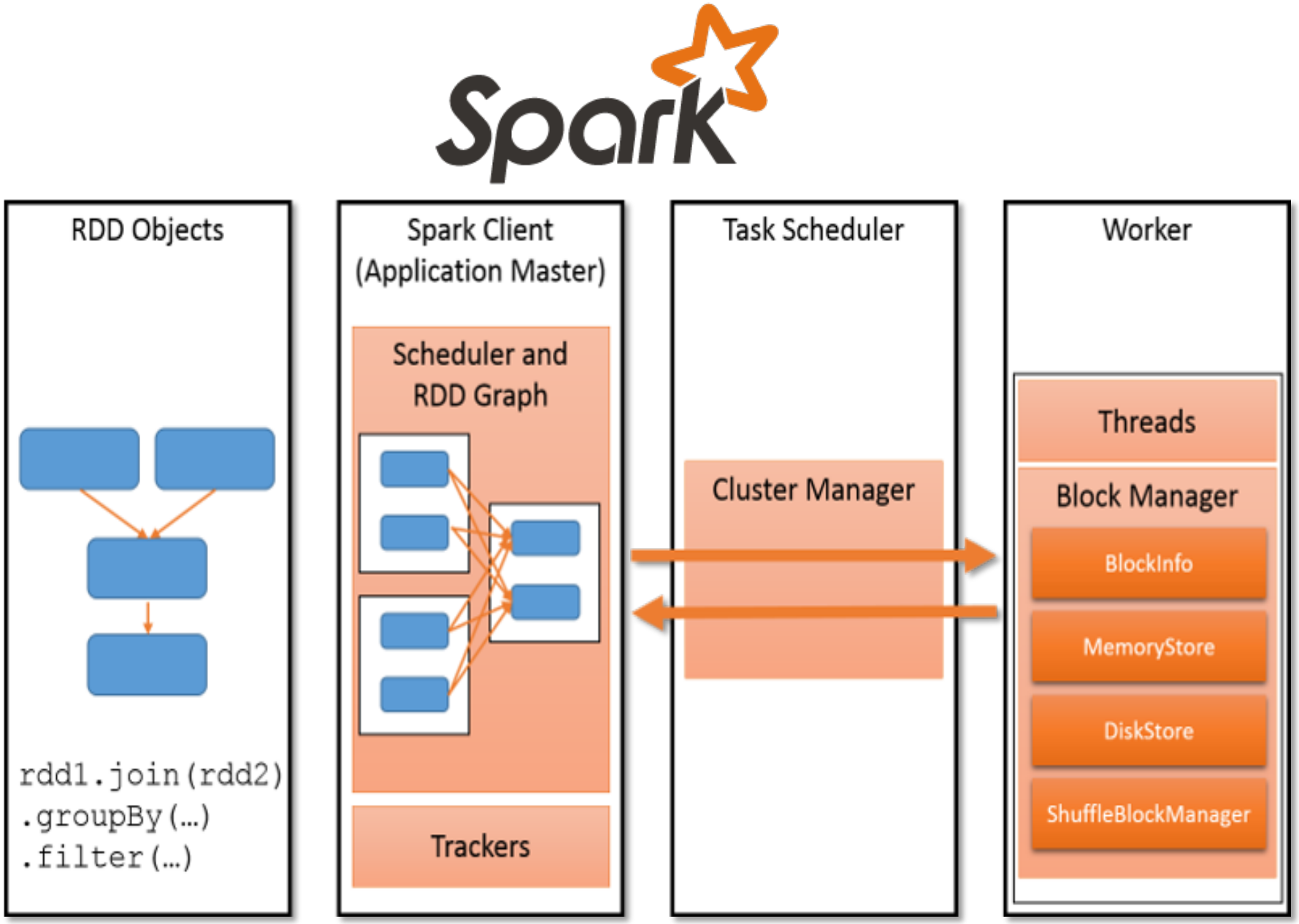
600KB compressed data frames

600KB compressed/file

* 52 files/year

* 3 years/run

~15 PB/year

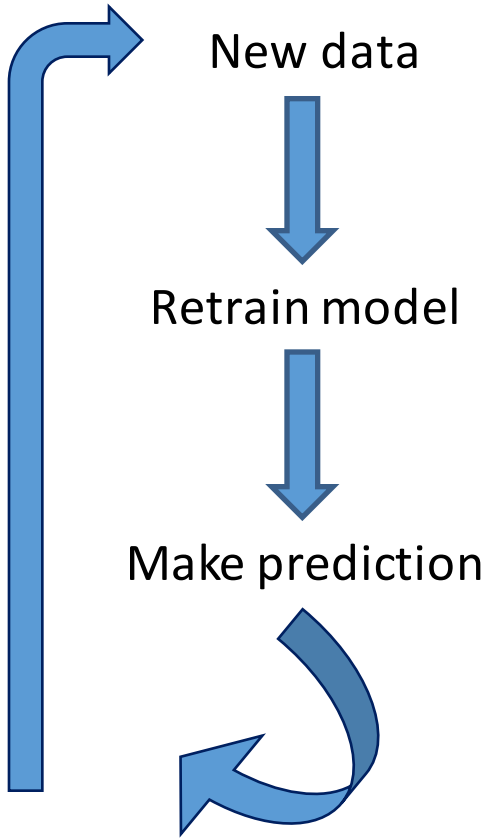


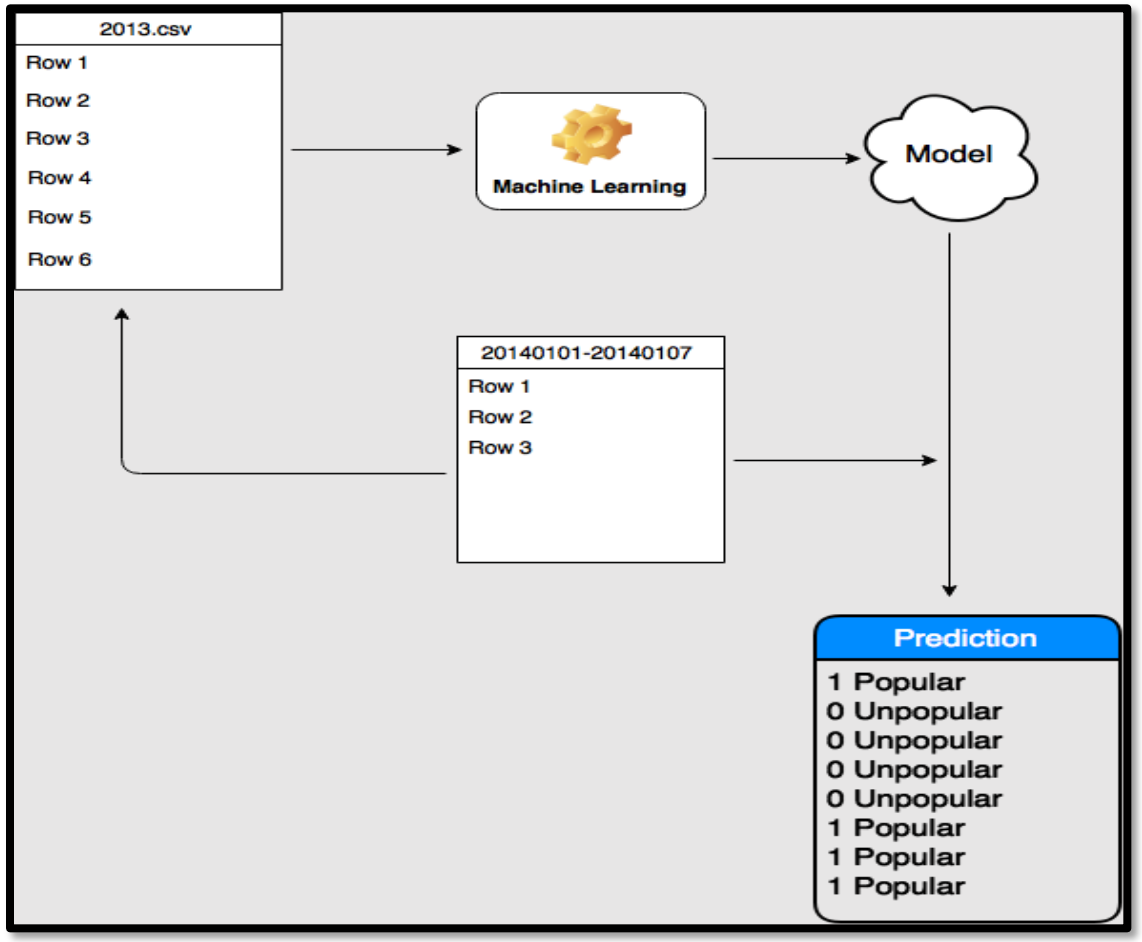
Source: 15-319 / 15-619 Cloud Computing, CMU

Apache Spark analysis

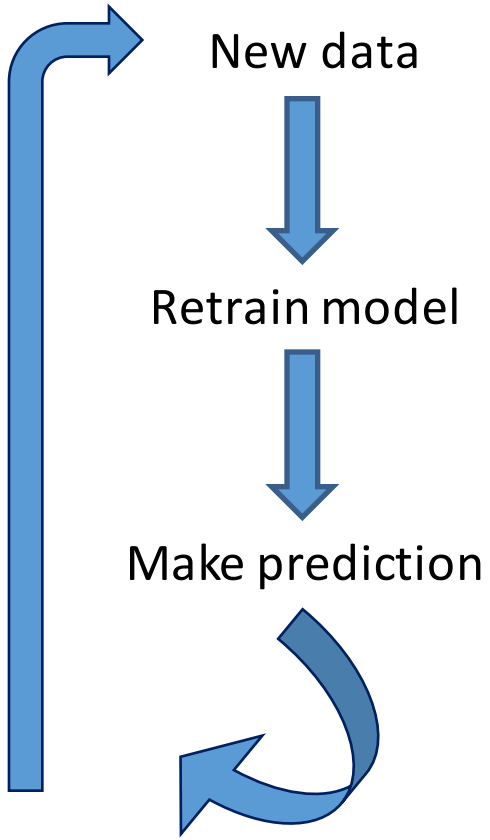
- Fast and compatible with already existing HDFS at CERN
- Run in Hadoop clusters through MESOS or Spark's standalone mode
  - Process data in HDFS
  - Batching of a week's data
  - Processing for new workloads like streaming (live prediction of each week), interactive queries, and machine learning.

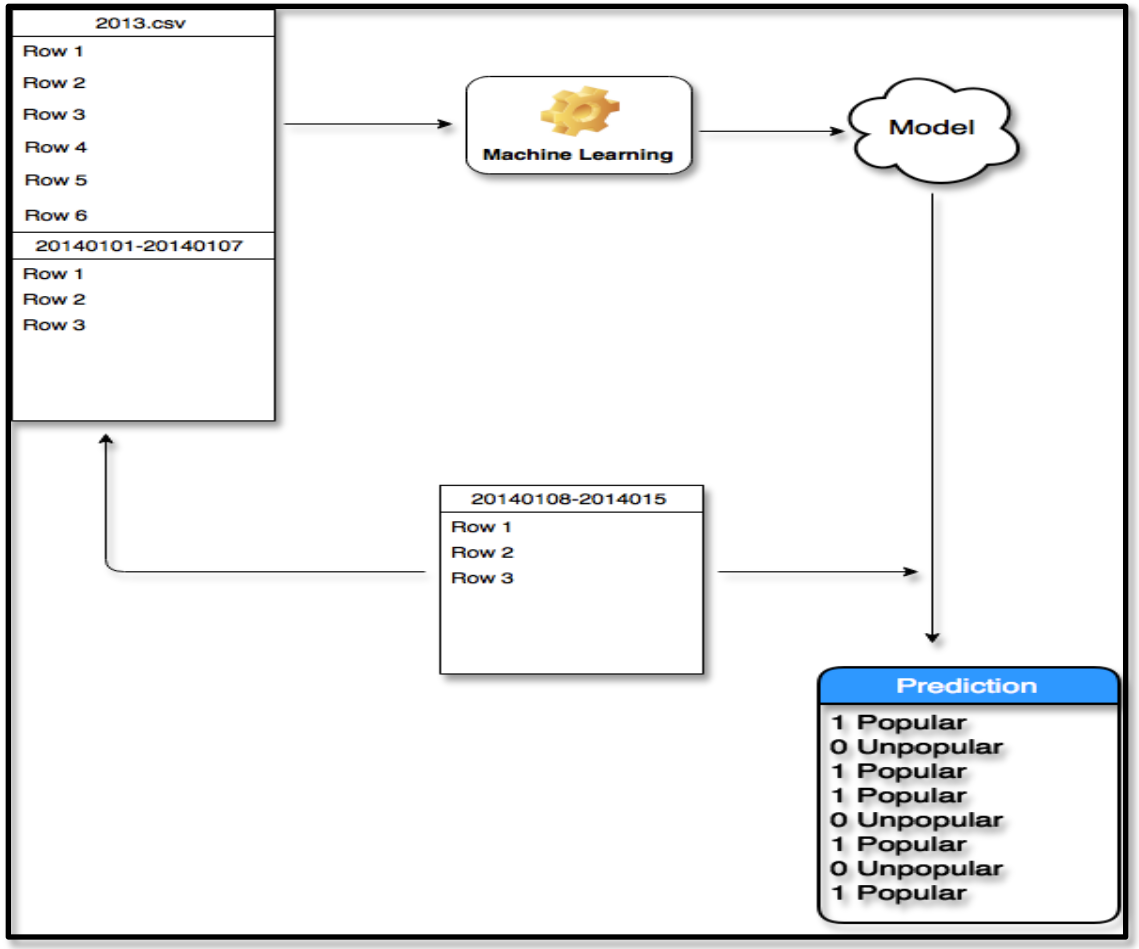
Rolling Forecast



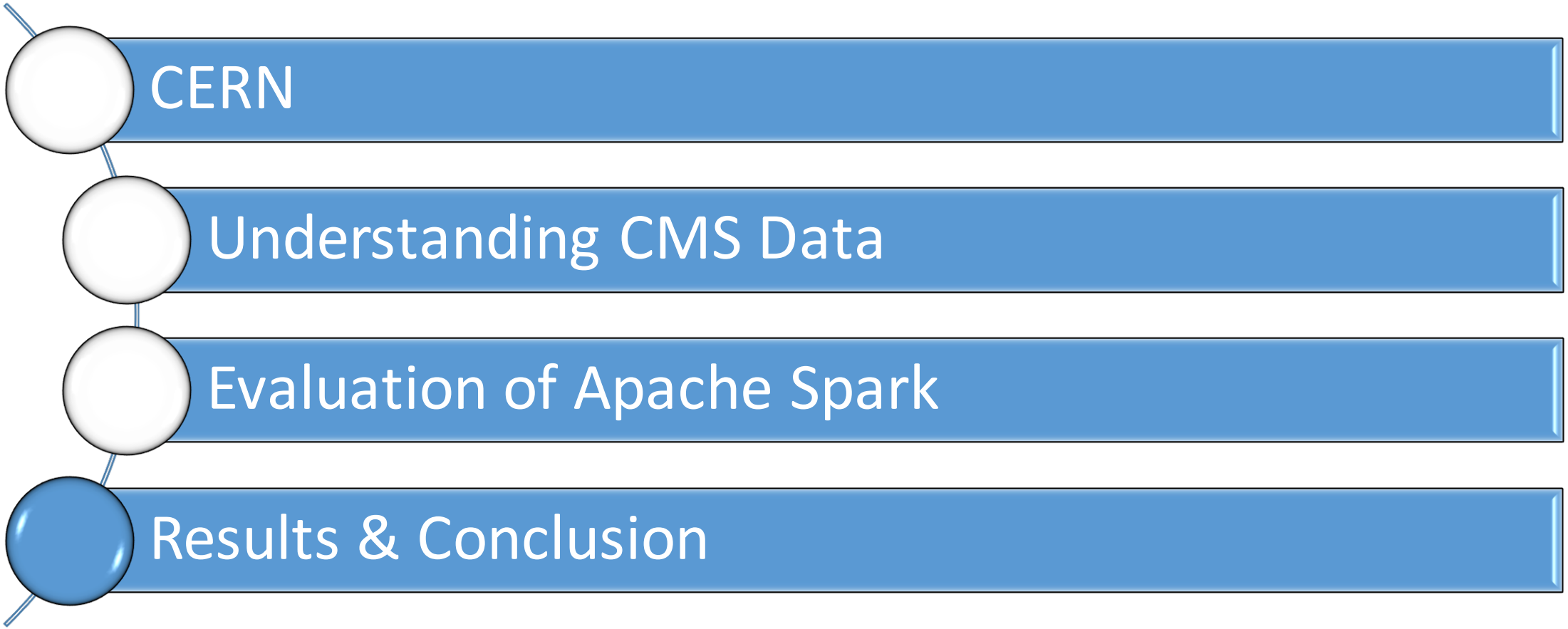


Rolling Forecast





Outline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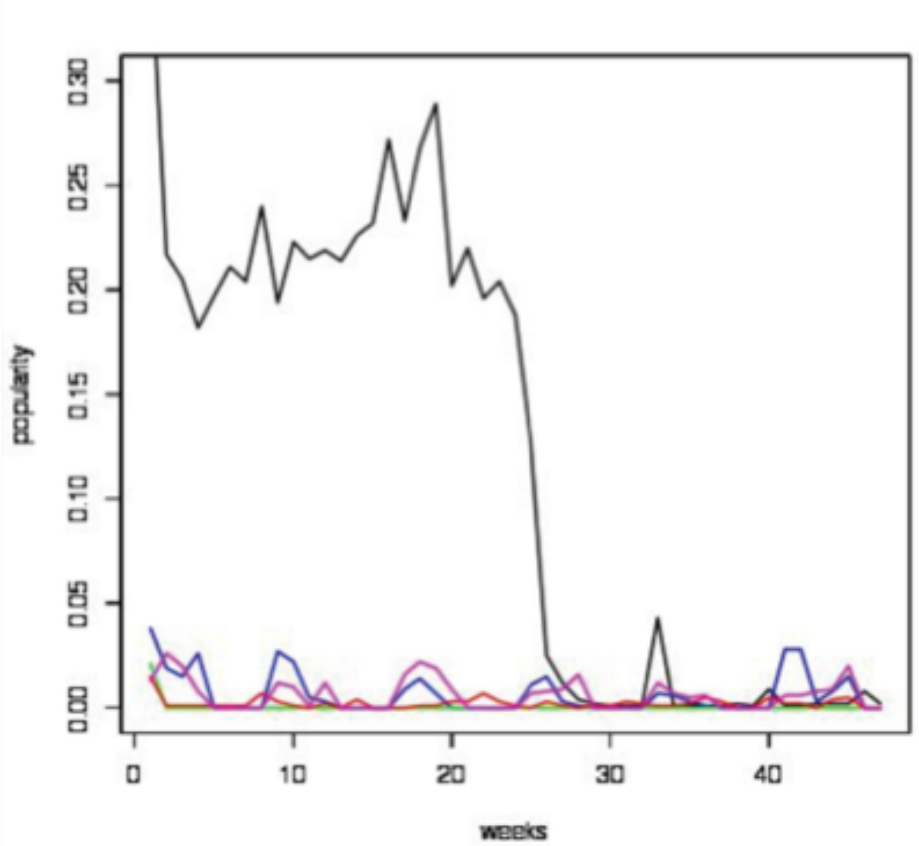
- Parallel analysis on distributed data
- Decreased total execution time for the individual algorithm or combined ensemble to execute

Input data **Apache Spark**

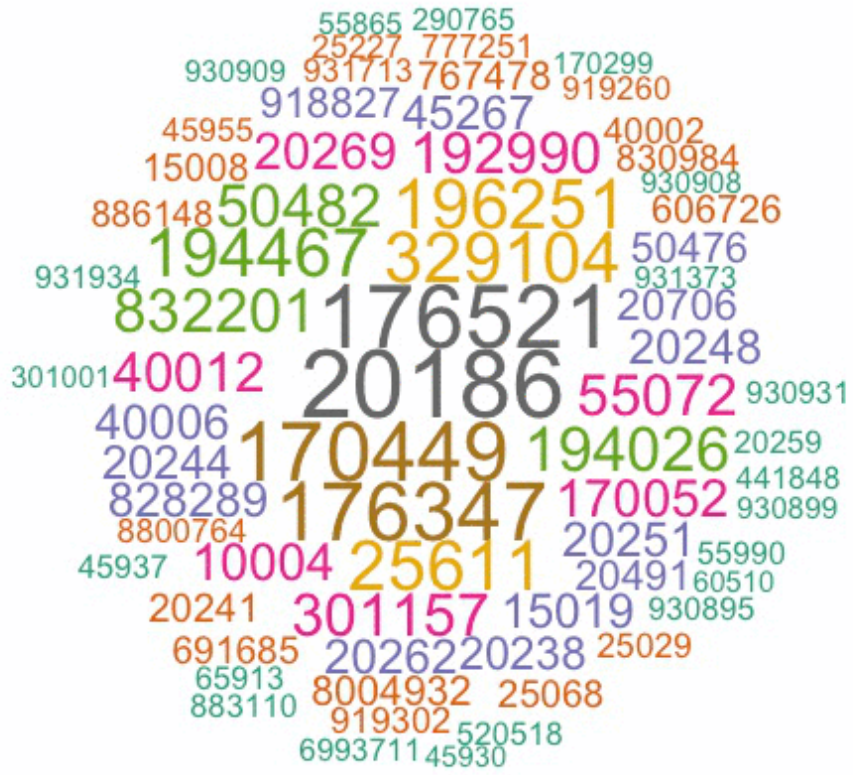
Popularity Metrics



Popularity of Random datasets

Source: https://github.com/dmwm/DMWMAnalytics/blob/master/Popularity/DCAFPilot/doc/talks/Pilot1/images/popularity.jpg

Popularity Metrics - nusers



Total number of users who accessed the dataset

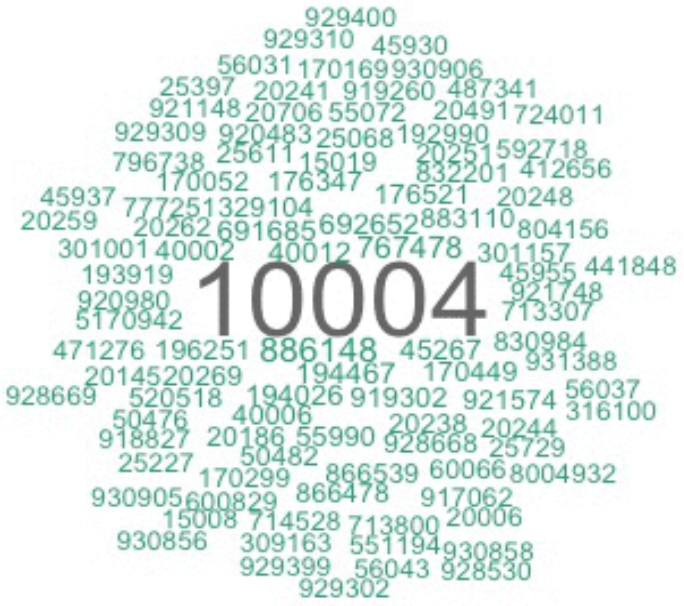
Source: https://github.com/dmwm/DMWMAnalytics/blob/master/Popularity/DCAFPilot/doc/talks/Pilot1/images/nusers_cloud.gif

Popularity Metrics - totcpu

Total CPU hours spent analyzing a dataset

Source: https://github.com/dmwm/DMWMAnalytics/blob/master/Popularity/DCAFPilot/doc/talks/Pilot1/images/cpu_cloud.gif

Popularity Metrics - naccess



Count of individual accesses to a dataset

Source: https://github.com/dmwm/DMWMAnalytics/blob/master/Popularity/DCAFPilot/doc/talks/Pilot1/images/naccess_cloud.gif

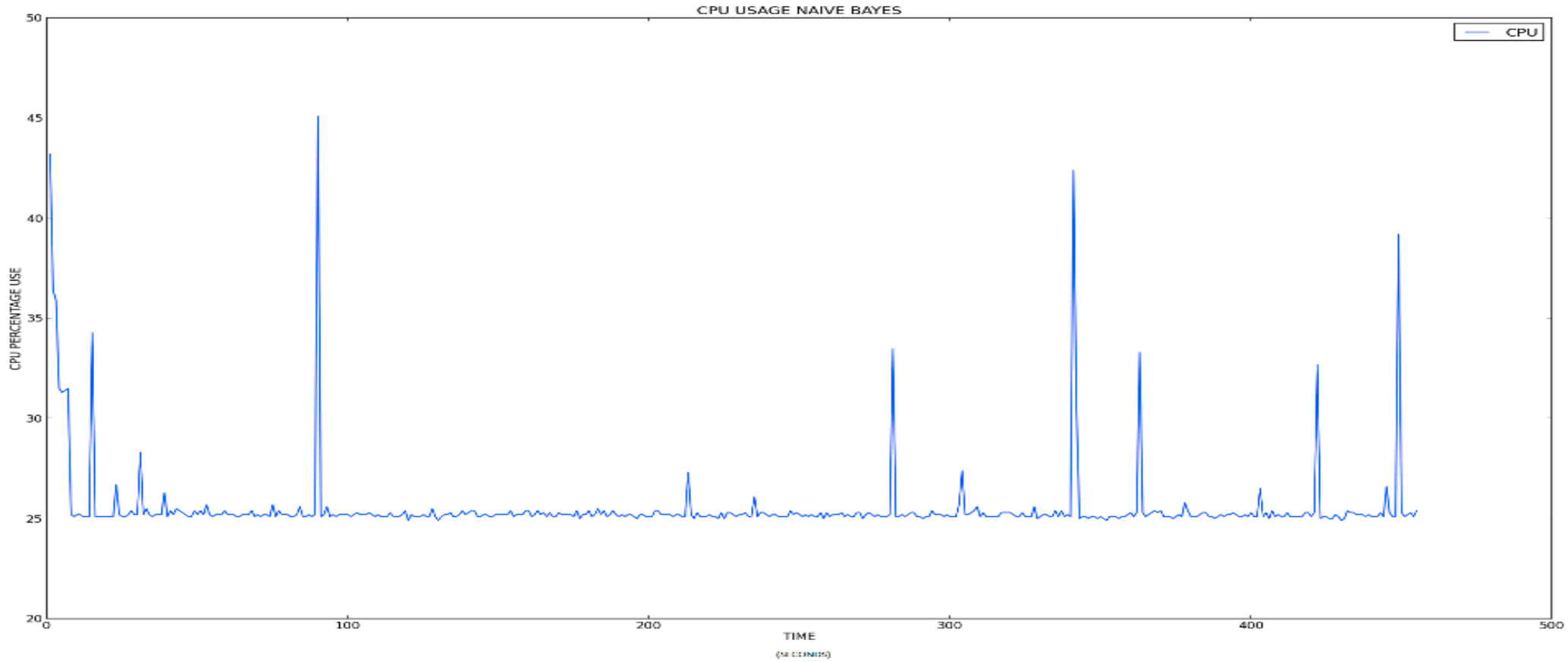
CPU Usage

- Using psutil (python system and process utilities)
  - /proc/pid/stat of pid
- Approximately 25% of the CPU is always being used by the algorithms

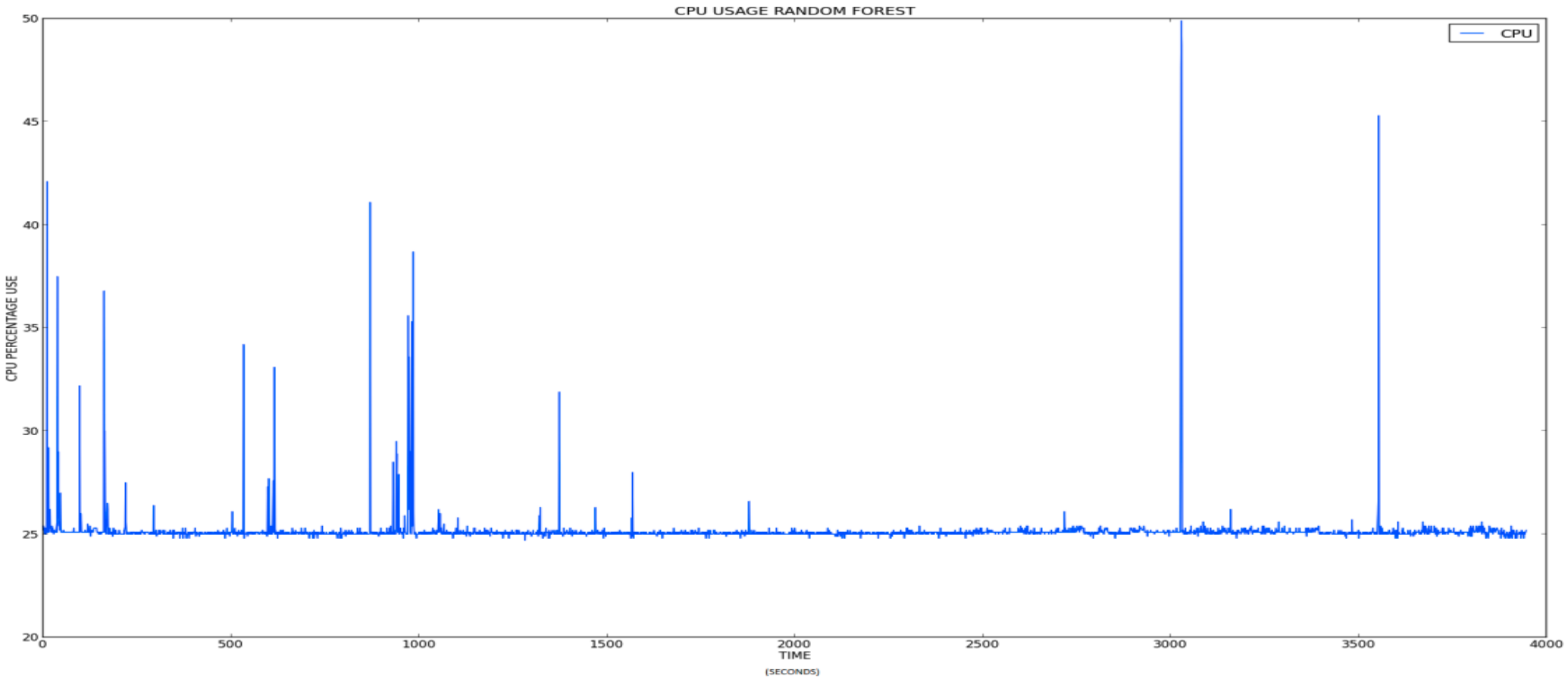
CPU Usage

- Importance
  - Lots of processes submitted to the CERN Grid
  - All processes should work in a cooperative environment
  - All processes should be able to access the required resources
- Statistical difference between CPU usage
  - Scikit-learn uses more CPU for longer time duration

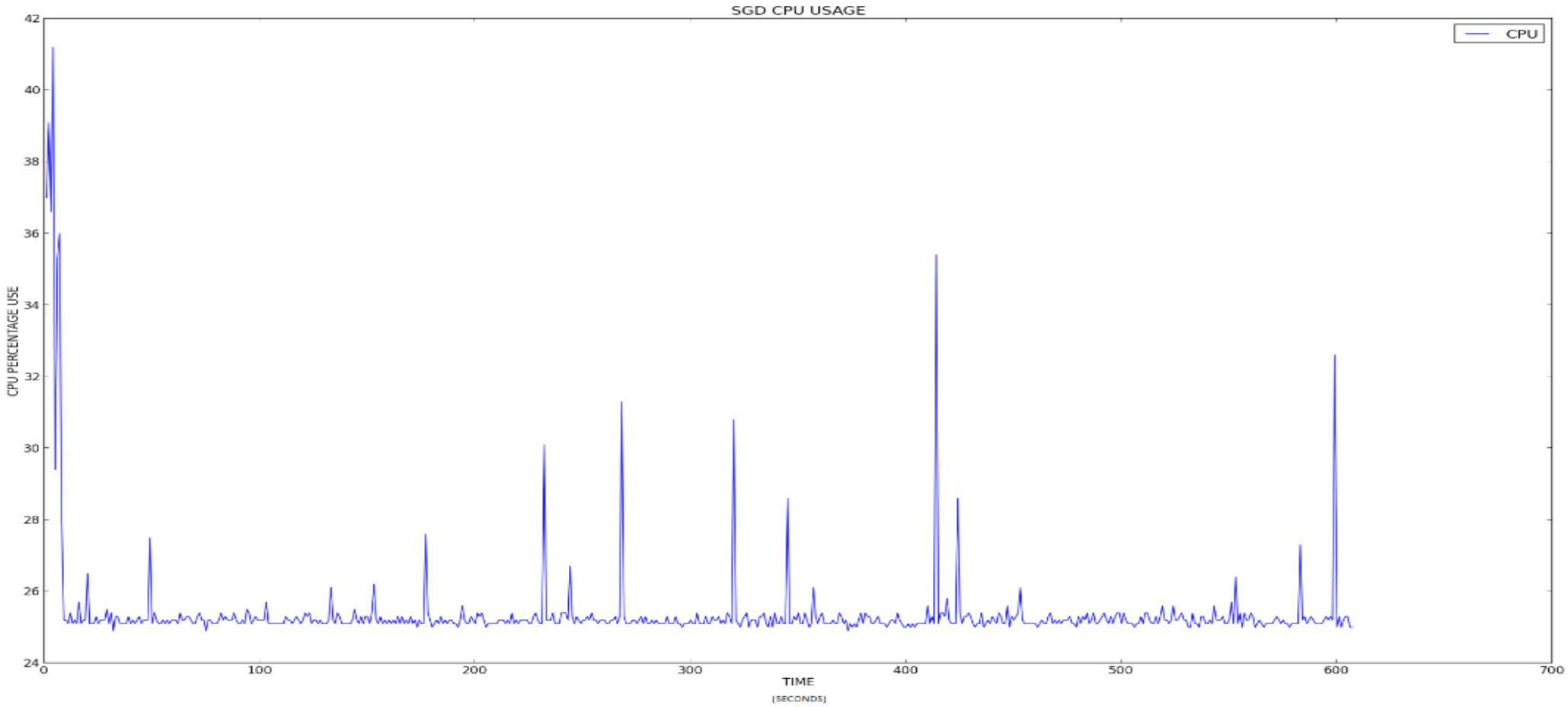
Naïve Bayes – Apache Spark



Random Forest – Apache Spark



Stochastic Gradient Descent – Apache Spark



Performance matrix – Apache Spark

Algorithm	Memory Used (GB)	Execution Time (Seconds)
Random Forest	5.072920	8184.136
Naïve Bayes	5.376336	1204.97
Stochastic Gradient Descent	5.181784	1261.94

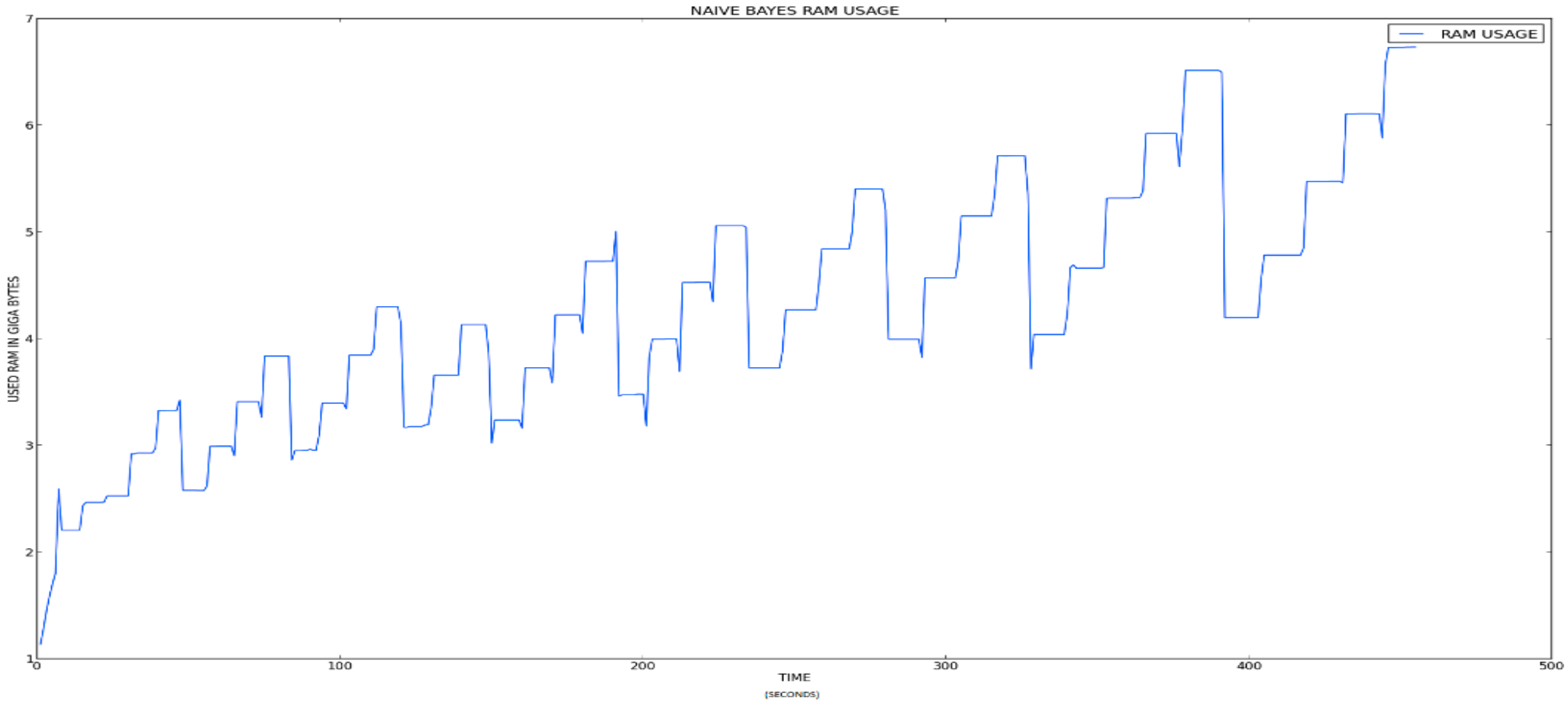
RAM Usage

- Incremental learning
  - With each iteration more RAM is utilized
  - Amount of data being processed is continually increased
- Graph does not indicate memory leak
  - Rolling approach
  - Incremental learning part

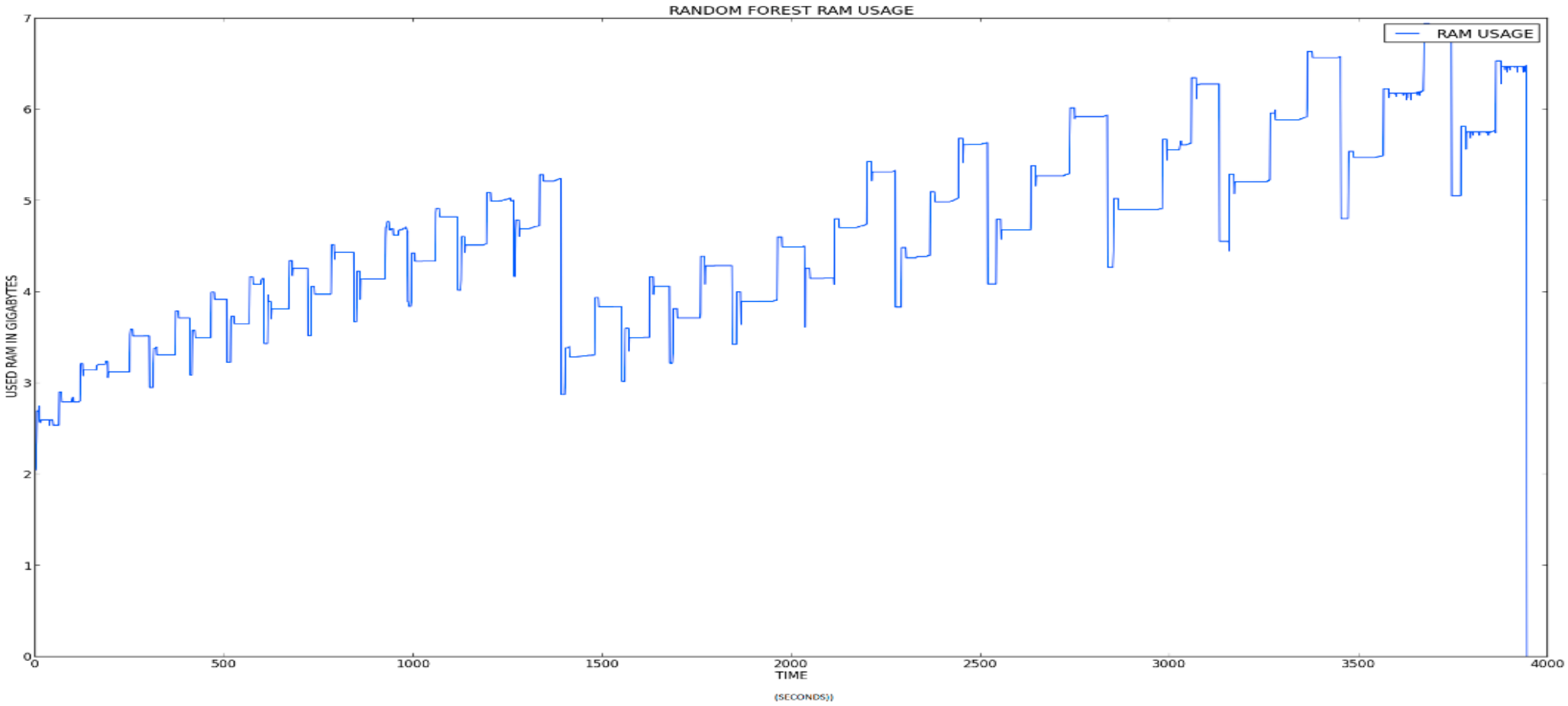
RAM Usage

- Statistical difference between RAM usage
  - Scikit-learn uses more RAM for longer time duration
  - RDD parallelism in Apache Spark

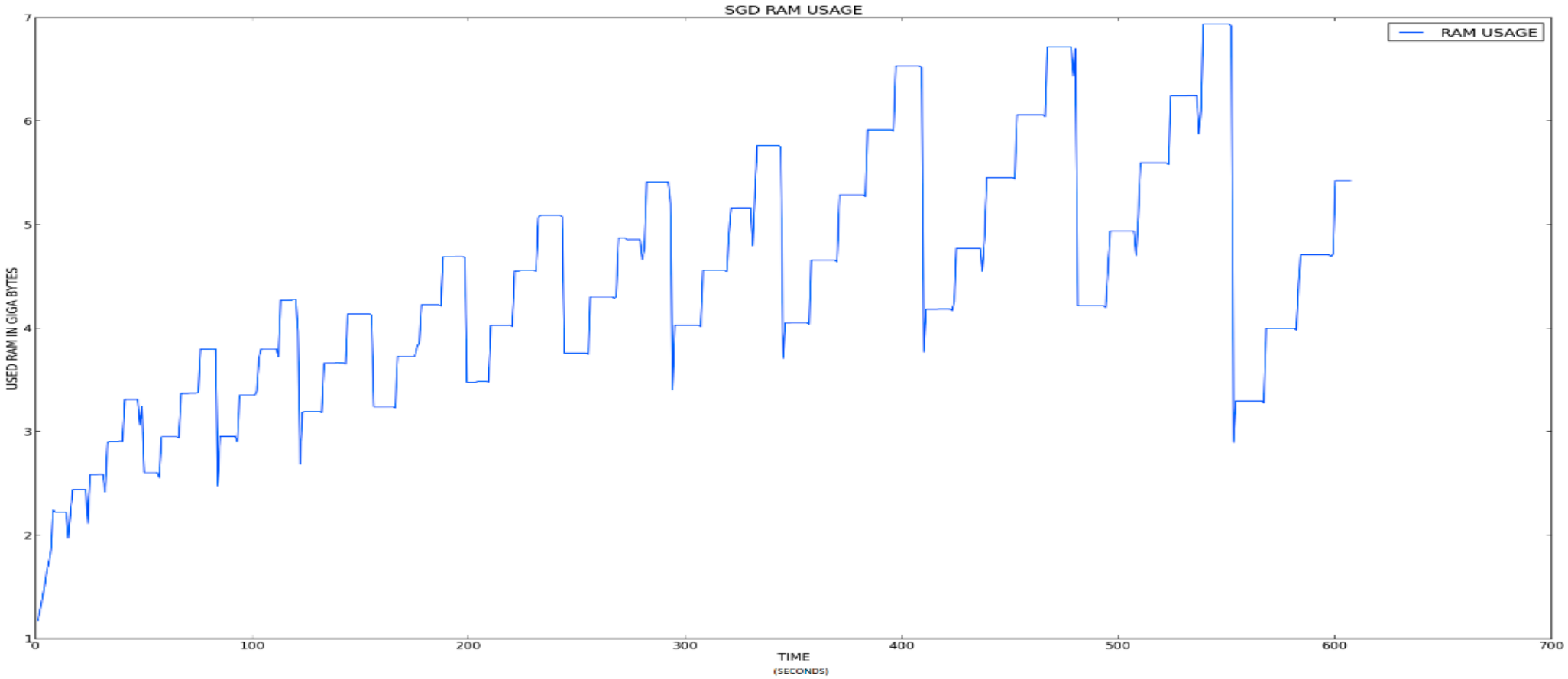
Naïve Bayes – Apache Spark



Random Forest – Apache Spark



Stochastic Gradient Descent – Apache Spark

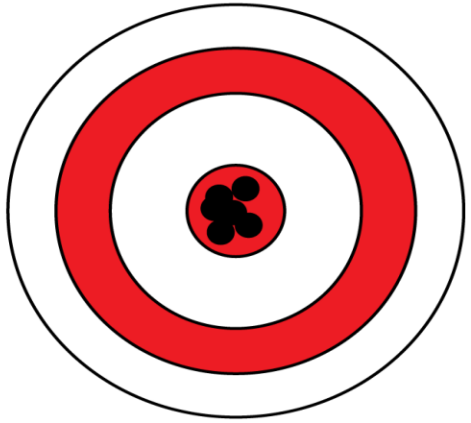


Results

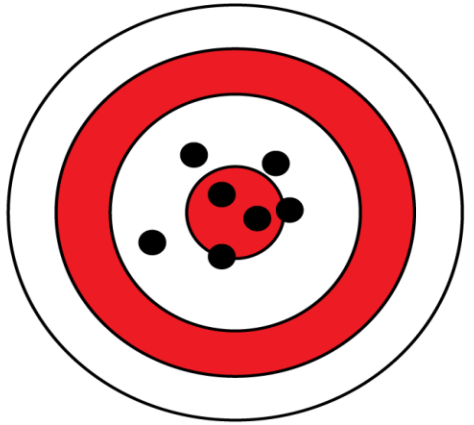
- False Positive Rate
  - FPR = FP / (FP + TN)
- False positive
  - Unnecessary replication
  - Dataset unpopular but predicted popular
- True Negative
  - Correct prediction
  - Dataset unpopular and predicted unpopular

Results

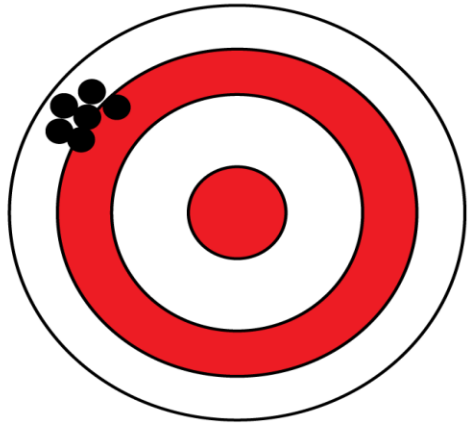
- Difference is not statistically significant



High precision and high recall
Returns many correctly labelled results



Returns many results
Most predictions incorrect



Returns few results
Predicted labels are correct

Results

- Accuracy problems because of data
  - Not reliable
  - Data can be unbalanced
  - Data Integrity
- Using the cross validation scoring method

```
from sklearn.metrics import accuracy_score
score(clf, test, target_test)
```

Confusion matrices

RF	P	N
T	570374	0
F	2	6438

SGD	P	N
T	568040	3351
F	2336	3042

NB	P	N
T	568415	6
F	12783	6432

Confusion matrix

Classifier	Accuracy	Precision	Recall	F1
RF	.98	.86	.98	.92
SGD	.96	.98	.62	.76

Classifier	Accuracy	Precision	Recall	F1
RF	.99	.99	1	.99
SGD	.99	.99	.99	.99

VS

From history to real

- Historical study of popularity & prediction of future popularity are two different concepts
- What was popular in the past
  - naccess, totcpu, nusers, likely to be related to popularity
- Predictions
  - Don't know the number of accesses
    - Use different features
    - From solid understanding (history) to future prediction is difficult
    - May not be able to use the best metrics

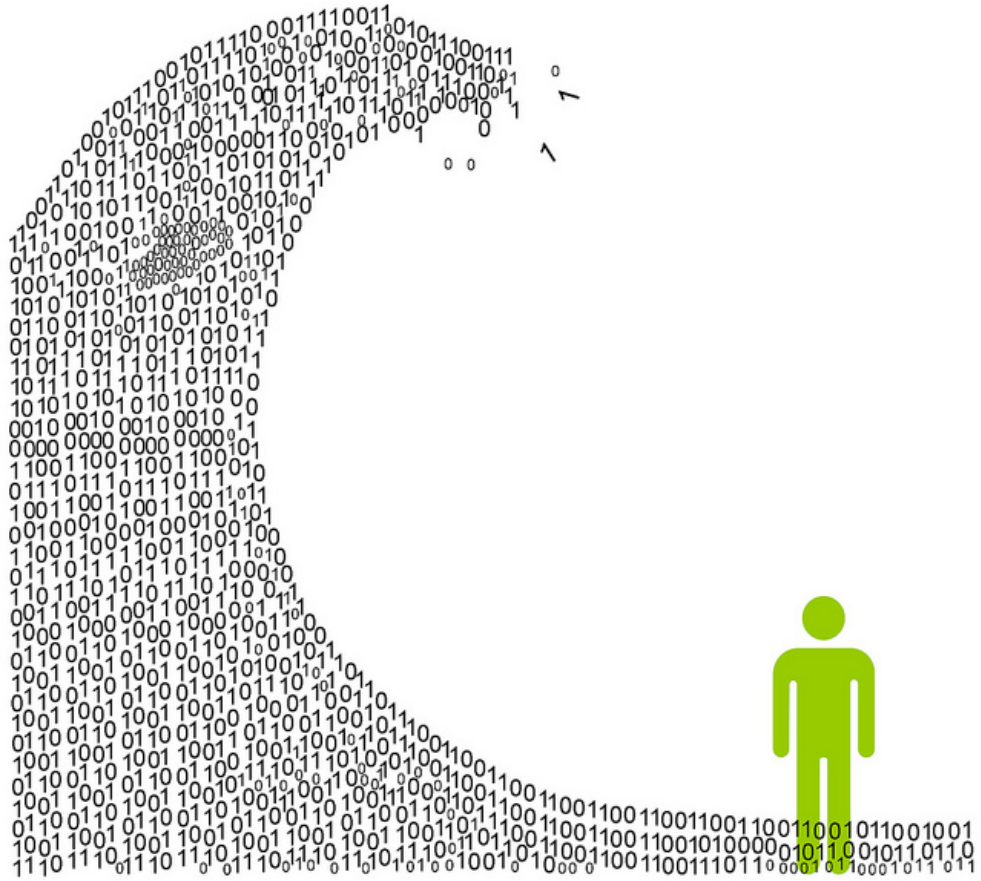
Apache Spark v/s scikit learn

- Real time results
- Mesos Cluster manager
- Interfaced with Hadoop Distributed File System (HDFS)
- Aggressive caching in memory
- Faster and Scalable
- RDD level parallelism
- Version Used:
  - Release 1.4.0

- Works directly as a library
- User-friendly
- Benchmarked models already in use
- Deployed over:
  - Python 2.7.5
  - Scikit version 0.16.0

Python scikit-learn

- High CPU usage ☹
- High RAM usage ☹
- More Time ☹



Apache Spark

- CPU usage looks Good ☺
- RAM usage looks Good ☺
- Less Time ☺

Thank You

References

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