R for HPC and big data

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Agenda

- about me
- HPC vs. Big Data
- variants of big data
- hadoop ecosystem and its history
- spark in detail
- spark integrations with R
- lab

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- BSC Thesis about clustering of time series
- anomaly detection project spark + R for music streaming data
- co-founder of predictr (R & time-series prediction)
- data scientist @T-Mobile Austria - master's thesis about fraud prevention (machine learning)

HPC parallelization - number crunching

- single threaded for loops by default for(x <- 1...10000000){callAFunction}
- additional packages (forEach, doParallel) help to parallelize but may be platform agnostic
- scaling out over multiple machines rather cumbersome (mpi, need to handle communication logic by application programmer = you)
- see cran parallel taskView for more parallelization packages
- Rcpp for seamless C++ integration => speed up loop

The FOUR V's of Big Data

From traffic patterns and music downloads to web history and medical records, data is recorded, stored, and analyzed to enable the technology and services that the world relies on every day. But what exactly is big data, and how can these massive amounts of data be used?

As a leader in the sector, IBM data scientists break big data into four dimensions: **Volume, Velocity, Variety and Veracity**

Depending on the industry and organization, big data encompasses information from multiple internal and external sources such as transactions, social media, enterprise content, sensors and mobile devices. Companies can leverage data to adapt their products and services to better meet customer needs, optimize operations and infrastructure, and find new sources of revenue.

By 2015
4.4 MILLION IT JOBS
will be created globally to support big data, with 1.9 million in the United States

Volume
SCALE OF DATA

40 ZETTABYTES
[43 TRILLION GIGABYTES]
of data will be created by 2020, an increase of 300 times from 2005

It's estimated that
2.5 QUINTILLION BYTES
[2.3 TRILLION GIGABYTES]
of data are created each day

6 BILLION PEOPLE
have cell phones

WORLD POPULATION: 7 BILLION

Most companies in the U.S. have at least
100 TERABYTES
[100,000 GIGABYTES]
of data stored

Variety
DIFFERENT FORMS OF DATA

As of 2011, the global size of data in healthcare was estimated to be
150 EXABYTES
[161 BILLION GIGABYTES]

By 2014, it's anticipated there will be
420 MILLION WEARABLE, WIRELESS HEALTH MONITORS

4 BILLION+ HOURS OF VIDEO
are watched on YouTube each month

30 BILLION PIECES OF CONTENT
are shared on Facebook every month

400 MILLION TWEETS
are sent per day by about 200 million monthly active users

Velocity
ANALYSIS OF STREAMING DATA

The New York Stock Exchange captures
1 TB OF TRADE INFORMATION
during each trading session

Modern cars have close to
100 SENSORS
that monitor items such as fuel level and tire pressure

By 2016, it is projected there will be
18.9 BILLION NETWORK CONNECTIONS
– almost 2.5 connections per person on earth

Veracity
UNCERTAINTY OF DATA

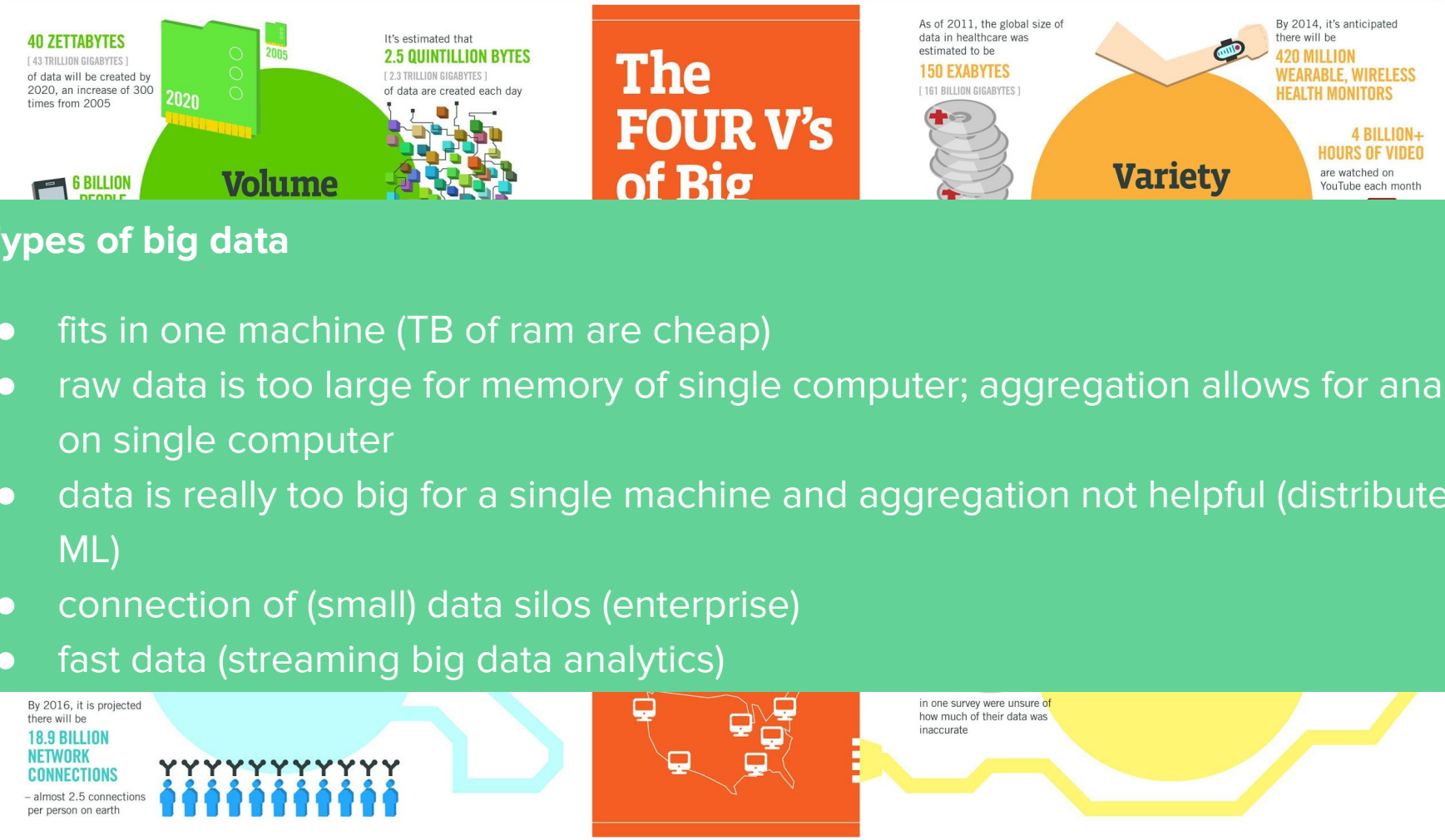
1 IN 3 BUSINESS LEADERS
don't trust the information they use to make decisions

in one survey were unsure of how much of their data was inaccurate

Poor data quality costs the US economy around
$3.1 TRILLION A YEAR

Sources: McKinsey Global Institute, Twitter, Cisco, Gartner, EMC, SAS, IBM, MEPTEC, QAS

IBM

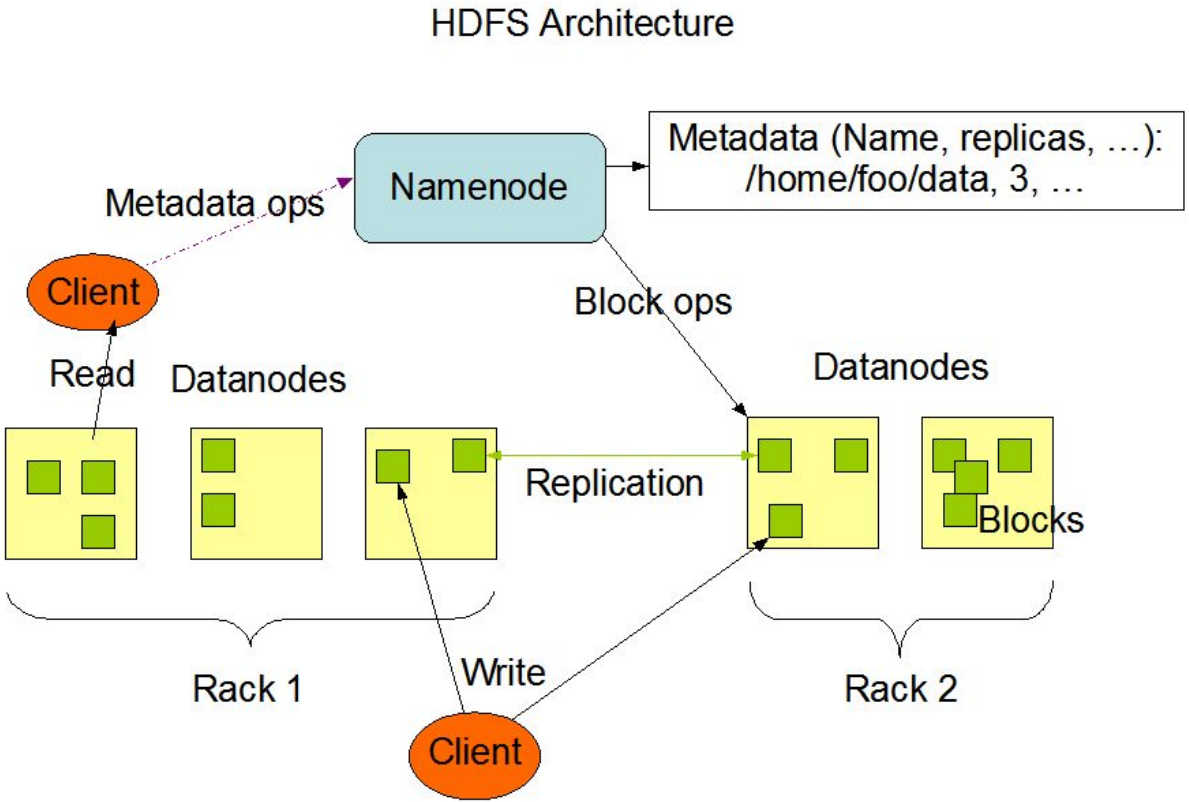


Types of big data

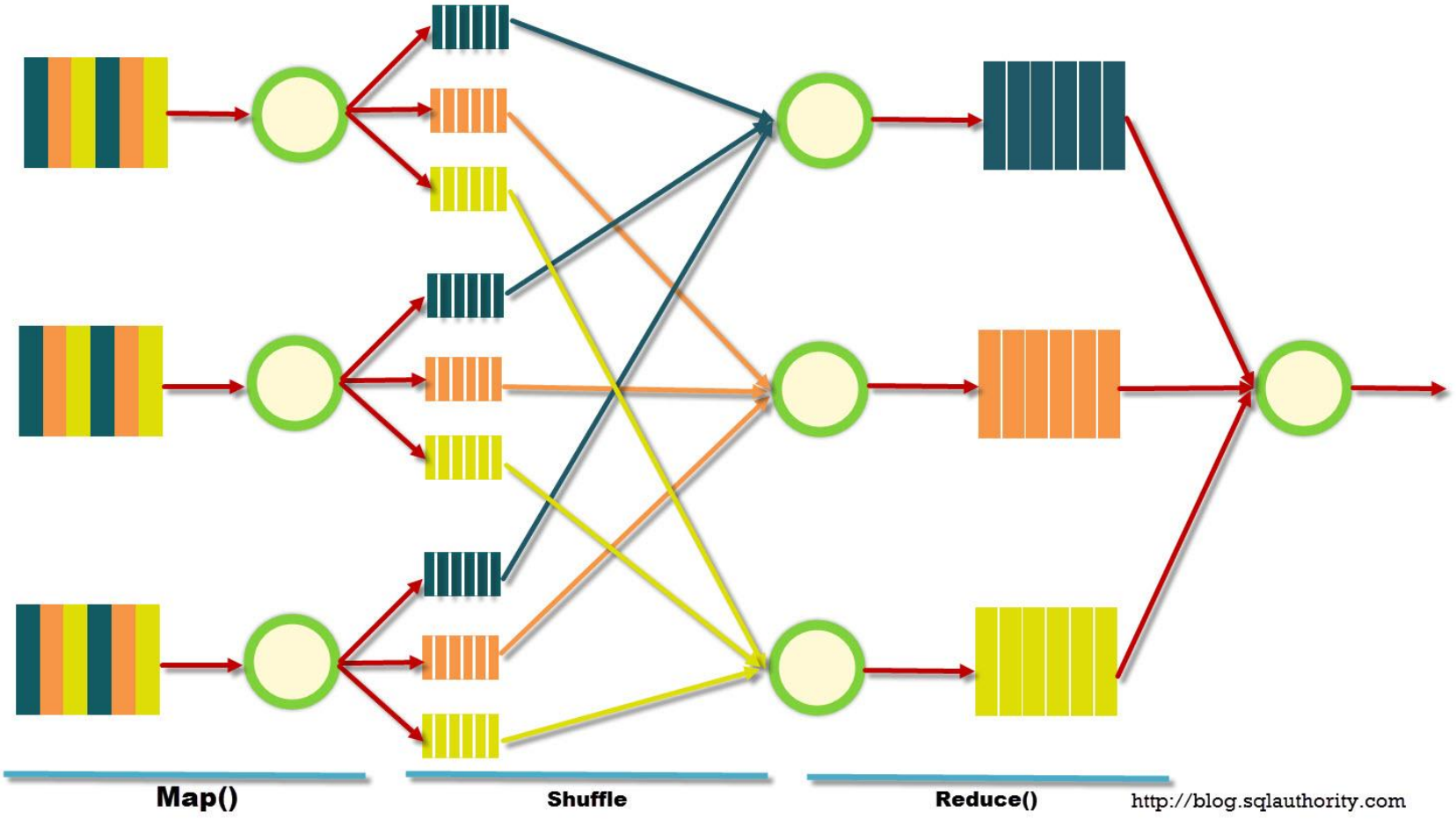
- fits in one machine (TB of ram are cheap)
- raw data is too large for memory of single computer; aggregation allows for analysis on single computer
- data is really too big for a single machine and aggregation not helpful (distributed ML)
- connection of (small) data silos (enterprise)
- fast data (streaming big data analytics)

Apache hadoop

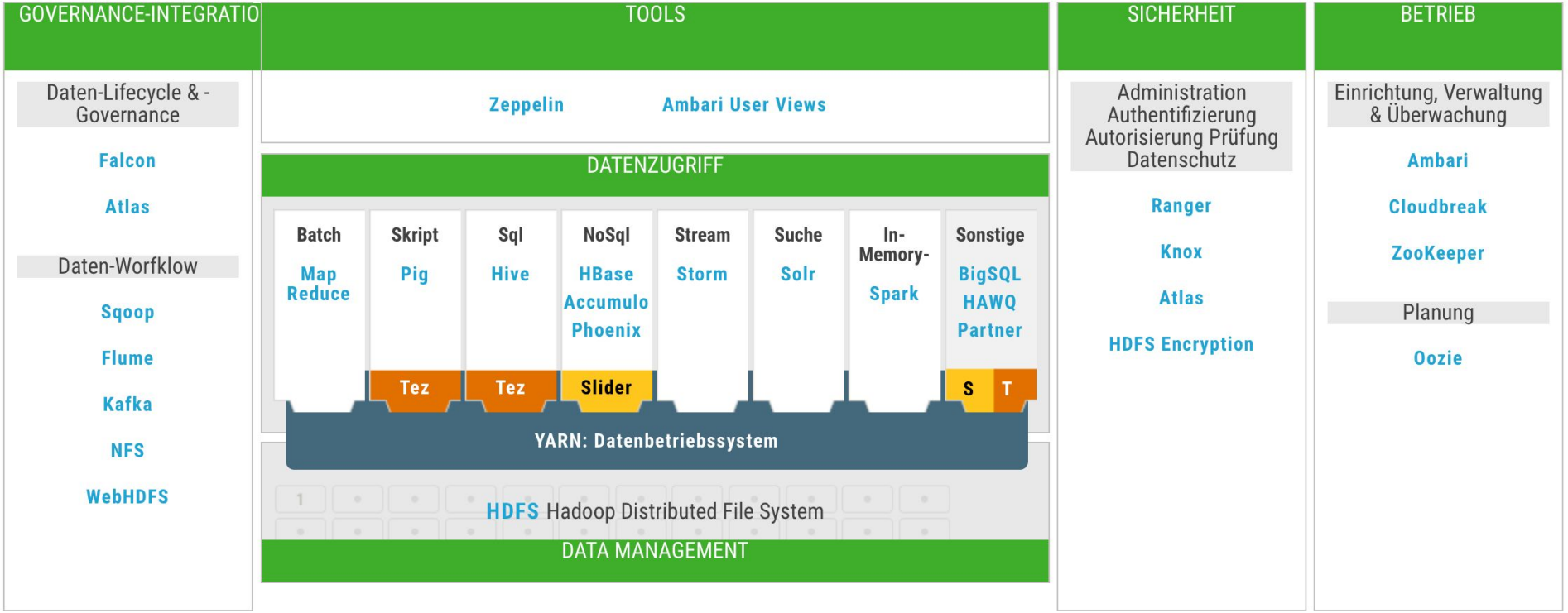
Hadoop Distributed File System (HDFS)



How MapReduce Works?



Hadoop ecosystem



Spark concept

Resilient Distributed Datasets (RDD)

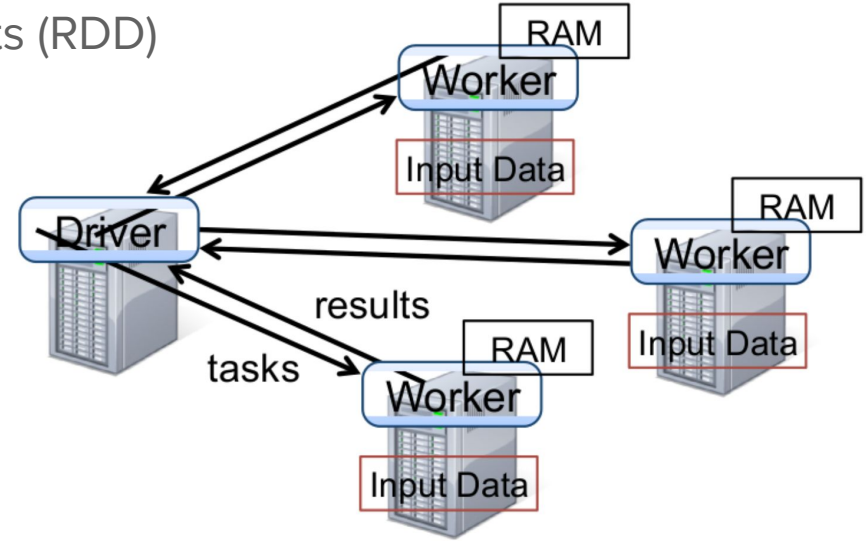


Figure 2: Spark runtime. The user's driver program launches multiple workers, which read data blocks from a distributed file system and can persist computed RDD partitions in memory.

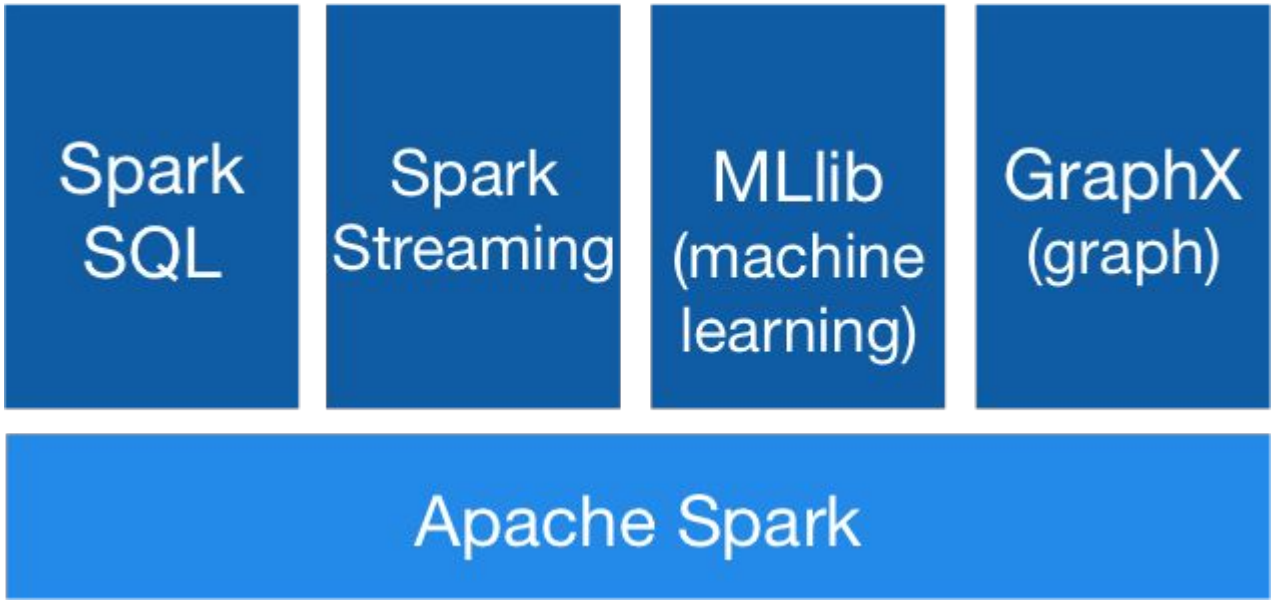
RDD properties

- resilient, distributed collections
- immutable
- transformations (map, filter, reduceByKey join,...)
- actions (reduce,collect,count,foreach,...)

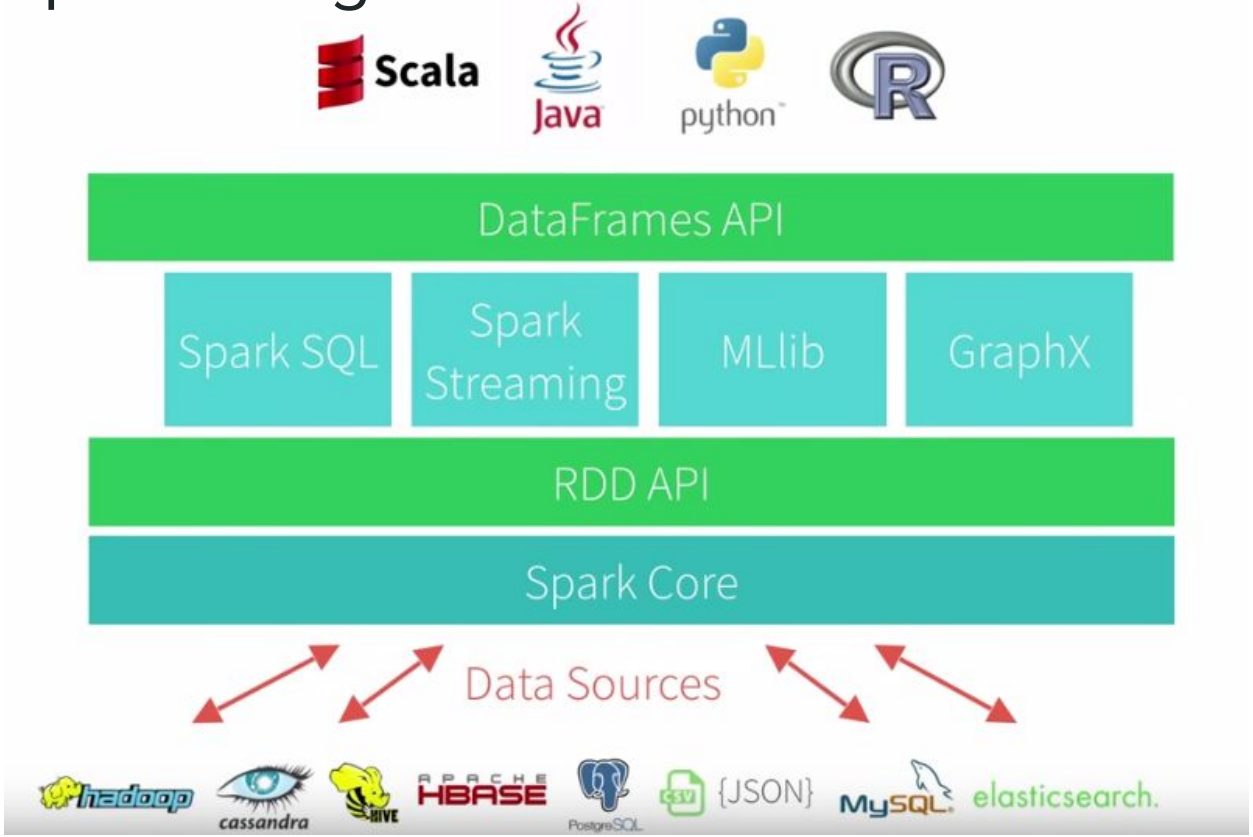
Word count

```
val textFile = sc.textFile("hdfs://...")
val counts = textFile.flatMap(line => line.split(" "))
                 .map(word => (word, 1))
                 .reduceByKey(_ + _)
```

Apache Spark Stack



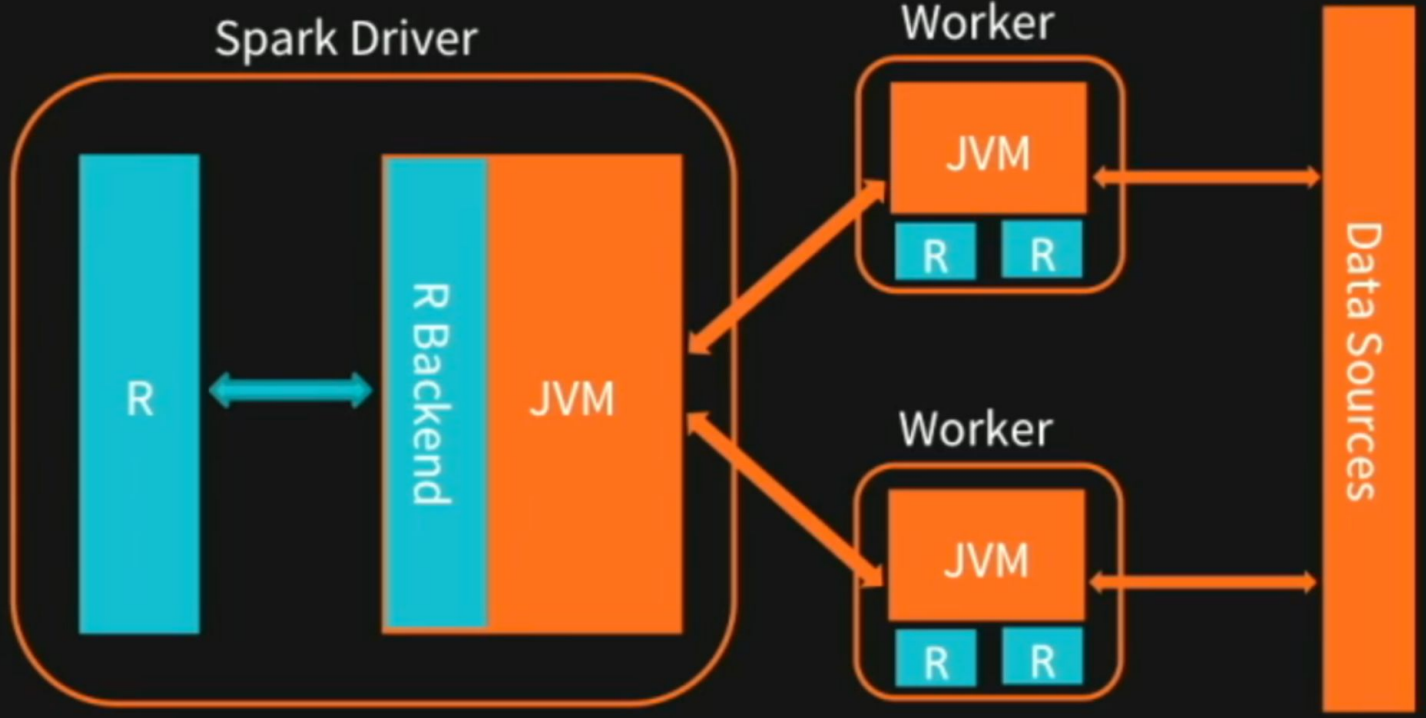
Apache Spark integrations

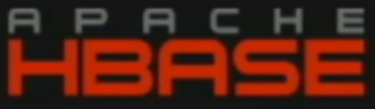


Integrations of R with Apache Spark

- sparkR (sprk-native)
- sparklyR (dplyr-style, more comfortable, only recently added important features)
- unix pipe

SparkR architecture (2.x)





tidy universe - why sparklyr

unique grammar for data manipulation helping reproducible research

```
library(dplyr)
```

```
starwars %>%
  filter(species ==
"Droid")
```

lab

sparklyR, java8, R, https://www.rstudio.com

lab code

Q&A - questions for the lab?

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bonus slides (if some time is left)

downsides of non spark-native languages (R, python)

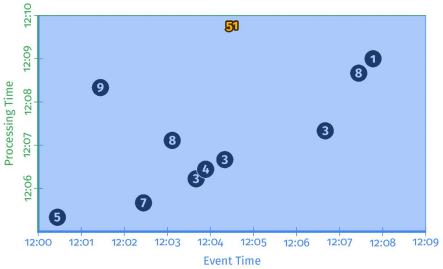
- don’t get the latest features (ml, ml-pipelines, streaming ...)
- exceptions will occur on multiple layers
- performance bottlenecks (serialization)
- deployment on local cluster (!)
- no good integration to spark-packages

future of big data

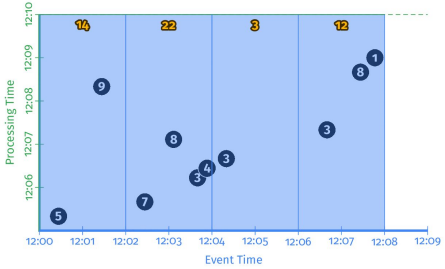
R and streaming analytics

- no spark integration
- PMML

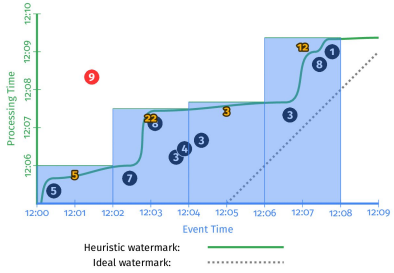
BEAM: converging big data engines **What Where When How**



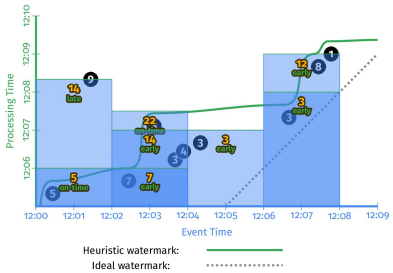
1
Classic Batch



2
Windowed Batch



3
Streaming



4
Streaming + Accumulation

R/python

- Reproducibility
- Data Provenance
- Collaboration
- Incrementality
- Data Scientist Autonomy
- Infrastructure Agnostic
- less complexity
- a different package in same direction:partools

A Containerized Data Lake

Pachyderm lets you store and analyze your data using containers.

Learn More | Try on GitHub

Pachyderm v1.4 is out and ready for production use!

Pachyderm is a data lake that offers complete **version control for data** and leverages the container ecosystem to provide **reproducible data processing.**

Version control for data

Pachyderm version controls all your data, similar to what Git does with code. You can view diffs of your data and collaborate with teammates using Pachyderm commits and branches. **Learn more →**

Q&A

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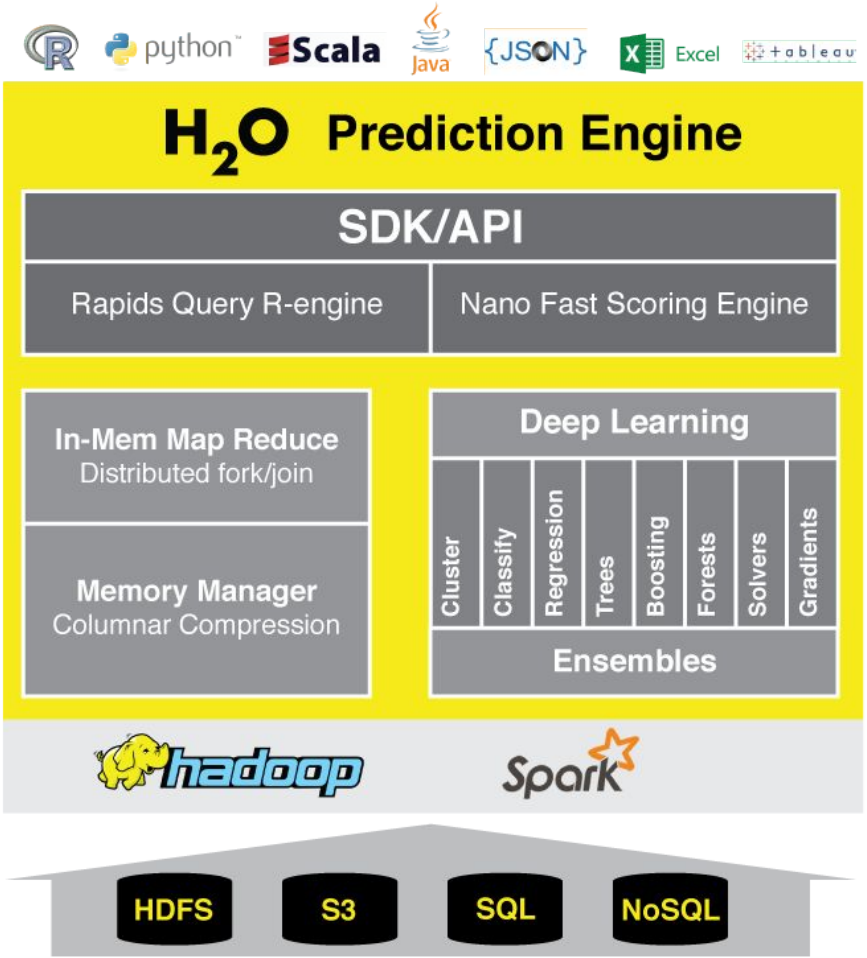
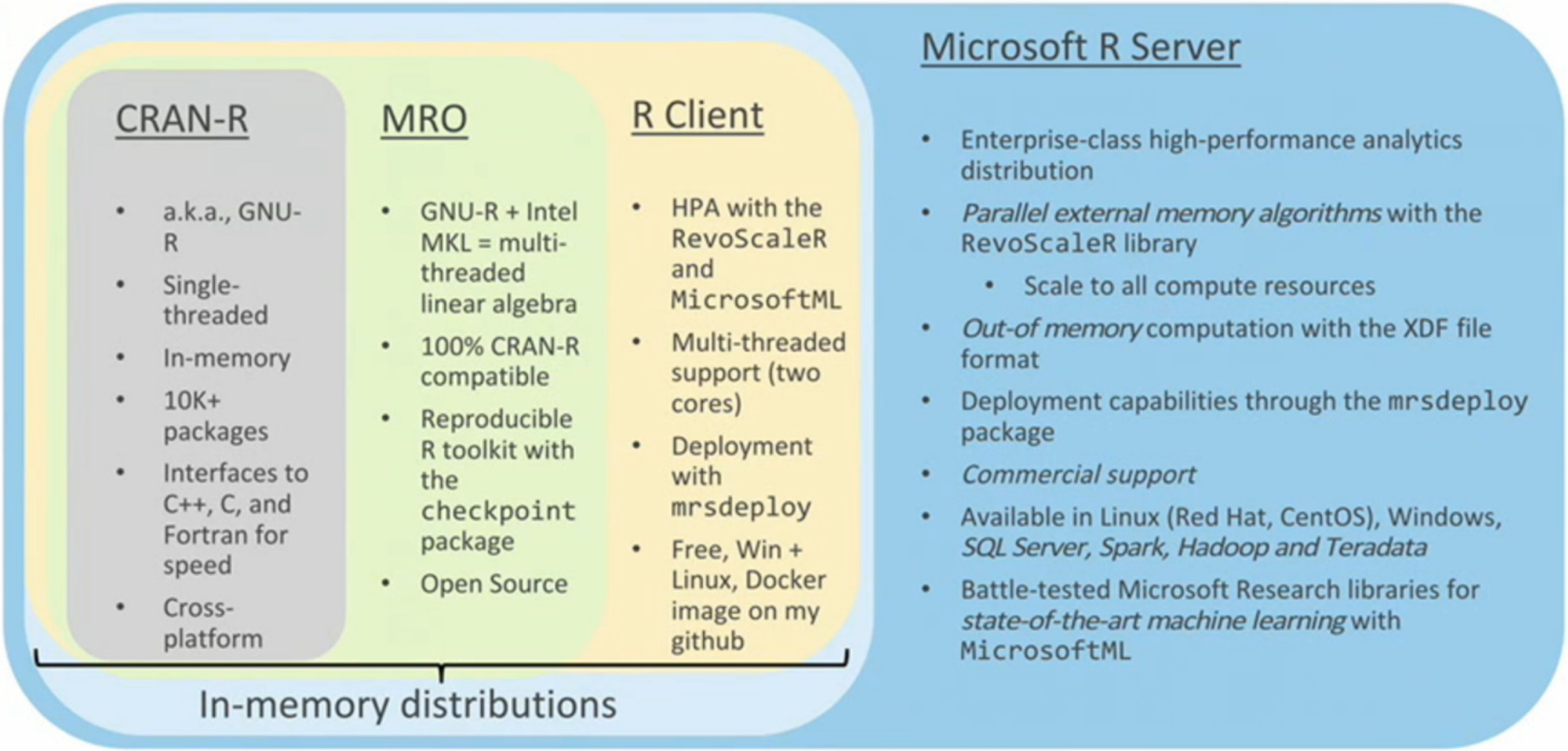

python
Scala
Java
{JSON}
Excel
tableau
H2O Prediction Engine
SDK/API
Rapids Query R-engine
Nano Fast Scoring Engine
In-Mem Map Reduce
Distributed fork/join
Memory Manager
Columnar Compression
Deep Learning
Cluster
Classify
Regression
Trees
Boosting
Forests
Solvers
Gradients
Ensembles
hadoop
Spark
HDFS
S3
SQL
NoSQL

R APIs for Spark

- SparkR
- ASF, Apache-licensed
- Ships with Apache-Spark since 1.4x
- SparkSQL and SparkML support through RPC
- UDF support through `gapply`, `dapply`, `spark.lapply`

- `sparklyr`
- On CRAN/github (0.5)
- Apache-licensed
- SparkSQL and SparkML support through `DBI`, `dplyr` and `RPC`
- UDF support announced (PR#78)
- Remote execution with Livy
- Extensions!

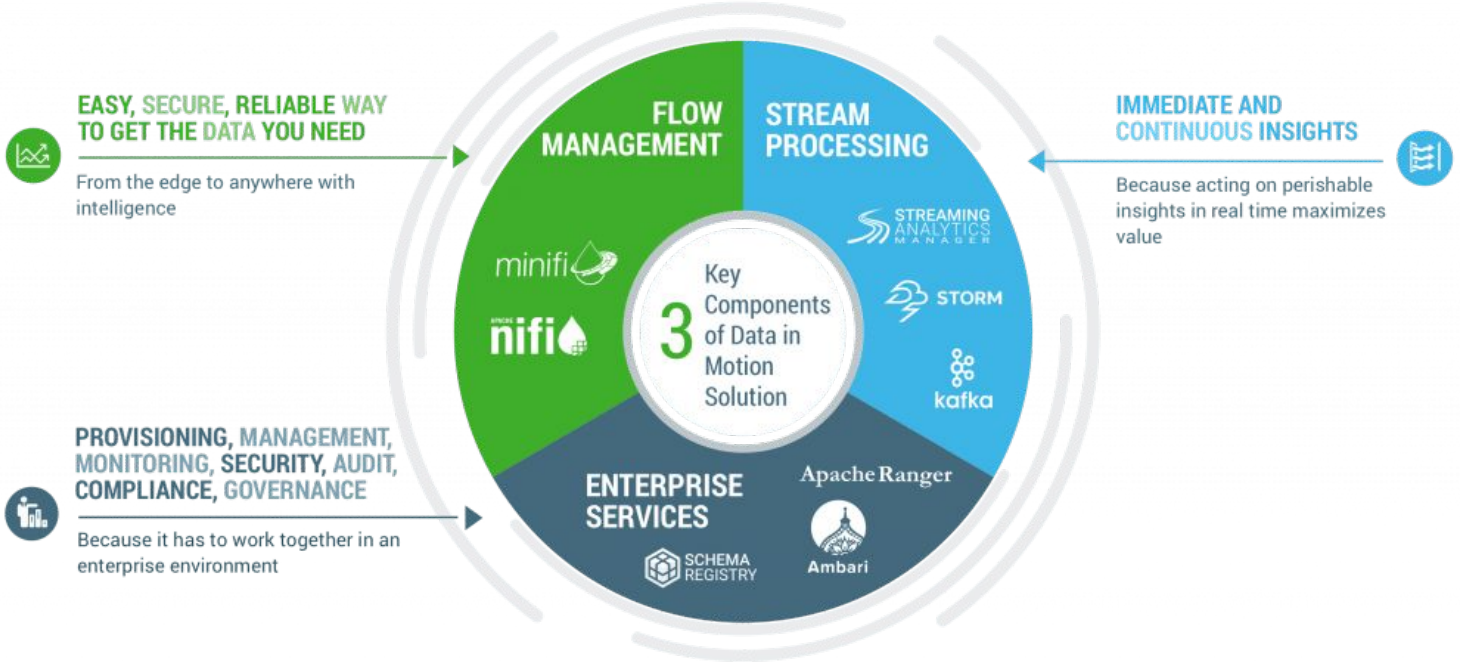
- `RxSpark`
- Commercially licensed
- Deploy `RevoScaleR` in Spark clusters
- Interop with `sparklyr`
- PEMA support
- Consume Parquet, and Hive Tables
- Robust UDF support with `rxDataStep`, `rxExec`, `rxExecBy`, and `foreach`
- Current version: 9.1


CRAN-R
a.k.a., GNU-R
Single-threaded
In-memory
10K+ packages
Interfaces to C++, C, and Fortran for speed
Cross-platform
MRO
GNU-R + Intel MKL = multi-threaded linear algebra
100% CRAN-R compatible
Reproducible R toolkit with the checkpoint package
Open Source
R Client
HPA with the RevoScaleR and MicrosoftML
Multi-threaded support (two cores)
Deployment with mrsdeploy
Free, Win + Linux, Docker image on my github
In-memory distributions
Microsoft R Server
Enterprise-class high-performance analytics distribution
Parallel external memory algorithms with the RevoScaleR library
Scale to all compute resources
Out-of memory computation with the XDF file format
Deployment capabilities through the mrsdeploy package
Commercial support
Available in Linux (Red Hat, CentOS), Windows, SQL Server, Spark, Hadoop and Teradata
Battle-tested Microsoft Research libraries for state-of-the-art machine learning with MicrosoftML

R cloud native

```
library(doAzureParallel)

# generate a credentials json file "cluster", then...

registerDoAzureParallel(cluster)

# Run 5 million option pricing simulations

closingPrices <- foreach(i = 1:50, .combine='c') %dopar% {

 replicate(100000, getClosingPrice())

}
```

Hadoop streaming



Machine Learning on spark with R

h2o.ai / rsparkling

microsoftR

Some interesting links

- https://longhowlam.wordpress.com/2017/02/15/r-formulas-in-spark-and-un-nesting-data-in-sparklyr-nice-and-handy/
- https://spark-summit.org/2017/events/extending-the-r-api-for-spark-with-sparklyr-and-microsoft-r-server/
- https://spark-summit.org/2017/events/apache-sparkr-under-the-hood-how-to-debug-your-sparkr-applications/
- http://tfe/2017/05/managing-spark-data-handles-in-r/
- https://de.slideshare.net/HadoopSummit/the-next-generation-of-data-processing-and-open-source
- https://docs.google.com/presentation/d/1SHie3nwe-pqmjGum_QDznPr-B_zXCjJ2VBDGdafZme8
- http://multithreaded.stitchfix.com/blog/2017/06/15/beware-r-in-production/
- http://www.win-vector.com/blog/2017/07/working-with-r-and-big-data-use-replyr/
- https://blogs.msdn.microsoft.com/rserver/2017/05/04/performance-rxexecby-vs-gapply-on-spark/
- https://www.wireframe.li/2017/07/24/running-sparkr-on-your-hadoop-cluster-without-pre-installed-r/
- sparklyR cheat sheet https://www.rstudio.com/resources/cheatsheets/
- http://r-posts.com/implementing-parallel-processing-in-r/