Lecture 1: Introduction to Spark and HPC

Shuo Zhou

COM6012: Scalable ML

https://images.techhive.com/images/article/2016/08/thinkstockphotos-462205183-100677632-large.jpg

Week 1 Objectives

- Summarise the challenges of the **big data problem**.
- Identify key data types across the **data structure spectrum** and describe the **Extract–Transform–Load** (ETL) process.
- Explain the **architecture, components, and resource management** of a Spark application, and implement simple PySpark programs.
- Explain the structure of the University's **high-performance computing (HPC) cluster**, and request resources to execute computational tasks.

Contents

- **The Big Data Problem: Why Spark?**
- What is Spark?: The Essentials
- An Example of Spark: Log Mining
- How to Use Spark: HPC and PySpark

Check-in code:
XX-XX-XX

Where Does Big Data Come From?

- Online activities:
  - Clicks
  - Billing events
  - Server requests
  - Transactions
  - Network messages
  - Faults
  - …

- Web + mobile platforms:

f YouTube bilibili

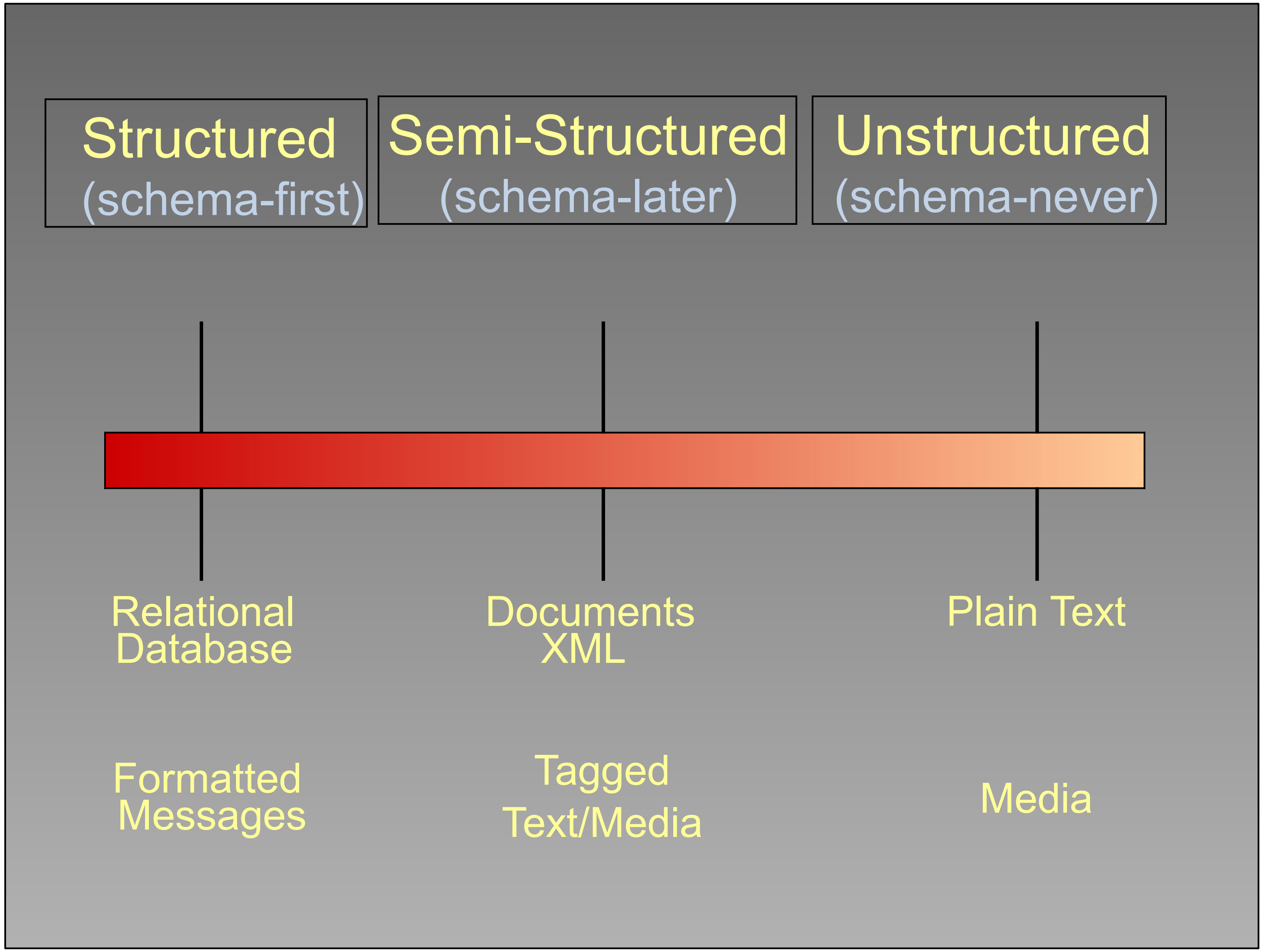
X TikTok amazon

Instagram weibo

Where Does Big Data Come From?

AI generated content

Data Structure Spectrum



Structured (schema-first)

Semi-Structured (schema-later)

Unstructured (schema-never)

Relational Database

Documents XML

Plain Text

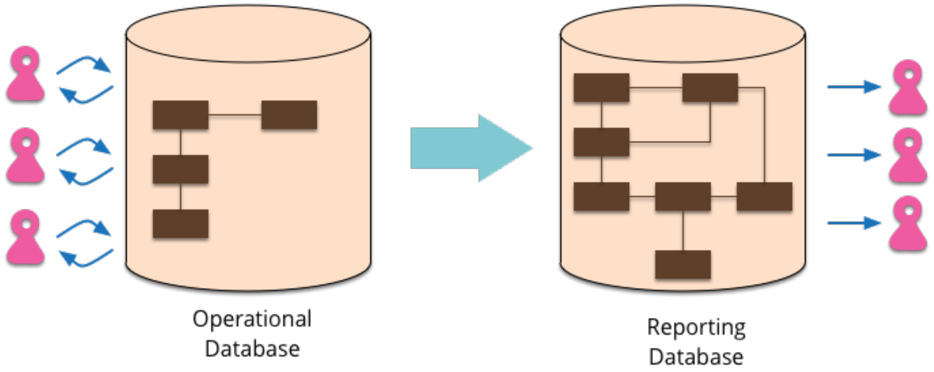
Formatted Messages

Tagged Text/Media

Media

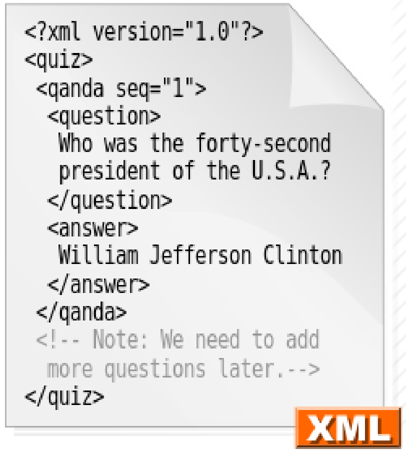
Structured Data

- Database: relational data model → how a database is structured and used
- Schema: the organisation of data as a blueprint of how the database is constructed
  - The programmer must statically specify the schema
- SQL: Structured Query Language

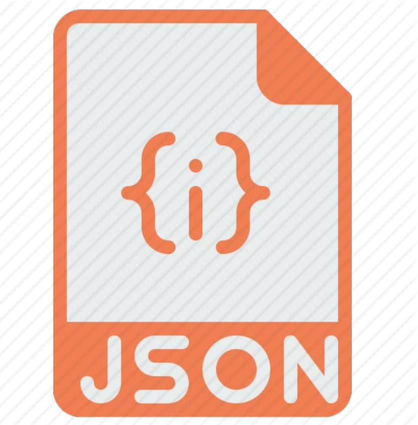


Semi-Structured Data

- Self-describing rather than formal structures, tags/markers to separate semantic elements
- The column types → the schema for the data
  - Spark dynamically infers the schema while reading each row
  - Programmer statically specifies the schema
- Examples:

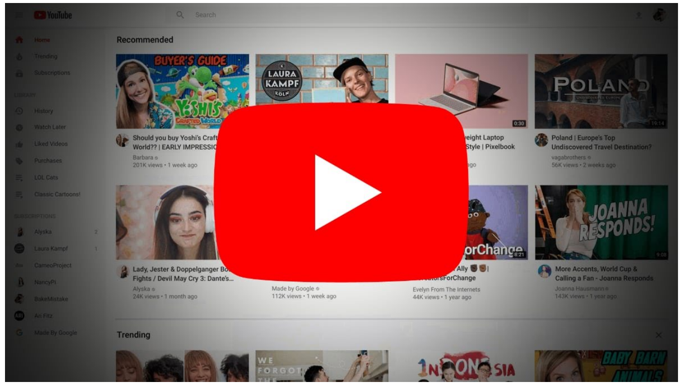


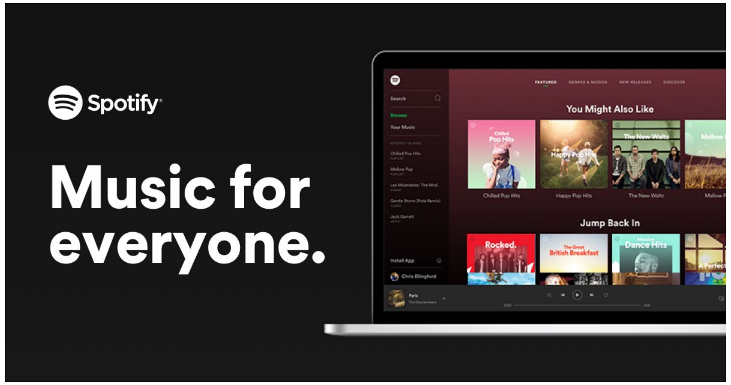
```
<?xml version="1.0"?>
<quiz>
 <qanda seq="1">
  <question>
   Who was the forty-second
   president of the U.S.A.?
  </question>
  <answer>
   William Jefferson Clinton
  </answer>
 </qanda>
 <!-- Note: We need to add
  more questions later.-->
</quiz>
```

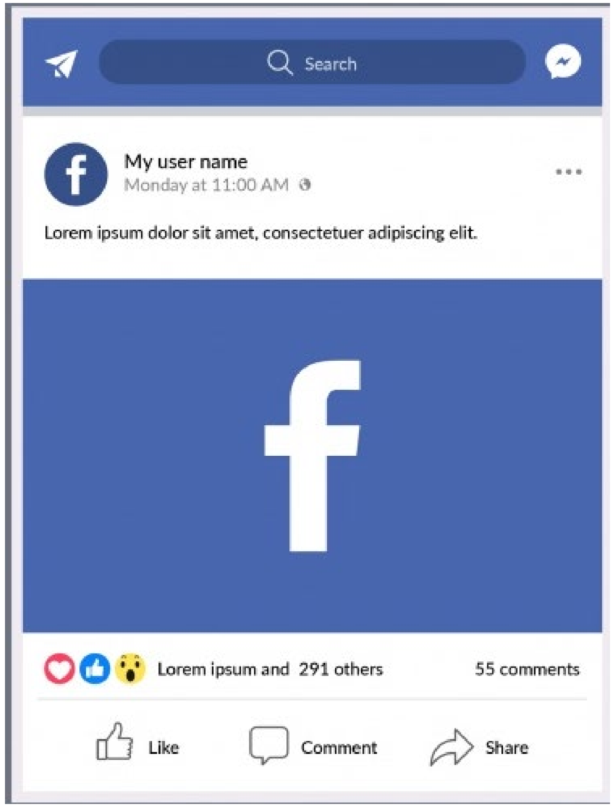


Unstructured Data

- Only one column with string or binary type
- Examples







My user name
Monday at 11:00 AM

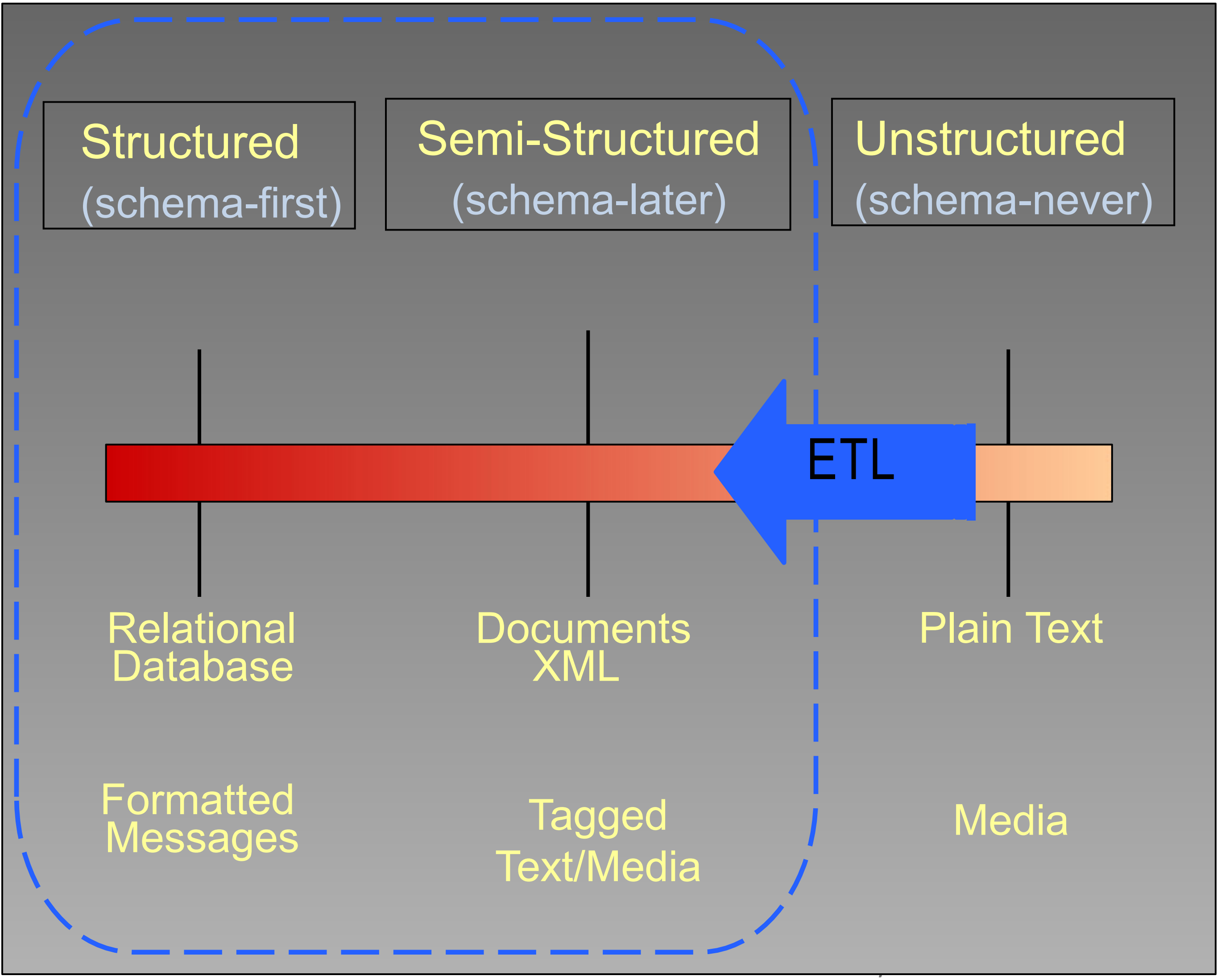
Lorem ipsum dolor sit amet, consectetuer adipiscing elit.

Lorem ipsum and 291 others 55 comments

- Note: File formats ≠ data structure

https://cdn.wccftech.com/wp-content/uploads/2019/11/YouTube-Redesign-2019-768x432.jpg
https://th.bing.com/th/id/OIP.MNR8Ck5DWZb32tkqOfLuXAAAAA?rs=1&pid=ImgDetMain
https://files.codingninjas.in/article_images/preparation-guide-for-facebook-1-1662401488.webp

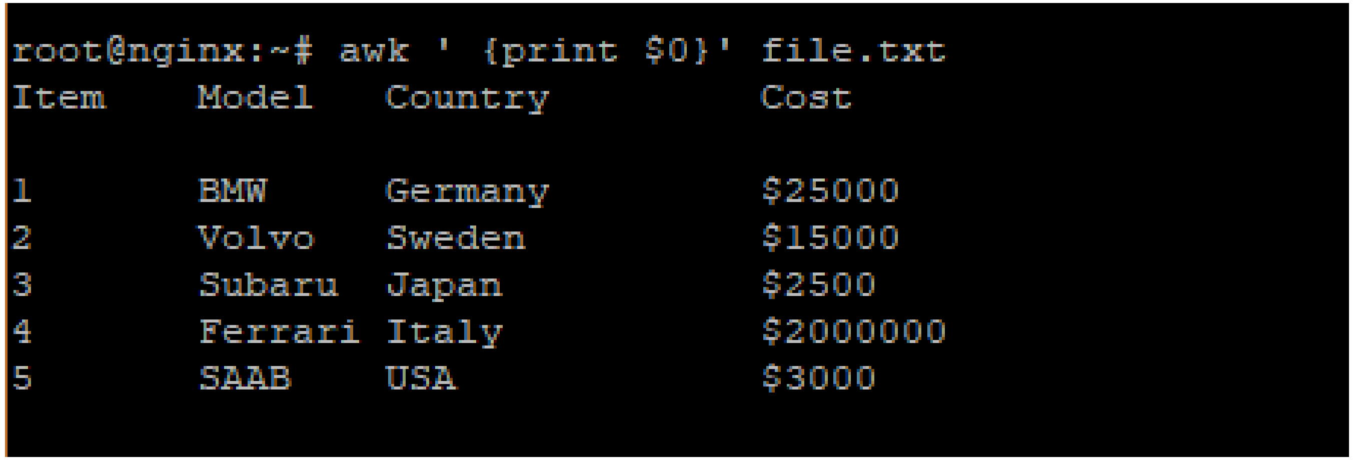
Traverse the Data Structure Spectrum



- Impose structure on unstructured data
  - Extract
  - Transform
  - Load

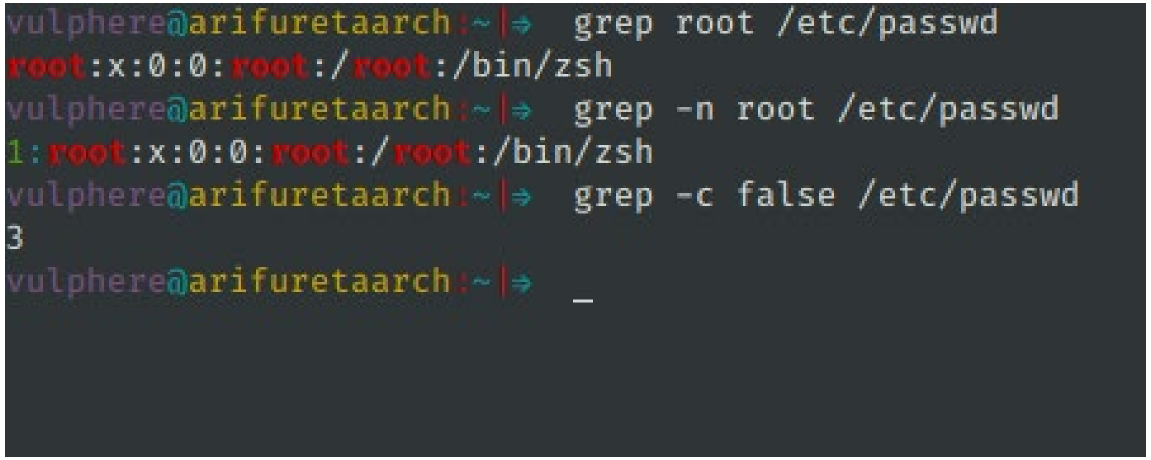
Traditional Analysis Tools

- Unix shell commands (awk, grep, ...)



```
root@nginx:~# awk ' {print $0}' file.txt
Item     Model    Country          Cost

1        BMW      Germany          $25000
2        Volvo    Sweden           $15000
3        Subaru   Japan            $2500
4        Ferrari  Italy            $2000000
5        SAAB     USA              $3000
```



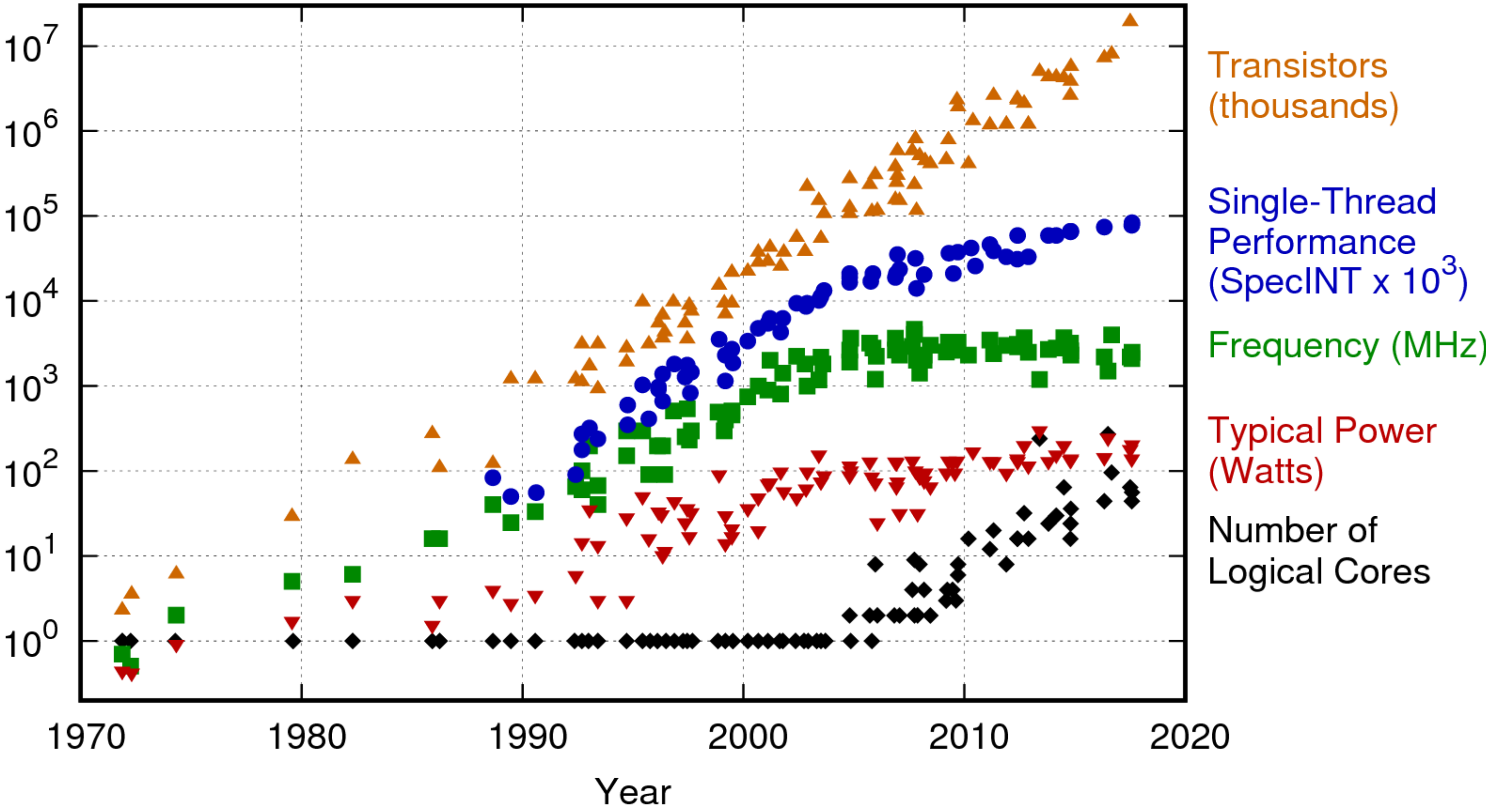
```
vulphere@arifuretaarch:~|⇒  grep root /etc/passwd
root:x:0:0:root:/root:/bin/zsh
vulphere@arifuretaarch:~|⇒  grep -n root /etc/passwd
1:root:x:0:0:root:/root:/bin/zsh
vulphere@arifuretaarch:~|⇒  grep -c false /etc/passwd
3
vulphere@arifuretaarch:~|⇒  _
```

All run on a single machine!

The Big Data Problem

- Data growing faster than computation speeds
- Growing data sources
  - Web, mobile, scientific, …
- Storage getting cheaper
- But, stalling CPU speeds and storage bottlenecks

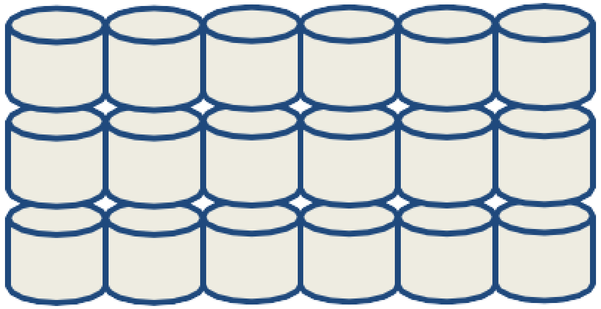
42 Years of Microprocessor Trend Data



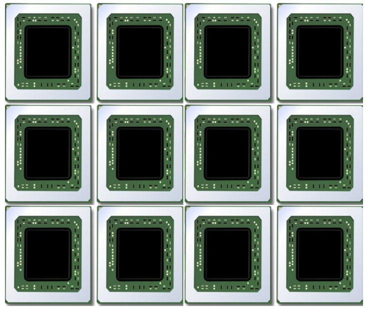
Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten
New plot and data collected for 2010-2017 by K. Rupp

Solution for the Big Data Problem

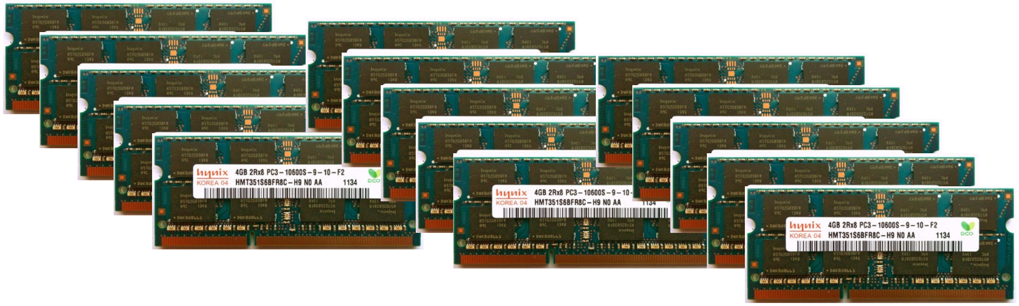
- One machine cannot process or *even store* all the data!
- Solution: **distribute** data over a **cluster** of machines



Lots of hard drives



… and CPUs



… and memory!

In this module

“Apache Spark is an industry-leading platform for distributed extract, transform, and load (ETL) workloads on large-scale data.”

– NVIDIA Technical Blog, Jun 12, 2023

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XX-XX-XX

Apache Spark

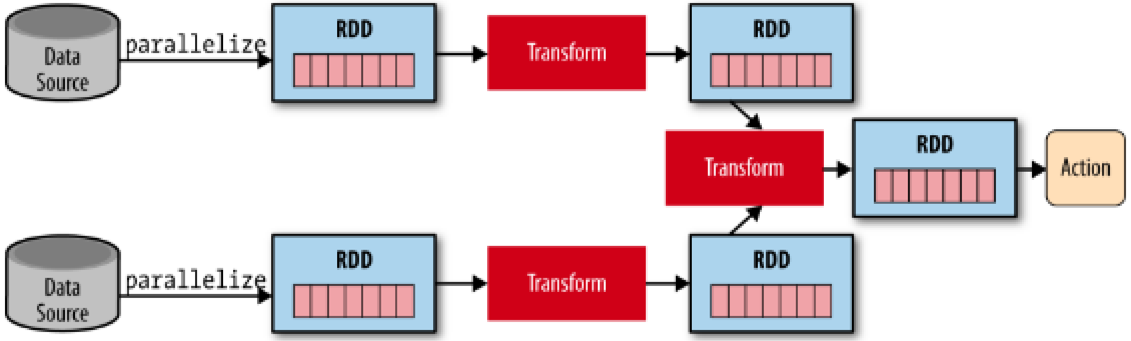
- Fast and general-purpose cluster computing engine
- Interoperable with hadoop MapReduce
- Improves efficiency through:
  - In-memory computing primitives
  - General computation graphs
- Improves usability through:
  - Rich APIs in Scala, Java, Python
  - Interactive shell

→ Up to 100× faster (2-10× on disk)

→ 2-5× less code

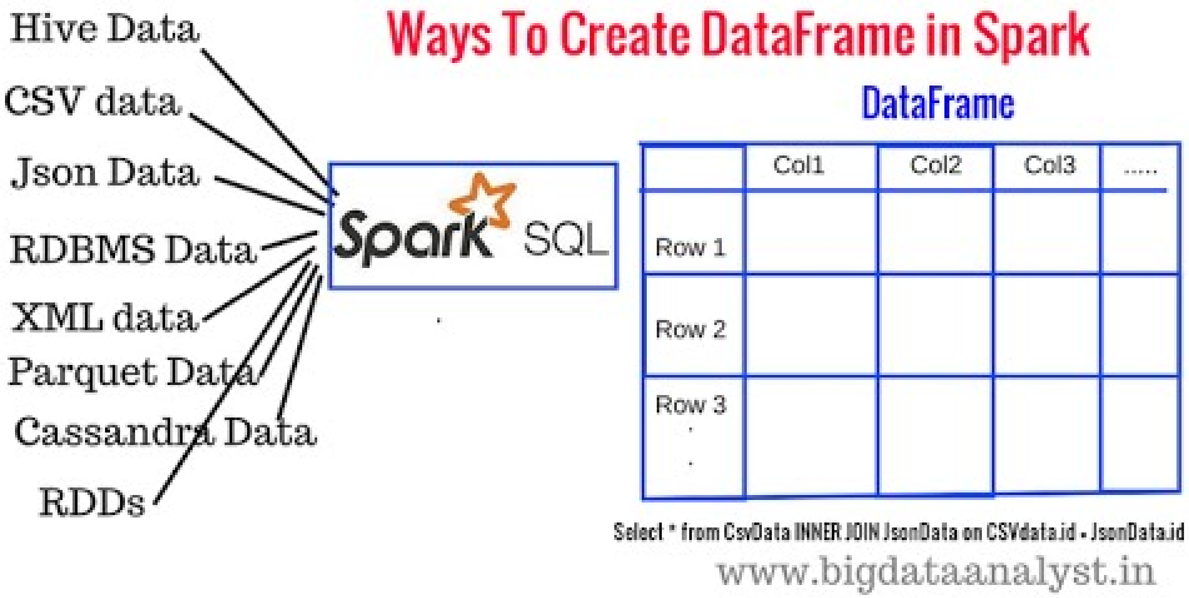
Spark Model

- Write programs in terms of transformations on distributed datasets
- Resilient Distributed Datasets (RDDs)
  - Collections of objects that can be stored in memory or disk across a cluster
  - Parallel functional transformations (map, filter, ...)
  - Automatically rebuilt on failure



Spark for Data Science

- DataFrames
  - Structured data (SQL)
  - Familiar API based on R/Python Pandas
  - Distributed, optimised implementation



Select * from CsvData INNER JOIN JsonData on CSVdata.id = JsonData.id

- Machine learning pipelines
  - Simple construction and tuning of ML workflows

Spark Computing Framework

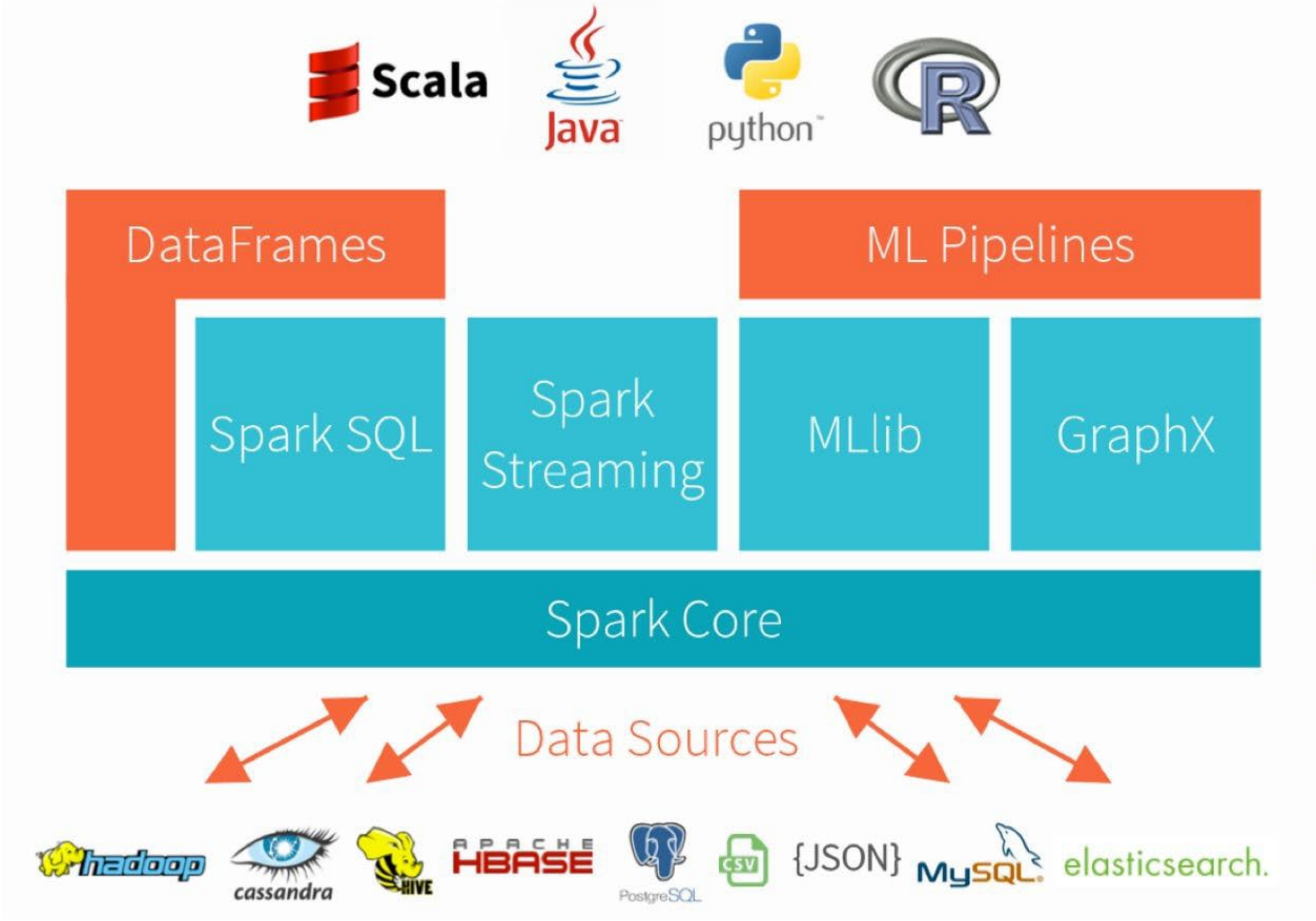
- Programming abstraction and parallel runtime to hide complexities of **fault-tolerance** and **slow** machines

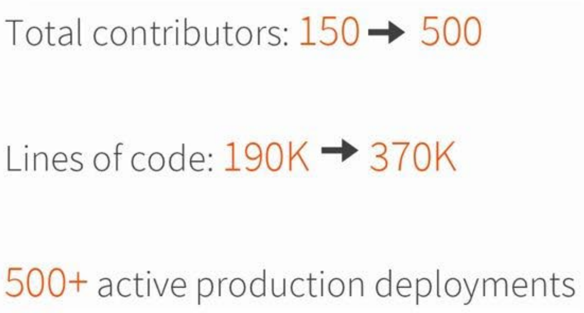
“Here’s an operation, run it on all of the data”

JUST DO IT.

- Don’t care where it runs (you schedule that)
- In fact, feel free to run it twice on different nodes (e.g. when it fails)

Apache Spark Ecosystem



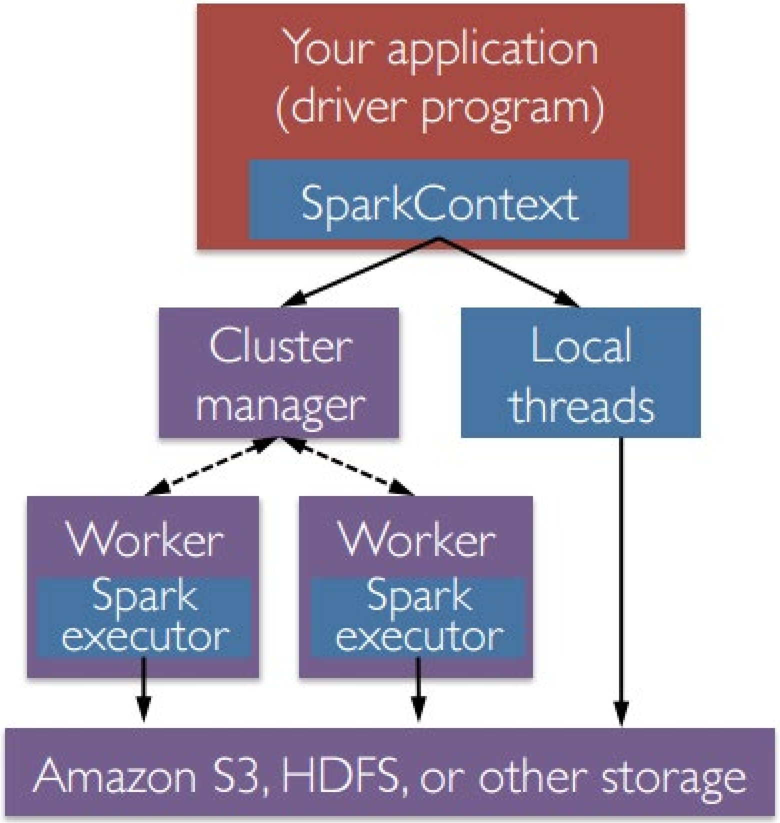

Total contributors: 150 → 500

Lines of code: 190K → 370K

500+ active production deployments

https://i.pinimg.com/originals/e7/f3/2d/e7f32d041846a5938a09e192bdf3885d.jpg

Spark Components



- A Spark program first creates a **SparkSession** object as the driver (including **SparkContext**)
  - Tells Spark how/where to access a cluster
  - Connect to cluster managers
- Cluster managers
  - Allocate resources across applications
- Spark executor (worker):
  - Access data storage
  - Run computations

SparkSession and SparkContext

- **SparkSession**
  - Entry point for DataFrame API, create DataFrames
  - PySpark shell automatically create SparkSession as spark
  - Programs: must create a new SparkSession first (see lab)
- **SparkContext**
  - Entry point for Spark functionality, create RDDs
  - Connect to a Spark cluster
  - Associated with a SparkSession
  - PySpark shell automatically create SparkContext as sc
  - Programs: sc = spark.sparkContext

The *‘Master’* Parameter for a SparkSession

- Determines cluster type and size

Master Parameter	Description
local	run Spark locally with one worker thread (no parallelism)
local[K]	run Spark locally with K worker threads (ideally set to number of cores)
spark://HOST:PORT	connect to a Spark standalone cluster; PORT depends on config (7077 by default)
mesos://HOST:PORT	connect to a Mesos cluster; PORT depends on config (5050 by default)

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XX-XX-XX

Spark Example: Log Mining (w/t RDD)

Load error messages from a log into memory, then interactively search for various patterns

Spark Example: Log Mining

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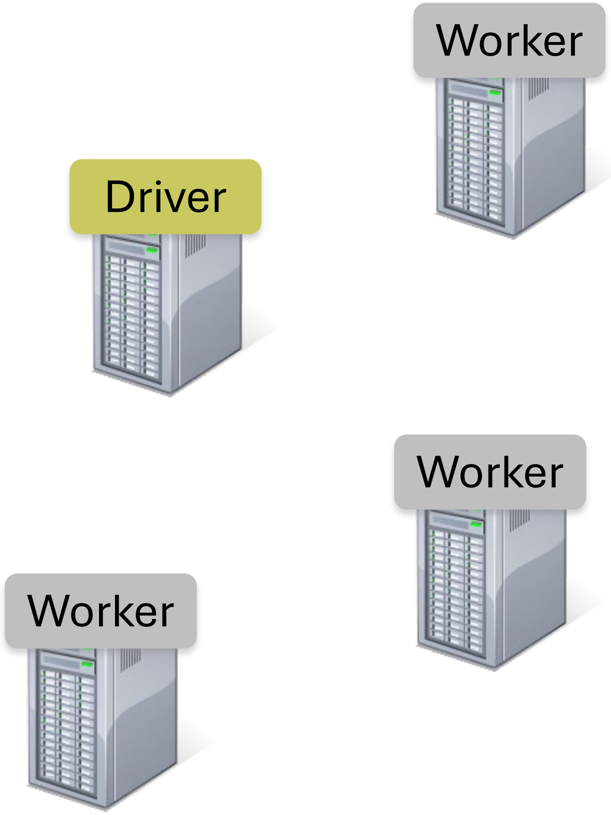
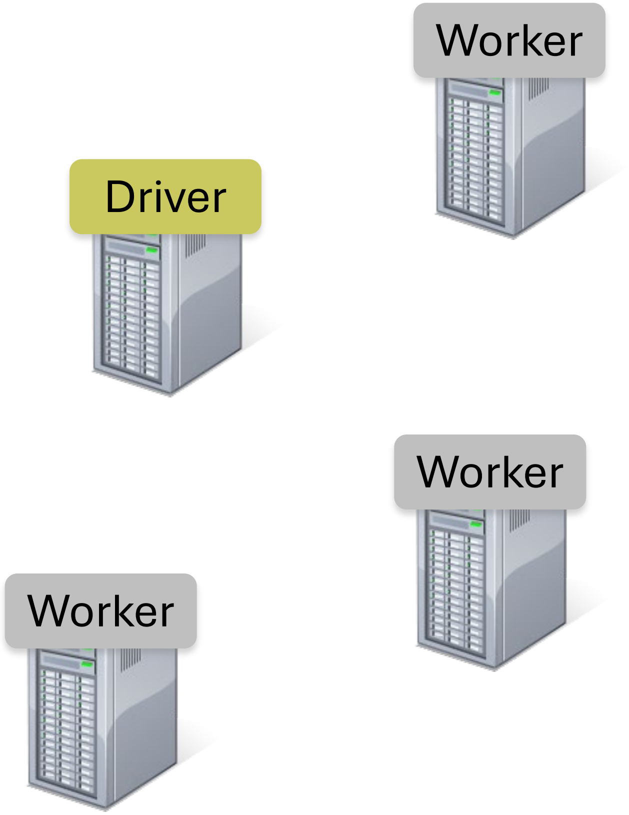


Spark Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile("hdfs://...")
```

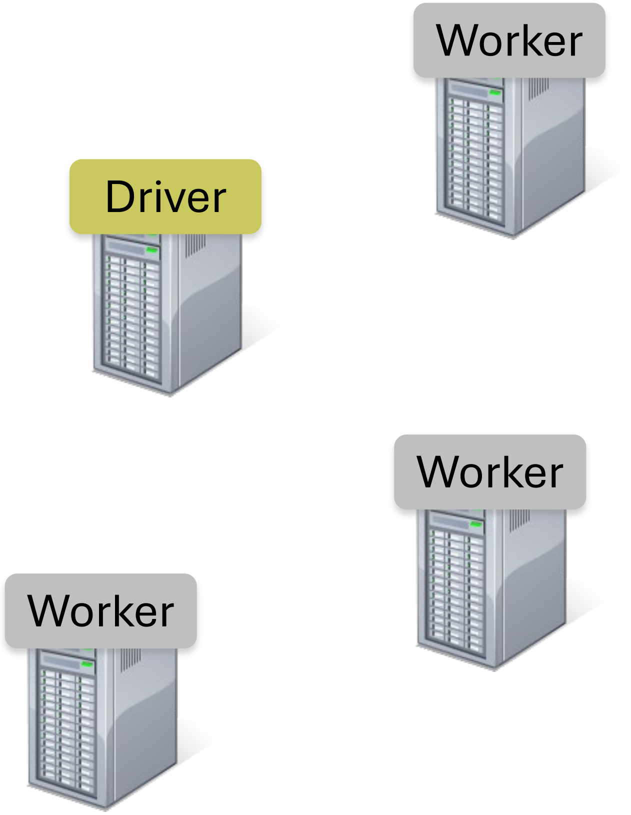


Spark Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

Base RDD

```
lines = spark.textFile(“hdfs://...”)
```



Spark Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

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errors = lines.filter(lambda s: s.startswith(“ERROR”))
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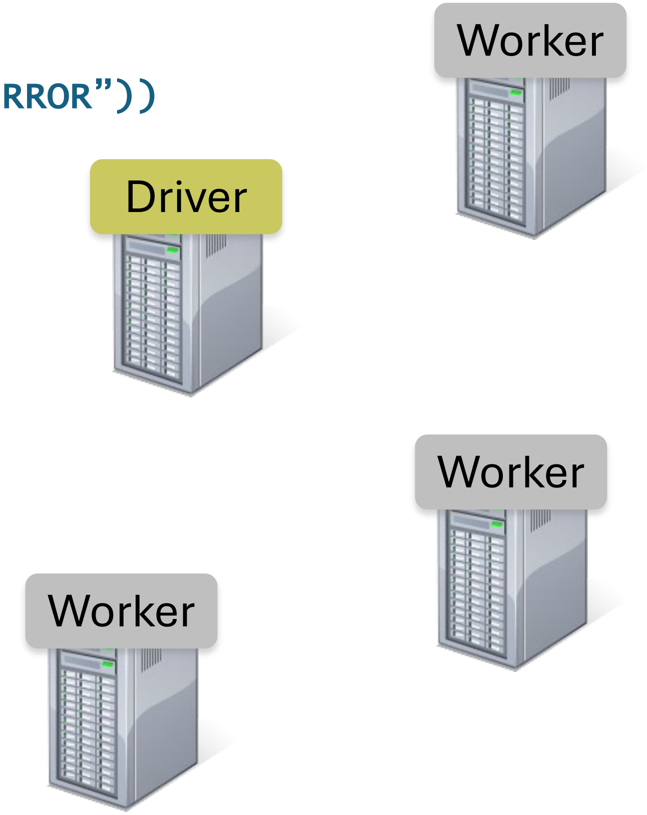
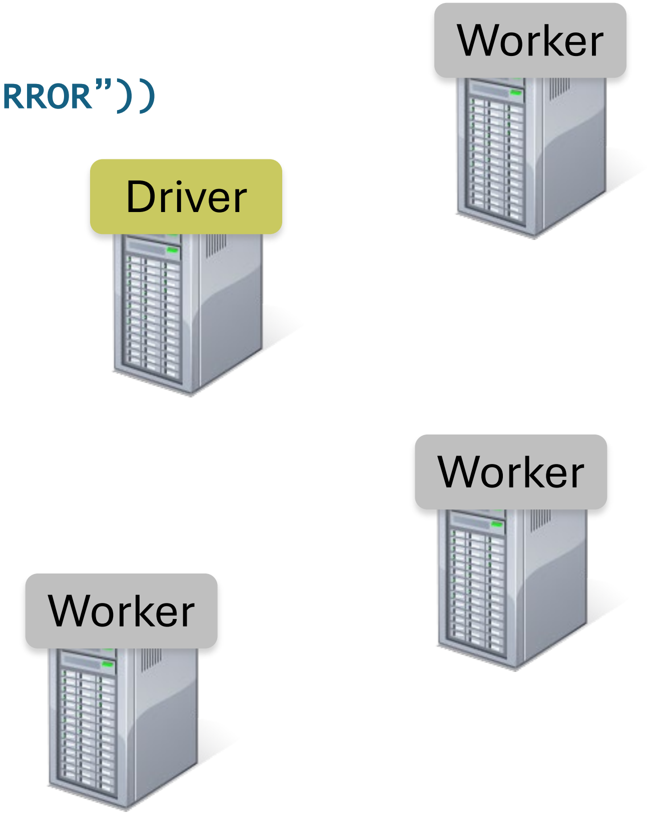


Spark Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

Transformed RDD

```
lines = spark.textFile(“hdfs://...”)
errors = lines.filter(lambda s: s.startswith(“ERROR”))
```



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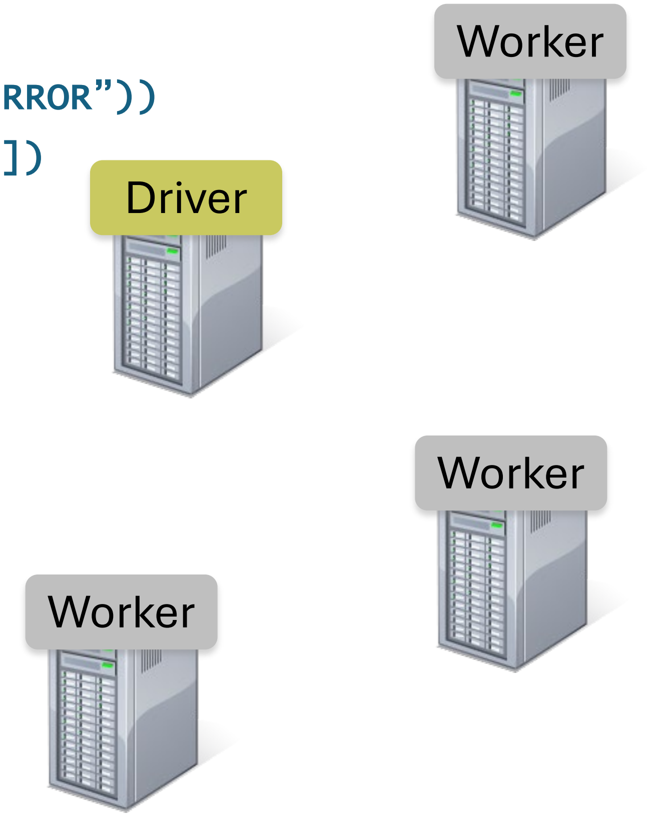
messages = errors.map(lambda s: s.split(“\t”)[2])
messages.cache()


messages.filter(lambda s: “mysql” in s).count()
```



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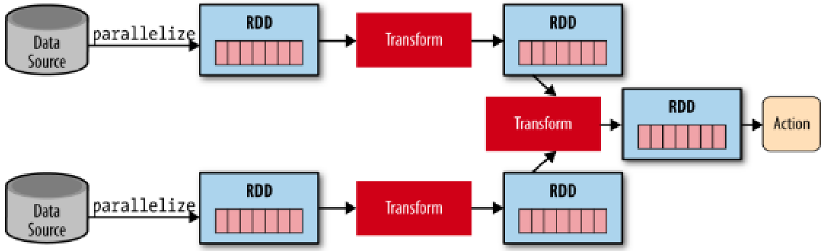

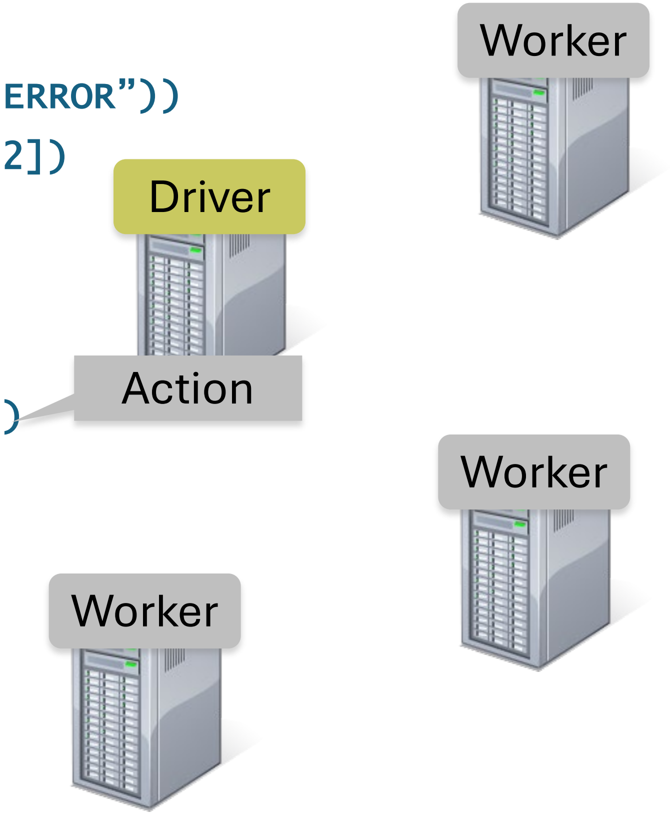

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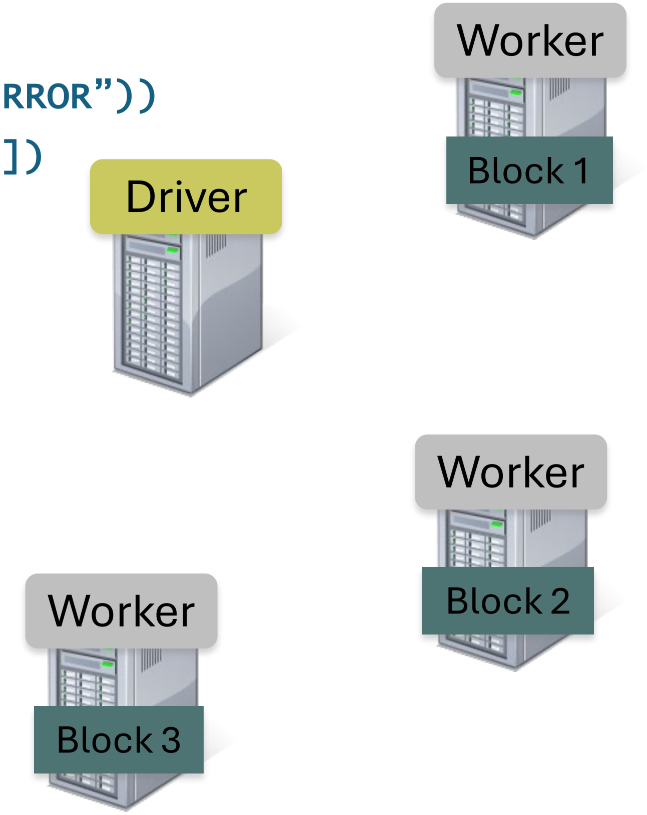

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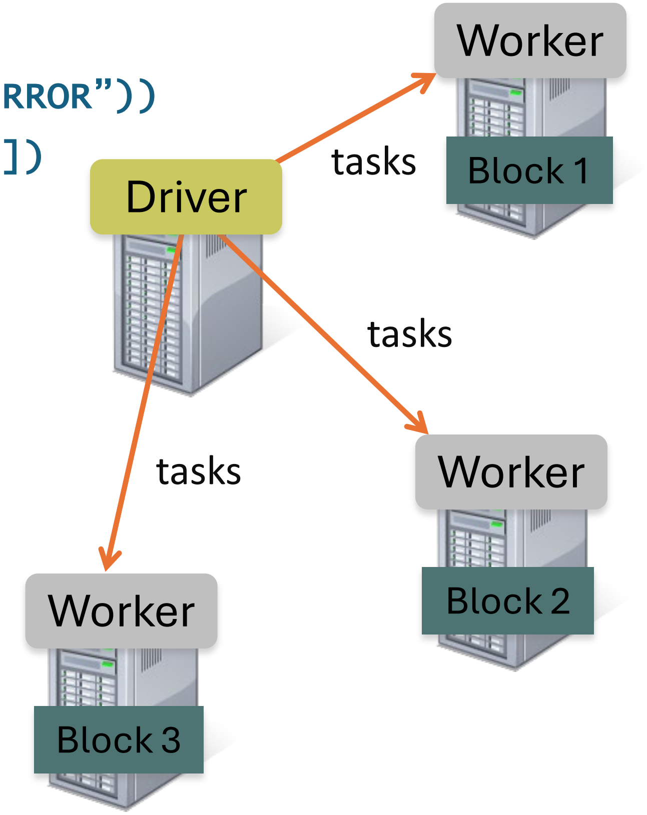

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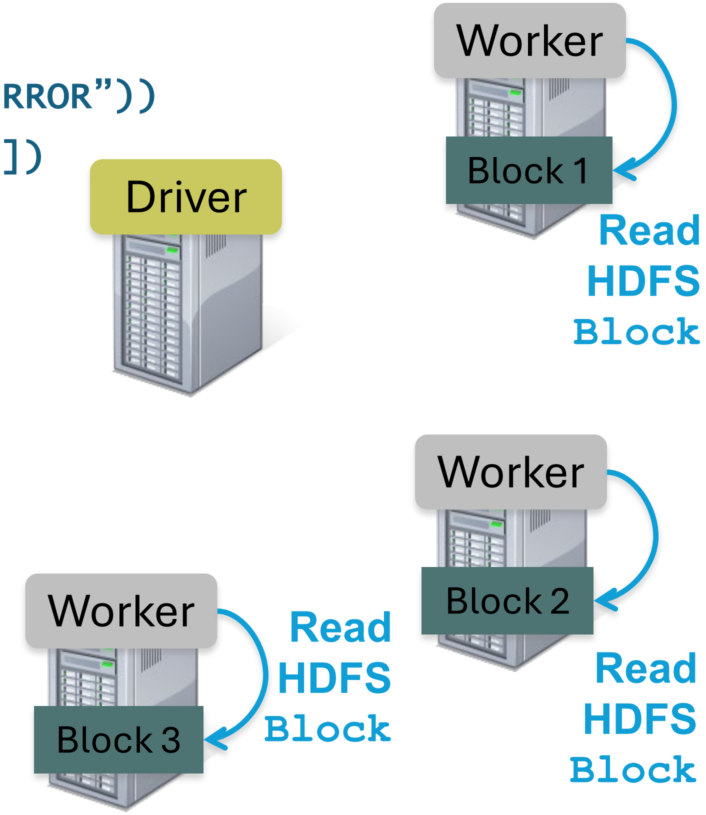

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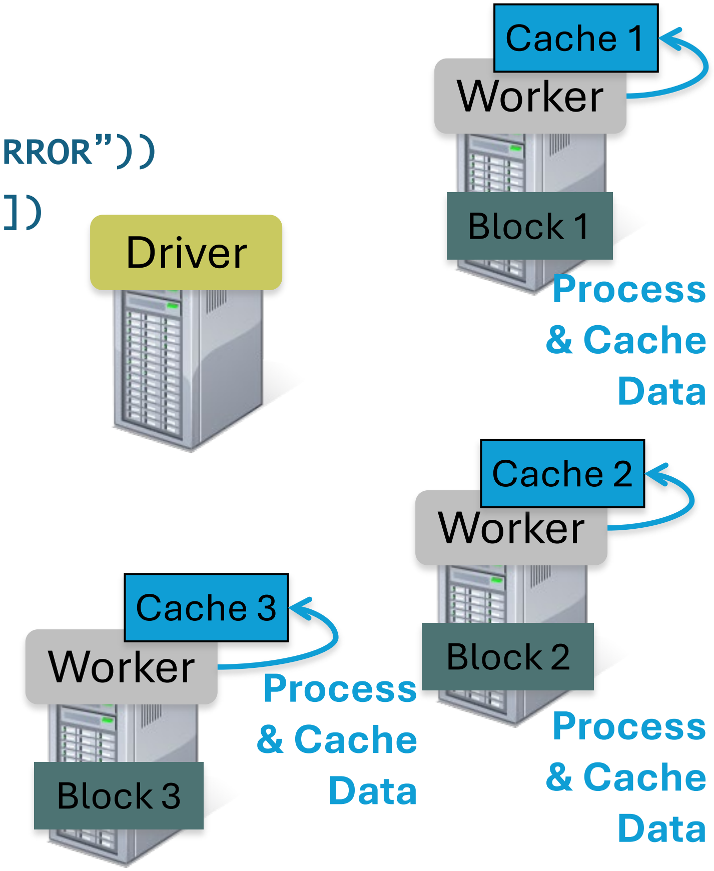

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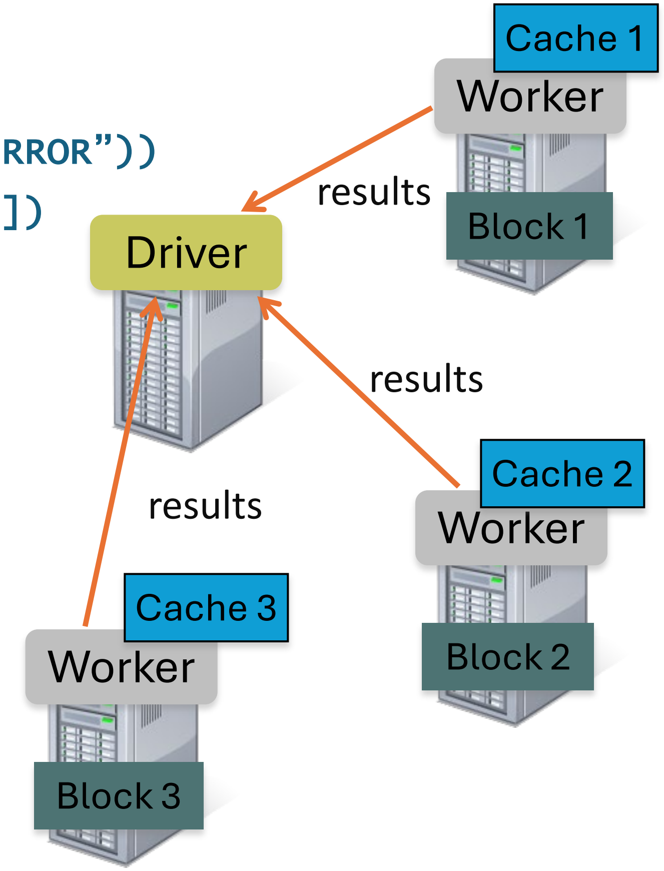

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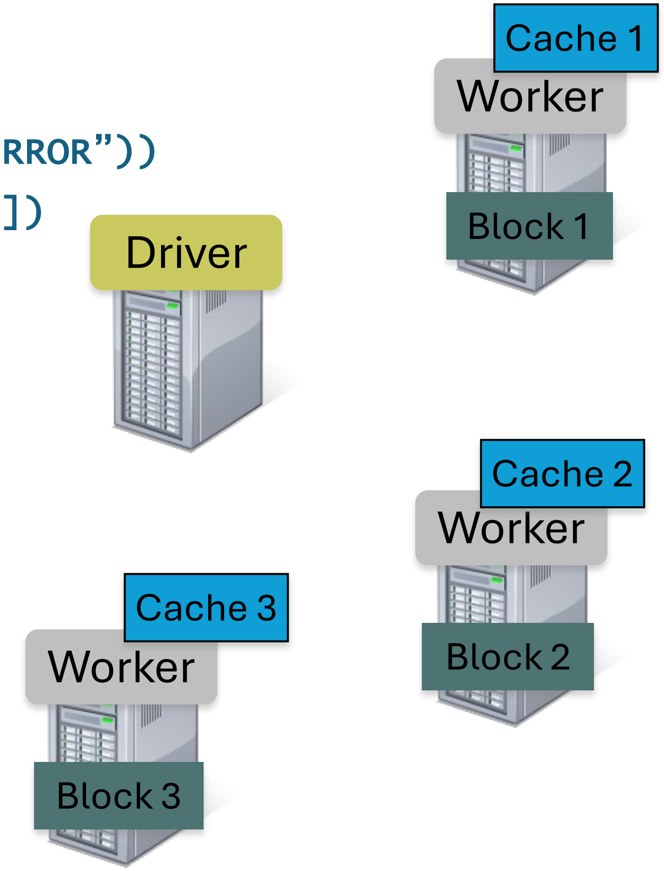

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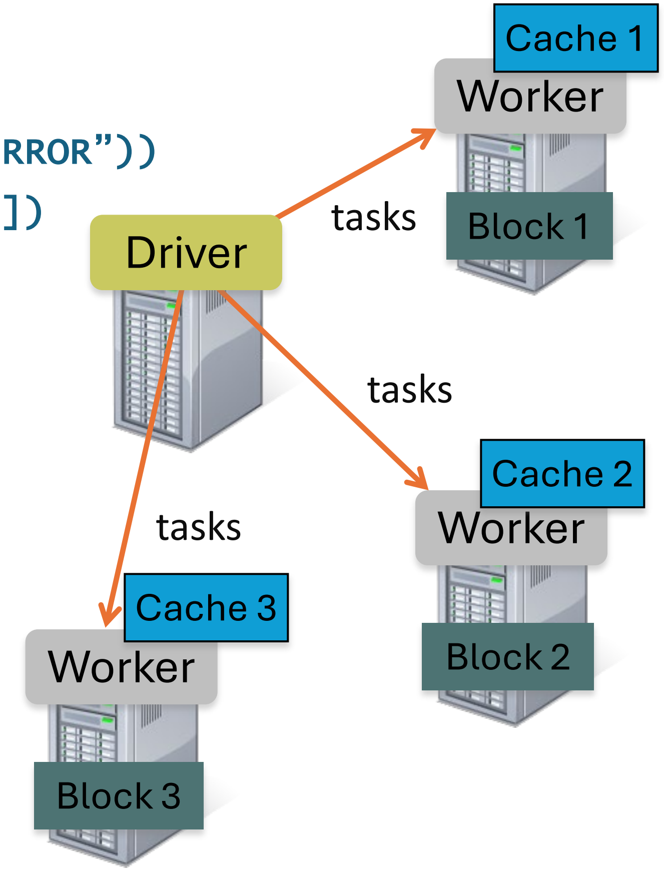

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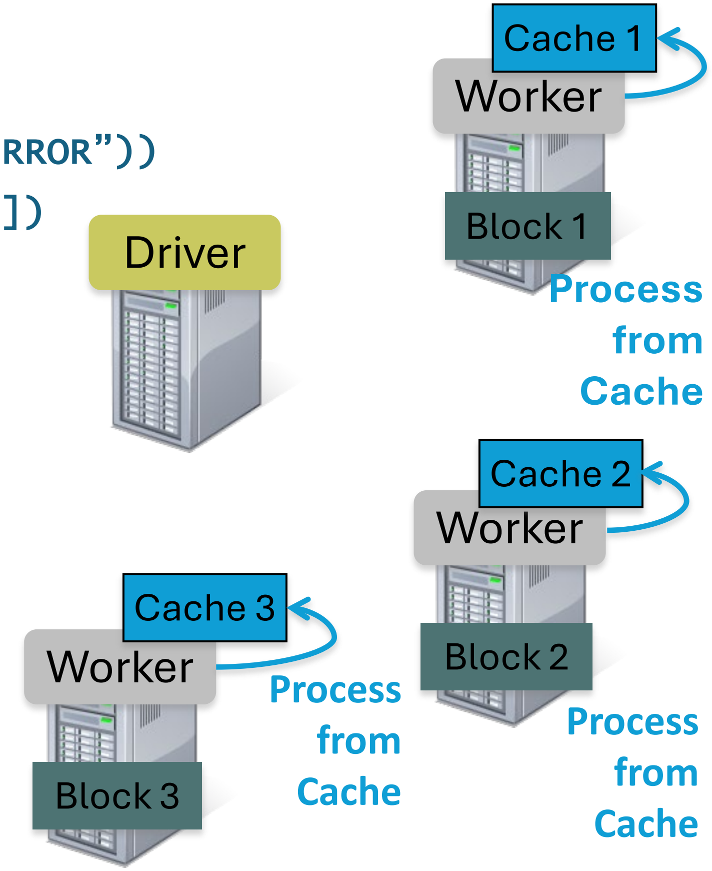

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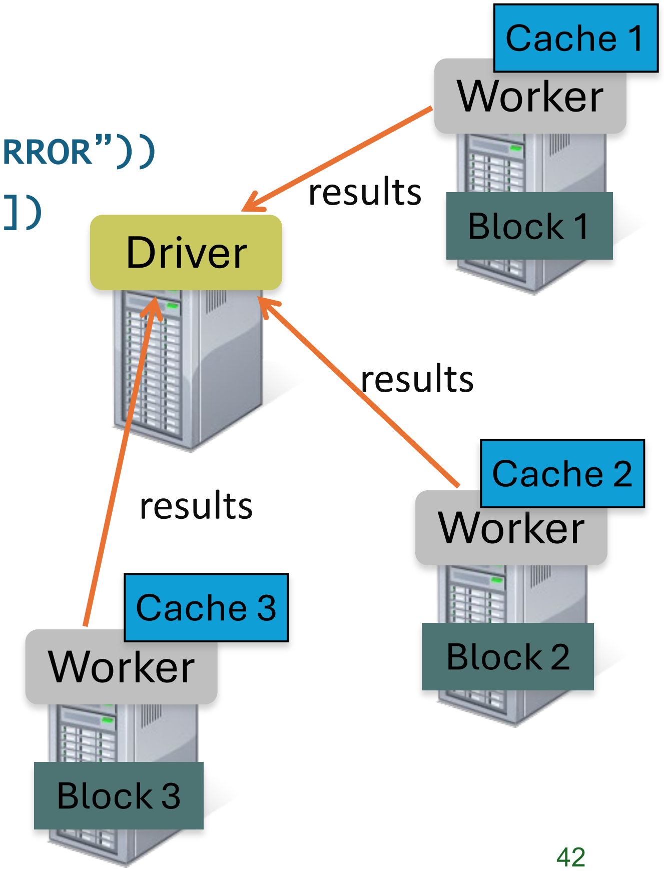

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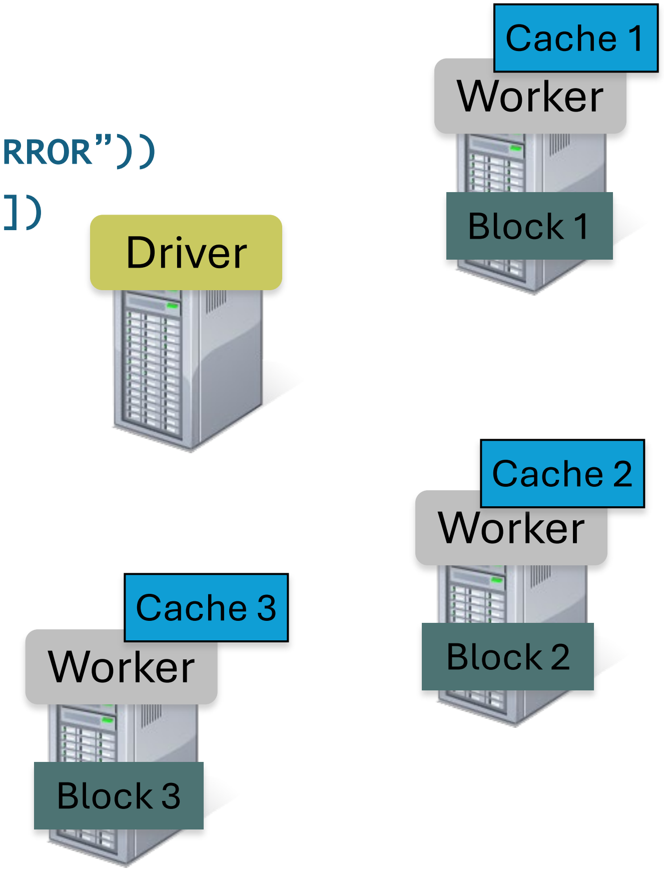

Cache your data → Faster results

Full-text search of Wikipedia

- 60GB on 20 EC2 machines
- 0.5 sec from mem vs. 20s for on-disk

Spark Program Lifecycle

- Create DataFrames from external data or create DataFrame from a collection in a driver program
- Lazily transform them into new DataFrames
- cache( ) some DataFrames for reuse
- Perform actions to execute parallel computation and produce results

Use Spark Transformations and Actions wherever possible: Search DataFrame reference API

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XX-XX-XX

University of Sheffield’s HPC

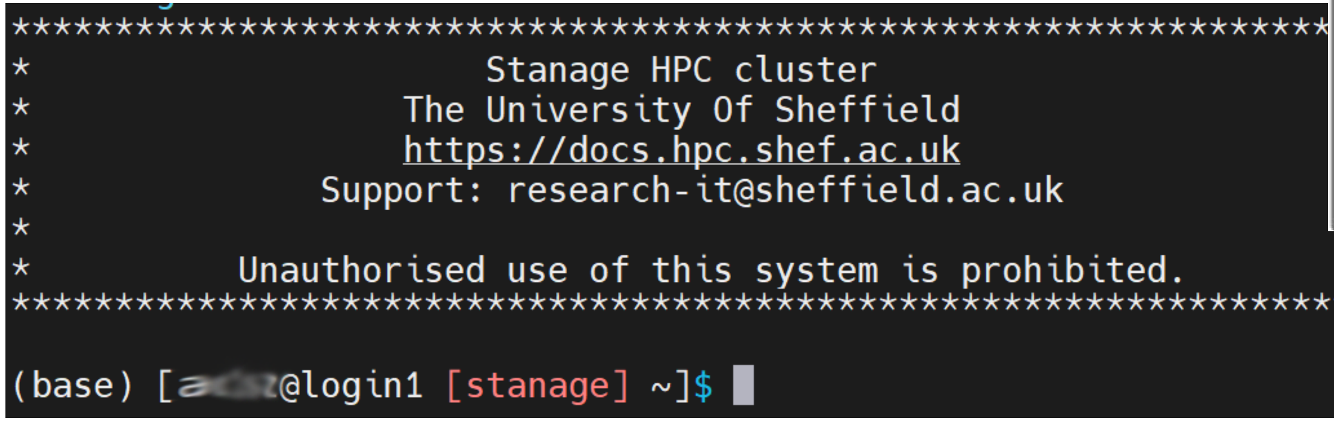
STANAGE

A photo of Stanage, the premier supercomputer at the University of Sheffield

- A HPC is a **cluster** made up of multiple large computers, called **nodes**.
- Each node is itself a powerful computer. The nodes can communicate data with each other with high-speed communications.
- Account created for you already!
- **Training:** HPC Driving License test (Assignment 0 - due 11th Feb)

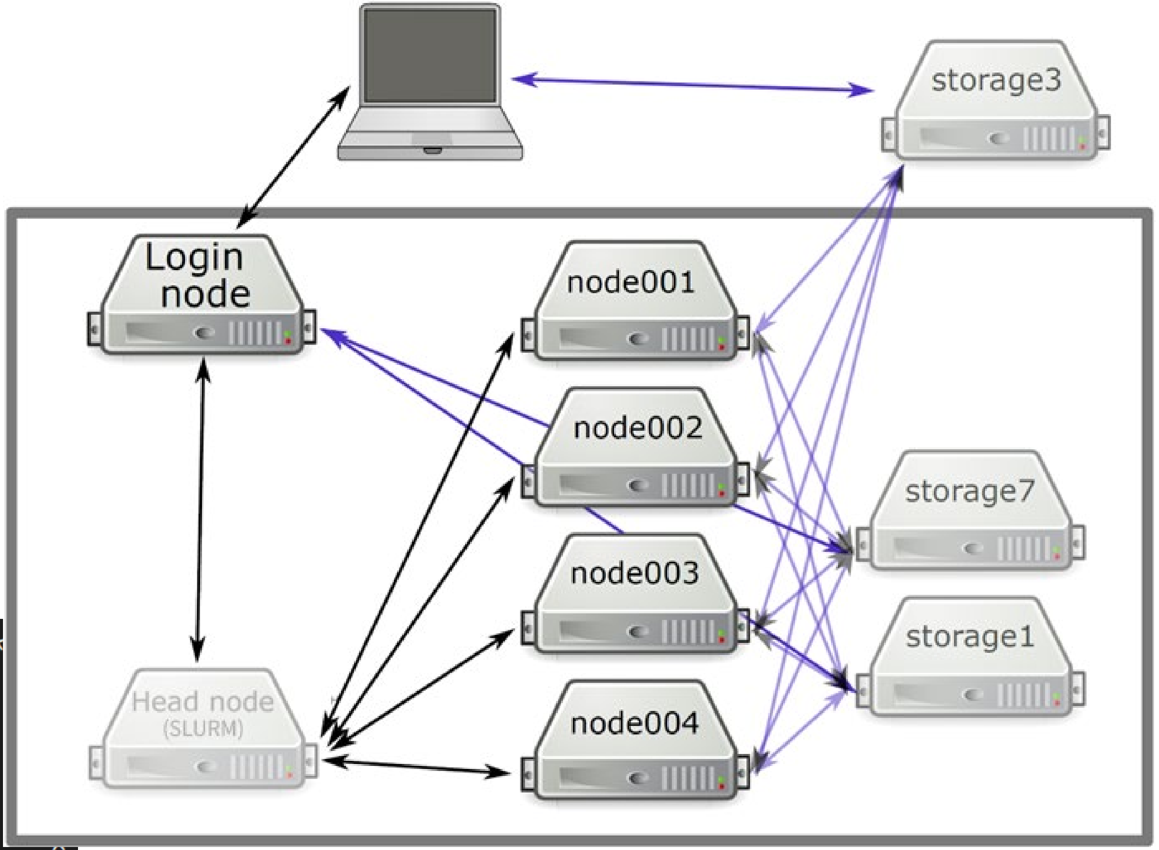
HPC Access and Structure

- SSH access via stanage.sheffield.ac.uk
  - Windows: MobaXTerm
  - Linux/MAC OS: terminal (command line)
- VPN: a **MUST** for when connecting on campus using Eduroam or off campus
- HPC login nodes are gateways to the cluster of worker nodes.



```
*****************************************************************
*                       Stanage HPC cluster
*                   The University Of Sheffield
*                   https://docs.hpc.shef.ac.uk
*               Support: research-it@sheffield.ac.uk
*
*         Unauthorised use of this system is prohibited.          *
*******************************************************************

(base) [[redacted]@login1 [stanage] ~]$ 
```



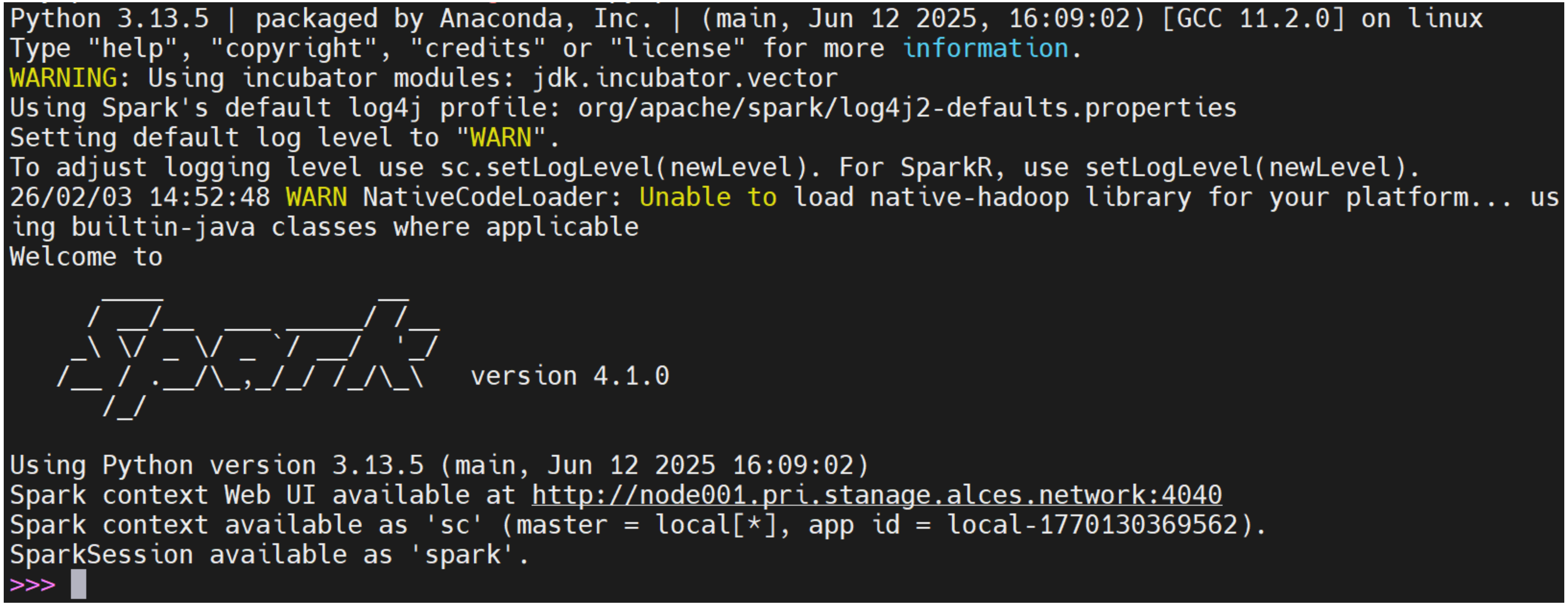
Storage on Stanage

Location	**Quota**	**Speed**	**Suitable for?**
/users/$USER	50GB	>	Personal data
/mnt/parscratch/	No limits	>>>	Temporary large files
/tmp	No limits	>>>	Temporary lots of small files

More information available at: https://docs.hpc.shef.ac.uk/en/latest/hpc/filestore.html

PySpark 4.1.0

- Need: Java, Python, Spark (See lab 1 on how to install on HPC)
- Interactive session: use pyspark to start a PySpark interactive shell

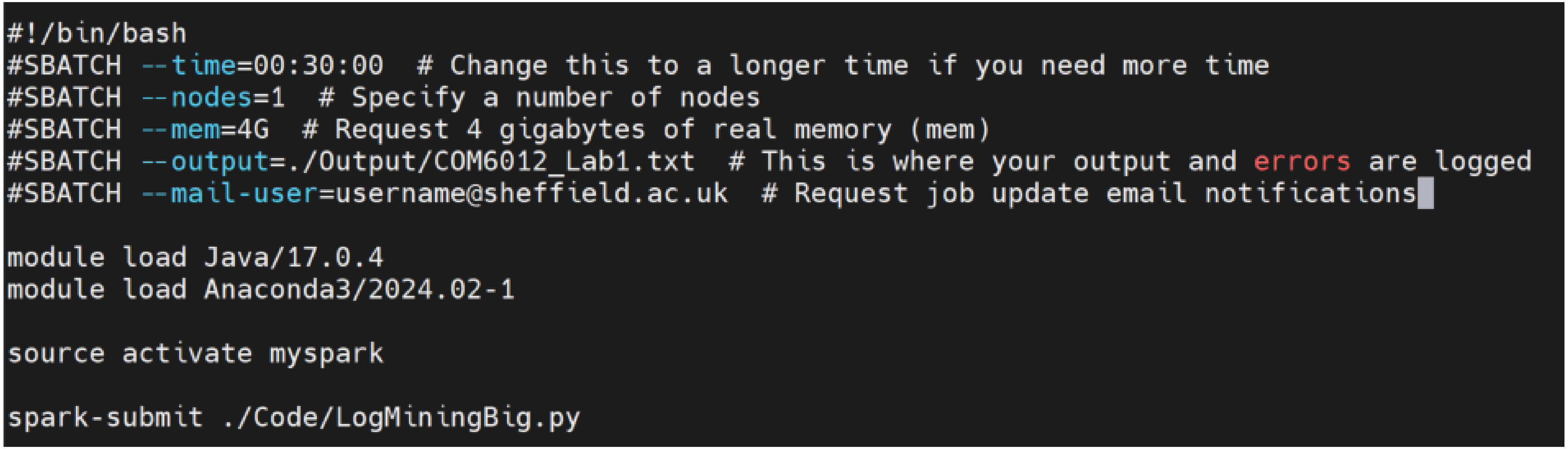


```
Python 3.13.5 | packaged by Anaconda, Inc. | (main, Jun 12 2025, 16:09:02) [GCC 11.2.0] on linux
Type "help", "copyright", "credits" or "license" for more information.
WARNING: Using incubator modules: jdk.incubator.vector
Using Spark's default log4j profile: org/apache/spark/log4j2-defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
26/02/03 14:52:48 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... us
ing builtin-java classes where applicable
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /__ / .__/\_,_/_/ /_/\_\   version 4.1.0
      /_/

Using Python version 3.13.5 (main, Jun 12 2025 16:09:02)
Spark context Web UI available at http://node001.pri.stanage.alces.network:4040
Spark context available as 'sc' (master = local[*], app id = local-1770130369562).
SparkSession available as 'spark'.
>>> 
```

Batch Session – Shell Script xx.sh

Create a file `Lab1_SubmitBatch.sh`

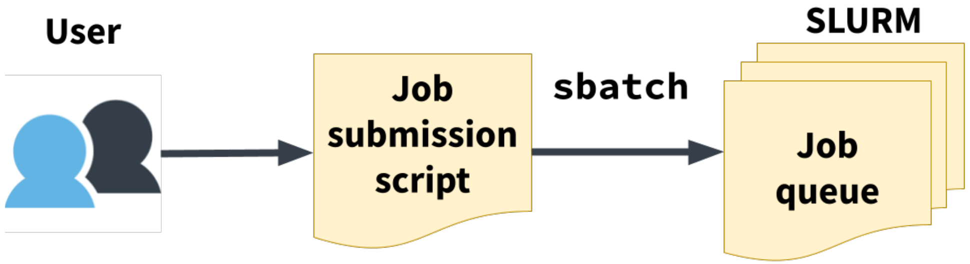


```
#!/bin/bash
#SBATCH --time=00:30:00  # Change this to a longer time if you need more time
#SBATCH --nodes=1  # Specify a number of nodes
#SBATCH --mem=4G  # Request 4 gigabytes of real memory (mem)
#SBATCH --output=./Output/COM6012_Lab1.txt  # This is where your output and errors are logged
#SBATCH --mail-user=username@sheffield.ac.uk  # Request job update email notifications

module load Java/17.0.4
module load Anaconda3/2024.02-1

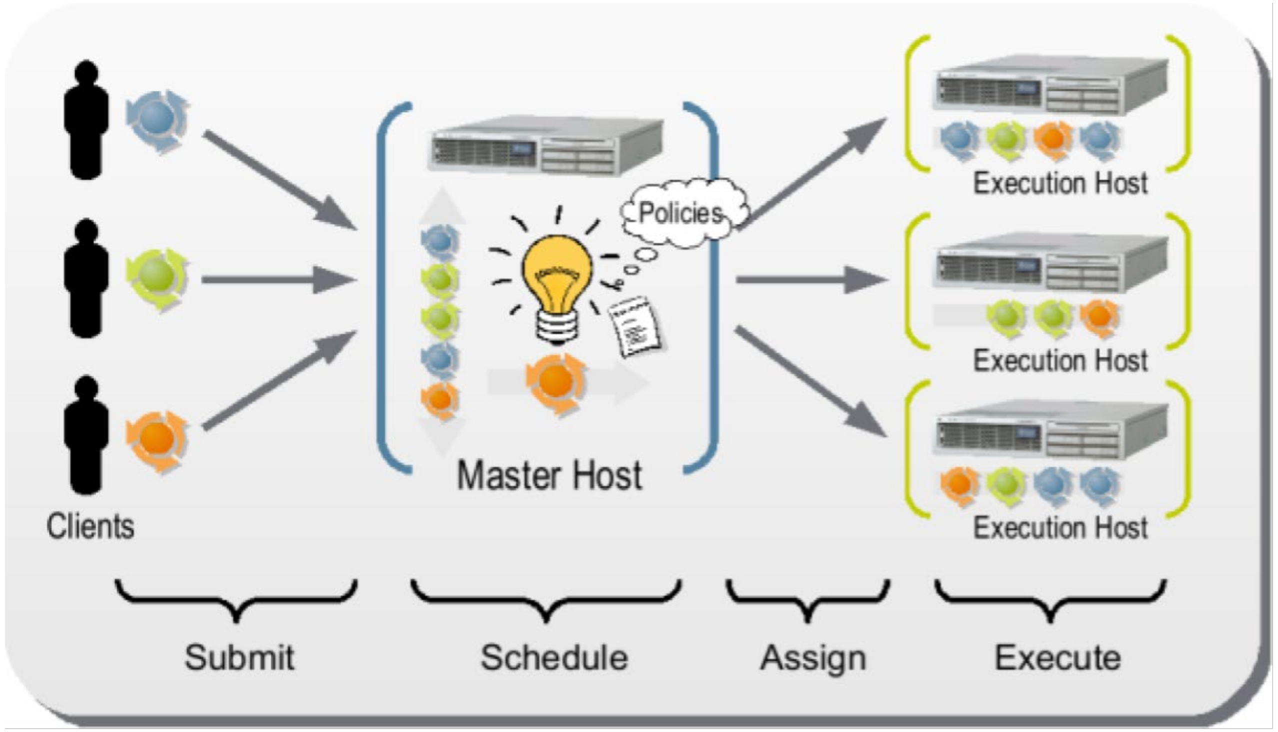
source activate myspark

spark-submit ./Code/LogMiningBig.py
```



Batch Session: Submit & Relax

- sbatch your job (can run at the login node): see Lab 1
- Then?
  - Close the terminal and leave
  - Wait for pre-set email notification
  - Check status: squeue
  - Cancel job: scancel
- How much resources to request
  1. Run short test jobs
  2. View resource utilisation
  3. Extrapolate
  4. Submit larger jobs

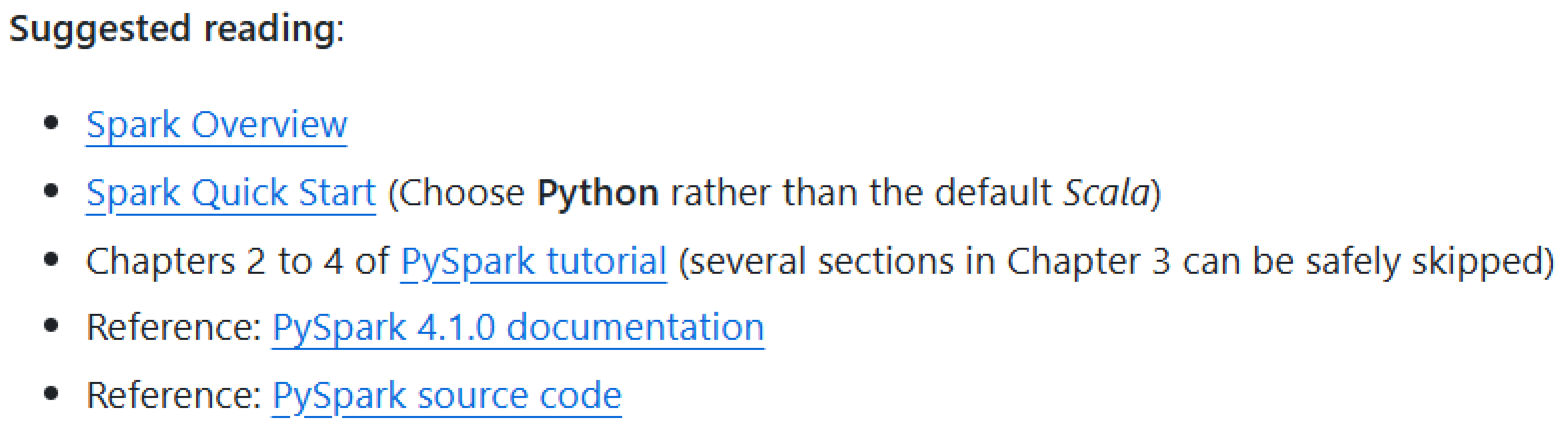


Summary of key concepts

- Data structure spectrum
  - Structured, semi-structured, unstructured data, schema, ETL
- Spark’s computing model and framework
  - RDDs, DataFrames, parallel transformation, fault-tolerance, …
- Components and lifecycle of a spark programme
  - SparkSession and SparkContext
  - Creating DataFrames, lazy transformations, caching, and actions
- Key features of the Stanage cluster
  - HPC structure, storage, interactive vs. batch session

Spark Resources

- Apache Spark open-source repository
- Apache Spark Documentation
- Learning Apache Spark with Python (Chapters 2 and 4)
- Suggested reading in labs



Suggested reading:

- Spark Overview
- Spark Quick Start (Choose **Python** rather than the default *Scala*)
- Chapters 2 to 4 of PySpark tutorial (several sections in Chapter 3 can be safely skipped)
- Reference: PySpark 4.1.0 documentation
- Reference: PySpark source code

Acknowledgements

- Some slides (sec. 1) are modified from the "Introduction to Apache Spark" course by Prof. A. D. Joseph, University of California, Berkeley.
- This module benefits from many open resources. See the acknowledgement on our GitHub page.
- There are many other resources that I have consulted but may somehow lost track of the origins.

Thank-you-word-cloud.jpg (967×522) (wikimedia.org)

Image sources for the logos

- Page 4:
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