Lecture 1: Introduction to Spark and HPC

Shuo Zhou

COM6012: Scalable ML

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
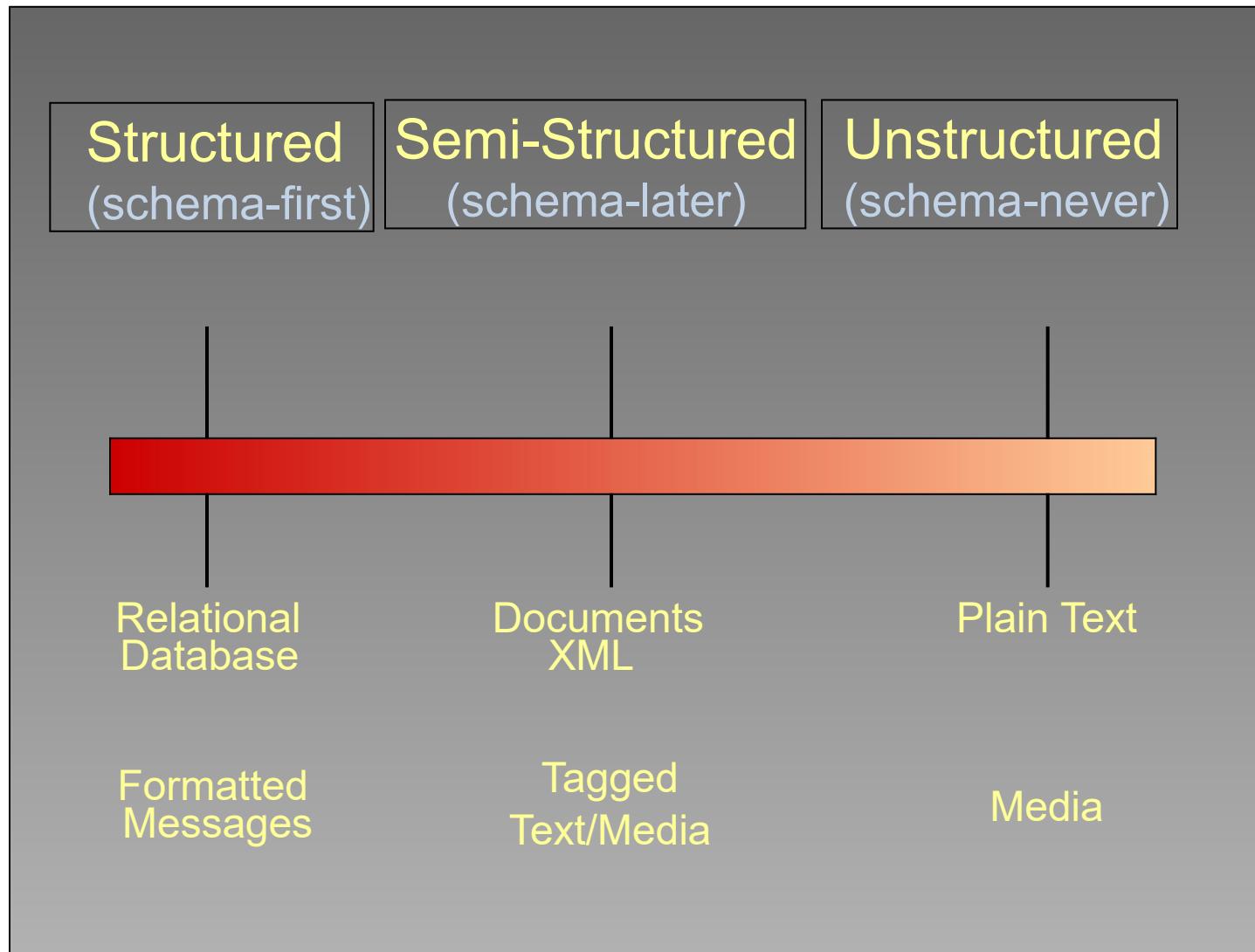 - Faults
  - ...

- Web + mobile platforms:

Where Does Big Data Come From?

AI generated content

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Data Structure Spectrum

Structured (schema-first)	Semi-Structured (schema-later)	Unstructured (schema-never)

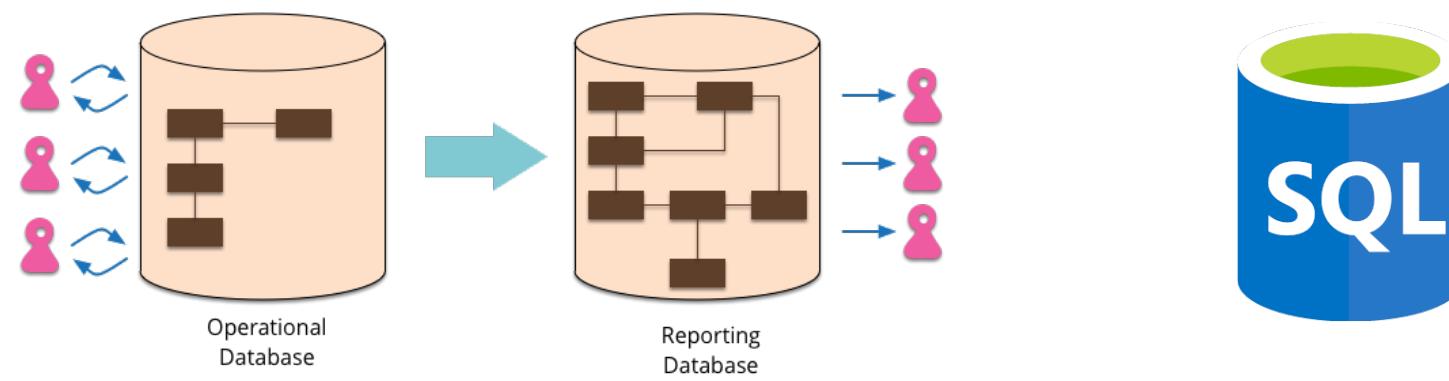Relational Database

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

Operational Database

Reporting Database

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
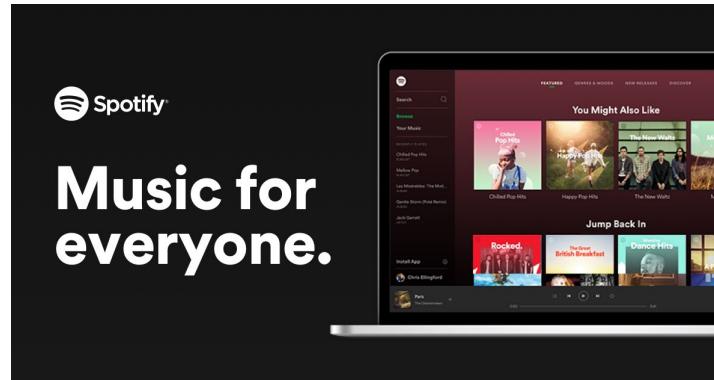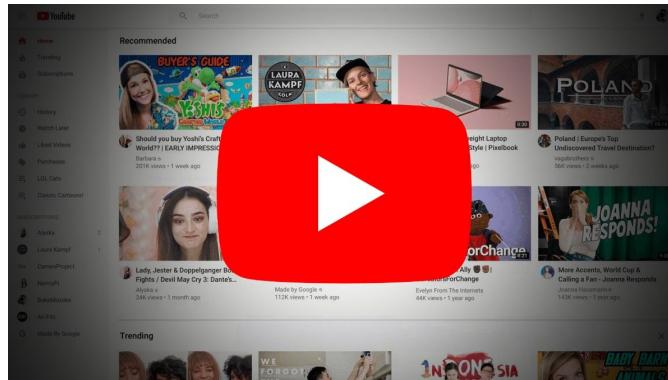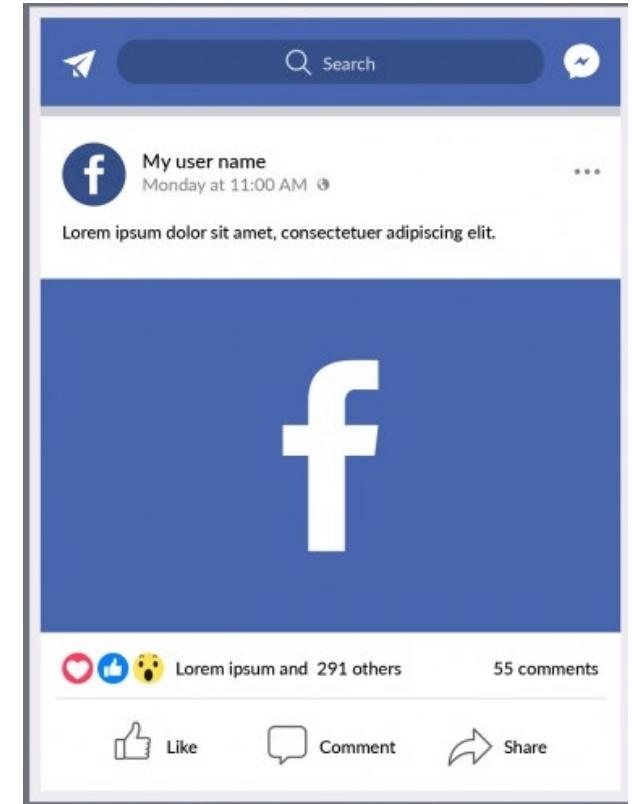 - Programmer statically specifies the schema

- Examples:

Unstructured Data

- Only one column with string or binary type

- Examples
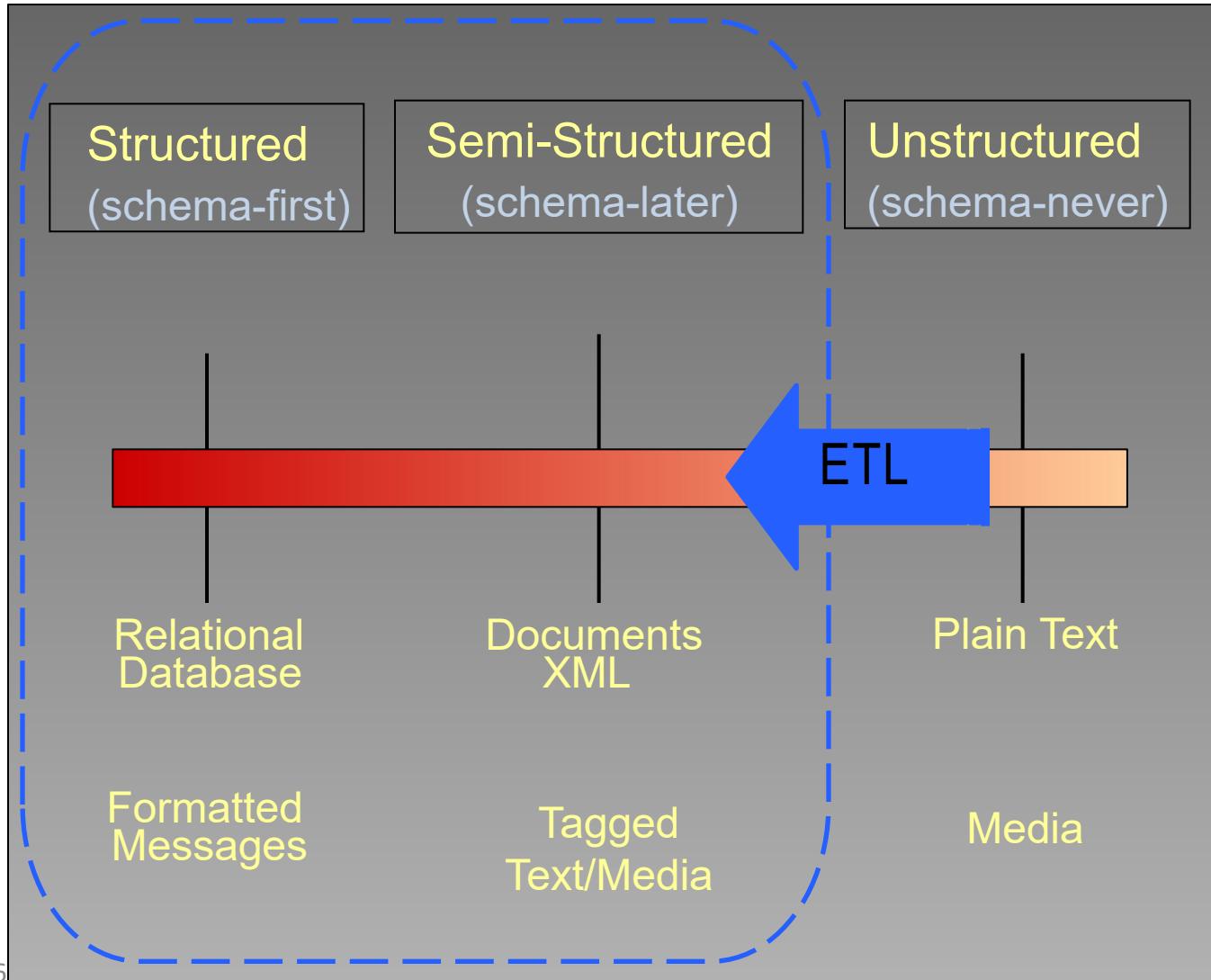
- Note: File formats ≠ data structure

Traverse the Data Structure Spectrum

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

Traditional Analysis Tools

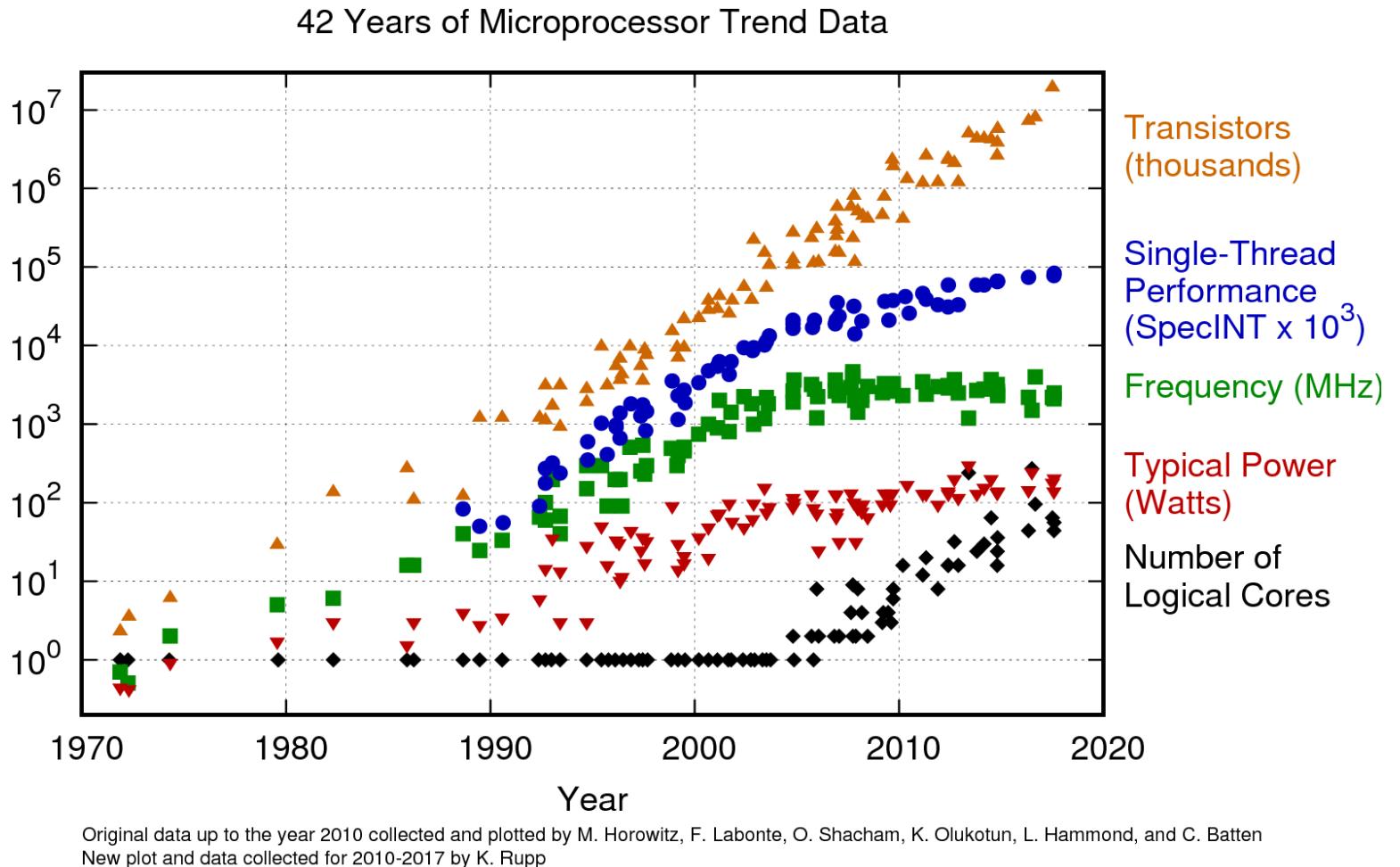- Unix shell commands (awk, grep, …)

All run on a single machine!
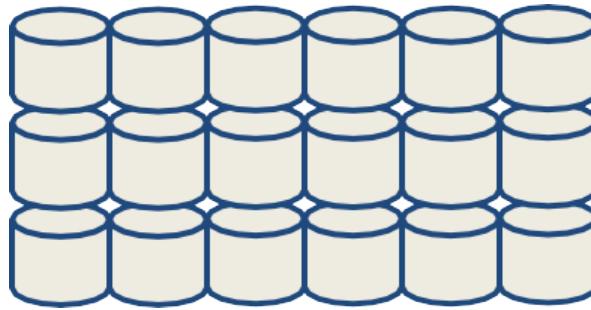
The Big Data Problem

- 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

Transistors (thousands)

Single-Thread Performance (SpecINT x 10^3)

Frequency (MHz)

Typical Power (Watts)

Number of Logical Cores

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
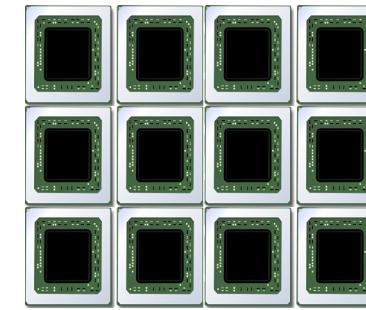
Solution for the Big Data Problem

- 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

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

Apache Spark

- Fast and general-purpose cluster computing engine
- Interoperable with

- Improves efficiency through:
  - In-memory computing primitives
  - General computation graphs

  → Up to 100× faster (2-10× on disk)

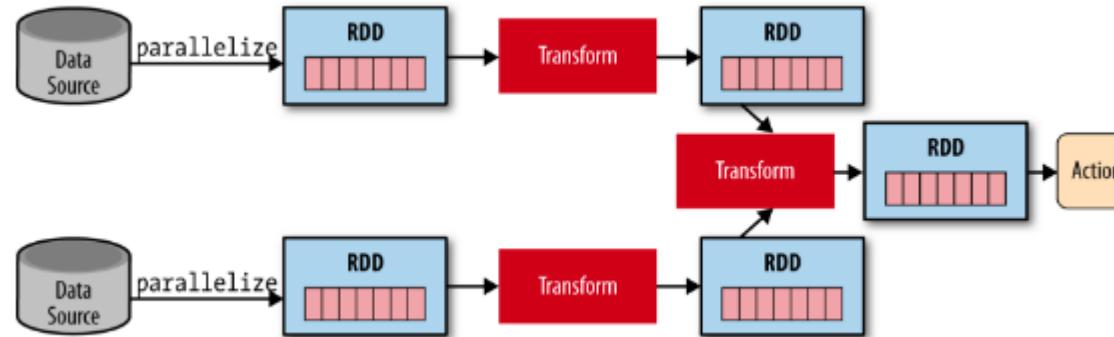- Improves usability through:
  - Rich APIs in Scala, Java, Python
  - Interactive shell

  → 2-5× less code
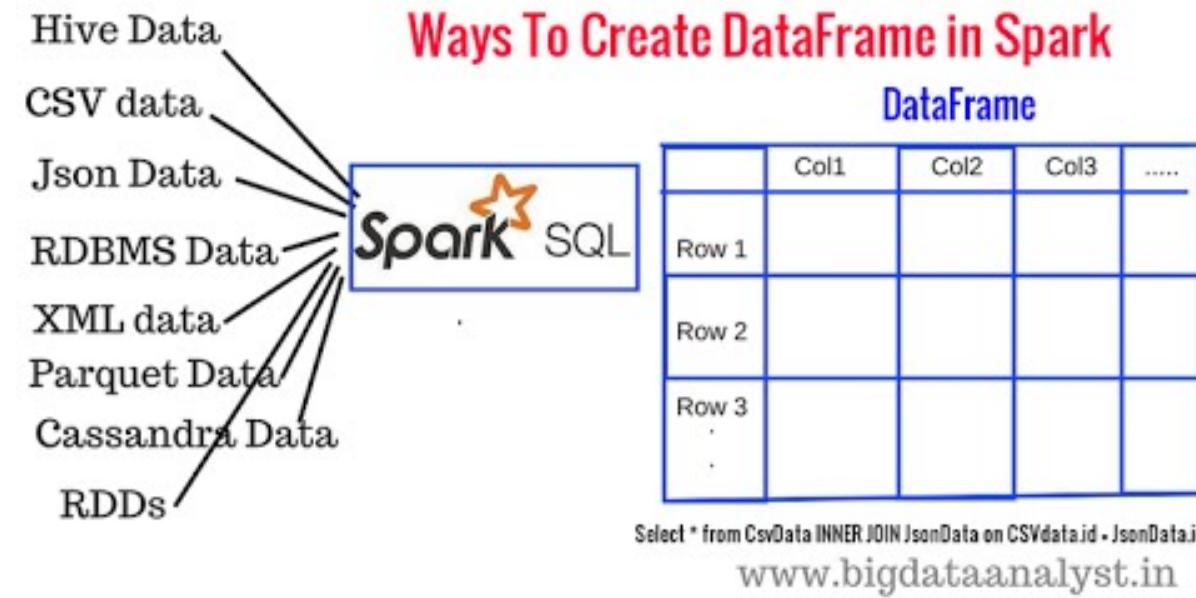
Spark Model

- 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

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

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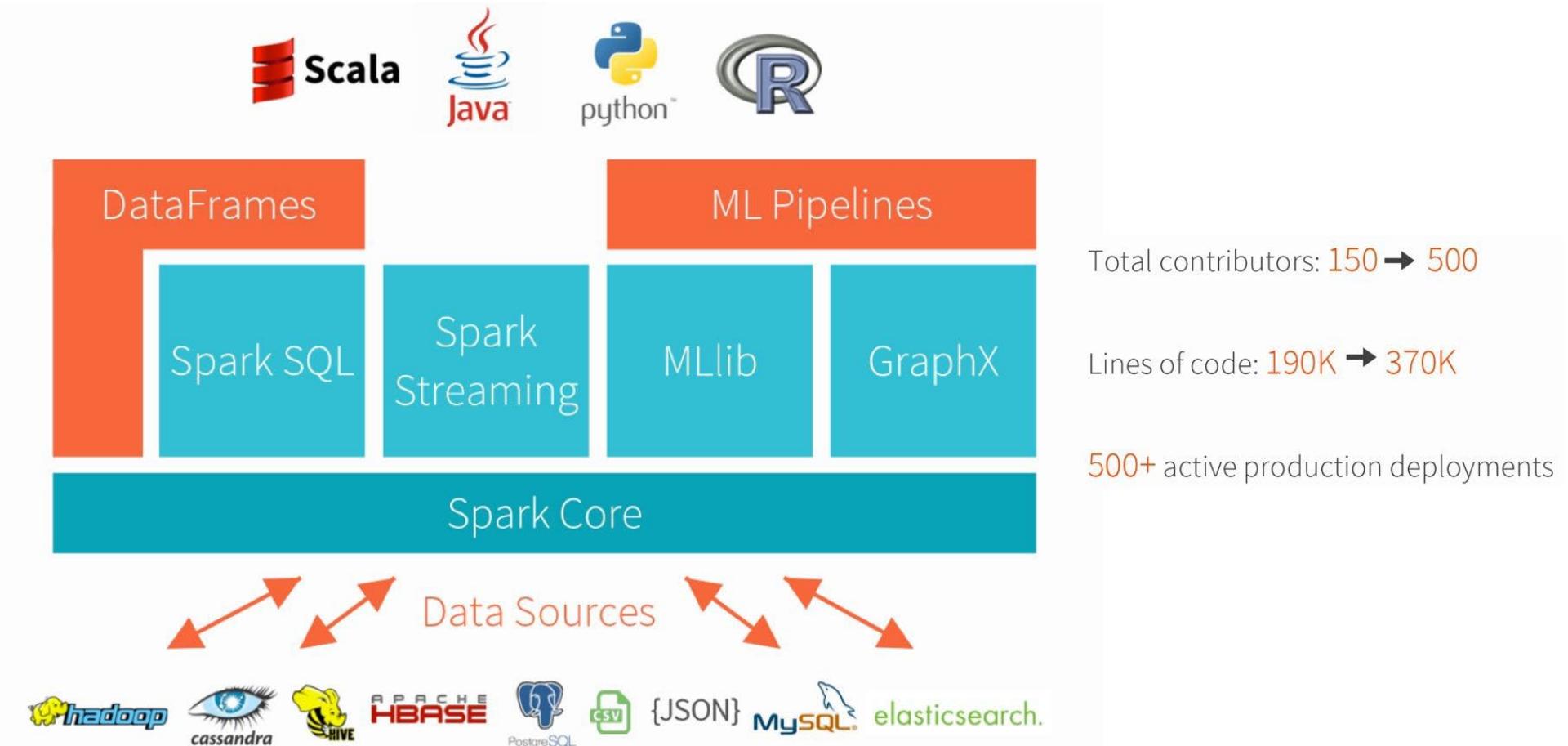
- Programming abstraction and parallel runtime to hide complexities of **fault-tolerance** and **slow** machines

  "Here's an operation, run it on all of the data"

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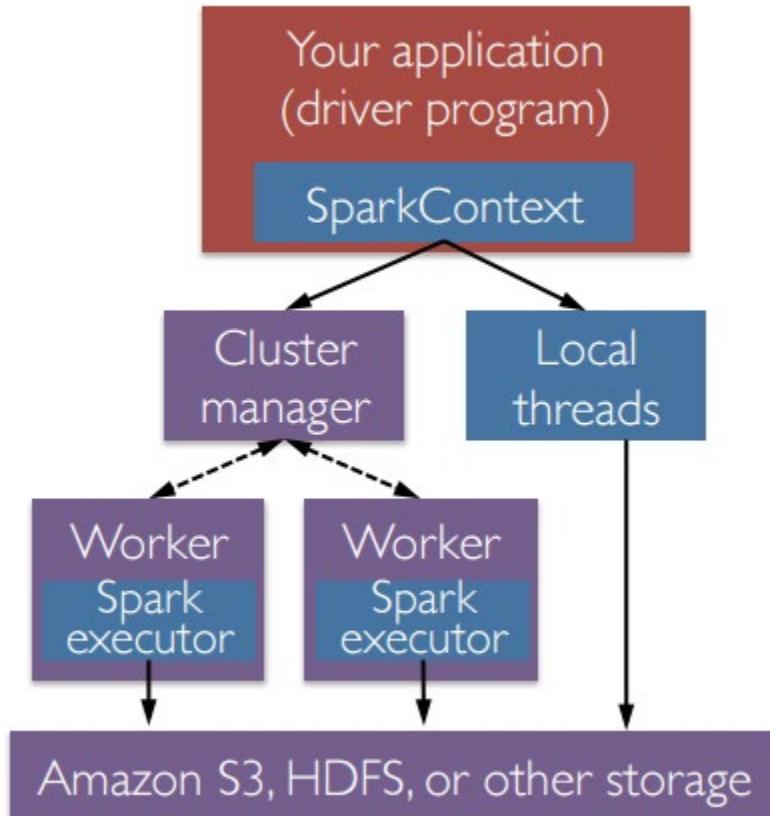
- Don't care where it runs (you schedule that)
- In fact, feel free to run it twice on different nodes (e.g. when it fails)

Apache Spark Ecosystem

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

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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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- The Big Data Problem: Why Spark?

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- **An Example of Spark: Log Mining**

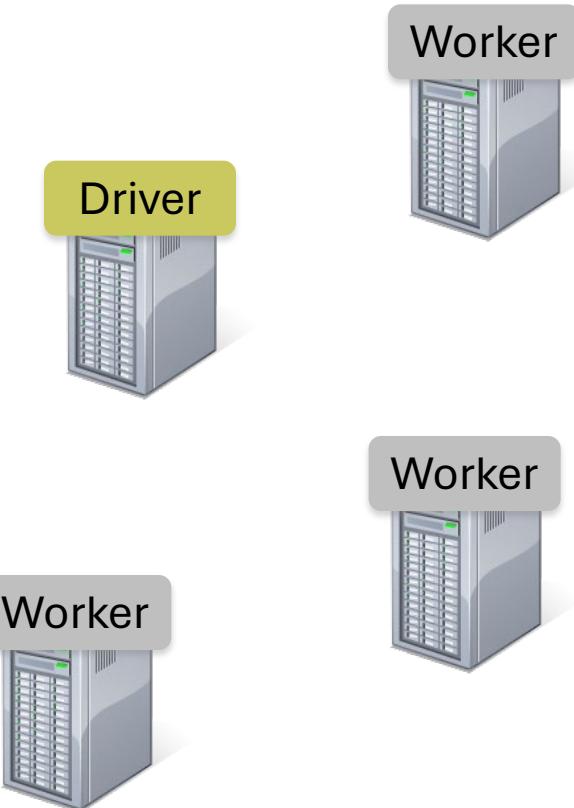- How to Use Spark: PySpark, HPC, Resources

Check-in code: XX-XX-XX

Spark Example: Log Mining (w/t RDD)
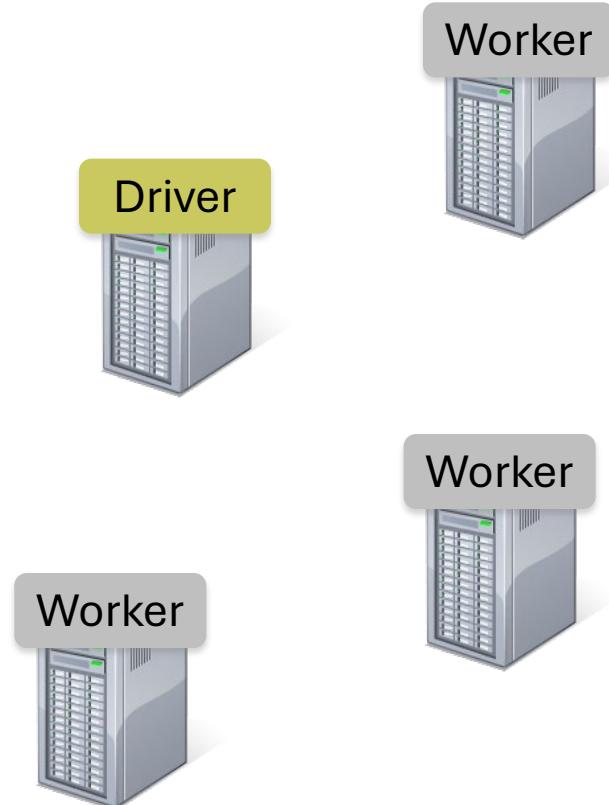
Load error messages from a log into memory, then interactively search for various patterns

Spark Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns
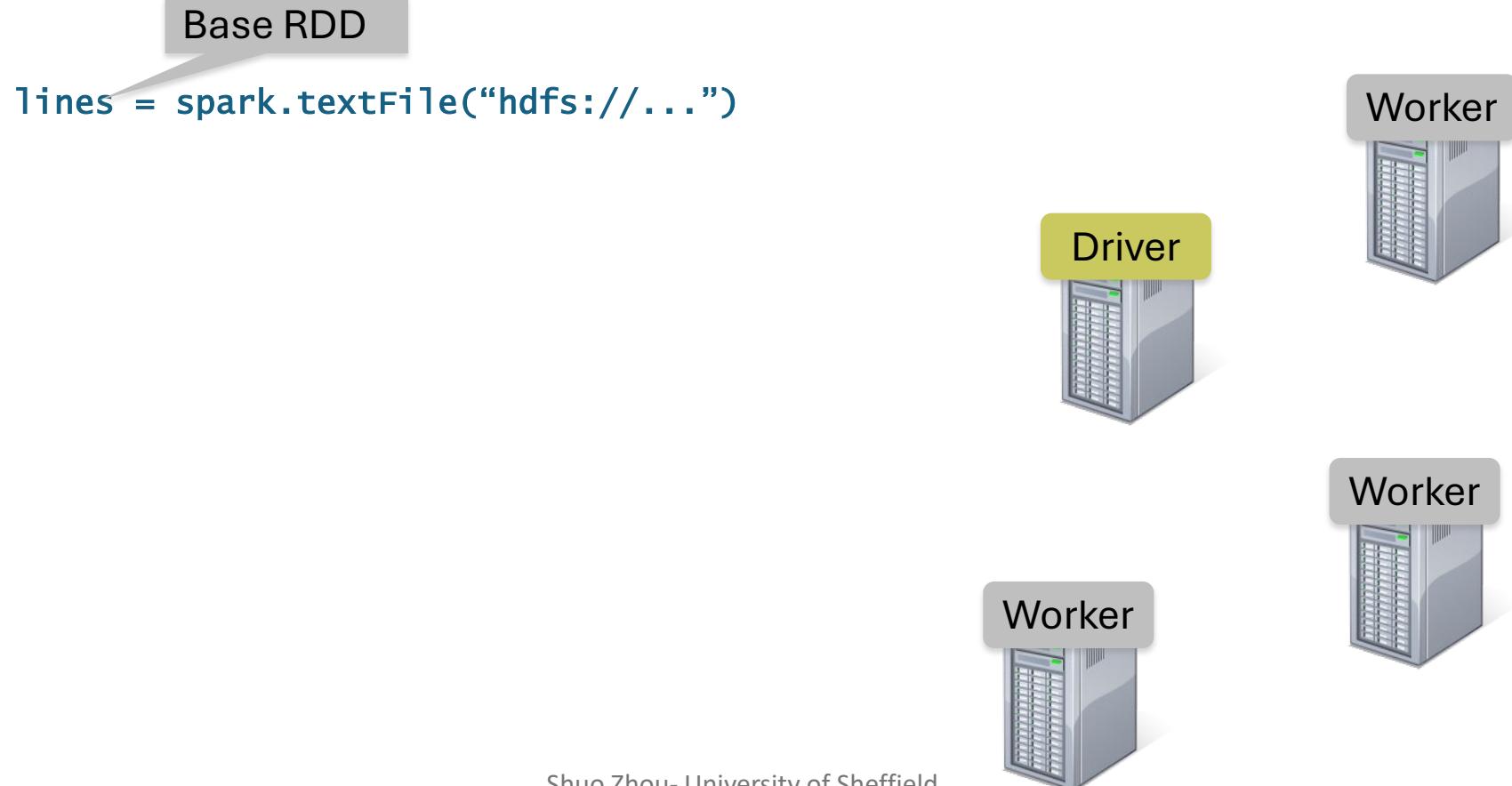
Spark Example: Log Mining

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

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

Worker

Driver

Worker

Worker

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"))
```

Worker

Driver

Worker

Worker

Spark Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns
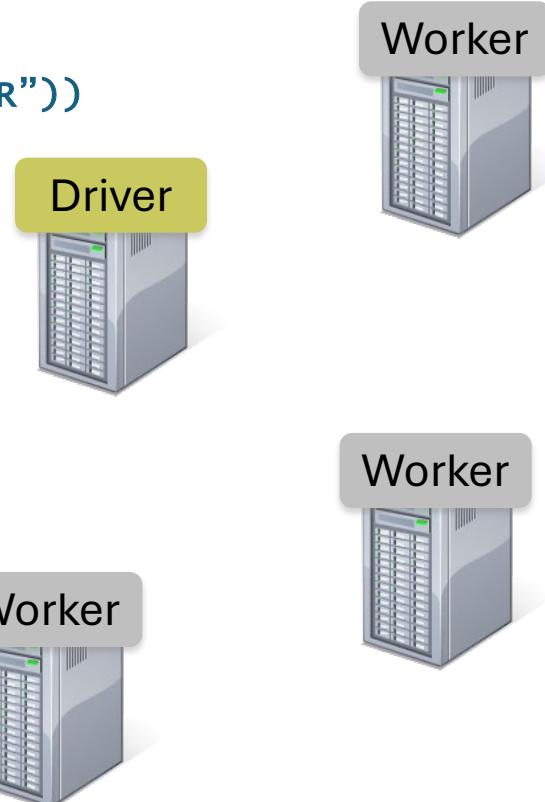
```
lines = spark.textFile("hdfs://...")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split("\t")[2])
messages.cache()


messages.filter(lambda s: "mysql" in s).count()
```
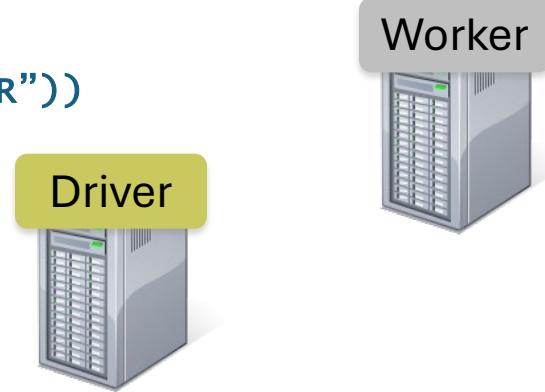
Worker

Driver

Worker

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Spark Example: Log Mining

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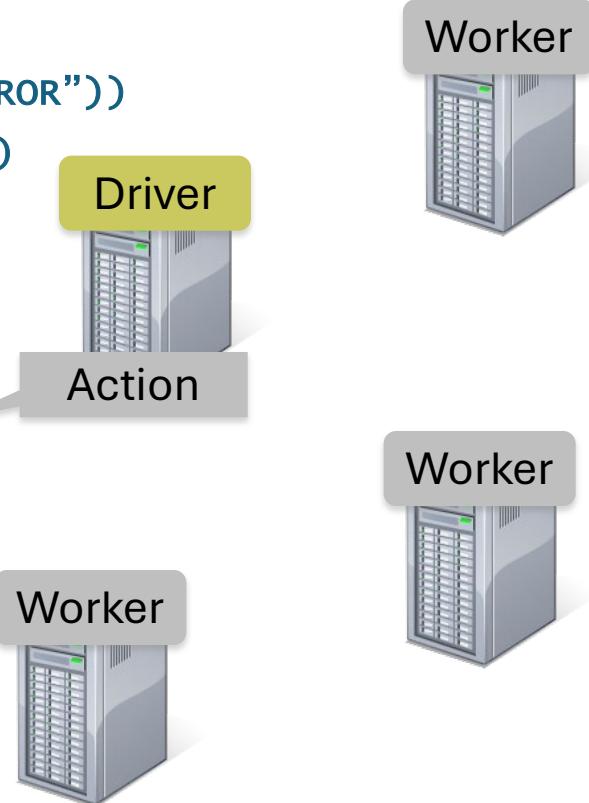Worker

Driver

Action

Worker

Worker

Spark Example: Log Mining

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Worker

Block 1
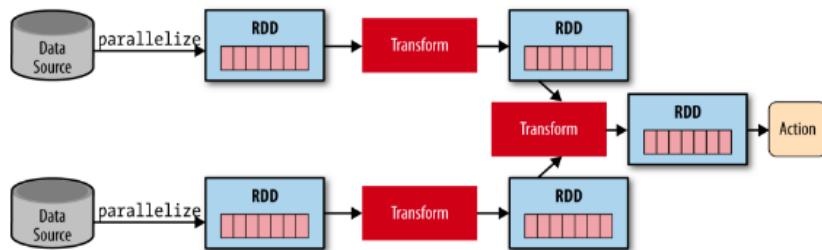
Driver

Worker

Block 2

Worker

Block 3

Spark Example: Log Mining

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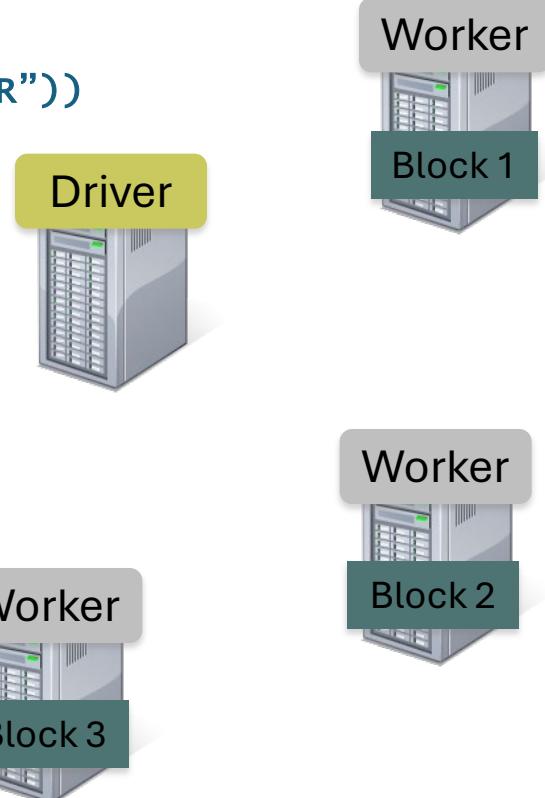
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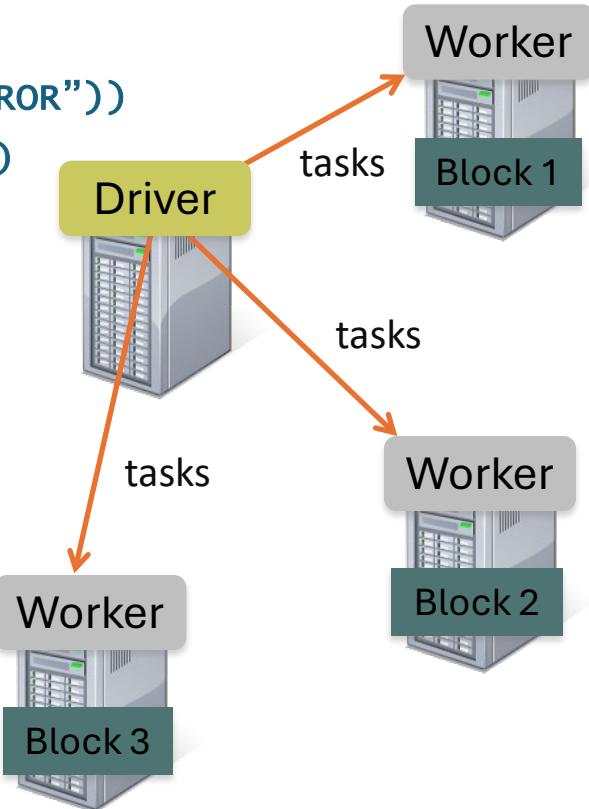
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```

Cache 1

Worker

Block 1

Process & Cache Data

Driver

Cache 2

Worker

Block 2

Cache 3

Worker

Block 3

Process & Cache Data

Process & Cache Data
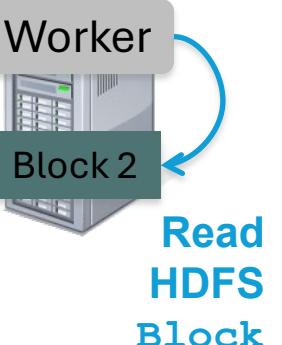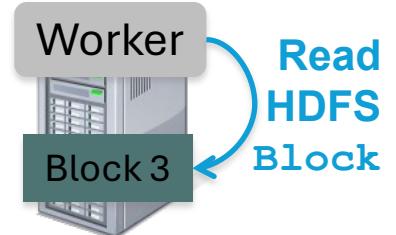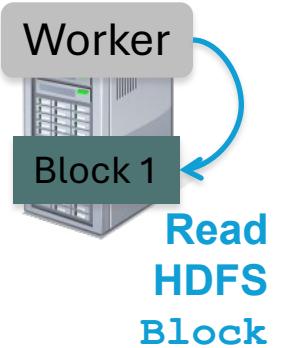
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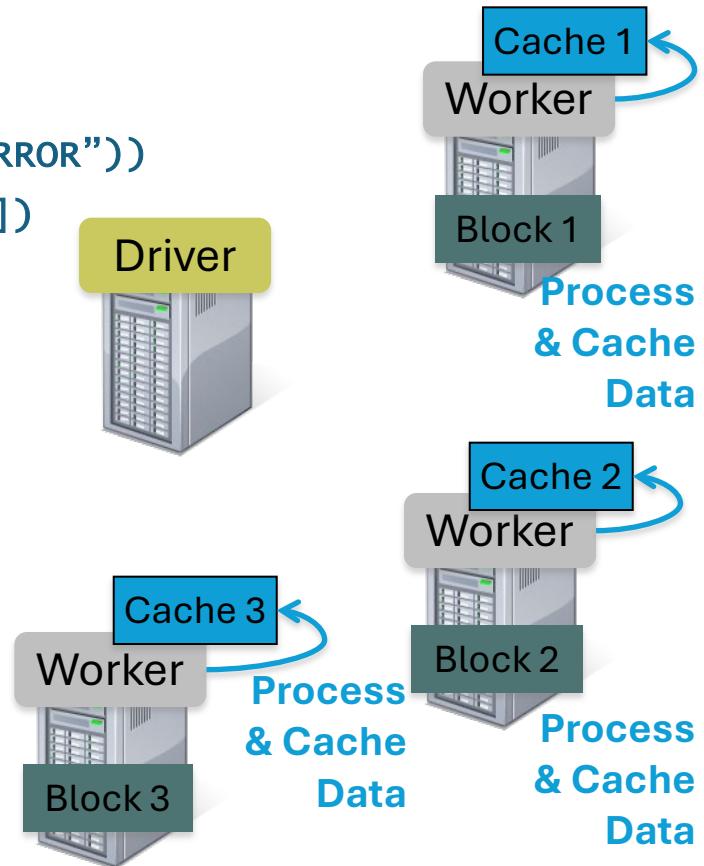
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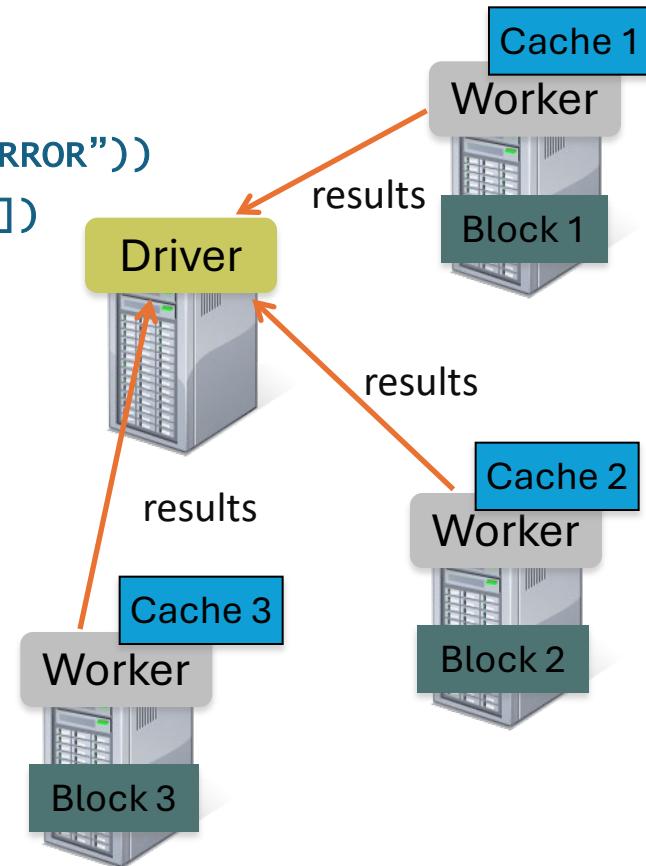
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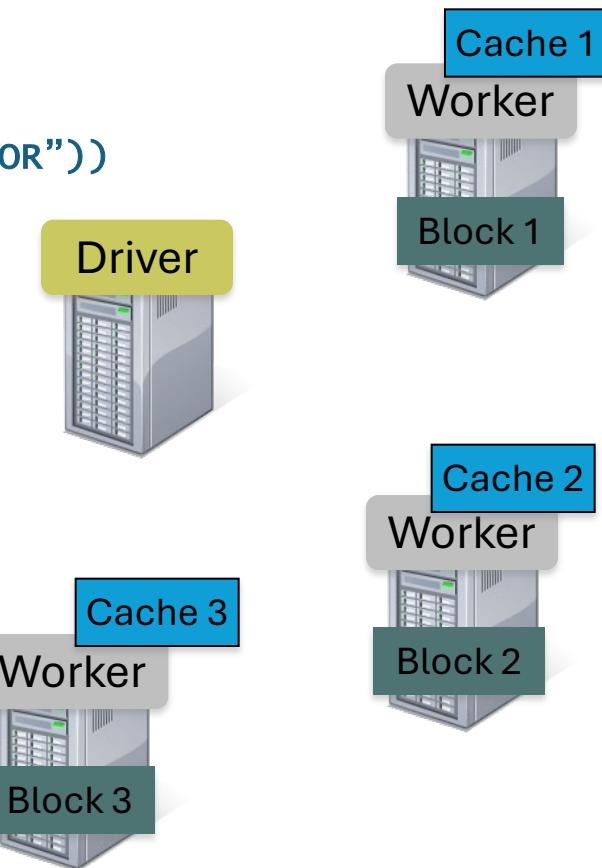
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messages.filter(lambda s: "mysql" in s).count()
messages.filter(lambda s: "php" in s).count()
```

Driver

Cache 1
Worker
Block 1
Process from Cache

Cache 2
Worker
Block 2
Process from Cache

Cache 3
Worker
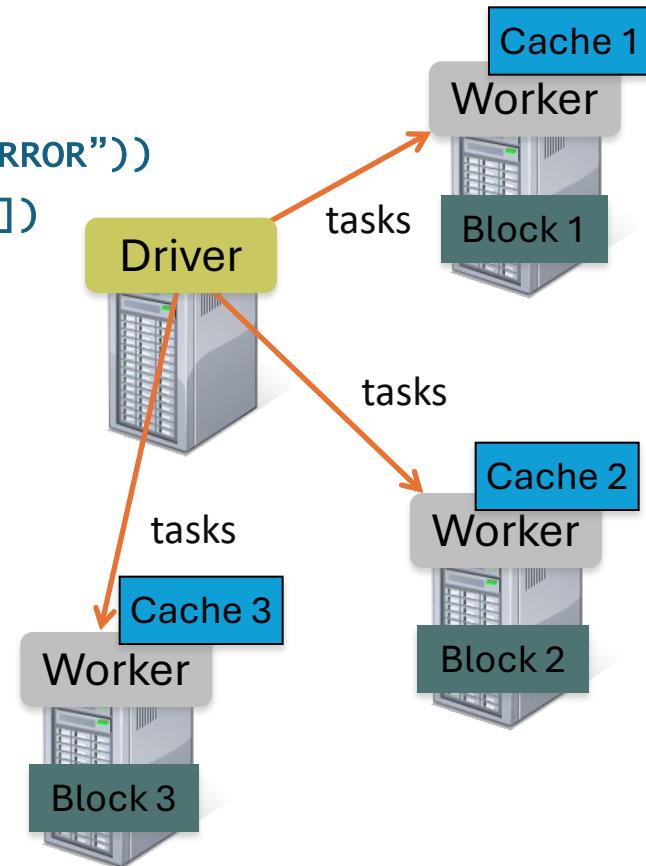Block 3
Process from Cache

Spark Example: Log Mining

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

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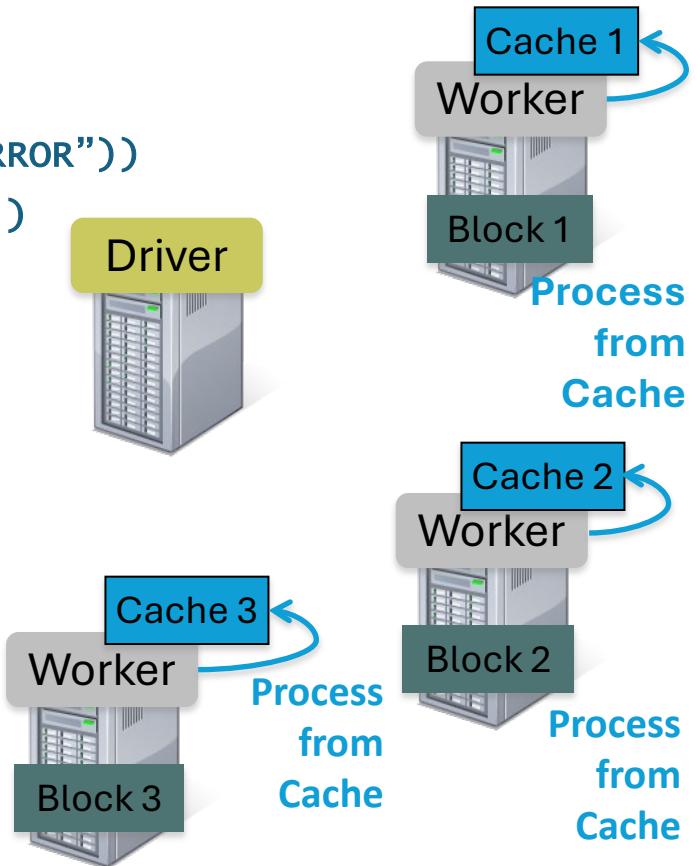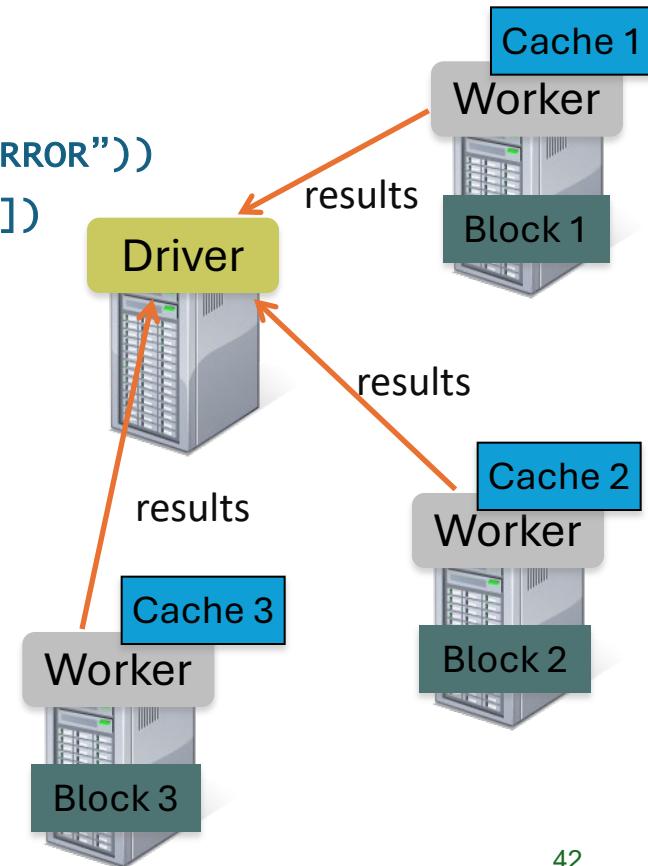
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messages.cache()
```

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

```
messages.filter(lambda s: "php" in s).count()
```

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

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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

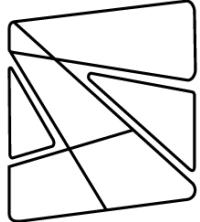- Perform actions to execute parallel computation and produce results

Use Spark Transformations and Actions wherever possible: Search [DataFrame reference API](#)

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University of Sheffield's HPC
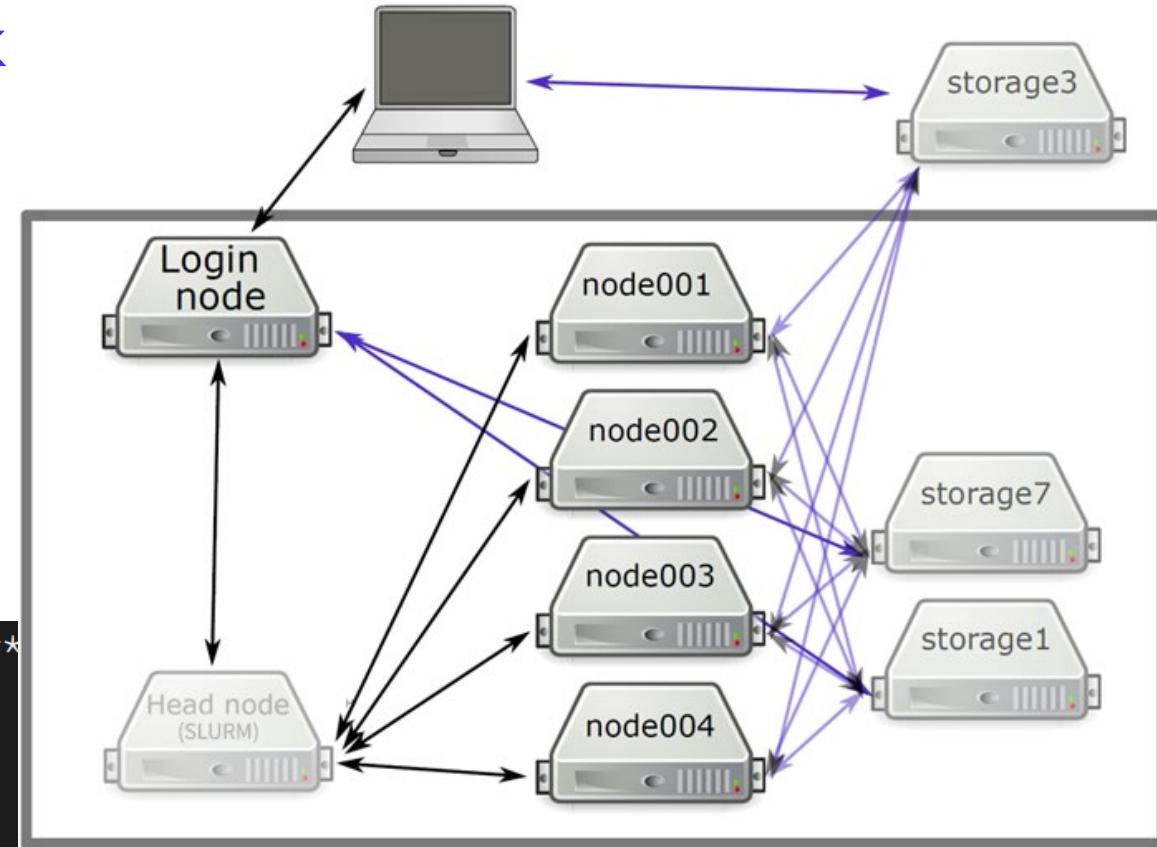

A photo of Stanage, the premier supercomputer at the University of Sheffield

- 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) [a    @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

Batch Session – Shell Script xx.sh
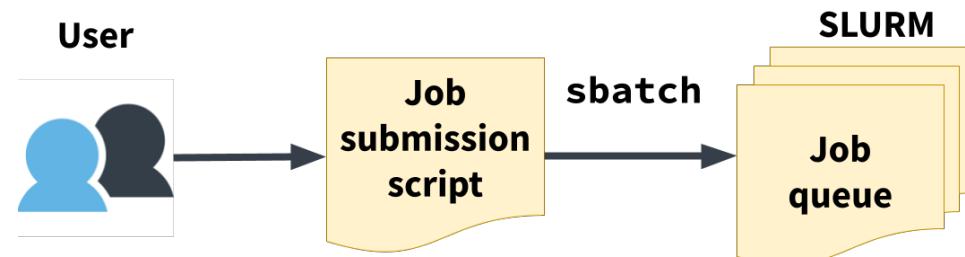
Create a file `Lab1_SubmitBatch.sh`

```
#!/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
```
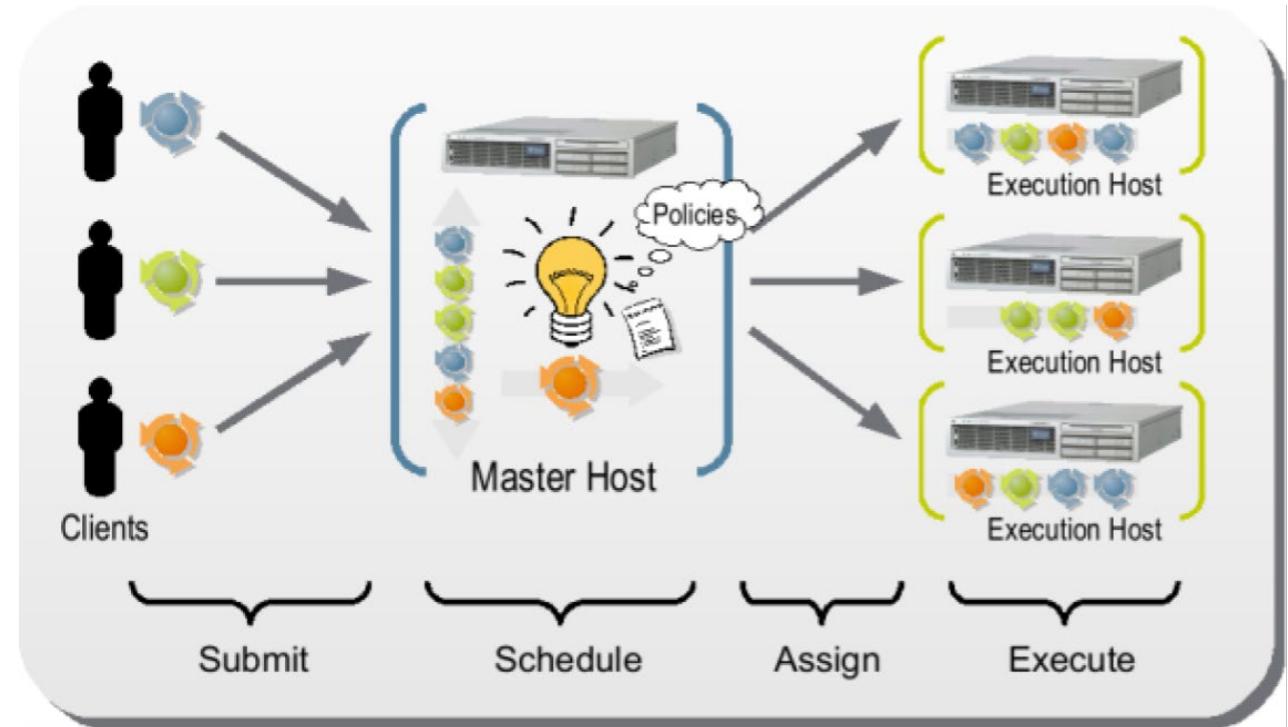
User

SLURM

Job submission script →**sbatch**→ Job queue

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:
  - https://upload.wikimedia.org/wikipedia/commons/thumb/b/b9/2023_Facebook_icon.svg/1024px-2023_Facebook_icon.svg.png
  - https://upload.wikimedia.org/wikipedia/en/thumb/a/a9/TikTok_logo.svg/1920px-TikTok_logo.svg.png
  - https://mmoculture.com/wp-content/uploads/2019/12/Bilibili-logo-768x307.png
  - https://upload.wikimedia.org/wikipedia/commons/thumb/2/20/YouTube_2024.svg/1920px-YouTube_2024.svg.png
  - https://upload.wikimedia.org/wikipedia/commons/thumb/0/06/Amazon_2024.svg/330px-Amazon_2024.svg.png
  - https://upload.wikimedia.org/wikipedia/commons/thumb/c/ce/X_logo_2023.svg/150px-X_logo_2023.svg.png
  - https://upload.wikimedia.org/wikipedia/en/thumb/6/6e/Sina_Weibo.svg/225px-Sina_Weibo.svg.png
  - https://upload.wikimedia.org/wikipedia/commons/thumb/9/95/Instagram_logo_2022.svg/195px-Instagram_logo_2022.svg.png
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