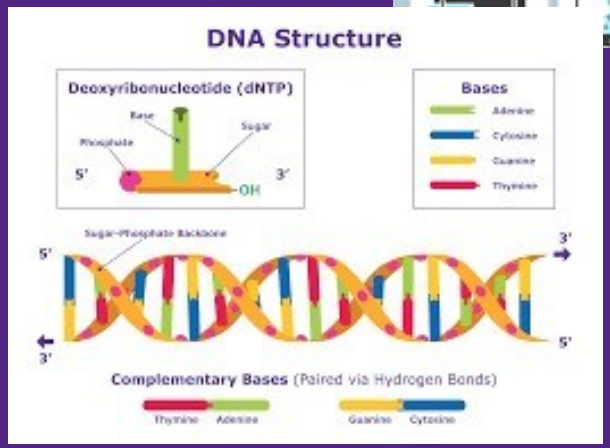
# Big Data and MapReduce

# Data Sources

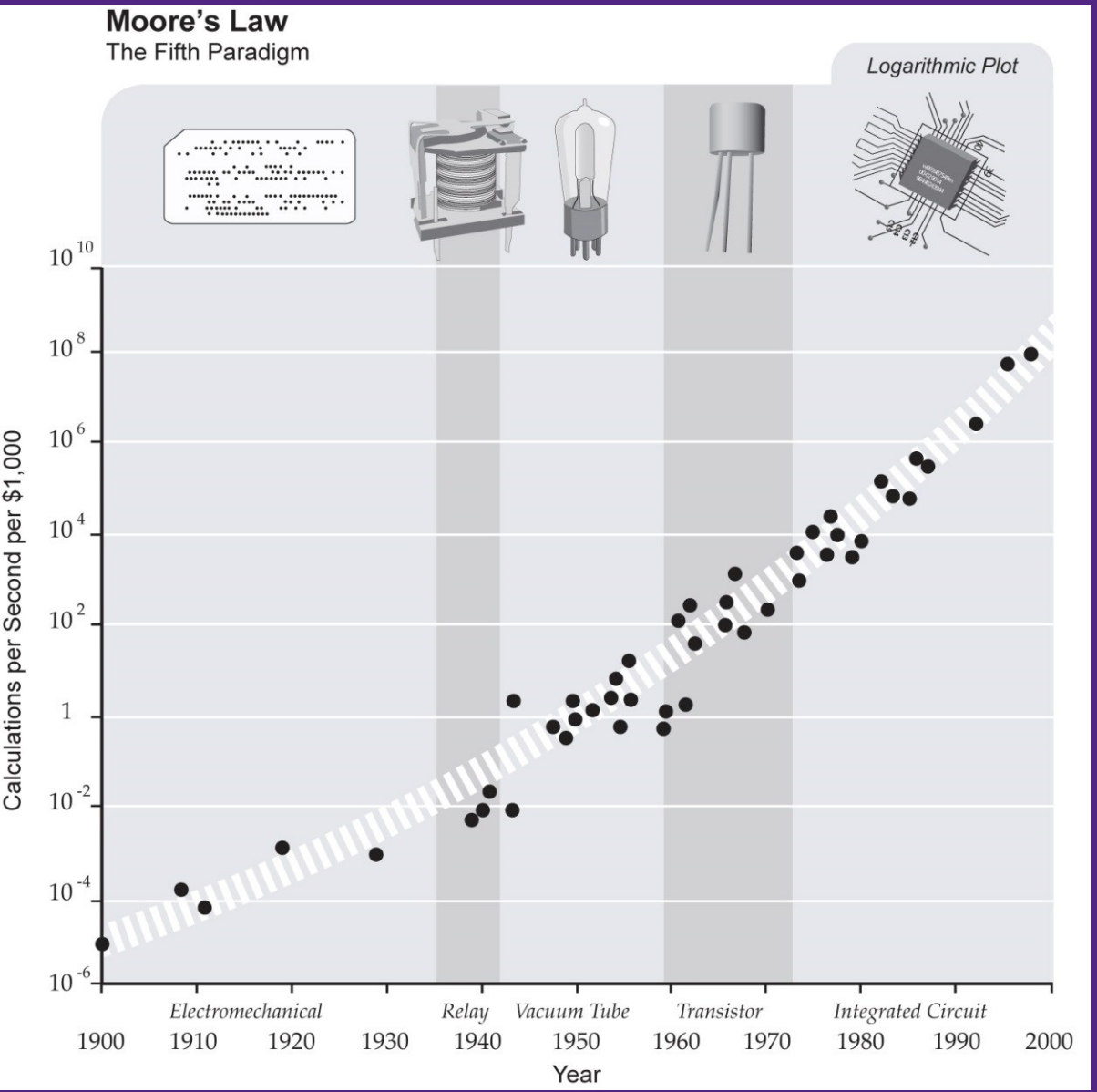


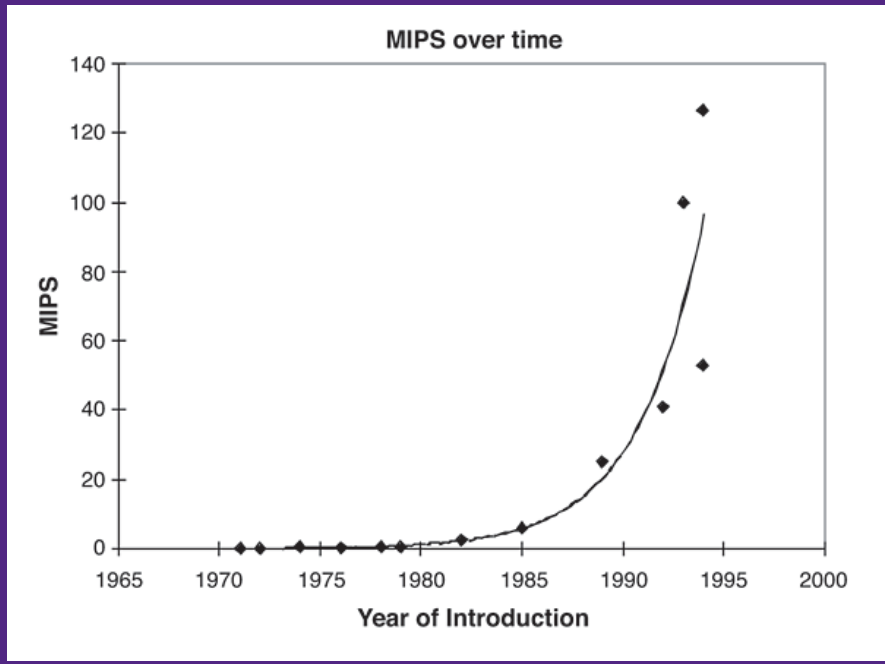
# Big Data

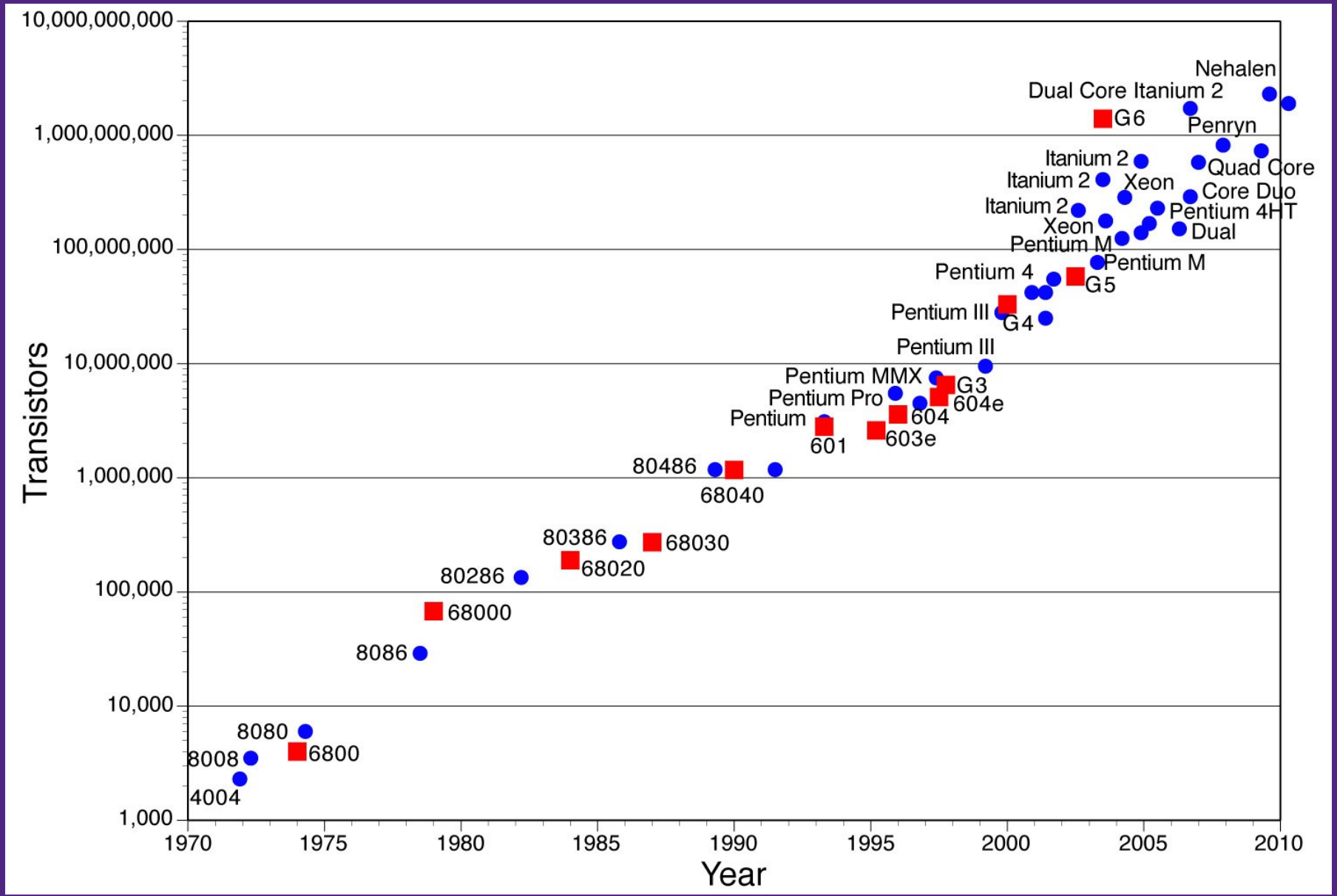
- “How much data is there?”
  - 2010: 1,200,000,000 TB
  - 2020: 38,500,000,000 TB
  - 2020: It would take 181 years to download all the data from the Internet
- Internet users generate about 2,500,000,000 TB each day
- Using big data, Netflix saves 1 billion dollars per year on customer retention

# Big Data vs Moore's Law

- Gordon Moore, 1965: The number of transistors on a chip will double about every two years.
- This "law" has held pretty much since then; forecasters are predicting an end around 2025.
- If data grew so fast we couldn't process it, there would be a harsher cap on the value of data, so this is intertwined with the importance of Big Data

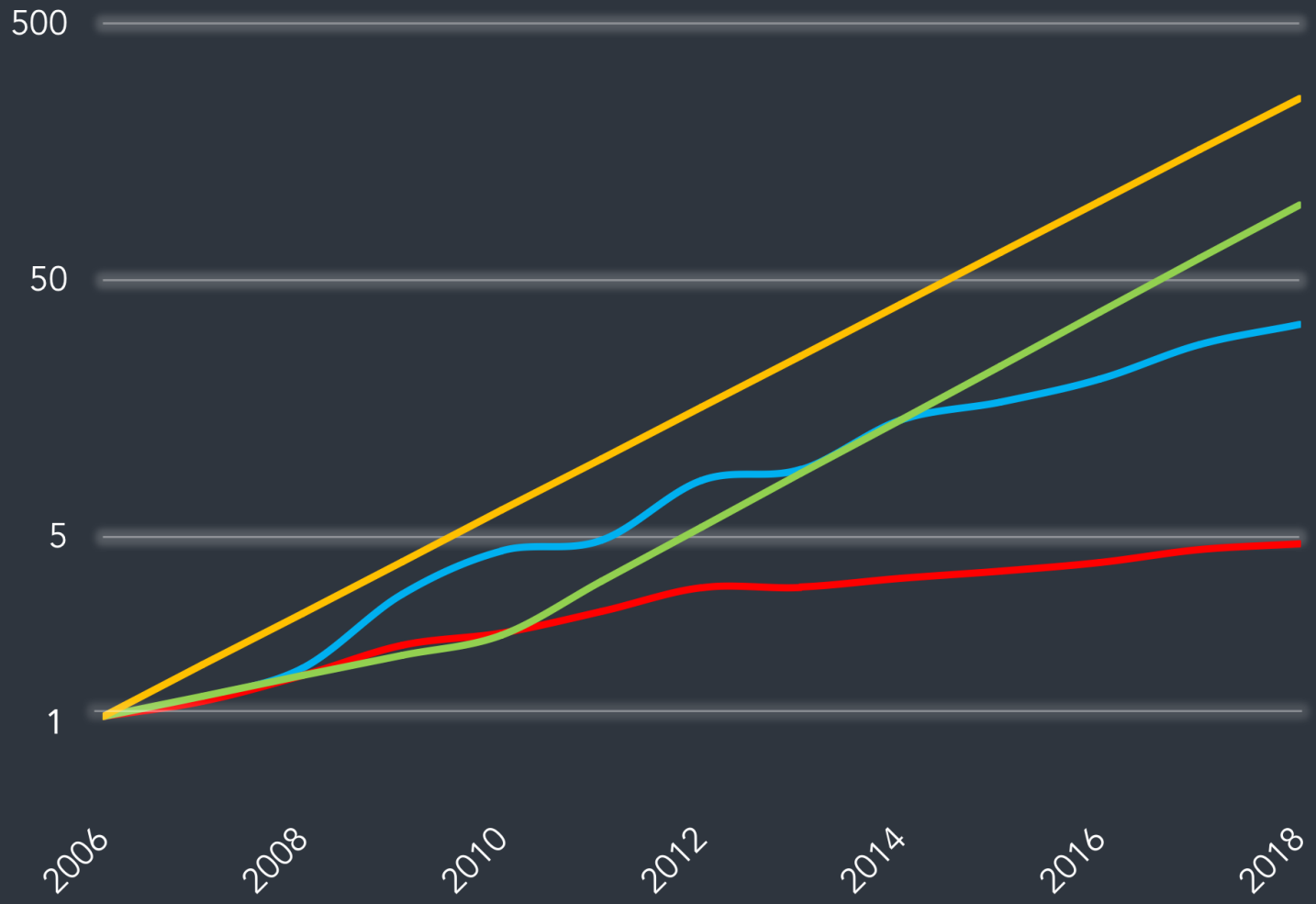

Moore's Law
The Fifth Paradigm
Logarithmic Plot
Calculations per Second per $1,000
$10^{10}$
$10^{8}$
$10^{6}$
$10^{4}$
$10^{2}$
1
$10^{-2}$
$10^{-4}$
$10^{-6}$
Electromechanical
Relay
Vacuum Tube
Transistor
Integrated Circuit
1900
1910
1920
1930
1940
1950
1960
1970
1980
1990
2000
Year


MIPS over time
MIPS
140
120
100
80
60
40
20
0
1965
1970
1975
1980
1985
1990
1995
2000
Year of Introduction


10,000,000,000
1,000,000,000
100,000,000
10,000,000
1,000,000
100,000
10,000
1,000
Transistors
1970
1975
1980
1985
1990
1995
2000
2005
2010
Year
4004
8008
8080
6800
8086
68000
80286
68020
80386
68030
68040
80486
601
Pentium
603e
604
604e
G3
Pentium Pro
Pentium MMX
Pentium III
G4
Pentium III
G5
Pentium 4
Pentium M
Pentium M
Dual
Xeon
Pentium 4HT
Itanium 2
Core Duo
Xeon
Itanium 2
Quad Core
Itanium 2
Penryn
G6
Dual Core Itanium 2
Nehalen

- Maybe not over?
- https://www.technologyreview.com/s/614247/the-worlds-most-advanced-nanotube-computer-may-keep-moores-law-alive/
- **“The world’s most advanced nanotube computer may keep Moore’s Law alive”**
- **Video showing prediction vs reality: https://www.reddit.com/r/dataisbeautiful/comments/cyngl1/moores_law_graphed_vs_real_cpus_gpus_1965_2019_oc**

# Rate of CPU Performance Increase is Slowing




(1) *2P SPECint®_rate 2006*
(2) *Specint® 2006*
(3) *62% CAGR*

# Scalable Computing

- Lots of data
- Relatively cheap to store
- Analyzing data has a lot of benefits
- However, for large amounts of data we need many computers and storage units
  - Need clusters of commodity computers

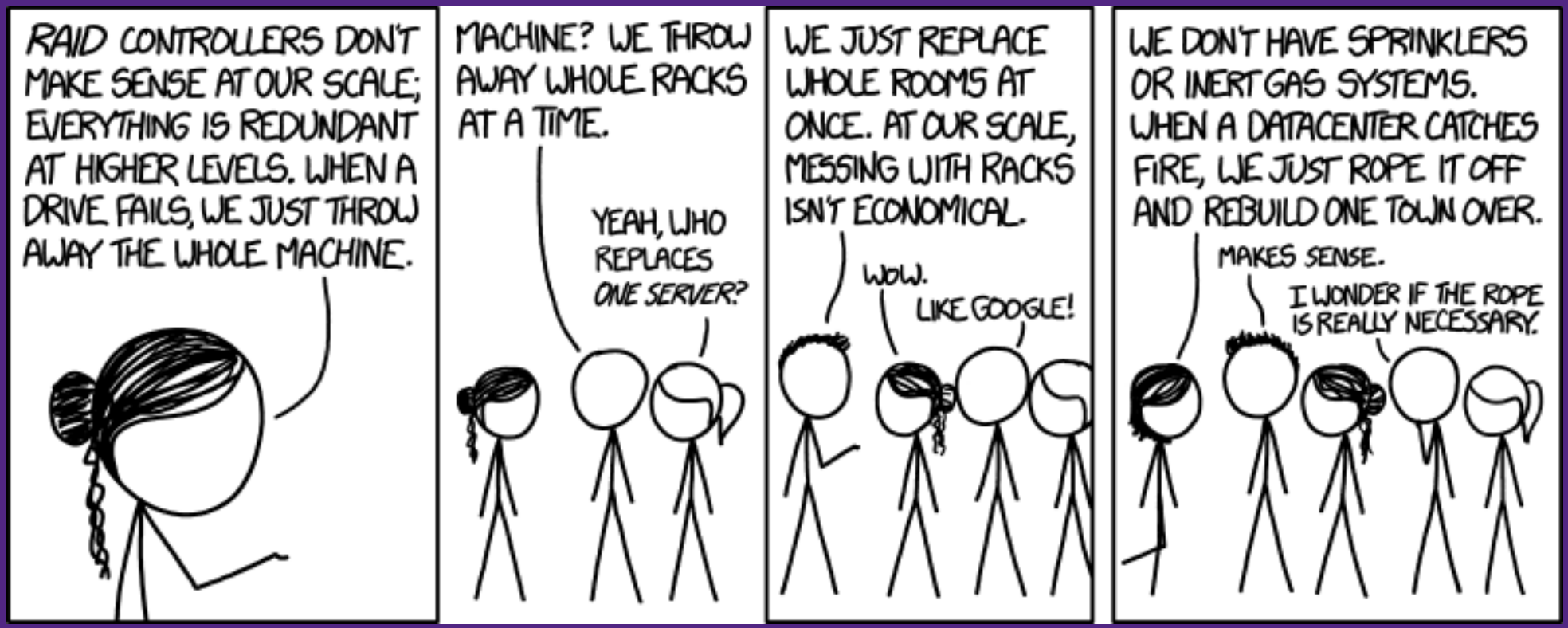
# Processing Large Datasets

- Centralizing data processing will not work for huge amounts of data.
- Data and processing often needs to be distributed
- Processing platforms need to enable multiple tasks to be execute on different chunks of data

# Processing Large Datasets

- How do we distribute computing tasks?
- How do we deal with the complexities of developing distributed software?
  - Data is distributed
  - Processing platforms need to enable multiple tasks to be executed on different chunks of the datasets
- What about failures?

# Processing Large Datasets




https://xkcd.com/1737/

# Simple, Large-scale computations

- Big data computation sounds fancy
- Mostly just counting stuff or adding stuff up
- TF-IDF
  - How many times does word appear in doc?
  - How many docs does a word appear in?
- Count-based language model
  - How often does “the” occur after “apple”?
- Neural network training
  - How often does my network make mistakes?

# Example

- Let's say that a retailer has a huge ledger with all of its sales representing stores in multiple cities

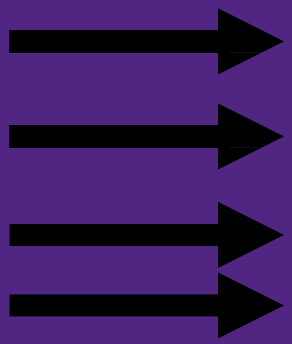
| Date | City | Product | Price |
|---|---|---|---|
| 2017-01-01 | London | earrings | 50 |
| 2017-05-01 | Toronto | purse | 150 |
| 2017-06-08 | Ottawa | belt | 50 |
| 2017-10-15 | London | jacket | 200 |

- You want to calculate the total sales per city

Map Reduce

# Example

One task goes through each entry in the ledger in order to calculate the sales per city



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| 2017-06-08 | Ottawa | belt | 50 |
| 2017-10-15 | London | jacket | 200 |

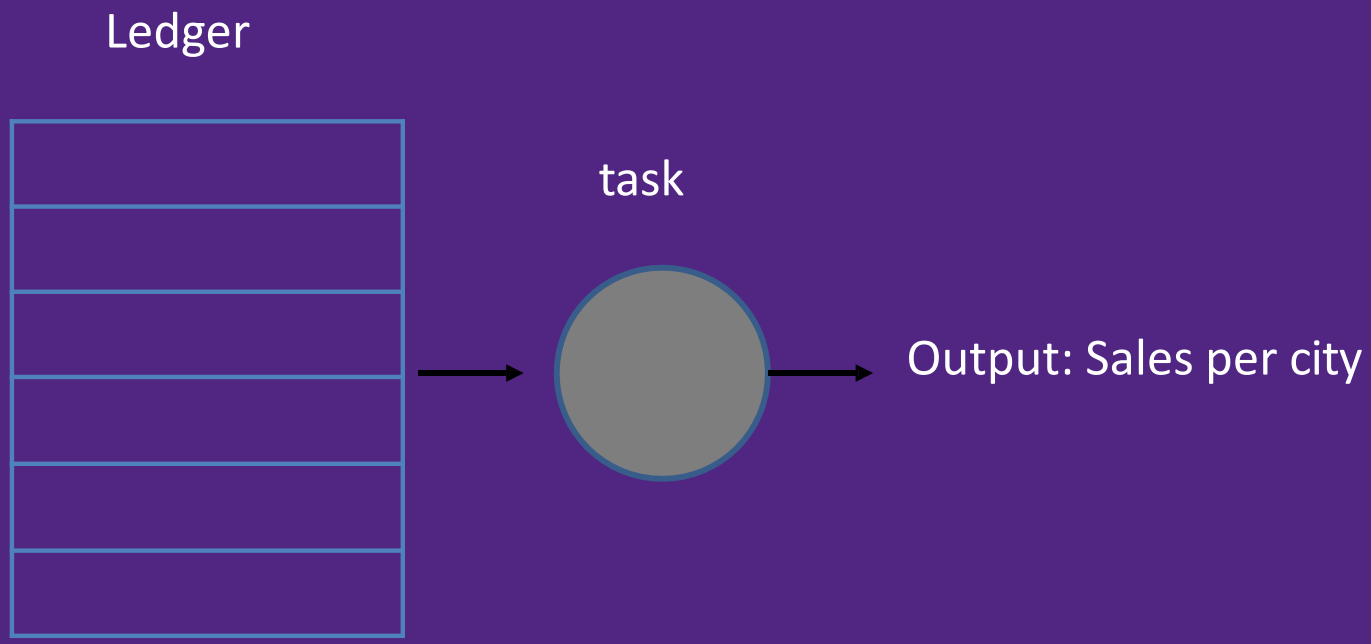
London 50

London 50, Toronto 150

London 50, Toronto 150, Ottawa 50

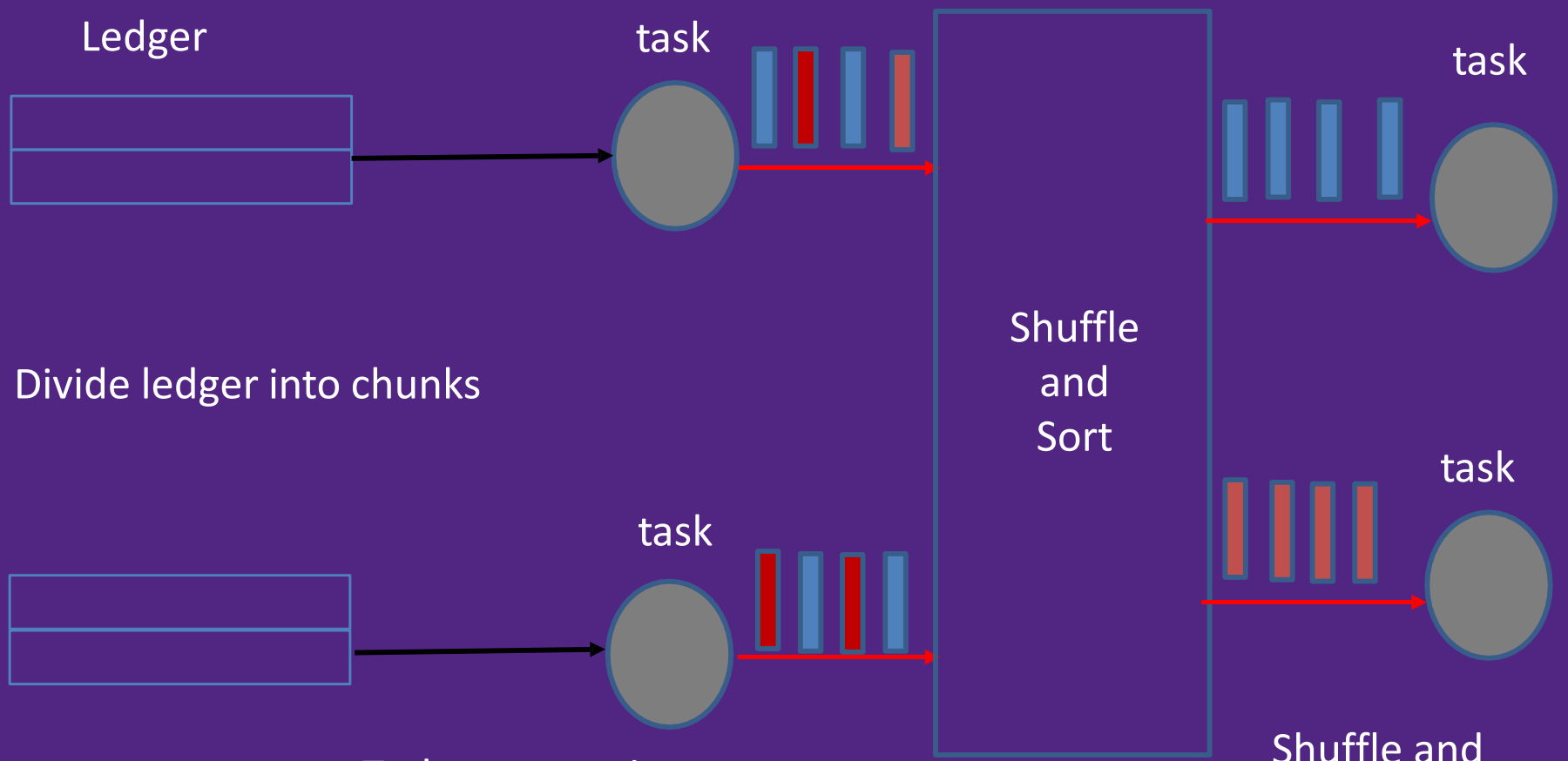
London 250, Toronto 150, Ottawa 50

# Example




What if we could have multiple tasks running?

# Example


Ledger
task
task
Shuffle
and
Sort
Divide ledger into chunks
task
task
Tasks extract city name and sales amount
Output: pairs (city, sales)
Shuffle and sort gives all pairs from same city to same task

# Large Data Set Analysis

- Iterate over a large set of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate interim results
- Generate final output

# Data Analytics in the Cloud

- Need a lot of servers
- These can come from a cloud provider

https://azure.microsoft.com/en-ca/resources/cloud-computing-dictionary/what-is-the-cloud

# Topics

- We will discuss a popular programming model and show examples of how it can be used.
- We will discuss the execution environment that includes a discussion of failure management

# MapReduce

# MapReduce History

- Google's invention (2003)
- Became known with a 2004 paper

# Example: MapReduce Applications

- Netflix: discover the most popular movies based on your viewing in order to provide suggestions
- LinkedIn: Discover who visited each member's profile
- E-Commerce providers: Identify favorite products based on users' interests or buying behavior.
  - Used by Amazon, Walmart, eBay

# Example: MapReduce Applications

- Financial Industries: Fraud detection
- Search Providers: Ranking content
- Google Maps: Locating roads linked to a given intersection; finding nearest feature to a given address

# MapReduce – What is it?

- *Programming model* for processing large data sets
- An *execution framework* that is able to run multiple tasks

# MapReduce Overview

- MapReduce is highly scalable and can be used across many computers.

- Many small machines can be used to process jobs that normally could not be processed even by a large machine.

# Before MapReduce

- Large scale data processing was difficult
  - Managing hundreds or thousands of processors
  - Managing parallelization and distribution
  - I/O scheduling
  - Status and monitoring
  - Fault/crash tolerance

- Programming models: MPI (Message-passing Interface)

# Programming Model

- Programmers specify two functions
  - Map
  - Reduce
- Inspired from map and reduce operations commonly used in functional programming languages like Lisp
- Have multiple workers (processes) on multiple machines run either map or reduce

# Map Operation

- Map: $(key_i, value_i) \rightarrow (key_j, value_j)$
  - Input: A key/value pair
  - Output: A key/value pair
- Evaluation
  - Function defined by user
  - Might need to parse input and extract relevant data
- Produces a new list of key/value pairs
  - Can be of different type from input pair

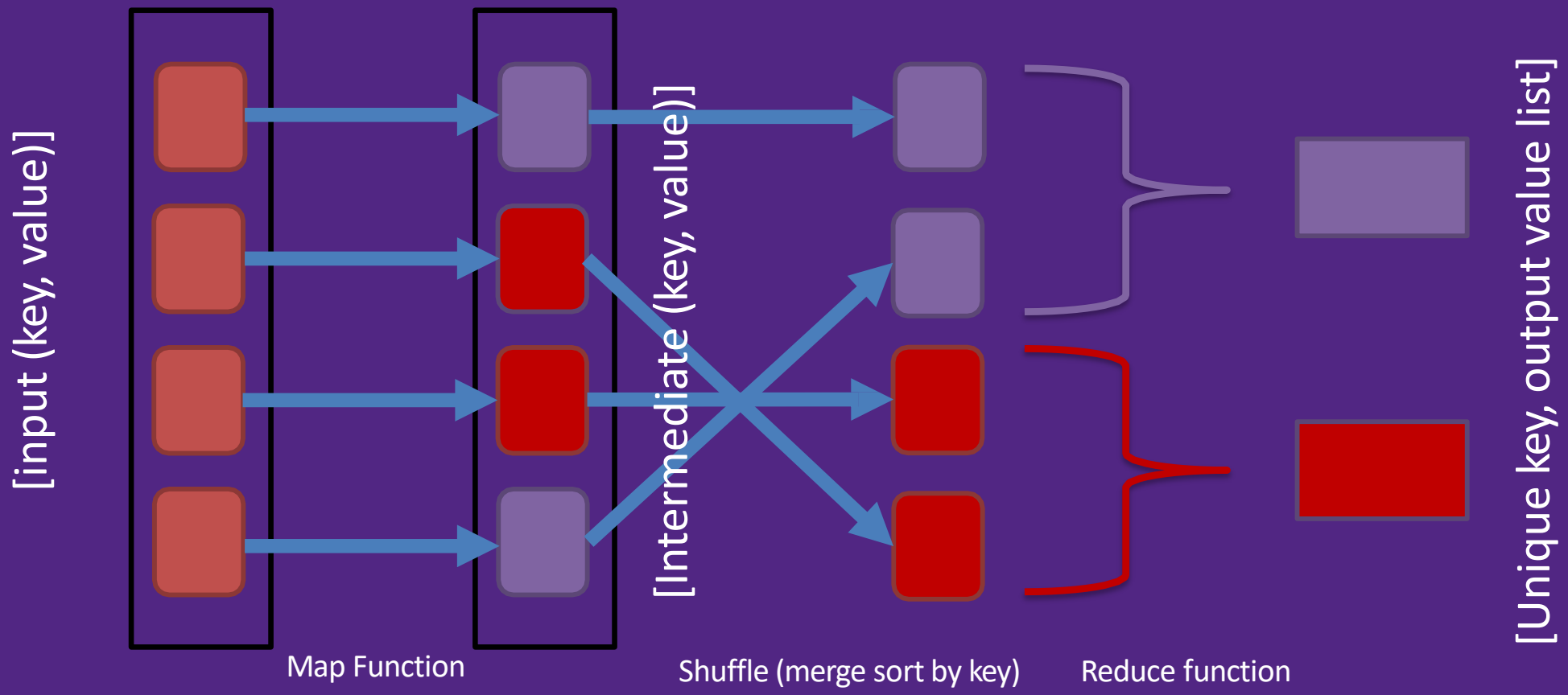
Example

# Reduce Operation

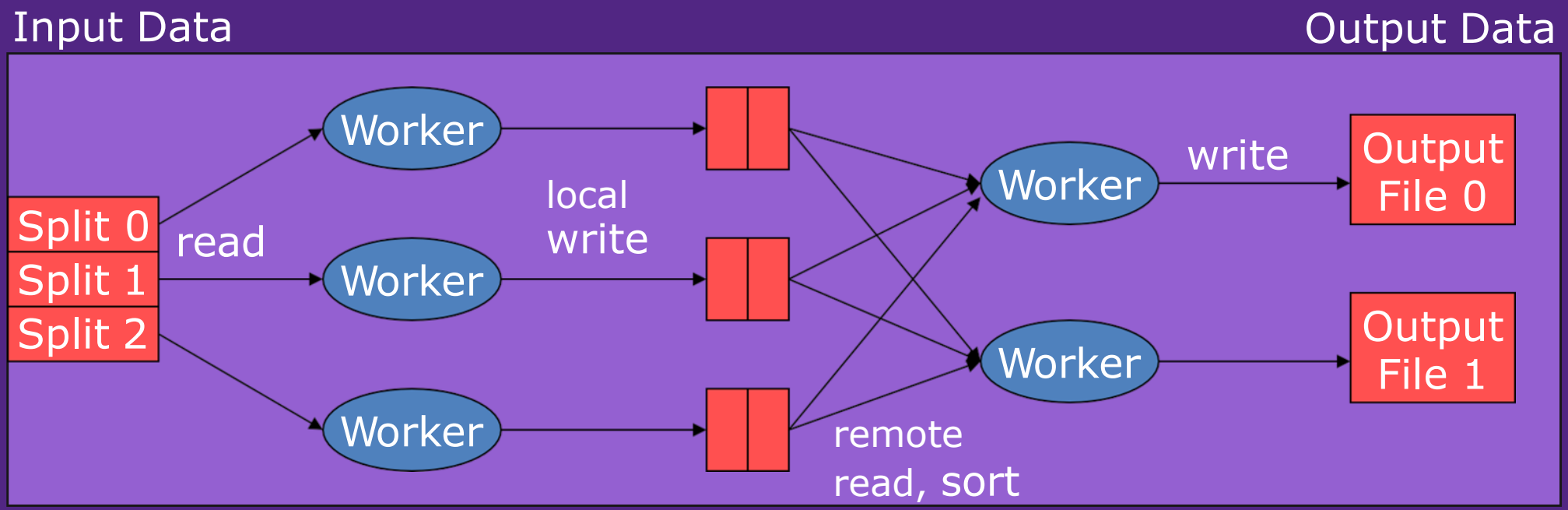
- Reduce: $(key_j,[val]_j) \rightarrow [val_k]$
- All the intermediate values associated with each $key_j$ produced by the mapper are combined together into a list, giving the pair $(key_j,[val]_j)$
- Reduce function is applied to each of these pairs

Example

# Programming Model



# MapReduce Workflow




**Map**

extract something you care about from each record

**Reduce**

aggregate, summarize, filter, or transform

# MapReduce Model

- The nice thing about the model is that a programmer writes the mapper code and the reducer code
- The Shuffle and Sort is handled by an environment like
  - Hadoop
  - Elasticsearch/Hadoop
  - MongoDB (but deprecated)
  - Riak

# Summary

- Big data are big
- Distributed computing is required
- MapReduce is an elegant programming model relevant to processing big, unstructured or structured data