Distributed Computing

Common Big Data Challenges

- Volume:
  - ***Too much data to store/process*** — reduce processing time and/or scale out computation/storage
    - Performing OCR on 1000s of articles simultaneously
  - ***Too big to fit in RAM*** (esp. when no cluster resource available)
    - Given 30GB of taxi trip records → *how to plot the trend?*
- Velocity — ***data comes in real-time*** → too much to store → process **on the fly**!
  - Detecting network failures from inspecting billions of packets per hour

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Parallel vs. Concurrent vs. Distributed Computing

Parallel vs. Concurrent vs. Distributed Computing

- Parallel Computing: taking full advantage of parallel architecture to speed up computation — *all about performance*
  - Data can be distributed to leverage additional processing power
- Concurrent Computing: enabling processes/tasks to progress without waiting for each other — *all about dependencies*
  - Parallel Computing in task graphs requires concurrency
- Distributed Computing: executing computations on distributed systems properly — *all about uncertainty*
  - Data are distributed by nature (e.g. because of their volume)

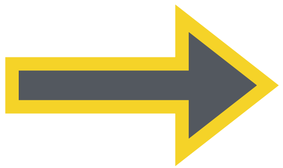
Big Data Computing

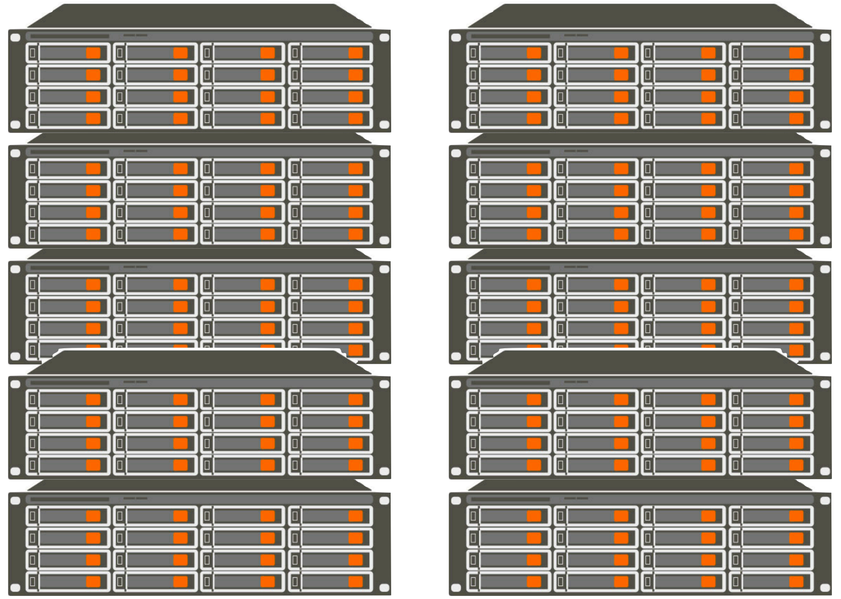
- Big Data requires distributed computing
  - part of the problem
  - to scale out storage and processing
- Big Data needs parallelism (thus, also concurrent) computing
  - focus on data parallelism for its scalability
- Big Data Platform usually
  - expose parallelism through a custom programming model
  - but handle most distributed computing issues behind the scene

Big Data Computing *needs* Scale Out!

- However, Scale Up is more efficient than Scale out
  - Minimal network communication (slowest in the bandwidth hierarchy)
  - Can fit even several TBs of RAM (compute@cusp has 1TB!)
  - Fast access for spatial (pre-fetch) and temporal (caching) locality
- Leverage multi-core architectures in distributed environment
  - Need to exhaust each machine resources before going across nodes
  - Hierarchical (non-uniform) memory access matters!

Scale Out Storage





1 machine
10 I/O Channels ~1 GB/s
Read 1 TB: ~17 minutes

10 machines
100 I/O Channels ~10 GB/s
Read 1 TB: ~2 minutes

Traditional Parallel Computing Model (HPC)

Network Storage System

Computing Nodes

data over the network

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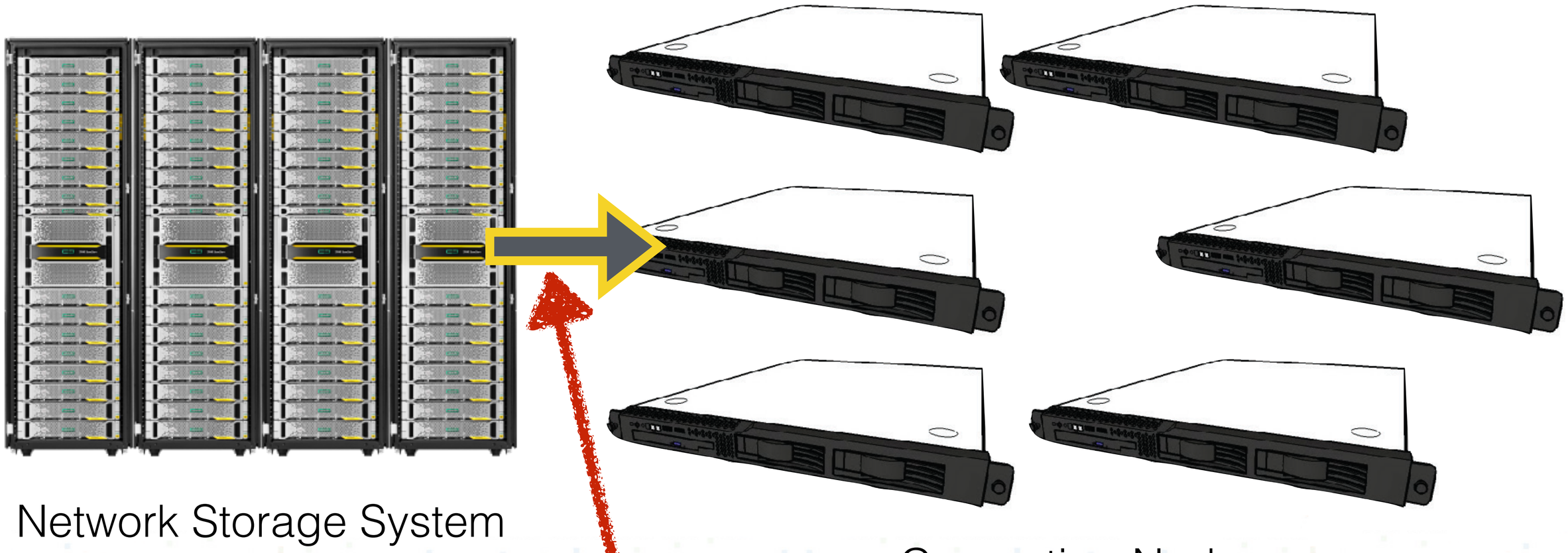

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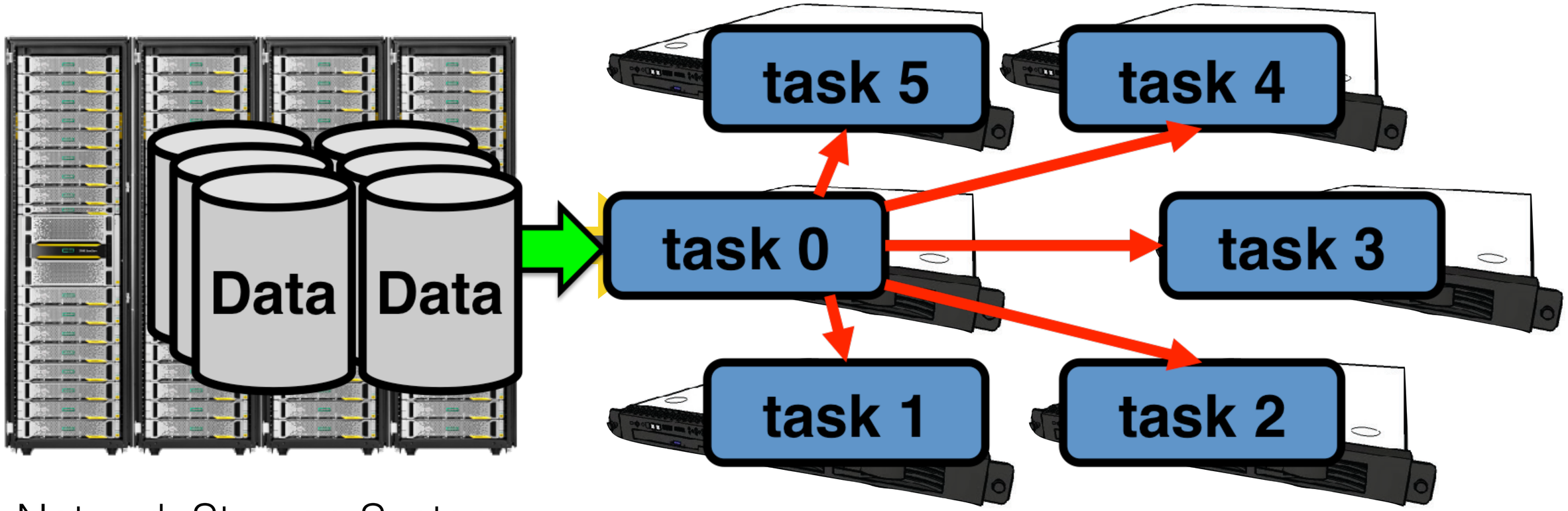

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[Glenn K. Lockwood. Conceptual overview of map-reduce and hadoop]

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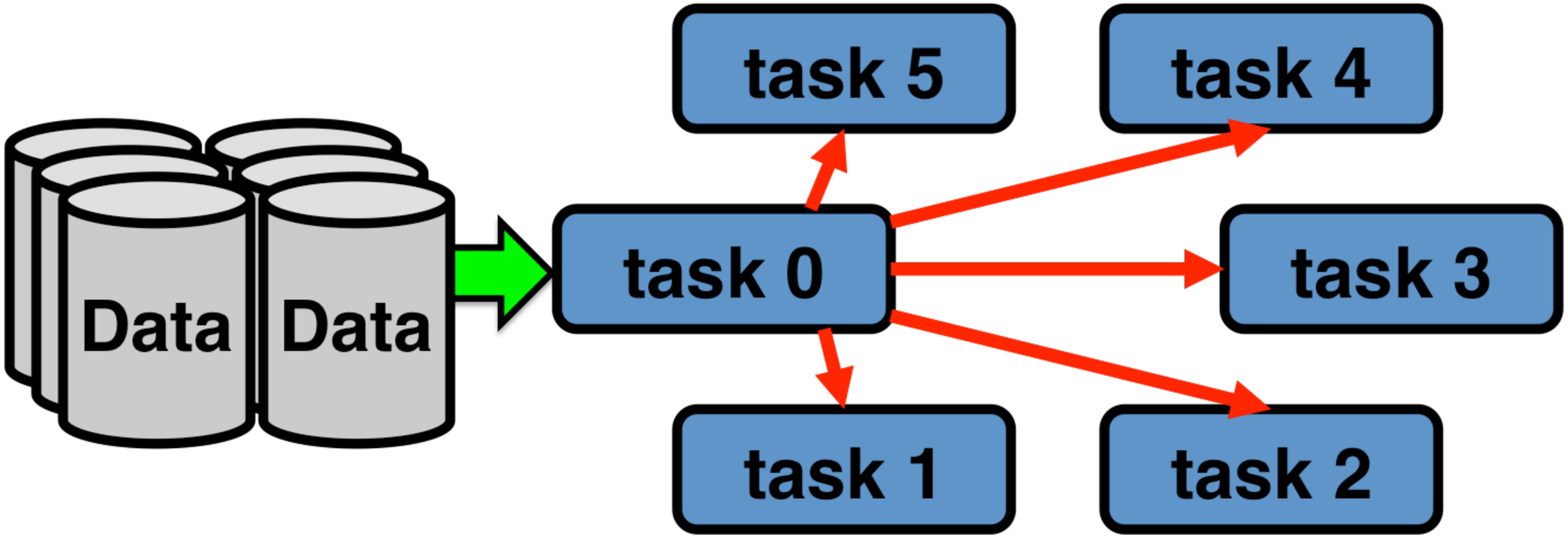

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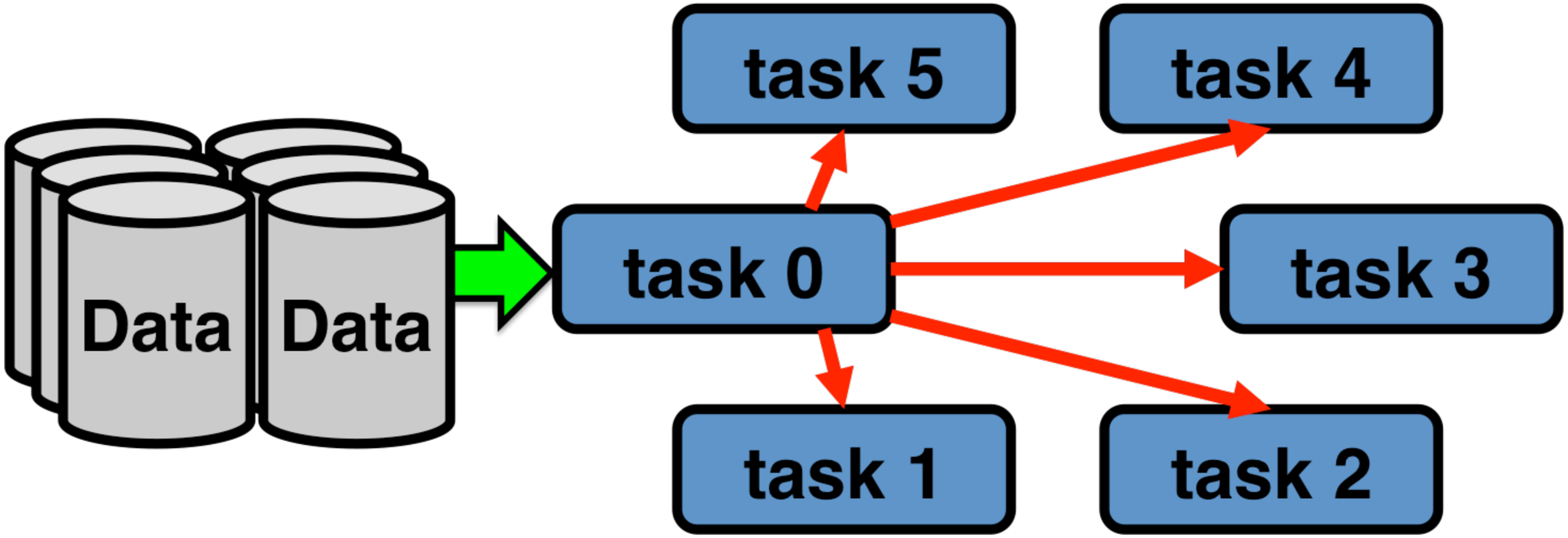
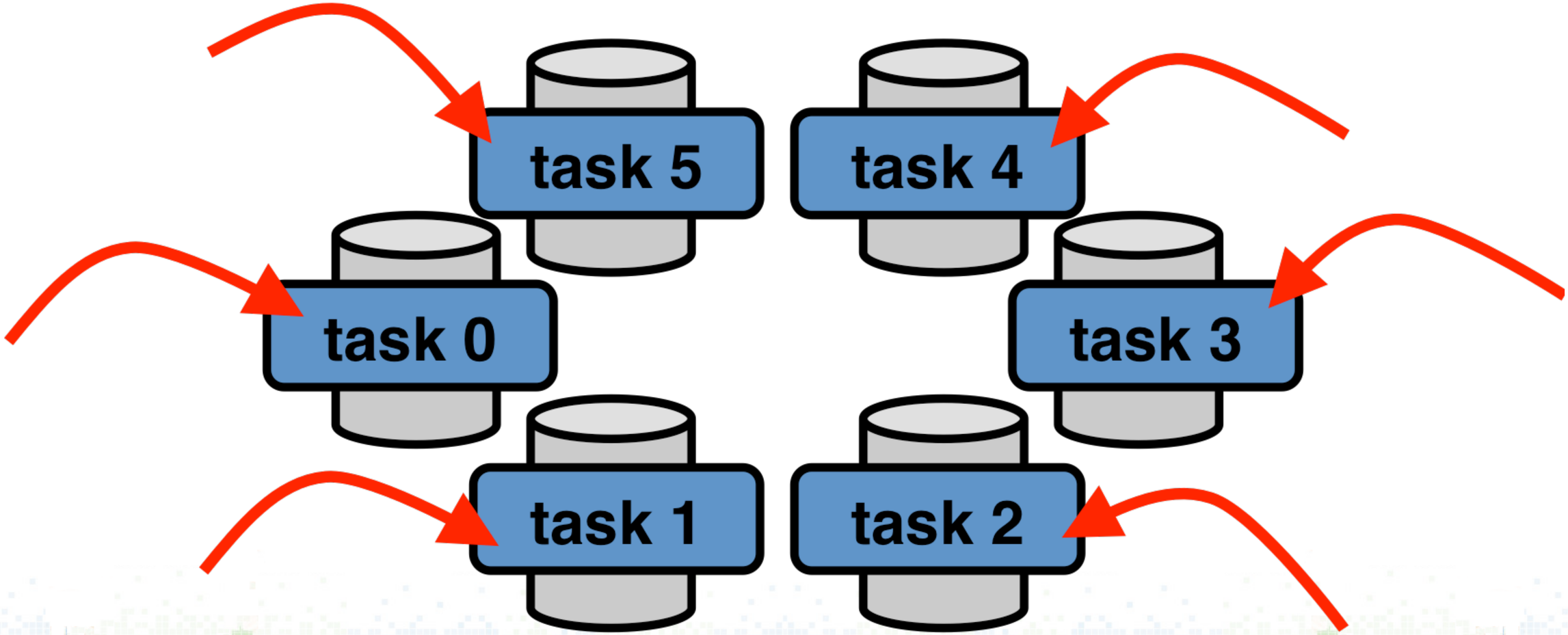


bring data to compute — *limit by connection bandwidth*

[Glenn K. Lockwood. Conceptual overview of map-reduce and hadoop]

Big Data Computing Model



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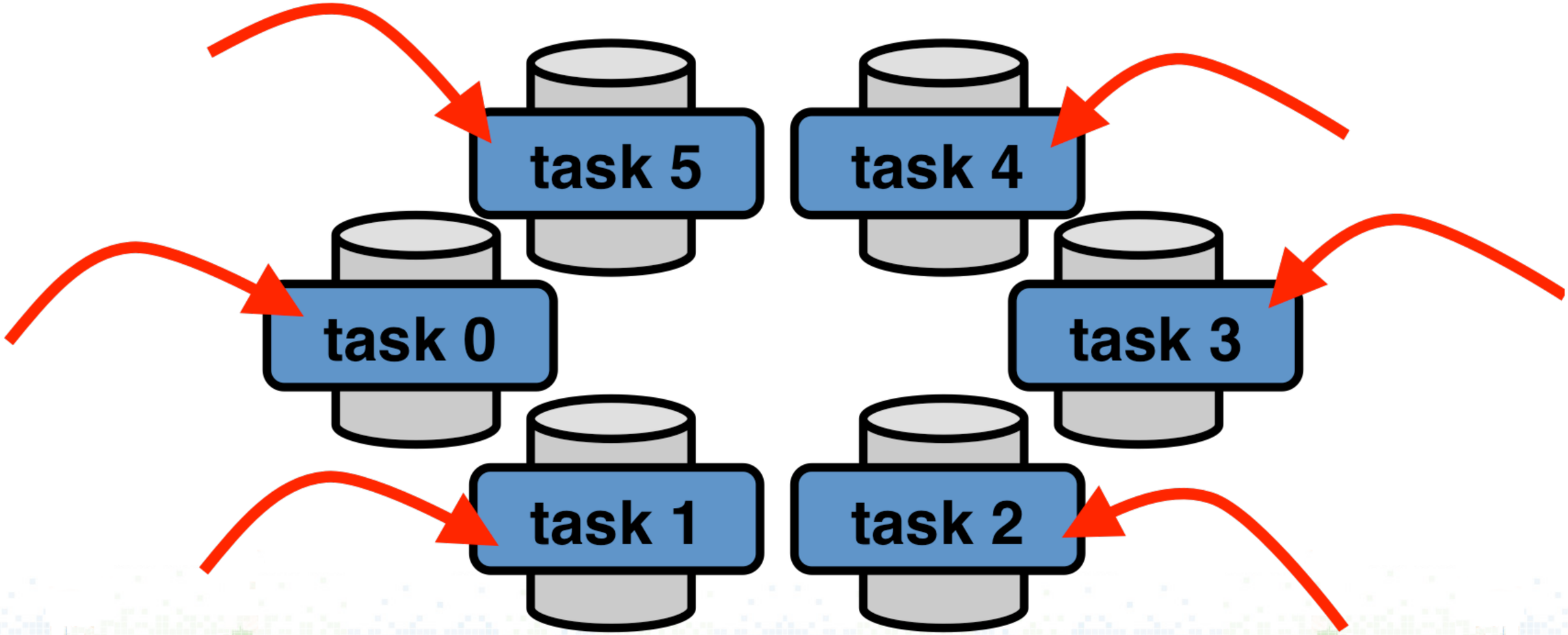
Big Data Computing Model

bring compute to data — *avoid data movement*



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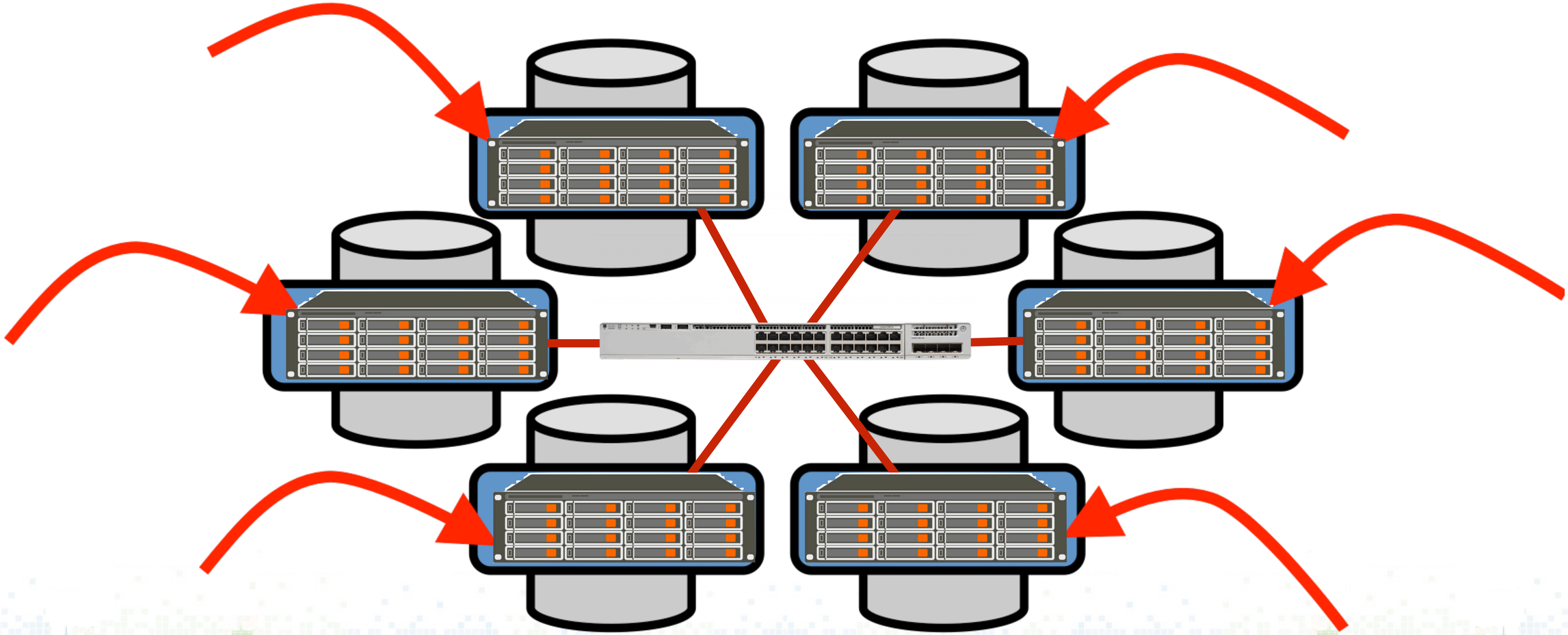

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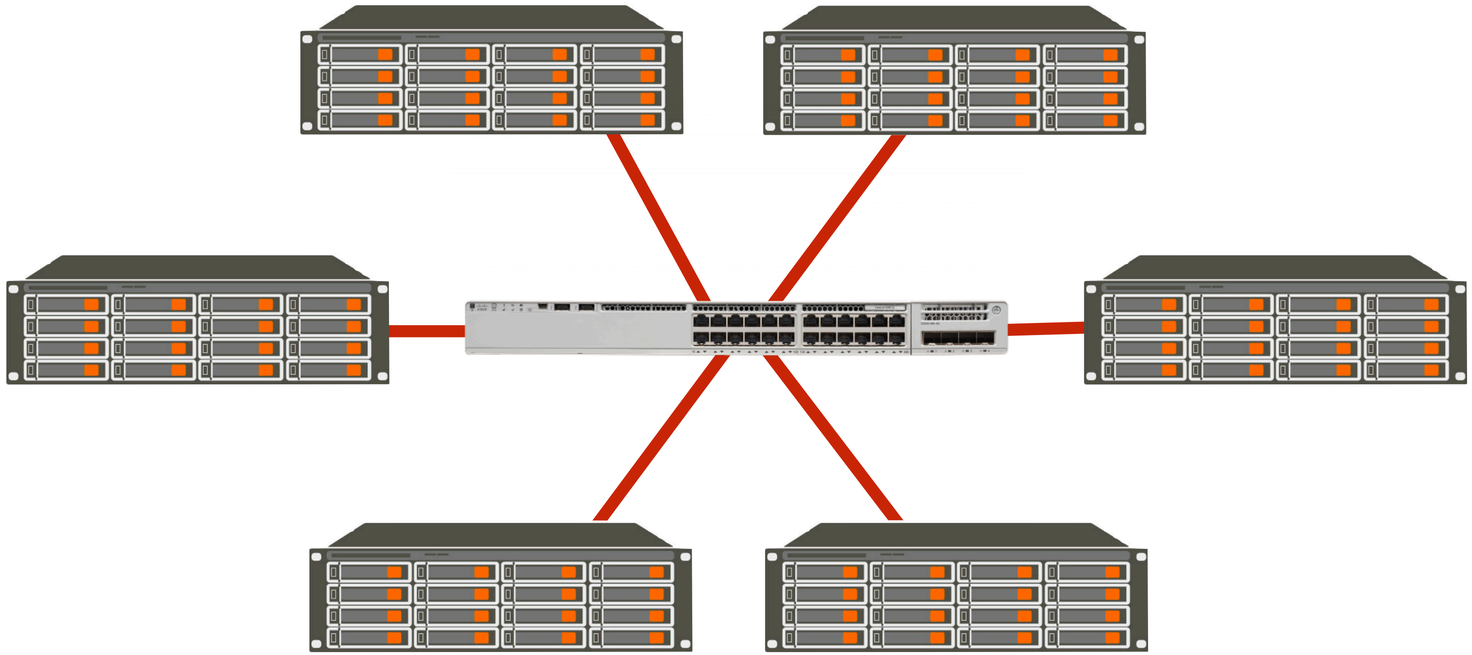

Challenges in Analyzing Big Data

- How to specify *data computation* so that the system can:
  - bring compute to the data
  - minimize moving or making changes to data
  - operate on collection of data
  - allow users to dictate *what* to be done to the data and LEAVING *how* it will be done to the platform
  - leveraging both scaling up and scaling out capabilities

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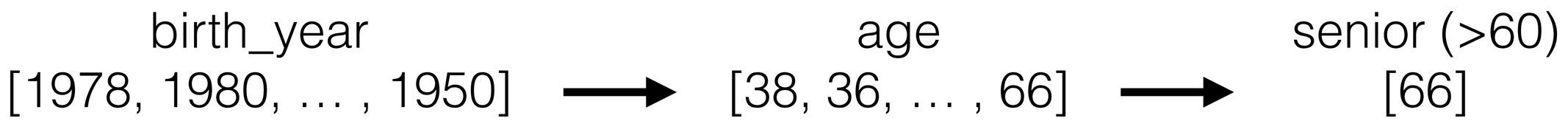
a declarative and/or functional language for data processing

Higher-Order Functions (Functional)

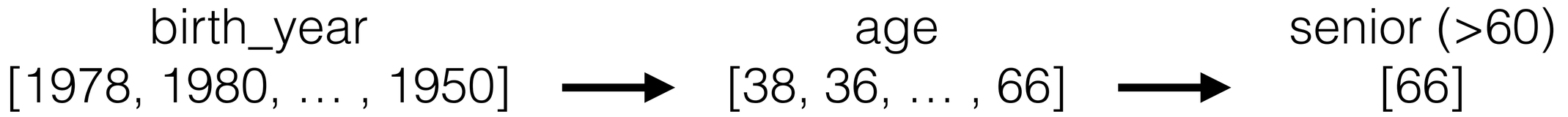
- Higher-Order functions (functional) are functions that:
  - take functions as arguments
  - **AND/OR** return functions as its results
- HOF is used to abstract common iteration operations
  - *focus on the* **what** *instead of the* **how**
- Using a predefined set of Higher-Order Functions, we can apply data transformation to data using our own **function** (aka transformation)
  - similar to streaming data elements through our function

Review: General Data Computing Model

- Given a collection of data records (e.g. a generator or list of records)
- Apply a series of *data transformations* to the collection
- Collect the final transformation



Example: How to do it in Python?



Example: How to do it in Python?

birth_year		age		senior (>60)
[1978, 1980, … , 1950]	→	[38, 36, … , 66]	→	[66]

```
age = []
for y in birth_year:
    age.append(2016-y)

senior = []
for y in age:
    if y>60:
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```
birth_year = pd.Series(birth_year)

age = 2016-birth_year

senior = age[age>60]
```

Example: How to do it in Python?

name,birth_year
[(‘A’,1978), … , (‘C’,1950)] → name,age
[(’A’,38), … , (’C’,66)] → name,senior
(>60 with name ‘C’)
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```
def AGE_TRANSFORM(y):
    return 2016-y

def AGE_FILTER(y):
    return y>60


age = []
for y in birth_year:
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```
age = map(AGE_TRANSFORM, birth_year)
```

```
senior = filter(AGE_FILTER, age)
```

Python's Core HOF

- map(): applies a function over an iterable to produce a new iterable

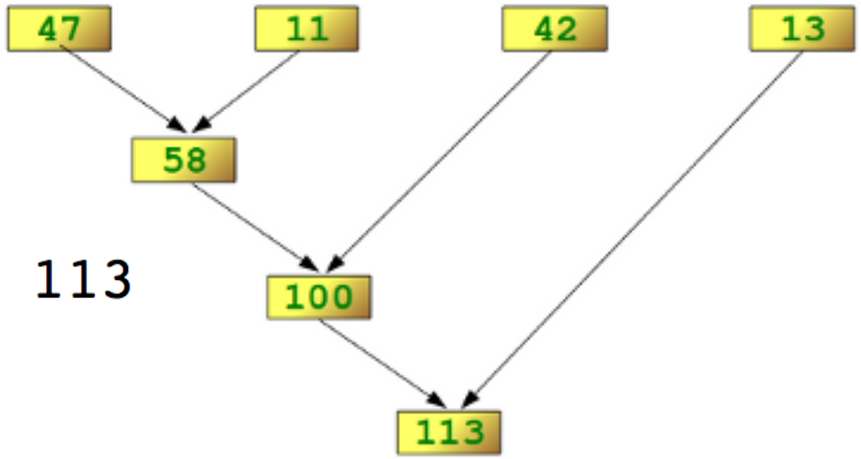
```
map(int, ['0', '1']) -> [0, 1]
```

- filter(): return only values that satisfy a predicate in the new iterable

```
filter(bool, [0, 1]) -> [1]
```

- reduce(): accumulate a sequence of values from left

```
reduce(operator.add, [47,11,42,13]) -> 113
```



- sorted(): return a new sorted list using a comparator
-

Anonymous function: *lambda*

- What if we only use a function once or would like to define it in-place?
- Python's anonymous lambda function:

```
lambda VAR1,VAR2,...,VARN: (expression on VAR1..N)
```

  - No name, no return statement, only an expression to evaluate
  - Come in handy in defining functions in HOF

```
x2 = lambda x: x*x
x2(10) # 100

x_y = lambda x,y: x+y
x_y(1,2) # 3
```

-

Python's Core HOF

- map(): applies a function over an iterable to produce a new iterable

```
map(lambda x: int(x)+1, ['0', '1']) -> [1, 2]
```

- filter(): return only values that satisfy a predicate in the new iterable

```
filter(lambda x: x<1, [0, 1]) -> [0]
```

- reduce(): accumulate a sequence of values from left to right

```
reduce(lambda x,y: x+y, [47,11,42,13]) -> 113
```

- sorted(): return a new sorted list using a comparator function

```
sorted(xrange(5))                          -> [0,1,2,3,4]
sorted(xrange(5), cmp=lambda x,y:y-x) -> [4,3,2,1,0]
```

List Comprehension

- Syntactic sugar for Higher-Order Functions (w/ select…from…where)
  - to construct lists in a mathematically beautiful way (no more append!)

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Why HOF matters?

- Big Data Platforms including Apache Spark (and the principals of Hadoop) are built on functional programming languages
  - has a smaller set of data processing constructs, thus, easier for the platforms to optimize parallelism
  - less prone to data states and copies
  - keep track of provenance (data + transformation)
- As a user, it keeps us more conscious about concurrency and parallelism
  - algorithm design at a high level (mathematically)

reduce() in Python 3

- Its usage is “discouraged”
  - “it is 99% better to use a for loop instead”
  - It is available in the “functools” module

```
from functools import reduce
```

- But for loop is not always possible for big data platforms
  - Still need an abstract way (specifying “what”, not “how”) for aggregation

Questions?

- Big Data Platforms need to abstract data transformation -> Higher-Order functions
  - Think Big Data -> think Functional!
- Resources on HOF:
  - https://wizardforcel.gitbooks.io/sicp-in-python/content/6.html — Higher-Order Functions
  - https://github.com/joelgrus/stupid-itertools-tricks-pydata — Functional Python for Learning Data Science
    - Slides included

Next Class

- *Hadoop: The Definitive Guide — Storage and Analysis at Internet Scale*
  - Please read Chapter 2 and 3 (MapReduce and HDFS)
- Google File System (papers on Class resources)