- **Hadoop HDFS**

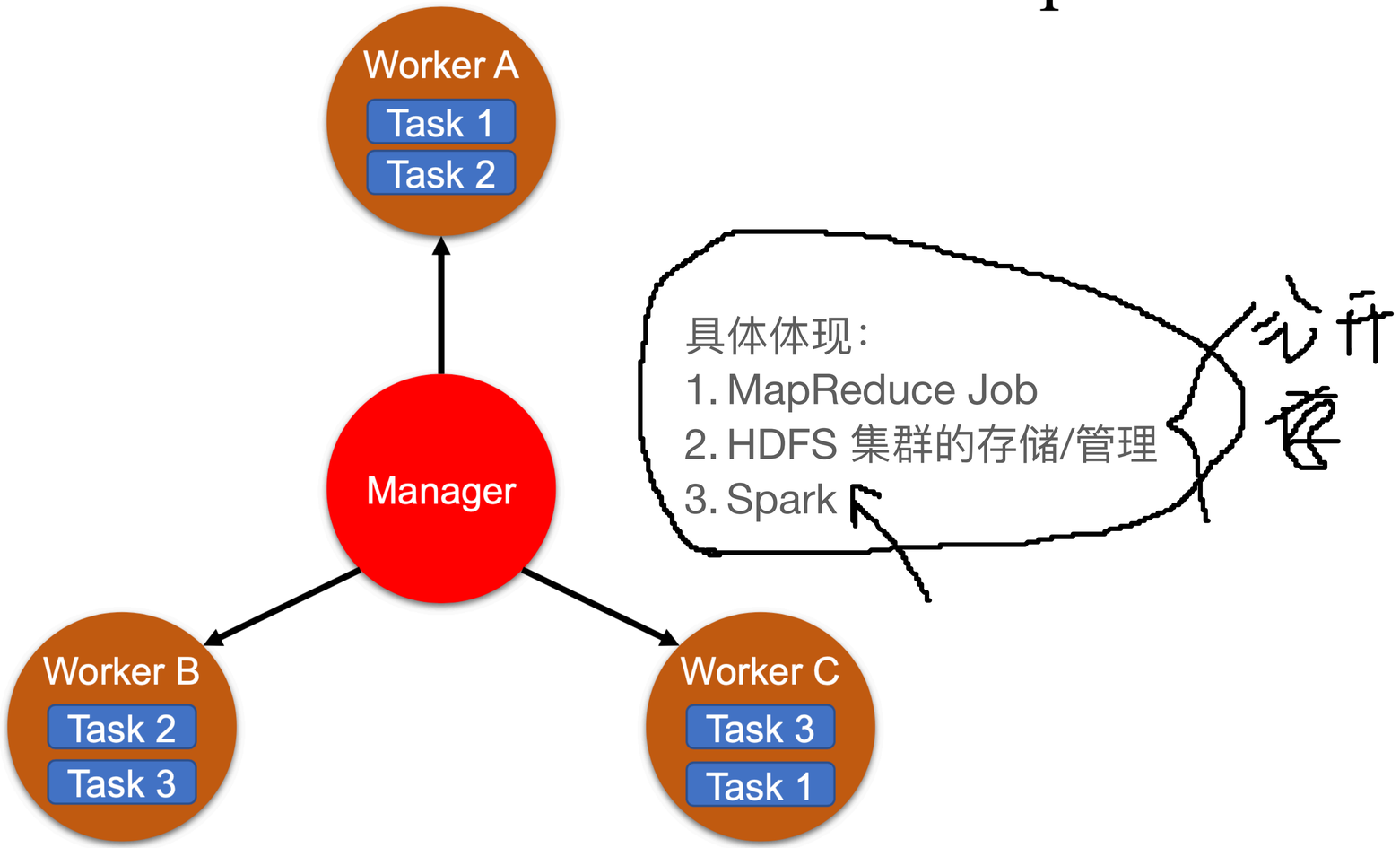
考点 1： hadoop 生态/框架的架构，重要组成部分

# Hadoop Ecosystem

- Core of Hadoop
  - Hadoop distributed file system (HDFS)
  - MapReduce
  - YARN (Yet Another Resource Negotiator) (from Hadoop v2.0)
- Additional software packages
  - Pig
  - Hive
  - Spark
  - HBase
  - …

# 考点 2： Master-Slave 架构（理解）

## The Master-Slave Architecture of Hadoop

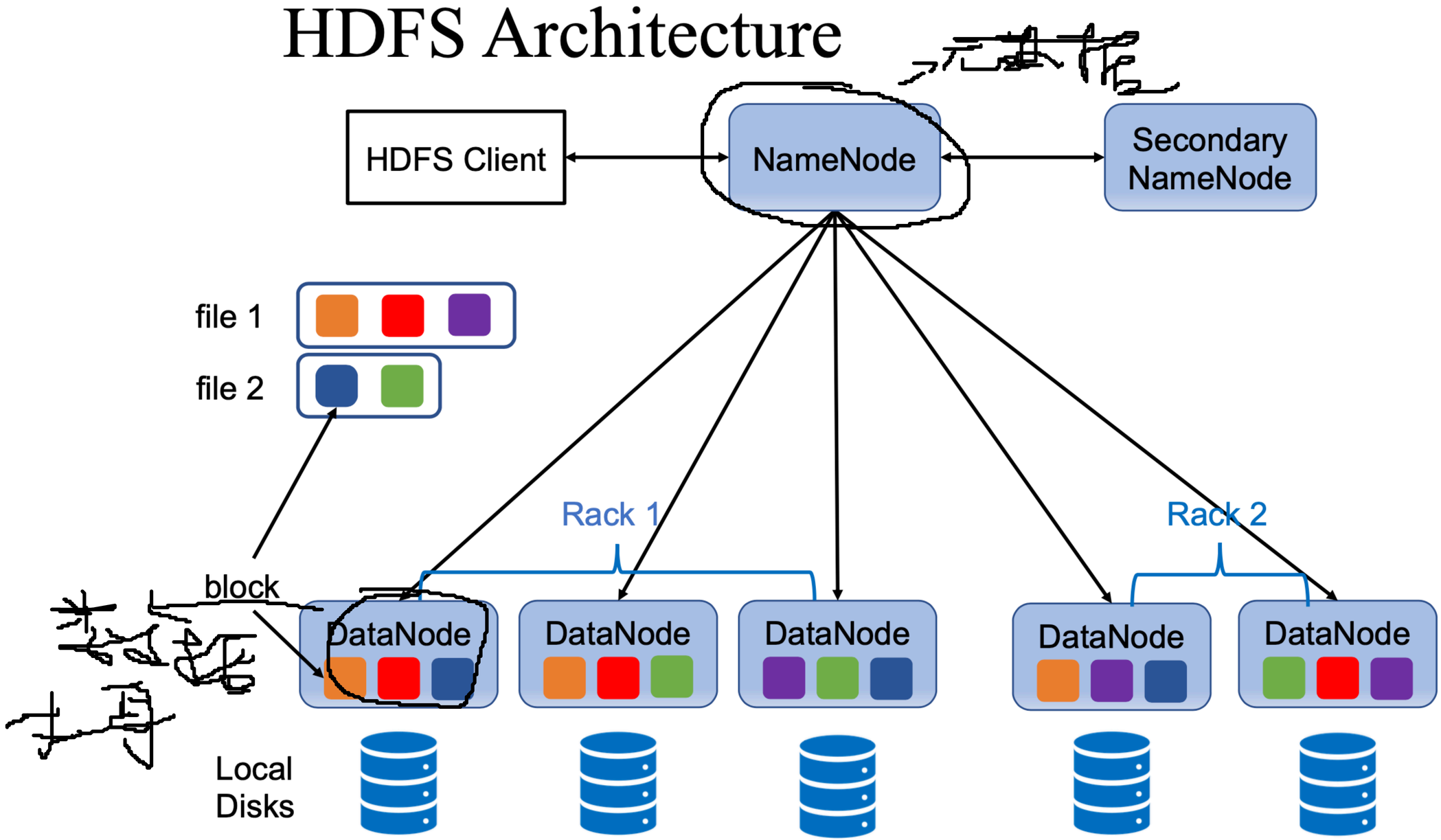


# Hadoop Distributed File Systems (HDFS)

- HDFS is a file system that
  - follows master-slave architecture
  - allows us to store data over multiple nodes (machines) ,
  - allows multiple users to access data.
  - just like file systems in your PC

- HDFS supports
  - distributed storage
  - distributed computation
  - horizontal scalability

考点 3： HDFS 架构/组成部分



考点 4： DN 1NN 2NN 的作用/区别/工作机制

# DataNode

- A commodity hardware stores the data
  - Slave node

- Functions
  - stores actual data
  - perform the read and write requests
  - report the health to NameNode (heartbeat)

考点 4： DN 1NN 2NN 的作用/区别/工作机制

# NameNode

- NameNode maintains and manages the blocks in the DataNodes (slave nodes).
  - Master node

不存数据本身

- Functions: 元数据
  - records the metadata of all the files
    - FsImage: file system namespace
    - EditLogs: all the recent modifications

name

replica infor

  - records each change to the metadata
  - regularly checks the status of datanodes
  - keeps a record of all the blocks in HDFS
  - if the DataNode failure, handle data recoveray

考点 4： DN 1NN 2NN 的作用/区别/工作机制

# Secondary NameNode

- Take checkpoints of the file system metadata present on NameNode
  - It is not a backup NameNode!

- Functions:
  - Stores a copy of FsImage file and Editlogs
  - Periodically applies Editlogs to FsImage and refreshes the Editlogs.
  - If NameNode is failed, File System metadata can be recovered from the last saved FsImage on the Secondary NameNode.

# 理解为什么要引入 Secondary？

1.如果所有的 Record 都存内存 —> 一断电就没了

2.如果所有的 Record 都存磁盘 —> 效率太低

3. 于是引入 fsimage edits 两个文件

4. 如果每次都是 NameNode 自己启动的时候合并 —> 启动速度太慢

5. 于是引入 Secondary Name Node 提醒他，帮他合并

6. NameNode 挂掉的时候，还可以把 Secondary NameNode 里面的文件拷贝过来进行补救

考点 4： DN 1NN 2NN 的作用/区别/工作机制

# NameNode vs. DataNode

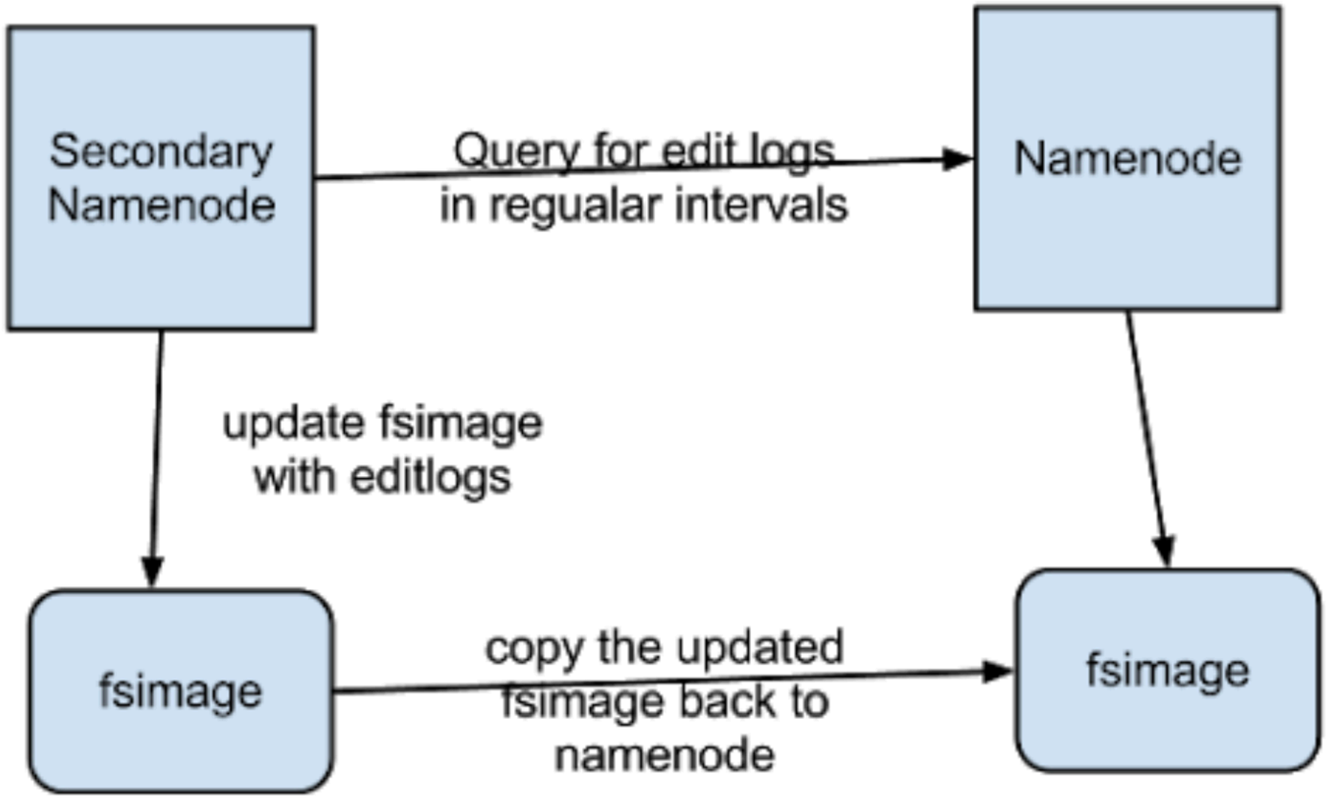
| | NameNode | DataNode |
|---|---|---|
| Quantity | One | Multiple |
| Role | Master | Slave |
| Stores | Metadata of files | Blocks |
| Hardware Requirements | High Capacity Memory | High Volume Hard Drive |
| Failure rate | Lower | Higher |
| Solution to Failure | Secondary NameNode | Replications |

Question 1 HDFS

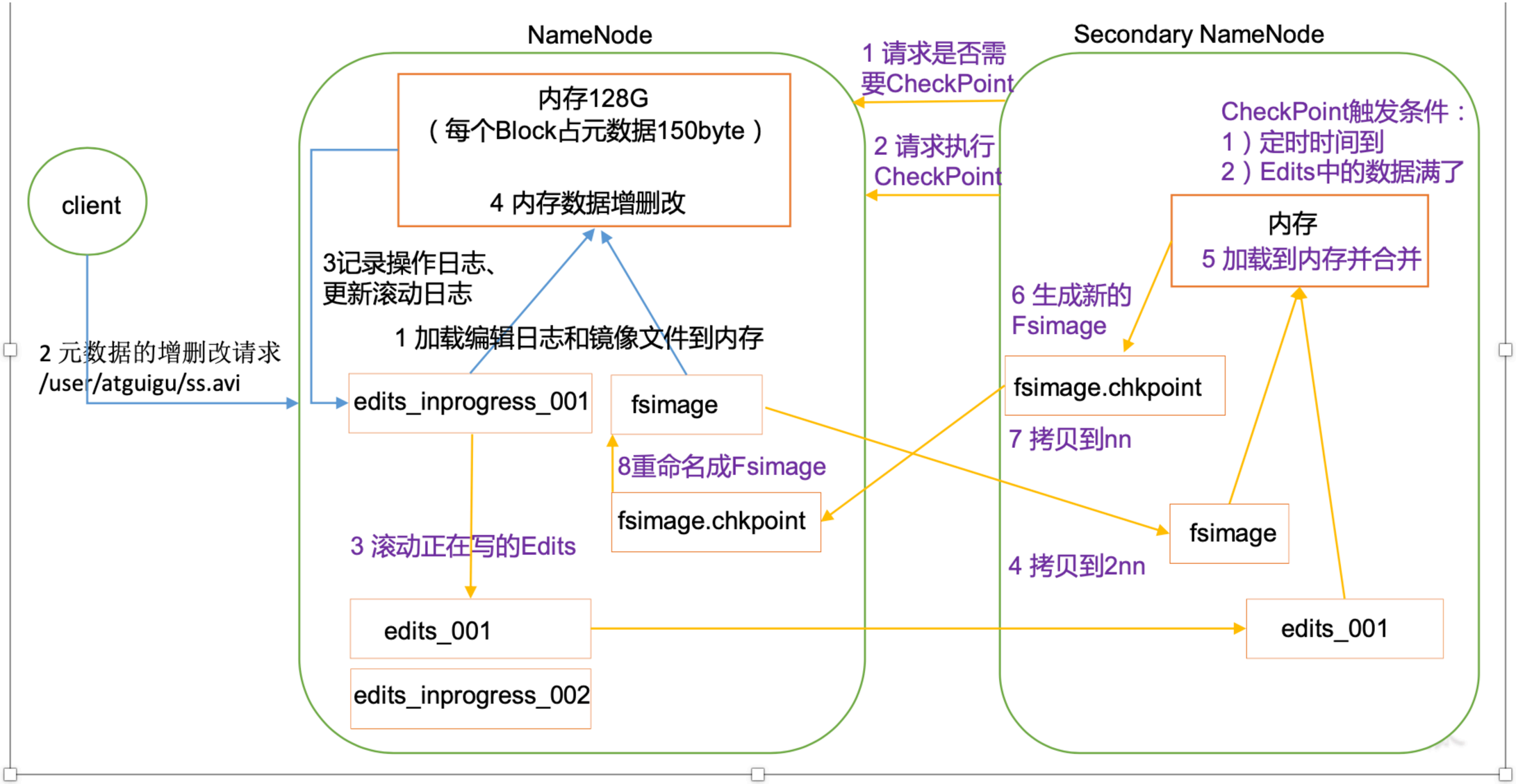
- Explain the difference between NameNode and DataNode.

# 考点 4： DN 1NN 2NN 的作用/区别/工作机制

## NameNode vs. Secondary NameNode



# 考点 4： DN 1NN 2NN 的作用/区别/工作机制　拓展



# NameNode 和 SecondaryNameNode 的工作机制（重点面试题） 拓展

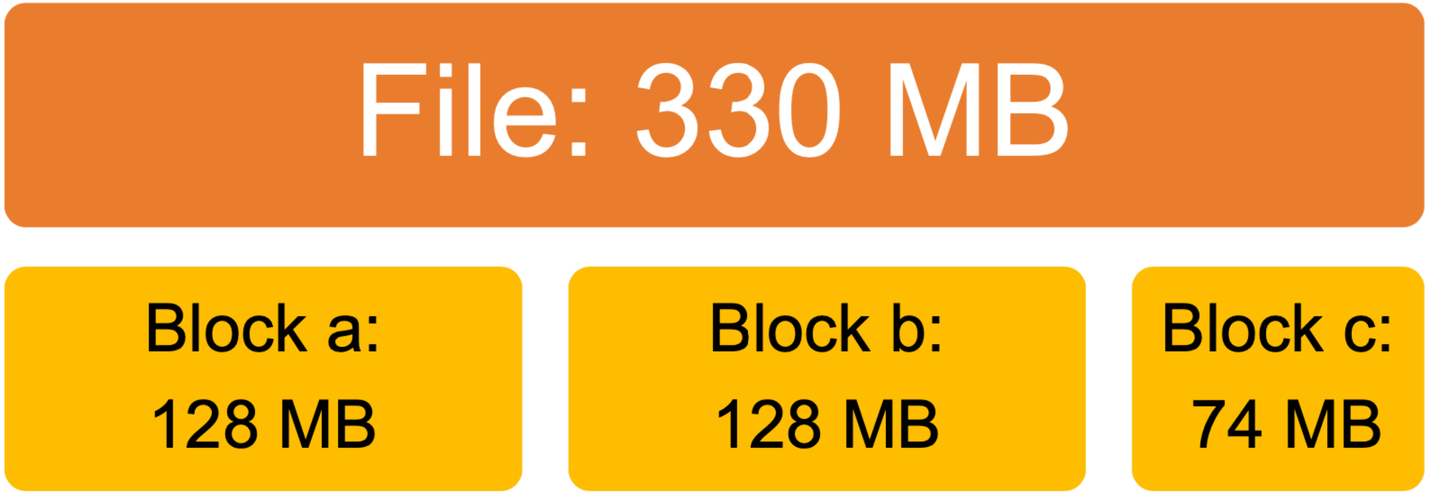
- 首先知道 NameNode 是用来存元数据的，元数据是通过两个不同的文件 edits，fdimage 共同存储的
- 其次 SecondaryNameNode 的任务就是提醒 NN 该合并了，并且帮他合并，以免 edits 这个 log 文件过大， 拖慢 NN 启动速度

> **正式的流程：**
>
> 1. NN 被启动的时候，第一件事就是合并上次生成的 edits，fdimage 文件然后加载到内存，并且生成一个新的空的 edits_inprogress_001 文件
> 2. 当 NameNode 中的数据需要修改更新时，这些更新的操作首先会被记录到这个 edits_inprogress_001 中，然后才在内存中作修改
> 3. 整个过程，每到一定时间（一小时），或者每到一定的 transcation 次数时(这个次数时 2nn 每过一分钟去询问 NN 你到 100万 次了吗，这个也是个参数可以设置)(取决于配置参数的设置)，SecondaryNameNode 会发出 checkPoint 请求
> 4. NN 收到 checkpoint 请求后，会另起一个 edits_inprogress_002 文件记录后续的更新， 此时把 edits_inprogress_001 (重命名为 edits_001 –001) 和 fdimage 拷贝给 SecondaryNameNode，供其合并
> 5. SecondaryNameNode 合并之后生成新的 fsimage.chkpoint 文件传回给 NN
> 6. NN 把收到的 fsimage.chkpoint 重命名成 fsimage 如此往复

考点 5： HDFS Block / replica / 机制

# Blocks

- Block is a sequence of bytes that stores data
  - Data stores as a set of blocks in HDFS
  - Default block size is 128MB (Hadoop 2.x and 3.x)
  - A file is spitted into multiple blocks



考点 5： HDFS Block / replica / 机制

# File, Block and Replica

- A file contains one or more blocks
  - Blocks are different
  - Depends on the file size and block size
  - $\# = \left\lceil \frac{file\ size}{block\ size} \right\rceil$
- A block has multiple replicas
  - Replicas are the same
  - Depends on the preset replication factor

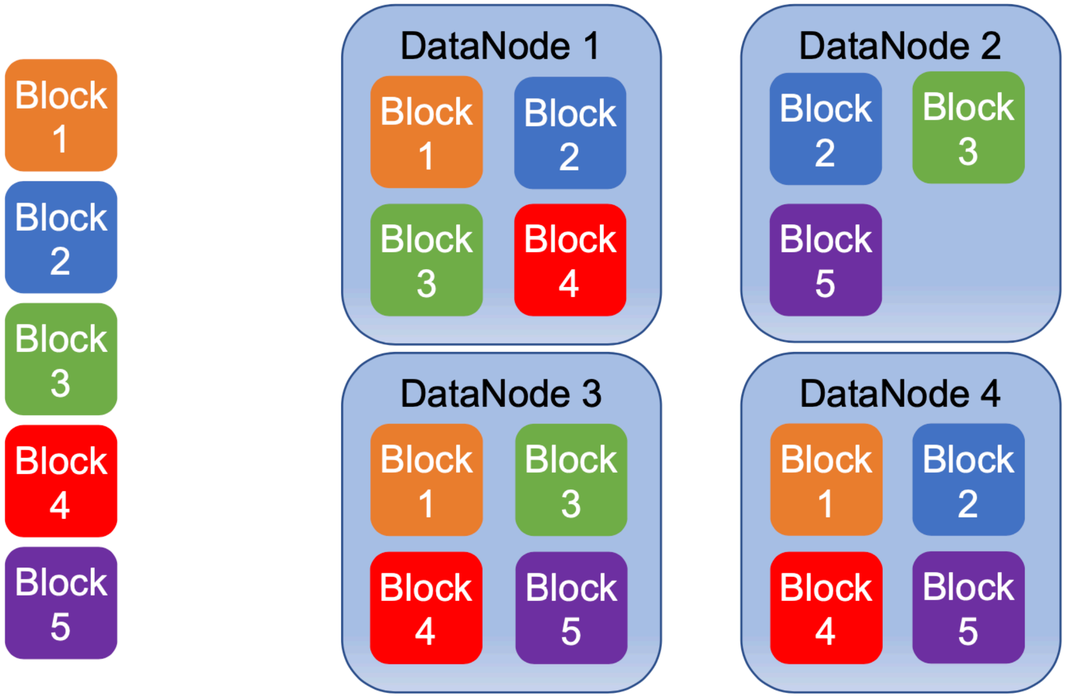
# 考点 5： HDFS Block / replica / 机制

注意区分分块和副本的概念，大文件分好块了之后

每个块都会被备份，存在不同的 DataNode中

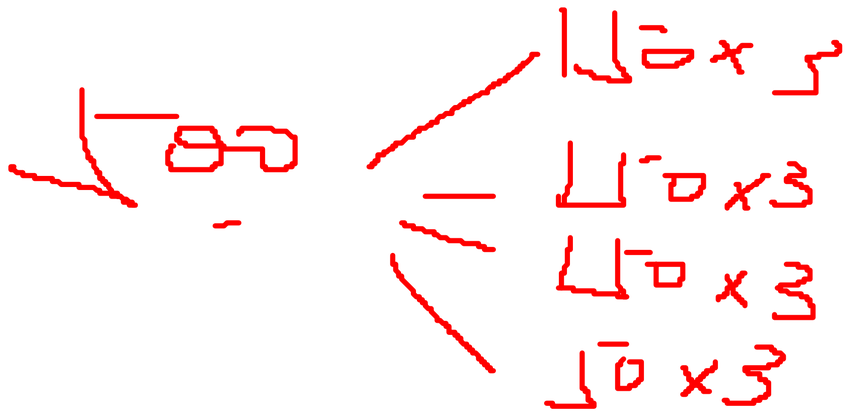
## Replication Management

- Each block is replicated 3 times and stored on different DataNodes



# Sample Question 1

- Given a file of 500MB, let block size be 150MB, and replication factor=3. How much space do we need to store this file in HDFS? Why?



考点 5.5： HDFS 分块大小的确定/为什么要分大块？/分小块或者小文件有什么弊端?

# Why Large Block Size?

- HDFS stores huge datasets
- If block size is small (e.g., 4KB in Linux), then the number of blocks is large:
  - too much metadata for NameNode
  - too many seeks affect the read speed
  - harm the performance of MapReduce too
- We don’t recommend using HDFS for small files due to similar reasons.
  - Even a 4KB file will occupy a whole block.

# 考点 5.5： 拓展 为什么是 128MB?

- **这个 128MB 取决于磁盘的传输速度**， 因为普遍计算机硬盘传输速度为 100MB/s, 而对于HDFS而言，寻址速度是传输速度的1/100是最理想的，而普遍寻址时间为10ms，则 10 * 100 = 1s， 所以 100MB/s * 1s = 100MB 是一个近似的比较理想的块大小，于是取整 128MB
- 如果 server 硬盘速度很快，可以增加这个大小

考点 6： HDFS 分块计算（不大可能再出题了，理解 Ass1 即可）

# What about Simultaneous Failure?

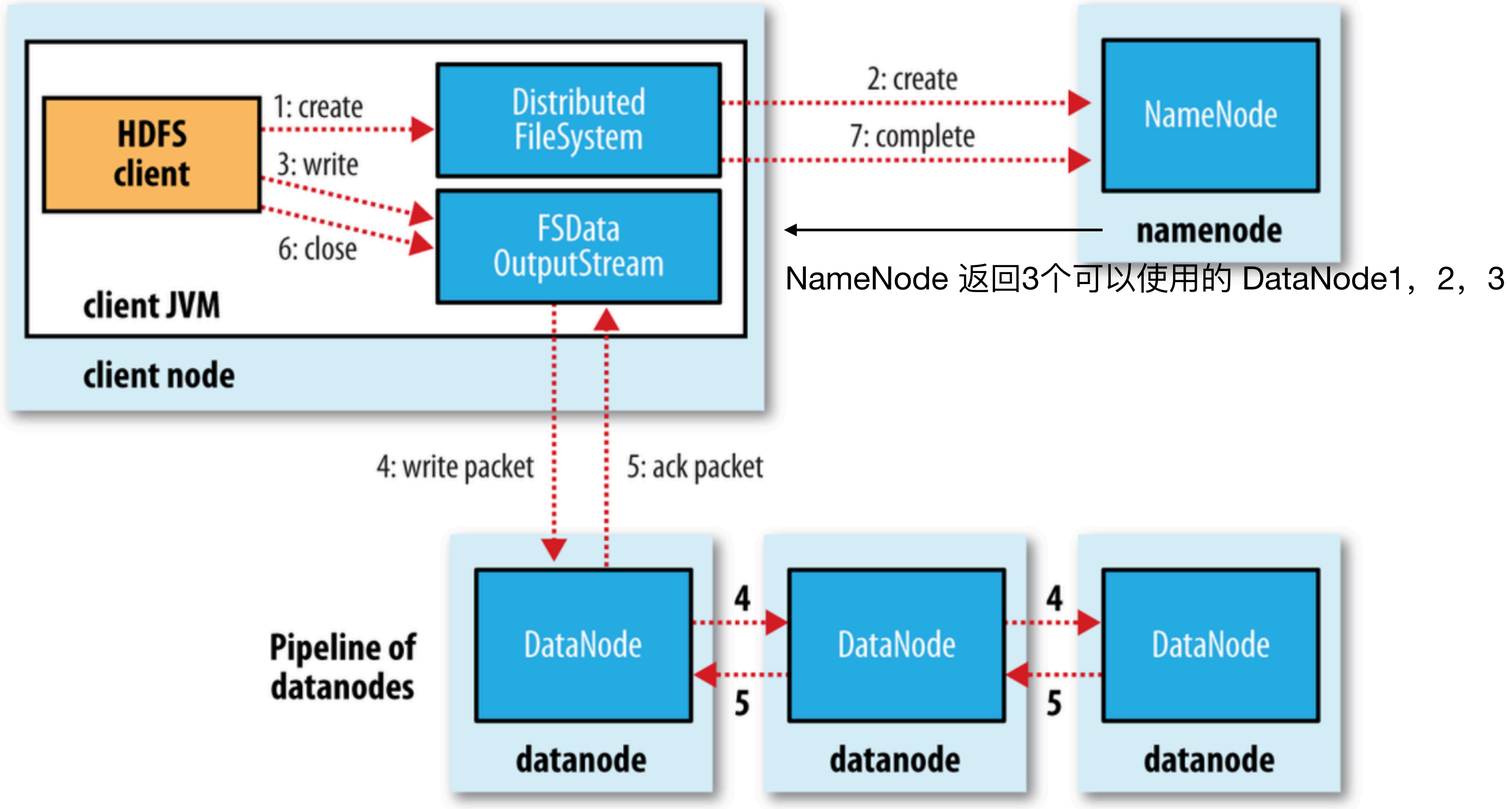
- In general
  - L1(k,N) = k*B-2*L2(k,N)-3*L3(k,N)
  - L2(k,N) = 2*L1(k-1,N)/(N-k+1)+L2(k-1,N)-L2(k-1,N)/(N-k+1)
  - L3(k,N) = L2(k-1,N)/(N-k+1)+L3(k-1,N)
- Let N = 4000, B = 750, we have

| Failed Nodes | 1st replicas lost | 2nd replicas lost | 3rd replicas lost |
|---|---|---|---|
| 50 | 36,587 | 454 | 2 |
| 100 | 71,332 | 1,811 | 15 |
| 150 | 104,272 | 4,037 | 52 |
| 200 | 135,441 | 7,095 | 123 |

# 考点 7： HDFS 读写流程

## Write in HDFS

- Create file – Write file – Close file




NameNode 返回3个可以使用的 DataNode1，2，3

# 考点 7： HDFS 读写流程

## Write in HDFS

- There is only single writer allowed at any time
- The blocks are writing simultaneously
- For one block, the replications are replicating sequentially
- The choose of DataNodes is random, based on replication management policy, rack awareness, …

客户端向 NameNode 请求上传文件的时候，NameNode 挑选哪些 DataNode？

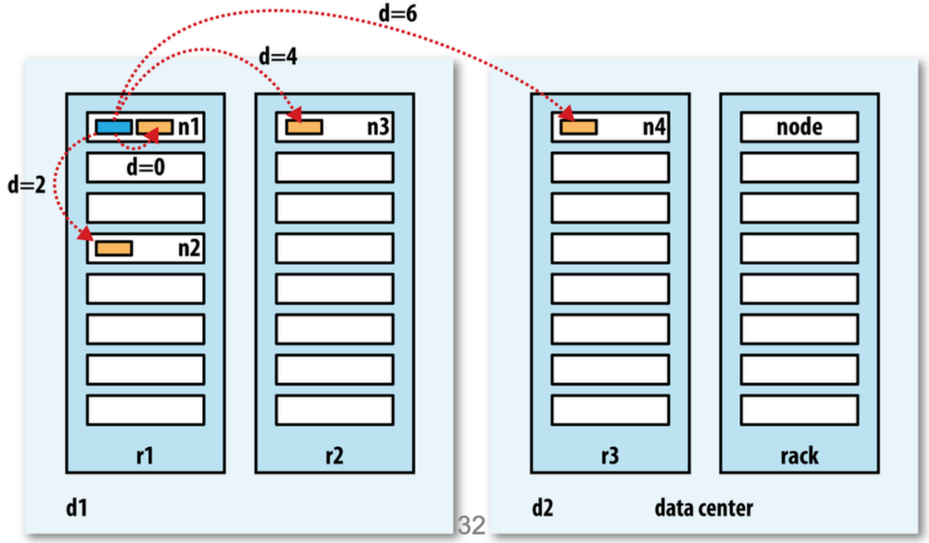
↓

机架感知 rack awareness

考点 8：HDFS 机架感知/网络拓扑

# Why Rack Awareness?

- Reduce latency
  - Write: to 2 racks instead of 3 per block
  - Read: blocks from multiple racks
- Fault tolerance
  - Never put your eggs in the same basket

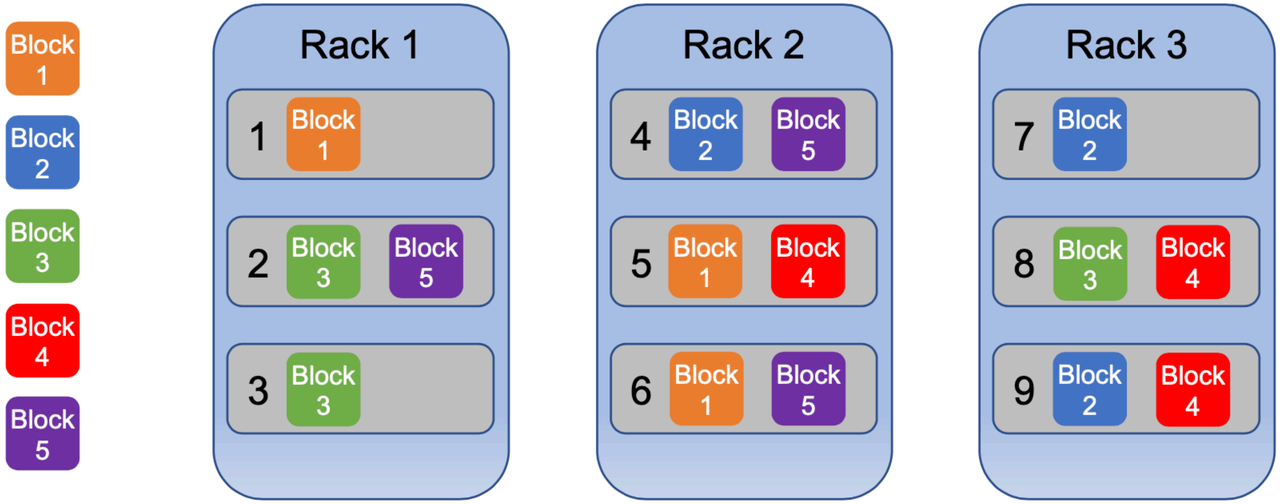


# 考点 8：HDFS 机架感知/网络拓扑

## 影响因素：网络 I/O传输

## Rack Awareness Algorithm

- If the replication factor is 3:
  - 1st replica will be stored on the local DataNode
  - 2nd on a different rack from the first.
  - 3rd on the same rack as 2nd, but on a different node.



# 考点 8：HDFS 机架感知/网络拓扑

Hadoop 3.2.1 官方解释：

https://hadoop.apache.org/docs/stable/hadoop-project-dist/hadoop-hdfs/HdfsDesign.html#Data_Replication

> For the common case, when the replication factor is three, HDFS’s placement policy is to put one replica on the local machine if the writer is on a datanode, otherwise on a random datanode in the same rack as that of the writer, another replica on a node in a different (remote) rack, and the last on a different node in the same remote rack.

# 考点 8：HDFS 机架感知/网络拓扑

## 网络拓扑计算距离

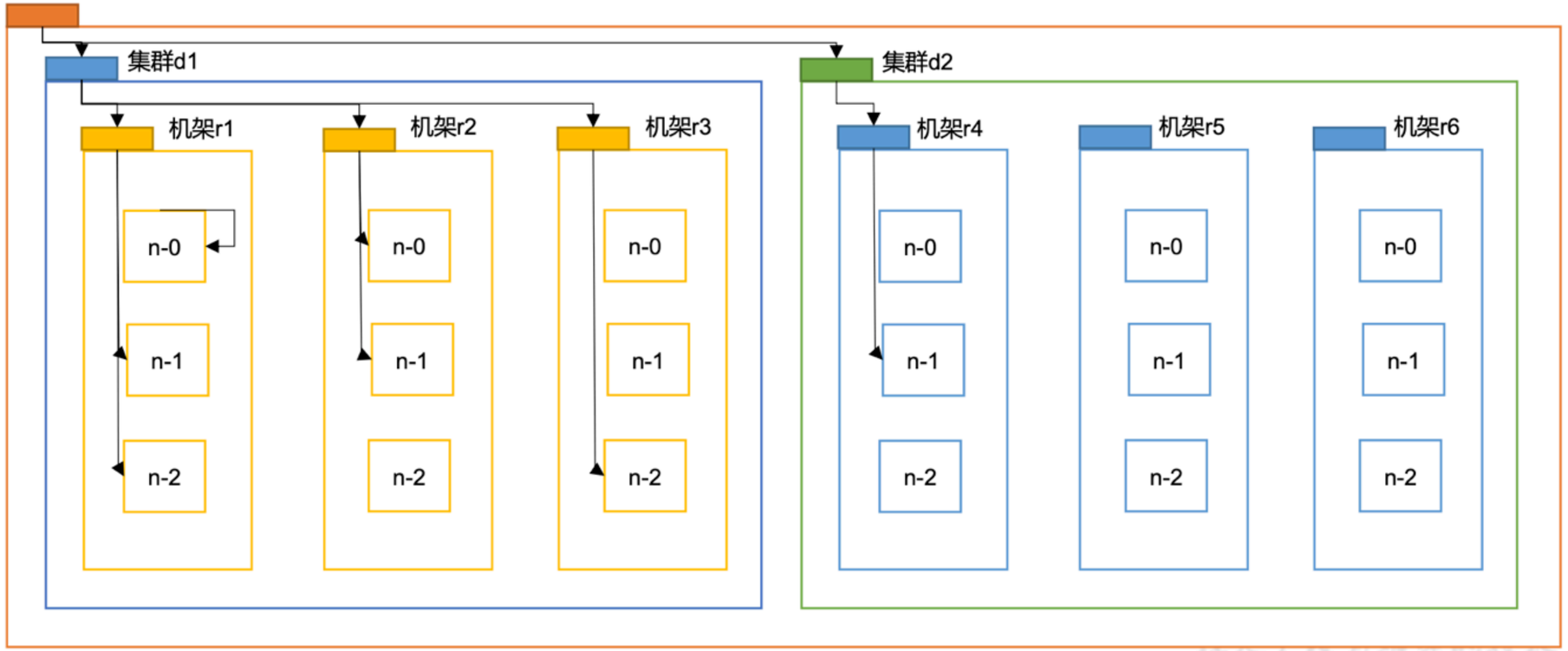
> **如何计算两个节点之间的距离?**
> 节点之间的距离 = 两个节点到达最近的公共路由/交换机的距离之和

Distance(/d1/r1/n0, /d1/r1/n0)=0（同一节点上的进程）

Distance(/d1/r1/n1, /d1/r1/n2)=2（同一机架上的不同节点）

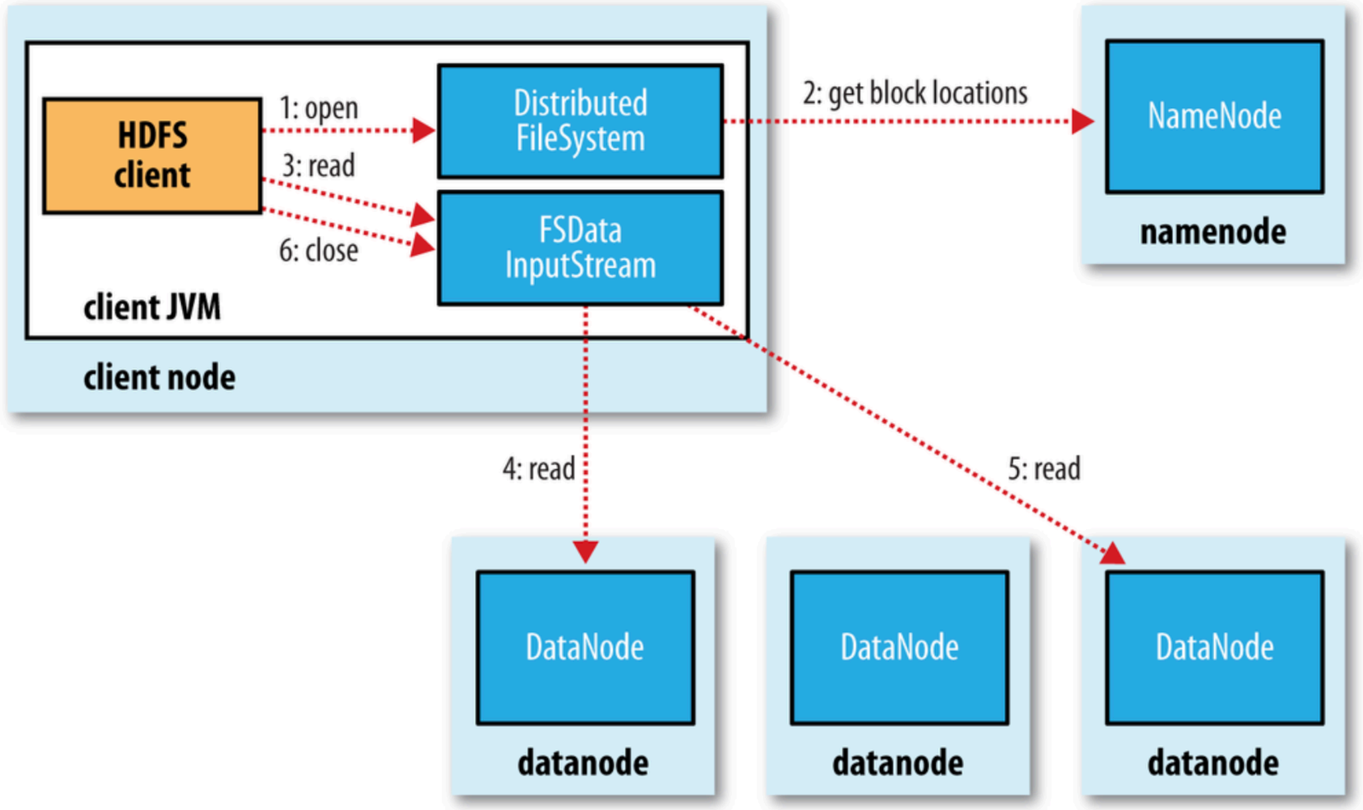
Distance(/d1/r2/n0, /d1/r3/n2)=4（同一数据中心不同机架上的节点）

Distance(/d1/r2/n1, /d2/r4/n1)=6（不同数据中心的节点）



# 考点 7： HDFS 读写流程

## Read in HDFS



# 考点 7： HDFS 读写流程

## Read in HDFS

- Multiple readers are allowed to read at the same time
- The blocks are reading simultaneously
- Always choose the closest DataNodes to the client (based on the network topology)
- Handling errors and corrupted blocks
  - avoid visiting the dataNode again
  - report to NameNode

考点 9： HDFS Erasure Coding

知识点：**什么是 HDFS Erasure Coding?**

**相对于 Replication 有什么特点?**

# HDFS Erasure Coding

一种替代 3 份复制品的存储方法

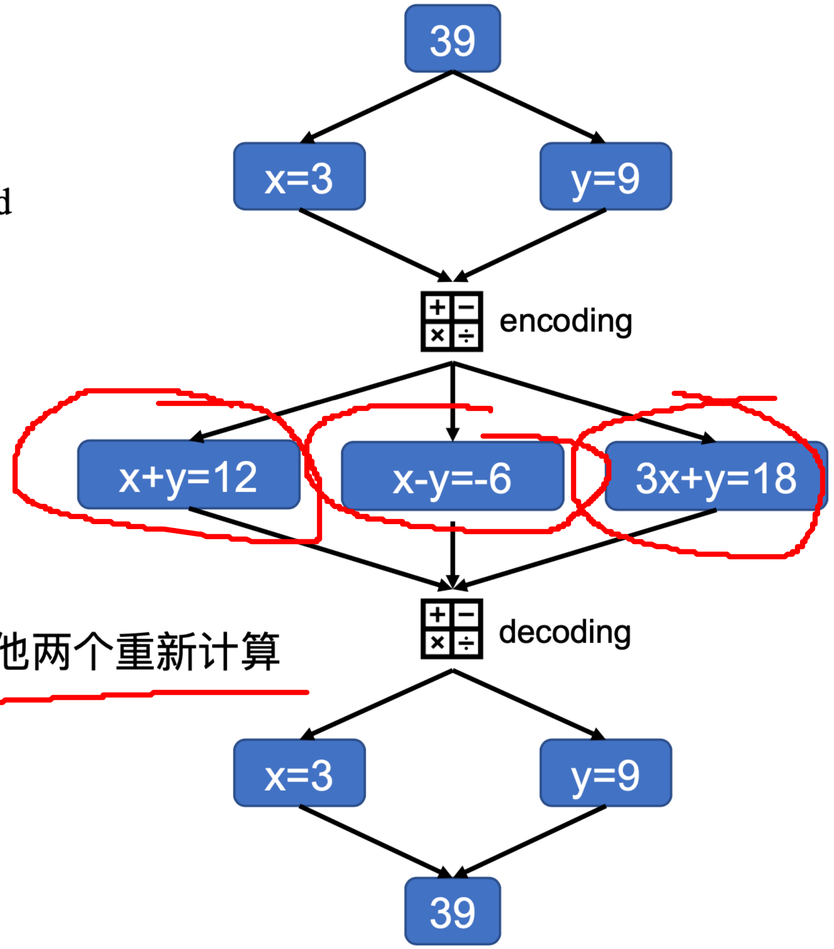
- Drawback of replication
  - space overhead (e.g., 200%)
  - rarely accessed replicas

- Erasure coding
  - same or better level of fault-tolerance
  - much less overhead
  - used in RAID

# 考点 9： HDFS Erasure Coding 概念理解

## Erasure Coding: Idea

- We can decode 39 using any two of the three equations
  - lose one equation does not matter, and we can recover it easily!



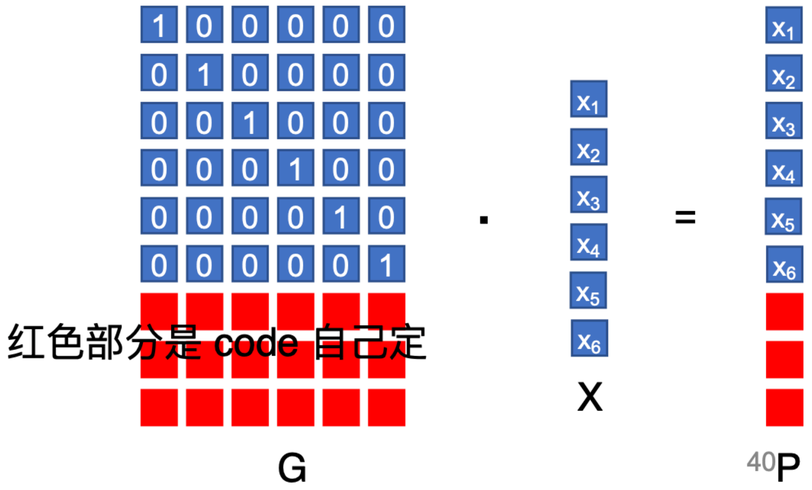

其中一个块丢了，还可以通过其他两个重新计算

考点 9.5： HDFS Erasure Coding 的计算（不太可能考）

# 知识点：6,3 RS 的计算

# Erasure Coding: (6,3)-Reed-Solomon

- Now consider $X = [x_1, \cdots, x_6]^T$ and $G = \begin{bmatrix} I_6 \\ g_1 \\ g_2 \\ g_3 \end{bmatrix}$
  - a matrix with any 6 rows from $G$ has full rank.
- Then we can have $P = G \cdot X$
- We can recover $X$ using any 6 rows from $G$ and $P$
  - $X = G'^{-1} \cdot P'$




G 是自己保存的，如果 P 中某些行丢了，我们可以通过对应行的 G 组成的矩阵的逆矩阵，来还原 X

raw data

parities

这里对于数学的要求：

- 矩阵的乘法
- 求一个矩阵的逆矩阵

# 考点 9.5： HDFS Erasure Coding 的计算（不太可能考）

$$
G = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -1 & 1 & 2 & 3 \\ 2 & 1 & -1 & 0 \end{pmatrix}
\qquad
X = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \end{pmatrix}
\qquad
P = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 17 \\ 1 \end{pmatrix}
$$

$$G \qquad X \qquad P$$

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -1 & 1 & 2 & 3 \\ 2 & 1 & -1 & 0 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 17 \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -1 & 1 & 2 & 3 \\ 2 & 1 & -1 & 0 \end{pmatrix} \longrightarrow \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 2 & 1 & -1 & 0 \end{pmatrix} \xrightarrow{\text{求逆}} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

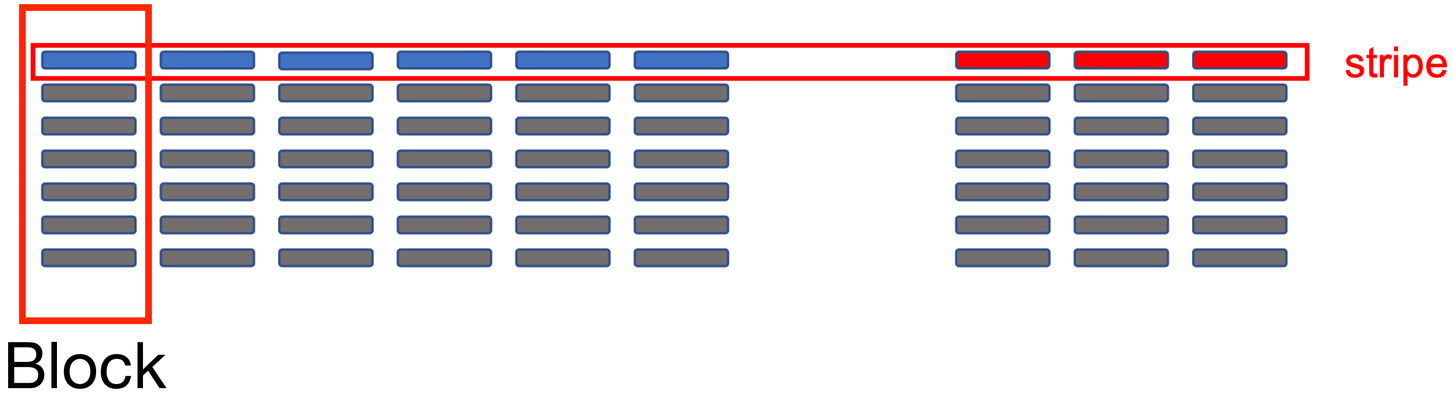
$G'$ $\qquad$ $G'^{-1}$

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 2 & 1 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 2 \\ 4 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \end{pmatrix}$$

$G'^{-1}$ $\qquad$ $P'$ $\qquad$ $X$ ✓

# 考点 9.5 Erasure Coding 的存储过程

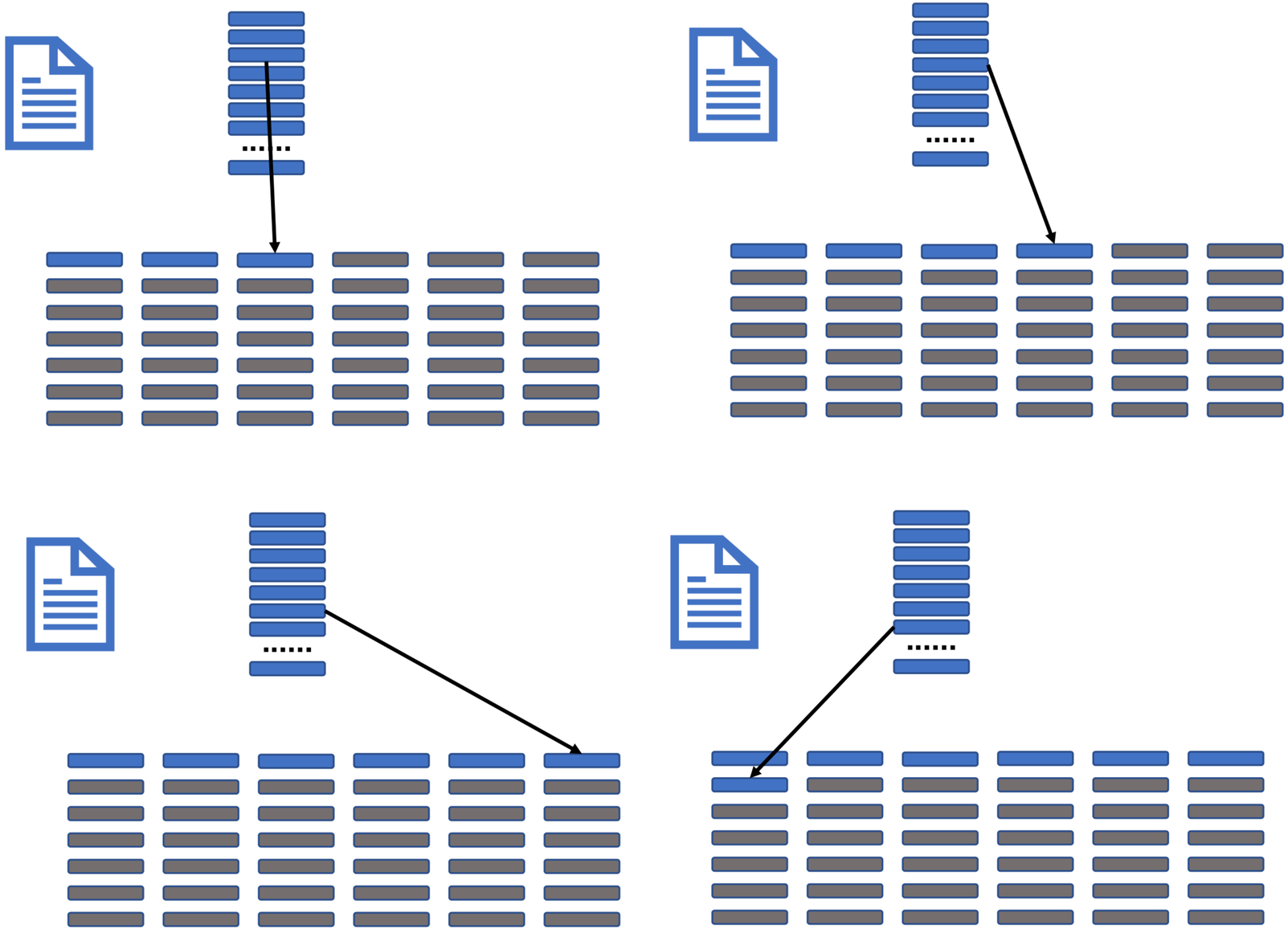
横着看是一个 Stripe
竖着看是一个 Block




每一个 Block 都被竖着分为 200 个 Cell （一个 Cell 64KB， 一个 Block 128 MB）

所有将要存储的文件，一律分成一个一个的 Cell ，按照从左到右，从上到下的顺序，存入 Block， 每存 6 个 cell ，就多存 3 个 cell 作为 parties 以便将来计算恢复丢失的 Data

# 考点 9.5 Erasure Coding 的存储过程

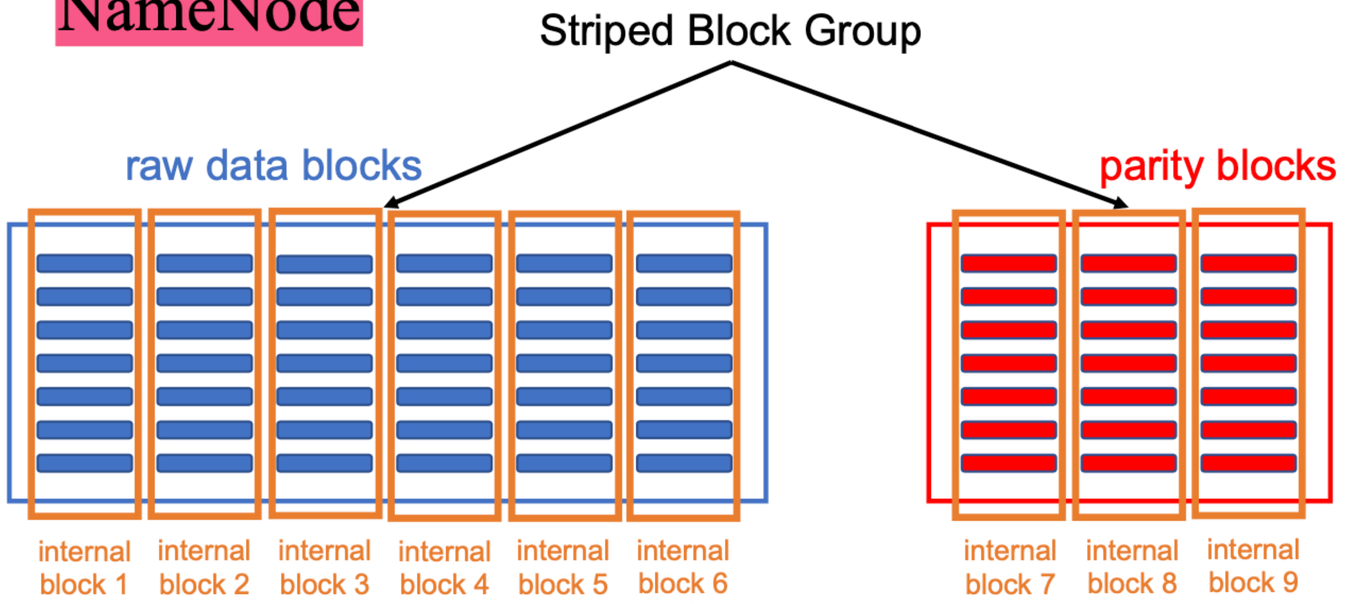


写文件的时候是横着写的，但是实际存储是数着存的

# Striped Block Management

考点 9.5 Erasure Coding 的存储过程

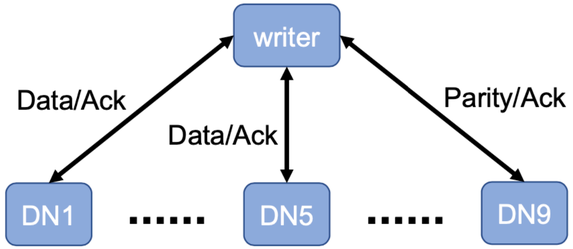
- Block group
  - Contains 6 raw data blocks and 3 parity blocks
  - The blocks will be stored in different DataNodes
  - Information of the block group will be stored in NameNode



# 考点 10 Erasure Coding 的读写流程

## Parallel write

- Client writes a block group of 9 DataNodes simultaneously

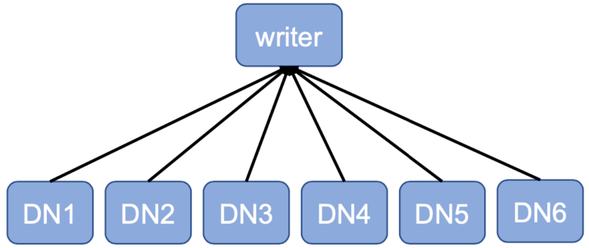



## Handle Write Failure

- Client ignores the failed DataNode and continue writing
- Can tolerant up to 3 failures
- Missing blocks will be reconstructed later

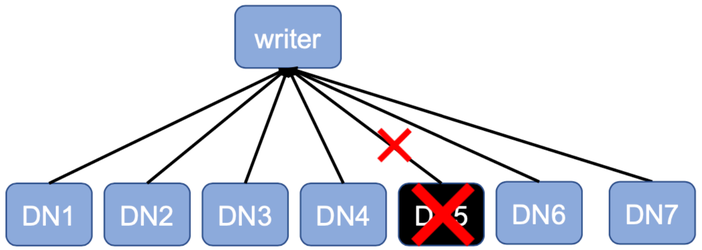
## Read

- Parallelly read from 6 DataNodes with data blocks




## Handle Read Failure

- Continue reading from any of the remaining DataNodes
- Reconstruct the failed nodes later



# 考点 10 Erasure Coding 与 Replication 的对比

## Replication vs. Erasure Coding

- EC is better for large and rarely accessed files.
  - HDFS users and admins can turn on and off erasure coding for individual files or directories.

| | Replication | Erasure Coding |
|---|---|---|
| storage overhead | High | Low |
| data durability | Yes | Yes (better) |
| data locality | Yes | No |
| write performance | Good | Poor |
| read performance | Good | Poor |
| recovery cost | Low | High |

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## 3-Replication vs. (6,3)-RS

| | 3-Replication | (6,3)-RS |
|---|---|---|
| **Durability** | | |
| Maximum Toleration | 2 | 3 |
| **Disk Space Consumption** | | |
| Data: n bytes | 3n | 1.5n |
| **Number of Client-DataNode connections** | | |
| Write | 1 | 9 |
| Read | 1 | 6 |

## 3-Replication vs. (6,3)-RS

- Number of blocks required to read the data

| # of Blocks | 3-Replication | (6,3)-RS |
|---|---|---|
| 1 | 1 | 6 |
| 2 | 2 | |
| 3 | 3 | |
| 4 | 4 | |
| 5 | 5 | |
| 6 | 6 | |

押题：

1. Describe the core component of Hadoop and the role they play ?

2. Name three techniques where follows the Master-Slave architecture
We learned in this course and describe the mechanism ?

3. Explained the reason why hadoop introduce a 2NN describe how it corporate with 1NN?

4. Discuss the disadvantage of Large Block size and Small Block size in HDFS?

5. Describe the mechanism of uploading a file to HDFS as well as how 1NN choose the DataNode?

6. Describe the pros and cons about replications and EC in HDFS ?

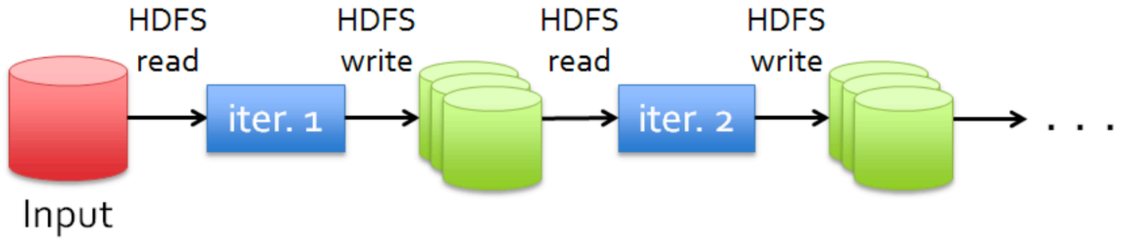
- **MapReduce Spark**

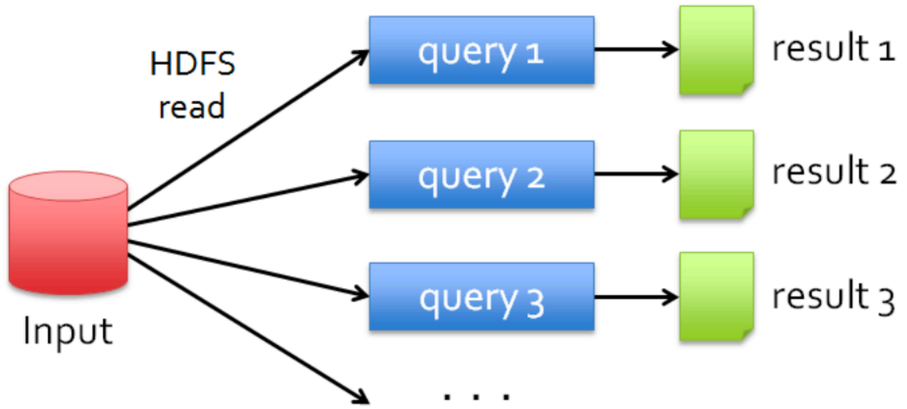
考点 1: MR 的缺点/Spark 的 motivation

# Limitations of MapReduce

- As a general programming model:
  - more suitable for one-pass computation on a large dataset
  - hard to compose and nest multiple operations
  - no means of expressing iterative operations
- As implemented in Hadoop
  - all datasets are read from disk, then stored back on to disk
  - all data is (usually) triple-replicated for reliability

# Data Sharing in Hadoop MapReduce




- **Slow** due to replication, serialization, and disk IO
- Complex apps, streaming, and interactive queries all need one thing that MapReduce lacks:
  - Efficient primitives for **data sharing**

关于MapReduce 的缺点一句话：因为总要读写磁盘，所以慢

Spark 怎么解决的？把中间计算过程全存在内存里

# 考点 2: Spark 的 Feature

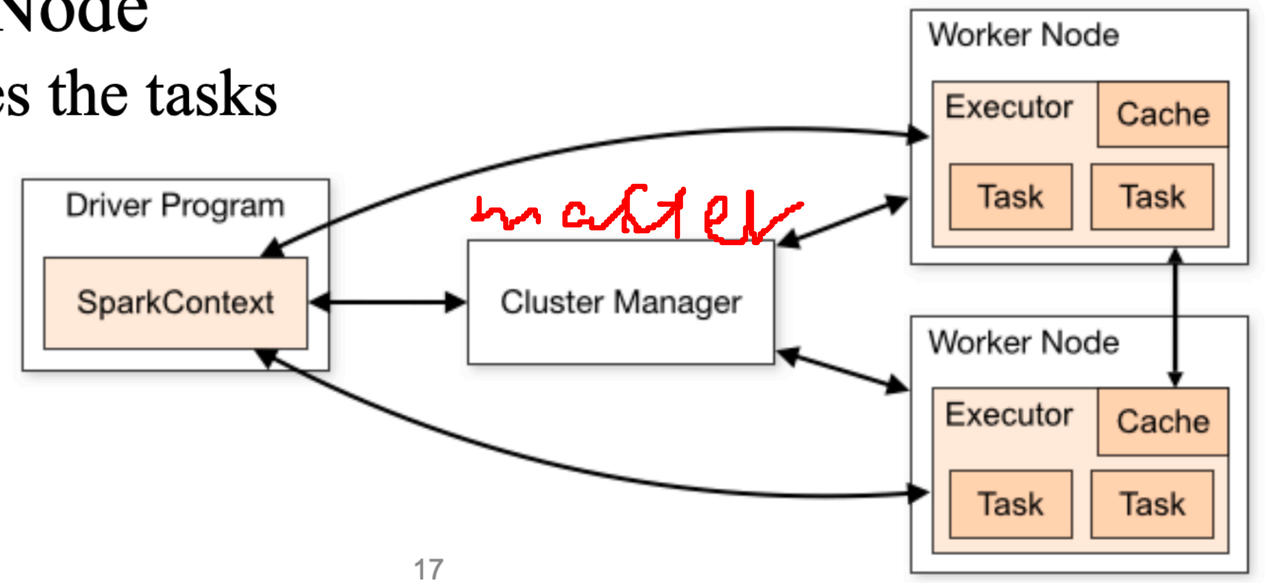
1. In memory
2. Parallel
3. Fault-tolerant
4. Lazy evaluation

- Apache Spark is an open-source cluster computing framework for real-time processing.
- Spark provides an interface for programming entire clusters with
  - implicit data parallelism
  - fault-tolerance
- Built on top of Hadoop MapReduce
  - extends the MapReduce model to efficiently use more types of computations

考点 3: Spark 的架构 / 组成部分 / worker / driver / executor / Manager

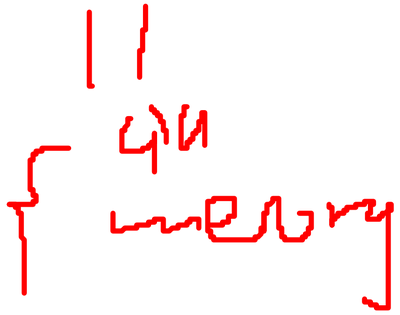
# Spark Architecture

- Master Node
  - takes care of the job execution within the cluster
- Cluster Manager
  - allocates resources across applications
- Worker Node
  - executes the tasks



# 考点 3: Spark 的架构 / 组成部分 / worker / driver / executor / Manager

1. Driver 程序的入口（main）里面声明了 SparkContext 是
2. Cluster Manager 是一台不管计算，只负责任务、资源调度的机器
3. Worker 是负责计算的机器
4. Executor 是真正实实在在的 JVM 线程

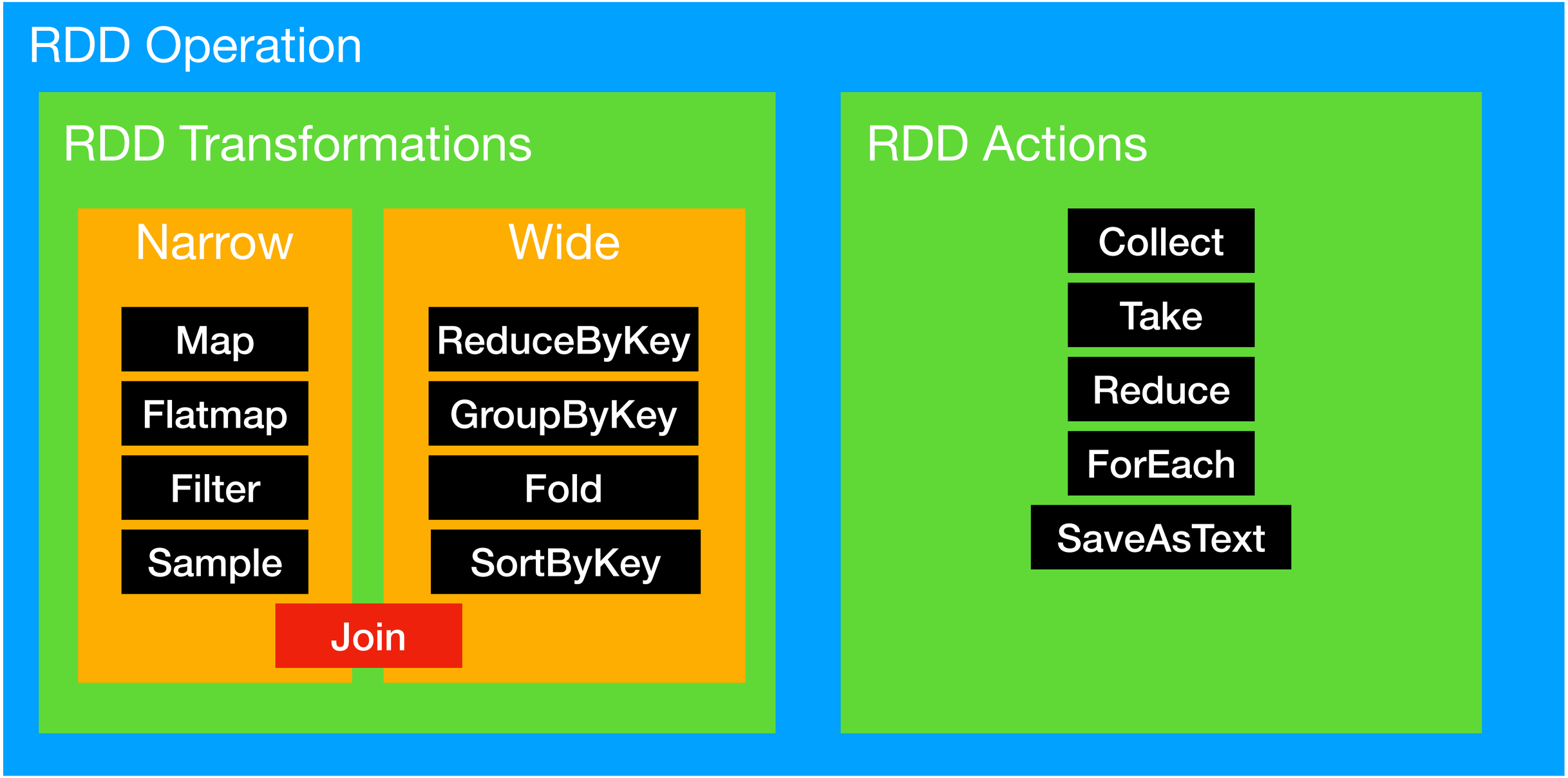


# 考点 4: Spark RDD / trans & action / lazy Evaluation

## Resilient Distributed Dataset (RDD)

- RDD is where the data stays
- RDD is the fundamental data structure of Apache Spark
  - is a collection of elements
    - Dataset
  - can be operated on in parallel
    - Distributed
  - fault tolerant
    - Resilient

# 考点 4: Spark RDD / trans & action / lazy Evaluation



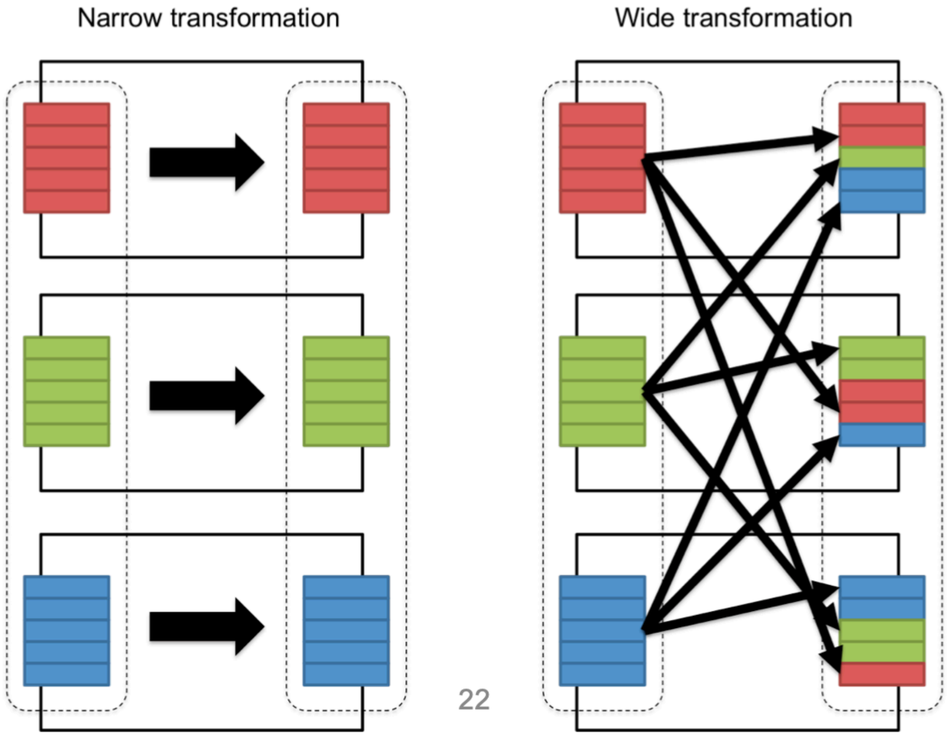
# Narrow and Wide Transformations

Narrow transformation
involves no data shuffling

- map
- flatMap
- filter
- sample

Wide transformation
involves data shuffling

- ~~sortByKey~~
- reduceByKey
- groupByKey
- join

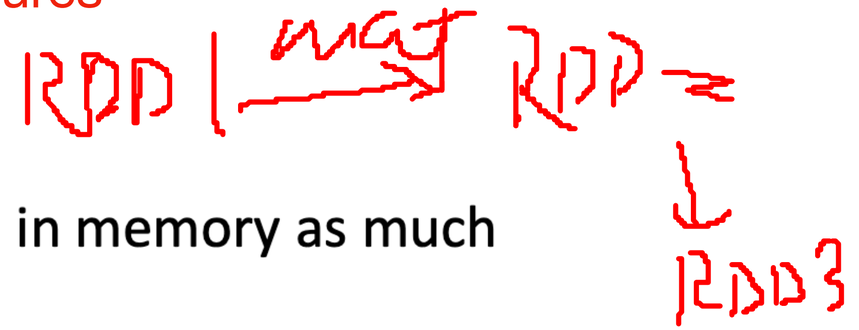





也可以从Data分区的角度来理解

考点 4.5 : Spark RDD features

# RDD Traits



- **In-Memory**, i.e. data inside RDD is stored in memory as much (size) and long (time) as possible
- **Immutable** or **Read-Only**, i.e. it does not change once created and can only be transformed using transformations to new RDDs
- **Lazy evaluated**, i.e. the data inside RDD is not available or transformed until an action is executed that triggers the execution
- **Cacheable**, i.e. you can hold all the data in a persistent "storage" like memory (default and the most preferred) or disk (the least preferred due to access speed)
- **Parallel**, i.e. process data in parallel
- **Typed**, i.e. values in a RDD have types, e.g. RDD[Long] or RDD[(Int, String)]
- **Partitioned**, i.e. the data inside an RDD is partitioned (split into partitions) and then distributed across nodes in a cluster (one partition per JVM that may or may not correspond to a single node)

# Question 2 Spark

- Given a large text file, your task is to find out the top-k most frequent co-occurring term pairs. The co-occurrence of (w, u) is defined as: u and w appear in the same line (this also means that (w, u) and (u, w) are treated equally). Your Spark program should generate a list of ***k*** key-value pairs ranked in descending order according to the frequencies, where the keys are the pair of terms and the values are the co-occurring frequencies (**Hint:** you need to define a function which takes an array of terms as input and generate all possible pairs).

# Sample Question 2

In [1]:
```
from pyspark import SparkConf, SparkContext
conf = SparkConf().setMaster("local").setAppName("hellow_9313")
sc = SparkContext(conf = conf).getOrCreate();
inputFile= ["hello world, there is an apple.",
        "If your program shows.",
        "If your program shows.",
        "this occurs because you may have multiple versions"]
textFile = sc.parallelize(inputFile)
words = textFile.map(lambda x: x.lower().split())
words.collect()
```

Out[1]:
```
[['hello', 'world,', 'there', 'is', 'an', 'apple.'],
 ['if', 'your', 'program', 'shows.'],
 ['if', 'your', 'program', 'shows.'],
 ['this', 'occurs', 'because', 'you', 'may', 'have', 'multiple', 'versions']]
```

In [2]:
```
def getAllPairs(line):
    sortedLine = sorted(line)
    for i in range(len(sortedLine)):
        for j in range(i + 1, len(sortedLine)):
            res += [((sortedLine[i], sortedLine[j]), 1)]
    return res
getAllPairs(['if', 'your', 'program', 'shows.'])
```

click to scroll output; double click to hide

Out[2]:
```
[(('if', 'program'), 1),
 (('if', 'shows.'), 1),
 (('if', 'your'), 1),
 (('program', 'shows.'), 1),
 (('program', 'your'), 1),
 (('shows.', 'your'), 1)]
```

# Sample Question 2

In [3]:
```
pairs = words.flatMap(getAllPairs).reduceByKey(lambda x, y: x + y)
topk = pairs.map(lambda x: (x[1],x[0])).sortByKey(False).map(lambda x: (x[1], x[0]))
topk.collect()
```

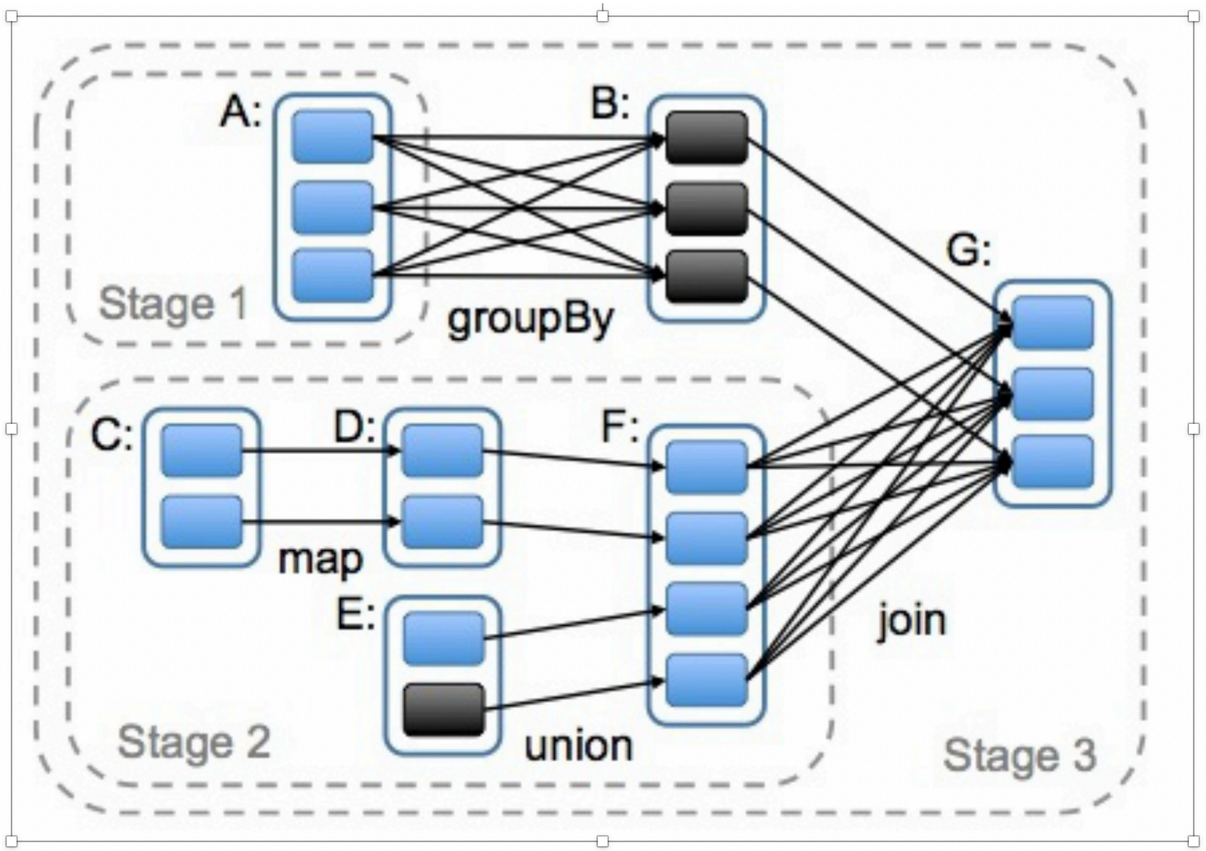
Out[3]:
```
[(('if', 'program'), 2),
 (('if', 'shows.'), 2),
 (('if', 'your'), 2),
 (('program', 'shows.'), 2),
 (('program', 'your'), 2),
 (('shows.', 'your'), 2),
 (('an', 'apple.'), 1),
 (('an', 'hello'), 1),
 (('an', 'is'), 1),
 (('an', 'there'), 1),
 (('an', 'world,'), 1),
 (('apple.', 'hello'), 1),
 (('apple.', 'is'), 1),
 (('apple.', 'there'), 1),
 (('apple.', 'world,'), 1),
 (('hello', 'is'), 1),
 (('hello', 'there'), 1),
 (('hello', 'world,'), 1),
 (('is', 'there'), 1),
 (('is', 'world,'), 1),
 (('there', 'world,'), 1),
```

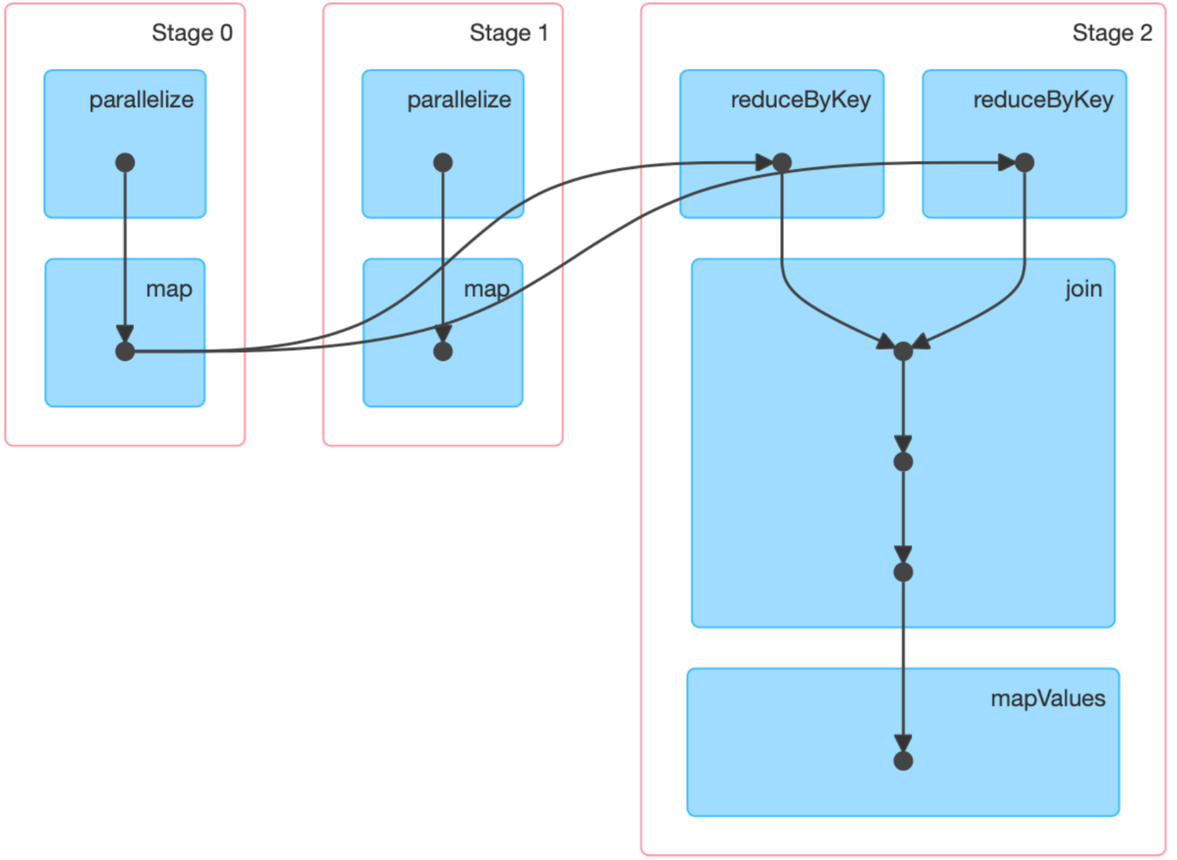
# 考点 5: Spark RDD Lineage / DAG / 阶段划分

DAG(Directed Acyclic Graph)叫做有向无环图，原始的RDD通过一系列的转换就就形成了DAG，根据RDD之间的依赖关系的不同将DAG划分成不同的Stage，对于窄依赖，partition的转换处理在Stage中完成计算。对于宽依赖，由于有Shuffle的存在，只能在parent RDD处理完成后，才能开始接下来的计算，因此**宽依赖是划分Stage的依据**。

判断阶段，要从后往前推

# 考点 5: Spark RDD Lineage / DAG 阶段划分

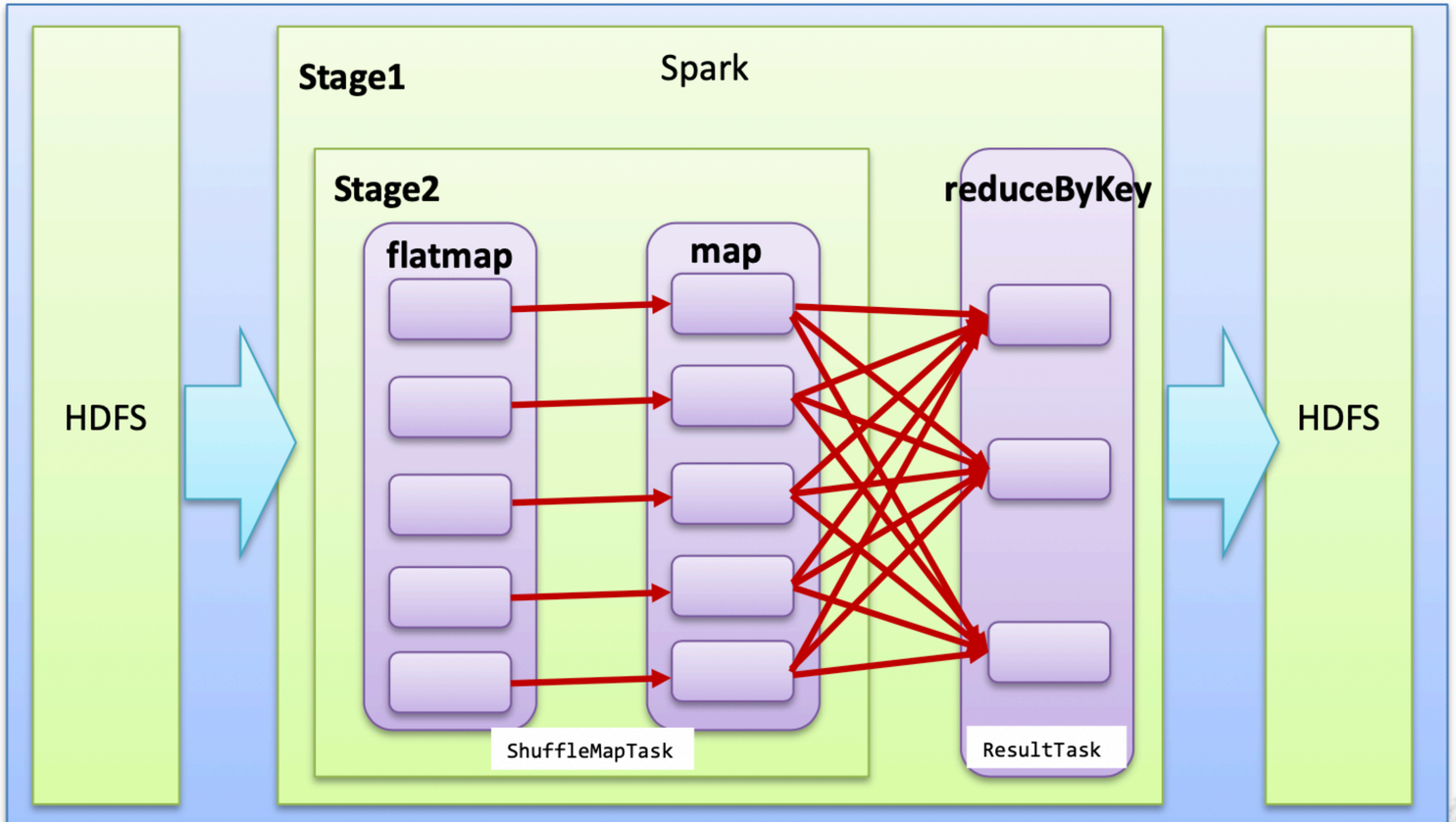


# 考点 5: Spark RDD Lineage / DAG 阶段划分

- Job：一个 Action 算子就会生成一个 Job
- Stage：根据 RDD 之间的依赖关系(DAG)的不同将 Job 划分成不同的 Stage，遇到一个宽依赖则划分一个 Stage。1 + num(shuffle)
- Task：一个 Stage 里面会有很多个 Task (一个分区就是一个 Task), 同一个阶段的 task 会并行计算

- 一个 Job 会有多个 Stage
- 一个 Stage 里面会有很多个 Task



# 考点 5.5：Spark RDD Lineage DAG 的区别

## Lineage vs. DAG in Spark

- They are both DAG (data structure)
- Different end nodes
- Different roles in Spark

1.Lineage 描述的是某一个 RDD 它的所有依赖关系
2.DAG 描述的是一个 Action 算子前所有 RDD 的依赖/阶段关系

# 考点 6: MapReduce Map/Reduce 过程 shuffle 过程

## 首先知道 MR job 工作的时候分为 MapTask 和 ReduceTask 两个阶段

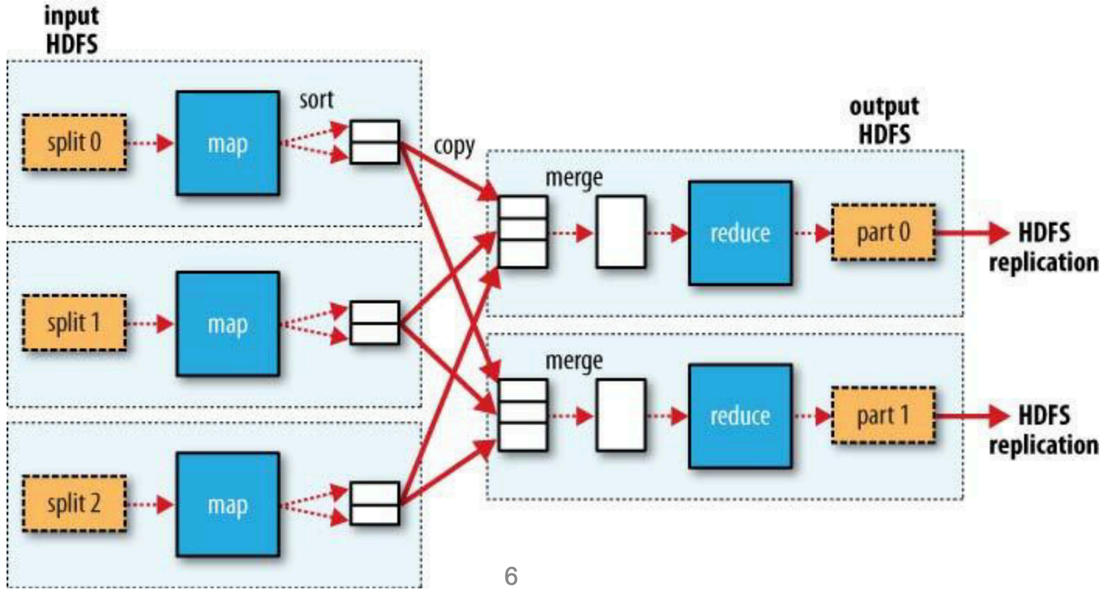
## MapReduce in Hadoop

- Map tasks write their output to local disk (not to HDFS)
  - Map output is intermediate output
  - Once the job is complete the map output can be thrown away
  - Storing it in HDFS with replication, would be overkill
  - If the node of map task fails, Hadoop will automatically rerun the map task on another node

- Reduce tasks don't have the advantage of data locality
  - Input to a single reduce task is normally the output from all mappers
  - Output of the reduce is stored in HDFS for reliability
  - The number of reduce tasks is not governed by the size of the input, but is specified independently

## More Detailed MapReduce Dataflow

- When there are multiple reducers, the map tasks partition their output:
  - One partition for each reduce task
  - The records for every key are all in a single partition
  - Partitioning can be controlled by a user-defined partitioning function



# 考点 6: MapReduce Map/Reduce 过程 shuffle 过程

MR 中 Shuffle 的意义在于： 把相同的 Key 聚合在一起，并对 Key 排序

## Shuffle in Hadoop (handled by framework)

- Happens between each Map and Reduce phase
- Use Shuffle and Sort mechanism
  - Results of each Mapper are sorted by the key
  - Starts as soon as each mapper finishes
- Use combiner to reduce the amount of data shuffled
  - Combiner combines key-value pairs with the same key in each par
  - This is not handled by framework!

考点 7: MapReduce Efficency 3 点

# The Efficiency of MapReduce in Spark

- Number of transformations
  - Each transformation involves a linearly scan of the dataset (RDD)
- Size of transformations
  - Smaller input size => less cost on linearly scan
- Shuffles
  - data transferring between partitions is costly
    - especially in a cluster!
      - Disk I/O
      - Data serialization and deserialization
      - Network I/O

押题：

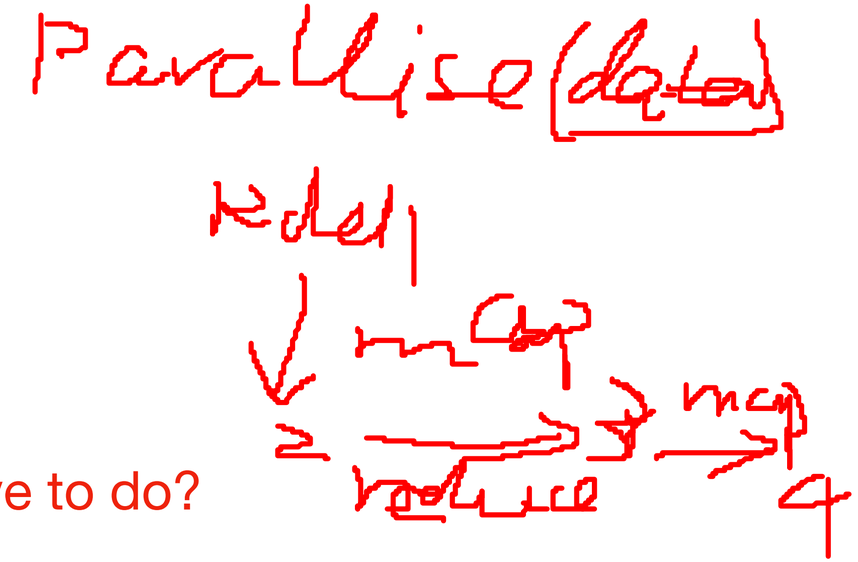
1. Describe the case where MR is not suitable for using compared with Spark and what is the main difference between these two?

2. Explain what is lazy evaluation in Spark and why its designed by this way?

3.Name three wide transformation and narrow transformation in Spark, explain their difference ?

4. Consider this scenario Draw the Linage Graph of RDD1：

```
data = ["hello", "world", "hello", "world", "word", "count", "hello"]
rdd1 = sc.parallelize(data)
rdd2 = rdd1.map(lambda word: (word, 1))
rdd3 = rdd2.reduceByKey(lambda a, b: a + b)
rdd4 = rdd3.map(lambda word: (word, 1))
```



5. Exaplain what happened in MR shuffle and why its expensive to do?

6. Exaplain what relations / difference between RDD and DataFrame?

极大可能出计算题，重在理解算法和流程

- **High Dimensional Similarity Search**

考点 1: LSH 概念 / 为什么要引入 LSH？

# Locality Sensitive Hashing

- Index: make the hash functions error tolerant
  - Similar data ⇒ same hash key (with high probability)
  - Dissimilar data ⇒ different hash keys (with high probability)
- Retrieval:
  - Compute the hash key for the query
  - Obtain all the data has the same key with query (i.e., candidates)
  - Find the nearest one to the query 对 Candidates 就要使用传统的距离计算公式
  - Cost:
    - Space: $O(n)$
    - Time: $O(1) + O(|cand|)$

# 考点 1: LSH 的两个重要部分

1.Hash Function 数学证明不需要掌握

2. Pr[h(q) = h(o)] 与不同距离公式的关系

3.And OR composition

# 考点 2: LSH functions- min hash

## MinHash - LSH Function for Jaccard Similarity

- Each data object is a set
  - $Jaccard(S_1, S_2) = \frac{|S_i \cap S_j|}{|S_i \cup S_j|}$
- Randomly generate a global order for all the elements in $C = \bigcup_1^n S_i$
- Let $h(S)$ be the minimal member of $S$ with respect to the global order
  - For example, $S = \{b, c, e, h, i\}$, we use inversed alphabet order, then re-ordered $S = \{i, h, e, c, b\}$, hence $h(S) = i$.

First Member

# 考点 2: LSH functions- min hash 的 pr 计算

## MinHash

- Now we compute $\Pr[h(S_1) = h(S_2)]$
- Every element $e \in S_1 \cup S_2$ has equal chance to be the first element among $S_1 \cup S_2$ after re-ordering
- $e \in S_1 \cap S_2$ if and only if $h(S_1) = h(S_2)$
- $e \notin S_1 \cap S_2$ if and only if $h(S_1) \neq h(S_2)$
- $\Pr[h(S_1) = h(S_2)] = Jaccard(S_1, S_2)$

$$\frac{|\{e_i | h_i(S_1) = h_i(S_2)\}|}{|\{e_i\}|} = \frac{|S_i \cap S_j|}{|S_i \cup S_j|} =$$

# Question 3 Finding Similar Items @696

Suppose we wish to find similar sets, and we apply locality-sensitive hashing with k=5 and l=2.

If two sets had Jaccard similarity 0.6, what is the probability that they will be identified in the locality-sensitive hashing as candidates (i.e. they hash at least once to the same super-hash)? You may assume that there are no coincidences, where two unequal values hash to the same hash value.

- The probability of $o$ is a nearest neighbor candidate of $q$ is
  - $1 - (1 - p_{q,o}^{k})^{l}$

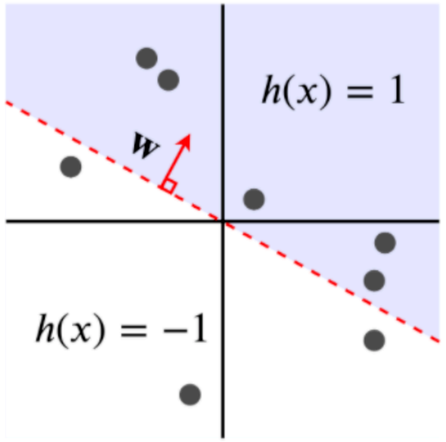
$1-(1-0.6^5)^2$

# 考点 2: LSH functions for different distance

Ass1 考过了不大可能考了

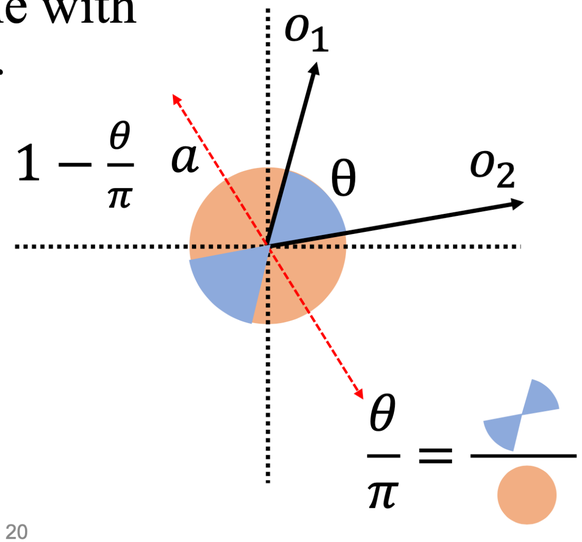
## SimHash – LSH Function for Angular Distance

- Each data object is a d dimensional vector
  - $\theta(x, y)$ is the angle between $x$ and $y$
- Randomly generate a normal vector $a$, where $a_i \sim N(0,1)$
- Let $h(x; a) = \text{sgn}(a^T x)$
  - $\text{sgn(o)} = \begin{cases} 1; if\ o \geq 0 \\ -1; if\ o < 0 \end{cases}$
  - $x$ lies on which side of $a$'s corresponding hyperplane




## SimHash

- Now we compute $\Pr[h(o_1) = h(o_2)]$
- $h(o_1) \neq h(o_2)$ iff $o_1$ and $o_2$ are on different sides of the hyperplane with $a$ as its normal vector
- $\Pr[h(o_1) = h(o_2)] = 1 - \frac{\theta}{\pi}$




$\frac{\theta}{\pi} =$ 

# 考点 2: LSH functions for different distance

很有可能在这里出题

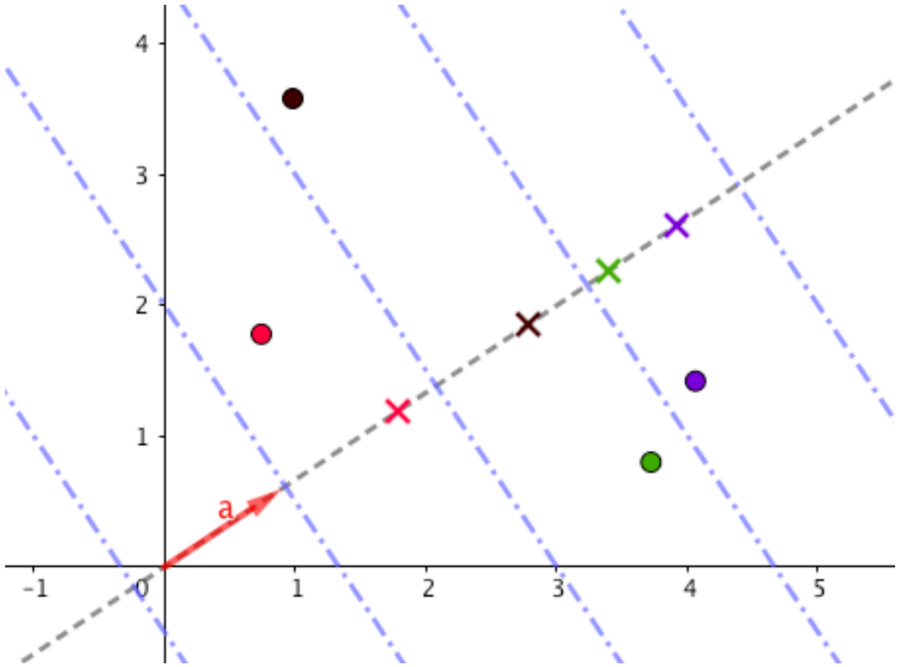
## p-stable LSH - LSH function for Euclidean distance

- Each data object is a d dimensional vector
  - $dist(x,y) = \sqrt{\sum_1^d (x_i - y_i)^2}$
- Randomly generate a normal vector $a$, where $a_i \sim N(0,1)$
  - Normal distribution is 2-stable, i.e., if $a_i \sim N(0,1)$, then $\sum_1^d a_i \cdot x_i \sim N(0, \|x\|_2^2)$
- Let $h(x;a,b) = \left\lfloor \frac{a^T x + b}{w} \right\rfloor$, where $b \sim U(0,1)$ and $w$ is user specified parameter
  - $\Pr[h(o_1;a,b) = h(o_2;a,b)] = \int_0^w \frac{1}{\|o_1,o_2\|} f_p\left(\frac{t}{\|o_1,o_2\|}\right)\left(1 - \frac{t}{w}\right) dt$
  - $f_p(\cdot)$ is the pdf of the absolute value of normal variable

# 考点 2: LSH functions for different distance

## p-stable LSH

- Intuition of p-stable LSH
  - Similar points have higher chance to be hashed together



Consider these data:

a = (2, -1)
b = 0.5
w = 4

- Let $h(x; a, b) = \left\lfloor \frac{a^T x + b}{w} \right\rfloor$;

| | Data | Hash | IfCandidate |
|---|---|---|---|
| **X1** | (1, 2) | 0 | Yes |
| **X2** | (-1, 3) | -2 | No |
| **X3** | (2, 2) | 0 | Yes |
| **Q** | (1, 1) | 0 | |

$$\left\lfloor \frac{(2,-1)(1,2)+0.5}{4} \right\rfloor$$

# 考点 2: AND-OR composition

- Recall for a single hash function, we have
  - $\Pr[h(o_1) = h(o_2)] = p(dist(o_1, o_2))$, denoted as $p_{o_1,o_2}$
- Now we consider two scenarios:
  - Combine $k$ hashes together, using AND operation
    - One must match all the hashes
    - $\Pr[H_{AND}(o_1) = H_{AND}(o_2)] = {p_{o_1,o_2}}^k$
  - Combine $l$ hashes together, using OR operation
    - One need to match at least one of the hashes
    - $\Pr[H_{OR}(o_1) = H_{OR}(o_2)] = 1 - (1 - p_{o_1,o_2})^l$
      - Not match only when all the hashes don't match

And : 生成 k 个 HashFunction 从而每个 data 对应一个 k 位的 hashcode

Or：重复 l 次得到 l 个hashtable, l 个 table 中只要有一个跟 Query 的Hash 相等即可被选为 candidate

K 是每一个 Data 对应的 HashCode 的 位数
相当于每次 hash 需要用的到 vector a 的个数

L 是 hash 的次数，hash L 次相当于生成了 L 个 HashTable 和 QueryCode
对于每一个 Data 只要这 L 个 HashCode 其中有一个与 QueryCode 匹配（每一位都匹配）
则这个 Data 就可以成为 Candidate

- The probability of $o$ is a nearest neighbor candidate of $q$ is
  - $1-(1-p_{q,o}^{k})^{l}$　　简单的二项分布问题

例子：

- Let $h(x; a, b) = \left\lfloor \frac{a^T x + b}{w} \right\rfloor$;

K = 1
L = 3

a = (2, -1)
b = 0.5
w = 4 table 1

| | Data | Hash | IfCandidate |
|---|---|---|---|
| **X1** | (1, 2) | 0 | Yes |
| **X2** | (-1, 3) | -2 | No |
| **X3** | (2, 2) | 0 | Yes |
| **Q** | (1, 1) | 0 | |

a = (1, 0)
b = 0.1
w = 2 table 2

| | Data | Hash | IfCandidate |
|---|---|---|---|
| **X1** | | | |
| **X2** | (-1, 3) | -1 | No |
| **X3** | | | |
| **Q** | (1, 1) | 0 | |

a = (1, 1)
b = 0.6
w = 100 table 3

| | Data | Hash | IfCandidate |
|---|---|---|---|
| **X1** | | | |
| **X2** | (-1, 3) | 0 | Yes |
| **X3** | | | |
| **Q** | (1, 1) | 0 | |

# The Drawback of LSH

- Concatenate k hashes is too "strong"
  - $h_{i,j}(o_1) \neq h_{i,j}(o_2) \Rightarrow H_i(q) \neq H_i(o)$ for any $j$
- Not adaptive to the distribution of the distances
  - What if not enough candidates?
  - Need to tune w (or build indexes different w's) to handle different cases

# 考点 3: False Positives and False Negatives

## False Positives and False Negatives

- False Positive:
  - returned data with $\mathrm{dist}(o, q) > r_2$
- False Negative
  - not returned data with $\mathrm{dist}(o, q) < r_1$
- They can be controlled by carefully chosen $k$ and $l$
  - It's a trade-off between space/time and accuracy

False positive： 某个 Data 本来不应该成为 Candidate， 却最终被选为 Candidate 了

False negative： 某个 Data 本来应该成为 Candidate， 却最终没被选为 Candidate

考点4:C2 LSH proj1 大家都比较熟悉

# The Framework of NNS using C2LSH

- Pre-processing
  - Generate LSH functions
    - Random normal vectors and random uniform values
- Index
  - Compute and store $h_i(o)$ for each data object $o$, $i \in \{1, \dots, m\}$
- Query
  - Compute $h_i(q)$ for query $q$, $i \in \{1, \dots, m\}$
  - Take those $o$ that shares at least $\alpha m$ hashes with $q$ as candidates
  - Relax the collision condition (e.g., virtual rehashing) and repeat the above step, until we got enough candidates

考点4:C2 LSH

# Pseudo code of Candidate Generation in C2LSH

```
candGen(data_hashes, query_hashes, αm, βn):
    offset ← 0
    cand ← ∅
    while true:
        for each (id, hashes) in data_hashes:
            if count(hashes, query_hashes, offset) ≥ αm:
                cand ← cand ∪ {id}
        if |cand| < βn:
            offset ← offset + 1
        else:
            break
    return cand
```

If match

# 考点4:C2 LSH

```
count(hashes_1, hashes_2, offset):
    counter ← 0
    for each hash_1, hash_2 in hashes_1, hashes_2:
        if |hash_1 − hash_2| ≤ offset:
            counter ← counter + 1
    return counter
```

假设 $\alpha m = 8$

考点4:C2 LSH

- At first consider $h(o) = h(q)$

Collision

HashCode(query)

| $q$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|
| $o_1$ | 1 | 0 | 2 | -1 | 1 | 2 | 4 | -3 | 0 | -1 |

- Consider $h(o) = h(q) \pm 1$ if not enough candidates

| $q$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|
| $o_1$ | 1 | 0 | 2 | -1 | 1 | 2 | 4 | -3 | 0 | -1 |

- Then $h(o) = h(q) \pm 2$ and so on…

| $q$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|
| $o_1$ | 1 | 0 | 2 | -1 | 1 | 2 | 4 | -3 | 0 | -1 |

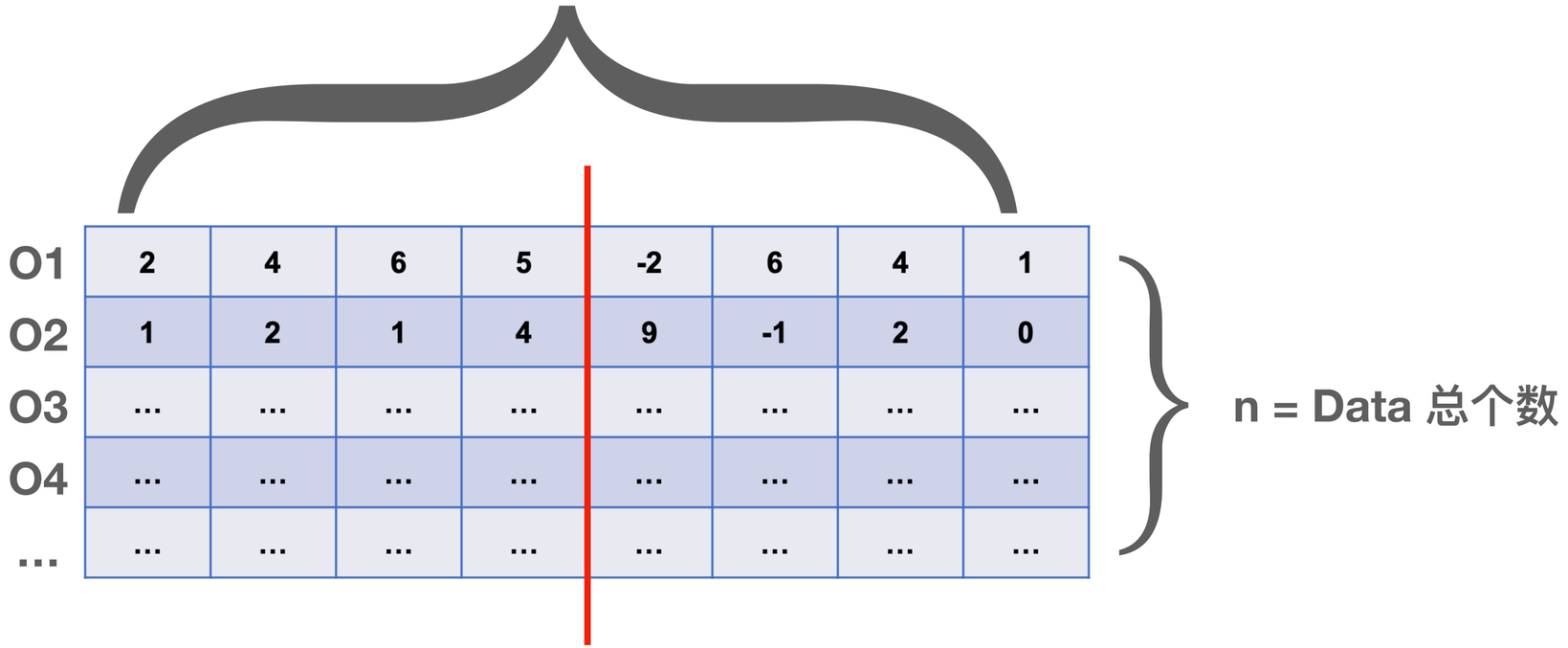
# Framework of PQ

- Pre-processing:
  - Step 1: partition data vectors
  - Step 2: generate codebooks (e.g., k-means)
  - Step 3: encode data

例子：

- Step 1: partition data vectors ✓

d = dimension 数 = 8




m = partiton 的个数 = 2

d/m = 每个分区的 dimension 数 = 4

例子：

- Step 2: generate codebooks (e.g., k-means)

使用 K-mean Cluster 的方法生成两个 codebook

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| O1 | 2 | 4 | 6 | 5 | -2 | 6 | 4 | 1 |
| O2 | 1 | 2 | 1 | 4 | 9 | -1 | 2 | 0 |
| O3 | … | … | … | … | … | … | … | … |
| O4 | … | … | … | … | … | … | … | … |
| … | … | … | … | … | … | … | … | … |

Codebook

| | | | | |
|---|---|---|---|---|
| $c_{1,0}$ | 2.1 | 3.6 | 5.3 | 6.6 |
| $c_{1,1}$ | 1.2 | 1.5 | 2.4 | 3.3 |
| $c_{1,2}$ | … | … | … | … |
| $c_{1,3}$ | … | … | … | … |

Codeword

| | | | | |
|---|---|---|---|---|
| $c_{2,0}$ | 3.3 | 4.1 | 2.7 | 1.4 |
| $c_{2,1}$ | … | … | … | … |
| $c_{2,2}$ | … | … | … | … |
| $c_{2,3}$ | … | … | … | … |

K = Center 的数量 = 4

d/m = 每个分区的 dimension 数 = 4

例子：

• Step 3: encode data

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| O1 | 2 | 4 | 6 | 5 | -2 | 6 | 4 | 1 |
| O2 | 1 | 2 | 1 | 4 | 9 | -1 | 2 | 0 |
| O3 | … | … | … | … | … | … | … | … |
| O4 | … | … | … | … | … | … | … | … |
| … | … | … | … | … | … | … | … | … |

| | | | | | |
|---|---|---|---|---|---|
| 00 | $c_{1,0}$ | 2.1 | 3.6 | 5.3 | 6.6 |
| 01 | $c_{1,1}$ | 1.2 | 1.5 | 2.4 | 3.3 |
| 10 | $c_{1,2}$ | … | … | … | … |
| 11 | $c_{1,3}$ | … | … | … | … |

| | | | | | |
|---|---|---|---|---|---|
| $c_{2,0}$ | 3.3 | 4.1 | 2.7 | 1.4 | 00 |
| $c_{2,1}$ | … | … | … | … | 01 |
| $c_{2,2}$ | … | … | … | … | 10 |
| $c_{2,3}$ | … | … | … | … | 11 |

| | |
|---|---|
| t1 | 00 |
| t2 | 01 |
| t3 | … |
| t4 | … |
| … | … |

每一个 Data 的每一个 Partition Vector
都对应 code book 里面的一个 center（codeword）
我们这个对应关系 encode 成 bit 的形式（节省存储空间）

| | |
|---|---|
| t1 | 00 → code 的位数 = Log k |
| t2 | 11 |
| t3 | … |
| t4 | … |
| … | … |

例子：

- Step 1: compute distance between q and codewords

| q | 1 | 3 | 5 | 4 | -3 | 7 | 3 | 2 |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| O1 | 2 | 4 | 6 | 5 | -2 | 6 | 4 | 1 |
| O2 | 1 | 2 | 1 | 4 | 9 | -1 | 2 | 0 |
| O3 | … | … | … | … | … | … | … | … |
| O4 | … | … | … | … | … | … | … | … |
| … | … | … | … | … | … | … | … | … |

| | | |
|---|---|---|
| t1 | 00 | 00 |
| t2 | 01 | 11 |
| t3 | … | … |
| t4 | … | … |
| … | … | … |

| | | | | | |
|---|---|---|---|---|---|
| 00 | $c_{1,0}$ | 2.1 | 3.6 | 5.3 | 6.6 |
| 01 | $c_{1,1}$ | 1.2 | 1.5 | 2.4 | 3.3 |
| 10 | $c_{1,2}$ | … | … | … | … |
| 11 | $c_{1,3}$ | … | … | … | … |

| | | | | | |
|---|---|---|---|---|---|
| $c_{2,0}$ | 3.3 | 4.1 | 2.7 | 1.4 | 00 |
| $c_{2,1}$ | … | … | … | … | 01 |
| $c_{2,2}$ | … | … | … | … | 10 |
| $c_{2,3}$ | … | … | … | … | 11 |

遍历 data 的 encode table 对于每一个 计算 $d^2(q,t) = \sum_{i=1}^{d}(q_i - p_i)^2$

以 t1 为例：

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2.1 | 3.6 | 5.3 | 6.6 | 3.3 | 4.1 | 2.7 | 1.4 |

每一位跟 q 相减，平方，加和

# Query Processing

- Compute ADC for every point in the database
  - How? 这里其实可以提前计算，并保存，避免重复计算
- Candidate = those with the $l$ smallest AD
- [Optional] Reranking (if $l > 1$):
  - Load the data vectors and compute the actual Euclidean distance
  - Return the one with the smallest distance

# Product Quantization

- Idea
  - Partition the dimension into m partitions
    - Accordingly a vector => subvectors
  - Use separate VQ with $k$ codewords for each chunk
- Example:
  - 8-dim vector decomposed into $m = 2$ subvectors
  - Each codebook has $k = 4$ codewords, (i.e., $c_{i,j}$)
  - Total space in bits:
    - Data: n $\cdot m \cdot log(k)$
    - Codebook: $m \cdot \frac{d}{m} \cdot k \cdot 32$

极大可能出大题，重在理解算法和流程

- **Data Streams**

考点1：Data Stream 和 传统 RDBMS 的对比

# DBMS vs. DSMS #2

- Traditional DBMS:
  - stored sets of relatively static records with no pre-defined notion of time
  - good for applications that require persistent data storage and complex querying
- DSMS
  - support on-line analysis of rapidly changing data streams
  - data stream: real-time, continuous, ordered (implicitly by arrival time or explicitly by timestamp) sequence of items, too large to store entirely, no ending
  - continuous queries

考点1：Data Stream 和 传统 RDBMS 的对比

# DBMS vs. DSMS #3

**DBMS**

- Persistent relations
  (relatively static, stored)
- One-time queries
- Random access
- “Unbounded” disk store
- Only current state matters
- No real-time services
- Relatively low update rate
- Data at any granularity
- Assume precise data
- Access plan determined by query processor, physical DB design

**DSMS**

- Transient streams
  (on-line analysis)
- Continuous queries (CQs)
- Sequential access
- Bounded main memory
- Historical data is important
- Real-time requirements
- Possibly multi-GB arrival rate
- Data at fine granularity
- Data stale/imprecise
- Unpredictable/variable data arrival and characteristics

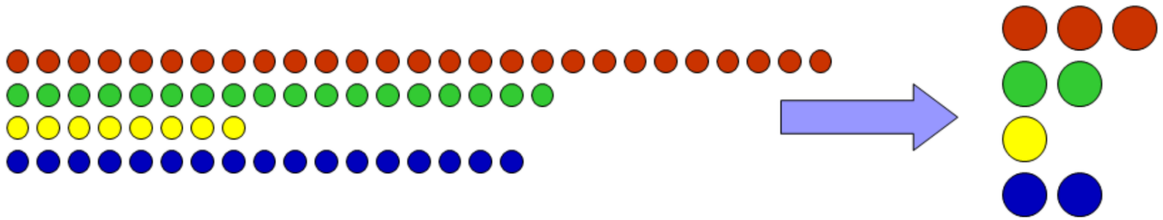
# 考点1.5：Data Stream 的三种查询类型

- Sampling
- Sliding window query
- Filtering

# 考点2：Sampling on Data Stream

## Sampling from a Data Stream

- Since we can not store the entire stream, one obvious approach is to store a **sample**



- Two different problems:
  - **(1)** Sample a **fixed proportion** of elements in the stream (say 1 in 10)
    - As the stream grows the sample also gets bigger
  - **(2)** Maintain a **random sample of fixed size** over a potentially infinite stream
    - As the stream grows, the sample is of fixed size
    - At any "time" ***t*** we would like a random sample of ***s*** elements
- **What is the property of the sample we want to maintain?**
  - For all time steps ***t***, each of ***t*** elements seen so far has equal probability of being sampled

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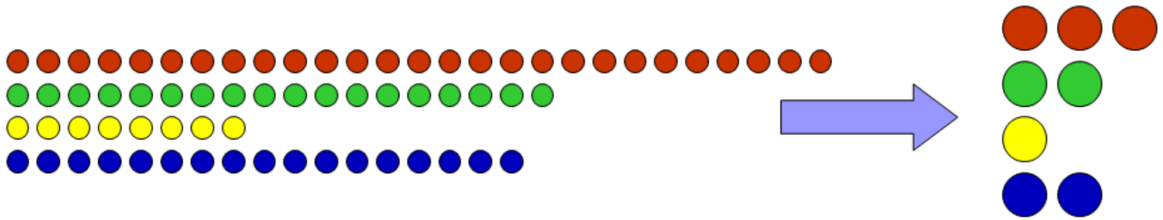

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    - At any "time" ***t*** we would like a random sample of ***s*** elements
- **What is the property of the sample we want to maintain?**
  - For all time steps ***t***, each of ***t*** elements seen so far has equal probability of being sampled

# Generalized Problem and Solution

- Problem: Give a data stream, take a sample of fraction a/b.
- Stream of tuples with keys:
  - Key is some subset of each tuple's components
    - e.g., tuple is (user, search, time); key is **user**
  - Choice of key depends on application
- To get a sample of a/b fraction of the stream:
  - Hash each tuple's key uniformly into ***b*** buckets
  - Pick the tuple if its hash value is at most ***a***

**How to generate a 30% sample?**

Hash into b=10 buckets, take the tuple if it hashes to one of the first 3 buckets

# 考点2：Sampling on Data Stream (fix size) 水塘抽样

## Solution: Fixed Size Sample

水塘抽样

- **Algorithm (a.k.a. Reservoir Sampling)**
  - Store all the first ***s*** elements of the stream to ***S***
  - Suppose we have seen ***n-1*** elements, and now the ***n$^{th}$*** element arrives (***n*** > ***s***)
    - With probability ***s/n***, keep the ***n$^{th}$*** element, else discard it
    - If we picked the ***n$^{th}$*** element, then it replaces one of the ***s*** elements in the sample ***S***, picked uniformly at random

- **Claim:** This algorithm maintains a sample ***S*** with the desired property:
  - After ***n*** elements, the sample contains each element seen so far with probability ***s/n***

# 考点2：Sampling on Data Stream (fix size) 水塘抽样

假设 Data Stream 流有1亿个， 我们的内存只够存 3 个
通过水塘抽样，保证1亿条数据过去后，随机抽取 3 个 Data 存下来：

一开始从空开始接受数据，前三条数据100%留下来
从第四条开始：
4th 有 3/4 的概率留下来
5th 有 3/5 的概率留下来
6th 有 3/6 的概率留下来
…
nth 有 3/n 的概率留下来

一旦确定某条数据留下来，原来存下来的3条，有相同的概率被新的替换

这样看来好像每一次的概率并不相等, 其实并不是这样
我们要看的是最终进入 S 中的概率
虽然第4个数进入set的概率比较大,但是到最后他被替换的概率也很大
每一个数留下来的概率都是 S/N （数学证明不大可能考）

考点3 :Sliding Window

# Sliding Windows

- A useful model of stream processing is that queries are about a ***window*** of length ***N*** – the ***N*** most recent elements received
- Interesting case: ***N*** is so large that the data cannot be stored in memory, or even on disk
  - Or, there are so many streams that windows for all cannot be stored

# 考点3 :Sliding Window

- A useful model of stream processing is that queries are about a ***window*** of length ***N*** – the ***N*** most recent elements received

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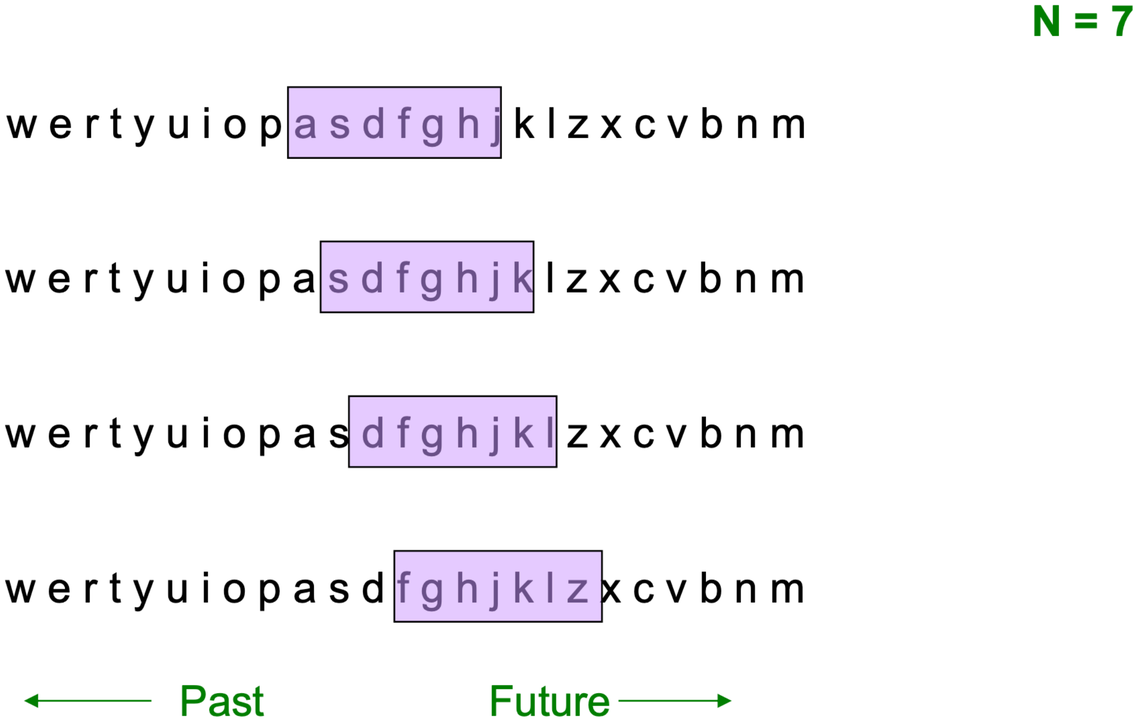
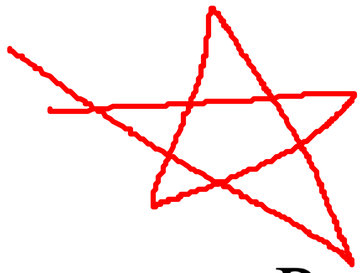
  - Or, there are so many streams that windows for all cannot be stored





# 考点4：Sliding Window - DGIM 算法流程

- Problem:
  - Given a stream of **0**s and **1**s
  - Be prepared to answer queries of the form: **How many 1s are in the last *k* bits?** where $k \leq N$

+

**What if we cannot afford to store *N* bits?**

- **E.g.**, we're processing 1 billion streams and $N$ = **1 billion**

=

DGIM Algorithm

# 考点4：Sliding Window - DGIM 算法流程

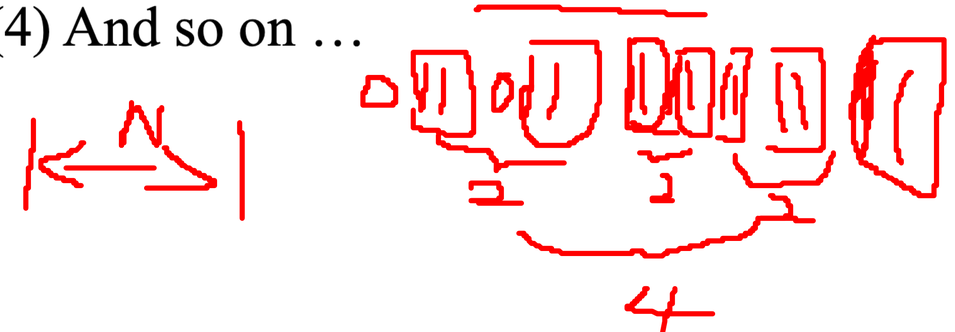
## Representing a Stream by Buckets

- The right end of a bucket is always a position with a 1
- Every position with a 1 is in some bucket 也就是说有些0是不在 bucket 里面的
- Either **one** or **two** buckets with the same **power-of-2 number** of **1s**
- Buckets do not overlap in timestamps
- **Buckets are sorted by size** N大→小
  - Earlier buckets are not smaller than later buckets
- Buckets disappear when their end-time is > $N$ time units in the past

# 考点4：Sliding Window - DGIM 算法流程-更新

## Updating Buckets

- When a new bit comes in, drop the last (oldest) bucket if its end-time is prior to $N$ time units before the current time
- 2 cases: Current bit is **0** or **1**
- If the current bit is 0: no other changes are needed
- If the current bit is 1:
  - (1) Create a new bucket of size 1, for just this bit
    - End timestamp = current time
  - (2) If there are now three buckets of size 1, combine the oldest two into a bucket of size 2
  - (3) If there are now three buckets of size 2, combine the oldest two into a bucket of size 4
  - (4) And so on …

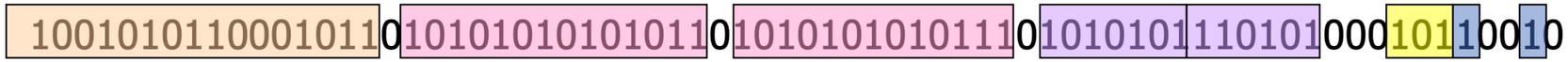


# 考点4：Sliding Window - DGIM 算法流程-更新

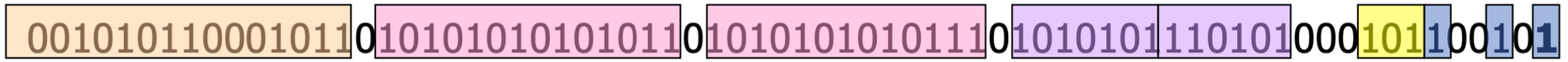
## Demo

### Example: Updating Buckets

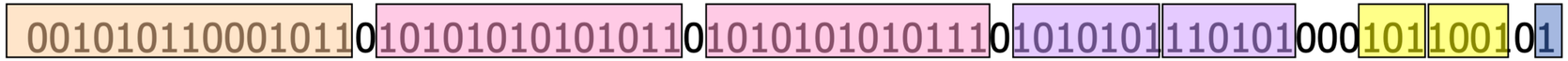
**Current state of the stream:**



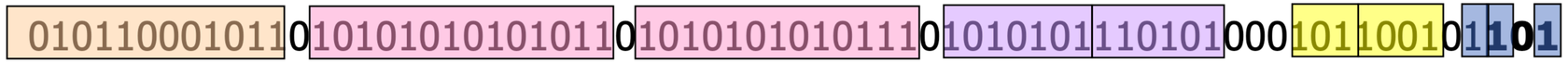

**Bit of value 1 arrives**



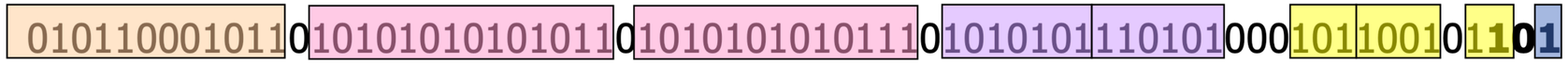

**Two white buckets get merged into a yellow bucket**



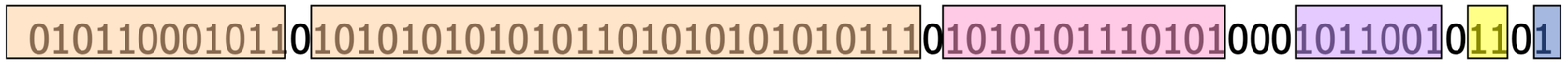

**Next bit 1 arrives, new orange white is created, then 0 comes, then 1:**




**Buckets get merged…**




**State of the buckets after merging**

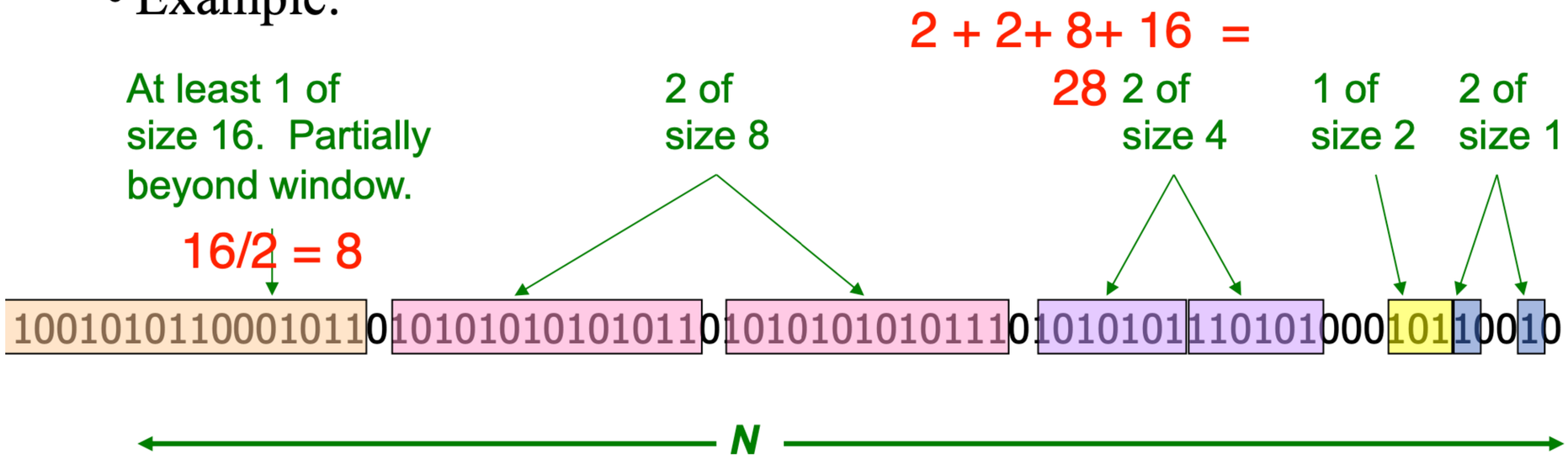


# 考点5：Sliding Window - DGIM 算法流程-query

## How to Query?

- Solution gives approximate answer, never off by more than 50%

- To estimate the number of 1s in the most recent N bits:
  - Sum the sizes of all buckets but the last
    - (note "size" means the number of 1s in the bucket)
  - Add half the size of the last bucket
- Remember: We do not know how many 1s of the last bucket are still within the wanted window
- Example:



考点6 : Sliding Window - DGIM Bucket 的时间戳

# DGIM: Timestamps

- Each bit in the stream has a timestamp, starting from **1**, **2**, …
- Record timestamps modulo $N$ (**the window size**), so we can represent any **relevant** timestamp in $O(\log_2 N)$ bits 0 <= timestamp mod N <= N - 1
  - E.g., given the windows size 40 ($N$), timestamp 123 will be recorded as 3, and thus the encoding is on 3 rather than 123

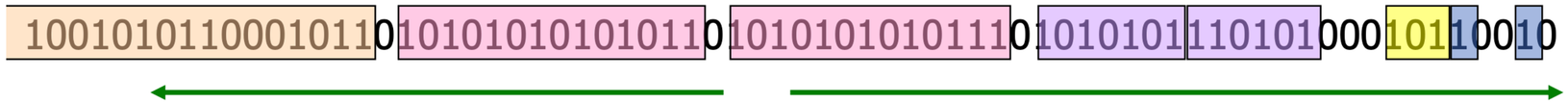
# 考点7：Sliding Window - DGIM Bucket 的表示 / 单个bucket的空间复杂度

## DGIM: Buckets

只需要把最右一位 bit 的timestamp 作为这个 bucket 的 timestamp

- A bucket in the DGIM method is a record consisting of:
  - (A) The timestamp of its end [$O(\log N)$ bits] 0 <= 时间戳 mod N <= N - 1
  - (B) The number of 1s between its beginning and end [$O(\log\log N)$ bits]
- Constraint on buckets:
  - Number of 1s must be a power of 2
  - That explains the $O(\log\log N)$ in (B) above

N = 2 ** r
r = log(N)
可以用 log( r ) bit 来表示 r



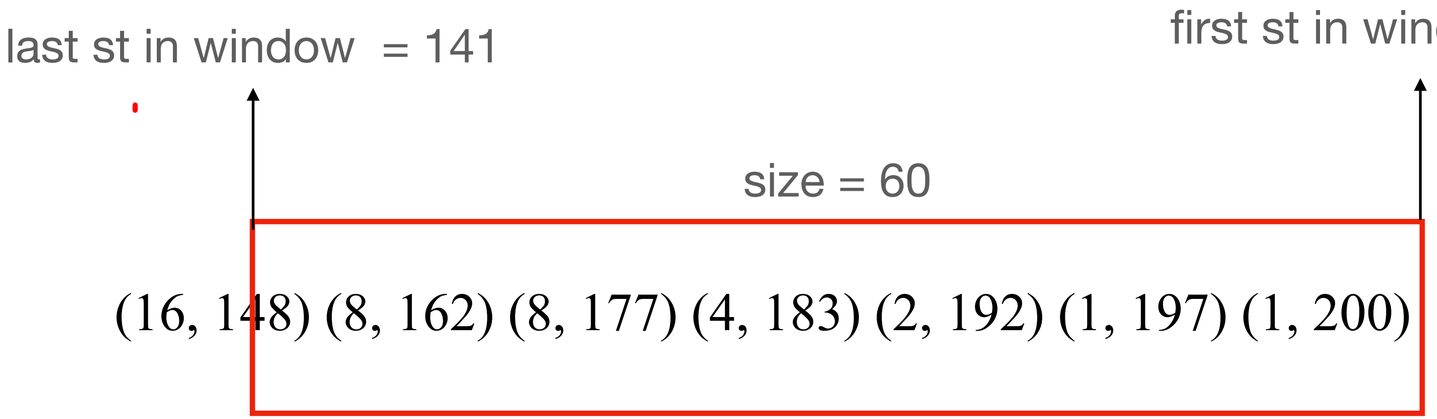

https://blog.csdn.net/tongtao_123/article/details/79959141

# Question 4 Mining Data Streams

Suppose we are maintaining a count of 1s using the DGIM method. We represent a bucket by (i, t), where i is the number of 1s in the bucket and t is the bucket timestamp (time of the most recent 1).

Consider that the current time is 200, window size is 60, and the current list of buckets is: (16, 148) (8, 162) (8, 177) (4, 183) (2, 192) (1, 197) (1, 200). At the next ten clocks, 201 through 210, the stream has 0101010101. What will the sequence of buckets be at the end of these ten inputs?

答：




| 201 | 202 | 203 | 204 | 205 | 206 | 207 | 208 | 209 | 210 |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 |

# Answer

There are 5 1s in the stream. Each one will update to windows to be: [each step 2 marks]

- (1) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(1, 197)(1, 200), (1, 202)

=> (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1, 202)

- (2) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1, 202), (1, 204)
- (3) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1, 202), (1, 204), (1; 206)

=> (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (2, 204), (1, 206)

=> (16, 148)(8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206)

- (4) Windows Size is 60, so (16,148) should be dropped.

(16, 148)(8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208) => (8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208)

- (5) (8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208), (1, 210)

=> (8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (2, 208), (1, 210)

# 考点 8：Bloom Filtering 布隆过滤器-算法流程

## Filtering Data Streams

- Each element of data stream is a tuple
- Given a list of keys **S**
- **Determine which tuples of stream are in *S***

- Obvious solution: Hash table
  - But suppose we **do not have enough memory** to store all of ***S*** in a hash table
    - E.g., we might be processing millions of filters on the same stream

# 考点 8：Bloom Filtering 布隆过滤器-算法流程

## Bloom Filter Example

Size of bucket n = 10　　size of bucket = 2

- Consider a Bloom filter of size m = 10 and number of hash functions k=3. Let H(x) denote the result of the three hash functions.
- The 10-bit array is initialized as below

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

- Insert $x_0$ with $H(x_0) = \{1, 4, 9\}$

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |

- Insert $x_1$ with $H(x_1) = \{4, 5, 8\}$

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 |

- Query $y_0$ with $H(y_0) = \{0, 4, 8\}$ => ???
- Query $y_1$ with $H(y_1) = \{1, 5, 8\}$ => ???　　**False positive!**

- Another Example: https://llimllib.github.io/bloomfilter-tutorial/

# 考点 8：Bloom Filtering 布隆过滤器-算法流程

## Bloom Filter

- Consider: $|\mathbf{S}| = m$, $|\mathbf{B}| = n$
- Use $k$ independent hash functions $h_1, \ldots, h_k$
- **Initialization:**
  - Set **B** to all **0s**
  - Hash each element $s \in S$ using each hash function $h_i$, set $\mathbf{B}[h_i(s)] = 1$ (for each $i = 1, .., k$)
- **Run-time:**
  - When a stream element with key $x$ arrives
    - If $\mathbf{B}[h_i(x)] = 1$ for all $i = 1, ..., k$ then declare that $x$ is in $S$
      - That is, $x$ hashes to a bucket set to **1** for every hash function $h_i(x)$
    - Otherwise discard the element $x$

# 考点 8：Bloom Filtering 布隆的特点

- **Creates false positives but no false negatives**
  - If the item is in ***S*** we surely output it, if not we may still output it

False positive： 某个 Data 本来不应该成为 Candidate， 却最终被选为 Candidate 了

False negative： 某个 Data 本来应该成为 Candidate， 却最终没被选为 Candidate

推荐阅读： https://blog.csdn.net/jiaomeng/article/details/1495500

# Bloom Filter – Analysis

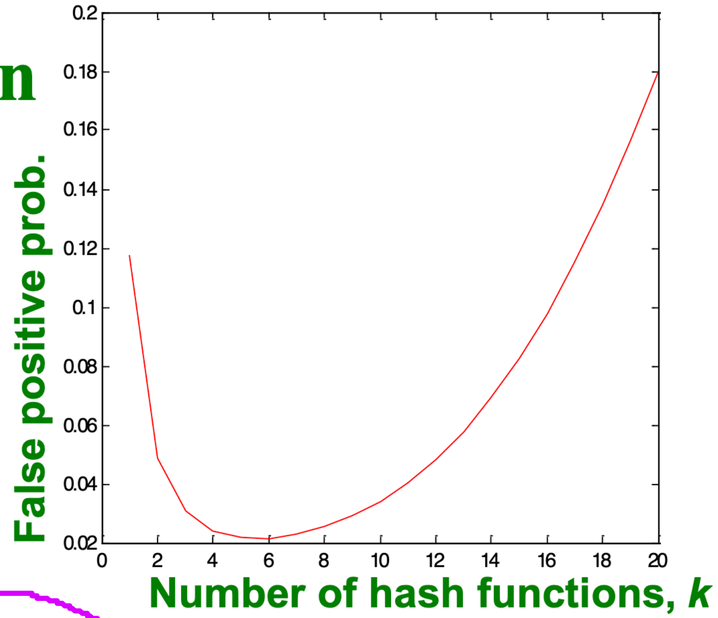
- **What fraction of the bit vector B are 1s?**
  - Throwing $k \cdot m$ darts at $n$ targets
  - So fraction of **1**s is $(1 - e^{-km/n})$
- But we have $k$ independent hash functions and we only let the element $x$ through **if all** $k$ hash element $x$ to a bucket of value **1**
- So, false **positive probability** = $(1 - e^{-km/n})^k$

# 考点 8：Bloom Filtering 布隆的错误率估计 / 最优的哈希函数个数

## Bloom Filter – Analysis (2)

- ***m* = 1 billion, *n* = 8 billion**
  - **k = 1**: $(1 - e^{-1/8}) = 0.1175$
  - **k = 2**: $(1 - e^{-1/4})^2 = 0.0493$

- **What happens as we keep increasing *k*?**




- "Optimal" value of ***k***: ***n/m* ln(2)**
  - **In our case:** Optimal **k = 8 ln(2) = 5.54 ≈ 6**
    - **Error at k = 6**: $(1 - e^{-1/6})^2 = 0.0235$