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Lecture 2

BU.330.740 Large Scale Computing on the Cloud

Minghong Xu, PhD.
Associate Professor

AWS Academy Courses

- AWS Academy invitations has been sent to you
- Use “@jh.edu”, no “@jhu.edu”
- **AWS academy learner lab [104575]**
  - $50 credit per student
  - Limited AWS services, some advanced features/instances are blocked
- Cloud foundations course [104574]
  - Overall introduction to all AWS services and cloud architecture
  - Voucher policy: https://www.awsacademy.com/forums/s/article/How-Learners-Can-Secure-Exam-Vouchers-through-the-AWS-Emerging-Talent-Community

Today's Agenda and Reminders

- MapReduce Framework
- Frequent Itemset Mining
- Lab1: AWS S3, EC2 and EMR
  - On-premise computing vs cloud computing, different mode, different experience
  - **It is normal to feel lost at first time**

- Submit your team roster if you have not done so

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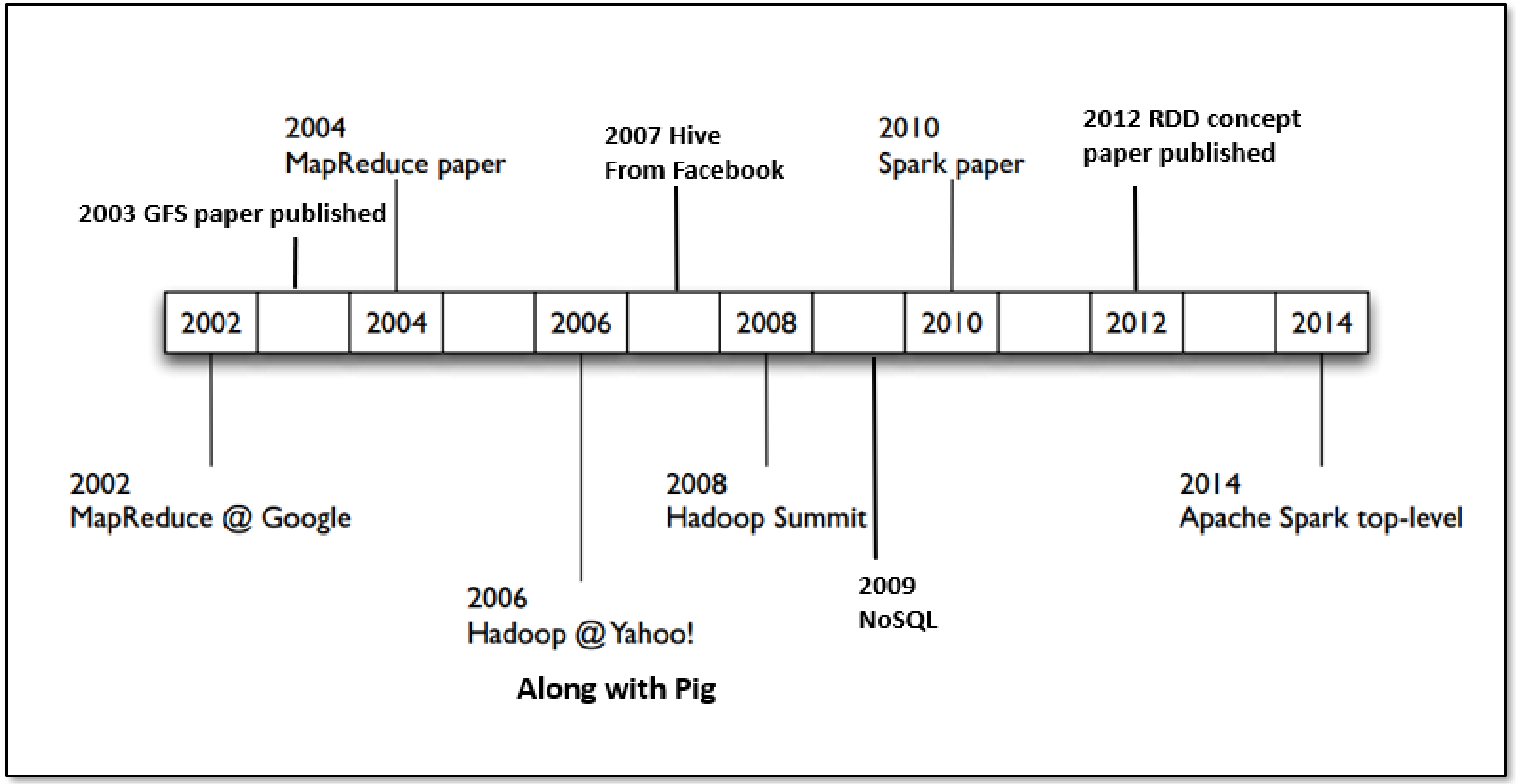
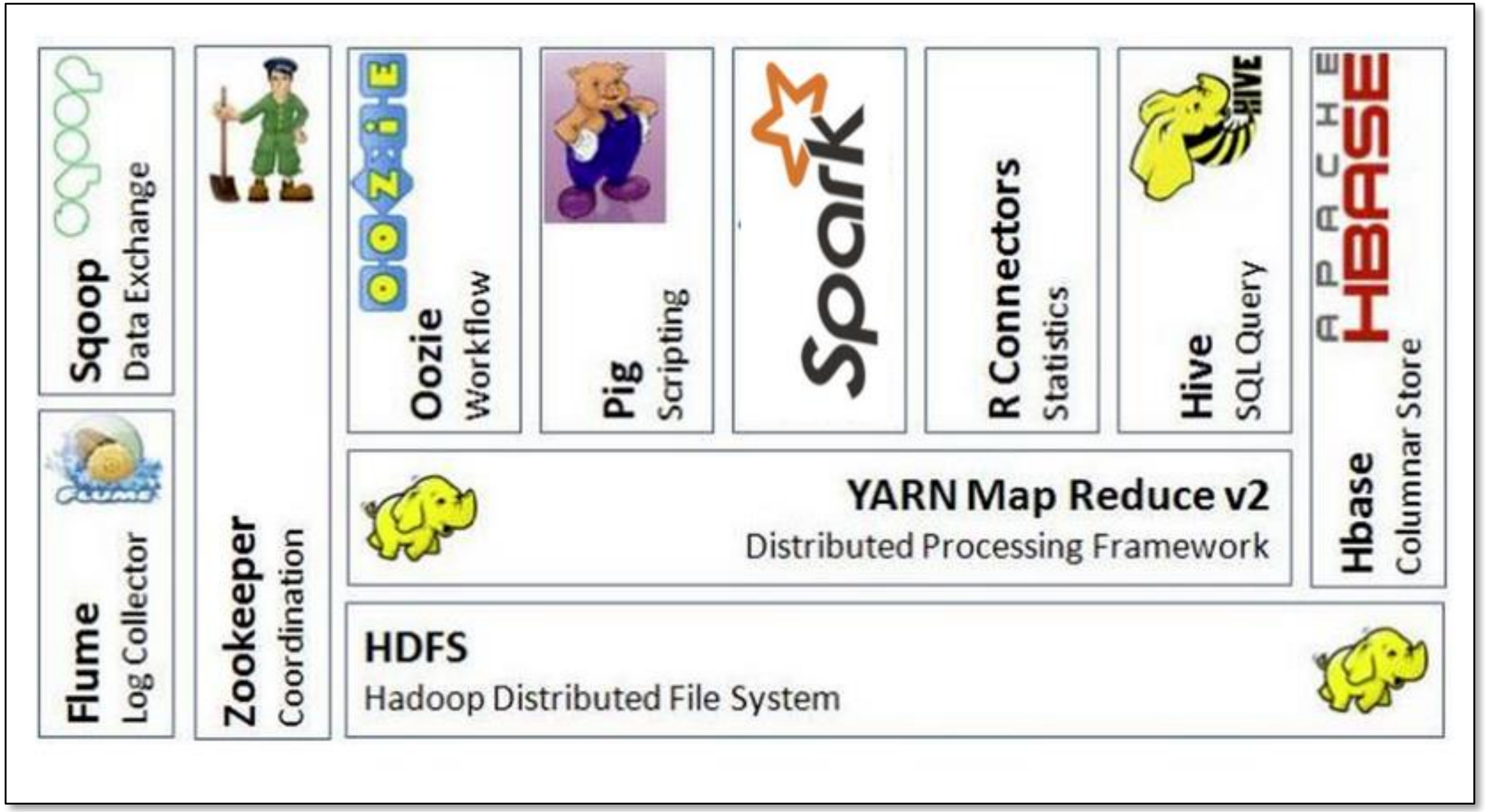
MapReduce Framework

Big Data Timeline



From BU.520.710 AI Essentials for Business

Hadoop Ecosystem



From BU.520.710 AI Essentials for Business

Distributed Processing: Parallelization

- Basic idea: Divide and Conquer
- One machine is not enough to process the data
  - Any company can have more than TBs of data
- Need to distribute the computing over several machines
  - E.g. AlphaZero uses 5000 nodes in parallel
- Basic questions: *How to divide? How to aggregate?*

Map and Reduce

- Map: the **divide** step
- Function to do map is called mapper

- Reduce: the **aggregate** step
- Function to do reduce is caller reducer

- Data processed by mapper and reducer is in the (key, value) format

Key Value Pair

- Recall: Python dictionary

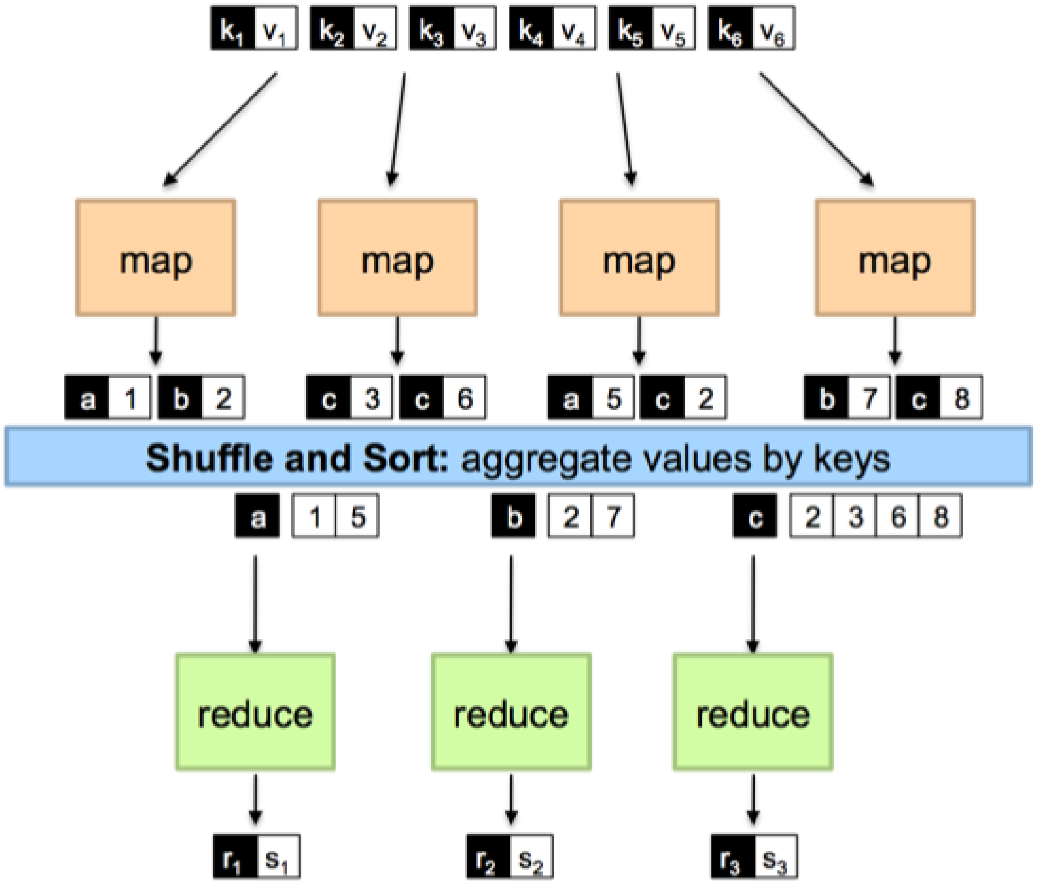
```
scoreBook={}
scoreBook["John"]=80
scoreBook["Jack"]=75

print(scoreBook)
print("Jack receives %s from my course" % convert2letter(scoreBook["Jack"]))
```

```
{'John': 80, 'Jack': 75}
Jack receives C from my course
```

- **Everything** in MapReduce is expressed using key value pair

Illustration



- Programmers define the key and value
- Mapper output a collection of key-value pairs which are input for the reducer
- Output from mapper is shuffled such that all same-key records go to same reducer
- Each reducer group records based on keys, then process each group of values and generate output
- Note: each reducer may receive multiple key sets

Word Count Example: Mapper

- **For example, count the occurrence of each word**
- Each mapper takes a line as input and breaks it into **words**
- Input: each line of the file
  - Key: line #
  - Value: the content of the line
  - Example: "I am a student at Carey Business School and I love Carey "
- Output: a set of key-value pairs
  - Key: one word
  - Value: 1
  - Example: (I, 1), (am, 1), (a, 1), (student, 1), (at, 1), (Carey, 1), (Business, 1), (School, 1), (and, 1), (I, 1), (love, 1), (Carey, 1)

Word Count Example: Reducer

- Each reducer sums the counts for each word
- Input example
  - (I, 1), (am, 1), (a, 1), (student, 1), (at, 1), (Carey, 1), (Business, 1), (School, 1), (and, 1), (I, 1), (love, 1), (Carey, 1)
- Output
  - Key: one word
  - Value: count of word
  - Example: (I, 2), (am, 1), (a, 1), (student, 1), (at, 1), (Carey, 2), (Business, 1), (School, 1), (and, 1), (love, 1)

Exercise

- Input: Final scores from different courses
- Output: Average score for each student

- You know how to achieve it using SQL
- Design it in a MapReduce style

Course ID	Student ID	Score
330740	A	100
330740	B	90
330740	C	80
330760	B	70
330760	C	60
330760	D	50
…	…	…

Exercise (Cont.)

- Mapper
  - Key:
  - Value:

- Reducer
  - Key:
  - Value:
  - Operation:

More About MapReduce

- *What is Google's incentive to design MapReduce?*
  - Refer to Appendix for PageRank and other algorithms built on MapReduce

- Chaining jobs: many problems can be solved with MapReduce by writing **several MapReduce jobs** which run in series to accomplish a goal
  - Each iteration can use the previous iteration's output as input
  - map1->reduce1->map2->reduce2->...

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Frequent Itemset Mining

Items Purchased Together

- *How companies like Amazon and Walmart know what products are frequently bought together?*
- Previous study reveals most frequent pair of products in store purchase

  - If customer purchase diaper, it's very likely he will also want beer
  - So let's make recommendation based on it
  - Or simply move them closer

https://bigdatabigworld.wordpress.com/2014/11/25/beer-and-nappies/

Frequent Itemset Mining

- Association rule learning/Market basket model/Apriori algorithm
- An unsupervised approach

- Item and basket (also called transaction)
  - Each basket contains a set of items (itemset)
- Assumptions:
  - The number of items in a basket is much smaller than the total number of items
  - The number of baskets are very large

An example

Transaction 1: {milk, bread, cereal}

Transaction 2: {milk, sugar, bread, eggs}

Transaction 3: {milk, bread, butter}

Transaction 4: {sugar, eggs}

Transaction 5: {strawberry, yogurt, cereal, blueberry}

Transaction 6: {strawberry, milk}

Support

- A set of items that appears in many baskets is said to be "frequent"

- Assume there is a number *s*, called the *support threshold*
- If *I* is a set of items, the *support* for *I* is the number of baskets for which *I* is a subset
- We say *I* is frequent if its support is *s* or more

Frequent Singletons

- Among the singleton sets, obviously {milk} and {bread} are quite frequent.
  - {milk} support is 4
  - {bread} support is 3
  - {cereal} support is 2
  - {sugar} support is 2
  - …
  - If we set threshold *s* = 3
    - Two frequent singleton itemsets: {milk}, {bread}

Transaction 1: {milk, bread, cereal}
Transaction 2: {milk, sugar, bread, eggs}
Transaction 3: {milk, bread, butter}
Transaction 4: {sugar, eggs}
Transaction 5: {strawberry, yogurt, cereal, blueberry}
Transaction 6: {strawberry, milk}

Frequent Doubletons

- {milk, bread} support=?
- {milk, cereal} support=?
- {sugar, eggs} support=?
- …
- If we set threshold *s* = 3?

Transaction 1: {milk, bread, cereal}
Transaction 2: {milk, sugar, bread, eggs}
Transaction 3: {milk, bread, butter}
Transaction 4: {sugar, eggs}
Transaction 5: {strawberry, yogurt, cereal, blueberry}
Transaction 6: {strawberry, milk}

Frequent Triples

- {milk, bread, cereal} support=?
- {milk, sugar, eggs} support=?
- {sugar, yogurt, eggs} support=?
- …

Transaction 1: {milk, bread, cereal}
Transaction 2: {milk, sugar, bread, eggs}
Transaction 3: {milk, bread, butter}
Transaction 4: {sugar, eggs}
Transaction 5: {strawberry, yogurt, cereal, blueberry}
Transaction 6: {strawberry, milk}

MapReduce Design - Singletons

- Mapper
  - Key:
  - Value:

- Reducer
  - Key:
  - Value:
  - Operation:

MapReduce Design - Doubletons

- Pseudocode and Python code will be given to you in lab 1
- You need to describe it in Assignment 1 Question 1
  - Hint: you need to get a pair of items

- Triples not required for this course
  - Reference: https://github.com/gautamdasika/Aprioiri-frequent-3-itemsets-with-Hadoop-MapReduce

Plagiarism Check

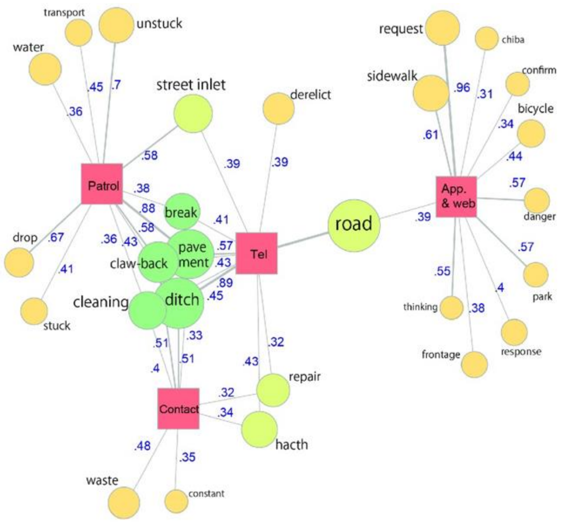
- Suppose we have

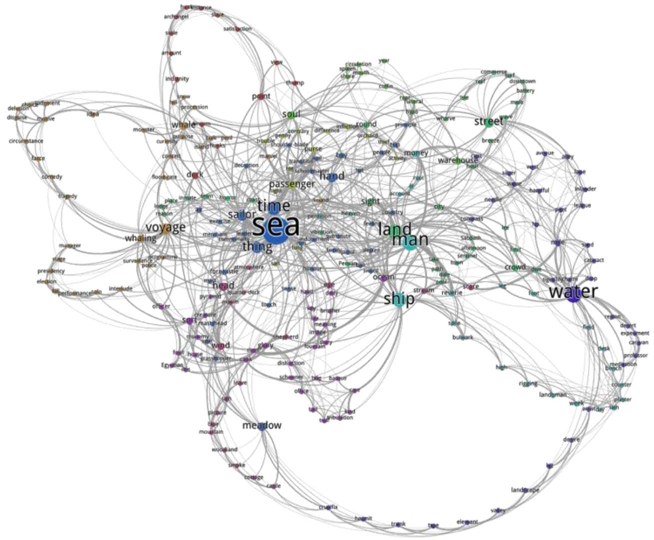
```
Article 1: sentence 1, sentence 2, sentence 3, …
Article 2: sentence 4, sentence 5, sentence 6, …
Article 3: sentence 7, sentence 8, sentence 9, …
Article 4: sentence 1, sentence 5, sentence 8, …
```

- We want to find out two articles having highest matching content
- *What is the transaction/basket? What is the item?*
- Assignment 1 Question 2
  - Hint: you will need to chain two MapReduce jobs

Association Rule Use Cases

- Co-occurrence analysis in text mining
- *How to figure out Elon Musk and Tesla are related?*
  - Humans may know it from our experience
  - How can machine learn it?
- Count number of articles that have different named entities co-occur





Discussion Time

- *Brainstorming other use cases of association rules*

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Lab 1: AWS S3, EC2 and EMR

AWS Services

- S3: Simple Storage Service
  - Cloud storage service by Amazon
  - https://aws.amazon.com/s3/
- EC2: Elastic Computer Cloud
  - Cloud computing service by Amazon
  - Choice of processor, storage, networking, operating system, etc.
  - https://aws.amazon.com/ec2/
- EMR: Elastic MapReduce
  - Cloud big data platform
  - https://aws.amazon.com/emr/
- Price table: https://aws.amazon.com/pricing/services/

Amazon S3

- Object-level storage
  - If you want to change a part of a file, you must make the change and then reupload the entire modified file
- Stores data as objects within resources called **buckets**
- Bucket name:
  - Universal and unique across all existing bucket names in Amazon S3
  - All lowercase with letters, numbers, dashes; symbols not allowed

EC2: Instance Type

- The instance type that you choose determines
  - Memory
  - Processing power (CPU)
  - Disk space and disk type (storage)
  - Network performance (bandwidth)
- https://aws.amazon.com/ec2/instance-types/
- https://aws.amazon.com/ec2/capacityblocks/pricing/

Instance Type (Cont.)

Instance type naming

- Example: t3.large
- T is the family name
- 3 is the generation number
- Large is the size

	General Purpose	Compute Optimized	Memory Optimized	Accelerated Computing	Storage Optimized
Instance Types	**a1, m4, m5, t2, t3**	**c4, c5**	**r4, r5, x1, z1**	**f1, g3, g4, p2, p3**	**d2, h1, i3**
Use Case	**Broad**	**High performance**	**In-memory databases**	**Machine learning**	**Distributed file systems**

EC2: Key Pair (Optional)

- **Note**: create your own key pair on EC2 if you register your own account on AWS
- We will use learner account key
- A key pair consists of
  - A public key that AWS stores
  - A private key that you store
- It enables secure connections to the instance
- Download if you create a new key pair
  - Save in a safe location
  - Only opportunity for you to save the private key file

MapReduce on AWS

- High level work flow:
  1. Store the data you want to process on AWS
     - Service to use: S3
  2. Create a computing cluster on AWS
     - Services to use: EC2, EMR
  3. Run your large scale computing program on the cluster
- It takes long for AWS to provision, thus we will switch step 1 and step 2 in lab

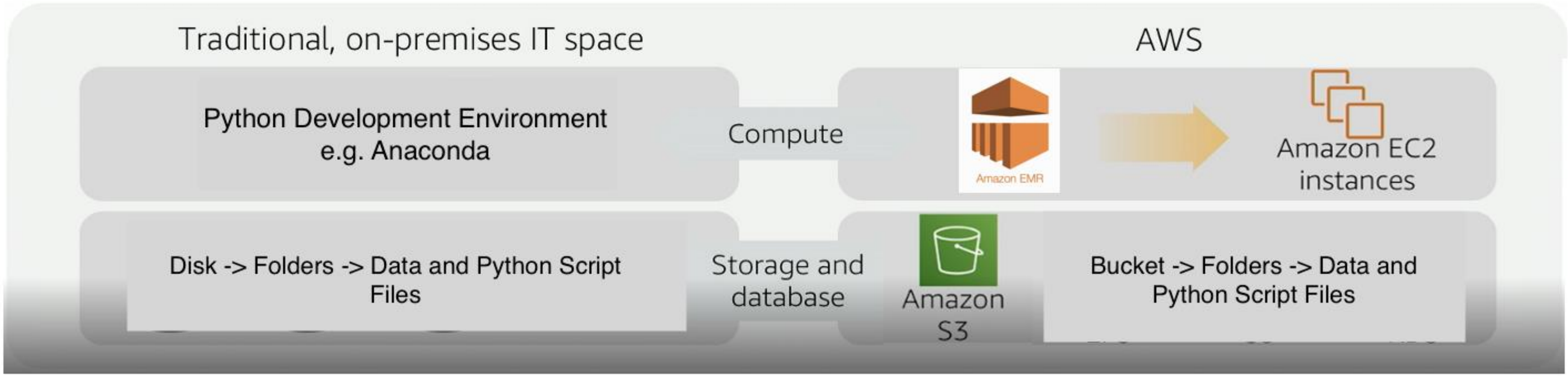
How to: Storage

- Create a S3 bucket
  - As you find an available space on your local disk
- Create a folder for input data to store your data file
  - As you create a new folder on the available disk, then move data files into it
- Create a folder for program scripts to store your script files
  - Same thing as step 2, but for .py files

How to: Compute

- Set up an EMR cluster
  - As you open a Python IDLE
  - Request some instances (machines/nodes), of certain types
- Add a step in cluster
  - As you run a Python program, but here MapReduce job

AWS Steps vs On-Premise Steps



- **Do not use blank space in any file/folder names on AWS**
- Blank/spaces cause troubles in programming

Hadoop Streaming

- A utility that comes with the Hadoop distribution
- It is a generic API which allows writing MapReduce in any language besides Java
  - **Python**
  - Perl
  - R
  - PHP
  - C++

Other Tips

- **Browsers Recommended: Chrome on iOS, or Edge on Windows**
- No coding, but only deploying
  - AWS uses Linux, Python written in Windows has issues
- Lab 1 cost: ~$1
- **On-premise computing vs cloud computing**
  - **Different mode, different experience**
  - **It is normal to feel lost at first time**

Learner Lab Restrictions on EC2 and EMR

- Supported Instance types: nano, micro, small, medium, and large
- Maximum of 9 concurrently running EC2 instances
- Maximum of 32 vCPU used by concurrently running instances
  - Caution: Any attempt to have 20 or more concurrently running instances (regardless of size), will result in immediate deactivation of the AWS account
- Example EMR cluster configuration details:
  - Cluster configuration: Instance groups, Primary: **m4.large**, Core: **m4.large**, Task -1: **m4.large**
  - Provisioning configuration: Core: 1 instance and Task -1: 1 instance
  - Security configuration: EC2 key pair: **vockey**
  - IAM roles: Amazon EMR service role: choose existing: **EMR_DefaultRole**, EC2 instance profile for Amazon EMR: choose existing: **EMR_EC2_DefaultRole**

Next Week

- Advanced Big Data Framework: Spark
- pySpark exercises on Google Colab

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Appendix: Search Engine and PageRank Algorithm

Search Engine

- Ranking System: first wave of transformative AI

- **<u>Number Game (take a guess):</u>**
- *How many webpages does Google sort through per day?*
- *How many different web pages on internet are there?*

- https://www.worldwidewebsize.com
- *How are search results determined?*

Yahoo! and Early Engine

Early Search Engines

- yahoo! : searchable directory
  - Originally entries were entered and categorized manually
  - Automated some gathering and classification process
  - Descriptive information about indexed sites
  - *Issue?*

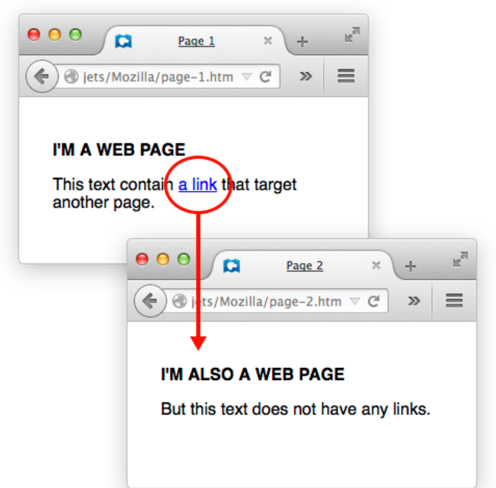
- Crawler based search engine
  - Crawling across the entire text of a web page
  - Listing the terms
  - *Issue?*

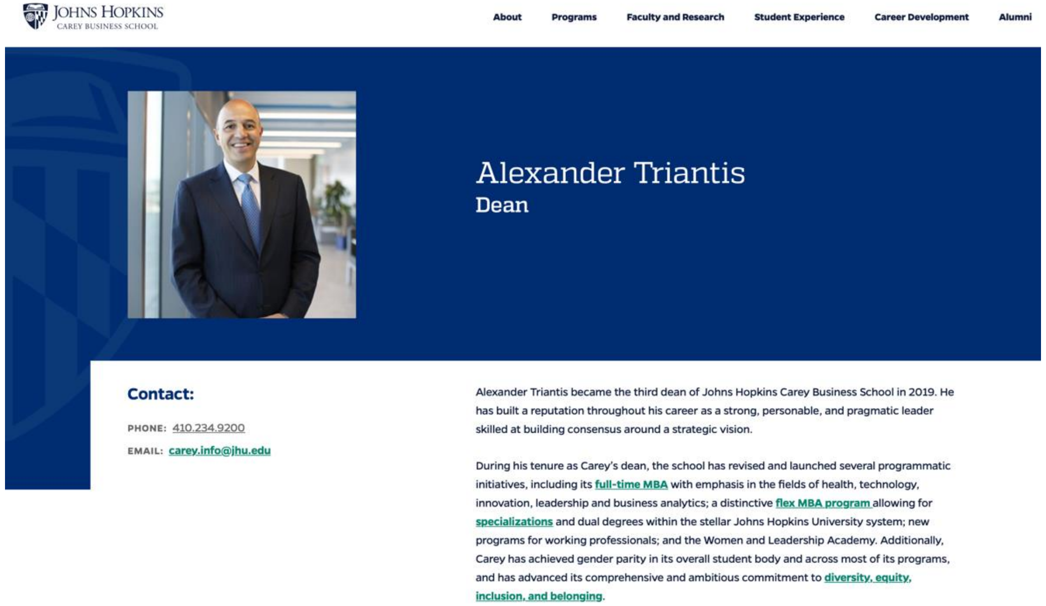
Term Spam

- Lead people to a web site by fooling search engine
  - if you are operating a site selling shirts
  - Add a term such as “movie” to your page, thousands of times
  - Same color as your site background
  - Make small fonts
  - Incorporate a lot of popular terms
- Result? Make search engines useless
- *Then what shall we do?*

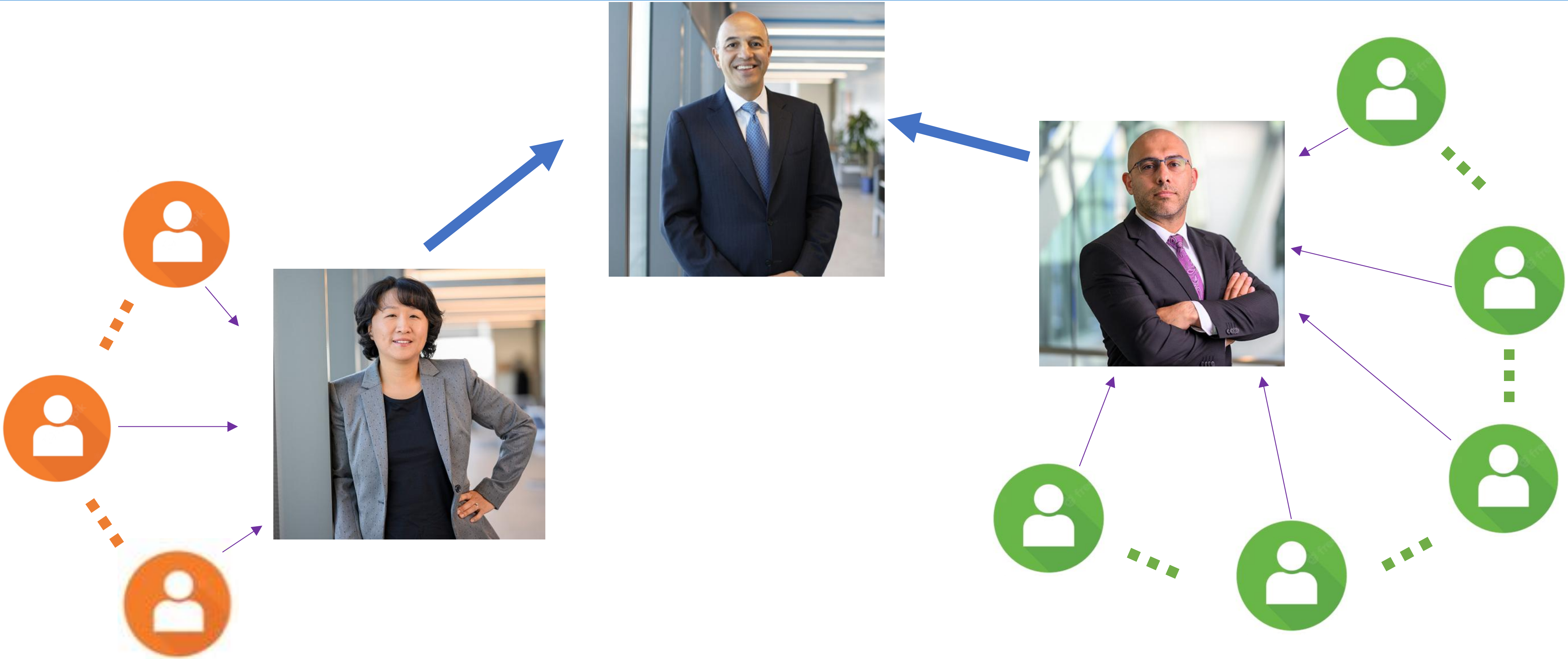
Link Analysis

- Simple Basic Idea: What other pages say about him, is more important than what he says about himself
- Links on the web pages as votes
- Pages “voted” by more pages are more important
  - ”vote with their feet”: users tend to place good/useful links on their own pages, rather than bad/useless ones
- *Can we still fool this type of search engine?*



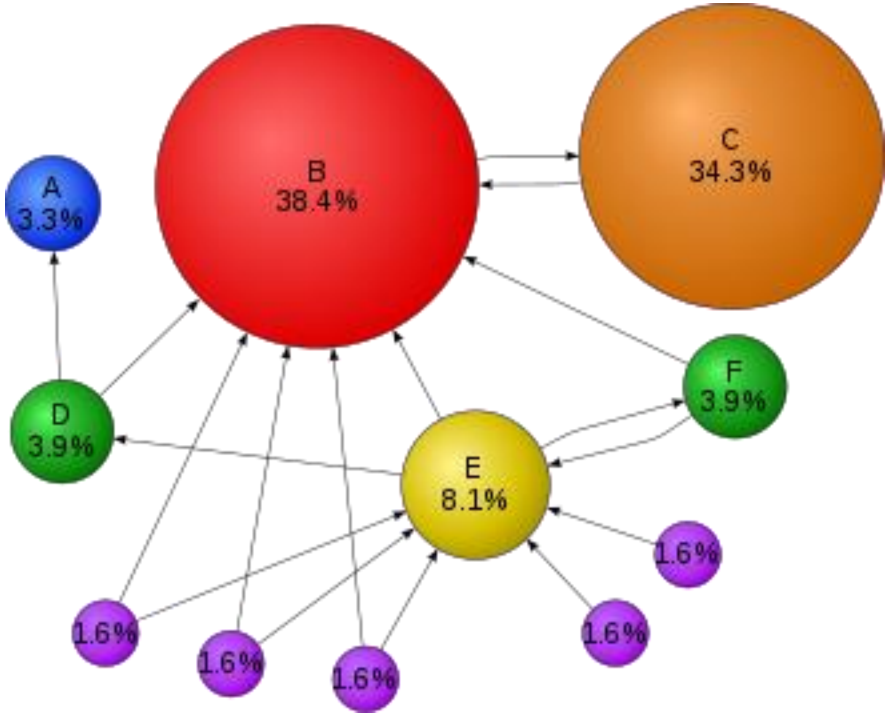


A Social Example



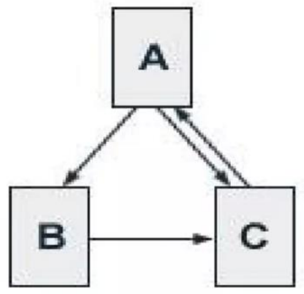
Example (Cont.)

- Insight: “quality” of vote is also important, besides of numbers



- Link passes 1 pt of ranking power
- Start with initial PageRank
- Compute ranking power changes
- Until equilibrium/convergence is reached

Illustration



Consider an imaginary web of 3 web pages.
And the inbound and outbound link structure is as shown in the figure. The calculations can be done by following method :

PR(A) = 0.5 + 0.5 PR(C)
= 0.5 + (0.5*1)
= 1

PR(B) = 0.5 + 0.5 (PR(A) / 2)
= 0.5 + 0.5 (1/2)
= 0.5 + (0.5 * 0.5)
= 0.5 + 0.25
= 0.75

PR(C) = 0.5 + 0.5 ((PR(A) / 2)+ PR (B))
= 0.5 + 0.5 (1/2 + 0.75)
= 0.5 + 0.5 (1.25)
= 0.5 + 0.625
= 1.125

PR (A) = (1-d) + d (PR (T1) / C (T1) + ... + PR (Tn) / C (Tn))

Where,
PR(A) is the PageRank of page A
PR(Ti) is the PageRank of pages Ti which link to page A
C(Ti) is the number of outbound links on page Ti and
d is a damping factor which can be set between 0 and 1

Iteration	PR(A)	PR(B)	PR(C)
0	1	1	1
1	1	0.75	1.125
2	1.0625	0.765625	1.1484375
3	1.07421875	0.76855469	1.15283203
4	1.07641602	0.76910400	1.15365601
5	1.07682800	0.76920700	1.15381050
6	1.07690525	0.76922631	1.15383947
7	1.07691973	0.76922993	1.15384490
8	1.07692245	0.76923061	1.15384592
9	1.07692296	0.76923074	1.15384611
10	1.07692305	0.76923076	1.15384615
11	1.07692307	0.76923077	1.15384615
12	1.07692308	0.76923077	1.15384615

Google and PageRank

- Developed in 1996
- By founders of Google

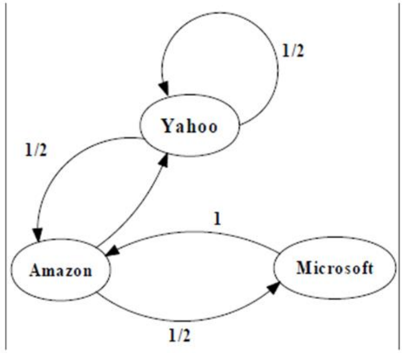
Larry Page and Sergey Brin in 2003

- PageRank works by counting the number and quality of links to a page to determine a rough estimate of how important the website is. The underlying assumption is that more important websites are likely to receive more links from other websites

Computing PageRank

- Perform matrix-vector multiplication a lot of times
- Until the vector is close to unchanged at one iteration

- Matrix-vector multiplication can be solved using MapReduce



$$M = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix}$$

$$\begin{bmatrix} \text{yahoo} \\ \text{Amazon} \\ \text{Microsoft} \end{bmatrix} = \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

$$\begin{bmatrix} 1/3 \\ 1/2 \\ 1/6 \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & 0 & 1 \\ 0 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

Other Algorithms using MapReduce

- Matrix-vector multiplication
  - Original purpose for Google to implement MapReduce
  - Map use index as the key
  - Reduce sums all the values at the same index
- Matrix-matrix multiplication
  - Similar to matrix-vector, but key is in 2-dimensional
- Relational-algebra operations
  - Selection, projection, union, intersection, difference, natural join, grouping and aggregation
  - Hive and Apache Pig use similar syntax as SQL, but speed up using MapReduce

Optional MapReduce Functions

- Programmers can also include the following two functions to optimize performance:
  - combine (k, v) → <k, v'>
    - Mini-reducers that run in memory after the map phase
    - Used as an optimization to reduce network traffic
  - partition (k', number of partitions) → partition for k'
    - Often a simple hash of the key, e.g., *hash(k') mod n*
    - Divides up key space for parallel reduce operations

References

- Kunpeng Zhang's notes (2019)