

# CS143

# Non-Relational Database (MongoDB)

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# JSON (JavaScript Object Notation)

- Syntax to represent objects in JavaScript
  - [{ "x": 3, "y": "Good"}, { "x": 4, "y": "Bad" }]
- One of the most popular data-exchange formats over Internet
  - As JavaScript gained popularity, JSON's popularity grew
  - Simple and easy to learn
  - Others popular formats include XML, CSV, ...

# Basic JSON Syntax

- Supports basic data types like numbers and strings, as well as arrays and “objects”
- Double quotes for string: “Best”, “UCLA”, “Worst”, “USC”
- Square brackets for array: [1, 2, 3, “four”, 5]
- Objects: (attribute, name) pairs. Use curly braces
  - { “sid”: 301, “name”: “James Dean” }
- Things can be nested
  - { “sid” : 301,  
“name”: { “first”: “James”, “last”: “Dean” },  
“classes”: [ “CS143”, “CS144” ] }

# RDBMS for JavaScript Object Persistence

- JavaScript applications need a “persistence layer” to store and retrieve JavaScript object
- Traditionally (until mid 2010) this was done with RDBMS
  - RDBMS as massive, safe, efficient, multi-user storage engine
- Q: How can we store JavaScript object in RDB?
- “Impedance mismatch”: Two choices
  1. Store object’s JSON as a string in a column
  2. “Normalize” the object into set of relations
- Q: Pros and cons of each approach?
- Q: Can we just create “native database” for JSON?

# MongoDB

- Database for JSON objects
  - Perfect as a simple persistence layer for JavaScript objects
  - “NoSQL database”
- Data is stored as a collection of documents
  - Document: (almost) JSON object
  - Collection: group of “similar” documents
- Analogy
  - Document in MongoDB ~ row in RDB
  - Collection in MongoDB ~ table in RDB

# MongoDB “Document”

```
{
  "_id": ObjectId(8df38ad8902c),
  "title": "MongoDB",
  "description": "MongoDB is NoSQL database",
  "tags": ["mongodb", "database", "NoSQL"],
  "likes": 100,
  "comments": [
    { "user": "lover", "comment": "Perfect!" },
    { "user": "hater", "comment": "Worst!" }
  ]
}
```

- `_id` field: primary key
  - May be of any type other than array
  - If not provided, automatically added with a unique `ObjectId` value
- Stored as BSON (Binary representation of JSON)
  - Supports more data types than JSON
  - Does not require double quotes for field names

# MongoDB “Philosophy”

- Adopts JavaScript “laissez faire” philosophy
  - Don’t be too strict! Be accommodating! Handle user request in a “reasonable” way
- Schema-less: no predefined schema
  - Give me anything. I will store it anywhere you want
  - One collection will store documents of *any* kind with no complaint
- No need to “plan ahead”
  - A “database” is created when a first collection is created
  - A “collection” is created when a first document is inserted
- Both blessing and curse

# MongoDB Demo

```
show dbs;
use demo;
show collections;
db.books.insertOne({title: "MongoDB", likes: 100});
db.books.find();
show collections;
show dbs;
db.books.insertMany([{{title: "a"}, {name: "b"}}]);
db.books.find();
db.books.find({likes: 100});
db.books.find({likes: {$gt: 10}});
db.books.updateOne({title: "MongoDB"}, {$set: { likes: 200 }});
db.books.find();
db.books.deleteOne({title: "a"});
db.books.drop();
show collections;
show dbs;
```



# Basic MongoDB Commands (1)

- `mongo`: start MongoDB shell
- `use <dbName>`: use the database
- `show dbs`: show list of databases
- `show collections`: show list of collections
- `db.colName.drop()`: delete `colName` collection
- `db.dropDatabase()`: delete current database

# Basic MongoDB Commands (2)

- CRUD operations
  - insertOne(), insertMany()
  - findOne(), find()
  - updateOne(), updateMany()
  - deleteOne(), deleteMany()
- Insertion: insertX( doc(s) )
  - db.books.insertOne({title: "MongoDB", likes: 100})
  - db.books.insertMany([{title: "a"}, {title: "b"}])

# Basic MongoDB Commands (3)

- Retrieval: findX(condition)
  - `db.books.findOne({likes: 100})`
  - `db.books.find({$and: [{likes: {$gte: 10}}, {likes: {$lt: 20}}]})`
    - Other Boolean/comparison operators: `$or`, `$not`, `$gt`, `$ne`, ...
- Update: updateX(condition, update\_operation)
  - `db.books.updateOne({title: "MongoDB"}, {$set: {title: "MongoDB II"}})`
  - `db.books.updateMany({title: "MongoDB"}, {$inc: {likes: 1}})`
    - Other update operators: `$mul` (multiply), `$unset` (remove field), ...
- Deletion: deleteX(condition)
  - `db.books.deleteOne({title: "MongoDB"})`
  - `db.books.deleteMany({likes: {$lt: 100}})`

# MongoDB Aggregates

- MongoDB supports complex queries through “aggregates”
- MongoDB aggregates are very much like SQL SELECT queries
  - stages – SQL SELECT clause
  - pipeline – SQL SELECT statement

# MongoDB Aggregates: Example

- { \_id: 1, cust\_id: "a", status: "A", amount: 50 }  
 { \_id: 2, cust\_id: "a", status: "A", amount: 100 }  
 { \_id: 3, cust\_id: "c", status: "D", amount: 25 }  
 { \_id: 4, cust\_id: "d", status: "C", amount: 125 }  
 { \_id: 5, cust\_id: "d", status: "A", amount: 25 }

```
db.orders.aggregate([
  { $match: { status: "A" } },
  { $group: {
    _id: "$cust_id",
    total: { $sum: "$amount" },
    count: { $sum: 1 }
  } },
  { $sort: { total: -1 } }
])
```

- Equivalent to SQL SELECT
  - Just \$match is fine, for example
  - In \$group stage, \_id is “group by attributes”

# Common Aggregate Stages

- `$match`  $\approx$  WHERE
- `$group`  $\approx$  GROUP BY
- `$sort`  $\approx$  ORDER BY
- `$limit`  $\approx$  FETCH FIRST
- `$project`  $\approx$  SELECT
- `$unwind`: replicate document per every element in the array
  - `{ $unwind: "y" } : { "x": 1, "y": [1, 2] } -> { "x": 1, "y": 1 }, { "x": 1, "y": 2 }`
- `$lookup`: “look up and join” another document based on the attribute value
  - `{ $lookup: { from: <collection to join>, localField: <local join attr>, foreignField: <remote join attr>, as: <output field name> } }`
  - Matching documents are returned as an array in <output field name>

# More on MongoDB aggregates

- Short tutorial: <https://studio3t.com/knowledge-base/articles/mongodb-aggregation-framework/>
- Reference: <https://docs.mongodb.com/manual/reference/method/db.collection.aggregate/>

# MongoDB vs RDB

- MongoDB document

- Preserves structure
  - Nested objects
- Potential redundancy
- Restructuring or combining data is complex and inefficient

- MongoDB: “laissez faire”

- No explicit db/collection creation
- No schema. Anything is fine

- RDB tuple

- “Flattens” data
  - Set of flat rows
- Removes redundancy
- Data can be easily “combined” using relational operators

- RDB: “Straight-jacket”

- Declare everything before use
- Reject if not compliant



# More on MongoDB

- We learned just the basic
- MongoDB has many more features
  - Transactions
  - Replication
  - (Auto)sharding
  - ...
- Read MongoDB documentation and online tutorials to learn more

# CS143

# Map Reduce (Spark)

Professor Junghoo “John” Cho

# Distributed Analytics using Cluster

- Often, our data is non-relational (e.g., flat file) and huge
  - Billions of query logs
  - Billions of web pages
  - ...
- Q: Can we perform analytics on large data quickly using thousands of machines?

# Example 1: Search Log Analysis

- Log of billions of queries. Count frequency of each query
  - Input query log:  
cat,time,userid1,ip1,referrer1  
dog,time,userid2,ip2,referrer2  
...
  - Output query frequency:  
cat 200000  
dog 120000  
...
- Q: How can we perform this task? How can we parallelize it?

# Example 1: Search Log Analysis (1)

- Step 1: “Transform” each line of query log into (query, 1)

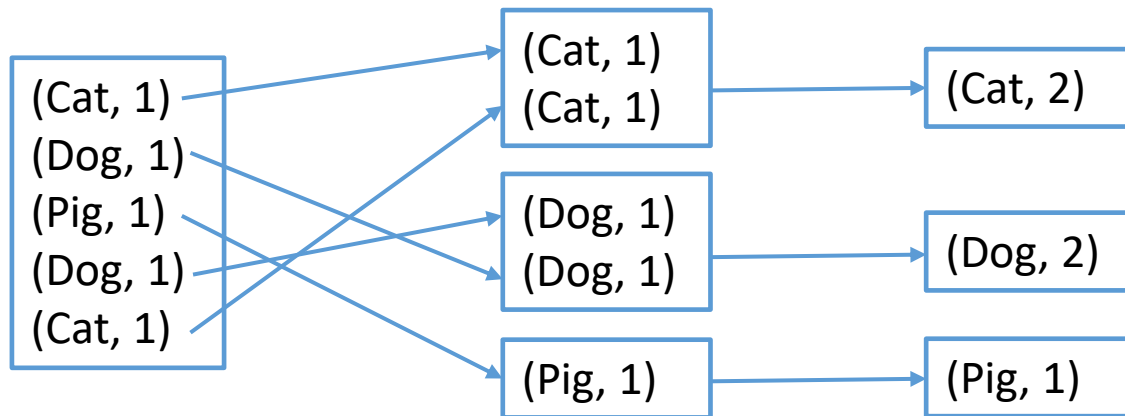
Cat, 12:30, 1.34.24.6, ...  
Dog, 12:30, 193.42.34.5, ...  
Pig, 12:31, 213.12.6.26, ...  
Dog, 12:32, 31.63.34.23, ...  
Cat, 12:33, 1.46.23.642, ..



(Cat, 1)  
(Dog, 1)  
(Pig, 1)  
(Dog, 1)  
(Cat, 1)

# Example 1: Search Log Analysis (2)

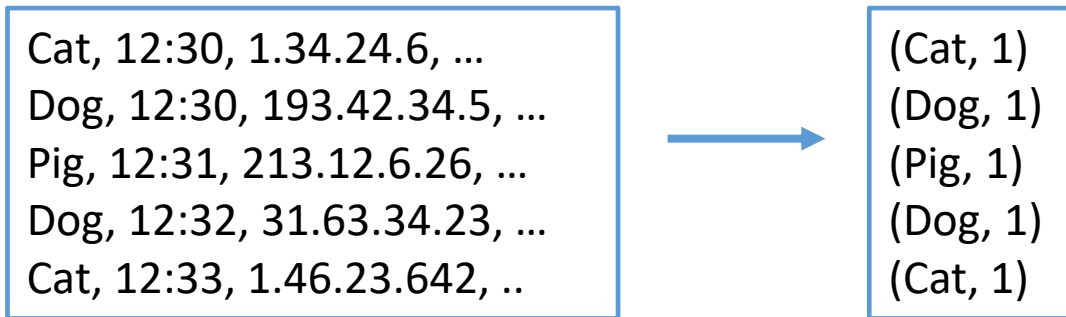
- Step 2: Collect all tuples with the same query and “aggregate” them



- Q: How can we parallelize the two steps?

# Example 1: Search Log Analysis (3)

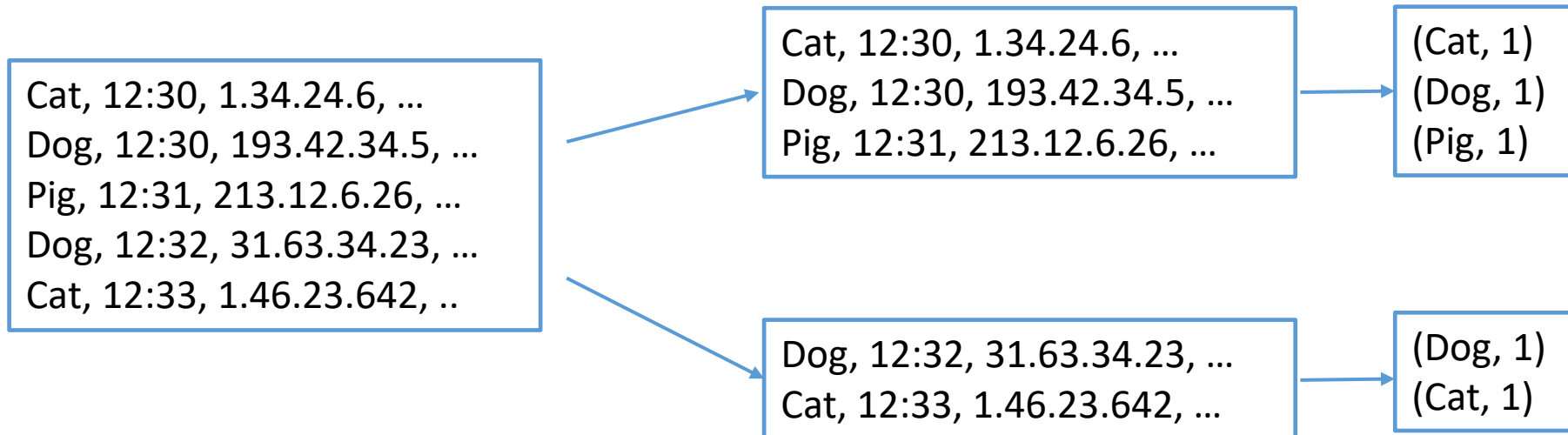
- Step 1: “Transform” each line of query log into (query, 1)



- Q: Can the transformation of each line be done independently of each other?

# Example 1: Search Log Analysis (4)

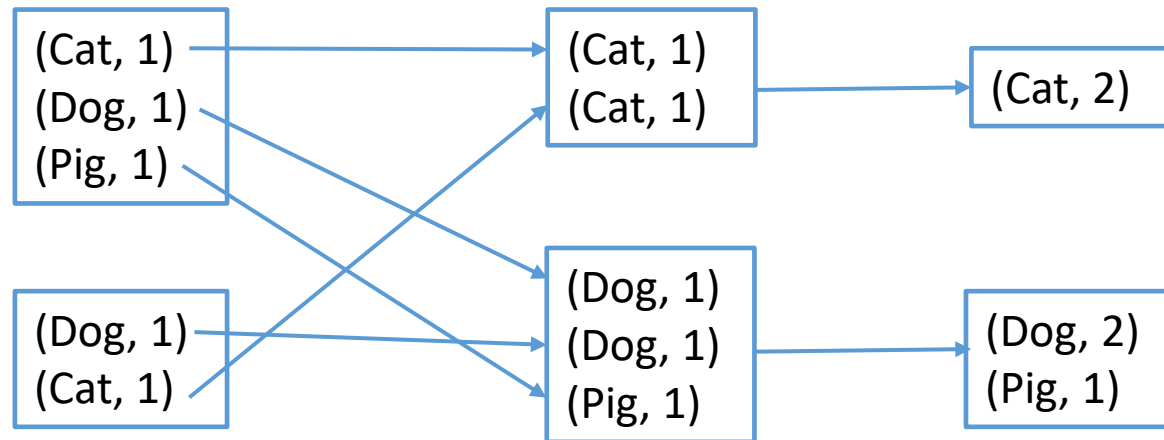
- Step 1: For parallel processing
  - Split input data into multiple independent chunks
  - Move each chunk to separate machine
  - Perform “transformation” on multiple machines in parallel





# Example 1: Search Log Analysis (5)

- Q: How do we parallelize the second “aggregation” step?
- Step 2: For parallel processing
  - Move the tuples with the same query to the same machine
  - Perform aggregation on multiple machine in parallel



# Example 2: Web Indexing

- 1 billion pages. Build “inverted index”
  - Input documents:
    - 1: cat chases dog
    - 2: dog loves cat
    - ...
  - Output index:
    - cat 1,2,5,10,20
    - dog 1,2,3,8,9
- Q: How can we do this?

# Example 2: Web Indexing (1)

- Step 1: “Transform” every document into (word, doc\_id) tuples

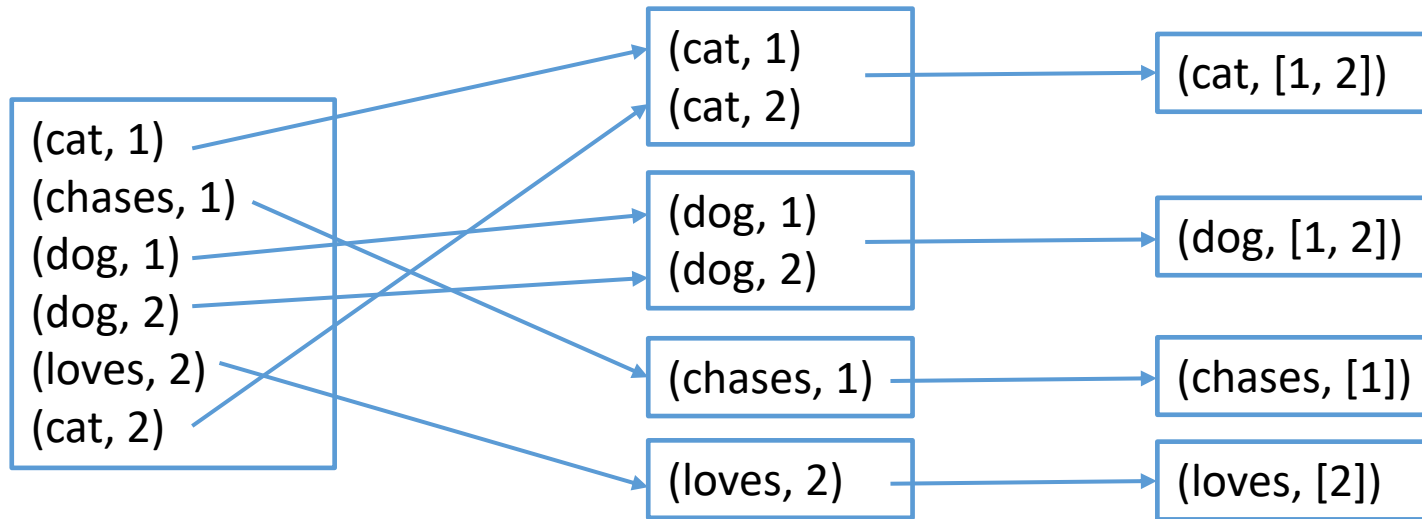
1: cat chases dog  
2: dog loves cat



(cat, 1)  
(chases, 1)  
(dog, 1)  
(dog, 2)  
(loves, 2)  
(cat, 2)

## Example 2: Web Indexing (2)

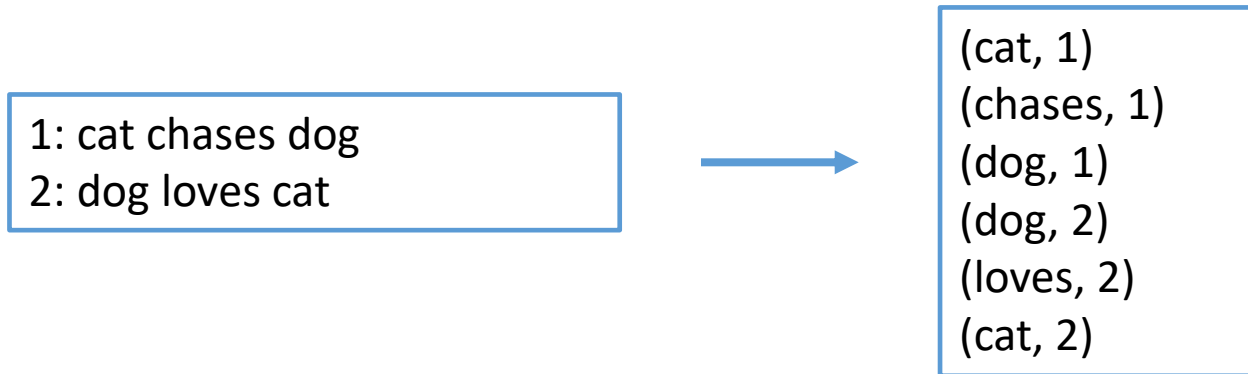
- Step 2: Collect all tuples with the same word and “aggregate” (or concatenate) the doc\_id's



- Q: How can we parallelize the two steps on multiple machines?

## Example 2: Web Indexing (3)

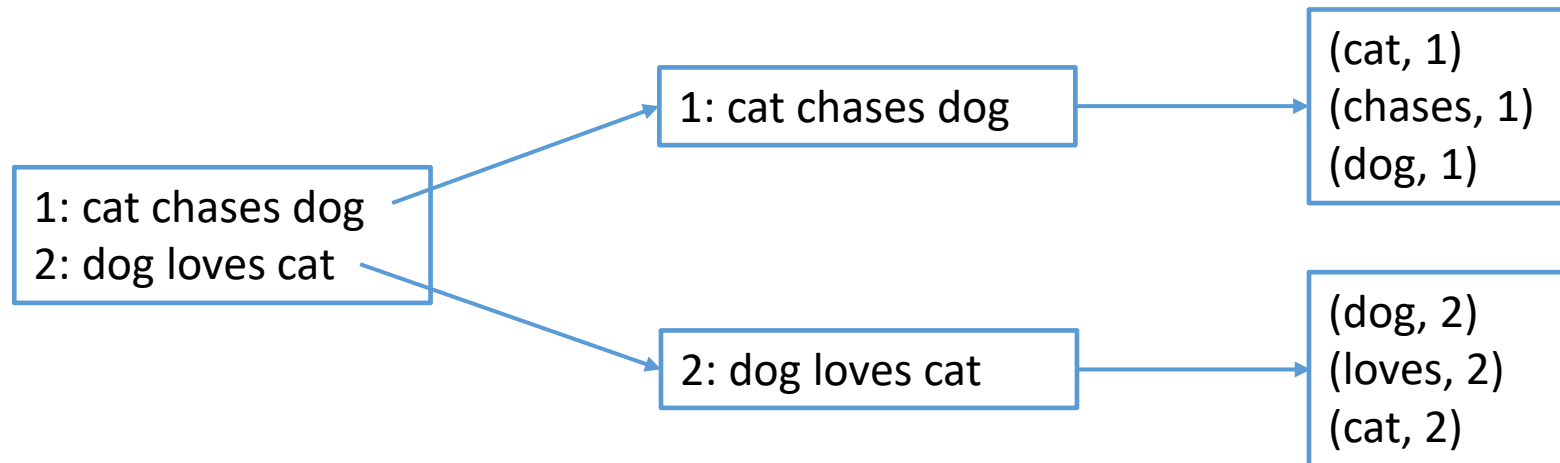
- Step 1: “Transform” every document into (word, doc\_id) tuples



- Q: Can the transformation of each document be done independently of each other?

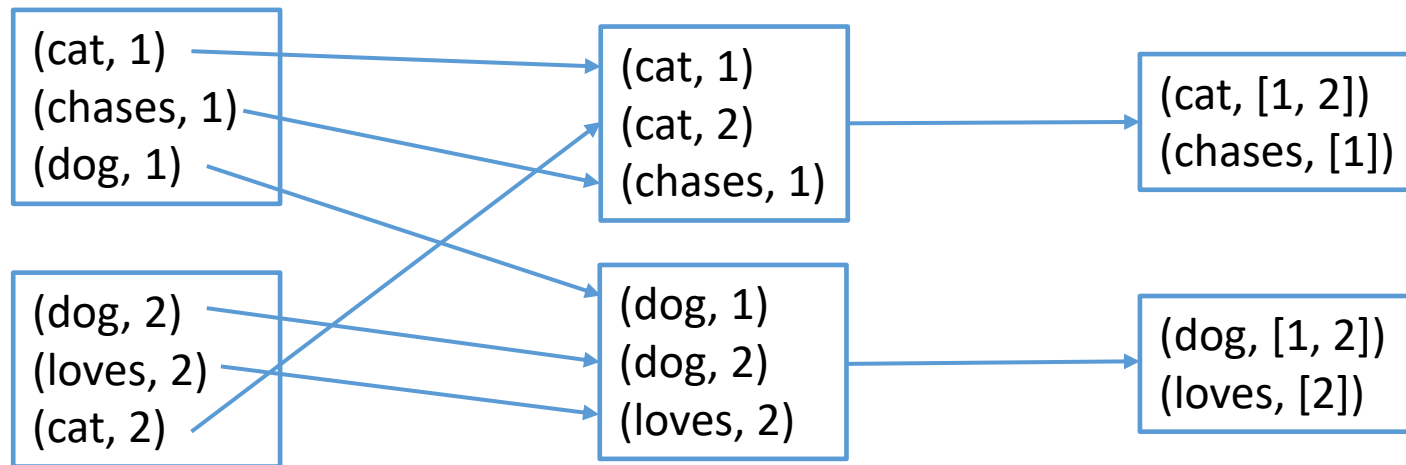
# Example 2: Web Indexing (4)

- Step 1: For parallel processing
  - Split input data into multiple independent chunks
  - Move each chunk to separate machine
  - Perform “transformation” on multiple machines in parallel



## Example 2: Web Indexing (5)

- Q: How can we parallelize second “concatenation step”?
- Step 2: For parallel processing
  - Move the tuples with the same word to the same machine
  - Perform aggregation on multiple machine in parallel



# Generalization (1)

- Input data consists of multiple independent units
  - Each line of query log
  - Each web page
- Partition input data into multiple “chunks” and distribute them to multiple machines
- Transformation/map input into (key, value) tuples
  - Query log:  $\text{query\_log\_line} \rightarrow (\text{query}, 1)$
  - Indexing:  $\text{web\_page} \rightarrow (\text{word}_1, \text{page\_id}), (\text{word}_2, \text{page\_id}), \dots$
- Reshuffle tuples of the same key to the same machine
- Aggregate/reduce the tuples of same keys
  - Query log:  $(\text{query}, 1), (\text{query}, 1), \dots \rightarrow (\text{query}, \text{count})$
  - Indexing:  $(\text{word}, 1), (\text{word}, 3), \dots \rightarrow (\text{word}, [1, 3, \dots])$
- Collect and output the aggregation results



# Generalization (2)

- The two examples are almost the same except
  - “The mapping function”
    - Query log:  $\text{query\_log\_line} \rightarrow (\text{query}, 1)$
    - Indexing:  $\text{web\_page} \rightarrow (\text{word}_1, \text{page\_id}), (\text{word}_2, \text{page\_id}), \dots$
  - “The reduction function”
    - Query log:  $(\text{query}, 1), (\text{query}, 1), \dots \rightarrow (\text{query}, \text{count})$
    - Indexing:  $(\text{word}, 1), (\text{word}, 3), \dots \rightarrow (\text{word}, [1, 3, \dots])$

# MapReduce Model

- Programmer provides
  1. Map function: “unit data”  $\rightarrow (k', v'), (k'', v''), \dots$
  2. Reduce function:  $(k, v_1), (k, v_2), \dots \rightarrow (k, \text{aggr}(v_1, v_2, \dots))$
- MapReduce handles the rest
  - Automatic data partition, distribution, and collection
  - Failure and speed-disparity handling
- Many systems exist supporting MapReduce model

# Hadoop

- First open-source implementation of MapReduce and GFS (Google File System)
  - Implemented in Java
- User implements map and reduce functions as:
  - `Mapper.map(key, value, output, reporter)`
  - `Reducer.reduce(key, value, output, reporter)`

# Spark

- Open-source cluster computing infrastructure
- Supports MapReduce and SQL
  - Supports data flow more general than simple MapReduce
- Input data is converted into RDD (resilient distributed dataset)
  - A collection of independent tuples
  - The tuples are automatically distributed and shuffled by Spark
- Supports multiple programming languages
  - Scala, Java, Python, ...
  - Scala and Java are much more performant than others

# Spark Example: Count words

```
lines = sc.textFile("input.txt")
words = lines.flatMap(lambda line: line.split(" "))
word1s = words.map(lambda word: (word, 1))
wordCounts = word1s.reduceByKey(lambda a,b: a+b)
wordCounts.saveAsTextFile("output")
```

# Key Spark Functions

- Transformation: Convert RDD tuple into RDD tuple(s)
  - map(): convert one input tuple into one output tuple
  - flatMap(): convert one input into multiple output tuples
  - reduceByKey(): specify how two input “values” should be aggregated
  - filter(): filter out tuples based on condition
- Action: Perform “actions” on RDD
  - saveAsTextFile(): save RDD in a directory as text file(s)
  - collect(): create Python tuples from Spark RDD
  - textFile(): create RDD from text (each line becomes an RDD tuple)

# What We Learned

- Large-scale data analytics on distributed cluster
- MapReduce model
- Spark