An Introduction to Apache Spark

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Outline

- Part I: Getting to know Spark
- Part II: Basic programming
- Part III: Spark under the hood
- Part IV: Advanced features

Part I: Getting to know Spark

Spark in a Nutshell

- General cluster computing platform:
 - Distributed in-memory computational framework.
 - SQL, Machine Learning, Stream Processing, etc.
- Easy to use, powerful, high-level API:
 - Scala, Java, Python and R.

Unified Stack

Spark SQL

Spark
Streaming
(real-time
processing)

MLlib (Machine Learning)

GraphX (graph processing)

Spark Core

Standalone Scheduler

YARN

Mesos

High Performance

- In-memory cluster computing.
- Ideal for iterative algorithms.
- Faster than Hadoop:
 - 10x on disk.
 - 100x in memory.

Brief History

- Originally developed in 2009, **UC Berkeley AMP Lab**.
- Open-sourced in 2010.
- As of 2014, Spark is a top-level Apache project.
- Fastest open-source engine for sorting 100 TB:
 - Won the 2014 <u>Daytona GraySort contest</u>.
 - Throughput: 4.27 TB/min

Who uses Spark, and for what?

A. Data Scientists:

- Analyze and model data.
- Data transformations and prototyping.
- Statistics and Machine Learning.

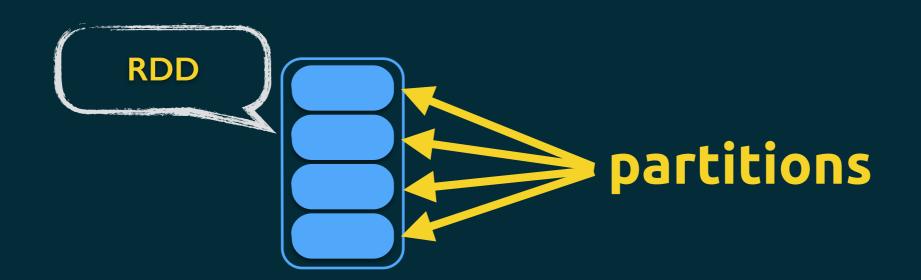
B. Software Engineers:

- Implement production data processing systems.
- Require a reasonable API for distributed processing.
- Reliable, high performance, easy to monitor platform.

Resilient Distributed Dataset

RDD is an **immutable** and **partitioned** collection:

- Resilient: it can be recreated, when data in memory is lost.
- Distributed: stored in memory across the cluster.
- Dataset: data that comes from file or created programmatically.



Resilient Distributed Datasets

- Feels like coding using typical Scala collections.
- RDD can be build:
 - 1. Directly from a datasource (e.g., text file, HDFS, etc.),
 - 2. or by applying a *transformation* to another RDD(s).
- Main features:
 - RDDs are computed lazily.
 - Automatically rebuild on failure.
 - Persistence for reuse (RAM and/or disk).

Part II: Basic programming

Spark Shell

```
$ cd spark
$ ./bin/spark-shell
```

Spark assembly has been built with Hive, including Datanucleus jars on classpath Welcome to

Using Scala version 2.10.4 (Java HotSpot(TM) 64-Bit Server VM, Java 1.7.0_71) Type in expressions to have them evaluated. Type :help for more information. Spark context available as sc.

scala>

Standalone Applications

Sbt:

"org.apache.spark" %% "spark-core" % "1.2.1"

Maven:

groupId: org.apache.spark

artifactId: spark-core_2.10

version: 1.2.1

Initiate Spark Context

```
import org.apache.spark.SparkContext
import org.apache.spark.SparkContext._
import org.apache.spark.SparkConf
object SimpleApp extends App {
 val conf = new SparkConf().setAppName("Hello Spark")
 val sc = new SparkContext(conf)
```

Rich, High-level API

map reduce

Rich, High-level API

map filter sort groupBy union join reduce
count
fold
reduceByKey
groupByKey
cogroup
zip

sample
take
first
partitionBy
mapWith
pipe
save

•••

Loading and Saving

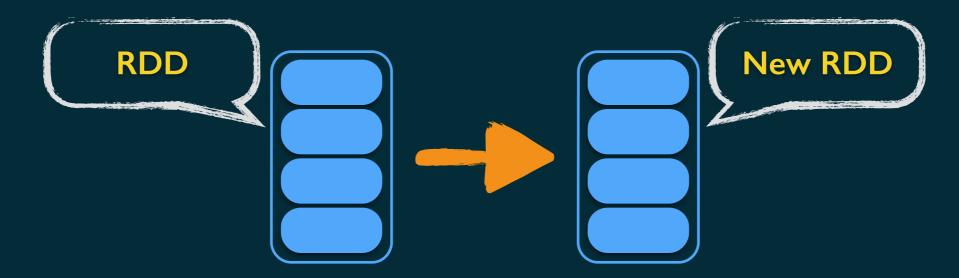
- File Systems: Local FS, Amazon S3 and HDFS.
- Supported formats: Text files, JSON, Hadoop sequence files, parquet files, protocol buffers and object files.
- Structured data with Spark SQL: Hive, JSON, JDBC, Cassandra, HBase and ElasticSearch.

Create RDDs

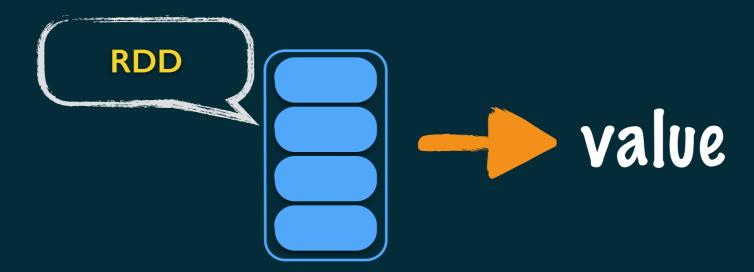
```
// sc: SparkContext instance
// Scala List to RDD
val rdd0 = sc.parallelize(List(1, 2, 3, 4))
// Load lines of a text file
val rdd1 = sc.textFile("path/to/filename.txt")
// Load a file from HDFS
val rdd2 = sc.hadoopFile("hdfs://master:port/path")
// Load lines of a compressed text file
val rdd3 = sc.textFile("file:///path/to/compressedText.gz")
// Load lines of multiple files
val rdd4 = sc.textFile("s3n://log-files/2014/*.log")
```

RDD Operations

1. Transformations: define new RDDs based on current one, e.g., filter, map, reduce, groupBy, etc.



2. Actions: return values, e.g., count, sum, collect, etc.



Transformations (I): basics

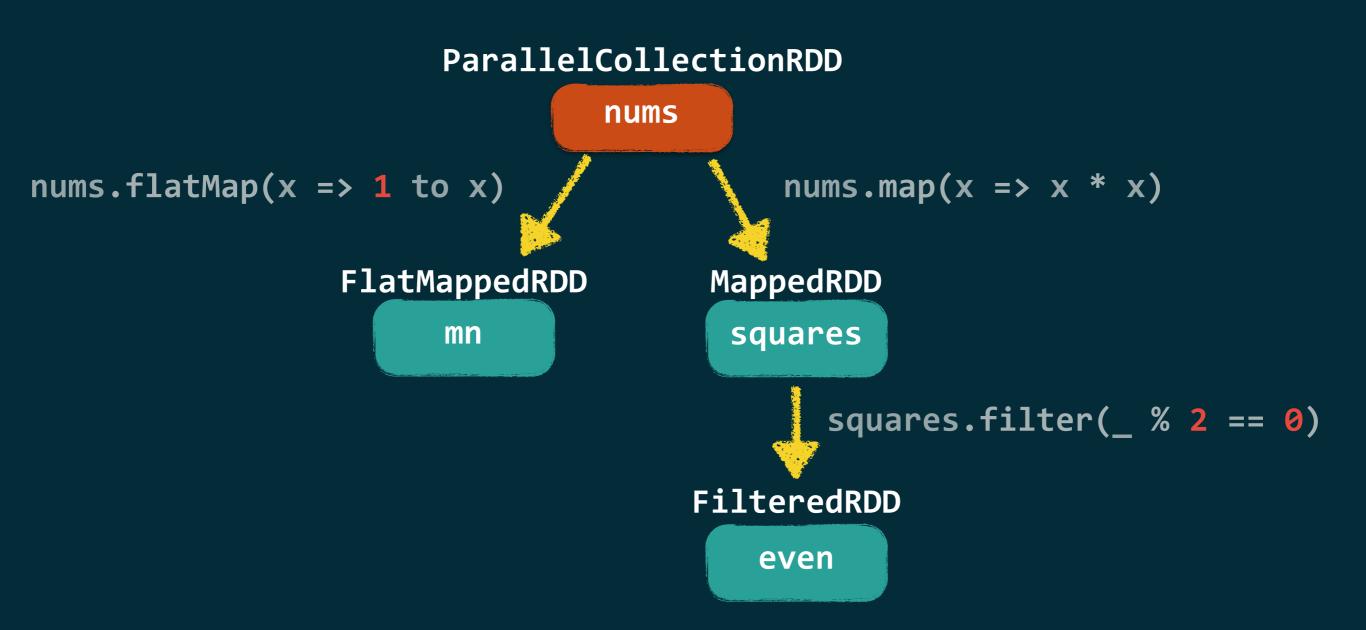
```
val nums = sc.parallelize(List(1, 2, 3))

// Pass each element through a function
val squares = nums.map(x => x * x) //{1, 4, 9}

// Keep elements passing a predicate
val even = squares.filter(_ % 2 == 0) //{4}

// Map each element to zero or more others
val mn = nums.flatMap(x => 1 to x) //{1, 1, 2, 1, 2, 3}
```

Transformations (I): illustrated



Transformations (II): key - value

```
val pets = sc.parallelize(List(("cat", 1), ("dog", 1),
("cat", 2)))
pets.filter{case (k, v) => k == "cat"}
// {(cat,1), (cat,2)}
pets.map{case (k, v) => (k, v + 1)}
// {(cat,2), (dog,2), (cat,3)}
pets.mapValues(v => v + 1)
// {(cat,2), (dog,2), (cat,3)}
```

Transformations (II): key - value

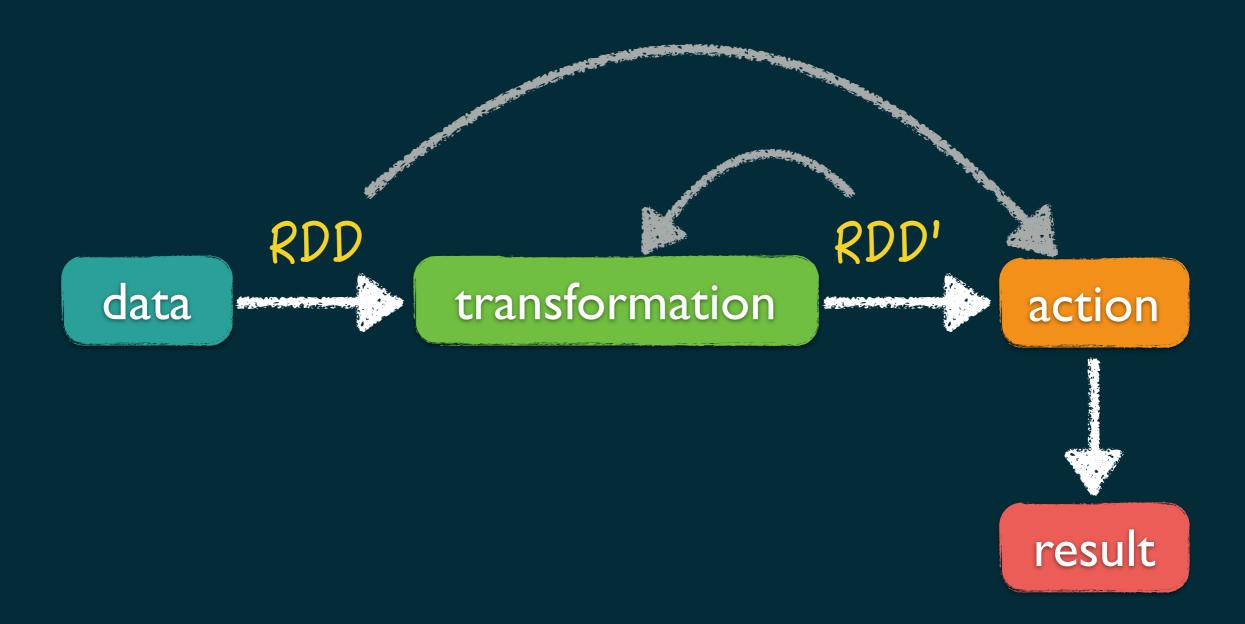
```
val pets = sc.parallelize(List(("cat", 1), ("dog", 1),
                            Key Value
("cat", 2)))
// Aggregation
pets.reduceByKey((1, r) => 1 + r) //{(cat,3), (dog,1)}
// Grouping
pets.groupByKey() //{(cat, Seq(1, 2)), (dog, Seq(1)}
// Sorting
pets.sortByKey() //{(cat, 1), (cat, 2), (dog, 1)}
```

Transformations (III): key - value

```
//RDD[(URL, page_name)] tuples
val names = sc.textFile("names.txt").map(...)...
//RDD[(URL, visit_counts)] tuples
val visits = sc.textFile("counts.txt").map(...)...
//RDD[(URL, (visit counts, page name))]
val joined = visits.join(names)
```

Basics: Actions

Workflow



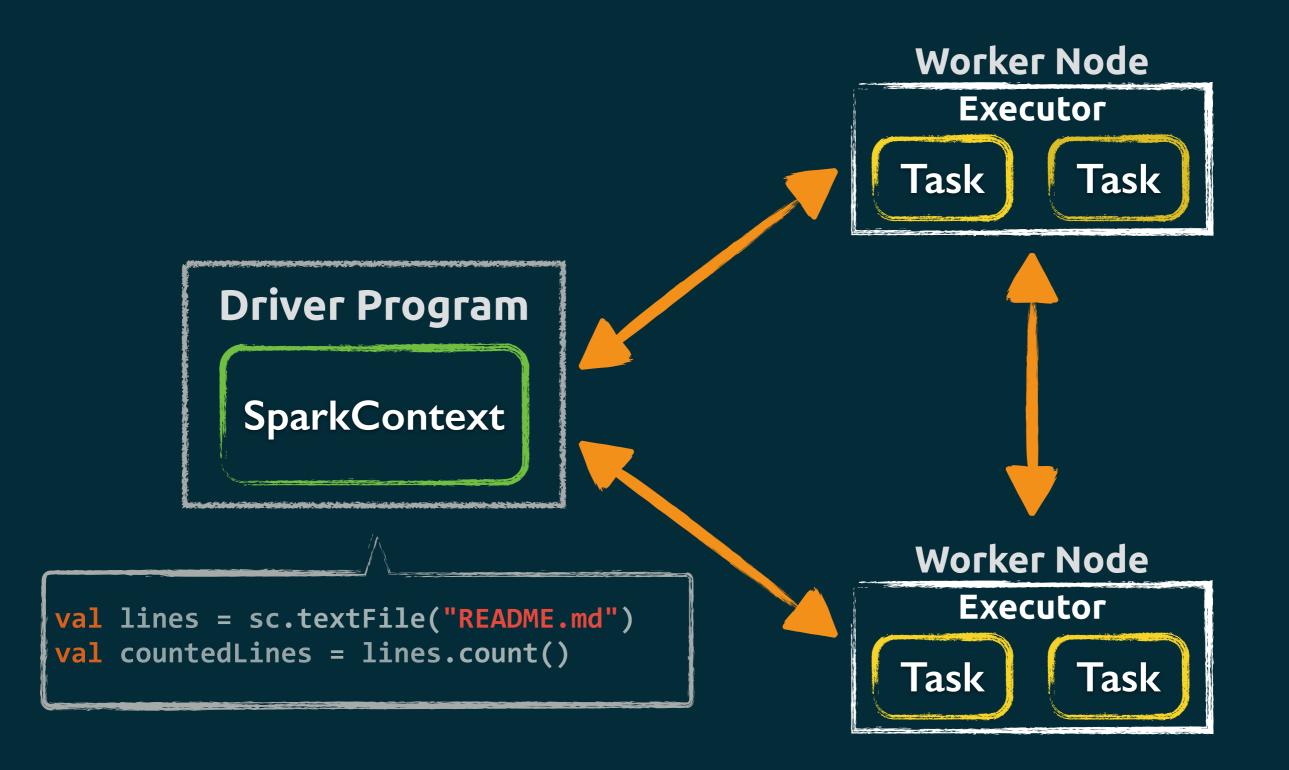
Part III: Spark under the hood

Units of Execution Model

- 1. Job: work required to compute an RDD.
- 2. Each job is divided to stages.
- 3. **Task**:
 - Unit of work within a stage
 - Corresponds to one RDD partition.



Execution Model



Example: word count

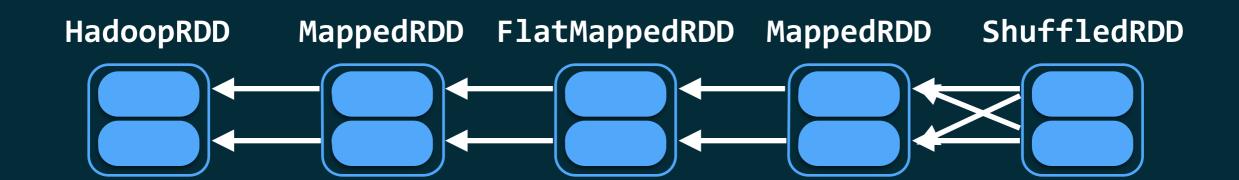
```
val lines = sc.textFile("hamlet.txt") to be or
val counts = lines.flatMap(_.split(" ")) // (a)
                 .map(word => (word, 1)) // (b)
                 .reduceByKey( + ) // (c)
            (a) "to" (b) ("to", 1)
"to be or" "be" ("be", 1) "or" ("or", 1)
                                            ("not", 1)
                       ("not", 1)
"not to be" "to" ("to", 1)
```

Visualize an RDD

Lineage Graph



Lineage Graph



Execution Plan

```
val lines = sc.textFile("hamlet.txt") // MappedRDD[1], HadoopRDD[0]
val counts = lines.flatMap(_.split(" ")) // FlatMappedRDD[2]
                 .map(word => (word, 1)) // MappedRDD[3]
                 .reduceByKey(_ + _) // ShuffledRDD[4]
                              pipelining
                                                     ShuffledRDD
    HadoopRDD
                 MappedRDD FlatMappedRDD MappedRDD
                                                      Stage 2
   Stage 1
```

Part IV: Advanced Features

Persistence

- When we use the same RDD multiple times:
 - Spark will recompute the RDD.
 - Expensive to iterative algorithms.
- Spark can persist RDDs, avoiding recomputations.

Levels of persistence

val result = input.map(expensiveComputation)
result.persist(LEVEL)

LEVEL	Space Consumption	CPU time	In memory	On disk
MEMORY_ONLY (default)	High	Low	Y	Ν
MEMORY_ONLY_SER	Low	High	Y	Ν
MEMORY_AND_DISK	High	Medium	Some	Some
MEMORY_AND_DISK_SER	Low	High	Some	Some
DISK_ONLY	Low	High	Ν	Y

Persistence Behaviour

- Each node will store its computed partition.
- In case of a failure, Spark recomputes the missing partitions.
- Least Recently Used cache policy:
 - Memory-only: recompute partitions.
 - Memory-and-disk: recompute and write to disk.
- Manually remove from cache: unpersist()

Shared Variables

- 1. Accumulators: aggregate values from worker nodes back to the driver program.
- 2. Broadcast variables: distribute values to all worker nodes.

Accumulator Example

```
val input = sc.textFile("input.txt")
                                          initialize the
val sum = sc.accumulator(0)
val count = sc.accumulator(0)
                                         accumulators
input
 .filter(line => line.size > 0)
 .flatMap(line => line.split(" "))
 .map(word => word.size)
 .foreach{
    size =>
       sum += size // increment accumulator
       count += 1 // increment accumulator
                                               driver only
val average = sum.value.toDouble / count.value
```

Accumulators and Fault Tolerance

- Safe: Updates inside actions will only applied once.
- Unsafe: Updates inside transformation may applied more than once!!!

Broadcast Variables

- Closures and the variables they use are send separately to each task.
- We may want to share some variable (e.g., a Map) across tasks/operations.
- This can **efficiently** done with broadcast variables.

Example without broadcast variables

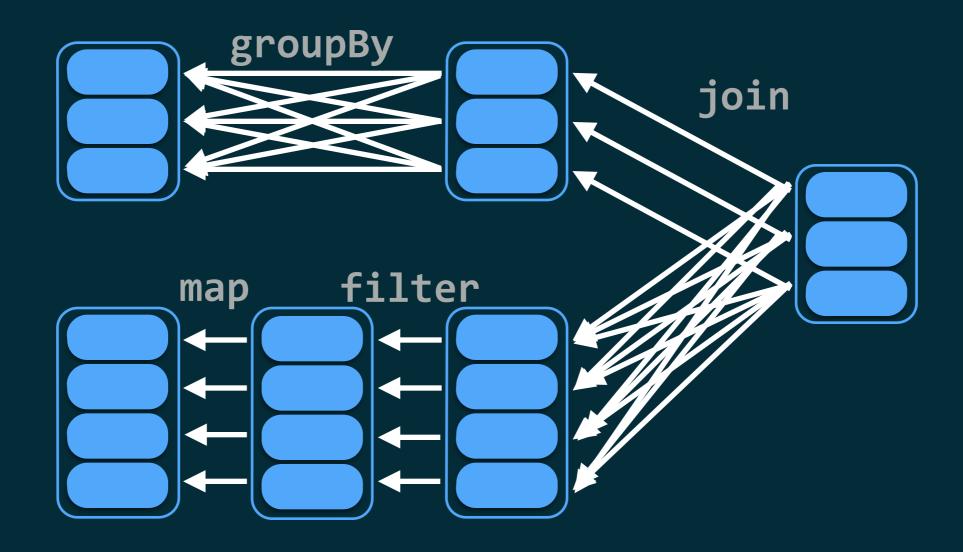
```
// RDD[(String, String)]
val names = ... //load (URL, page name) tuples
// RDD[(String, Int)]
val visits = ... //load (URL, visit counts) tuples
// Map[String, String]
val pageMap = names.collect.toMap
                          CAUTION pageMap is sent along
val joined = visits.map{
                                with every task
  case (url, counts) =>
    (url, (pageMap(url), counts))
```

Example with broadcast variables

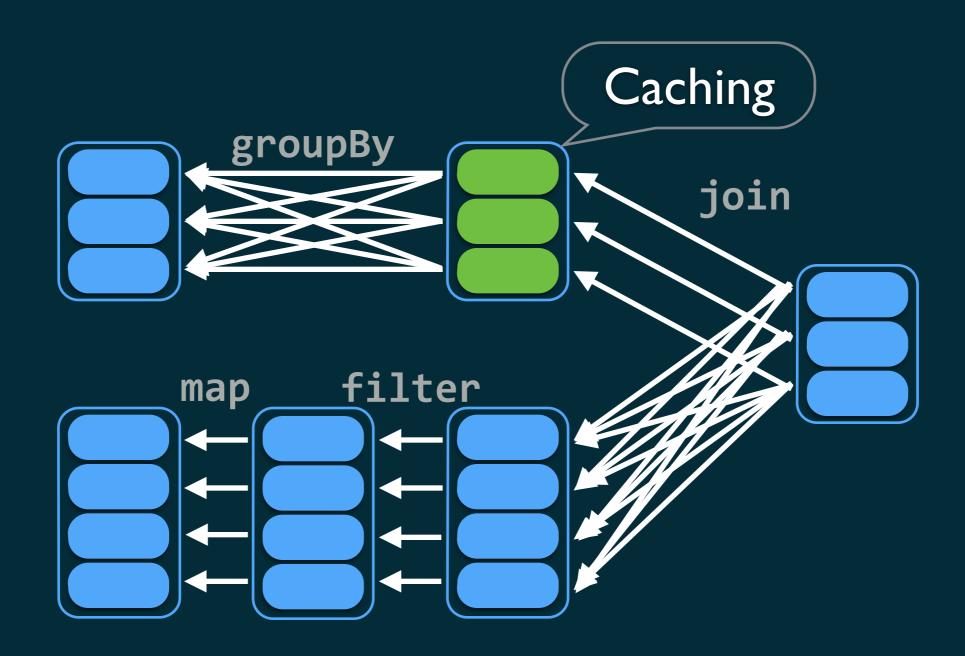
```
// RDD[(String, String)]
val names = ... //load (URL, page name) tuples
// RDD[(String, Int)]
val visits = ... //load (URL, visit counts) tuples
// Map[String, String]
val pageMap = names.collect.toMap
                                Broadcast variable
val bcMap = sc.broadcast(pageMap)
(url, (bcMap.value(url), counts))
```

Appendix

Staging



Staging



Staging

