Popular Open Source Data Processing Frameworks

Giri Iyengar

Cornell University

gi43@cornell.edu

April 23, 2018

Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 1 / 20

э

・ 何 ト ・ ヨ ト ・ ヨ ト

Agenda for the week

- Pig
- Spark
- Storm
- BlinkDB
- Druid

< □ > < □ > < □ > < □ > < □ >

Overview





Giri lyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 3 / 20

Hadoop



Figure: Hadoop Ecosystem

Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 4 / 20

3

A D N A B N A B N A B N

Hadoop



Metadata (Name, replicas, ...): /home/foo/data_3.... Namenode Metadata ops Client Block ops Read Datanodes Datanodes Replication Blocks Write Rack 1 Rack 2 Client

HDFS Architecture

Figure: HDFS

<ロト < 四ト < 三ト < 三ト

Figure: MR Framework

3

Pig Demo

Apache > Hadoop > Pig > docs > r0.17.0 hedooo Project Wiki Pig 0.17.0 Documentation - Pig Overview Getting Started Pig Latin Basics Getting Started User Defined Functions Pig Setup Control Structures **Requirements** Download Pig Shell and Utility Build Pig Commands Performance and Efficiency Testing and Diagnostics Running Pig Execution Modes Interactive Mode Visual Editors H Batch Mode Administration Index Running jobs on a Kerberos secured cluster Miscellaneous Short lived jobs Long lived jobs Pig Latin Statements Loading Data Working with Data Storing Intermediate Results Storing Final Results Debugging Pig Latin Pig Properties Pig Tutorial Running the Pig Scripts in Local Mode Running the Pig Scripts in Mapreduce Mode, Tez Mode or Spark Mode Pig Tutorial Files Pig Script 1: Query Phrase Popularity Pig Script 2: Temporal Query Phrase Popularity

Figure: Pig Reference Manual

Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 6 / 20

イロト 不得下 イヨト イヨト 二日

- Use commodity hardware to achieve super stable, reliable, data processing
- Reliable data storage via replication HDFS
- Generic Computation approach Map Reduce
- Extremely well-suited for batch processing on 1000s of nodes handling Petabytes of data

- Speed and sophistication required for data processing has grown tremendously
- Complex algorithms like Machine Learning and Graph Analysis are much more common
- E.g. ML requires multiple passes over the data not suited for Map Reduce style computing
- Streaming analysis of real-time data is increasingly important
- Both one-pass aggregations and multi-pass analysis applications need to be supported

< □ > < □ > < □ > < □ > < □ > < □ >

Overview





Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 9 / 20

◆□> ◆圖> ◆臣> ◆臣> 三臣:

Apache Spark

Created by Matei Zaharia as part of his Doctoral work at UC Berkeley. Designed to address some of the limitations observed with Hadoop.

Stated goal is to scale to 10s of thousands of compute nodes

Giri lyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 10 / 20

イロト イポト イヨト イヨト

Spark Stack



Figure: Spark Stack

Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 11 / 20

э

・ 何 ト ・ ヨ ト ・ ヨ ト

Spark Cluster Overview



Figure: Spark Stack

Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 12 / 20

< □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > <

Resilient Distributed Dataset

Spark revolves around the concept of a resilient distributed dataset (RDD), which is a fault-tolerant collection of elements that can be operated on in parallel. There are two ways to create RDDs: parallelizing an existing collection in your driver program, or referencing a dataset in an external storage system, such as a shared filesystem, HDFS, HBase, or any data source offering a Hadoop InputFormat.

イロト イポト イヨト イヨト

- Basic Abstraction in Spark
- Immutable, Partitioned collection of elements that can be operated in parallel
- Supports Lazy evaluations

э

< □ > < 同 > < 回 > < 回 > < 回 >

Map Reduce Intermediate Data



Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 15 / 20

э

イロト イポト イヨト イヨト

Spark Intermediate Data



Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 16 / 20

▲□▶ ▲圖▶ ▲ 臣▶ ▲ 臣▶ 臣 のへで

Properties of RDD

- In-Memory
- Lazy
- Fault-Tolerant
- Immutability
- Partitioned
- Persistent
- Parallel

- Location-Stickiness
- Typed
- Coarse-Grained Operations (whole RDD and not individual elements)
- No limitations (bound by available system memory)

э

- ∢ ⊒ →

→ ∃ →

Spark DataFrames

This API is inspired by data frames in R and Python (Pandas), but designed from the ground-up to support modern big data and data science applications. It is an extension to the existing RDD API.

< □ > < □ > < □ > < □ > < □ > < □ >

- Ability to scale from kilobytes of data on a single laptop to petabytes on a large cluster Support for a wide array of data formats and storage systems
- State-of-the-art optimization and code generation through the Spark SQL Catalyst optimizer
- Seamless integration with all big data tooling and infrastructure via Spark
- APIs for Python, Java, Scala, and R

- 4 回 ト 4 ヨ ト 4 ヨ ト



Giri Iyengar (Cornell Tech)

Data Processing Frameworks

April 23, 2018 20 / 20