Pigeon: an Effective Distributed, Hierarchical Datacenter Job Scheduler

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Datacenter job scheduling challenges-I

Large scale

Cluster size is large

Tens of thousands of nodes/workers

The number of tasks in a job can be larger

Tens of thousands of tasks in a job

-- More than 50K tasks in a job in the Cloudera trace

Datacenter job scheduling challenges-II

Heterogeneous workload

Short jobs (e.g., user facing applications)

---call for short response time

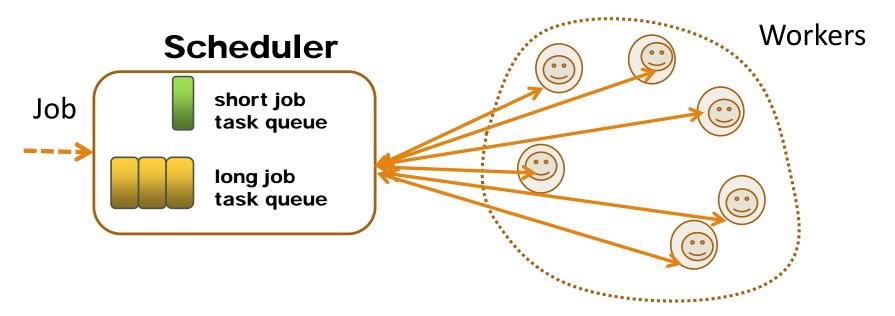
Long jobs (e.g., Data backup)

--call for mean response time guarantee

Centralized job scheduling

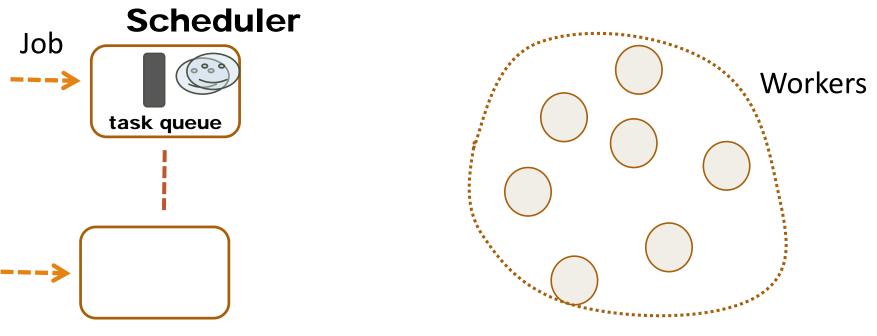
Scalability problem

A scheduler manages all the workers' resources in a cluster



Distributed scheduling-Sparrow

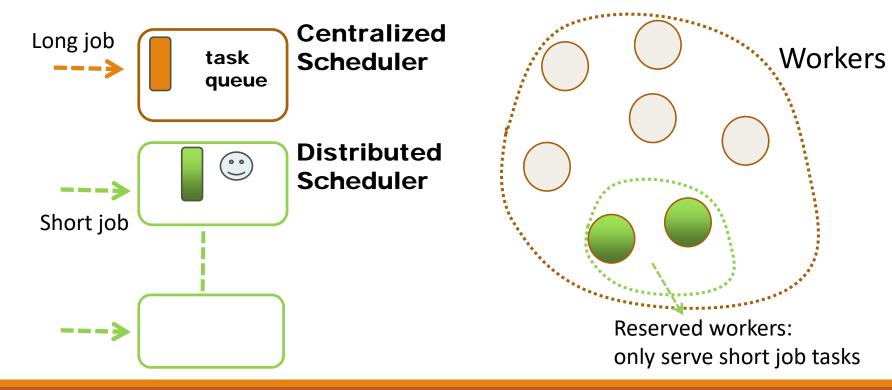
Low efficinecy: unbalanced probing



A scheduler needs to maintain all probes.

Hybrid scheduling-Eagle, Hawk All short jobs are put to reserved workers

Scalability problem



Pigeon Contributions

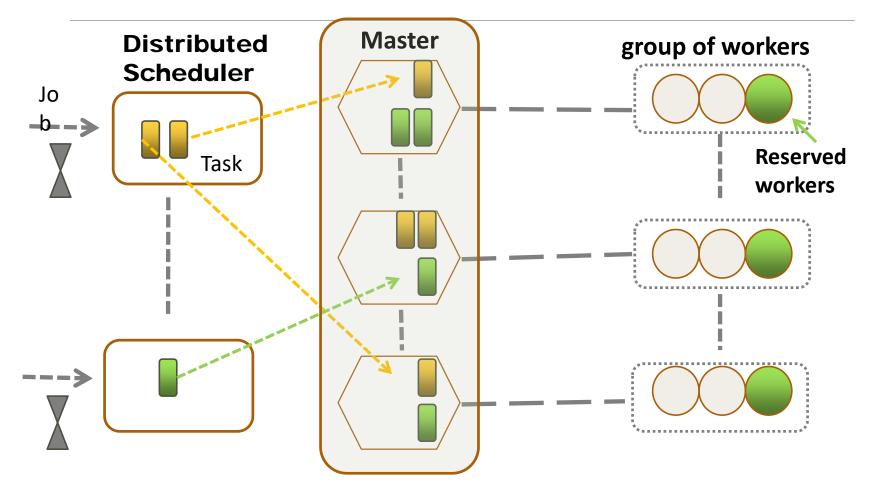
 Introduce a master level for task distribution New architecture, hierarchical job scheduler
 Fully solve scalability problem

3. High efficiency

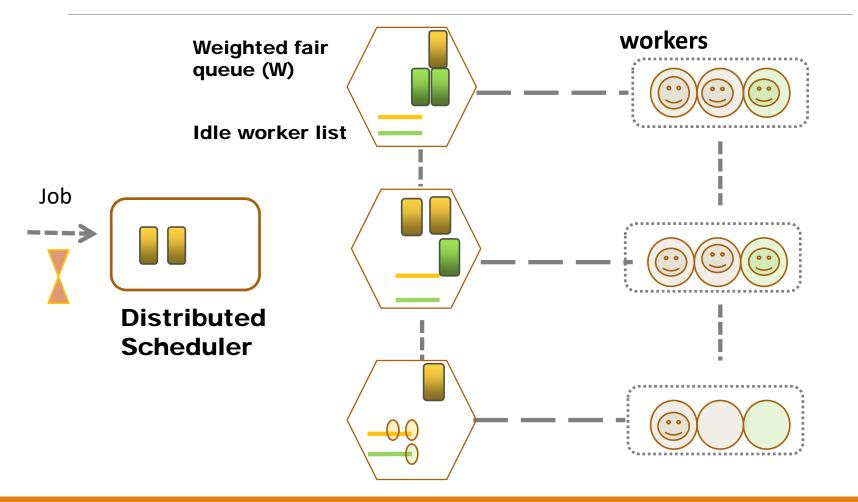
Centrally manage a Receive tasks from group of workers job schedulers Overview of Pigeon

Dispatch tasks to workers

Master is job agnostic



Job scheduling in Pigeon



Why is Pigeon better?

Solve key challenges in existing schedulers

Scalable: greatly reduce status maintenance costs in job schedulers

Group size 100: # of master is 1% # of workers,

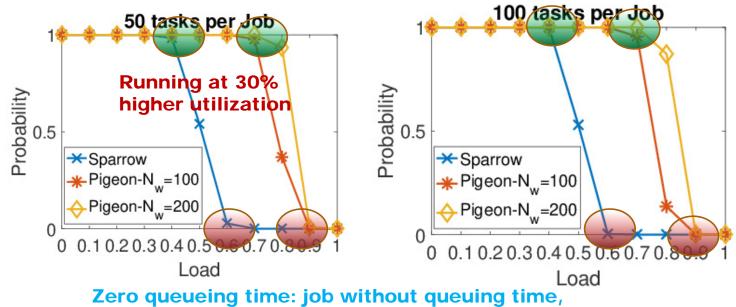
reduce 99% status maintenance cost

Efficiency: Remove head-of-line blocking Have statistical multiplexing gain within a group

Group size 100: run at 90% load, the probability of a task finding an idle worker in a group is 1-0.9¹⁰⁰ =99.99734!!

Modeling and Analysis

Consider a single type of jobs, the fanout degree in a job is less than the number of masters. The task queuing time in a master is a M/M/K queue (K is the group size)



The task execution time in a job is the same

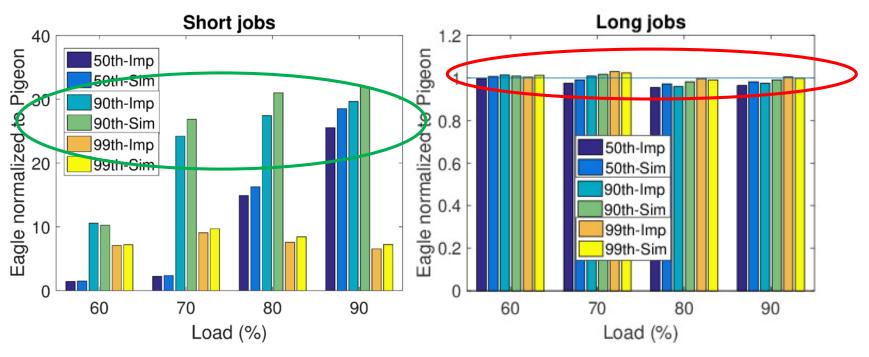
Evaluation--Implementation

- □ Spark plug-in, Amazon EC2 cloud
- □ 120-worker cluster (3 groups in Pigeon)

Measurement metrics:
 50th, 90th and 99th percentile short and long job completion time

- Compare with state-of-the-art schedulers: Eagle and Sparrow
- □ Source codes: https://github.com/ruby-/pigeon/

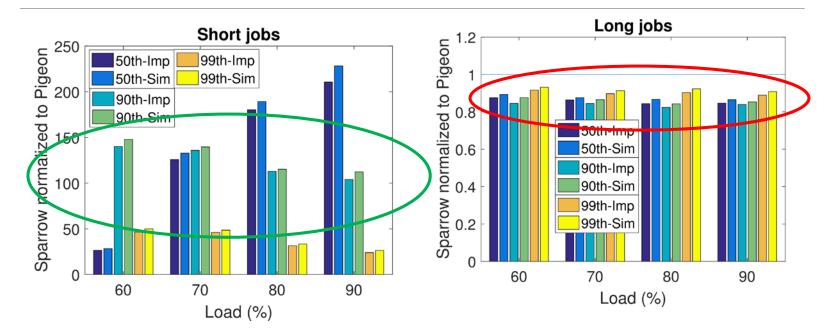
Pigeon vs Eagle--Implementation



Eagle normalized to Pigeon

20x~30x short job performance gains

Pigeon vs Sparrow--Implementation



Sparrow normalized to Pigeon

Pigeon works in a real cluster

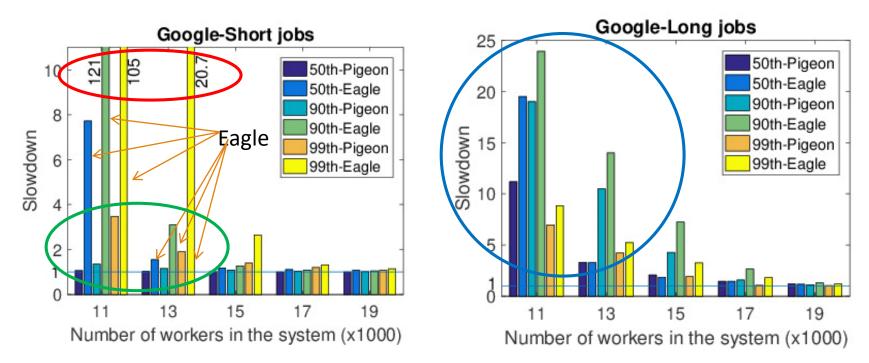
Evaluation—Large Scale Simulation

- **Event-driven simulator**
- □ Google, Yahoo and Cloudera traces
- **Cluster size 3000--19000 workers**

Measurement metrics:
 50th, 90th and 99th percentile short and long job completion time

Compare with state-of-the-art hybrid scheduler: Eagle

Pigeon is really scalable and efficient Google trace



Slowdown=job completion time / job execution time

Big performance gains for short job at high loads Slightly better performance gains for long jobs

Conclusion

Pigeon: a new distributed and hierarchical job scheduler, new scheduling architecture

- 1. Excellent scalability better than existing schedulers
- 2. High efficiency with multiplexing

Thank you! Questions ??