### Static Scheduling in Clouds

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# Motivation (1)

Cloud computing gives the *illusion* of  $\infty$  (virtual) resources.

Actually there is a finite amount of (physical) resources.

We would like to efficiently share those resources:

- being able to distinguish high priority (serving customer *now*) from low priority (batch) requests;
- schedule accordingly.

Therefore, we should be able to plan ahead computations.

# Motivation (2)

Dynamic Scheduling: use work queues, priorities, but limited.

Without knowledge of jobs, this is the best you can do.

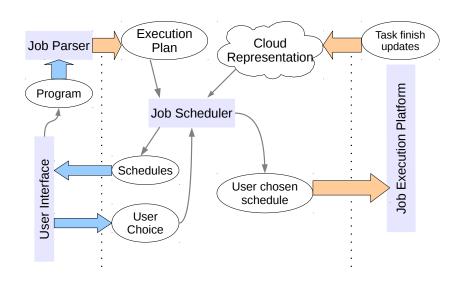
We need to ask the user for:

- what kind of resources his job require;
- a deadline/priority for his job.

In exchange we can give him an expected completion time.

We can also offer choice. (time is money.)

#### Flextic Overview

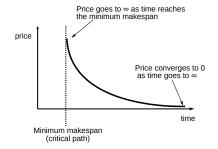


## Giving incentive to plan in advance

The scheduler returns not one but many possible schedules with different finish times.

Use a pricing model to associate a cost to the schedules.

Include the "scheduling difficulty" in the cost, give a discount to schedule with later finish time.

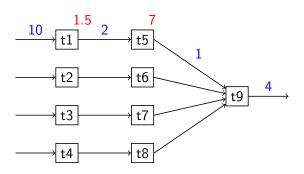


Problem: static scheduling is hard.

Only possible if the scheduler can handle the work load.

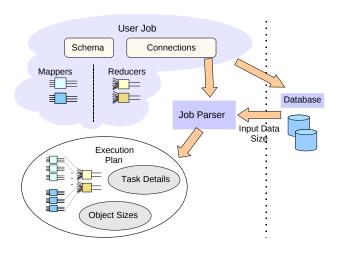
So we set up to make scheduling cheap(er).

### Jobs Model

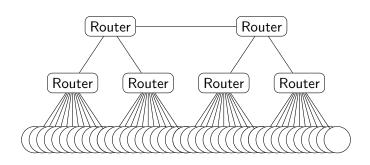


- A Job is a directed acyclic task (DAG) of tasks.
- Node are marked with worst case duration.
- Edges are marked with data transfer.
- duration and data can be parametric in the input.

### Parametric Jobs



### Infrastructure Model



#### Datacenter as a tree-like graph:

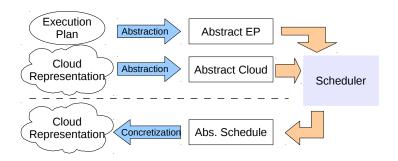
- internal nodes are router;
- leaves are compute nodes (computation speed);
- edges specifies the bandwidth.

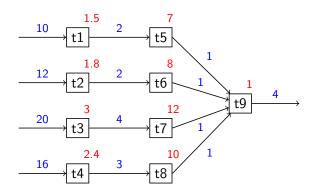
# Scheduling Large Jobs using Abstraction [EuroSys 2011]

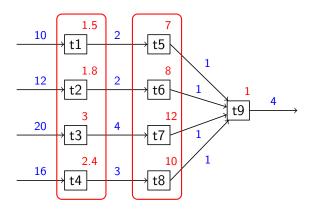
Assumption: job and infrastructure regularity

Idea: regularity makes large scale scheduling feasible

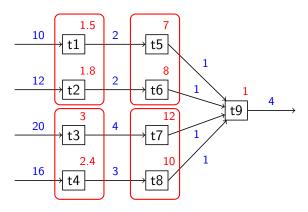
How: Using abstraction techniques

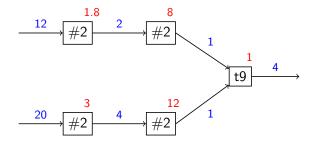






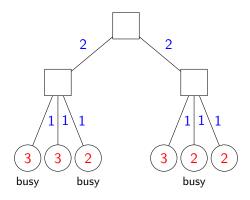






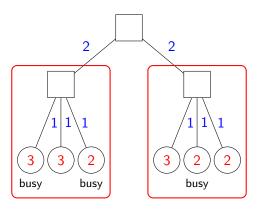
### Abstraction for infrastructure:

Merge nodes to according to network topology:



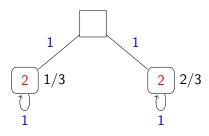
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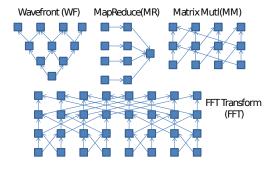
# Experiments, part 1: simulation

#### datacenter:



2-tier datacenter Half of the nodes: speed x, Other half: speed 1.5  $\times$ 

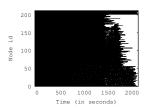
#### On the job side:



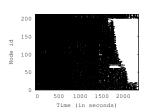
### Experiments: the cost of abstraction

We then compare Fisch and Blind to a concrete greedy scheduler (baseline) on a sequence of 100 jobs (10-5000 tasks each). Latency is given per tasks.

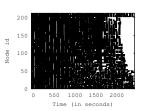
Latency	Utilization
(ms)	
293	96 %
0.27	92 %
0.16	91 %
	(ms) 293 0.27



(a) Baseline

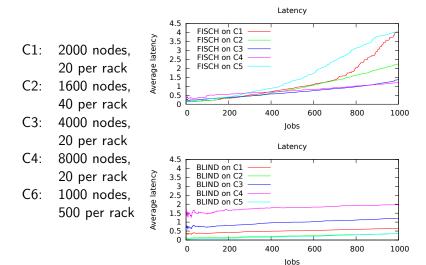






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### Experiments: scaling



## Experiments, part 2: real world

Caution: static scheduling alone will not work.

- Task duration are conservative estimates;
- Variability of the performance of the compute node.

We use static scheduling with backfilling.

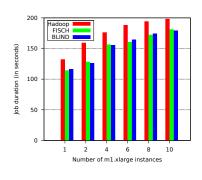
#### Job:

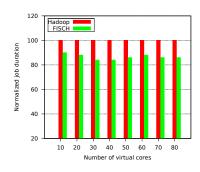
- The jobs are MapReduce jobs doing image transformation.
- Mapper: 8.1 seconds on average, estimate is 40 seconds
- Reducer: Identity operation

#### Infrastructure:

- Hadoop streaming version 0.19.0
- Amazon EC2 m1.xlarge instances (15GB RAM, 4 cores)
- Number of mappers = 50 \* number of instances

### Experiments: compared to Hadoop





#### Observations:

- The Hadoop framework requires large runtime overhead: results in slowdown of the job execution.
- Static scheduling allows to prefetch data, whereas dynamic scheduling does not

### Conclusion

There is an opportunity to apply methods developed to solve computationally hard problem in verification to other area. While preserving a solid theoretical basis.

Questions?