Scheduling Large Jobs by Abstraction Refinement

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A Word on Our Background

- Formal Verification Community
- My work: Formal Verification of Concurrent Programs and Distributed Systems
- In general, formal verification is undecidable. In many relevant cases, it is computationally hard. We develop techniques that make verification tractable.

A View into Our World

```
Program P:

X := 0 ; Y := 5
while (X < 50)
{
    X := X + 1
    Y := Y - 1
}
assert(Y < 5)
```

Build Abstraction

Track Predicate $Y < 5$

```
Program P1:

X := 0 ; Y := 5
while (*) {
    X := X + 1
    Y := Y - 1
}
assert(Y < 5)
```

Refine Abstraction

```
Program P2:

X := 0 ; Y := 5
X := X + 1
Y := Y - 1
while (*) {
    X := X + 1
    Y := Y - 1
}
assert(Y < 5)
```

We want to prove that P is correct.

First approach: Run the whole program concretely.

Second approach: Use abstraction refinement!

In general

- What is an abstraction?
  - A concise representation of a system
  - Rely on over-approximations or under-approximations of the behavior of the system
  - A good abstraction loses a lot of irrelevant information and little relevant information
  - What is relevance? Depends on what property we are looking for!

In general

- Why do we use abstractions?
  - They often allow fast efficient solutions where concrete solutions are tedious, or even infeasible.
  - If an abstraction is too coarse for some purpose, one always has a possibility to refine it closer to the real system

We abstract all the time!

- The idea is not limited to formal verification community!

In daily life

A: Mr. X has 3 fast cars !

[ABSTRACTION]

B: Which ones?

A: Aston Martin, Lamborghini, Ferrari!

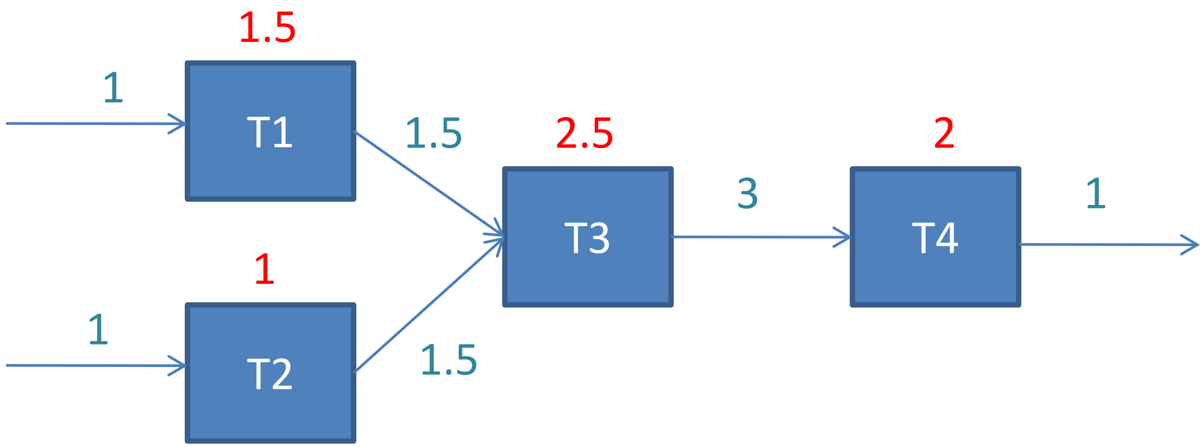
[REFINEMENT]

In technology

- Image and video compression
- Program analysis
- Machine learning (classification)
- In general, whenever the concrete system is too big to handle!

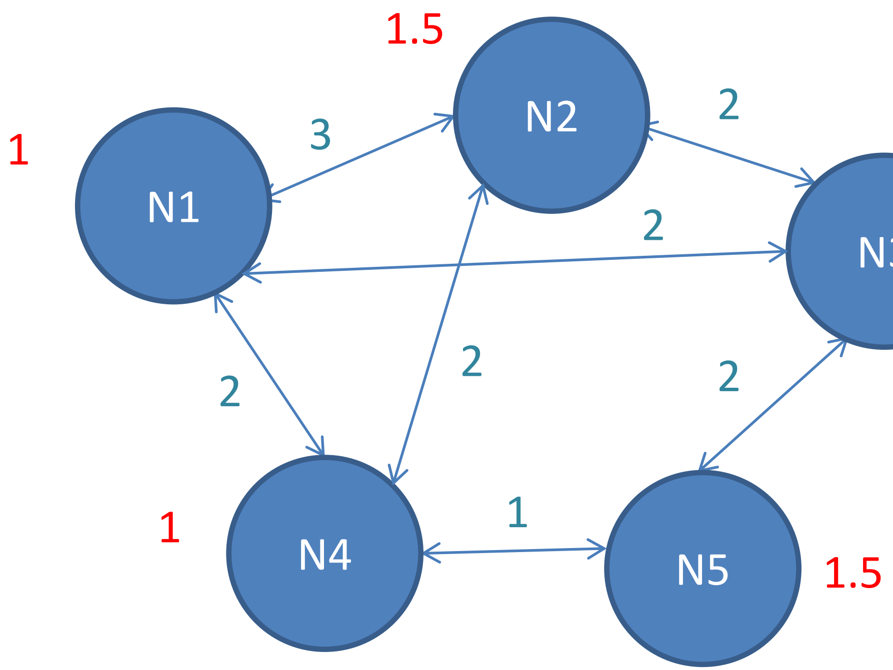
THE CLOUD SCHEDULING PROBLEM

Job



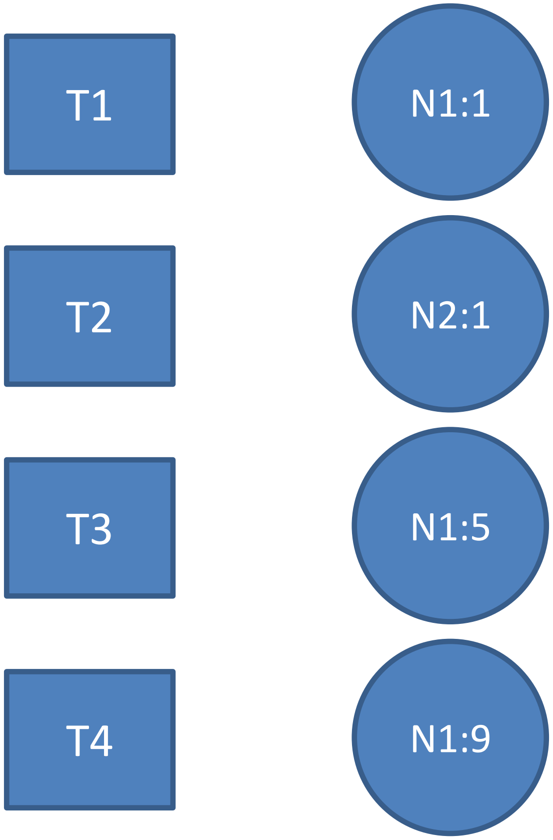
- A directed acyclic graph (DAG) of tasks
- Nodes marked with worst case computing duration
- Edges marked with data transfer
- These can be estimated for a large class of jobs in NLP, machine learning, image processing, bioinformatics (parametrized by input size)

Cloud



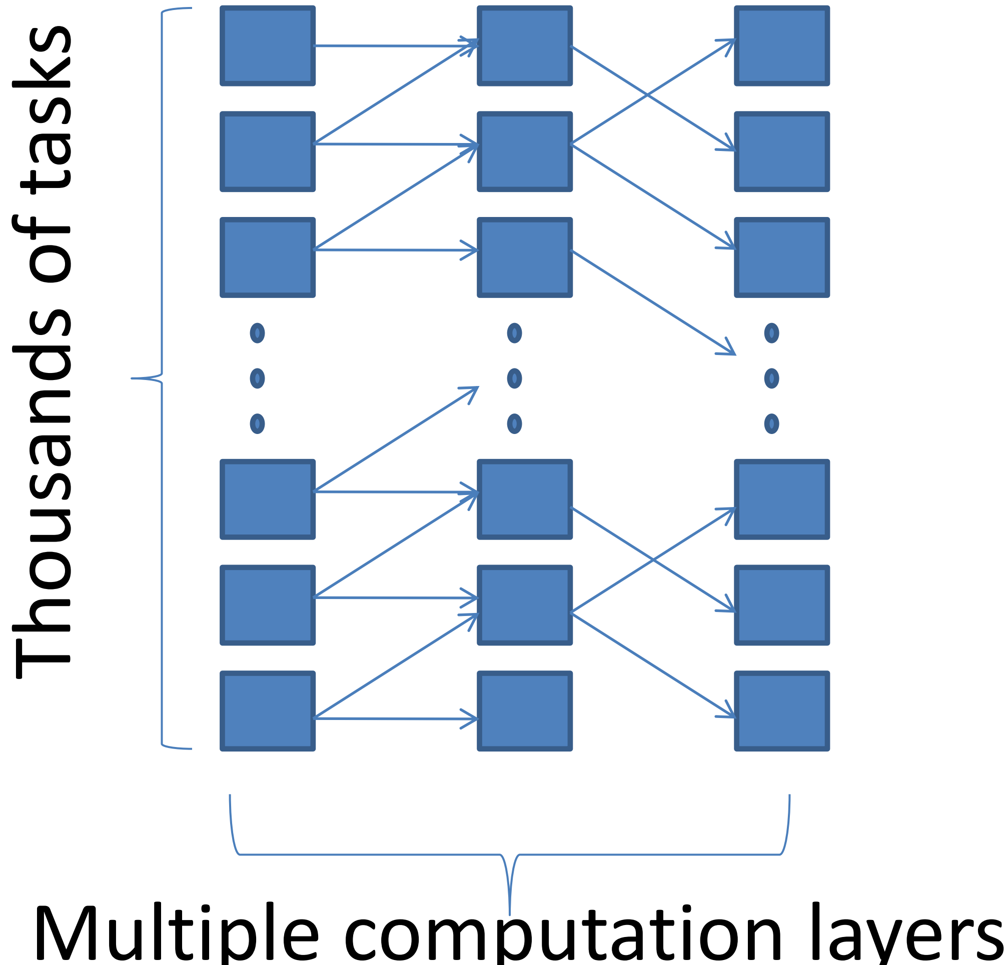
- A connected graph
- Nodes marked with computation power
- Edges marked with link bandwidth

Schedule

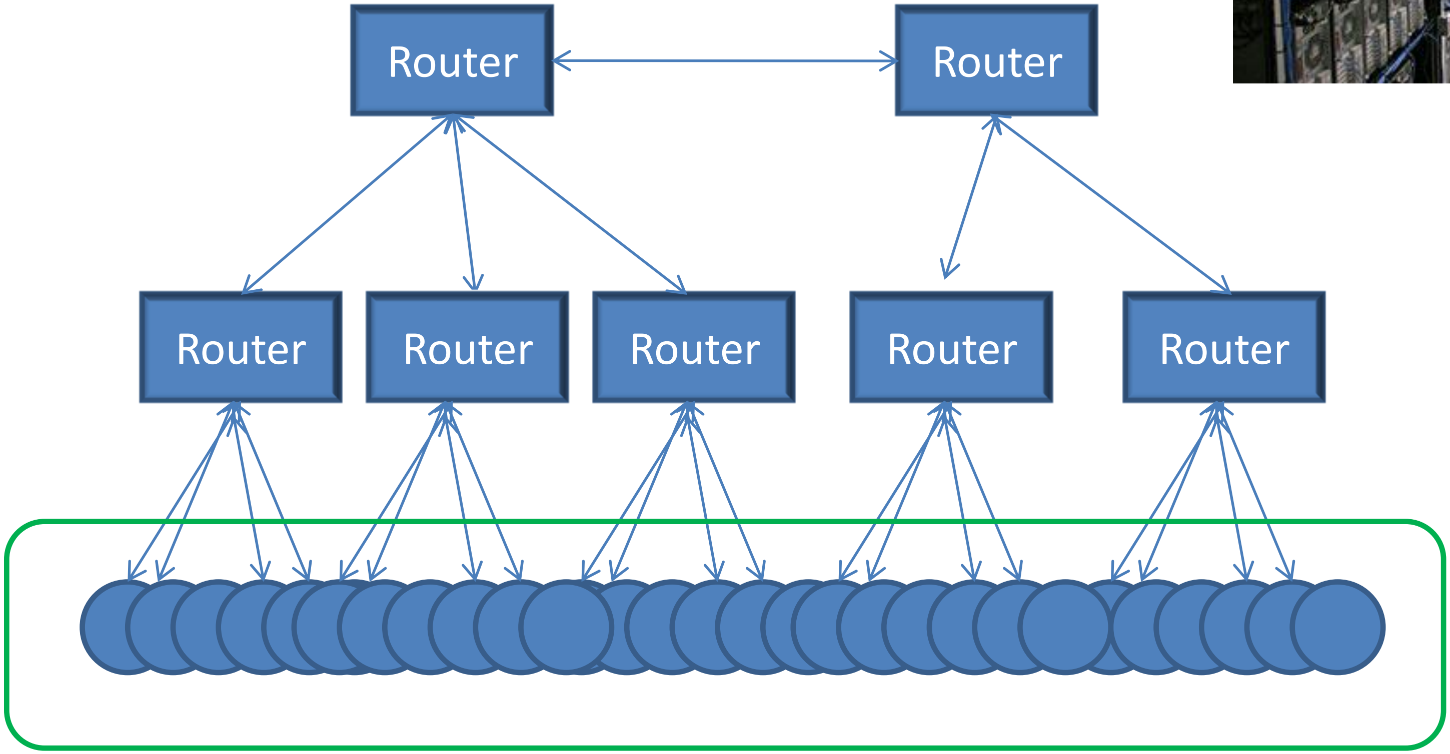


- A function from tasks to node-start time pairs

A Large Job



A Data Center

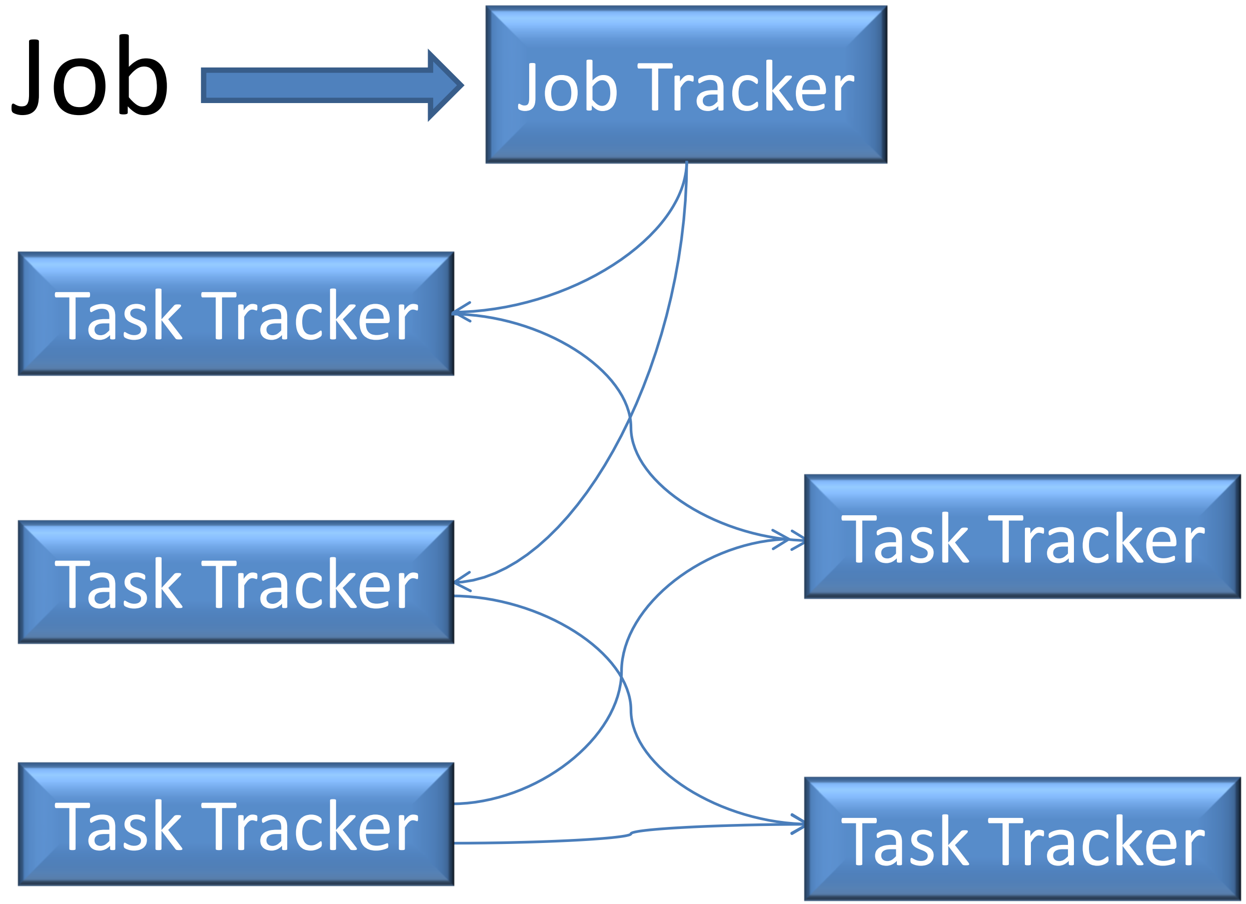


Thousands of Compute Nodes

Given the scale, conventional wisdom says:

Use dynamic scheduling

Example: Hadoop



Hadoop

Dynamic scheduling using Task Queues

↓

Does not allow apriori knowledge of when a job finishes

↓ ↓

A user cannot be promised a deadline

A cloud cannot plan ahead on future resource usage

Certainly, if task characteristics are not available, dynamic scheduling is the best option!

Can we do better?

- We have talked a lot about managing data over the past few years
- As computation moves to the cloud, we might want to manage that too!
- Can we plan ahead our computation?

Static Scheduling

- Static schedule: a schedule computed before executing the job
- Benefits:
  - The user can be promised a deadline
  - The resources can be planned
- Drawbacks:
  - Generally computationally expensive

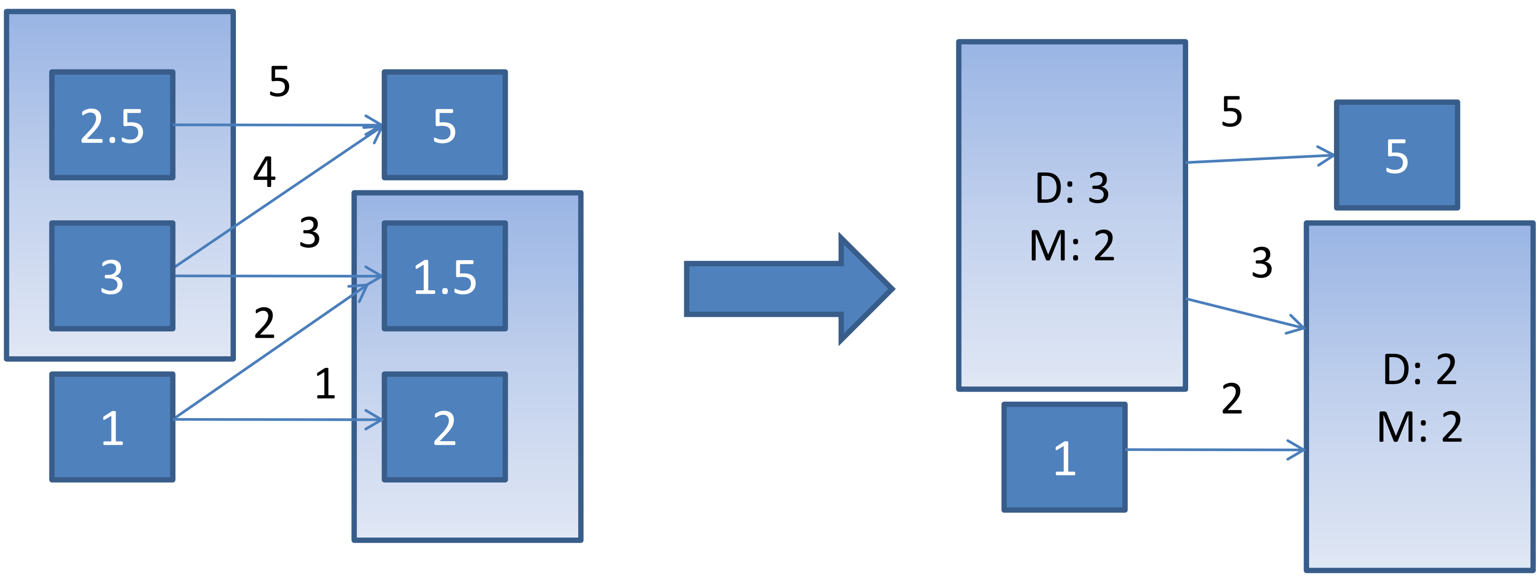
Static Scheduling

- Computing optimal schedule: NP-hard
- Heuristics (Greedy, deadline division etc.): |J|.|C|
- With 1000 tasks job and 200 nodes cloud, a greedy scheduler takes up to 5 minutes!

The Core Idea

- Over-approximate the resource requirements of the job J to get Abs J
- Under-approximate the computing power of the cloud C to get Abs C
- Get a static schedule for (Abs J, Abs C). Use it as a schedule for J, C

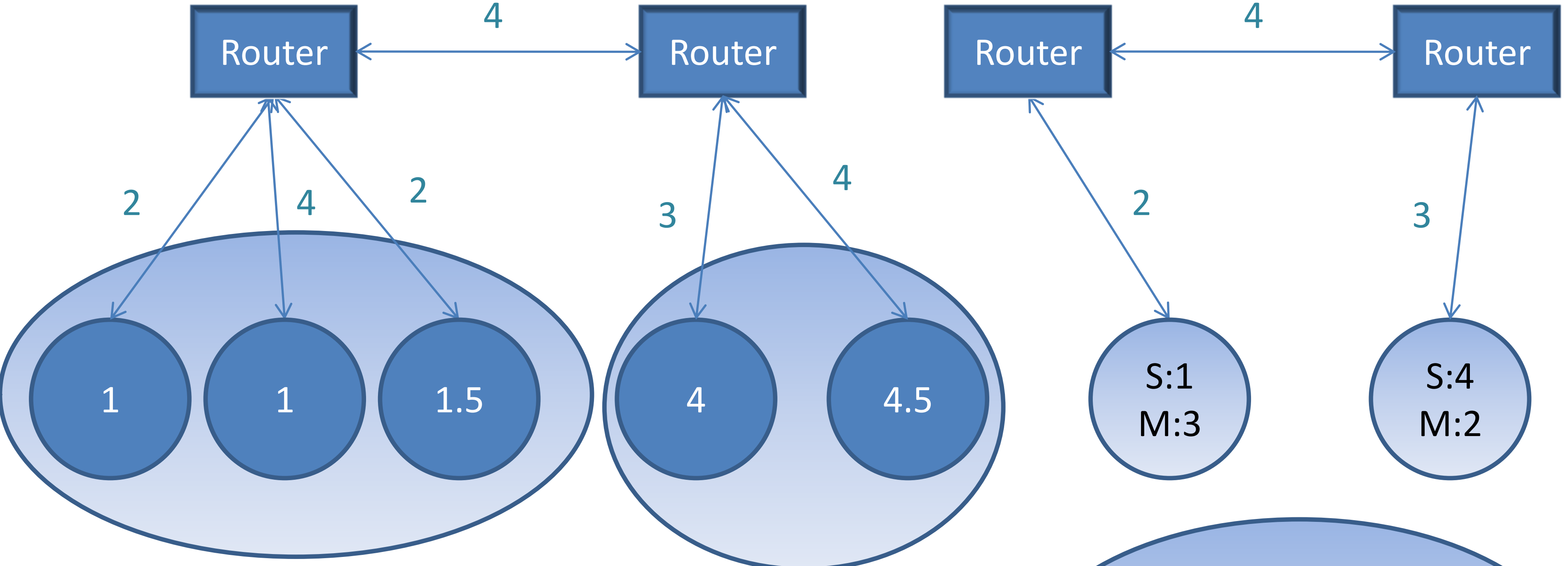
Job Abstraction



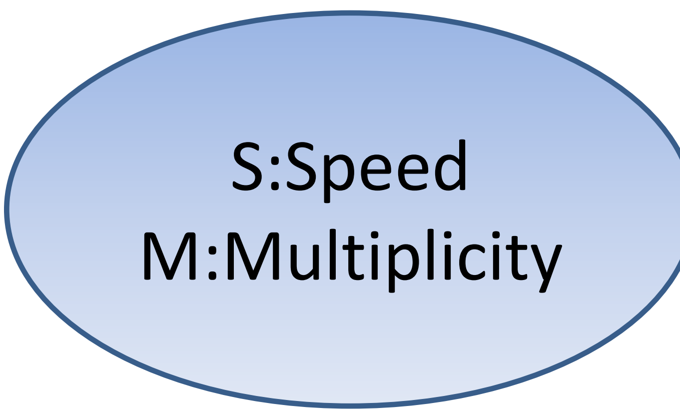
An over-approximation of resource requirements

D = Duration
M = Multiplicity

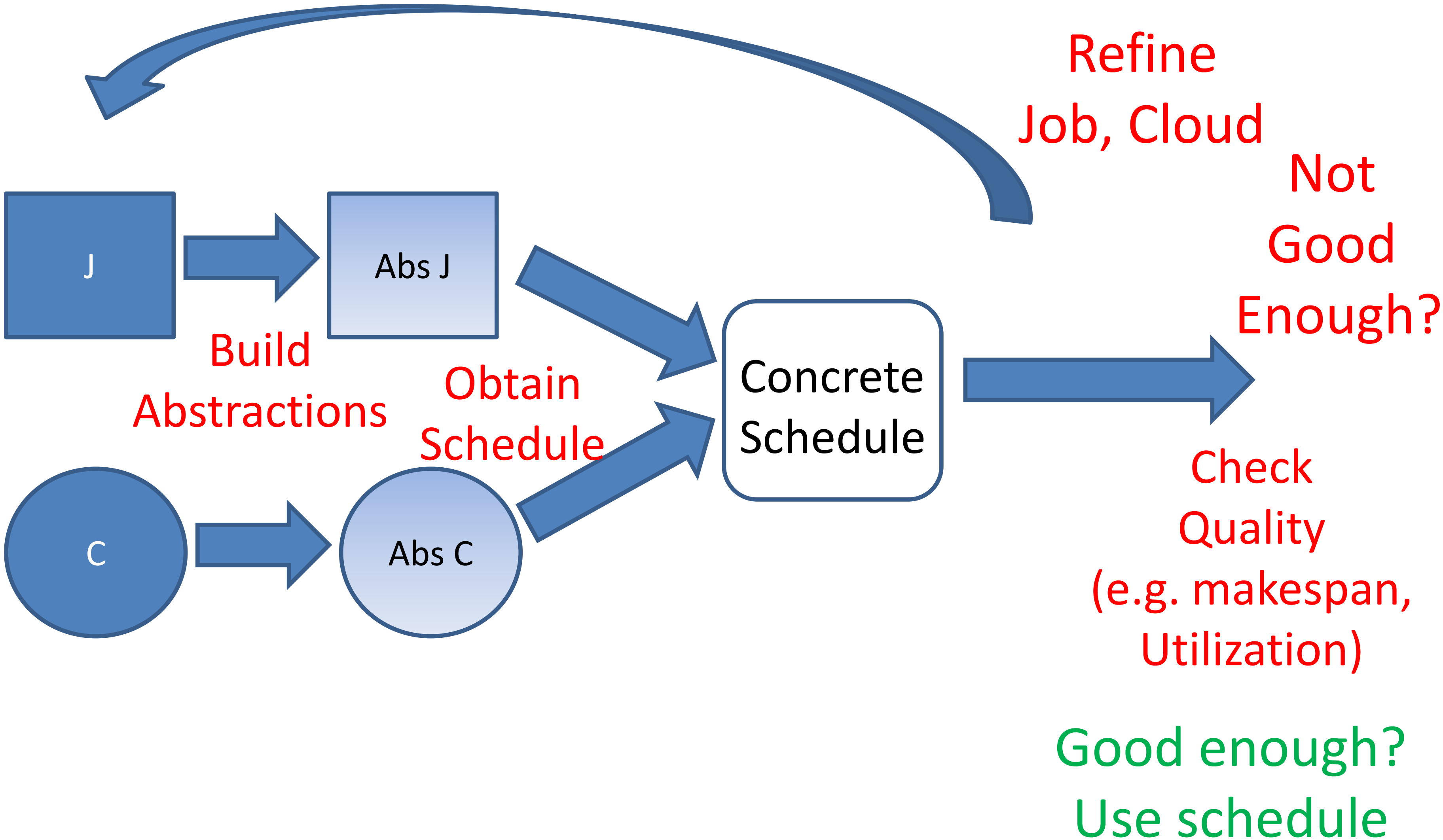
Data Center Abstraction



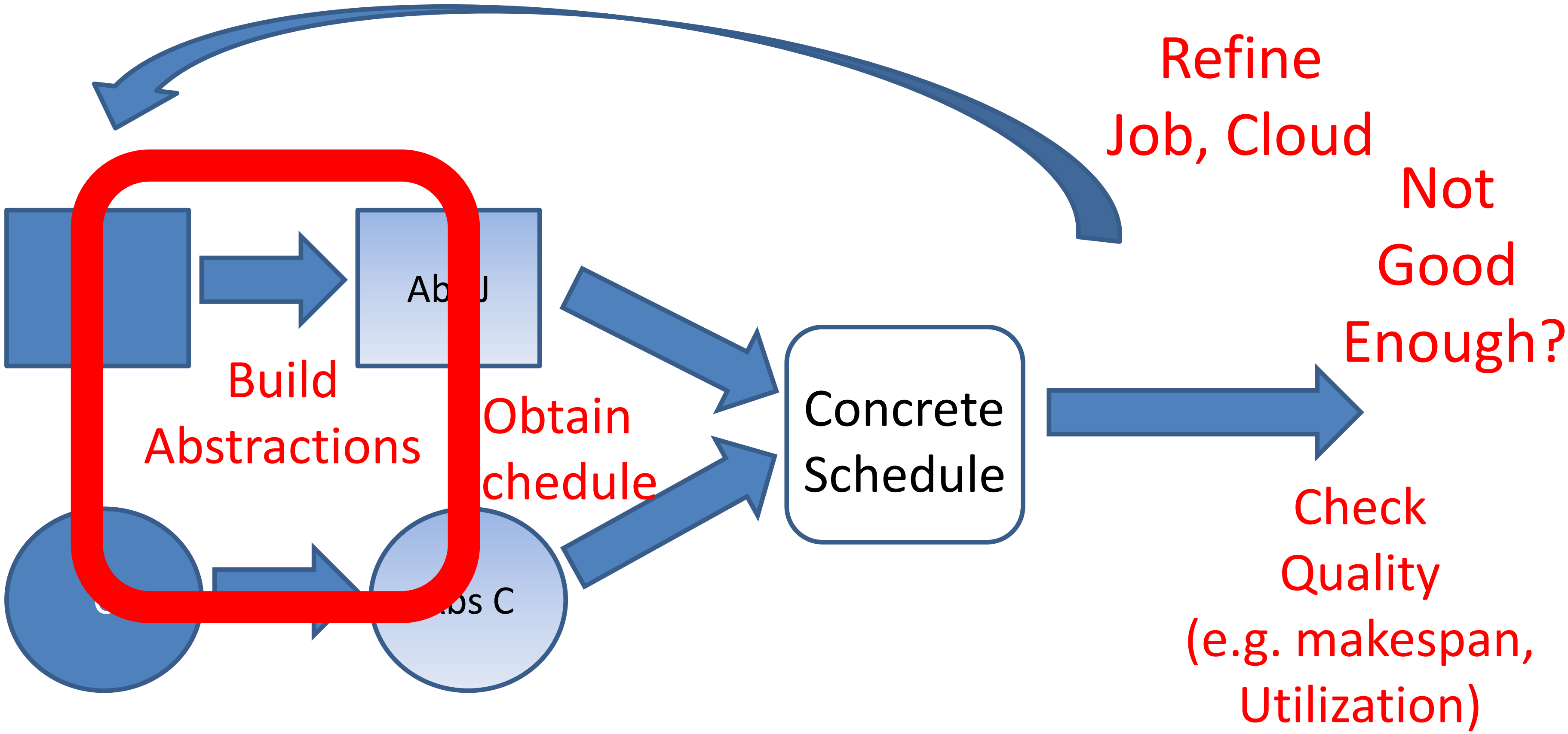
An under-approximation of available resources



Generic AR Scheduler



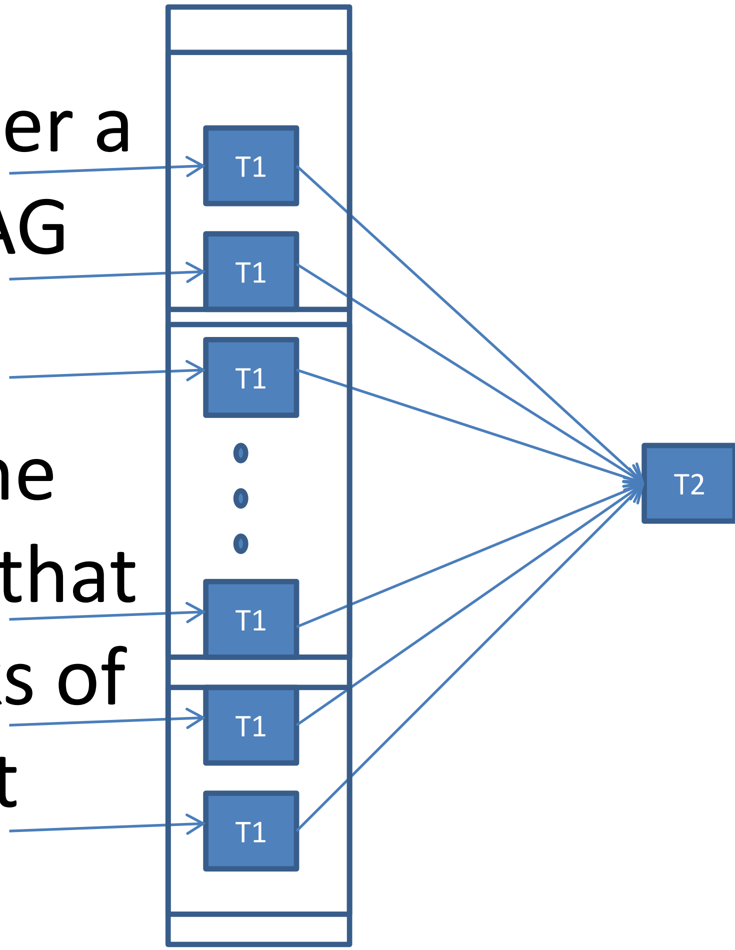
Generic AR Scheduler



Important Job Abstractions

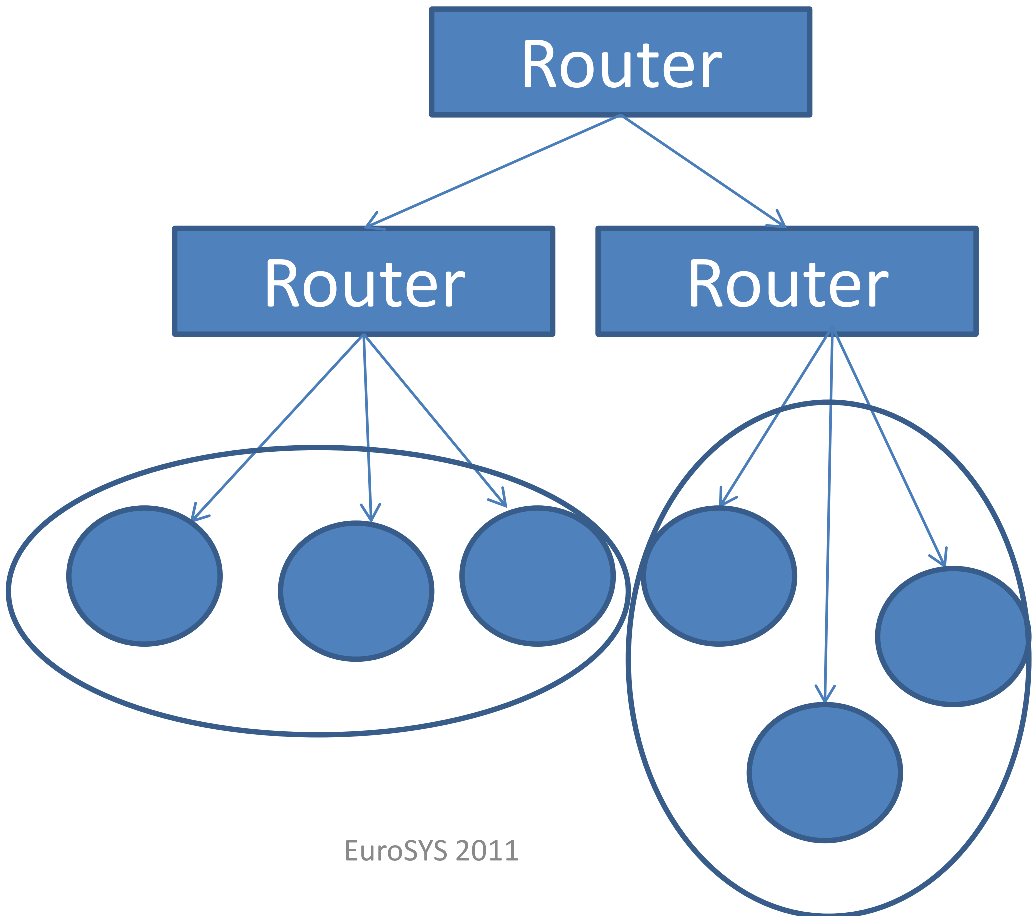
- Topological: Group tasks as per a topological sort of the job DAG
- X-similar: Partition tasks in the topological sort in a manner that no abstract task has two tasks of duration D1 and D2 such that

  D2 > D1.X

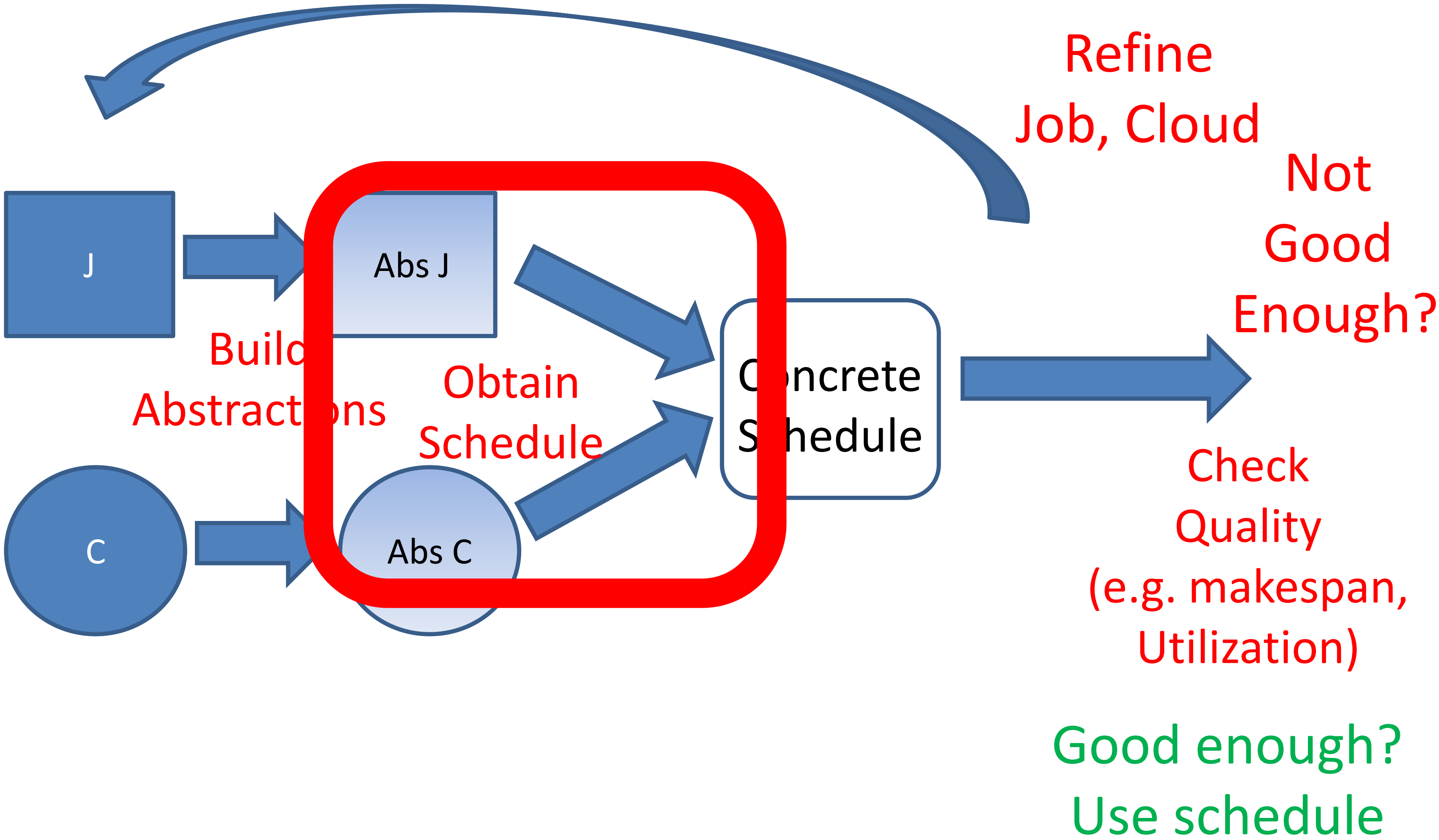


Important Cloud Abstraction

- Rack abstraction: Create an abstract node for a group of nodes on a rack



Generic AR Scheduler



Two AR Schedulers

- FISCH – Free Intervals Scheduler
- BLIND – Buddy Lists IN Datacenters

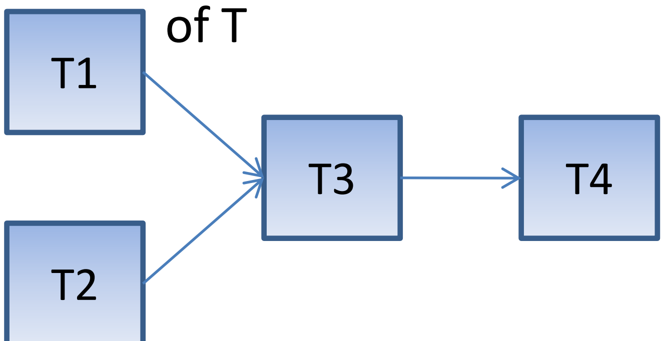
THE FISCH SCHEDULER

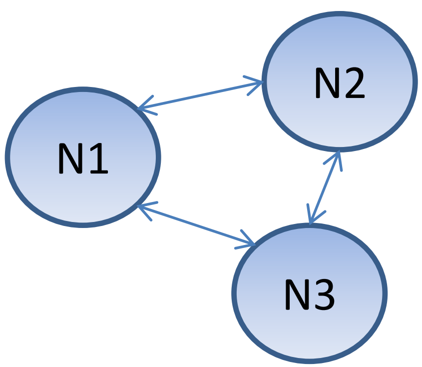
Abstractions for FISCH

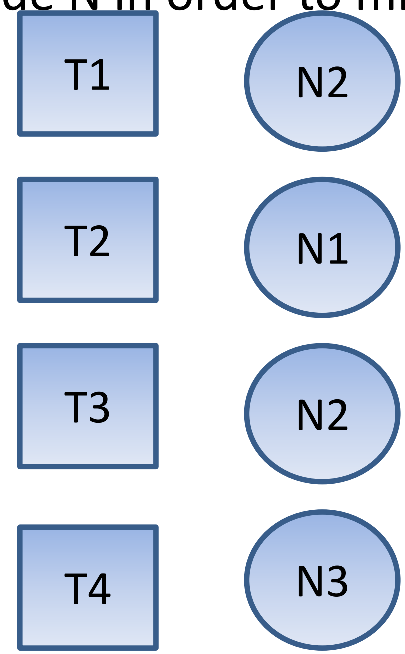
- Starts with topological abstraction of job
- Keeps a constant rack abstraction of cloud

FISCH: A Greedy Abstract Scheduler

- While an abstract tasks is yet to be scheduled :
  - Choose an abstract task T such that all predecessors of T have been scheduled
  - Schedule T on an abstract node N in order to minimize the finish time of T







A schedule for all concrete tasks in T1 has been computed

Checking for An Abs Task on An Abs Node

N1: (2, 5), (8, 12), (20, 25)
N2: (4, 9), (12, 35), (42, 45)
N3: (10, 20), (25, 32), (35, 45)

- One possible data structure:
  - Every abstract node consists of the information as a sequence of (start_time, end_time) pairs when a concrete node is busy
- To schedule an abstract task of duration D and multiplicity M, we search for M D-sized gaps
- Complexity: O(number of tasks scheduled)

Search Engine 101

D1: Eurosys 2011 was held in the Austrian city of Salzburg.

D2: Salzburg is a beautiful city. .

D3: How do I get to Salzburg?

- To search for Salzburg in these documents: we can go through each document one by one (Imagine Google doing that!)
- OR We can maintain a data structure as follows:
  - Salzburg: (D1, Line 4); (D2, Line 1), (D3, Line 2)
  - city: (D1, Line 3); (D2, Line 2)
- This data structure is known as the inverted index
- Benefit: Finite dictionary size leads to cost amortization

Inverted Indices in FISCH

Node: (start, end) sequence
N1: (2, 5), (8, 12), (20, 25)
N2: (4, 9), (12, 35), (42, 45)
N3: (10, 20), (25, 32), (35, 45)

Inverting Indices

Interval size: (Node, start) sequence
3: (N1, 5), (N2, 9), (N3, 32)
5: (N3, 20)
7: (N2, 35)
8: (N1, 12)
_ : (N1, 25), (N2, 45), (N3, 45)

Benefit:
To get M intervals of size D, we simply
look at entries of N >= D, and return
first M intervals.

FISCH Summary

- Starts with a topological abstraction of the job, and a rack-abstraction of the cloud
- Uses inverted data structure to keep track when every concrete node is free or busy
- Greedy scheduler
- Refines the topological job abstraction when necessary
- Many details described in the paper!

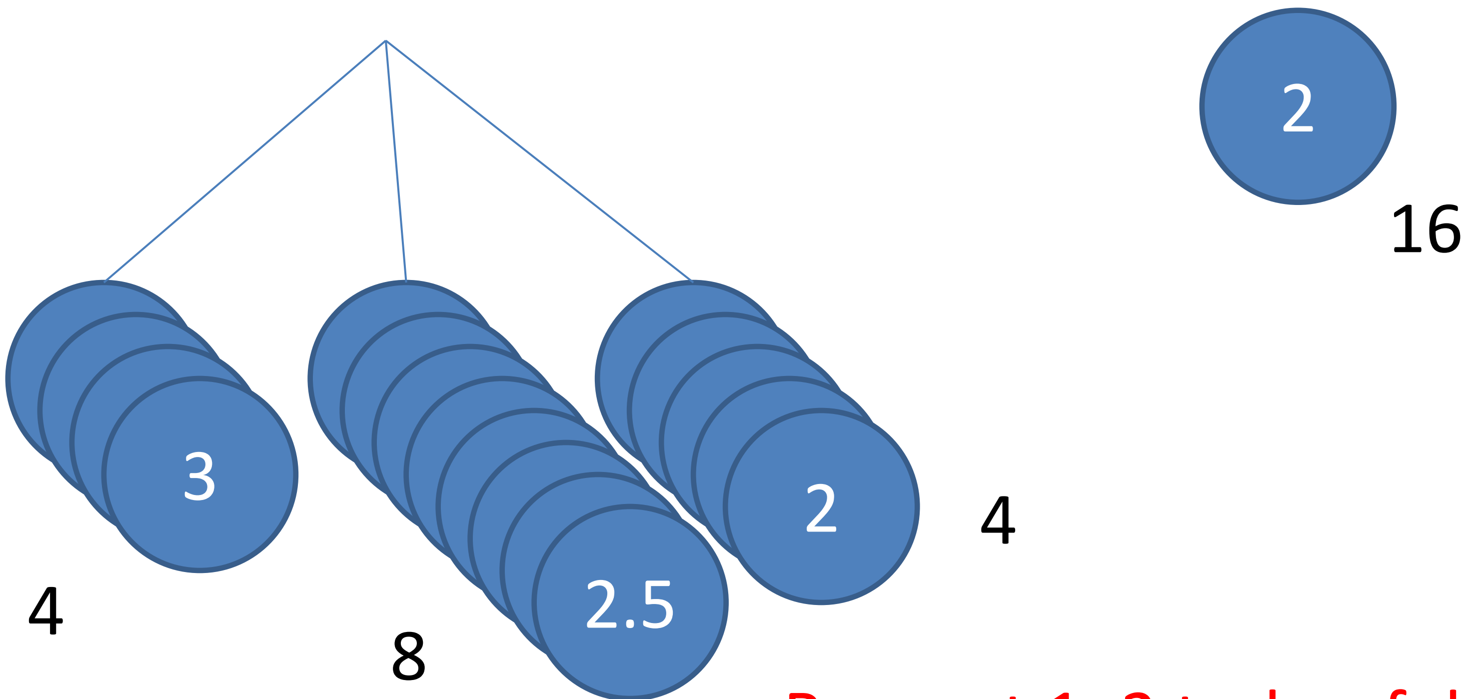
THE BLIND SCHEDULER

Abstractions

- Start with an X-similar topological job abstraction

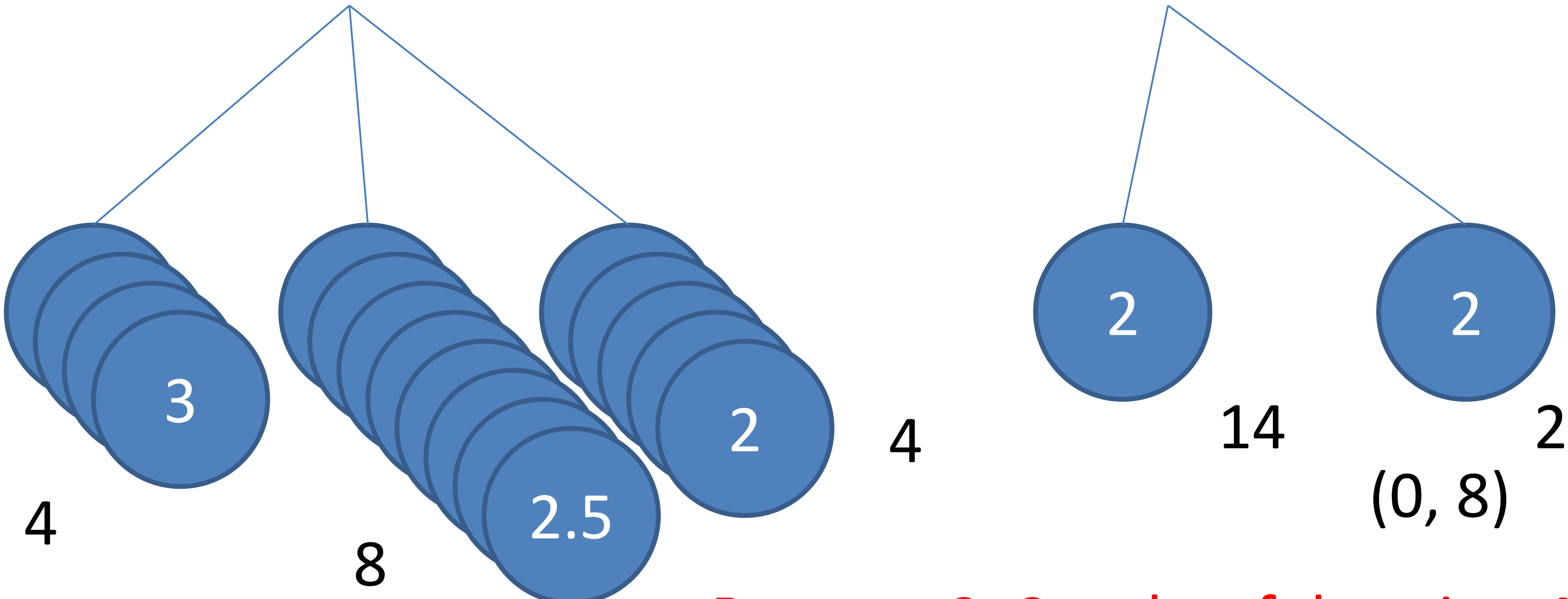
- A single abstract node as cloud abstraction

BLIND by example



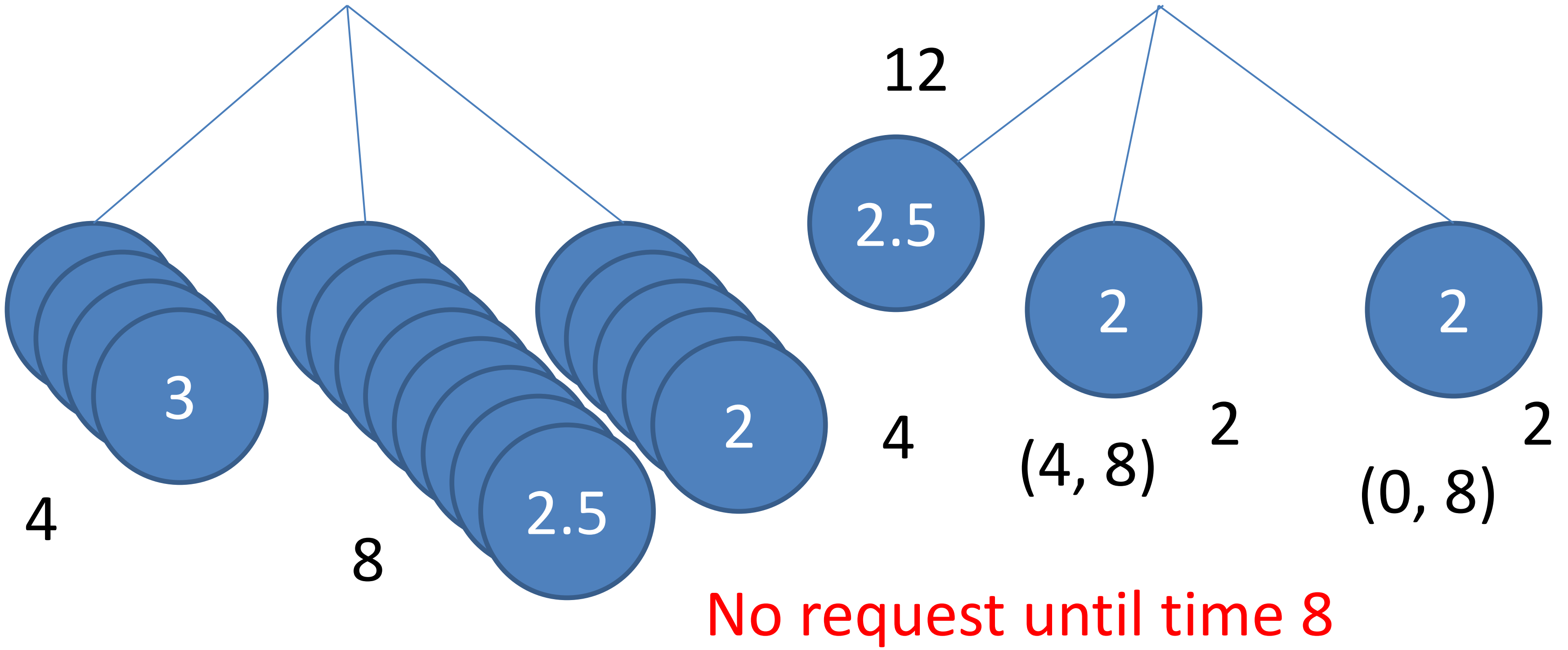
Request 1: 2 tasks of duration 8 at time 0

BLIND by example

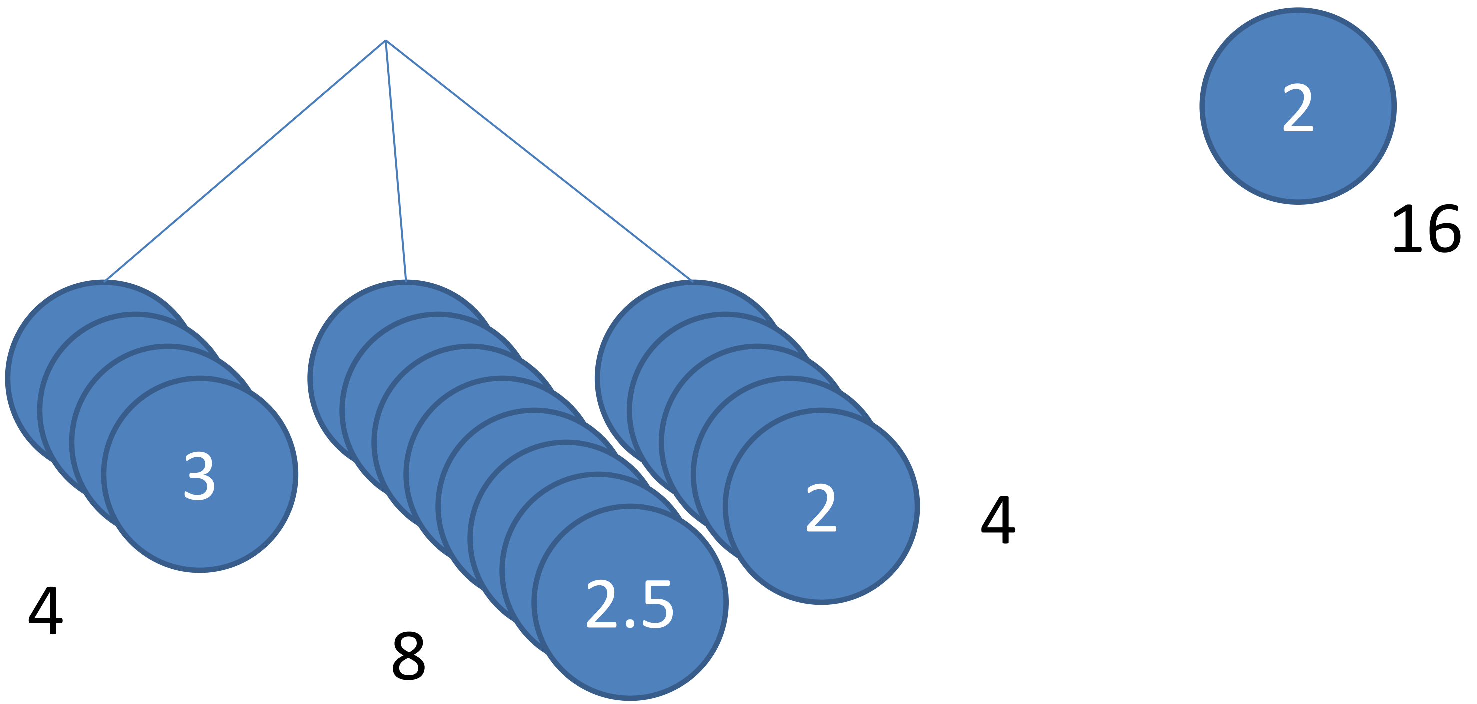


Request 2: 2 tasks of duration 4 at time 4

BLIND by example



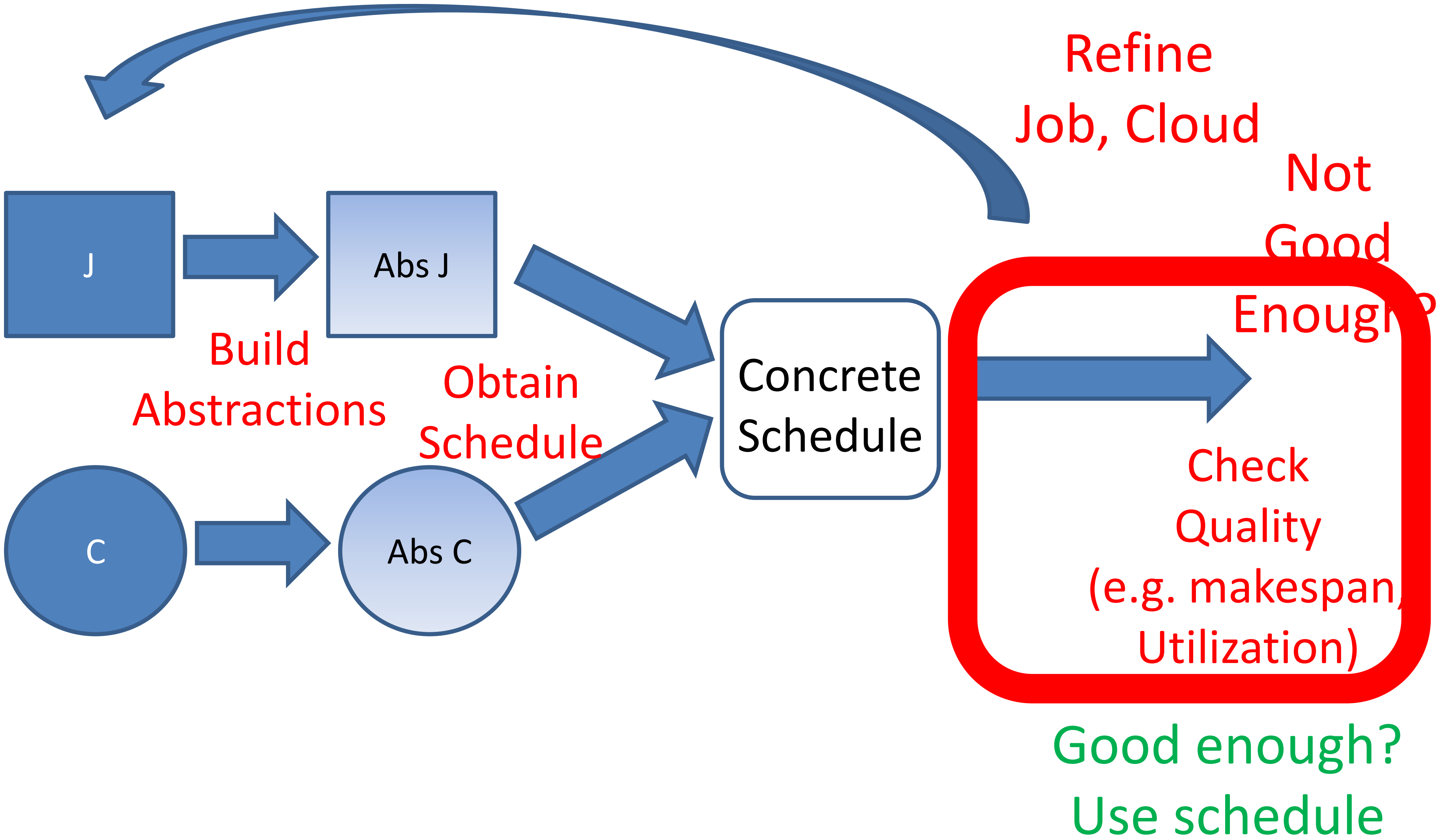
BLIND by example



BLIND Summary

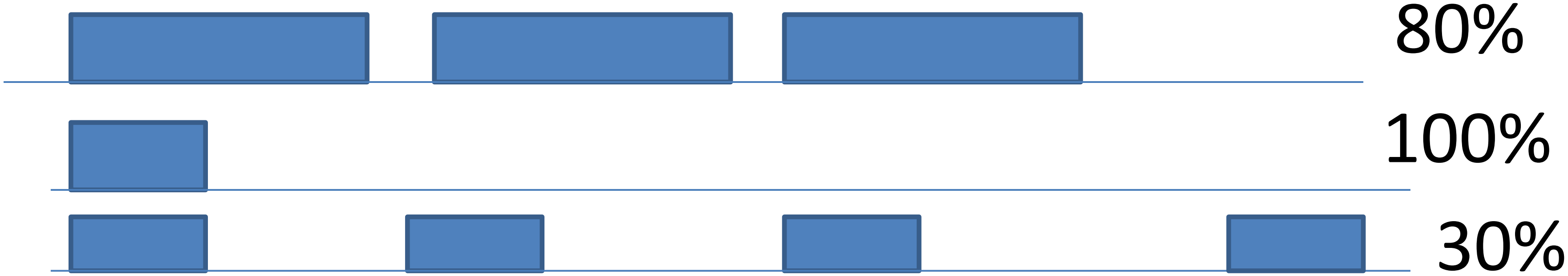
- Keep the abstraction of the cloud just as coarse as required
- On an incoming scheduling request, fragment the abstraction in a minimal fashion
- More details in the paper

Generic AR Scheduler



Check Quality: 2 Metrics

- Cloud Utilization: What is the proportion of used intervals to total scheduling duration across all nodes?

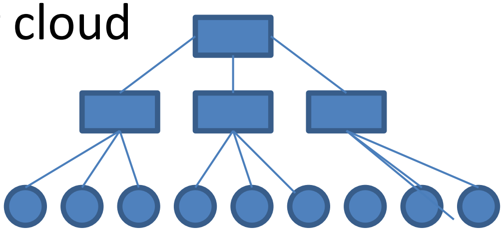


- Schedule Makespan: Compared to a sequential execution of the job, how much better is the duration of the schedule?

Simulation Experiments

Clouds

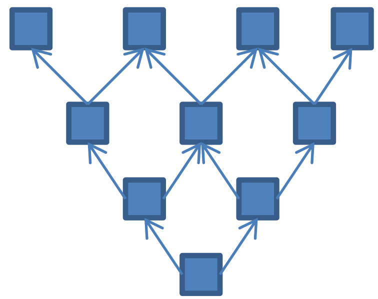
2-tier cloud



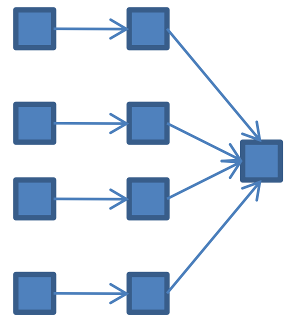
Half of the nodes: speed x, Other half: speed 1.5 x

Jobs

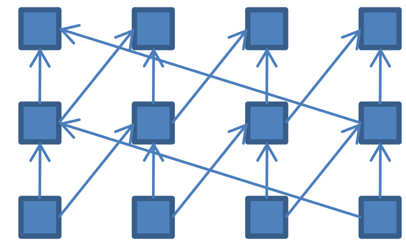
Wavefront (WF)

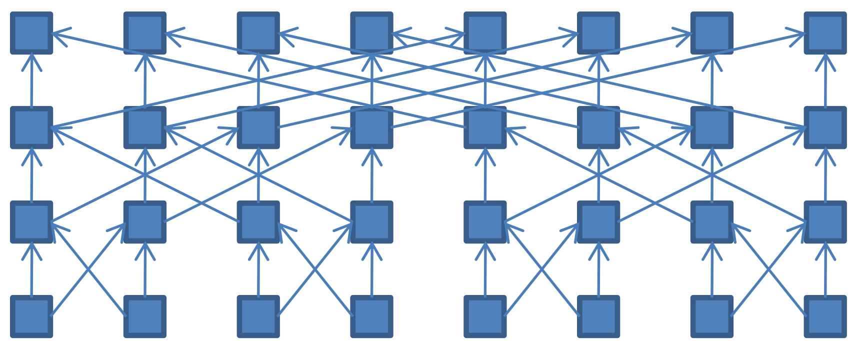


MapReduce(MR)



Matrix Mutl(MM)





FFT Transform (FFT)

Simulation Results 1

- We create a sequence of 1000 jobs (each job with 1000 tasks with nonuniform data and compute requirements)
- We measure scheduling latency per task and cloud utilization on 2-tier cloud with 1600 nodes

Job	Latency (ms)	Util	Latency (ms)	Util
MR	0.34	86%	0.32	93%
MM	1.34	55%	1.95	77%
FFT	1.89	68%	1.40	78%
WF	1.57	49%	0.71	62%

Simulation Results 2

- We then compare FISCH and BLIND to a concrete greedy scheduler on a sequence of 100 jobs
- We measure scheduling latency per task and cloud utilization on 2-tier cloud with 210 nodes

Scheduler	Latency (ms)	Utilization
Baseline	293	96%
FISCH	0.27	92%
BLIND	0.16	91%

More Simulation Results

- … in the paper

COMPARISON WITH HADOOP

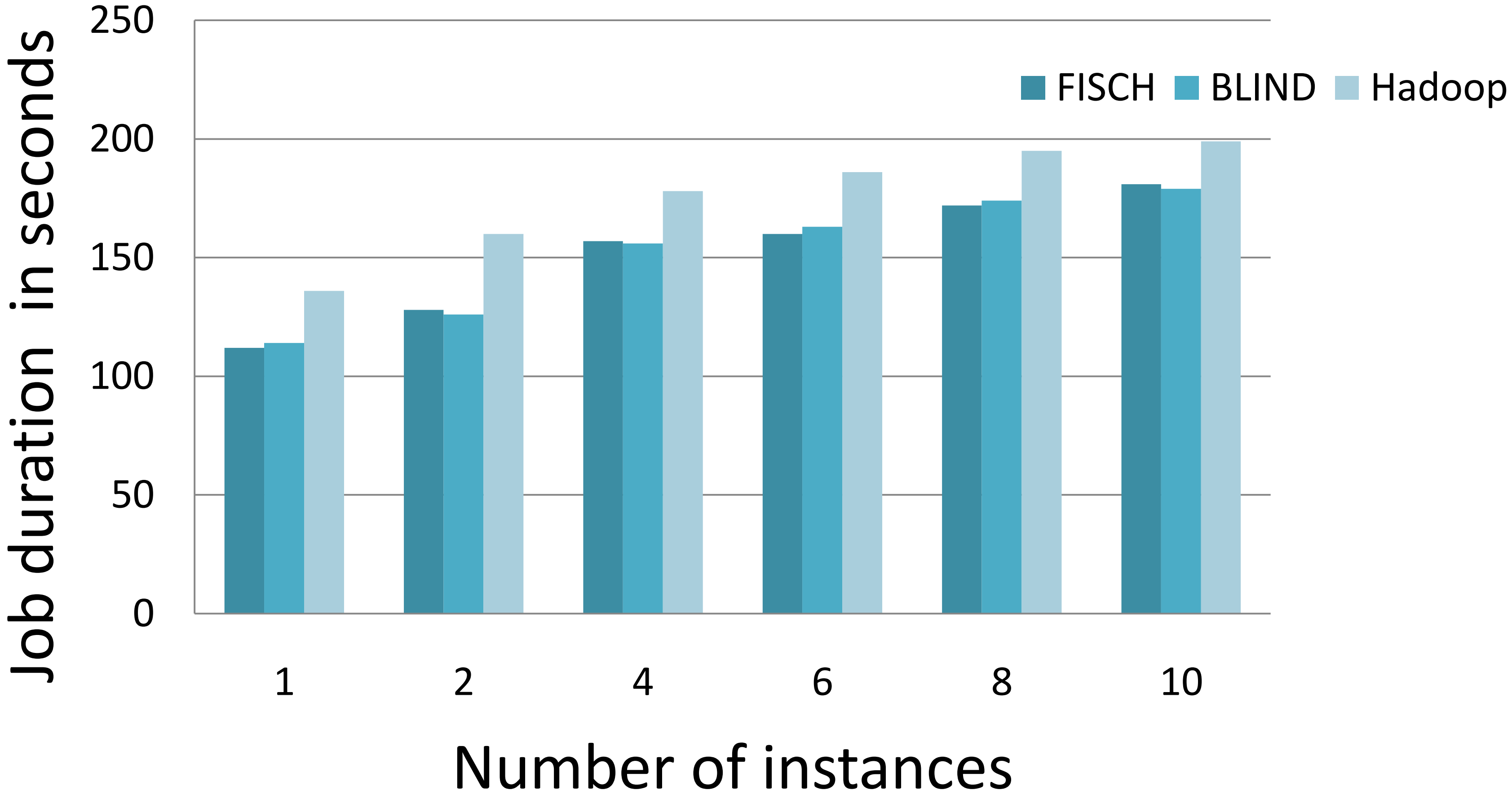
A Word of Caution

- Static scheduling alone will not work in a data center due to
  - High variability in data center performance
  - Task durations are conservative estimates
- For comparison to Hadoop, we used static scheduling with backfilling (a dynamic scheduling technique)
- In this work (and the paper), we focus on static part, as there lies the foundation of this work

Setup

- Job
  - A MapReduce Image Transformation Job
  - Size of each image: 4 MB
  - Mapper: An image transformation, requires 8.1 seconds on average, set the estimate to 40 seconds (use backfilling to use empty spaces)
  - Reducer: Identity operation
- Cloud
  - Amazon EC2 m1.xlarge instances (15GB RAM, 4 virtual cores, 64-bit)
  - Number of mappers = 50 * number of instances
- Hadoop streaming version 0.19.0

Results



Job duration in seconds
250
200
150
100
50
0
FISCH
BLIND
Hadoop
1
2
4
6
8
10
Number of instances

Observations

- The Hadoop framework requires large runtime overhead: results in slowdown of the job execution

- Offline scheduling allows to prefetch data in case of multiple computation stages, whereas dynamic scheduling does not

Conclusion

- Proposed a new "offline" alternative for scheduling jobs on datacenters
- Goal: bring a deep theoretical concept from the formal methods community to build better systems
- We believe we have just scratched the surface of some appealing techniques for managing computation on the cloud
- Feel free to dive in!

Questions?