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Robust Assignments

• What happens if a machine fails?



Robust Assignments

• What happens if a machine fails?



Robust Assignments

- What happens if a machine fails?
- How to reassign?



New Model: Redundancy

- Inspired by real systems architectures
- Split each demand in half: \bigcirc \longrightarrow \bigcirc
- Assign each half to distinct machines

Chaojie Zhang, Alok Gautam Kumbhare, Ioannis Manousakis, Deli Zhang, Pulkit A. Misra, Rod Assis, Kyle Woolcock, Nithish Mahalingam, Brijesh Warrier, David Gauthier, Lalu Kunnath, Steve Solomon, Osvaldo Morales, Marcus Fontoura, Ricardo Bianchini: *Flex: High-Availability Datacenters With Zero Reserved Power*. ISCA 2021

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• *m* machines



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- *n* demands arrive online with sizes:
- Must assign demand to edge (pair of machines) upon arrival such that:
 - Nominal constraint: Load incident to each machine is ≤ 1
 - Failover constraint: In every failover scenario (single machine failure), the load incident to each machine is $\leq B$



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Goal: maximize utilization (total size of assigned demands) until first demand that needs to be rejected

Related Work

- Multiple Knapsack [Chandra Chekuri, Sanjeev Khanna. SIAM J. Comput. 2005]
- Coupled placement [Madhukar R. Korupolu, Adam Meyerson, Rajmohan Rajaraman, Brian Tagiku. Math. Prog. 2015]
- Do not capture failover constraints (depends on how load is arranged on a machine's edges)

Our Results

Compared to optimal offline policy that knows all demands but also assigns demands in same order until rejecting

Theorem (Worst Case): $(\frac{1}{2} - o(1))$ - competitive deterministic algorithm

Theorem (Stochastic): If all demand sizes are drawn i.i.d. from an unknown distribution, then (1 - o(1)) - competitive algorithm w.h.p.

• No deterministic algorithm is better than $\frac{1}{2}$ - competitive

Worst Case: Idea



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Worst Case: Idea

 $degree = \frac{1}{\epsilon} - 1$ (assume B = 1)



- Minimize impact of failover by spreading out demands
- Ideally, want to make clique of machines for same size demands
- ... but need to make sure we don't run out of machines

- Assume $B = 1 \Rightarrow$ want to arrange demands of size $\frac{1}{k}$ in a K_k
- Assume all demand sizes are $\frac{1}{k}$ for integer k

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Stochastic Model: Idea

• Each demand size drawn i.i.d. from distribution μ

Algorithm: Suppose we already assigned first n' demands:

- Compute (near-) optimal assignment of realized demand sizes into minimum number of machines
- Use this assignment to assign the subsequent n' online arrivals

Realized first n'



Stochastic Model: Idea

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Theorem (Monotone Matching): Given sequences $X_1, ..., X_n$ and $Y_1, ..., Y_n$ (arriving online) drawn i.i.d. from the same distribution, we can compute a matching from Y's to X's such that w.h.p.:

- If Y_i is matched to X_j , then $Y_i \leq X_j$
- At most o(n) of the Y's are unmatched

How to use template:

- Compute monotone matching from n' next online arrivals to the realized first n'
- If matched, then assign arrival to corresponding slot in template
- Else, assign arrival to its own separate edge



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Conclusion

- Introduce Online Demand Scheduling with Failover
- Worst Case
 - Competitive ratio $\rightarrow \frac{1}{2}$ as $m \rightarrow \infty$
 - Tight lower bound
 - Reserve cliques for different sizes

• Stochastic i.i.d.:

- Competitive ratio $\rightarrow 1$ as $m \rightarrow \infty$
- Learn from past arrivals using template assignments
- Monotone matching theorem