Optimizing Networked Systems with Limited Information

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Symmetric Matching Interdiction

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[in submission]
A recent study of malicious network traffic observed at Microsoft data centers made the surprising observation that a large volume of attack traffic originated from virtual machines hosted within the data centers.

Samuel Haney

March 30, 2017 3 / 24
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(network operator’s view)

minimize regret: amount of routable legitimate traffic not routed
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Symmetric Matching Interdiction

When each server has unit capacity, this formalization can be simply stated as follows.

**Definition (Symmetric Matching Interdiction (SMI))**

Given a graph $G$, find matching $M$ such that the maximum matching in $G \setminus M$ is minimized.
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Given a graph $G$, find matching $M$ such that the maximum matching in $G \setminus M$ is minimized.
Claim

Any maximal matching is a 2-approximation to the optimal interdiction matching.
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Proof Sketch.

The optimal solution removes some of these edges (the edges removed must satisfy matching constraints).

On the remaining graph, there is always a matching that is at least half the size of the (original) number of blue edges.
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Symmetric Matching Interdiction Results

- We give a non-trivial algorithm that finds a 3/2-approximation (improving on the 2-approximation from the previous slide).

- Symmetric matching interdiction is APX-hard, i.e. cannot be approximated better than a constant.
Why do we call it symmetric interdiction?
  ▶ standard interdiction: remove k edges to minimize some objective

Symmetric interdiction models denial of service attacks
  ▶ adversary and user have the same constraints
  ▶ other problems fit in the symmetric interdiction framework: flows, \( b \)-matching, demand matching

We show that in general, an \( \alpha \)-approximation to an optimization problem is a \((1 + \alpha)\)-approximation to the corresponding interdiction problem.
Capacity Planning

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[ongoing]
- The internet is growing fast

- CDNs need to scale up capacities rapidly

- This project explores how to plan expanded capacity using noisy predictions of future need.
“Overall, the U.S. economy seems likely to expand at a moderate pace over the second half of 2007, with growth then strengthening a bit in 2008 to a rate close to the economy’s underlying trend.”

—Bernanke, 2007
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—Bernanke, 2007

Can we develop algorithms whose performance degrades gracefully with decreasing accuracy of predictions?
Robust and Probabilistic Failure-Aware Placement

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[ACM SPAA 2016]
How do we place tasks to improve availability in presence of failures?
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![Diagram showing placement of tasks with identical subtasks and failure points indicated with 'X'.]
Results

RobustFAP (nodes have reliability weight):

- Problem is co-NP hard.
- PTAS/approximation algorithms
RobustFAP (nodes have reliability weight):

- Problem is co-NP hard.
- PTAS/approximation algorithms

ProbFAP (nodes have probability of failure):

- PTAS based on Poisson approximation techniques
High Availability in Clusters

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[in submission]
Given cluster of nodes and VMs does there exist a packing such that for all failures of k nodes there is a disruption-free repacking?

Given packing of VMs into nodes of a cluster, is there a disruption-free repacking for all failures of k nodes?

Industry standard is Martello-Toth, a heuristic for Multiple Knapsack. How effective is it?
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**Sounds like a $\Pi_2$ complete problem. It probably is. We show NP-hard and coNP-hard.**

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**We propose a stochastic framework for comparing heuristics. Show that water-filling is superior to Martello-Toth.**
Online Service with Delay

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[STOC 2017]
- Service requests arrive over time
- Service can be delayed to facilitate batching with future requests in a nearby location ...
- ... but future is unknown!
- Dual objectives: minimize movement, minimize delay

- Motivation: models the fundamental tradeoff between batching requests and immediate response
  - Operating systems
  - Operations research
  - Scheduling theory

- Result: We give an algorithm with polylog(n) competitive ratio for this problem
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- ...but future is unknown!
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- Extension: what if there are multiple (k) repairmen (servers)?
- Algorithm decides not only when to serve a request, but also which person to dispatch

- Result: We give an algorithm with k*polylog(n) competitive ratio for this problem
Network Scheduling

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[ongoing]
Programmers/organizations want to use cloud services for jobs.
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Latency between services mainly determines the performance of a job.
Given a task graph and a datacenter network, can we produce a mapping from the tasks to the datacenter nodes?
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Thank You!