To Reserve or Not to Reserve: Optimal Online Multi-Instance Acquisition in IaaS Clouds

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Growing Cloud-Computing Costs

- Drastic increase in enterprise spending on Infrastructure-as-a-Service (IaaS) clouds
  - 41.7% annual growth rate by 2016 [Cloud Times'12]
  - IaaS cloud is the *fastest-growing* segment

amazon web services™

ElasticHosts
Flexible Servers in the Cloud

GOGRID
Control in the Cloud™

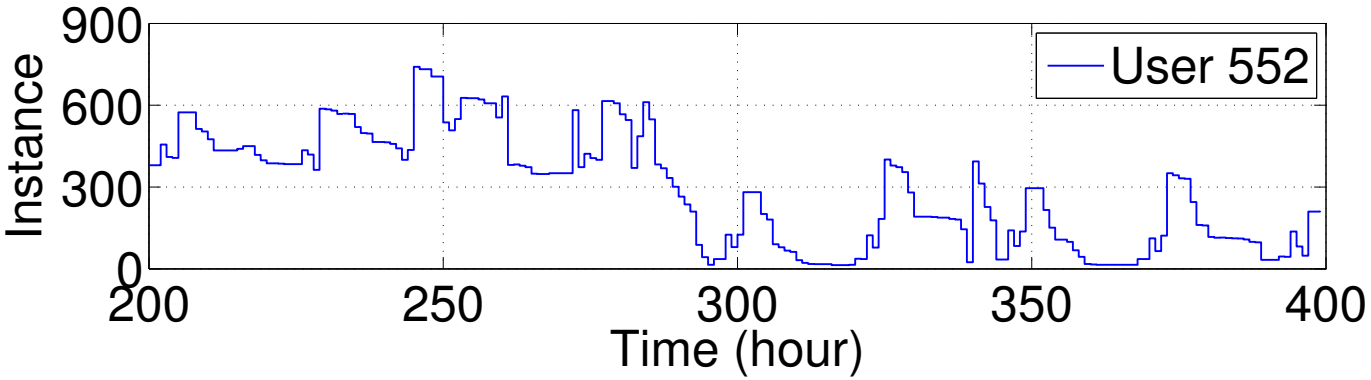
Tradeoffs in Cloud Pricing Options

- On-demand Instances
  - No commitment
  - Pay-as-you-go
- Reserved Instances
  - Reservation fee + discounted price
  - Suitable for long-term usage commitment

Instance Type	Pricing Option	Upfront	Hourly
Standard Small	On-Demand	$0	$0.08
	1-Year Reserved	$69	$0.039
Standard Medium	On-Demand	$0	$0.16
	1-Year Reserved	$138	$0.078

Multi-Instance Acquisition Problem

- Workload (demand) is time-varying



- When should I reserve an instance?
- How many instances should I reserve?

Predict the Future?

- Existing works rely on prediction of future demand
  - [Hong SIGMETRICS'11, Bodenstein ICIS'11, Vermeersch Thesis'11, Wang ICDCS'13]
- However…
  - Prediction is needed for long-term future
    - Instance reservation period is typically months to years
  - Precise prediction not possible
  - Demand history may be limited
    - E.g., startup companies, new services

How well can we make instance reservation decisions online, without any *a priori* information about the future demand?

Our Main Contributions

- Propose two online reservation algorithms that offer the best provable cost guarantees
  - Deterministic: $(2\text{-}\alpha)$-competitive
  - Randomized: $e/(e\text{-}1+\alpha)$-competitive
    - α : normalized discounted price under reservation $(0 \leq \alpha \leq 1)$
- Study practical performance gains using Google cluster workload traces

Problem Formulation

Pricing of On-Demand and Reserved Instances

- On-demand Instances
  - Fixed hourly price: p
  - Cost of running for h hours: ph
- Reserved Instances
  - Upfront reservation fee + discounted price
  - Normalized reservation fee: 1
  - Reservation period: τ hours
  - Cost of running for h hours: $1 + \alpha ph$
    - α : normalized discounted price under reservation $(0 \leq \alpha \leq 1)$

User Demand and Reservation

At time t (discrete time), the user

- Has demand for d_t instances (time-varying)
- *Newly* reserves r_t instances
  - Available reserved instances: $\sum_{i=t-\tau+1}^{t} r_i$
- Launches o_t on-demand instances
  - Total available instances:

$$o_t + \sum_{i=t-\tau+1}^{t} r_i \geq d_t$$

Optimal Offline Algorithm

- Make instance purchase decisions o_t and r_t with knowledge of all future demands d_{t+1}, d_{t+2}, $\cdots$

On-demand cost Reservation cost

$$\min_{\{r_t, o_t\}} \quad C = \sum_{t=1}^{T} (o_t p + r_t + \alpha p (d_t - o_t)) \ ,$$

$$\text{s.t.} \quad o_t + \sum_{i=t-\tau+1}^{t} r_i \geq d_t \ ,$$

$$o_t, r_t \in \{0, 1, 2, \dots\}, t = 1, \dots, T \ .$$

  - Can be solved by dynamic programming, but is *computationally prohibitive*

Online Instance Reservation

- Make instance purchase decisions o_t and r_t without seeing future demands $d_{t+1}, d_{t+2}, \ldots$

On-demand cost Reservation cost

$$\min_{\{r_t, o_t\}} \quad C = \sum_{t=1}^{T} (o_t p + r_t + \alpha p (d_t - o_t)) \ ,$$

$$\text{s.t.} \quad o_t + \sum_{i=t-\tau+1}^{t} r_i \geq d_t \ ,$$

$$o_t, r_t \in \{0, 1, 2, \ldots\}, t = 1, \ldots, T \ .$$

  - What is the best that one can do?

Measure of Optimality

- Compare an online reservation algorithm with the optimal offline reservation
- An online algorithm A is *γ-competitive* if it incurs at most γ times the optimal offline cost
  - For any demand sequence $\mathbf{d} = d_1, d_2, \ldots$

$$C_A(\mathbf{d}) \leq \gamma\, C_{\mathrm{OPT}}(\mathbf{d})$$

  - Aims to minimize the competitive ratio γ

The Best Possible Outcome

Lemma 1: The best achievable competitive ratio is $2-\alpha$ for *deterministic* online algorithms, and is $e/(e-1+\alpha)$ for *randomized* online algorithms.

Bahncard problem [Fleischer TCS'01]:

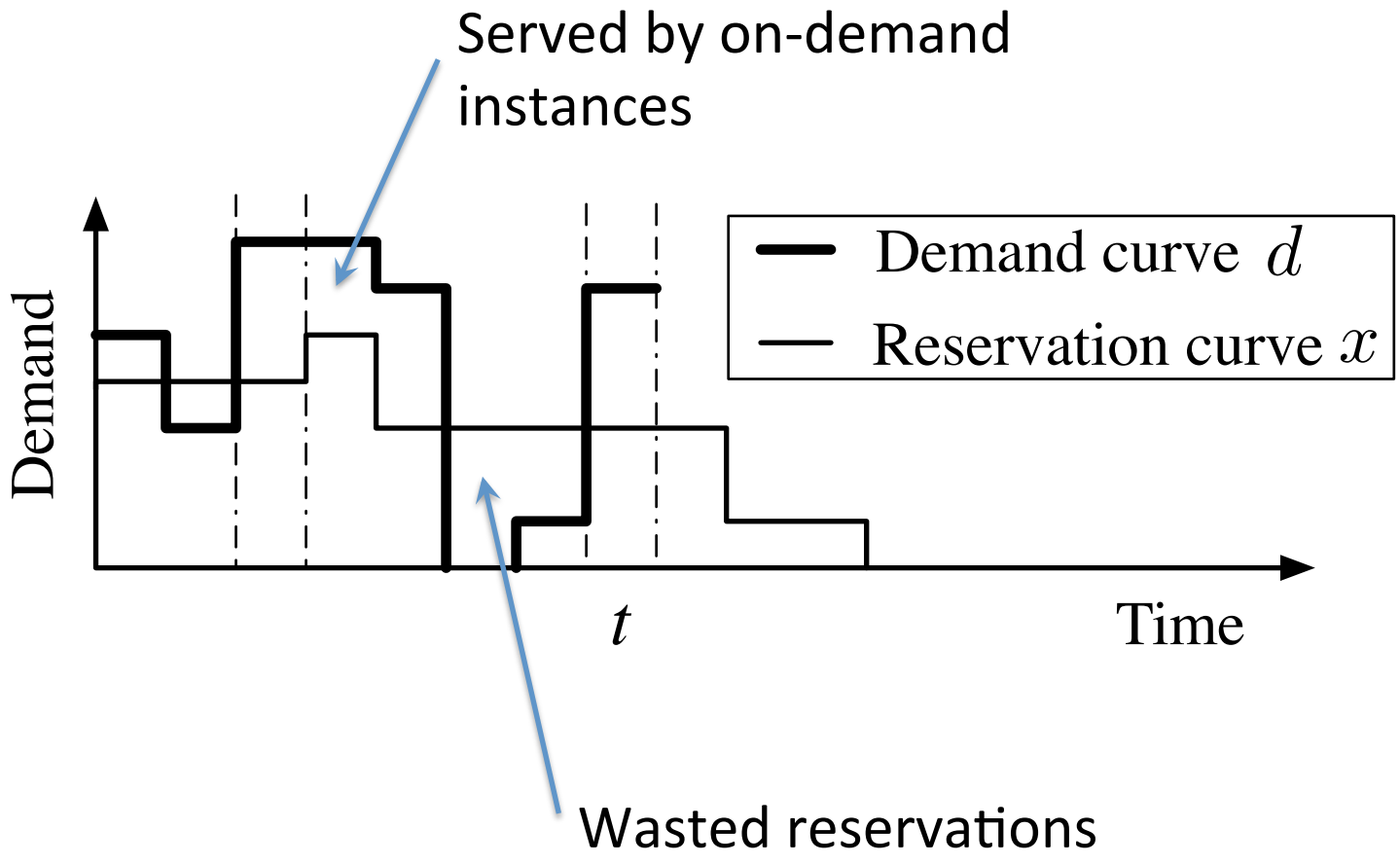
- Goal: reduce cost of using the Deutsche Bahn
- User may buy tickets on-demand or buy an annual Bahncard to enjoy discounted tickets
- No knowledge about user's travel plans or travel frequency

Is the optimal competitive ratio achievable with multiple instances?

- "Multi-Bahncard" problem
- Naïve extension: separate Bahncards
  - Does not work

Optimal Deterministic Online Algorithm

Demand and Reservation Curves

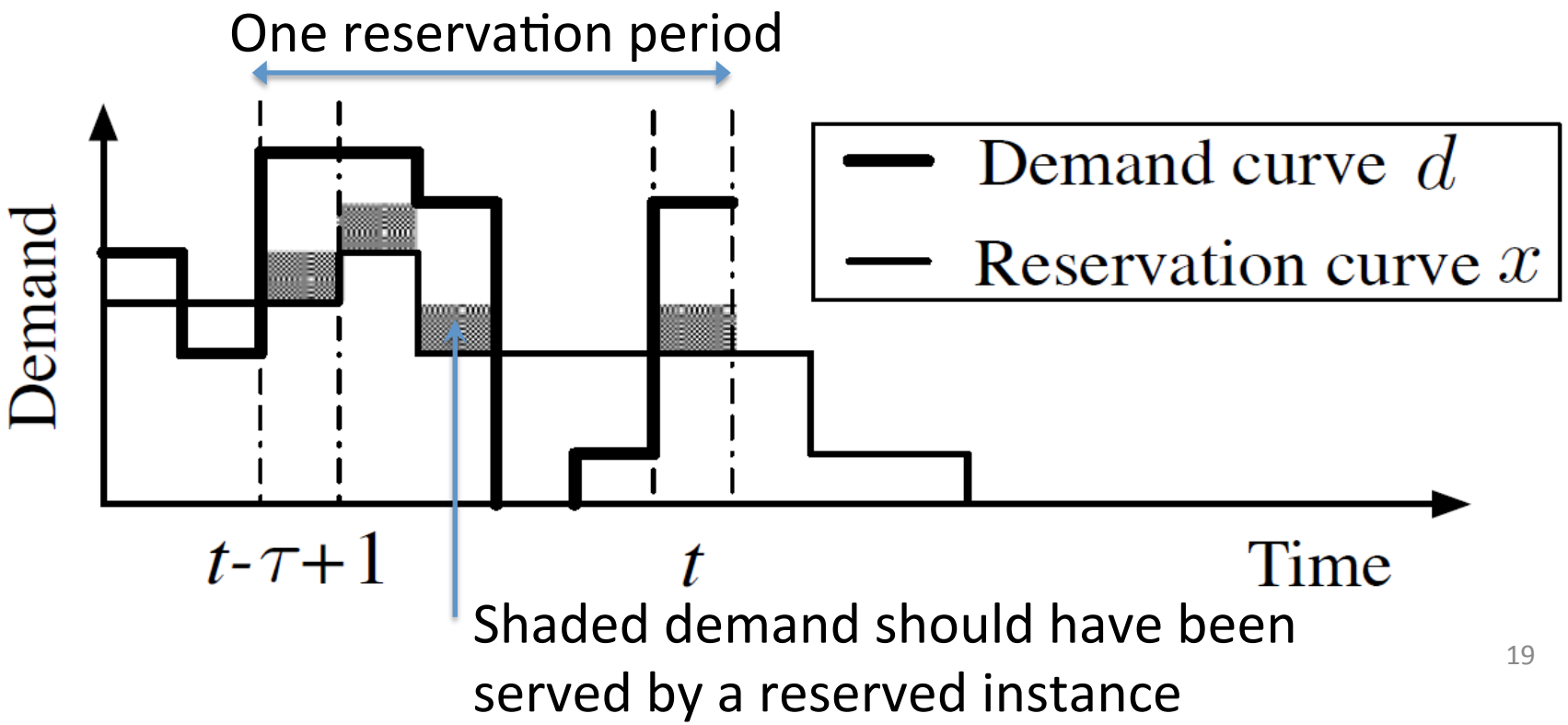


Break-Even Point

- Let c be the cost of one on-demand instance to serve workload that spans a reservation period.
- Using a reserved instance instead, the cost is $1+\alpha c$
- Break-even point: $c = 1+\alpha c$
  - Let $\beta=1/(1-\alpha)$
  - $c = \beta$: Break even
  - $c < \beta$: On-demand is better
  - $c > \beta$: Reservation is better

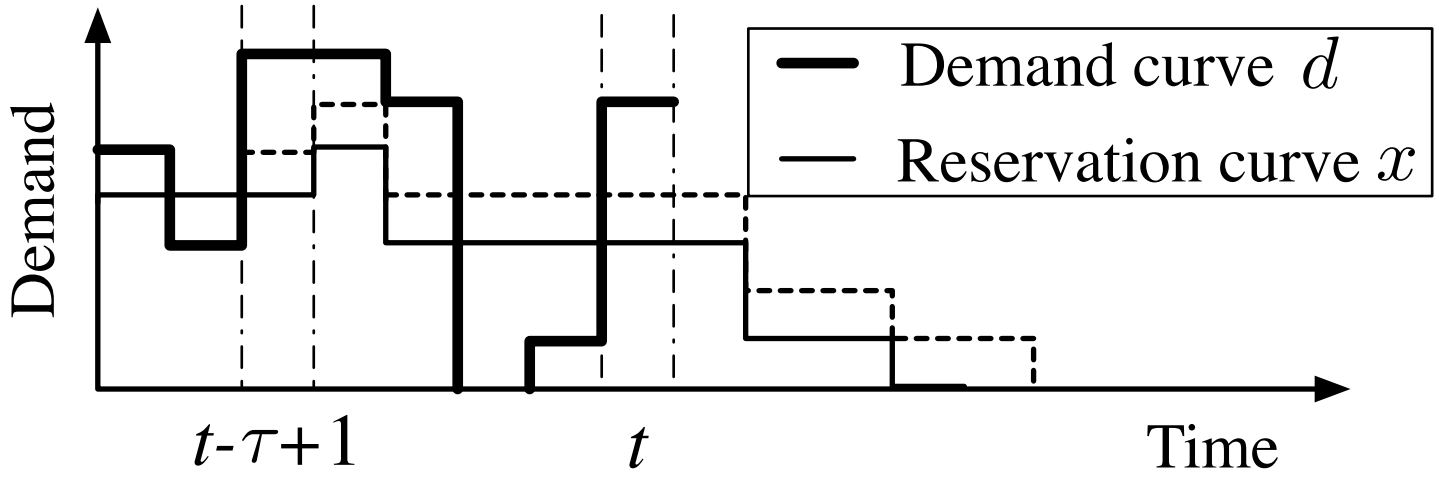
Regret and Compensation

- At time t, look back for one reservation period.
- If the incurred on-demand cost $> \beta$, reserve a new instance: $r_t = r_t + 1$.



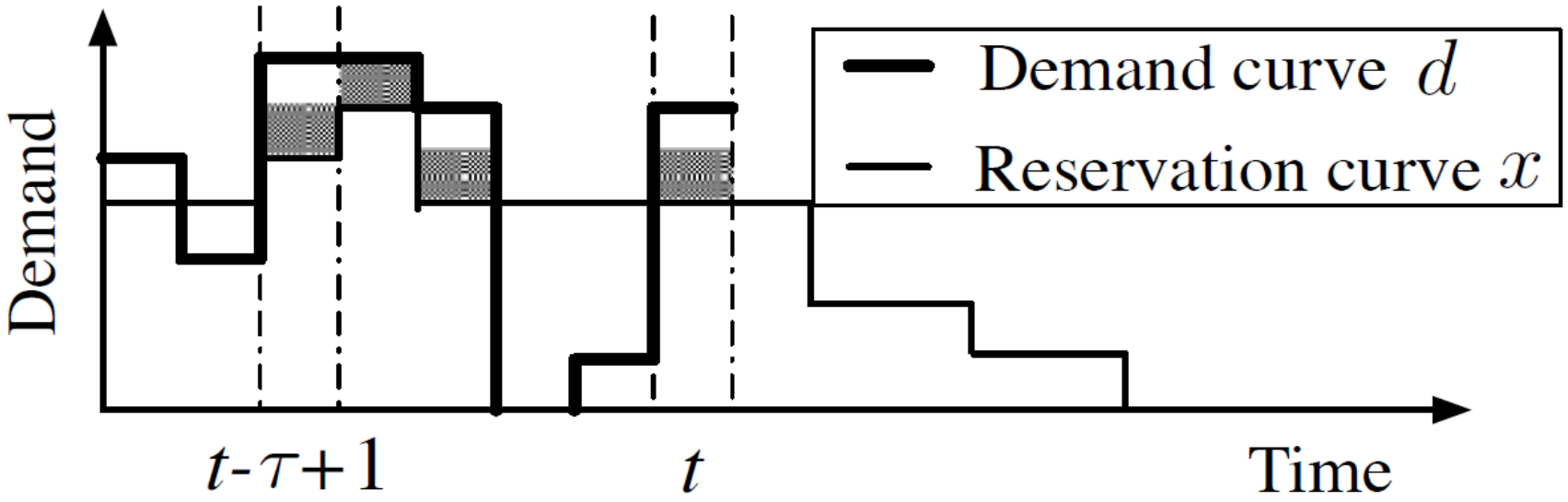
Update Reservation Curve

- If a new instance is reserved, update the reservation curve, both forward and backward.



Repeat until No Regret

- Repeat to reserve more new instances, until the (virtual) incurred on-demand cost $< \beta$.



Proposition 1: The deterministic online algorithm is $(2\text{-}\alpha)$-competitive, and hence is *optimal* among all deterministic online algorithms.

Optimal Randomized Online Algorithm

Basic Idea

- Can use different thresholds z (other than the break-even point β) to decide whether to reserve an instance
  - A family of deterministic algorithms $\{A_z\}$
- The smaller z, the more aggressive the reservation strategy
  - $z = 0$: All-reserved
  - $z = +\infty$: All-on-demand

Basic Idea (Cont'd)

- Randomly choose from the family of deterministic algorithms $\{A_z\}$
  - Strike balance between reserving too aggressively and too conservatively
  - Randomly pick threshold z according to the following density function

$$f(z) = \begin{cases} (1-\alpha)e^{(1-\alpha)z}/(e-1+\alpha), & z \in [0,\beta), \\ \delta(z-\beta)\cdot\alpha/(e-1+\alpha), & \text{o.w.}, \end{cases}$$

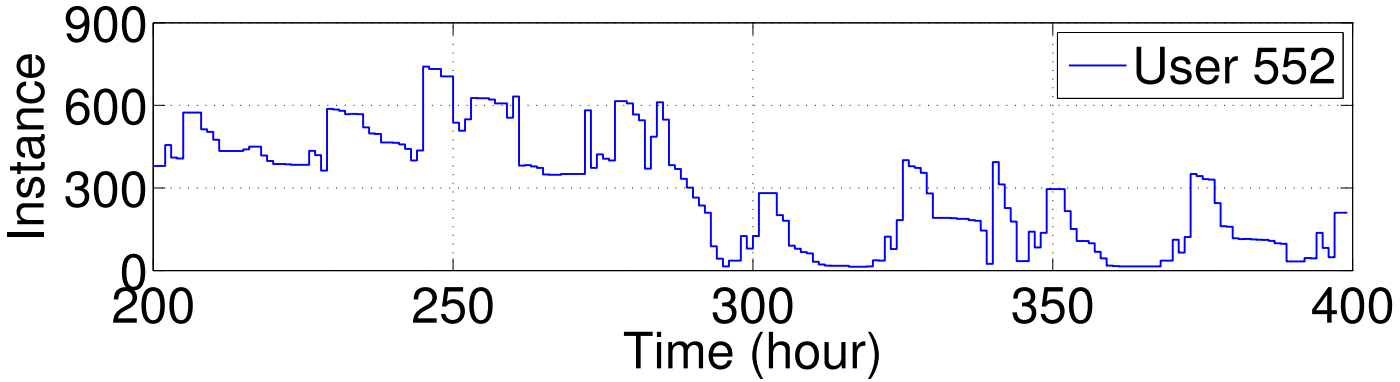
  - Make instance reservation decisions based on deterministic algorithm A_z

- **Proposition 2:** The randomized online algorithm is $e/(e\text{-}1+\alpha)$-competitive, and hence is *optimal* among all online algorithms.

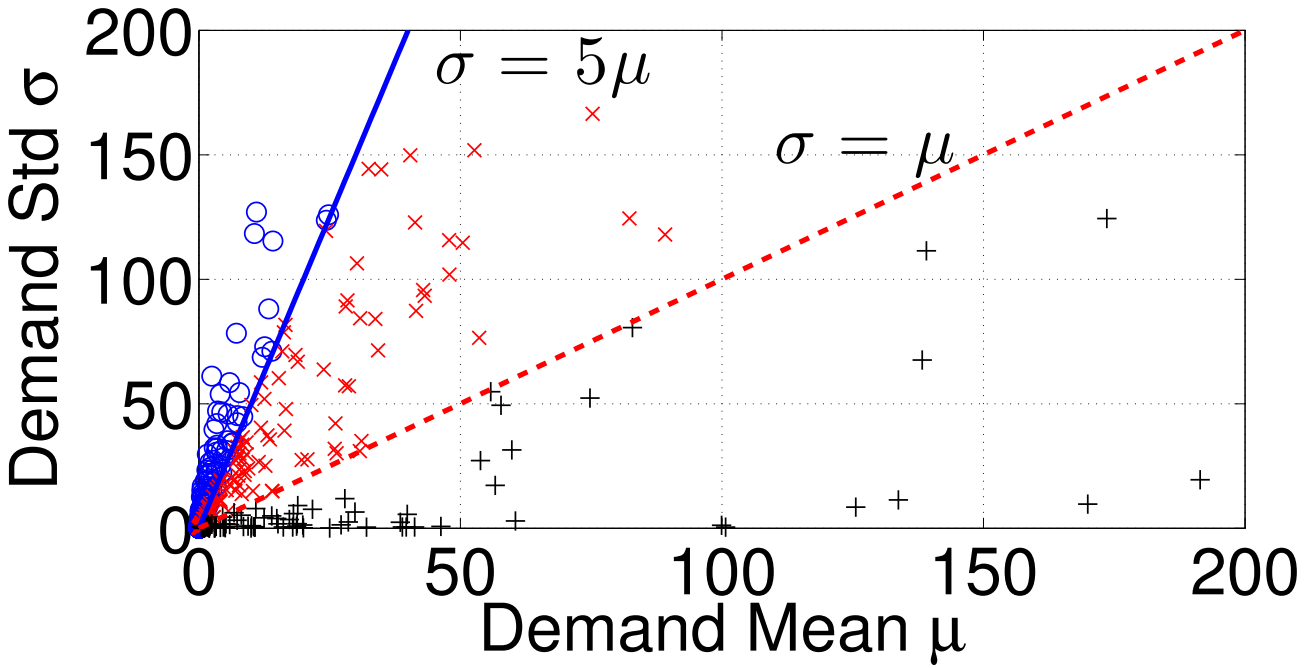
Trace-Driven Simulations

Dataset and Preprocessing

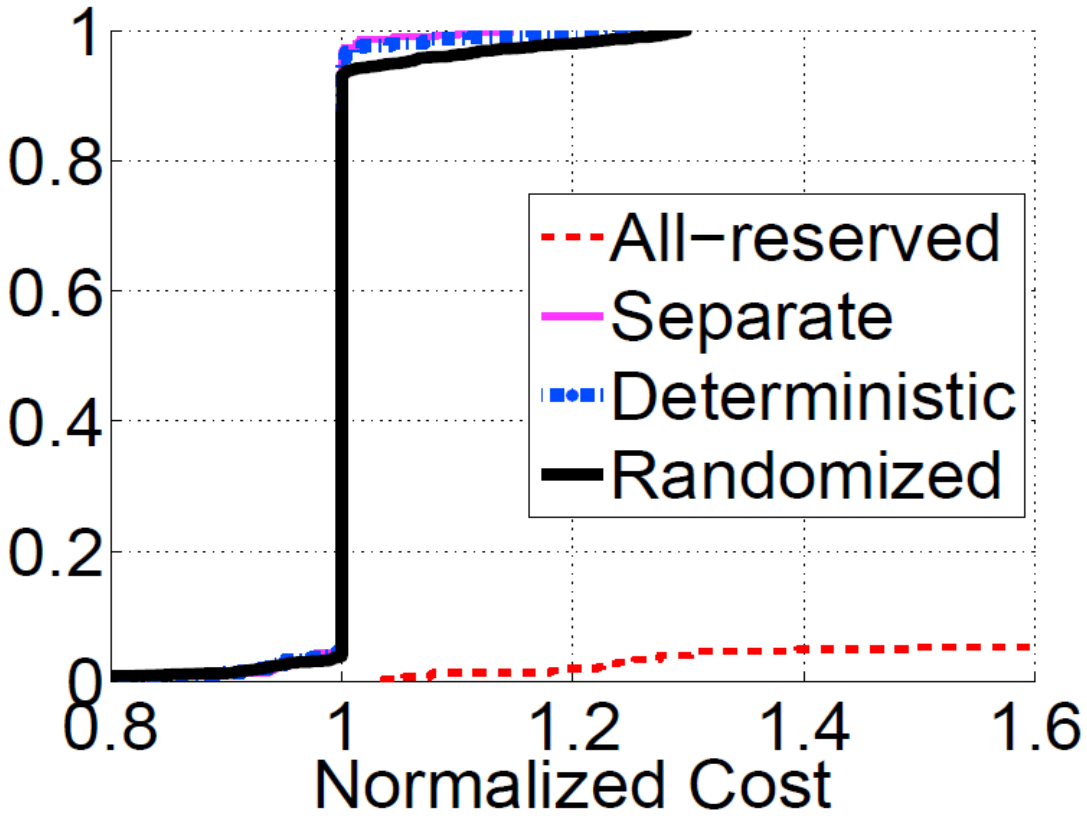
- Google cluster traces
  - 900+ users' usage traces in 1 month
  - We convert users' computing demand data to IaaS instance demands



- Users are classified into 3 groups based on demand fluctuation level
  - Standard deviation vs. mean in hourly demand



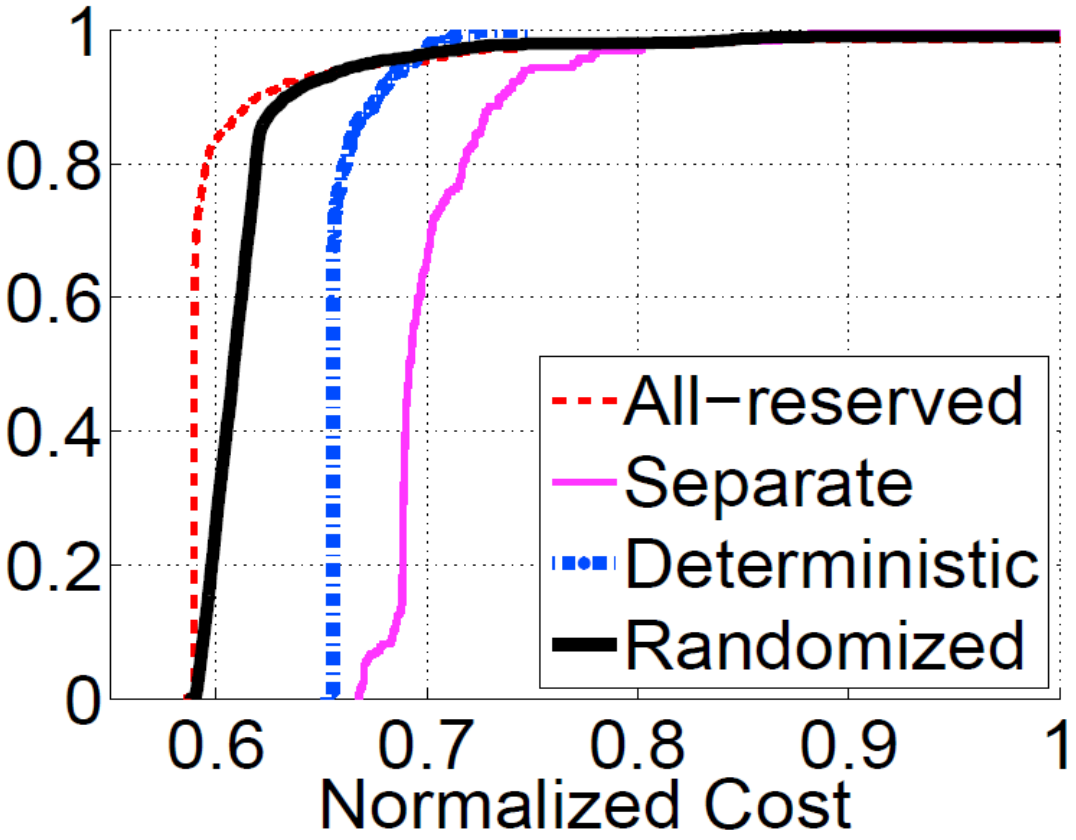
CDF of Cost Normalized to All-On-Demand



High demand fluctuation

"*Separate*": stack demands and treat each layer as a virtual user, each individualy solving the Bahncard problem.

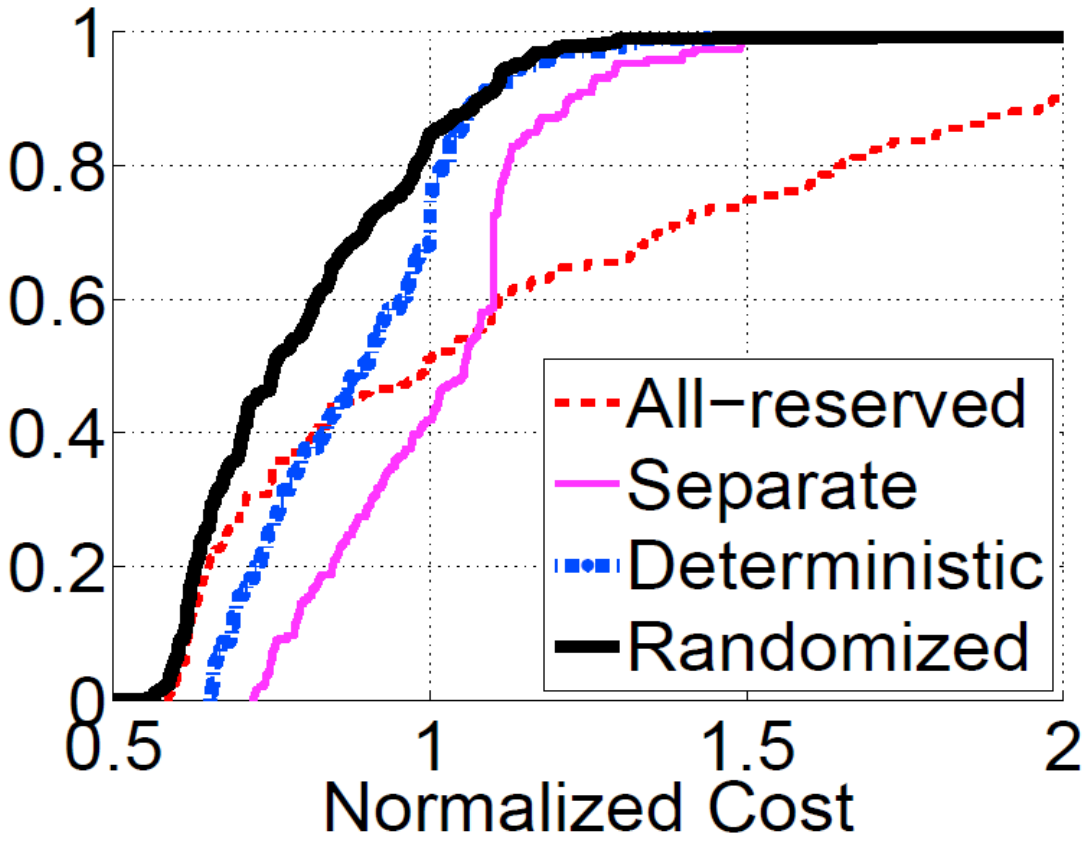
CDF of Cost Normalized to All-On-Demand



Low demand fluctuation

"*Separate*": stack demands and treat each layer as a virtual user, each individually solving the Bahncard problem.

CDF of Cost Normalized to All-On-Demand



Medium demand fluctuation

"*Separate*": stack demands and treat each layer as a virtual user, each individually solving the Bahncard problem.

Conclusions

- Deterministic and randomized online multi-instance reservation algorithms without future demand information
  - Optimal competitive ratio vs. optimal offline algorithm
  - Substantial performance gain over a wide range of demand fluctuation levels
- Extension to cases where short-term predictions are reliable
- Open problem: multiple reservation options