A Theory of Auto-Scaling for Resource Reservation in Cloud Services

Konstantinos Psychas, Javad Ghaderi Columbia University

Performance 2020: 38th International Symposium on Computer Performance, Modeling, Measurements and Evaluation November 2-6 2020, Milan(Online)



▶ We will use terms **job** and **server**

Both treated as abstract multidimensional resource vectors

Model



Normalized Workload (jobs per server) $\boldsymbol{\rho} := (\rho_1, \rho_2, \cdots, \rho_J)$

#jobs from each type that can simultaneously fit in the server $\boldsymbol{k} = (k_1, k_2, \cdots, k_J) \in \mathcal{K} \subset \mathbb{R}^J$

How to schedule when workload is known

$$\max_{\mathbf{X},\mathbf{Y}} \quad \sum_{j} u_{j} Y_{j}$$

s.t.
$$Y_j \leq \hat{Y}_j^L, \, \forall j \in \mathcal{J}$$

$$\sum_{\mathbf{k}\in\mathcal{K}} X_{\mathbf{k}} k_j \ge Y_j, \ \forall j\in\mathcal{J}$$

$$\sum_{\mathbf{k}\in\mathcal{K}} X_{\mathbf{k}} = L, \quad X_{\mathbf{k}} \ge 0, \ \forall \mathbf{k}\in\mathcal{K}$$

- Even if relaxed still hard (exponential number of variables)
- Needs to be solved every time workload changes
- Unclear how to change assignment when servers are already full
- There can be consistent error in ρ causing loss

Example
$$\widehat{Y} = L \rho$$

Solving Static Optimization: Ordering Configuration by total Reward

Reward of configuration

$$U(\mathbf{k}) = \sum_{j=1}^{J} u_j k_j$$

- ► $U(\mathbf{k})$ induces an ordering for all $\mathbf{k} \in \mathcal{K}$
- Define for $\mathcal{K}_s \subseteq \mathcal{K}$ MaxReward $(\mathcal{K}_s) = \arg \max U(\mathbf{k})$ $\mathbf{k} \in \mathcal{K}_s$

Solving Static Optimization: Greedy Placement Algorithm (GPA)



How good is greedy?

Consider normalized rewards $(L \rightarrow \infty)$

- ► Optimal Reward *U*^{*}[*ρ*]
- ► Greedy Reward U^(g)[**p**]

Without extra assumptions

 $U^{(g)}[\boldsymbol{\rho}] \ge \frac{1}{2} U^{\star}[\boldsymbol{\rho}]$

 $U^{(g)}[\rho] \ge (1 - e^{-1})U^{*}[\rho]$

Monotone Greedy Property

If
$$\boldsymbol{\rho}_1 \geq \boldsymbol{\rho}_2$$
 then $U^{(g)}[\boldsymbol{\rho}_1] \geq U^{(g)}[\boldsymbol{\rho}_2]$

Online Algorithm: Server Groups

Server Group	Accept	Reject
Goal	Try to Fill	Try to Empty
Schedule in it	Yes	No
Migration	Migrate from a Reject Group filled slot to an Accept Group slot that empties	

Online Algorithm: (CRA) Classification and Reassignment Algorithm

- Get solution of GPA
 - ▶ Input $\widehat{Y}^L = Y^L + / arrival/departure + g(L)\mathbf{1}_J$
 - ► $g(L) = \omega(\log L)$: reservation factor
- Match server assignment to GPA solution
 - Matches configurations in decreasing reward order

CRA Example [Iteration *i*]



Dynamic Reservation Algorithm (DRA)

On arrival

- Run CRA
- In which slot to deploy the job arrived
- Answer: Any empty slot in Accept Group if exists

- On departure
- Run CRA
- Which job to migrate in the slot that emptied
- Answer: Any job in a slot of Reject Group if exists

Informal Main Result

- Fraction of servers in each configuration of DRA \rightarrow Fraction of servers in each configuration of GPA for input ρL when $L \rightarrow \infty$
- ▶ Normalized Reward of DRA → Greedy Reward $U^{(g)}[\rho]$

Simulations (Testing GPA approximation)

Generated 50 random setups

- 6VM types one per pair
- Rewards: 8vCPU + GB
- Servers: 80vCPU, 640GB
- > Normalized workload ρ_j in [0.2, 2.0]

	Men	nory: G	B per CF	рU	
Memory-Opt		CPU-Opt		Regular	
8 or 16		1 or 2		4	
vCPU					
1	Small		Large	e	
1	2 or 4	or 8	32 or	64	

Computed $U^{(g)}[\rho]/U^{*}[\rho]$ for each setup

- Worst ≈ 0.86 [worst in theory 0.5]
- Average ≈ 0.97
- Optimal = 1.00 [23/50 setups]

Simulations (Testing with Google Trace)



- 1 million tasks
- ▶ 3 priorities
- 8 different sizes
- $\mathbf{>} 3 \times 8 = 24 \text{ types}$

Thank You