# Online Load Balancing and Machine Scheduling

- CT Network Theory Seminar -

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### **Outlines**

- Introduction of Online Balancing
- Results of Greedy Algorithm
- 3 Constant Competitive Ratio for Related Machines
- 4 Competitive Ratio  $O(\log n)$  for Unrelated Machines

### Online Problems

- Input: A request sequence  $\sigma = \sigma(1), \sigma(2), \ldots$ ;
- Online: An algorithm M has to serve each request online without knowledge of future requests. Each request must be served before serving the next requests.
- **Objective:** The goal is to serve the entire request sequence so that the objective function is minimized.

# The Online Load-Balancing Problem

### Input:

- The *n* related/unrelated machines
- A sequence of jobs  $\sigma = (\vec{p}(1), \vec{p}(2), \dots, \vec{p}(k))$
- Each job  $j \in \sigma$  denoted by its "load vector":

$$\vec{p}(j) = (p_1(j), p_2(j), \dots, p_n(j)), \text{ where } p_i(j) \ge 0.$$

#### **Definition of Load:**

- Assign a job j to a machine i increases the load on the machine i by  $p_i(j)$
- $\ell_i(j)$  denotes the load on machine i after already assigning jobs 1 through j:

$$\ell_k(j) = \begin{cases} \ell_k(j-1) + p_k(j), & \text{if } k = i \\ \ell_k(j-1), & \text{otherwise} \end{cases}$$

# The Online Load-Balancing Problem (2)

#### **Notations of Offline Algorithm:**

- Given a sequence of jobs  $\sigma = (\vec{p}(1), \vec{p}(2), \dots, \vec{p}(k))$
- $\mathscr{A}^*$  denotes off-line (optimal) algorithm
- $\ell_i^*(j)$  denotes the load on machine i achieved by  $\mathscr{A}^*$  after assigning jobs 1 to j in  $\sigma$

#### **Objective:**

- $L^*(k) = \max_i \ell_i^*(k)$ : the maximum load (optimal) by  $\mathscr{A}^*$
- $L(k) = \max_{i} \ell_i(k)$ : the maximum load by online algorithms
- Online algorithms try to minimize L(k)
- Objective: minimize the competitive ratio:  $\sup \{L(k)/L^*(k)\} \text{ for any length } k \text{ and all possible sequences } \sigma$
- k may be omitted for  $L^*(k)$  and L(k)

### Three Machine Models

Each job  $j \in \sigma$  denoted by its "load vector":

$$\vec{p}(j) = (p_1(j), p_2(j), \dots, p_n(j)), \text{ where } p_i(j) \ge 0.$$

- Identical machimes: each job j:  $p_i(j) = p_{i'}(j)$  for any two machines: i and i'
- Related machines: for any jobs j and j' and machines i and i':

$$\frac{p_i(j)}{p_{i'}(j)} = \frac{p_i(j')}{p_{i'}(j')} = \frac{v_{i'}}{v_i}, \text{ where } v_i : \text{speed of machine } i$$

- Identical is a special case of related machines:
- Unrelated machimes  $(1/\infty)$ : all other cases
  - e.g.,  $p_i(j) = +\infty$ , i.e., a job j not runnable on some machines i

### Greedy Algorithm for Load Balancing Problem

#### **Greedy Algorithm:**

• Algorithm: for each job j, assign it to a machine k s.t.,  $k = \operatorname{argmin}\{\ell_i(k-1) + p_i(j)\}$ 

#### **Identical Machines:**

• competitive ratio:  $2 - \epsilon$ 

#### **Related Machines:**

• Competitive ratio:  $O(\log n)$ , lower bound:  $\Omega(\log n)$ 

#### **Unrelated Machines:**

• Competitive ratio: O(n), lower bound:  $\Omega(n)$ 

### Competitive Ratio of Greedy for Unrelated Machines

#### Theorem 2.1

The competitive ratio of the greedy algorithm is at most n for unrelated machines.

#### Proof.

- Each job j has a minimum load min<sub>i</sub>  $p_i(j)$
- $\mathscr{S}_{i}^{*}$ : jobs assigned to machine *i* by offline algorithms

$$nL^* \geq \sum_i \ell_i^* = \sum_i \sum_{j \in \mathscr{S}_i^*} p_i(j) \geq \sum_j \min_i p_i(j)$$

- Claim: the maximum load by greedy  $\leq \sum_{i} \min_{i} p_{i}(j)$
- Assume: after assigning j-1,  $L(j-1) \leq \sum_{j' \leq j-1} \min_i p_i(j')$
- When j arrives, greedy chooses machine m, the resulting load at most  $L(j-1)+p_m(j) \leq \sum_{i' < j} \min_i p_i(j')$
- $L(j) \le \sum_{i' \le j} \min_i p_i(j')$  implies  $L \le \sum_j \min_i p_i(j') \le nL^*$

```
procedure Assign-R(\vec{p}, \vec{\ell}, \Lambda):
       /* \Lambda — current estimate of L^*.
       Let S := \{i | \ell_i + p_i \le 2\Lambda\};
       if S = \emptyset
           then b := fail
           else begin
             k := \min\{i | i \in S\};
             \ell_k := \ell_k + p_k:
             b := success
          end;
       return(\vec{\ell}, b).
end.
```

Fig. 3. Algorithm Assign-R.

#### Theorem 3.1

If  $\lambda^* \leq \Lambda$ , then Algorithm Assign-R never fails. Thus, the load on a machine never exceeds  $2\Lambda$ 

#### Proof.

- By contradiction, assumes it fails first on a job j.
- r: the fastest machine whose load  $\leq L^*$ , if no r=0 $r=\max\{i\mid \ell_i\,(j-1)< L^*\}$
- Clearly,  $r \neq n$ , otherwise j is on n  $(\ell_n(j-1) + p_n(j) \leq 2L^*)$
- Define  $\Gamma = \{i \mid i > r\}$ : overloaded machines faster than r
- Clearly,  $\Gamma \neq \emptyset$  since r < n
- $\mathscr{S}_i/\mathscr{S}_i^*$ : jobs assigned to machine *i* by online/offline algo.

### Proof (Cont.)

• Now, to show: it exists a job  $s \in \bigcup_{i \in \Gamma} \mathscr{S}_i$  but  $s \notin \bigcup_{i \in \Gamma} \mathscr{S}_i^*$ 

$$\begin{split} \sum_{i \in \Gamma, s \in \mathscr{S}_i} p_n(s) &= \sum_{i \in \Gamma s, \in \mathscr{S}_i} \frac{p_n(s)}{p_i(s)} p_i(s) \\ &= \sum_{i \in \Gamma} \frac{v_i}{v_n} \sum_{s \in \mathscr{S}_i} p_i(s) > \sum_{i \in \Gamma} \frac{v_i}{v_n} L^* \\ &\geq \sum_{i \in \Gamma} \frac{v_i}{v_n} \sum_{s \in \mathscr{S}_i^*} p_i(s) = \sum_{i \in \Gamma, s \in \mathscr{S}_i^*} p_n(s) \end{split}$$

- We know a job s assigned to  $i \in \Gamma$  by online but to  $i' \notin \Gamma$  by offline
- Our assumption:  $p_{i'}(s) \leq L^* \leq \Lambda$
- Since  $r \ge i'$ , it implies r at least as fast as i'

#### Theorem 3.1

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#### Proof (Cont.)

- We know a job s assigned to  $i \in \Gamma$  by online but to  $i' \notin \Gamma$  by offline
- Our assumption:  $p_{i'}(s) \leq L^* \leq \Lambda$
- Since  $r \ge i'$ , it implies r at least as fast as i'
- Since job s assigned before j then  $\ell_r(s-1) \leq \ell_r(j-1) \leq L^*$
- But, this means that online algo should have placed job s on r or a slower machine instead of i, which is a contradiction.  $\square$

# Doubling Approach

#### Theorem 3.2

For any load balancing problem, let  $\mathrm{ALG}_{\Lambda}$  be a parameterized online algorithm satisfying  $\mathrm{OPT}\left(\sigma\right) \leq \Lambda \implies \mathrm{ALG}_{\Lambda}\left(\sigma\right) \leq c \cdot \Lambda$  (e.g.,  $\mathrm{Assign-R}$  with c=2 for related machines). Then there is an algorithm  $\mathrm{ALG}$  s.t., for all  $\sigma$ ,  $\mathrm{ALG}\left(\sigma\right) \leq 4c \cdot \mathrm{OPT}\left(\sigma\right)$ .

- ALG executes in stages, each stage correspond to the mos recent estimate of  $\Lambda$ .
- Stage 0,  $\Lambda_0 = \mathrm{OPT}(j=0)$ , easy to compute the optimal for the first job.
- Each stage j, ALG uses  $\mathrm{ALG}_\Lambda$  to assign jobs until it fails and start a new stage by doubling  $\Lambda$
- Stage k,  $\Lambda = 2^k \Lambda_0$

# Proof of Doubling Approach

#### Proof.

- To prove  $ALG(\sigma) \le 4c \cdot OPT(\sigma)$  for any sequence  $\sigma$
- Suppose ALG terminates at the stage *h*.
- If h = 0, it is clear ALG  $(\sigma) \le c \cdot \text{OPT}(\sigma)$
- Let r be the first job for the stage h, and  $\sigma_j$  denotes the subsequence processed in stage j
- Clearly, stage h-1 failed on  $\sigma_{h-1}r$ , while  $\mathrm{ALG}_\Lambda$  has  $\Lambda=2^{h-1}\Lambda_0$
- Thus,  $OPT(\sigma) \ge OPT(\sigma_{h-1}r) > 2^{h-1}\Lambda_0$
- Moreover

$$\mathrm{ALG}\left(\sigma\right) = \sum_{j=0}^{h} \mathrm{ALG}\left(\sigma_{j}\right) \leq \sum_{j=0}^{h} c \cdot 2^{j} \Lambda_{0} = c \left(2^{h+1} - 1\right) \Lambda_{0}$$

### Competitive Ratio for Assign-R for Related Machines

#### Corollary 3.3

ASSIGN-R Algorithm can be modified to achieve a competitive ratio of 8.

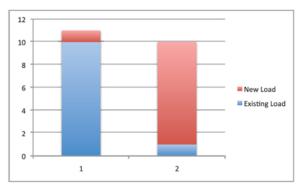
• Normalization:  $\tilde{\ell}_i = \ell_i / \Lambda$   $\tilde{p}_i = p_i / \Lambda$ • Find a machine s minimizing  $\Delta_i = \alpha^{(\tilde{\ell}_i(j-1) + \tilde{p}_i(j))} - \alpha^{\tilde{\ell}_i(j-1)}$ 

```
procedure Assign-U(\vec{p}, \vec{\ell}, \Lambda, \beta);
       /* Λ — current estimate of L*.
       /* \beta — designed performance guarantee of the algorithm.
       Let s be the index minimizing \Delta_i = a^{(\tilde{\ell}_i + \tilde{p}_i)} - a^{\tilde{\ell}_i}:
       if \ell_s + p_s > \beta \Lambda
          then b := fail
          else begin
             \ell_s := \ell_s + p_s:
             b := success
          end;
       return(\vec{\ell}, b).
end.
```

Fig. 2. Algorithm Assign-U.

# Intuitive Understanding of Assign-U Algorithm

- Assign-U minimizing  $lpha^{ ilde{\ell}_i(j-1)} \left(lpha^{ ilde{
  ho}_i(j)} 1
  ight)$
- ullet Greedy minimizing  $\left( ilde{\ell_i} \left( j 1 
  ight) + ilde{p_i} \left( j 
  ight) 
  ight)$
- Greedy choose machine 2
- But Assign-U chooses machine 1 since  $1.5^{10+1}-1.5^{10}\approx 22.83 < 51.16\approx 1.5^{10}-1.5^1~(\alpha=1.5)$



#### Theorem 4.1

If  $\lambda^* \leq \Lambda$ , then there exits  $\beta = O(\log n)$  s.t., Algorithm Assign-U never fails. Thus, the load on a machine never exceeds  $\beta\Lambda$ 

#### Proof.

- State after j-1 jobs,  $\alpha, \gamma > 1$  ( $\alpha \approx 2, \gamma \approx 1$ )
- assumption:  $L^*(j) \le L^* \le \Lambda$
- potential function:

$$\Phi(j) = \sum_{i=1}^{n} \alpha^{\tilde{\ell}_{i}(j)} \left( \gamma - \tilde{\ell}_{i}^{*}(j) \right)$$

### Proof (Cont.)

• Let the job j assigned to machine i' (i) by online (offline)

$$\Phi(j) = \sum_{i=1}^{n} \alpha^{\tilde{\ell}_{i}(j)} \left( \gamma - \tilde{\ell}_{i}^{*}(j) \right)$$

• Compute  $\Phi(j) - \Phi(j-1)$  as follows:

$$\begin{split} &= \left(\gamma - \tilde{\ell}_{i'}^*(j-1)\right) \left(\alpha^{\tilde{\ell}_{i'}^*(j)} - \alpha^{\tilde{\ell}_{i'}^*(j-1)}\right) - \alpha^{\tilde{\ell}_i(j)} \tilde{p}_i(j) \\ &\leq \gamma \left(\alpha^{\tilde{\ell}_{i'}^*(j-1) + \tilde{p}_{i'}(j)} - \alpha^{\tilde{\ell}_i(j-1)}\right) - \alpha^{\tilde{\ell}_i(j-1)} \tilde{p}_i(j) \\ &\leq \gamma \left(\alpha^{\tilde{\ell}_i^*(j-1) + \tilde{p}_i(j)} - \alpha^{\tilde{\ell}_i(j-1)}\right) - \alpha^{\tilde{\ell}_i(j-1)} \tilde{p}_i(j) \\ &= \alpha^{\tilde{\ell}_i(j-1)} \left(\gamma \left(\alpha^{\tilde{p}_i(j)} - 1\right) - \tilde{p}_i(j)\right). \end{split}$$

### Proof (Cont.)

- $\Phi(j) \Phi(j-1) \le \alpha^{\tilde{\ell}_i(j-1)} \left( \gamma \left( \alpha^{\tilde{p}_i(j)} 1 \right) \tilde{p}_i(j) \right)$
- As offline assigns job j to machine i,  $0 \le \tilde{p}_i(j) \le L^*/\Lambda \le 1$
- To prove  $\Phi(j) \Phi(j-1) \le 0$ , we need to show  $\gamma(\alpha^x 1) \le x$  for  $x \in [0, 1]$ . It is true for  $\alpha = 1 + 1/\gamma$
- Clearly,  $\Phi(0) = \gamma n$
- Recall  $\Phi(j) = \sum_{i=1}^{n} \alpha^{\tilde{\ell}_i(j)} \left( \gamma \tilde{\ell}_i^*(j) \right)$
- Thus,  $\sum_{i=1}^{n} \alpha^{\tilde{\ell}_i(j)} (\gamma 1) \leq \gamma n$

$$L = \max_{i} \ell_{i}(k) = \Lambda \, \max \tilde{\ell}_{i}(k)$$

$$\leq \Lambda \cdot \log_a \left( \frac{\gamma}{\gamma - 1} n \right) = O(\Lambda \log n)$$



### Questions & Answers

# Thanks for your Listening, and welcome your questions!

