



Online Combinatorial Optimization Problems

DTC/LOCo

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Maximization or minimization problems in which, for each input there is a set of feasible solutions and, for each solution there is a cost associated with it.

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As an example, lets take a greedy online algorithm for the Online Steiner Tree problem.

Greedy Online Steiner Tree Algorithm

Algorithm 1: OST Algorithm. Input: (G, d) $T \leftarrow (\emptyset, \emptyset)$; while a new terminal j arrives do $\mid T \leftarrow T \cup \{ path(j, V(T)) \};$ end return T;

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The OST Algorithm is $O(\log n)$ -competitive. Also, it is known a $\Omega(\log n)$ lower bound to the competitive ratio of any algorithm for this problem [Imase and Waxman 1991].

Online problems allow us to capture the uncertainty related to input data that arrives over time. This characteristic is common in several problems from operations research and computer science:

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- Dynamic data structures: list access problem.
- Memory management: paging problem.
- Sustainability: ski-rental and parking permit problems.
- Network design: online versions of Steiner tree and facility location problems.

Minimization problem whose input is a number of machines and a list of tasks with sizes. A feasible solution is an assignment of each task to a machine, and its cost is the maximum load between the machines.

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Greed Online Load Balancing Algorithm

Algorithm 2: OLB Algorithm.

Input: *M* For each machine i = 1, ..., M set its load l(i) to 0; $i^* \leftarrow 1$; while a new task j arrives do $\begin{vmatrix} a(j) \leftarrow i^*; \\ l(i^*) \leftarrow l(i^*) + s(j); \\ choose machine with minimum load as new <math>i^*$; end

return a;

Let i^* be the machine with the maximum load, j be the last task assigned to i^* , and $l(i^*) = l + s(j)$.

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We have $OPT \ge s(j)$ and $OPT \ge I + \frac{s(j)}{M}$.

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$$\begin{split} \mathrm{ALG} &= l + s(j) \\ &\leq \mathrm{OPT} - \frac{s(j)}{M} + s(j) \\ &\leq \mathrm{OPT} + \left(1 - \frac{1}{M}\right) \mathrm{OPT} \\ &= \left(2 - \frac{1}{M}\right) \mathrm{OPT} \ . \end{split}$$

Lower Bound for OLB Algorithm

Consider a list with M(M-1) tasks of size 1 followed by a task of size M.


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We have ALG = 2M - 1 and OPT = M.

Minimization problem whose input is the price M to buy skies and a list informing when the snow melt. A feasible solution is a list informing when we rent or buy skies, and its cost is 1 for each renting day plus M if you buy.

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Ski Rental Application and Generalization

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Also, it may be generalized to the Parking Permit Problem [Meyerson 2005].

Ski Rental Algorithm

Algorithm 3: Intuitive SR Algorithm.

```
Input: M
Set day j and total renting cost r to 0;
while a new snow day happens do
```

```
if r + 1 < M then

| Rent skies at day j and r \leftarrow r + 1;

else

| Buy skies if still don't have them;

end

i \leftarrow i + 1;
```

end

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| Rent skies at day j and r \leftarrow r + 1;
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| Buy skies if still don't have them;
end
j \leftarrow j + 1;
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end

This algorithm is 2-competitive. Why?

Ski Rental LP Formulations

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Linear programming relaxation

$$\begin{array}{ll} \min & Mx + \sum_{j=1}^n y_j \\ \text{s.t.} & x + y_j \geq 1 & \text{for } j = 1, \dots, n, \\ & x \geq 0, y_j \geq 0 & \text{for } j = 1, \dots, n, \end{array}$$

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and its dual

$$\begin{array}{ll} \max & \sum_{j=1}^{n} \alpha_j \\ \text{s.t.} & \sum_{j=1}^{n} \alpha_j \leq M \quad \text{for } j = 1, \dots, n, \\ & \alpha_j \leq 1 \qquad \qquad \text{for } j = 1, \dots, n, \\ & \alpha_j \geq 0 \qquad \qquad \text{for } j = 1, \dots, n. \end{array}$$

Primal-Dual Ski Rental Algorithm

Algorithm 4: Primal-Dual SR Algorithm.

Input: *M* Set day *j'* to 0; while a new snow day happens do increase $\alpha_{j'}$ until one of the following happens: (a) $\alpha_{j'} = 1$; /* rent skies setting $y_j = 1$ */ (b) $M = \alpha_{j'} + \sum_{j=1}^{j'-1} \alpha_j$; /* buy skies setting x = 1 */ $j' \leftarrow j' + 1$; end

Does it remember the previous algorithm?

Primal-Dual SR Algorithm is 2-Competitive

Recalling that the cost of any dual feasible solution is at most the cost of ${\rm OPT},$ we have

Primal-Dual SR Algorithm is 2-Competitive

Recalling that the cost of any dual feasible solution is at most the cost of OPT, we have

$$ALG = Mx + \sum_{j=1}^{n} y_j$$
$$\leq \sum_{j=1}^{n} \alpha_j + \sum_{j=1}^{n} \alpha_j$$
$$< 2OPT .$$



















Online Facility Location LP Formulation

Online Facility Location LP Formulation

Linear programming relaxation

$$\begin{array}{ll} \min & \sum_{i \in F} f(i) y_i + \sum_{j \in D} \sum_{i \in F} d(j,i) x_{ji} \\ \text{s.t.} & x_{ji} \leq y_i & \text{for } j \in D \text{ and } i \in F, \\ & \sum_{i \in F} x_{ji} \geq 1 & \text{for } j \in D, \\ & y_i \geq 0, x_{ji} \geq 0 & \text{for } j \in D \text{ and } i \in F, \end{array}$$

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and its dual

$$\begin{array}{ll} \max & \sum_{j \in D} \alpha_j \\ \text{s.t.} & \sum_{j \in D} (\alpha_j - d(j, i))^+ \leq f(i) & \text{for } i \in F, \\ & \alpha_j \geq 0 & \text{for } j \in D. \end{array}$$
Online Facility Location Algorithm

Algorithm 5: OFL Algorithm.

Input:
$$(G, d, f, F)$$

 $F^{a} \leftarrow \emptyset; D \leftarrow \emptyset;$
while a new client j' arrives do
increase $\alpha_{j'}$ until one of the following happens:
(a) $\alpha_{j'} = d(j', i)$ for some $i \in F^{a};$ /* connect only */
(b) $f(i) = (\alpha_{j'} - d(j', i)) + \sum_{j \in D} (d(j, F^{a}) - d(j, i))^{+}$ for some
 $i \in F \setminus F^{a};$ /* open and connect */
 $F^{a} \leftarrow F^{a} \cup \{i\}; D \leftarrow D \cup \{j'\}; a(j') \leftarrow i;$
end
return $(F^{a}, a);$

The OFL has competitive ratio
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[Nagarajan and Williamson 2013] give a dual-fitting analysis for the algorithm by [Fotakis 2007].

Acknowledgements

Thank you!

Questions?