

# Online Lower Bounds via Duality

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# Outline

- ▶ Background & Intuition
- ▶ Multidimensional Vector Bin Packing
- ▶ Online Capital Investment

# Background & Intuition

- ▶ Competitive ratio is the benchmark to measure the performance of an online algorithm
  - ▶ For any input sequence  $\sigma$
  - ▶  $ALG(\sigma) \leq c \cdot OPT(\sigma) + a$
  - ▶ Then ALG is c-competitive
- ▶ Need to know if an online algorithm is “good enough”
- ▶ Try to prove there is a lower bound for all online algorithms’ competitive ratio.

# Cont'd

- ▶ Find a linear programming problem where the variables represent online problem's solution and the objective function is the competitive ratio of that solution.
- ▶ The optimal solution would be a lower bound for any online algorithms' competitive ratios.
- ▶ Solving such problem is hard
- ▶ Duality theory
  - ▶ Dual solutions are primal solutions' lower bounds

# Outline

- ▶ Construct some parameterized collections of input sequences.
- ▶ Encode constraints that any feasible algorithm must obey.
- ▶ Select proper objective function such that optimizing it is equivalent to minimizing the competitive ratio.
- ▶ Derive parameterized dual linear program.
- ▶ Find feasible solutions to get a valid lower bound.

# Multidimensional Vector Bin Packing

- ▶ Vectors  $\{v_1, \dots, v_n\}$  arrive in an online manner
  - ▶  $v_i = (v_i(1), \dots, v_i(d)) \in [0, 1]^d$
- ▶ Assign incoming vectors into bins whose capacities for any coordinate is 1.
- ▶  $\sum_{i \in B_j} v_i(k) \leq 1$  for all Bin  $B_j$  and all coordinates  $k$
- ▶ Here we consider the relaxed version that all vectors are “splittable”.
- ▶  $v \rightarrow \alpha_1 v, \alpha_2 v, \dots, \alpha_n v$  where  $\sum \alpha_i = 1$

# Cont'd

- ▶ Input Sequences:
- ▶  $d$  phases, each phase contains the same type of vector
  - ▶  $A$  of  $v_1 = (1, 0, 0, \dots, 0)$
  - ▶  $2A$  of  $v_2 = (\frac{1}{2}, 1, 0, \dots, 0)$
  - ▶ ...
  - ▶  $dA$  of  $v_d = (\frac{1}{d}, \frac{1}{d}, \frac{1}{d}, \dots, \frac{1}{d}, 1)$
- ▶ Offline optimal at the end of phase  $j$  is  $j \cdot A$
- ▶ Any  $c$ -competitive algorithm must open at most a total amount of  $c \cdot j \cdot A$  fractional bins.

# Cont'd

- ▶  $x_{i,j}$  be the total fraction of vectors of type  $v_i$  that the online algorithm assigns to bins that are opened in phase  $j$  ( $i \geq j$ ).
- ▶  $\sum_{r=j}^d x_{r,j} \cdot v_r(k) \cdot A \leq c \cdot A$
- ▶ In phase  $j$ , the opened bins can store the vectors coming within and after phase  $j$ .
- ▶  $\sum_{r=1}^i x_{i,r} = i$
- ▶ Vectors coming in at phase  $i$  should be fully assigned.
- ▶ The objective function is  $c$



# Cont'd

- ▶ Ignored some constraints then we get dual program.

- ▶ normalizing all variables by the term  $\sum_k \sum_j z_{k,j}$ , competitive ratio becomes 
$$\frac{\sum_r y_r}{\sum_k \sum_j z_{k,j}}$$

**The dual linear program:**

$$\begin{aligned} \max \quad & \sum_{r=1}^d y_r \\ \text{s.t.} \quad & \sum_{k=1}^d \sum_{j=1}^d z_{k,j} \leq 1 \\ & y_i \leq i \cdot z_{i,j} + \sum_{r=j}^{i-1} z_{r,j} \\ & z_{k,j} \geq 0, \end{aligned}$$

# Cont'd

- ▶ Try  $y_i = \frac{1}{i}$ ,
- ▶ Consider a differentiable function  $f_j(x)$ , where  $f_j'(k)$  approximately represents  $z_{k,j}$

$$i \cdot f_j'(i) + \int_j^i f_j'(x) dx \geq \frac{1}{i} \iff$$

$$x \cdot f_j'(x) + f_j(x) - f_j(j) \geq \frac{1}{x}.$$

- ▶ By solving the differential equation,

$$f_j(x) = \frac{\ln(x/j)}{x}, \quad f_j'(x) = \frac{1 - \ln(x/j)}{x^2}.$$

- ▶ Feasible dual variables assignment

$$y_i = \frac{1}{i}, \quad z_{k,j} = \begin{cases} \frac{1 - \ln(k/j)}{k^2} & \text{if } j \leq k \leq \lfloor e \cdot j \rfloor, \\ 0 & \text{otherwise.} \end{cases}$$

# Cont'd

- ▶ Verify if this solution is feasible
- ▶ Then the competitive ratio has a lower bound:

$$\frac{\sum_{i=1}^d y_i}{\sum_{k=1}^d \sum_{j=1}^d z_{k,j}} \geq \frac{H(d)}{\frac{H(d)}{e} + \sum_j \frac{1}{j^2}} \rightarrow e,$$

- ▶ In their literature review, a  $(1 + \varepsilon)e$ -competitive algorithm exists for original problem when all vector's coordinates are at most  $O\left(\frac{\varepsilon^2}{\log d}\right)$
- ▶ This lower bound indicates that algorithm is almost optimal

# Online Capital Investment

- ▶ Produce many units of commodities at minimum cost, where orders for units arrive online.
- ▶ Each machine  $m_i$  has a capital cost  $c_i$  and production cost  $p_i$ .
  - ▶ Algorithm choose to buy a machine for cost  $c_i$
  - ▶ Algorithm choose to use machine produce units for  $p_i$  per unit.
- ▶ Here we consider the relaxed version that the machine can be bought partially.

# Cont'd

- ▶ Problem setting:
- ▶  $n$  machines,  $i$ th one have capital cost of  $i + 1$  and a production cost of  $2^{-i^2}$
- ▶ Input Sequence:
  - ▶  $n$  phases.
  - ▶ In phase  $k$ ,  $2^{k^2} - 2^{(k-1)^2}$  orders are introduced
- ▶ Offline Optimal:
  - ▶ For input with only  $k$  phases, buy  $k$ th machine and produce units.
  - ▶  $\text{OPT} = k+2$

# Cont'd

## ► Variables:

- $x_{k,i}$  the fraction bought of the  $i$ th machine in the  $k$ th phase.
- $q_{k,i}$  the fraction of products produced by the  $i$ th machine in the  $k$ th phase.

min  $c$

$$\text{s.t.: } \sum_{r=1}^k x_{r,i} \geq q_{k,i} \quad \text{cons. } y_{k,i}$$

$$\sum_{i=1}^n q_{k,i} = 1 \quad \text{cons. } w_k$$

$$\sum_{r=1}^k \sum_{i=1}^n (i+1)x_{r,i} + \sum_{i=1}^n 2^{k^2-i^2} q_{k,i} \leq c(k+2) \quad \text{cons. } z_k$$

$$c, x_{k,i}, q_{k,i} \geq 0, \quad ,$$

# Cont'd

- ▶ Normalizing variables by the term  $\sum_k (k+2)z_k$ , competitive ratio becomes

$$\frac{\sum_k w_k}{\sum_k (k+2)z_k}$$

- ▶ Try let  $y_{k,i} = \begin{cases} w_k, & k \leq i \\ 0, & k > i \end{cases}$

**The dual linear program:**

$$\begin{aligned} \max \quad & \sum_{k=1}^n w_k \\ \text{s.t.} \quad & \sum_{k=1}^n (k+2) \cdot z_k \leq 1 && \text{cons. } c \\ & (i+1) \sum_{r=k}^n z_r \geq \sum_{r=k}^n y_{r,i} && \text{cons. } x_{k,i} \\ & y_{k,i} \geq w_k - z_k \cdot 2^{k^2-i^2} && \text{cons. } q_{k,i} \\ & y_{k,i}, z_k \geq 0, \end{aligned}$$

# Cont'd

- ▶ By substituting  $y$ , we get

$$(i+1) \sum_{r=k}^n z_r \geq \sum_{r=k}^i w_r \quad \text{cons. } x_{k,i}.$$

- ▶ Empirically take  $w_r = \frac{1}{r}$ , consider differentiable functions  $f(x), g(x)$ , where  $f'(k), g'(i)$  approximately represents  $z_k, w_i$ . Then  $g'(x) = \frac{1}{x}$

$$(i+1) \int_k^{n+1} f'(x) dx \geq \int_k^{i+1} g'(x) dx \iff$$
$$f(n+1) - f(k) \geq \frac{\ln(\frac{i+1}{k})}{i+1},$$

which holds for

$$f(x) = -\frac{1}{e \cdot x}, \quad f'(x) = \frac{1}{e \cdot x^2},$$



# Cont'd

- ▶ Verify if this solution is feasible
- ▶ Then the competitive ratio has a lower bound:

$$\frac{\sum_{k=1}^n w_k}{\sum_{k=1}^n (k+2)z_k} = \frac{e \cdot \ln(n \cdot \epsilon) \cdot (1 - \epsilon)}{\sum_{k=1}^n \frac{k+2}{k(k+1)}} \geq$$
$$\frac{e \cdot \ln(n \cdot \epsilon) \cdot (1 - \epsilon)}{H(n) + C_1} \rightarrow e \cdot (1 - \epsilon),$$

- ▶ In their literature review, a  $e$ -competitive algorithm exists.
- ▶ This lower bound indicates that algorithm is almost optimal

# Some drawbacks

- ▶ Input sequences can be difficult to construct.
- ▶ Need to formulate problems to LPs with competitive ratios as objective functions.
- ▶ Only obtained lower bound on the competitive ratios, may need to design algorithms to achieve such competitive ratios.

# Lessons learned

- ▶ Due to the online settings, algorithms have no information about future. They need to balance all possible future inputs.
- ▶ A systematic method to obtain online deterministic and randomized lower bounds on the competitive ratio.
- ▶ This method can also help designing online algorithms.