

# Solving Linear Programs with Fast Online Learning Algorithms

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# Problem of interest

We want solve an LP with  $m$  constraints and  $n$  variables

$$\begin{aligned} \max_{\mathbf{x}} \quad & \langle \mathbf{c}, \mathbf{x} \rangle \\ \text{subject to} \quad & \mathbf{Ax} \leq \mathbf{b} \\ & \mathbf{0} \leq \mathbf{x} \leq \mathbf{1} \end{aligned}$$

- The formulation covers many types of LPs including set covering, set packing, resource allocation...
- Seeking to approximately optimize it with help of **online algorithms**

# Dual problem and optimality condition

The dual problem is given by

$$\begin{aligned} \min_{\mathbf{y}, \mathbf{s}} \quad & \langle \mathbf{b}, \mathbf{y} \rangle + \langle \mathbf{1}, \mathbf{s} \rangle \\ \text{subject to} \quad & \mathbf{s} \geq \mathbf{c} - \mathbf{A}^T \mathbf{y} \\ & \mathbf{y}, \mathbf{s} \geq \mathbf{0} \end{aligned}$$

and optimality condition exhibits a strong relation between primal and dual.

$$x_j^* \in \begin{cases} \{0\}, & c_j < \langle \mathbf{a}_j, \mathbf{y}^* \rangle \\ [0, 1], & c_j = \langle \mathbf{a}_j, \mathbf{y}^* \rangle \\ \{1\}, & c_j > \langle \mathbf{a}_j, \mathbf{y}^* \rangle \end{cases}$$

- Primal largely determined by the dual through the optimality condition
- We adopt a dual-based approach

# Dual reformulation and online algorithm

The dual problem can be reformulated as a finite-sum problem

$$\min_{\mathbf{y} \geq \mathbf{0}} \frac{1}{n} \sum_{j=1}^n \langle \mathbf{d}, \mathbf{y} \rangle + [c_j - \langle \mathbf{a}_j, \mathbf{y} \rangle]_+ =: \frac{1}{n} \sum_{j=1}^n f(\mathbf{y}, j), \quad (\mathbf{d} = \mathbf{b}/n)$$

We propose two popular online algorithms to optimize the dual problem

**Explicit online subgradient** applies projected subgradient method

$$\mathbf{y}^{k+1} = \arg \min_{\mathbf{y} \geq \mathbf{0}} \left\{ \langle \mathbf{f}'(\mathbf{y}^k, k), \mathbf{y} - \mathbf{y}^k \rangle + \frac{1}{2\gamma} \|\mathbf{y} - \mathbf{y}^k\|^2 \right\}$$

**Implicit online proximal point** applies proximal point method

$$\mathbf{y}^{k+1} = \arg \min_{\mathbf{y} \geq \mathbf{0}} \left\{ f(\mathbf{y}, k) + \frac{1}{2\gamma} \|\mathbf{y} - \mathbf{y}^k\|^2 \right\}$$

- Iterate through a **permutation** of columns in an “online fashion”.
- Primal value  $x^k$  is obtained using  $\mathbf{y}^k, \mathbf{y}^{k+1}$  and the optimality condition

# Theoretical guarantees of online algorithms

## Theorem

Let  $\hat{\mathbf{x}}$  be the output of the online algorithm, then

$$\mathbb{E}[\langle \mathbf{c}, \hat{\mathbf{x}}^* \rangle - \langle \mathbf{c}, \hat{\mathbf{x}} \rangle] \leq \mathcal{O}\left(\frac{m \log n}{K} + \sqrt{\frac{n}{K}} \log n + \sqrt{\frac{mn}{K}}\right)$$

$$\mathbb{E}[\|\mathbf{A}\hat{\mathbf{x}} - \mathbf{b}\|_+] \leq \mathcal{O}\left(\frac{m}{K} + \sqrt{\frac{mn}{K}}\right).$$

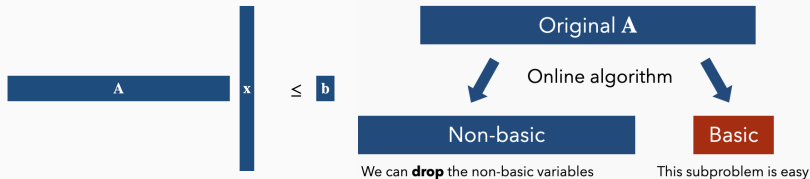
after we go through the permutation of LP columns  $K$  times.

- Sub-linear optimality and constraint violation bound
- We can improve the bound by  $\sqrt{K}$  by copying each LP variable  $K$  times
- Implementation can be very cheap if we exploit sparsity of  $\mathbf{A}$ .

# Application: LP Sifting/Column generation

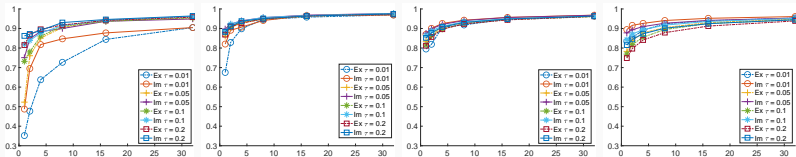
Our method can help solving large-scale LPs with column generation.

Given an LP with  $n \gg m$ , column generation



- finds a subset of variables **likely** to take  $> 0$  (basic) in  $x^*$
- primal output  $\hat{x}$  of online algorithm can be used as a likelihood estimate
- the dual solution can also be used for dual stabilization

# Numerical results: approximate LP solver



**Figure 1:** Left to right: LP of different sizes. The x-axis represents parameter  $K$  (how many times we copy each LP column) ranging in  $\{1, 2, 4, 8, 16, 32\}$ . The y-axis shows the relative optimality.

# Numerical results: LP Sifting

We choose LP datasets with more variables than rows

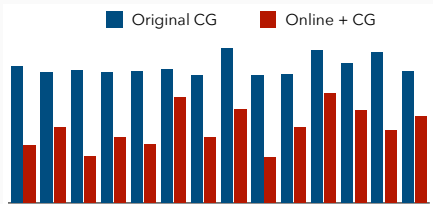
**Table 1:** Datasets collected from large-scale LP benchmark

Dataset	Row	Column	Dataset	Row	Column
rail507	507	6.4e+04	rail516	516	4.8e+04
rail582	582	5.6e+04	rail2586	2586	9.2e+05
rail4284	4284	1.0e+06	scpm1	5000	5.0e+05
scpn2	5000	1.0e+06	scpl4	2000	2.0e+05
scpj4scip	1000	1.0e+05	scpk4	2000	1.0e+05
s82	87878	1.7e+06	s100	14733	3.6e+05
s250r10	10962	2.7e+05	-	-	-



# Numerical results: LP Column generation

Data	Acc	Data	Acc
scpm1	100%	rail507	90%
scpn2	100%	rail516	88%
scpl4	100%	rail2586	94%
scpk4	100%	rail4284	96%



- Online algorithm achieves high accuracy in basis status identification.
- LP column generation benefits from it

- We propose to apply online algorithms to solve LPs
- Online algorithms can approximately solve LPs
- Online algorithms also benefits exact LP solving

Thanks for listening !