Bilevel Programming with(out) Intervals

The Best, the Worst and the Corrected

Optimization Seminar (22.3.2021)

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Linear Bilevel Programming

Linear Bilevel Programming

 $\min_{x,y} c^{T}x + d^{T}y$ s. t. $A_{1}x + B_{1}y \ge b_{1}$ $y \in M(x)$

where
$$M(x) = \operatorname{argmin}_y a^T y$$

s. t. $A_2 x + B_2 y \ge b_2$

Constraint Region: $\{(x, y) : A_1x + B_1y \ge b_1, A_2x + B_2y \ge b_2\}$ **Inducible Region:** $\{(x, y) : A_1x + B_1y \ge b_1, y \in M(x)\}$

Linear Bilevel Programming: An Example

 $\min_{x,y} y$ $y \leq 3$ $y \in \operatorname{argmax}_y \{y :$ $x + y \leq 5,$ $-x + y \leq 2,$ $x, y \geq 0 \}$



 $min_{x,y} y$ $y \le 3$ $y \in argmax_y \{y:$ $x + y \le 5,$ $-x + y \le 2,$ $x, y \ge 0\}$



Linear Bilevel Programming: Complexity

Theorem (Jeroslow, 1985; Ben–Ayed & Blair, 1990) Linear bilevel programming is NP-hard.

Theorem (Hansen et al., 1992) Linear bilevel programming is strongly NP-hard.

Reduction from the KERNEL problem on graphs:

$$\max_{x} \min_{y} \left\{ -\sum_{j} y_{j} : \\ x_{j} + x_{k} \leq 1, \qquad \forall j, k : (v_{j}, v_{k}) \in A, \\ y_{j} \leq 1 - x_{j}, \qquad \forall j \\ y_{j} \leq 1 - x_{k}, \qquad \forall j, k : (v_{j}, v_{k}) \in A, \\ x, y \geq 0 \right\}$$

High-point relaxation: We relax the lower-level optimality condition (i.e., drop the follower's objective), but ensure feasibility on the constraint region

 $\{(x, y): A_1x + B_1y \ge b_1, A_2x + B_2y \ge b_2\}.$

Properties of the high-point relaxation and the inducible region (IR) for linear bilevel programs (Bialas & Karwan, 1982; Bard, 1983):

- IR is a union of faces of the high-point relaxation,
- IR is a connected set, if there are no coupling constraints,
- if the program is feasible, then there exists an **optimal solution**, which is a **vertex of the high-point relaxation**.

Interval Linear Bilevel Programming: The First Attempt [Calvete & Galé, 2012]

 $\begin{aligned} \min_{x,y} & [c]^T x + [d]^T y \\ \text{s. t.} & [A_1] x + [B_1] y \ge [b_1] \\ & y \in M(x) \end{aligned}$

where $M(x) = \operatorname{argmin}_{y} [a]^{T} y$ s. t. $[A_2]x + [B_2]y \ge [b_2]$

→ Compute the **best** and the **worst optimal value**, set of optimal solutions, etc., over all scenarios (bilevel programs) with coefficients from the given intervals.

Interval linear BP: Example I

```
\min_{X,y} [1, 2]X + [-2, -1]y

y \in \arg\min_{y'} \{ [-1, 2]y' : (x, y') \in \operatorname{conv}\{(2, 4), (3, 7), (9, 9), (12, 3), (5, 1)\} \}
```



 $\min_{x,y} x + y_1 + y_2$ $y \in \arg\min_{v} \{[\underline{a_1}, \overline{a_1}]y_1 + [\underline{a_2}, \overline{a_2}]y_2 :$ $-3x - 3y_1 + 2y_2 \le 1$, $x + 2y_1 \le 4$, $y_2 \le 2$, $x \le 2$, $x, y_1, y_2 \ge 0$ **y**₂ (0, 2, 2)(2, 0, 2) (0,2,0)(2, 0, 0)

Bilevel Programming with Interval Objectives

 $\min_{x,y} [c]^T x + [d]^T y$ $y \in M(x)$

where $M(x) = \operatorname{argmin}_{y} [a]^{T} y$ s. t. $Ax + By \ge b, x, y \ge 0$

Remark: The best and the worst optimal values of the bilevel interval problem occur at vertices of the constraint region

 $S = \{(x, y) : Ax + By \ge b, x, y \ge 0\}.$

$$\min_{x,y} [c]^T x + [d]^T y$$

$$y \in \arg\min_{y'} \{a^T y' : Ax + By' \ge b, x, y \ge 0\}$$

→ The **inducible region remains unchanged** for all scenarios.

Theorem

The best optimal value of the interval linear BP can be found by solving the scenario (\underline{c} , \underline{d} , a).

The worst optimal value of the interval linear BP can be found by solving the scenario $(\overline{c}, \overline{d}, a)$.

Theorem

The best optimal value of the interval linear BP can be found by solving the scenario (\underline{c} , \underline{d} , a).

Proof:

Let (x^l, y^l) be an optimal solution of the scenario $(\underline{c}, \underline{d}, a)$ and let (x^*, y^*) be optimal for some scenario (c, d, a) with $c \in [c]$, $d \in [d]$. Since the inducible region does not change, we have

$$\underline{c}^T x^l + \underline{d}^T y^l \leq \underline{c}^T x^* + \underline{d}^T y^*.$$

Moreover, since x, y are non-negative, we have

$$\underline{c}^T x^* + \underline{d}^T y^* \leq c^T x^* + d^T y^*.$$

Thus, the scenario $(\underline{c}, \underline{d}, a)$ yields the best optimal value.

Lower-level Interval Objective Function

$$\min_{x,y} c^T x + d^T y$$

$$y \in \arg \min_{y'} \{ [a]^T y' : Ax + By' \ge b, x, y \ge 0 \}$$

Theorem

If the inducible region does not change for any vertex point of [a], then the best and the worst optimal values coincide and can be found by solving the linear bilevel program

$$\min_{x,y} c^T x + d^T y$$

$$y \in \arg\min_{y'} \{ \underline{a}^T y' : Ax + By' \ge b, x, y \ge 0 \}.$$

Consider the linear program on the constraint region

$$\min_{x,y} c^T x + d^T y : Ax + By \ge b, x, y \ge 0.$$
(1)

Let (x^*, y^*) be an optimal solution of (1). Then, (x^*, y^*) is the **best optimum** of the interval bilevel program, if it **belongs to the inducible region** for some $a^* \in [a]$, or, if the following linear system has a solution:

$$u^{T}B \leq a, \quad a^{T}y^{*} = (b - Ax^{*})^{T}u,$$

$$\underline{a} \leq a \leq \overline{a}, \qquad (2)$$

$$u \geq 0.$$

In the following algorithm,

 $W^{[l]}$: denotes the set of adjacent extreme points of $(\mathbf{x}^{[l]}, \mathbf{y}^{[l]})$ so that $(\mathbf{x}, \mathbf{y}) \in W^{[l]}$ implies $\mathbf{c}\mathbf{x} + \mathbf{d}\mathbf{y} \ge \mathbf{c}\mathbf{x}^{[l]} + \mathbf{d}\mathbf{y}^{[l]}$, *T*: denotes the set of analyzed and discarded extreme points and *W*: denotes the set of extreme points that will be analyzed later.

KBB algorithm:

Step 1. Put $i \leftarrow 1$. Solve the linear programming problem (1) to obtain the optimal solution $(\mathbf{x}^{[1]}, \mathbf{y}^{[1]})$. Let $W \leftarrow \{(\mathbf{x}^{[1]}, \mathbf{y}^{[1]})\}$ and $T \leftarrow \emptyset$. Go to Step 2. Step 2. Set $(\mathbf{x}^{*}, \mathbf{y}^{*}) \leftarrow (\mathbf{x}^{[i]}, \mathbf{y}^{[i]})$ and check system (2). If the system is feasible, stop; $(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})$ is the best optimal solution. Otherwise, go to Step 3. Step 3. Let $T \leftarrow T \cup \{(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})\}$ and $W \leftarrow (W \cup W^{[i]}) - T$. Go to Step 4. Step 4. Set $i \leftarrow i + 1$ and choose $(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})$ so that $\mathbf{cx}^{[i]} + \mathbf{dy}^{[i]} \leftarrow \min\{\mathbf{cx} + \mathbf{dy} : (\mathbf{x}, \mathbf{y}) \in W\}$. Go to Step 2.

> "The ordered **best extreme points** of the constraint region with respect to the upper-level objective are sequentially computed (by **examining neighbors**), until a **point of the inducible region** for some $a \in [a]$ is found."

Theorem

Let $(x^*, y^*) = (x^k, y^k)$ be the best extreme point of the constraint region S (with respect to the upper-level objective), so that there exists $a^* \in [a]$ such that $(x^*, y^*) \in IR_{a^*}$. Then, the point (x^*, y^*) is the best optimal solution of the interval linear BP.

Theorem

The algorithm KBB finds the best optimal solution of the interval linear bilevel program.

Again, we can use system (2) to check **feasibility** (whether (x^*, y^*) belongs to the inducible region for some $a \in [a]$):

$$u^T B \leq a$$
, $a^T y^* = (b - Ax^*)^T u$, $\underline{a} \leq a \leq \overline{a}$, $u \geq 0$.

To check **optimality** (i.e., if (x^*, y^*) is the solution for some $a \in [a]$), we consider the set

$$\Psi_{(x^*,y^*)} = \{a \in [a] : uG = a, u \ge 0\},\$$

where Gy = g is the subset of constraints $By \ge b - Ax$, $y \ge 0$, which are binding at (x^*, y^*) .

KBW algorithm:

Step1. Put $i \leftarrow 1$. Solve the linear programming problem (9) to obtain the optimal solution $(\mathbf{x}^{[1]}, \mathbf{y}^{[1]})$.

 $\begin{array}{l} \max \mathbf{cx} + \mathbf{dy} \\ \text{s.t.} \quad (\mathbf{x}, \mathbf{y}) \in S. \end{array} \tag{9}$ $\begin{array}{l} \text{Let } W \leftarrow \{(\mathbf{x}^{[1]}, \mathbf{y}^{[1]})\}, W^e \leftarrow \emptyset, W^p \leftarrow \emptyset \text{ and } T \leftarrow \emptyset. \text{ Go to Step 2.} \\ \text{Step2. Calculate } \psi_{(\mathbf{x}^{[0]}, \mathbf{y}^{[1]})}\}, W^e \leftarrow \emptyset, \text{set } W^e \leftarrow W^e \cup \{(\mathbf{x}^{[1]}, \mathbf{y}^{[1]})\}. \text{ Go to Step 8. Otherwise, set } W^p \leftarrow W^{[1]} - (T \cup W^e). \text{ If } \\ W^p = \emptyset, \text{ stop; } (\mathbf{x}^{[1]}, \mathbf{y}^{[1]}) \text{ is the worst optimal solution. Otherwise, set } \psi_* \leftarrow \psi_{(\mathbf{x}^{[1]}, \mathbf{y}^{[1]})}, \text{ go to Step 3.} \\ \text{Step3. If } W^p = \emptyset, \text{ go to Step 8. Otherwise go to Step 4.} \\ \text{Step4. Choose } (\mathbf{\hat{x}}, \mathbf{\hat{y}}) \text{ so that} \\ \mathbf{c} \mathbf{\hat{x}} + \mathbf{d} \mathbf{\hat{y}} \leftarrow \max\{\mathbf{cx} + \mathbf{dy}: (\mathbf{x}, \mathbf{y}) \in W^p\}. \end{array}$

Calculate $\psi_{(\hat{\mathbf{x}},\hat{\mathbf{y}})}$. If $\psi_{(\hat{\mathbf{x}},\hat{\mathbf{y}})} = \emptyset$, set $W^e \leftarrow W^e \cup \{(\hat{\mathbf{x}}, \hat{\mathbf{y}})\}$, $W^p \leftarrow W^p - \{(\hat{\mathbf{x}}, \hat{\mathbf{y}})\}$. Go to Step 3. Step5. If $\psi^* \cap \psi_{(\hat{\mathbf{x}},\hat{\mathbf{y}})} = \emptyset$, set $W^p \leftarrow W^p - \{(\hat{\mathbf{x}}, \hat{\mathbf{y}})\}$, go to Step 3. Otherwise, go to Step 6. Step6. Set $\psi^* \leftarrow \psi^* - \psi_{(\hat{\mathbf{x}},\hat{\mathbf{y}})}$. If $\psi^* = \emptyset$, set $T \leftarrow T \cup \{(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})\}$, go to Step 8. Otherwise, go to Step 7. Step7. Set $W^p \leftarrow W^p - \{(\hat{\mathbf{x}}, \hat{\mathbf{y}})\}$. If $W^p = \emptyset$, stop; $(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})$ is the worst optimal solution. Otherwise, go to Step 4. Step8. Set $W \leftarrow (W \cup W^{[i]}) - (T \cup W^e)$. Set $i \leftarrow i + 1$ and choose $(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})$ so that $\mathbf{cx}^{[i]} + \mathbf{dy}^{[i]} \leftarrow \max\{\mathbf{cx} + \mathbf{dy} : (\mathbf{x}, \mathbf{y}) \in W\}$. Go to Step 2.

Similar idea to KBB, but now both **feasibility and optimality** conditions for the solution have to be tested in the algorithm (only feasibility is not sufficient).

$$\min_{\substack{x,y \\ y \in \text{arg } \min_{y'} \{[a]^T y' : Ax + By' \ge b, x, y \ge 0\}}$$

Theorem

The **best optimal solution** of the interval bilevel program is obtained by applying the KBB algorithm to the program with upper-level objective vectors $c = \underline{c}$, $d = \underline{d}$.

The **worst optimal solution** of the interval bilevel program is obtained by applying the KBW algorithm to the problem with upper-level objective vectors $c = \overline{c}$, $d = \overline{d}$.

Interval Linear Bilevel Programming: The Revised Algorithm [Mishmast Nehi & Hamidi, 2015]

Counterexample I

```
\min_{\substack{x,y \\ y \in \text{arg min} \\ y'}} 0x + 1y 

y \in \arg\min_{\substack{y' \\ (x, y') \in \text{conv}\{(2, 4), (3, 7), (9, 9), (12, 3), (5, 1)\}}
```



Counterexample II



value of the upper level objective function with this process. The general process of KBW algorithm is correct; in this algorithm use is made of the W^p to study candidate point $(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})$, but what is to be noted in this algorithm is that to study point $(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})$, not only its adjacent extreme points, but also all those extreme points (remained from W^p in the previous iterations) that have not been analyzed or have not been discarded should be evaluated too. The step 2 shortcoming in KBW algorithm in relation (16) has been corrected in the proposed revised algorithm. On the one hand, point $(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})$ cannot be used in its own evaluation; so, in order to solve these problems, it is necessary that relation

$$W^{p} \leftarrow W^{[l]} - (T \cup W^{e}) \tag{15}$$

in KBW algorithm be modified as follows:

$$W^{p} \leftarrow W^{p} \cup W^{[i]} - (T \cup W^{e} \cup \{(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})\})$$

$$\tag{16}$$

And, on the other hand, no precise definition is given for $W^{[i]}$ in the paper. We can have the following more precise definition:

 $W^{[l]}$: denotes the set of adjacent extreme points of $(\mathbf{x}^{[l]}, \mathbf{y}^{[l]})$ so that for each $(\mathbf{x}, \mathbf{y}) \in W^{[l]}$:

$$\begin{cases} \mathbf{c}\mathbf{x} + \mathbf{d}\mathbf{y} \leqslant \mathbf{c}\mathbf{x}^{[l]} + \mathbf{d}\mathbf{y}^{[l]}, & \text{if } \psi_{(\mathbf{x}^{[l]}, \mathbf{y}^{[l]})} = \emptyset. \end{cases}$$

$$\tag{17}$$

$$\int \mathbf{c} \mathbf{x} + \mathbf{d} \mathbf{y} < \mathbf{c} \mathbf{x}^{[i]} + \mathbf{d} \mathbf{y}^{[i]}, \quad \text{if } \psi_{(\mathbf{x}^{[i]}, \mathbf{y}^{[i]})} \neq \emptyset.$$

Revised KBW: Example

```
\min_{\substack{x,y \\ y \in \text{arg min} \\ y'}} 0x + 1y 

y \in \arg\min_{\substack{y' \\ (x, y') \in \text{conv}\{(2, 4), (3, 7), (9, 9), (12, 3), (5, 1)\}}
```



 $\min_{x,y} [c]^T x + [d]^T y$ s. t. $[A_1]x + [B_1]y \ge [b_1]$ $x, y \ge 0$ $y \in M(x)$

where $M(x) = \operatorname{argmin}_{y} [a]^{T} y$ s. t. $[A_{2}]x + [B_{2}]y \ge [b_{2}]$ $y \ge 0$ Consider the constraint region

 $\{(x, y): [A_1]x + [B_1]y \ge [b_1], \ [A_2]x + [B_2]y \ge [b_2], \ x, y \ge 0\}.$

Remark: The best and the worst optimal value of the fully interval bilevel linear program occur at vertices of \overline{S} , \underline{S} , respectively, where

 $\overline{S} = \{(x, y) : \overline{A_1}x + \overline{B_1}y \ge \underline{b_1}, \ \overline{A_2}x + \overline{B_2}y \ge \underline{b_2}, \ x, y \ge 0\},\$ $\underline{S} = \{(x, y) : \underline{A_1}x + \underline{B_1}y \ge \overline{b_1}, \ \underline{A_2}x + \underline{B_2}y \ge \overline{b_2}, \ x, y \ge 0\}.$

Theorem

The **best** and the **worst optimal values** of the fully interval bilevel linear program are the optimal values of the following problems, respectively:

 $\begin{array}{ll} \min_{x,y} \ \underline{c}^T x + \underline{d}^T y & \min_{x,y} \ \overline{c}^T x + \overline{d}^T y \\ \text{s. t. } \overline{A_1} x + \overline{B_1} y \geq \underline{b_1}, & \text{s. t. } \underline{A_1} x + \underline{B_1} y \geq \overline{b_1}, \\ x, y \geq 0 & x, y \geq 0 \\ y \in \arg\min\{ \ [a]^T y : & y \in \arg\min\{ \ [a]^T y : \\ \overline{A_2} x + \overline{B_2} y \geq \underline{b_2}, & \underline{A_2} x + \underline{B_2} y \geq \overline{b_2}, \\ y \geq 0 \ \} & y \geq 0 \end{array}$

→ Extended KBB and RKBW algorithms

• Methods for computing **the best and the worst optimal values** for bilevel linear programs with interval objectives are available.

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- These methods were also further extended to be used for fully interval bilevel linear programs.
- Still, many related questions and problems in interval bilevel programming remain open.

Thank you for your attention!

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