A fast combinatorial algorithm for the bilevel knapsack problem with interdiction constraints

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- We are interested in solving this problem exactly
- Objective: win the horse race


## Game theoretic interpretation of BKP

Given: $n$ items, weights $w^{U}, w^{L} \in \mathbb{Z}_{\geq 0}^{n}$, profits $p \in \mathbb{Z}_{\geq 0}^{n}$, capacities $C^{U}, C^{L} \in \mathbb{Z}_{\geq 0}$.

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- Objective: Select $X$ to minimize the maximum profit the Follower can get


## Bilevel programming interpretation of BKP

Given: $n$ items, weights $w^{U}, w^{L} \in \mathbb{Z}_{\geq 0}^{n}$, profits $p \in \mathbb{Z}_{\geq 0}^{n}$, capacities $C^{U}, C^{L} \in \mathbb{Z}_{\geq 0}$. Objective: $\min _{X \in \mathcal{U}} \max _{Y \in \mathcal{L}(X)} \sum_{i \in Y} p_{i}$
where

$$
\begin{aligned}
\mathcal{U} & =\left\{X \subseteq\{1, \ldots, n\}: \sum_{i \in X} w_{i}^{U} \leq C^{U}\right\} \\
\mathcal{L}(X) & =\left\{Y \subseteq\{1, \ldots, n\} \backslash X: \sum_{i \in Y} w_{i}^{L} \leq C^{L}\right\}
\end{aligned}
$$

(upper/leaders knapsack)
(lower/followers knapsack)

## Motivation: bilevel programming

BKP is a bilevel integer programming problem:

$$
\begin{array}{ll}
\min & c^{T} x+d^{T} y \\
\text { s.t. } & A x \leq b \\
& x \in \mathbb{Z}^{n}  \tag{BIP}\\
& y \in \arg \max \left\{f^{T} y: G x+H y \leq g, y \in \mathbb{Z}^{p}\right\}
\end{array}
$$

$y$ must be optimal for a second optimization problem (depending on $x$ ).

## History and motivation: bilevel programming

Why bilevel?

- Competing parties (military, business)
- Semi-cooperating parties (federal and regional governments)
- A natural way to get harder versions of classical problems


## History and motivation: bilevel knapsack

Complexity of BKP (Caprara, Carvalho, Lodi and Woeginger, 2014)

- $\sum_{2}^{p}$-complete
- no polysize IP formulation unless the polynomial hierarchy collapses
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- General bilevel solvers are far from the performance of problem-specific methods...


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However...

- BKP is perhaps one of the "easiest" $\sum_{2}^{p}$-complete problems
- General bilevel solvers are far from the performance of problem-specific methods... and this paper only widens that gap


## History and motivation: bilevel knapsack

- DeNegre (2011) introduced the problem. Solved instances with $\leq 15$ items
- Caprara, Carvalho, Lodi and Woeginger (2016): Solved instances with $\leq 50$ items
- Tang, Richard and Smith (2016): Solved instances with $\leq 30$ items
- Fischetti, Ljubic, Monaci, and Sinnl (2019). Solved instances with $\leq 55$ items
- Lozano, Bergman and Cire (2022). Solved instances with $\leq 50$ items
- Della Croce and Scatamacchia (2018). Solved instances with $\leq 500$ items (henceforth the DCS algorithm)
.... and more on approximation, complexity, problem variants, etc


## Lower bounds and upper bounds

$$
\begin{aligned}
\min _{X \in \mathcal{U}} & \sum_{i \in Y}^{n} p_{i} \\
\text { such that } & Y \in \underset{Y \in \mathcal{L}(X)}{\operatorname{argmax}} \sum_{i \in Y} p_{i}
\end{aligned}
$$

- Feasible solution $\Longrightarrow$ upper bound
- Lower bounds are harder: first published 2018 (DCS algorithm)


## Our contributions

All previous exact algorithms use MIP solvers.
We present a combinatorial algorithm which outperforms the previous best method, the DCS algorithm.

Our key insight: a new way of relaxing bilevel problems.

## Preliminaries

- $X$ : upper level/leader's items
- $Y$ : lower level/follower's items
- Items are enumerated by $\{1, \ldots, n\}$ and ordered such that

$$
\frac{p_{1}}{w_{1}^{L}} \geq \frac{p_{2}}{w_{2}^{L}} \geq \cdots \geq \frac{p_{n}}{w_{n}^{L}}
$$

## Branch and bound

A node is a pair $(X, i)$ where

- $i \in\{1, \ldots, n+1\}$ and
- $X \in \mathcal{U}$
- $X \cap\{i, \ldots, n\}=\emptyset$

Cannot take item 2


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A leaf $(X, n+1)$ is a complete Leader's solution, so we can solve $\max \left\{\sum_{i \in Y} p_{i}: Y \in \mathcal{L}(X)\right\}$ to get an upper bound.

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At each internal node we perform a bound test, to check if searching that branch is worthwhile.

## Branch and bound: bound test

For node $(X, i)$, is it possible that $\exists X^{\prime} \supseteq X$ and $\exists Y^{\prime} \in \mathcal{L}\left(X^{\prime}\right)$ with $\left(X^{\prime}, Y^{\prime}\right)$ optimal?
If not, there is no point to explore the children of $(X, i)$.

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If not, there is no point to explore the children of $(X, i)$.

To test this, we compute a lower bound at each node and test if it exceeds the current best upper bound.

## Lower bound

Consider a node $(X, i)$. In all descendants $\left(X^{\prime}, i^{\prime}\right)$ of $(X, i)$, we have $X^{\prime} \supseteq X$ and $i^{\prime}>i$. We want to lower bound the solution for such $\left(X^{\prime}, i^{\prime}\right)$ which are leaves.

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We split this computation into two parts:

1. Lower bound using items $\{1, \ldots, i-1\}$ (prefix)
2. Lower bound using items $\{i, \ldots, n\}$ (postfix)

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Note that:

- We know that the Leader uses capacity $\sum_{i \in X} w_{i}^{U}$ on the prefix
- This leaves $C^{U}-\sum_{i \in X} w_{i}^{U}$ for the postfix
- We don't know how much capacity the Follower uses on the prefix or the postfix, but any guess will give a lower bound.

Lower bound: items $\{1, \ldots, i-1\}$ (prefix)

Given: Leader's items $X$, and (guessed) lower capacity $c^{L}$.

- $X$ has already been decided on $\{1, \ldots, i-1\}$
- So it suffices to find the optimal $Y$ on items $\{1, \ldots, i-1\} \backslash X$ with capacity $c^{L}$
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## Definition

Let $K(S, c)$ denote the optimal objective value of the 0-1 knapsack problem with profits $\left(p_{i}\right)_{i \in S}$, weights $\left(w_{i}^{L}\right)_{i \in S}$ and capacity $c$.

- The desired bound is $K\left(\{1, \ldots, i-1\} \backslash X, c^{L}\right)$.


## Lower bound: items $\{i, \ldots, n\}$ (postfix)

Given: remaining leader's capacity $c^{U}$, guessed follower's capacity $c^{L}$.
We relax the problem from bilevel to $2 n$-level. The players alternative turns, considering one item at a time.

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Given: remaining leader's capacity $c^{U}$, guessed follower's capacity $c^{L}$.
We relax the problem from bilevel to $2 n$-level. The players alternative turns, considering one item at a time.

- Round 2i-1: If $w_{i}^{U}+\sum_{j \in X} w_{j}^{U} \leq c^{U}$, Leader can add item $i$ to $X$.

- Round 2i: If $i \notin X$ and $w_{i}^{L}+\sum_{j \in Y} w_{j}^{L} \leq c^{L}$, Follower can add item $i$ to $Y$.

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Given: remaining leader's capacity $c^{U}$, guessed follower's capacity $c^{L}$.
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- Round $2 \mathbf{2}$ - 1: If $w_{i}^{U}+\sum_{j \in X} w_{j}^{U} \leq c^{U}$, Leader can add item $i$ to $X$.

- Round 2i: If $i \notin X$ and $w_{i}^{L}+\sum_{j \in Y} w_{j}^{L} \leq c^{L}$, Follower can add item $i$ to $Y$.


## What's changed? Intuition

- The Leader (minimizer) gets more information
- The Follower (maximizer) gets less information

Net result: a lower bound

## Solving the modified game

The modified game admits a pseudopolytime algorithm by dynamic programming:

$$
\begin{aligned}
& \omega\left(i, c^{U}, c^{L}\right)= \\
& \left\{\begin{array}{ll}
\infty & \text { if } c^{U}<0 \\
-\infty & \text { if } c^{L}<0 \\
0 & \text { if } c^{U} \geq 0, c^{L} \geq 0 \text { and } i>n \\
\min \begin{cases}\omega\left(i+1, c^{U}-w_{i}^{U}, c^{L}\right), \\
\max \left\{\begin{array}{l}
\omega\left(i+1, c^{U}, c^{L}-w_{i}^{L}\right)+p_{i}, \\
\omega\left(i+1, c^{U}, c^{L}\right)
\end{array}\right\} & \text { if } c^{U} \geq 0, c^{L} \geq 0 \text { and } i \leq n .\end{cases}
\end{array} .\right.
\end{aligned}
$$

## Theorem

$\omega\left(i, c^{U}, c^{L}\right)$ is the optimal objective value of the modified game when restricted to items $\{i, \ldots, n\}$ with Leader's capacity $c^{U}$ and Follower's capacity $c^{L}$.

## Postfix lower bound formalized

## Definition

Let $\operatorname{OPT}\left(i, c^{U}, c^{L}\right)$ be the optimal objective value for BKP when restricted to items $\{i, \ldots, n\}$ with Leader's capacity $c^{U}$ and Follower's capacity $c^{L}$.

Theorem (Postfix lower bound)
For all $i \in[n], 0 \leq c^{U} \leq C^{U}$, and $0 \leq c^{L} \leq C^{L}$, we have

$$
\omega\left(i, c^{U}, c^{L}\right) \leq O P T\left(i, c^{U}, c^{L}\right)
$$

## Combining prefix and postfix

Let $c \in\left[0, C^{L}\right]$ be a guess for how much capacity the Follower uses on the prefix. Recall:

- Prefix lower bound: $K(\{1, \ldots, i-1\} \backslash X, c)$
- Postfix lower bound: $\omega\left(i, C^{U}-\sum_{j \in X} w_{j}^{U}, C^{L}-c\right)$

Theorem

$$
K(\{1, \ldots, i-1\} \backslash X, c)+\omega\left(i, C^{U}-\sum_{j \in X} w_{j}^{U}, C^{L}-c\right)
$$

is a lower bound for node $(X, i)$, and it can be computed in pseudopolynomial time.

## Extensions \& improvements: Solving trivial instances faster

Our lower bound is expensive: it requires pseudopolynomial time and memory. Can we avoid computing it?

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Our lower bound is expensive: it requires pseudopolynomial time and memory. Can we avoid computing it?

Sometimes! Can get a much weaker lower bound in polytime by solving a linear program inspired by the DCS algorithm. Using this and a greedy upper bound, we can detect and solve trivial instances near instantly.

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Ok, but the lower bound is still expensive.
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Ok, but the lower bound is still expensive.
Can we compute less of it?
Yes! We can use sparse dynamic programming tables, like the classical DP-with-lists approach for knapsack.

This makes it practical to solve instances with arbitrarily large capacity.

Extensions \& improvements: generalizations

Can this approach be applied to more problems?

## Extensions \& improvements: generalizations

Can this approach be applied to more problems?
Yes! Easy to generalize to:

- Bounded knapsack problem
- Multidimensional knapsack problem
- Min-max regret knapsack problem
- ... hopefully many more


## Implementation

- We implemented the algorithm in $\mathrm{C}++$
- We reimplemented the DCS algorithm in C++ with Gurobi; our reimplementation generally matches or exceeds the performance of the original implementation
- DCS is parallelized via Gurobi
- In our algorithm, only the dynamic programming is parallelized
- We test on all instances from the literature, and generate some more


## Computational results

Selected instances: generated by Fischetti, Monaci and Sinnl (2018), with $n$ up to 500 and capacity up to 25000 .

|  | DCS |  |  |  | Comb |  |  |  |
| :--- | :---: | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Class | \#Opt | \#Best | Avg | Max | \#Opt | \#Best | Avg | Max |
| uncorrelated | 50 | 0 | 3.66 | 13.38 | 50 | 50 | 0.64 | 7.1 |
| weak correlated | 50 | 0 | 13.49 | 72.64 | 50 | 50 | 0.39 | 4.76 |
| strong correlated* | 41 | 0 | 689.58 | 3,600 | 50 | 50 | 0.46 | 5.02 |
| inverse strong corr.* | 38 | 0 | 919.91 | 3,600 | 50 | 50 | 1.17 | 31.11 |
| almost strong corr.* $^{\text {subset-sum* }}$ | 40 | 0 | 815.4 | 3,600 | 50 | 50 | 0.35 | 4.28 |
| even-odd subset-sum* $^{*}$ | 35 | 0 | $1,087.18$ | 3,600 | 42 | 42 | 588.57 | 3,600 |
| even-odd strong corr.* | 36 | 0 | $1,033.98$ | 3,600 | 42 | 42 | 582.37 | 3,600 |
| similar weight uncorr. | 41 | 0 | 747.12 | 3,600 | 50 | 50 | 0.73 | 17.06 |
| s0 | 0 | 22.89 | 79.85 | 50 | 50 | 0.12 | 0.35 |  |

(Running times in seconds)

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| s. | 0 | 22.89 | 19.85 | 50 | 50 | 0.12 | 0.30 |  |

(Running times in seconds)

## Performance profile: all instances from the literature



Lower bound strength in practice vs theory

- The relaxed game is optimal for BKP on $85 \%$ of instances
- There is a (contrived) family of instances where it has gap $O(n)$ :

| item no. | $p$ | $w^{U}$ | $w^{L}$ |
| :---: | :---: | :---: | :---: |
| 1 | 1 | 1 | 1 |
| 2 | 2 | 2 | 2 |
| $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ |
| $n-1$ | $n-1$ | $n-1$ | $n-1$ |
| $n$ | $\binom{n}{2}$ | $\binom{n}{2}$ | $\binom{n}{2}+1$ |

- But with branch-and-bound, we solve this family near instantly



## Conclusion

- Our solver has better performance on $99 \%$ of instances
- We solved $74 \%$ of the unsolved instances in the literature
- Key takeaway: relax the bilevel problem to $2 n$ alternating levels: this gives a strong lower bound


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## Future work / Open problems

- Is there a "fast" algorithm for subset-sum instances?
- What other problems would benefit from this type of relaxation?
- What can be said, theoretically, about the performance of our algorithm on particular instance classes?

Thanks for your attention!

