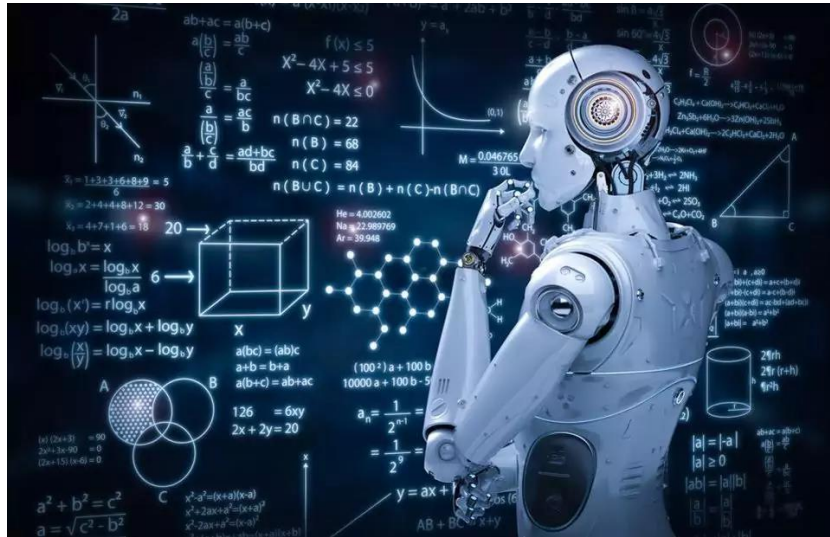


Branch & Learn with Post-hoc Correction for Predict+Optimize with Unknown Parameters in Constraints

Xinyi Hu ¹, Jasper C.H. Lee ², Jimmy H.M. Lee ¹

1. The Chinese University of Hong Kong

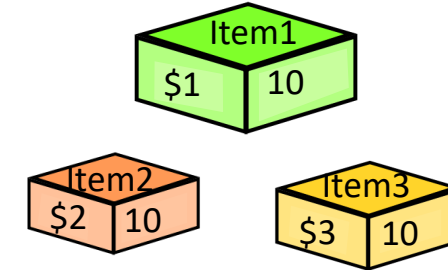
2. University of Wisconsin–Madison



Machine learning



Capacity: 2000



Constraint optimization

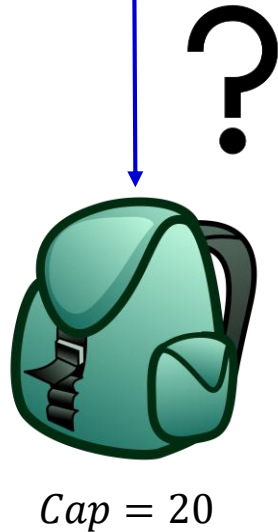
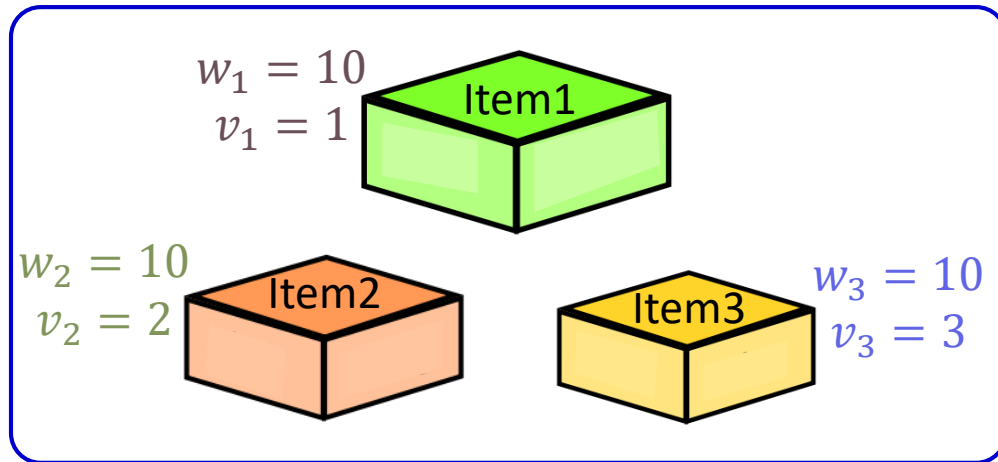


Predict+Optimize

[Elmachtoub and Grigas, Management Science 2022]

Optimization problems
with unknown parameters

Knapsack Problem



- 3 items, each with a weight w_i and a value v_i , the capacity Cap is 20.

Problem parameters

- Select items so that
 - the total weight is no more than the capacity and
 - the total value is maximized

• Optimization Problem (OP):

Decision variable

$$x_i = \begin{cases} 0, & \text{the } i\text{th item is not selected} \\ 1, & \text{the } i\text{th item is selected} \end{cases}$$

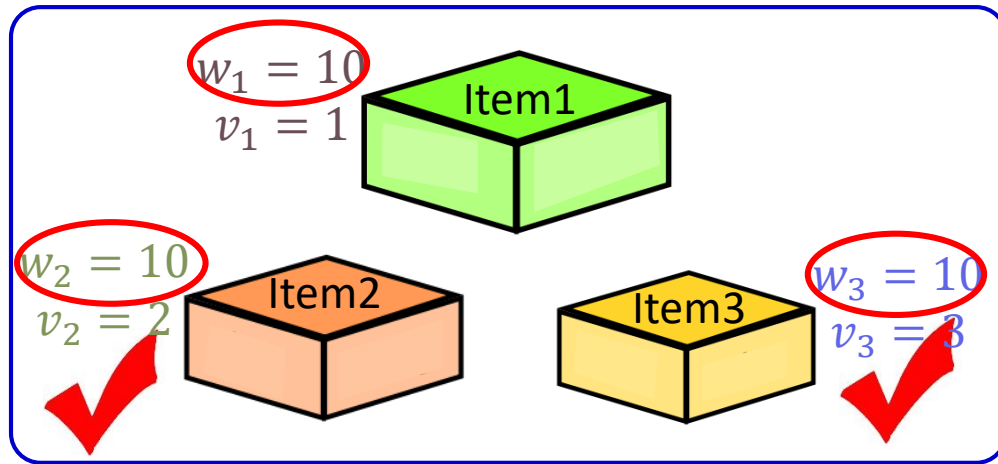
Objective function

$$\max_x x_1 + 2x_2 + 3x_3$$

Constraints

$$\begin{aligned} \text{s.t. } & 10x_1 + 10x_2 + 10x_3 \leq 20 \\ & x_i \in \{0,1\} \forall i \in \{1,2,3\} \end{aligned}$$

Knapsack Problem



?



$Cap = 20$

Optimal solution:

$$\{x_1 = 0, x_2 = 1, x_3 = 1\}$$

- 3 items, each with a weight w_i and a value v_i , the capacity Cap is 20.

Problem parameters

- Select items so that
 - the total weight is no more than the capacity and
 - the total value is maximized

• Optimization Problem (OP):

Decision variable

$$x_i = \begin{cases} 0, & \text{the } i\text{th item is not selected} \\ 1, & \text{the } i\text{th item is selected} \end{cases}$$

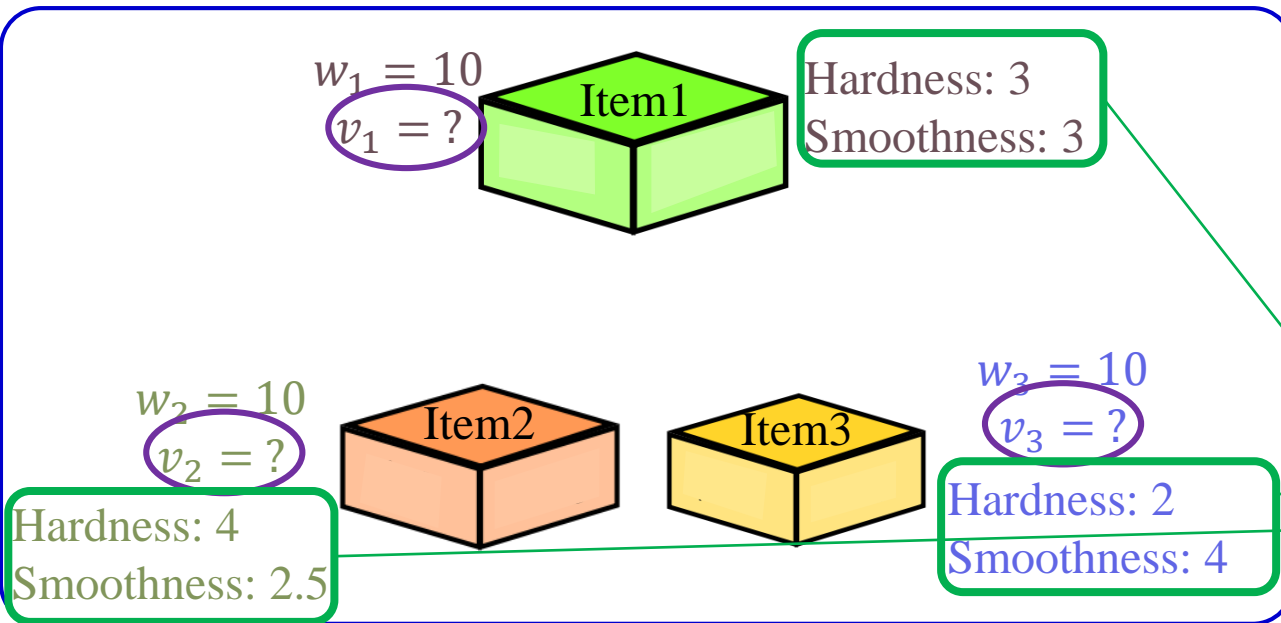
Objective function

$$\max_x x_1 + 2x_2 + 3x_3$$

Constraints

$$\begin{aligned} \text{s.t. } & 10x_1 + 10x_2 + 10x_3 \leq 20 \\ & x_i \in \{0,1\} \forall i \in \{1,2,3\} \end{aligned}$$

Knapsack Problem with Unknown Values



- The value v_i is unknown.
- Select items so that
 - the total weight is no more than the capacity and
 - the total value is maximized

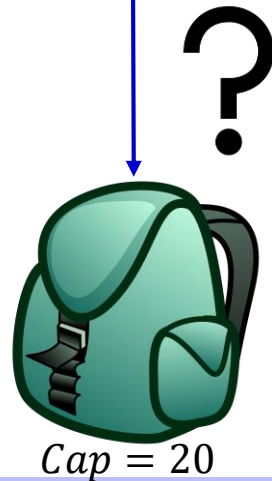
• OP with Unknown Parameters:

- θ : unknown parameters, e.g., $\theta = \{v_1, v_2, v_3\}$

• A: feature matrix

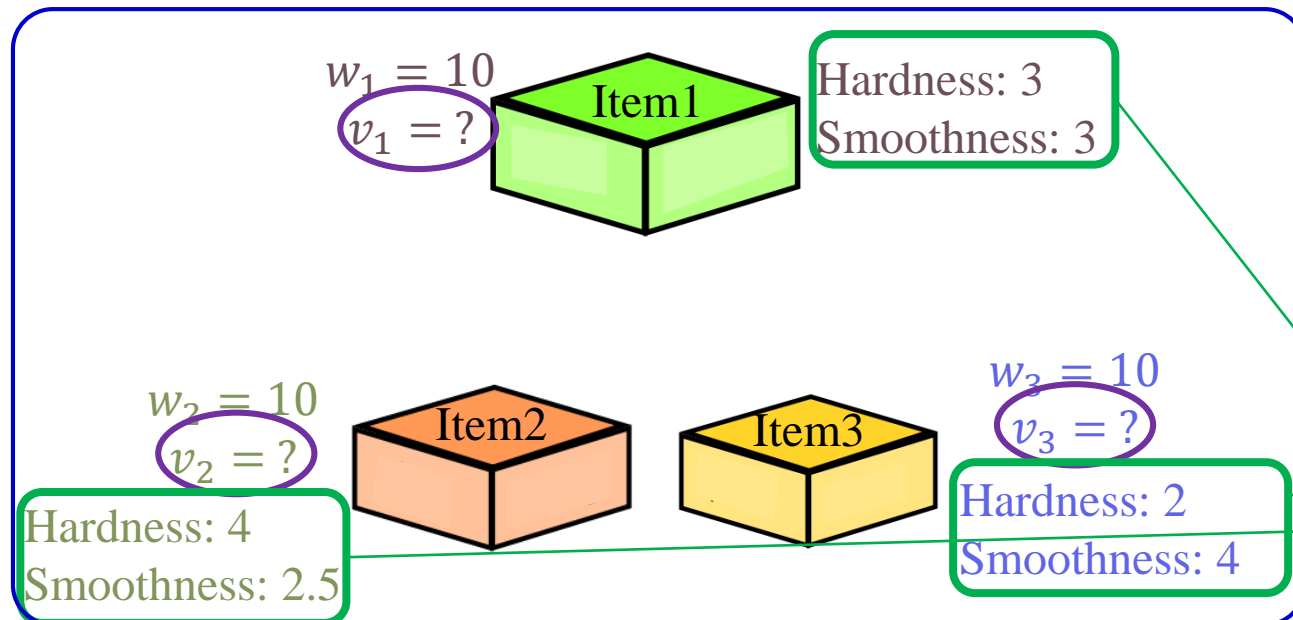
- Hardness
- Smoothness

$$A = \begin{bmatrix} 3 & 3 \\ 4 & 2.5 \\ 2 & 4 \end{bmatrix}$$

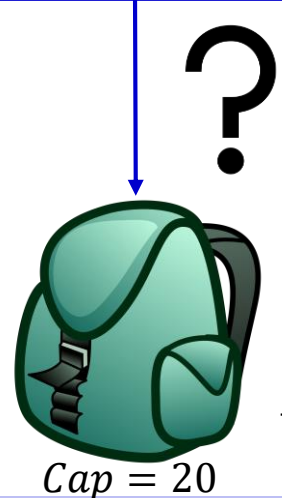


Optimal solution:
 $\{x_1 = ?, x_2 = ?, x_3 = ?\}$

Knapsack Problem with Unknown Values



- The value v_i is unknown.
- Select items so that
 - the total weight is no more than the capacity and
 - maximize the total value
- **OP with Unknown Parameters:**
 - θ : unknown parameters, e.g., $\theta = \{v_1, v_2, v_3\}$
 - A : feature matrix
 - Hardness
 - Smoothness
 - $A = \begin{bmatrix} 3 & 3 \\ 4 & 2.5 \\ 2 & 4 \end{bmatrix}$
 - Historical data: $\{(A^1, \theta^1), (A^2, \theta^2), \dots, (A^k, \theta^k)\}$

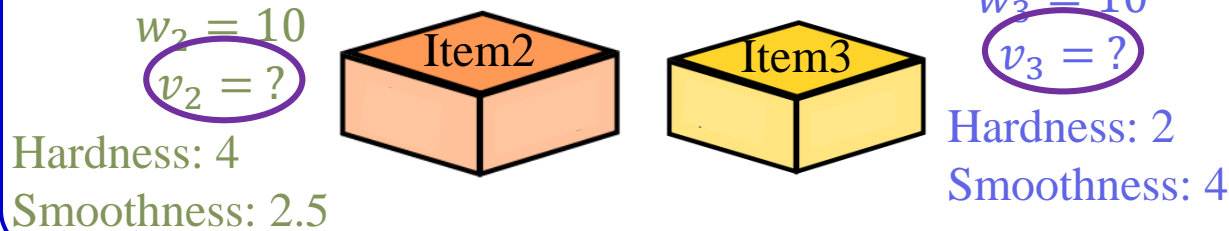
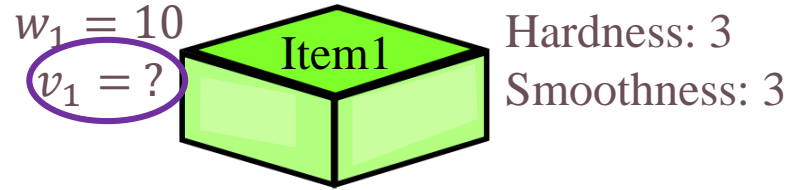


Optimal solution:
 $\{x_1 = ?, x_2 = ?, x_3 = ?\}$

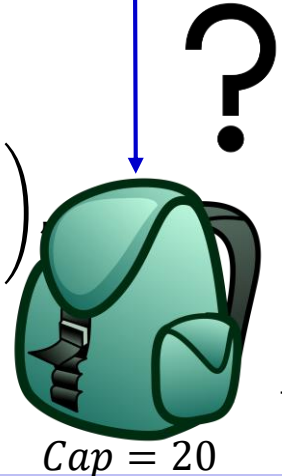
Historical features True parameters

$$(A^i, \theta^i) = \left(\begin{bmatrix} 2 & 2 \\ 2 & 3 \\ 3 & 1 \end{bmatrix}, \begin{bmatrix} 3 \\ 4 \\ 2 \end{bmatrix} \right)$$

Knapsack Problem with Unknown Values



Historical data:
 $(A^1, \theta^1), \dots,$
 $(A^i, \theta^i) = \left(\begin{bmatrix} 2 & 2 \\ 2 & 3 \\ 3 & 1 \end{bmatrix}, \begin{bmatrix} 3 \\ 4 \\ 2 \end{bmatrix} \right)$
 ...



Optimal solution:
 $\{x_1 = ?, x_2 = ?, x_3 = ?\}$

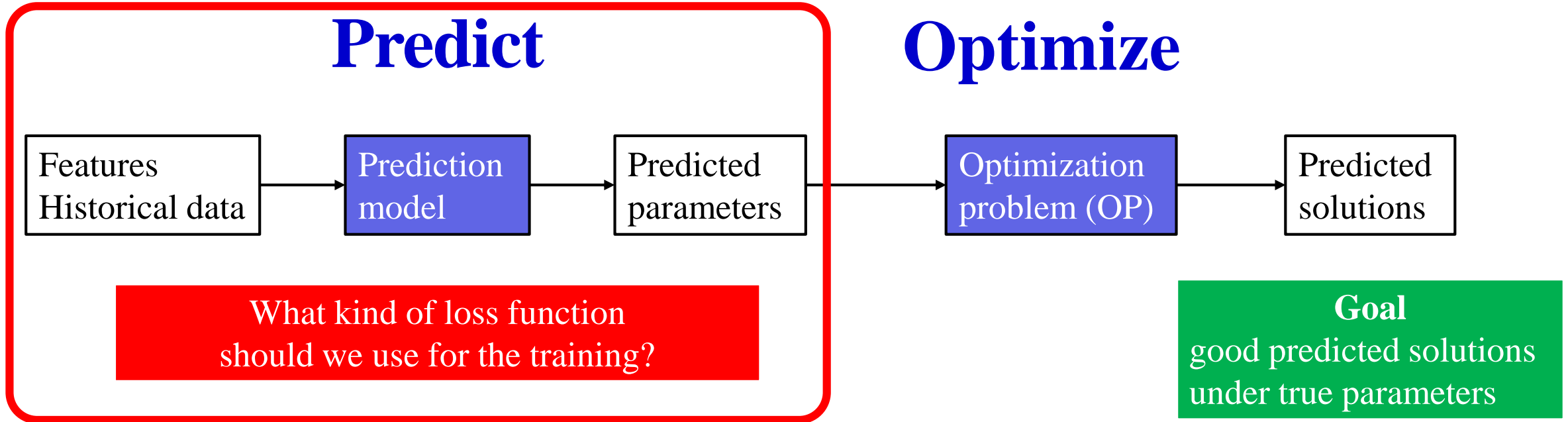
• OP with Unknown Parameters:

$$x_i = \begin{cases} 0, & \text{the } i\text{th item is not selected} \\ 1, & \text{the } i\text{th item is selected} \end{cases}$$

$$\begin{aligned} \max_x & v_1 x_1 + v_2 x_2 + v_3 x_3 \\ \text{s.t.} & 10x_1 + 10x_2 + 10x_3 \leq 20 \\ & x_i \in \{0,1\} \forall i \in \{1,2,3\} \end{aligned}$$

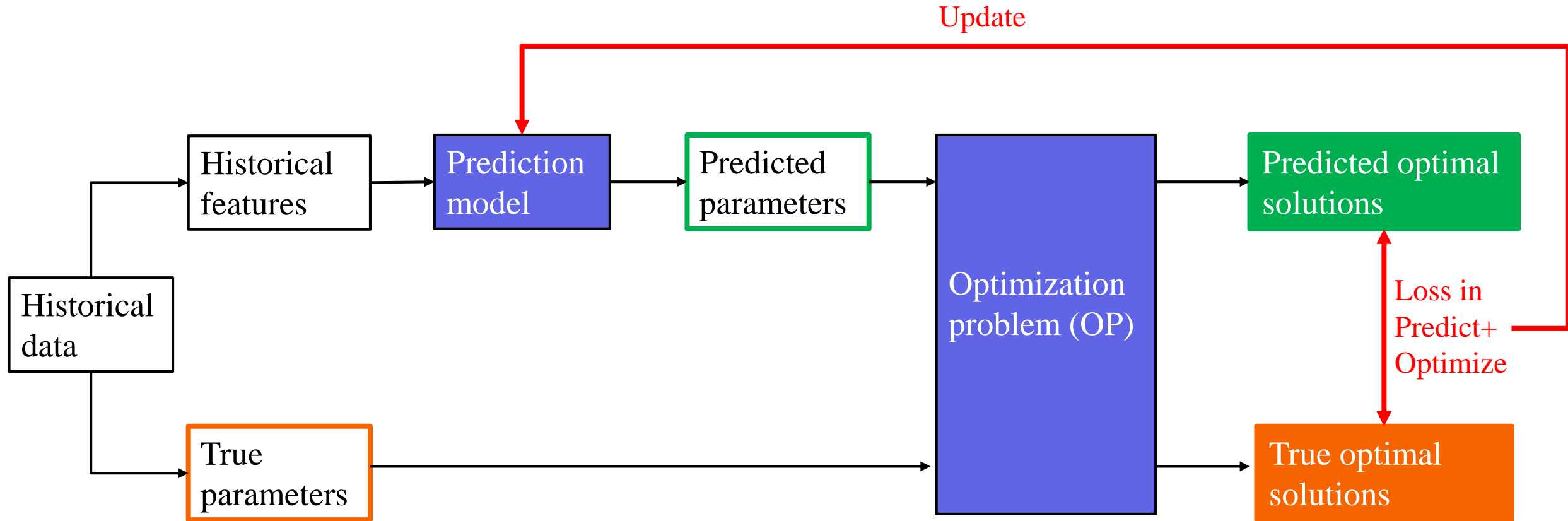
Unknown parameters

The Pipeline

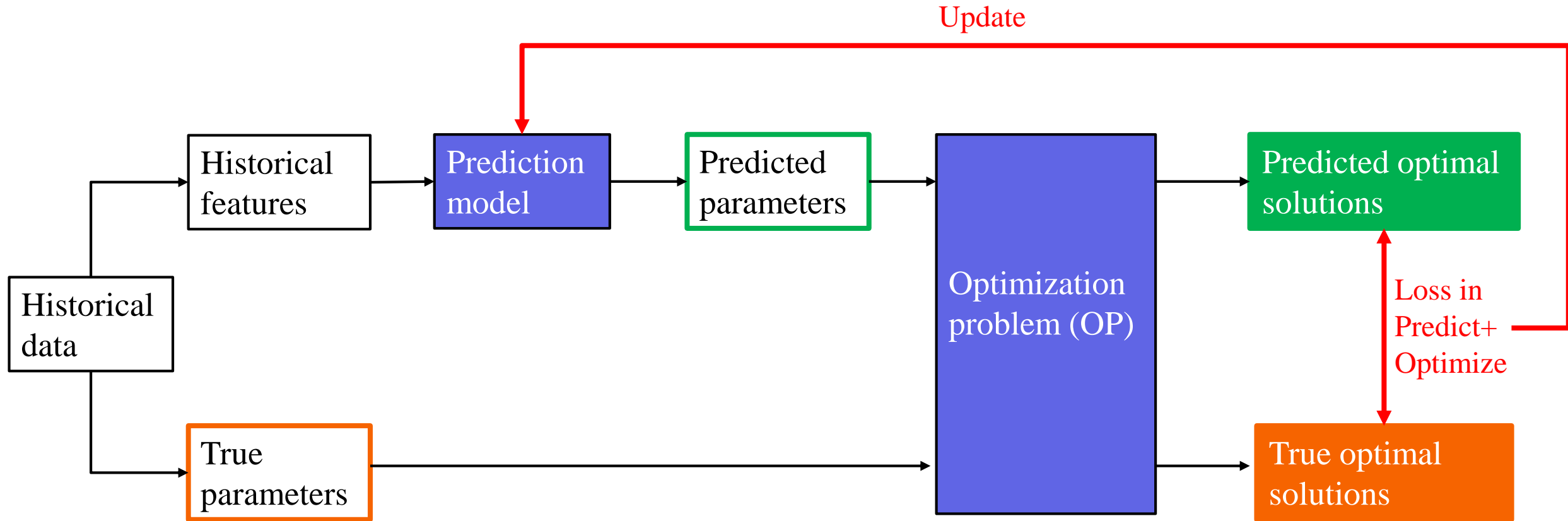


Predict+Optimize

Aims to incorporate optimization problems into the loss function



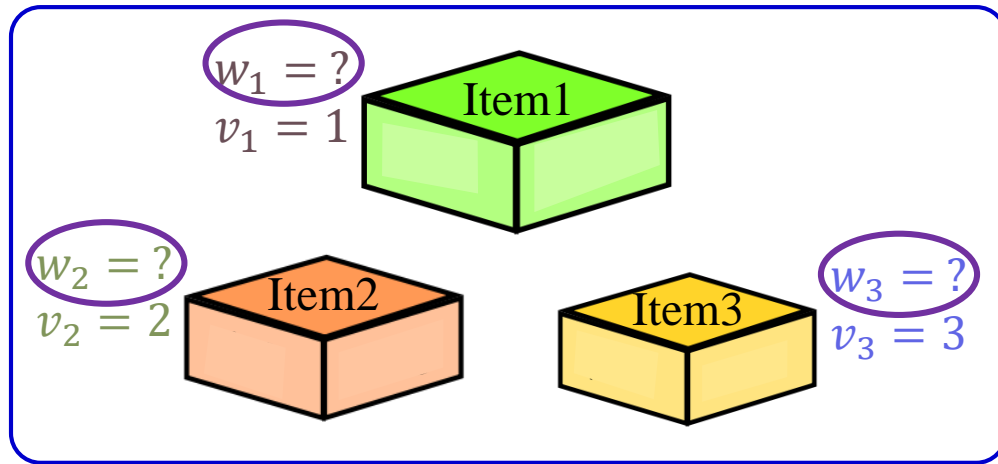
Unknown Parameters in Objectives



- Regret ([Demirović et al., 2019a], [Elmachtoub and Grigas, Management Science 2022]):

$$\| \text{True optimal value} - \text{Predicted optimal value} \|$$

Unknown Parameters in Constraints



?



Cap = 20

Optimal solution:
 $\{x_1 = ?, x_2 = ?, x_3 = ?\}$

- Knapsack with unknown weights

$$\begin{aligned} & \max_x x_1 + 2x_2 + 3x_3 \\ \text{s.t. } & w_1 x_1 + w_2 x_2 + w_3 x_3 \leq 20 \\ & x_i \in \{0, 1\} \forall i \in \{1, 2, 3\} \end{aligned}$$

Unknown parameters
in constraints

E.g.,

- Predicted weights:

$$\{\widehat{w}_1 = \widehat{w}_2 = \widehat{w}_3 = 5\}$$

- Predicted optimal solution:

$$\{x_1 = x_2 = x_3 = 1\}$$

infeasible

- True weights:

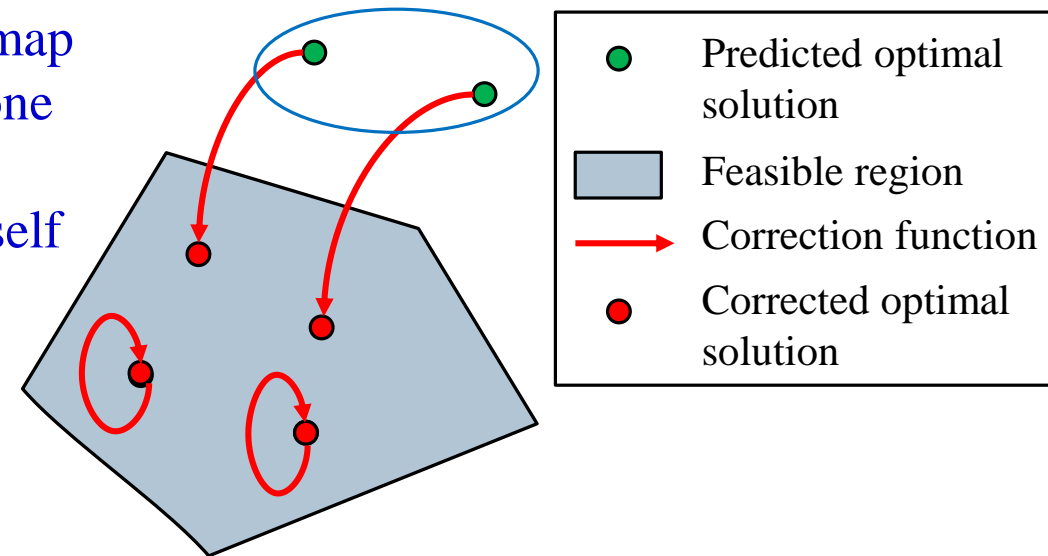
$$\{w_1 = w_2 = w_3 = 10\}$$

Unknown Parameters in Constraints

Some applications allow solution modification after true parameters are revealed

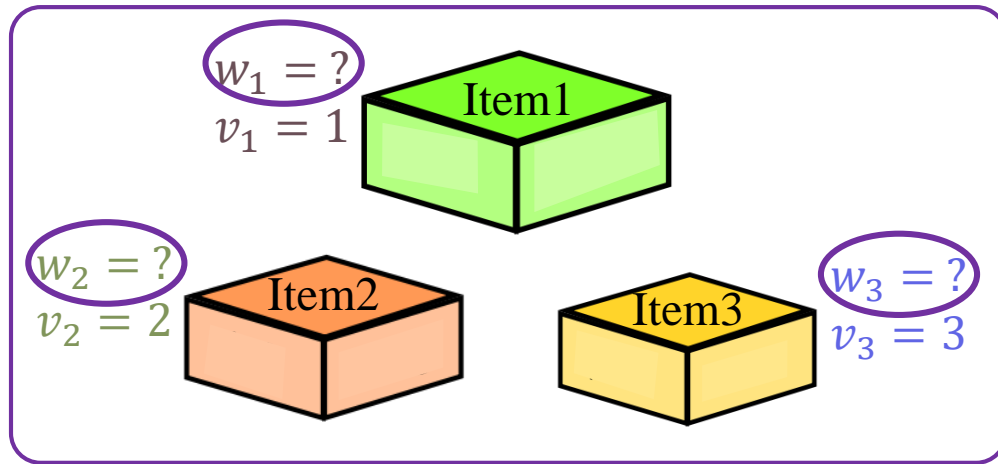
[Hu et al., AAI 2023]

- **Correction function** should map
 - (a) each infeasible solution to one in the feasible region
 - (b) every feasible solution to itself



The space of possible correction functions:
problem and application specific

Post-hoc Correction: Knapsack Example



?



Cap = 20

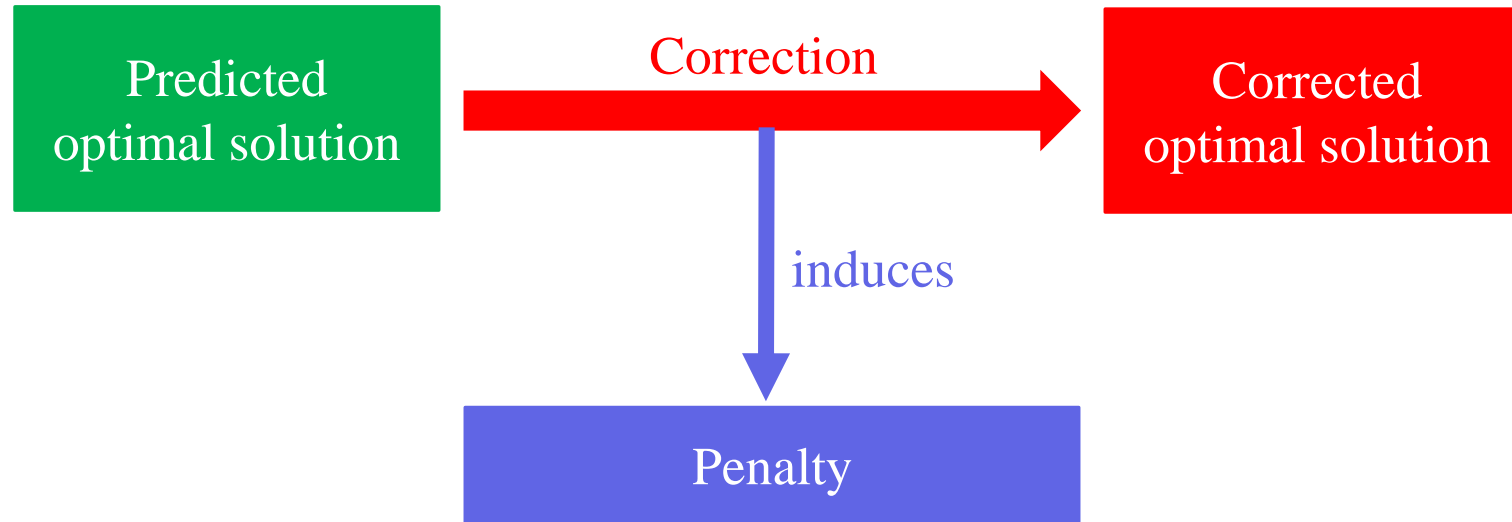
Optimal solution:
 $\{x_1 = ?, x_2 = ?, x_3 = ?\}$

- If the weights are unknown?

$$\begin{aligned} \max_x \quad & \sum_i v_i x_i \\ \text{s. t.} \quad & \sum_i w_i x_i \leq \text{Cap} \\ & x_i \in \{0,1\} \forall i \in \{1,2,3\} \end{aligned}$$

- When the total weight of the selected items exceeds the capacity:
 - Correction function: remove the items one by one in increasing order of the ratios of value/weight
- Penalty function: removal fee
 - problem and application specific

Unknown Parameters in Constraints



- Post-hoc regret ([Hu et al., AAI 2023]):

$$\| \text{True optimal value} - \text{Corrected optimal value} \| + \text{Penalty}$$

- When only the objective contains unknown parameters, degenerates into Regret

Our Contributions

- Handles optimization problems with unknown parameters in both the objective and constraints

Prior works

- Most focus on unknown parameters **only in objective**
 - [Mandi et al., ICML 2022]
 - [Jeong et al., ICML 2022]
 - [Guler et al., AAI 2022]
 - [Hu et al., NeurIPS 2022]
 - ...
- Focus on unknown parameters **in both objective and constraints**
 - [Hu et al., AAI 2023]
 - New loss: post-hoc regret (**non-differentiable**)
 - An approximation method for covering and packing LPs
 - Use an approximation of post-hoc regret

Our work

- Focus on unknown parameters **in both objective and constraints**
 - An exact method for recursively and iteratively solvable problems
 - Use post-hoc regret
 - Experimentally compare the proposed exact method with the prior approximation method
 - Empirically study different combinations of the 2 key components of the framework

Branch & Learn with Post-hoc Correction

- Assumption: the prediction model is linear
- To train models without computing gradients
 - Adopt the coordinate descent based method proposed by previous work [Hu et al., NeurIPS 2022]

Previous work [Hu et al., NeurIPS 2022] :

- For unknown parameters only in **objectives**
- Use **Regret** as the loss function

Algorithm 1: Branch & Learn

Input: A Para-OP $P(\theta)$ and a training data set $\{(A^1, \theta^1), \dots, (A^n, \theta^n)\}$
Output: a coefficient vector $\alpha \in \mathbb{R}^m$

```
1 Initialize  $\alpha$  arbitrarily and  $k \leftarrow 0$ ;  
2 while not converged  $\wedge$  resources remain do  
3    $k \leftarrow (k \bmod m) + 1$ ;  
4   Initialize  $L$  to be the zero constant function;  
5   for  $i \in [1, 2, \dots, n]$  do  
6      $(P_\gamma^i, I_0) \leftarrow \text{Construct}(P(\theta), k, A^i)$  ;  
7      $E^i(\gamma) \leftarrow \text{Convert}(P_\gamma^i, I_0)$ ;  
8      $L^i(\gamma) \leftarrow \text{Evaluate}(\mathbb{I}(E^i), \theta^i, I_0)$ ;  
9      $L(\gamma) \leftarrow L(\gamma) + L^i(\gamma)$ ;  
10   $\alpha_k \leftarrow \arg \min_{\gamma \in \mathbb{R}} L(\gamma)$ ;  
11 return  $\alpha$ ;
```

- Update prediction model coefficients via coordinate descent
- Each iteration contains 3 functions:
 - Construct(): construct an OP with unknown parameters
 - Convert(): solve the OP with unknown parameters and get predicted optimal solution
 - Evaluate(): compute the Regret

Branch & Learn with Post-hoc Correction

- Assumption: the prediction model is linear
- To train models without computing gradients
 - Adopt the coordinate descent based method proposed by previous work [Hu et al., NeurIPS 2022]

Previous work [Hu et al., NeurIPS 2022] :

- For unknown parameters only in **objectives**
- Use **Regret** as the loss function

Algorithm 1: Branch & Learn

Input: A Para-OP $P(\theta)$ and a training data set $\{(A^1, \theta^1), \dots, (A^n, \theta^n)\}$
Output: a coefficient vector $\alpha \in \mathbb{R}^m$

```
1 Initialize  $\alpha$  arbitrarily and  $k \leftarrow 0$ ;  
2 while not converged  $\wedge$  resources remain do  
3    $k \leftarrow (k \bmod m) + 1$ ;  
4   Initialize  $L$  to be the zero constant function;  
5   for  $i \in [1, 2, \dots, n]$  do  
6      $(P_\gamma^i, I_0) \leftarrow \text{Construct}(P(\theta), k, A^i)$ ; 2nd change:  
7      $E^i(\gamma) \leftarrow \text{Convert}(P_\gamma^i, I_0)$ ;  
8      $L^i(\gamma) \leftarrow \text{Evaluate}(\mathbb{I}(E^i), \theta^i, I_0)$ ;  
9      $L(\gamma) \leftarrow L(\gamma) + L^i(\gamma)$ ;  
10   $\alpha_k \leftarrow \arg \min_{\gamma \in \mathbb{R}} L(\gamma)$ ;  
11 return  $\alpha$ ;
```

2nd change:
change Evaluate()

Our work:

- For unknown parameters in **objectives and constraints**
- Use **Post-hoc Regret** as the loss function

Algorithm 2: Branch & Learn with Post-hoc Correction

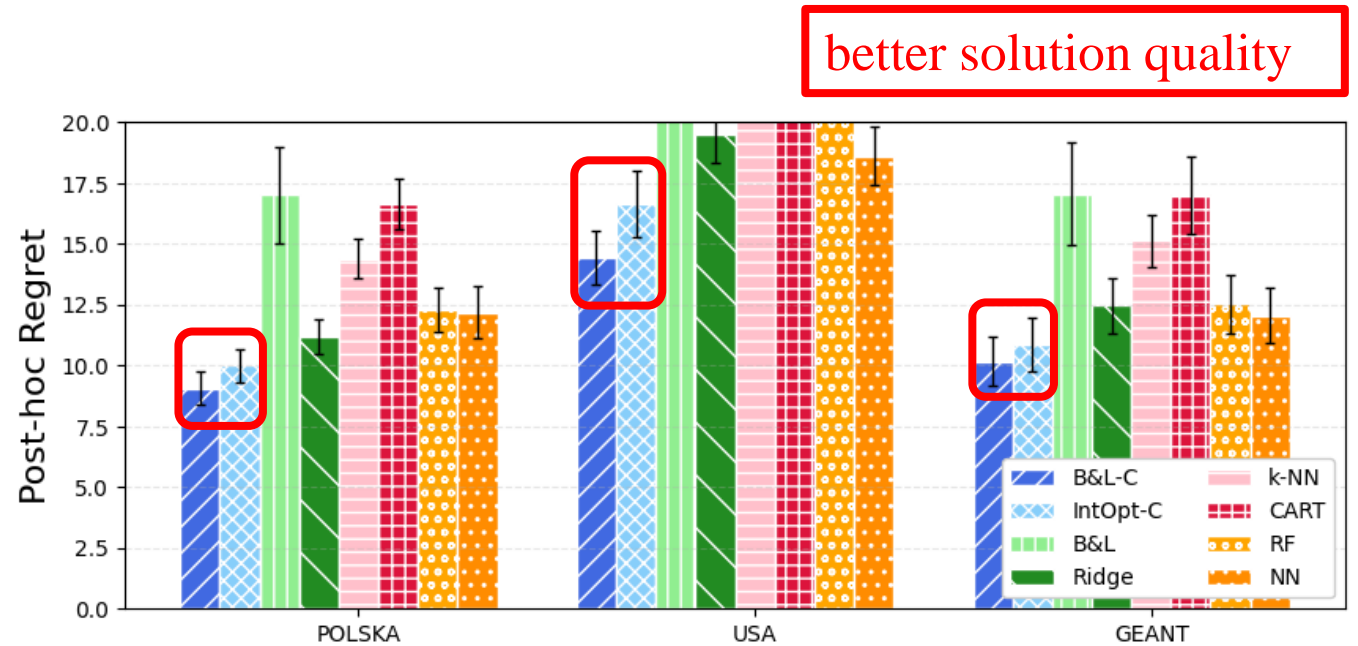
Input: A Para-COP $P(\theta)$ and a training data set $\{(A^1, \theta^1), \dots, (A^n, \theta^n)\}$
Output: a coefficient vector $\alpha \in \mathbb{R}^m$

```
1 Initialize  $\alpha$  arbitrarily and  $k \leftarrow 0$ ;  
2 while not converged  $\wedge$  resources remain do  
3    $k \leftarrow (k \bmod m) + 1$ ;  
4   Initialize  $L$  to be the zero constant function;  
5   for  $i \in [1, 2, \dots, n]$  do  
6      $(P_\gamma^i, I_0) \leftarrow \text{Construct}(P(\theta), k, A^i)$ ;  
7      $E^i(\gamma) \leftarrow \text{Convert}(P_\gamma^i, I_0)$ ;  
8      $C^i(\gamma) \leftarrow \text{Correct}(E^i, \theta^i, I_0)$ ;  
9      $L^i(\gamma)^* \leftarrow \text{Evaluate}(\mathbb{I}(E^i), \mathbb{I}(C^i), \theta^i, I_0)$ ;  
10     $L(\gamma)^* \leftarrow L(\gamma)^* + L^i(\gamma)^*$ ;  
11     $\alpha_k \leftarrow \arg \min_{\gamma \in \mathbb{R}} L(\gamma)^*$ ;  
12 return  $\alpha$ ;
```

1st change: add
one function

Experimental Evaluation

- Experimentally compare the exact method with the prior approximation method
- E.g., Maximum Flow with Unknown Edge Capacities
 - Packing LP
 - Aim: find the largest flow sent from a source to a terminal in a directed graph
 - Constraint: the flow sent on each edge cannot exceed the edge capacity
- B&L: the prior exact method using **Regret**
- IntOpt-C: the prior approximation method using **an approximation of Post-hoc Regret**
- B&L-C: the proposed exact method using **Post-hoc Regret**

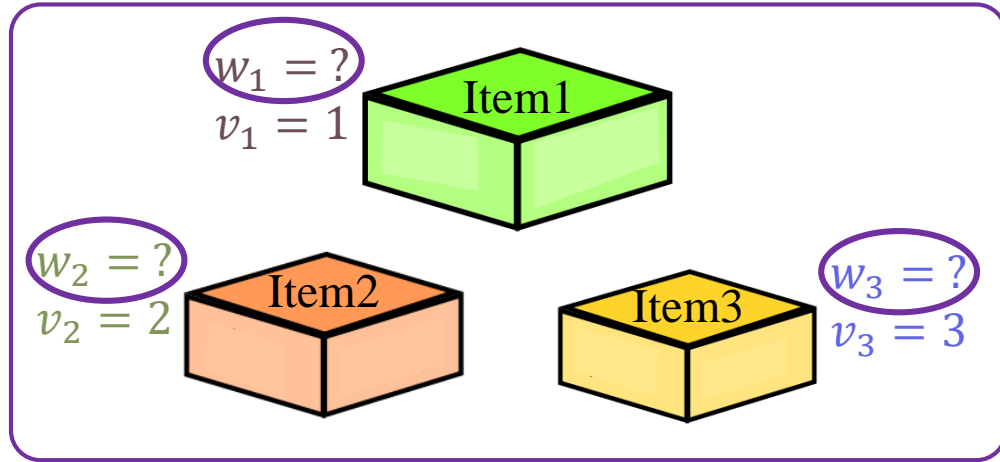


better solution quality

longer runtime

Runtime(s)	POLSKA	USANet	GEANT
B&L-C	66.54	411.67	48.32
IntOpt-C	18.65	132.22	15.48
B&L	40.30	288.43	29.90
RF	4.11	11.00	11.89
NN	10.33	12.82	13.89

Experimental Evaluation



?

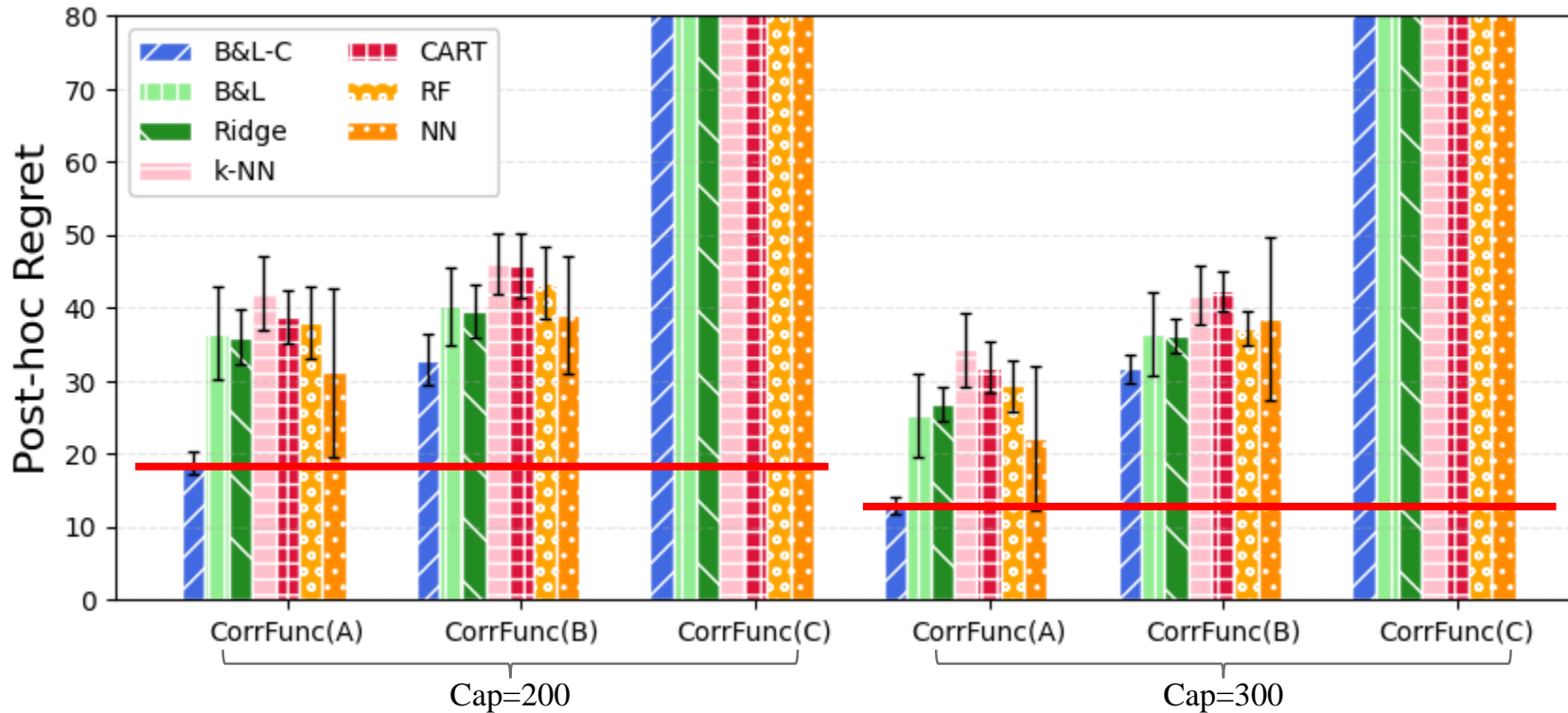


Cap = 20

Optimal solution:
 $\{x_1 = ?, x_2 = ?, x_3 = ?\}$

- Empirically study different combinations of the correction function and the penalty function on 3 OPs
- E.g., 0-1 Knapsack with Unknown Weights
 - **3 correction functions**
 - A: remove the items one by one in increasing order of the ratios of value/weight
 - B: remove the items one by one in decreasing order of the weights
 - C: remove all items
 - **2 penalty functions**
 - I: when the i -th item is removed, $\sigma_i v_i$ units of value is deducted
 - II: whenever a selected item is removed, K (a constant) units of value is deducted

Experimental Evaluation



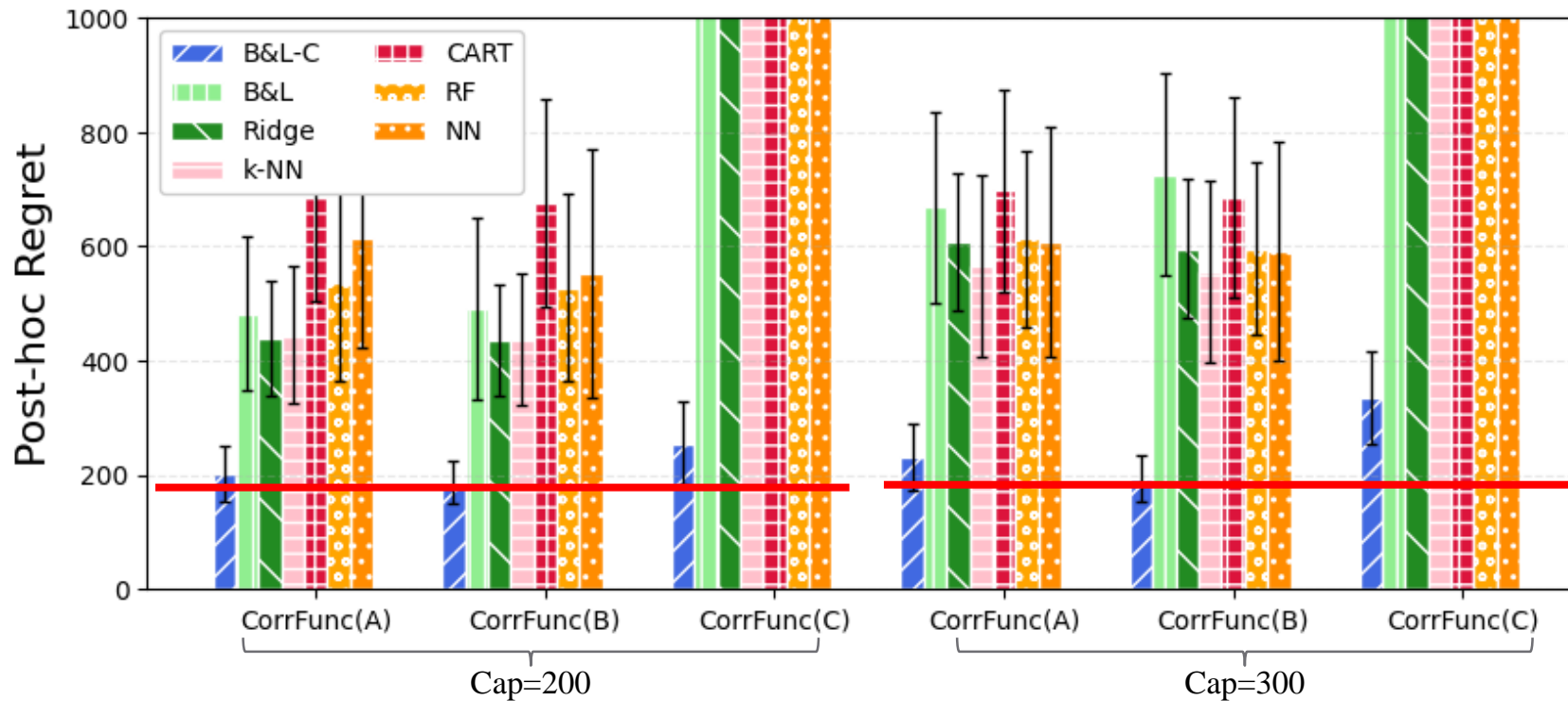
Penalty Function I:

Post-hoc Regrets achieved by using Correction Function A are much smaller than Post-hoc Regrets achieved by using Correction Function B or C

→ Correction Function A is more suitable to use than Correction Functions B or C

Post-hoc Regrets for 0-1 knapsack with unknown weights using different correction functions with Penalty Function I.

Experimental Evaluation



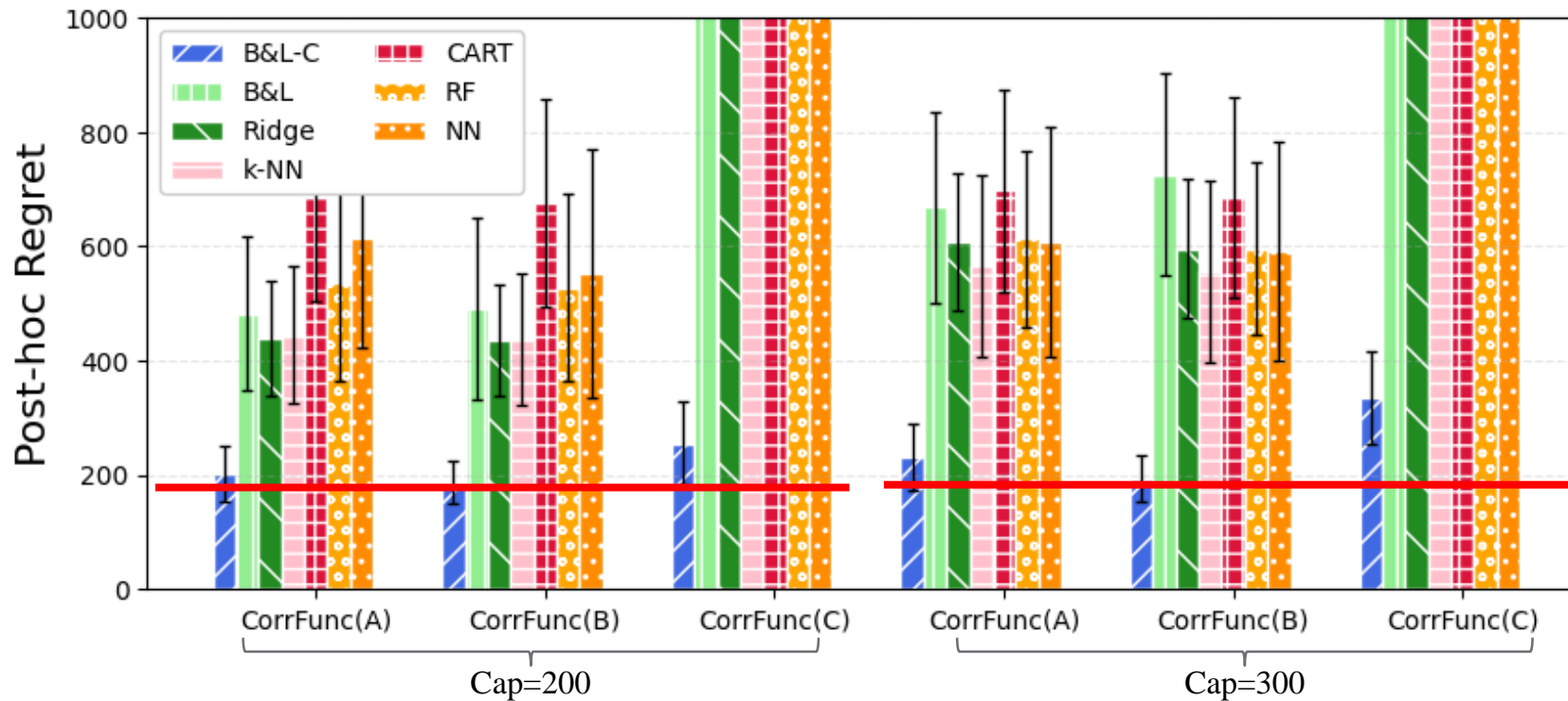
Post-hoc Regrets for 0-1 knapsack with unknown weights using different correction functions with Penalty Function II.

Penalty Function II:

Post-hoc Regrets achieved by using Correction Function B **are smaller than** Post-hoc Regrets achieved by using Correction Function A or C

→ Correction Function B is more suitable to use than Correction Functions A or C

Experimental Evaluation



Post-hoc Regrets for 0-1 knapsack with unknown weights using different correction functions with Penalty Function II.

- Correction Function A: remove the items one by one in increasing order of the ratios of value/weight
- Correction Function B: remove the items one by one in decreasing order of the weights
- Correction Function C: remove all items
- Penalty Function II: whenever a selected item is removed, K (a constant) units of value is deducted

Contributions

- An exact method for recursively and iteratively solvable problems with unknown parameters in both objectives and constraints
- Experimentally compare the proposed exact method with the prior approximation method
- Empirically study different combinations of the 2 key components of the framework

Questions? xyhu@cse.cuhk.edu.hk