







# Multi-Stage Predict+Optimize for (Mixed Integer) Linear Programs

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## **Problem Setting**

### Aim to Solve: Optimization problems (OPs) with unknown parameters

Given: related information of unknown parameters

- Features
- Historical data (features, true parameters)

**Predict** unknown parameters and solve the OP

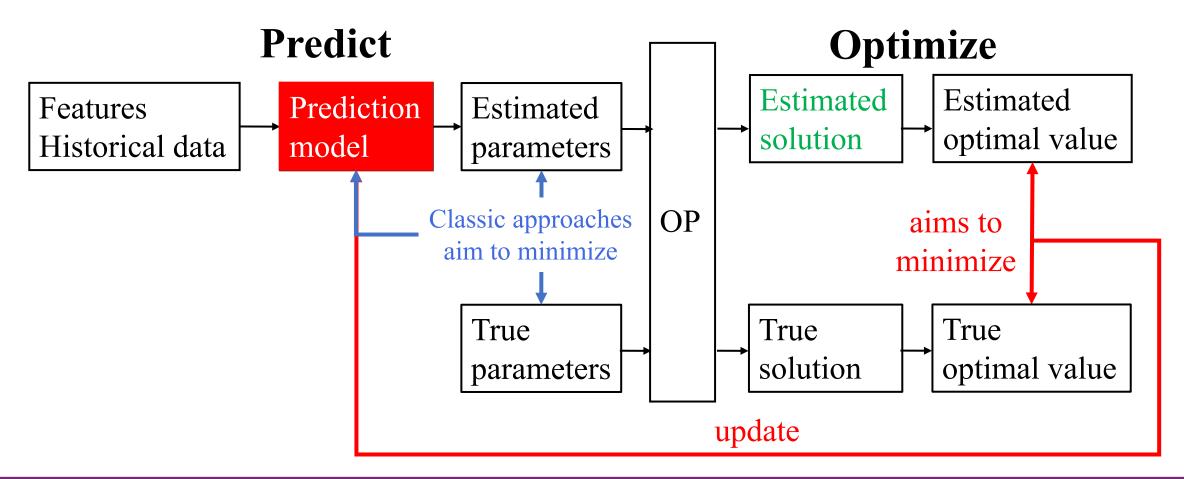
# Predict+Optimize

[Elmachtoub and Grigas, Management Science 2022]

### Pipeline: Predict+Optimize

#### Goal

Good estimated solutions under true parameters



### **Motivation**

#### Motivation

- Prior frameworks: *all* unknown parameters are *revealed simultaneously*
- Excluding applications
  - Unknown parameters are gradually released
  - New decisions need to be made across many stages

Our goal: OPs with gradually revealed unknown parameters

### **Motivating Scenario**

### OP with *gradually revealed* unknown parameters

Nurse rostering problem:

Every Wednesday, make nurses schedule for the next week (5 days)

Min: total costs for hiring nurses

Subject to: meet patients' demands





Unknown

#### Hospital:

make weekly schedule under *unknown patients' demands*  $\boldsymbol{\theta} = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5) \in \mathbb{R}^5$ 



#### Appointment system



### Very unfriendly to patients

Reservations closing at some time points



#### Prior works':

reservations for the whole next week are closed this Sunday

### Contributions

#### **Motivation**

• Prior frameworks: *all* unknown parameters are *revealed simultaneously* 

#### **Contributions**

- Multi-Stage Predict+Optimize Framework
  - The *first* P+O framework for OPs with *gradually revealed* unknown parameters
- Three End-to-End Training Algorithms

# [Contribution 1] Multi-Stage Predict+Optimize Framework

#### Predicted demands

$$\widehat{\boldsymbol{\theta}}^{(0)} = \left(\widehat{\theta}_1^{(0)}, \dots, \widehat{\theta}_5^{(0)}\right)$$

True demands (newly revealed)

True demands (previously revealed)

None

None

#### **Decisions**

Stage 0 solution  $\hat{x}^{(0)}$ :

Solve original OP using *predictions*  $\widehat{\boldsymbol{\theta}}^{(0)}$ 

Rest
Work

Nurse ID	Mon	Tue	Wed	Thur	Fri
1					
2					
3					

Stages (Time points)

Stage 0 (This Wednesday)

### More patient-friendly setting:

- Reservations are closed the day before each working day
- Update future predictions and future schedule everyday

# [Contribution 1] Multi-Stage Predict+Optimize Framework

#### Predicted demands

 $\widehat{\boldsymbol{\theta}}^{(t)} = (\widehat{\theta}_{t+1}^{(t)}, \dots, \widehat{\theta}_{5}^{(t)})$ : new predictions for the Day t+1 and after

True demands (newly revealed)

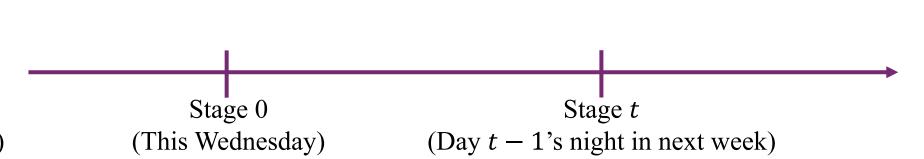
True demands (previously revealed)

Decisions

Rest Work

Stages (Time points)  $\theta_t$ : patient demand for the next day, i.e., the Day t

 $\theta_1, \dots, \theta_{t-1}$ : patient demands for the previous t-1 days already reveal



## [Contribution 1] Multi-Stage Predict+Optimize Framework

#### Predicted demands

True demands (newly revealed)

True demands (previously revealed)

**Decisions** 



Stages (Time points)

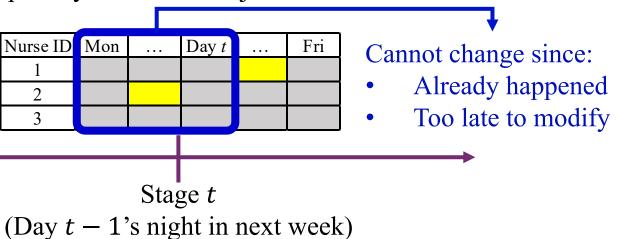
Stage t solution  $\hat{x}^{(t)}$ :

Stage 0

(This Wednesday)

Solve Stage t OP using revealed demands  $\theta_1, \dots, \theta_t$  and new predictions  $\widehat{\boldsymbol{\theta}}^{(t)}$ 

- Stage *t* OP modifies the original OP by:
  - Adding constraints that the first t day's schedule cannot be changed
  - Adding a penalty term to the objective



# [Contribution 2] End-to-End Training Algorithms

#### **Contributions**

- Multi-Stage Predict+Optimize Framework
  - The *first* P+O framework for OPs with *gradually revealed* unknown parameters
- Three End-to-End Training Algorithms
  - Baseline:
    - A straightforward generalization of the prior work [Hu et al., NeurIPS 2023]
    - Only trains a *single neural network* in Stage 0
  - Sequential Coordinate Descent (SCD)
  - Parallel Coordinate Descent (PCD)



#### Core idea:

Trains one neural network (NN) and update predictions *per stage* 

# **Key Experiment Results**

#### Method list:

#### **Proposed**

- Baseline
- *SCD*
- *PCD*

BAS: Best results obtained Among allStandard regression methods

#### Evaluation:

"Win rate" tables: the number of simulations where the proposed beat BAS

Price group	Stage num	Baseline beats BAS	SCD beats BAS	PCD beats BAS
I over profit	4	93.33%	96.67%	86.67%
Low-profit	12	73.33%	100.00%	90.00%
High-profit	4	66.67%	96.67%	73.33%
	12	76.67%	100.00%	80.00%

#### Production and sales problem.

Capital	Stage num	Transaction factor	Baseline beats BAS	SCD beats BAS	PCD beats BAS
25	4	0.01	53.33%	86.67%	73.33%
		0.05	66.67%	90.00%	86.67%
		0.1	70.00%	93.33%	90.00%
	12	0.01	66.67%	93.33%	83.33%
		0.05	80.00%	96.67%	93.33%
		0.1	83.33%	100.00%	96.67%
50	4	0.01	60.00%	80.00%	66.67%
		0.05	66.67%	93.33%	83.33%
		0.1	70.00%	96.67%	90.00%
	12	0.01	70.00%	83.33%	83.33%
		0.05	73.33%	90.00%	86.67%
		0.1	76.67%	100.00%	90.00%

#### Investment problem

Extra nurse payment	Baseline beats BAS	SCD beats BAS	PCD beats BAS
15	70.00%	70.00%	70.00%
20	73.33%	86.67%	80.00%
25	73.33%	96.67%	83.33%
30	73.33%	86.67%	76.67%

Nurse rostering problem

#### Takeaways: Solution Quality

- SCD outperforms BAS in almost all simulations
- PCD and Baseline outperform BAS in most simulations

### **Contributions**

- Multi-Stage Predict+Optimize Framework
  - The first P+O framework for OPs with gradually revealed unknown parameters
- Three End-to-End Training Algorithms
  - Baseline
  - Sequential Coordinate Descent
  - Parallel Coordinate Descent

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