Improving the Efficiency of Cancer Treatment Logistics through Predictive and Prescriptive Analytics

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HANALOG

POLYTECHNIQUE MONTRÉAL

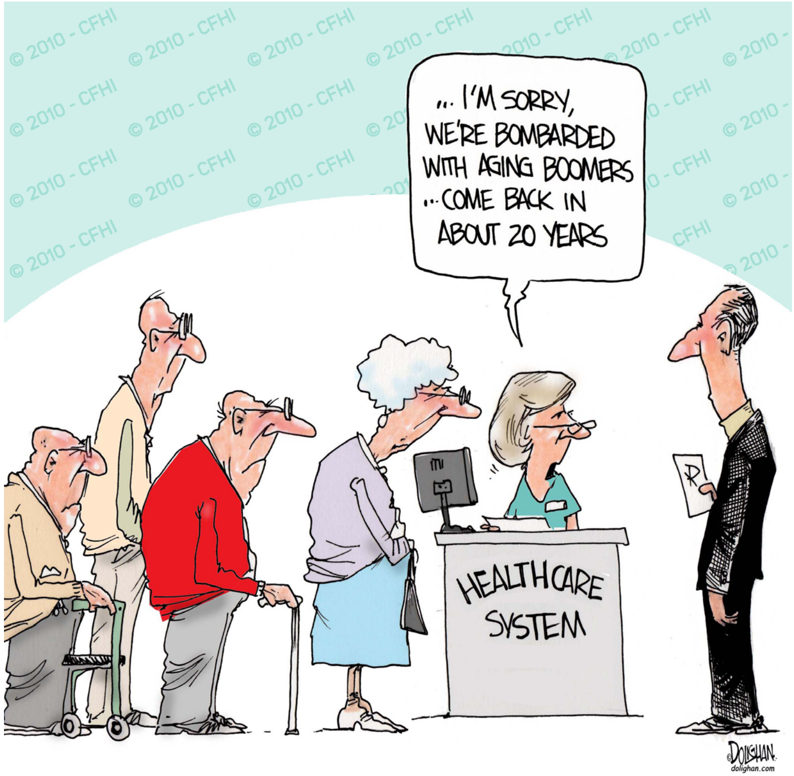
Healthcare systems

One person is diagnosed with cancer every
3 minutes in Canada, 20 seconds in USA.

One person dies from cancer every
7 minutes in Canada, 1 minute in USA.

First cause of mortality in Canada (30%):
- 45% of Canadian will develop cancer
- 5 year survivability 66%

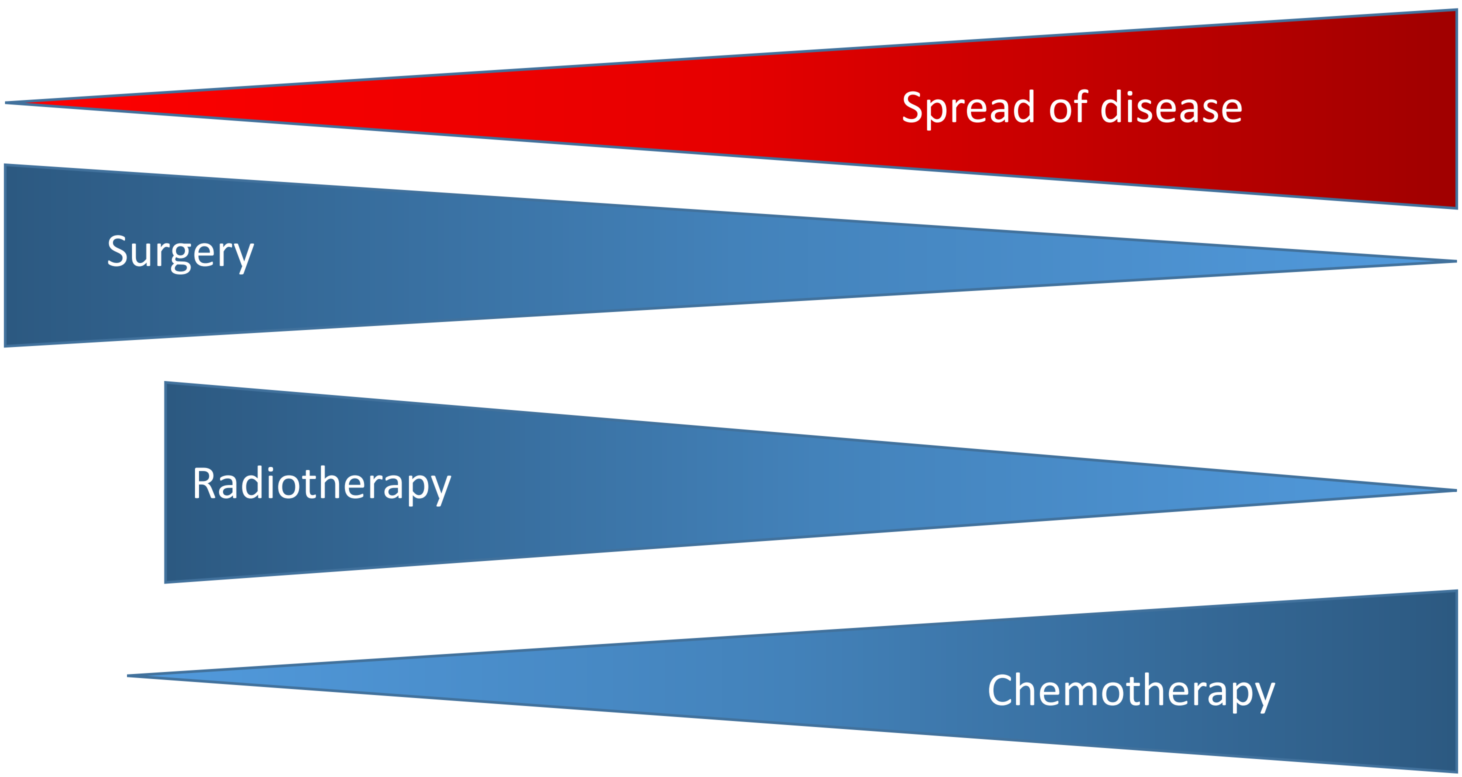
Ever increasing of new cancer cases:
- 12% within 4 years
- Aging of population;
- Demographic growth.



How to treat all these patients while keeping excellent care ?

What are your treatment options ?

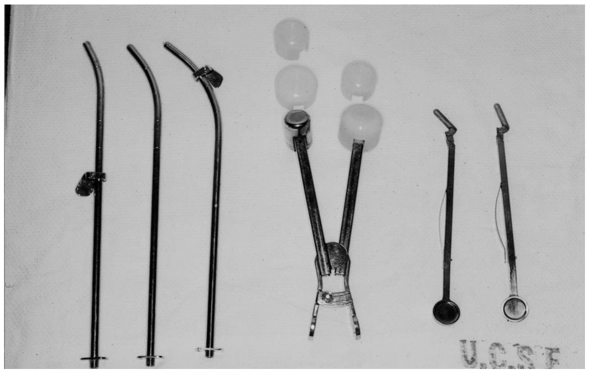
Local | Locally advanced | Metastatic

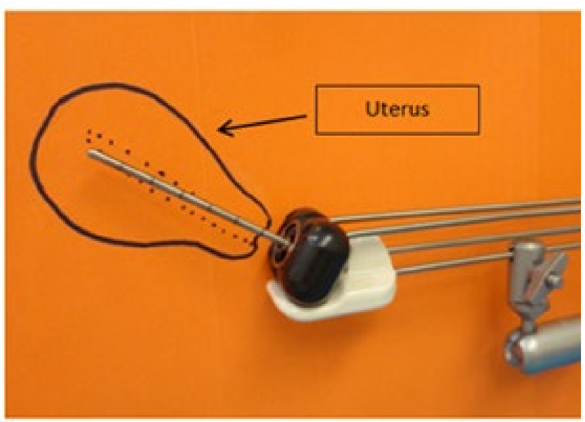


About 50% of cancer patients will receive radiotherapy

Tools

Internal





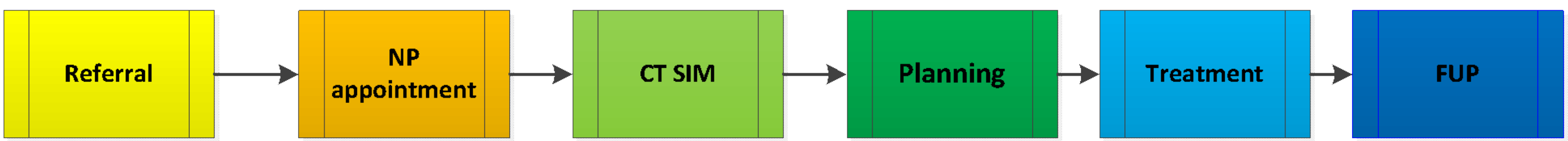
External

Vickers 6 Prototype Newcastle-on-Tyne 1960

Teams

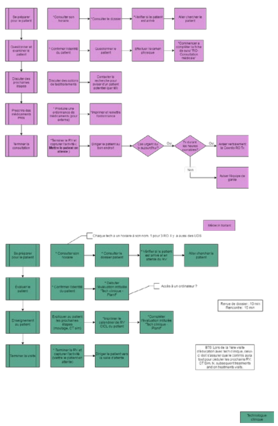
	Chemotherapy	Radiotherapy
Prescribes	Oncologist	Radiation Oncologist
Prepares	Pharmacist	Physicist
Delivers	Nurse	Therapist

Care Trajectory

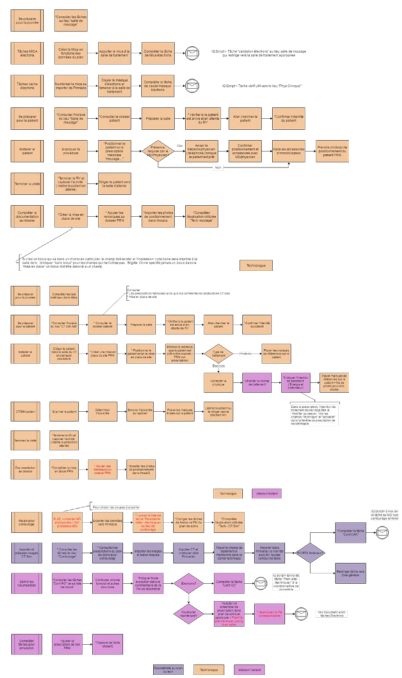


Care Trajectory in details

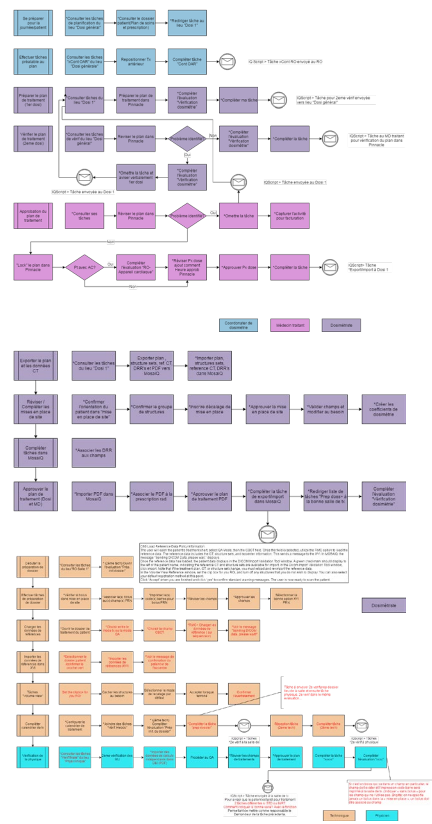
NP appointment



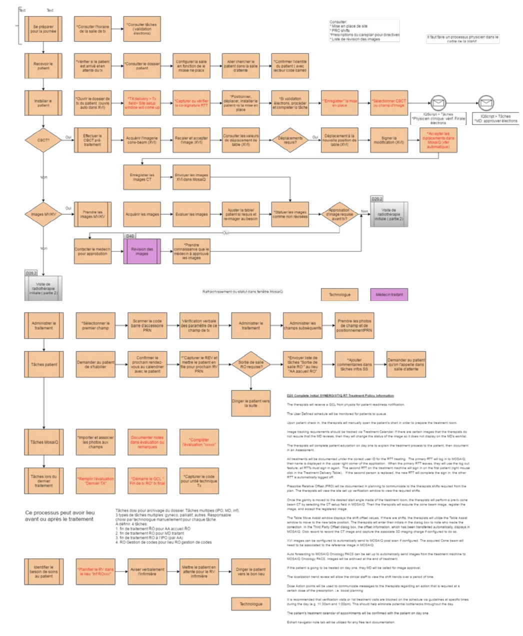
CT SIM



Planning

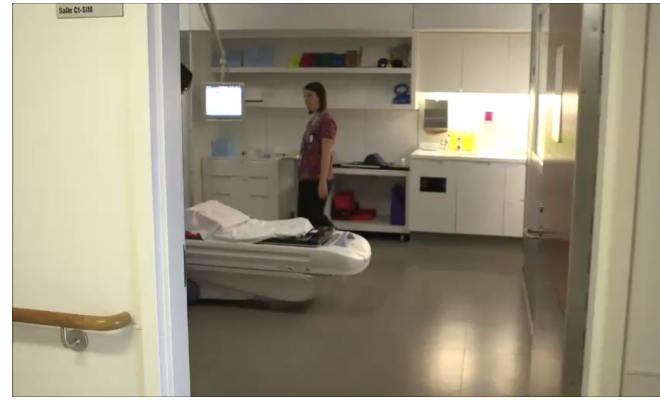


Treatment

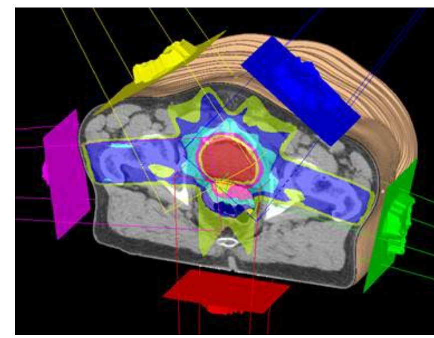


Important steps

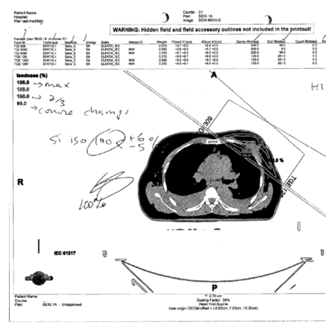
Simulation:
- Uses: CT, MRI, PET-CT
- Used for treatment planning purposes
- 3D model of the human body



Treatment Planning
- Calculates radiation deposition in the human body
- Multi-criteria optimization solver
- Server farm, GPU calculations, etc.



Plan approval



Linear accelerator
- mm accuracy
- 100x more powerful than a radiology X-ray

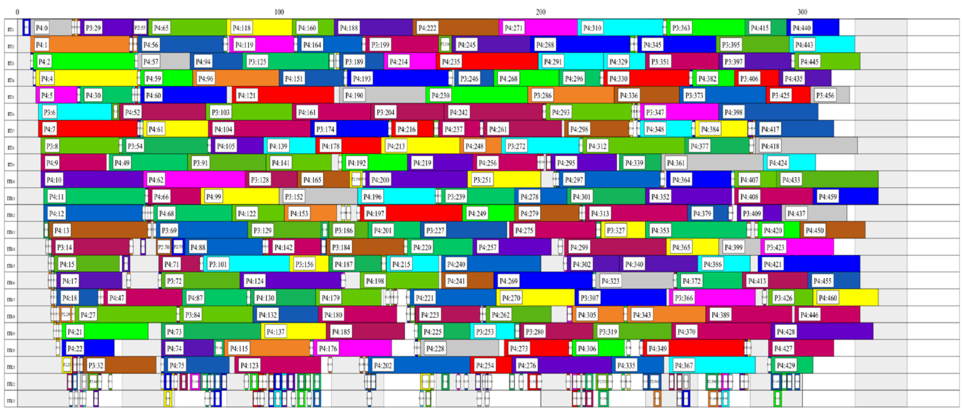
(Q1) when to book a patient ?

Patient arrives

how much time ?

Patient is treated

Considering existing calendar…



… and patient priorities

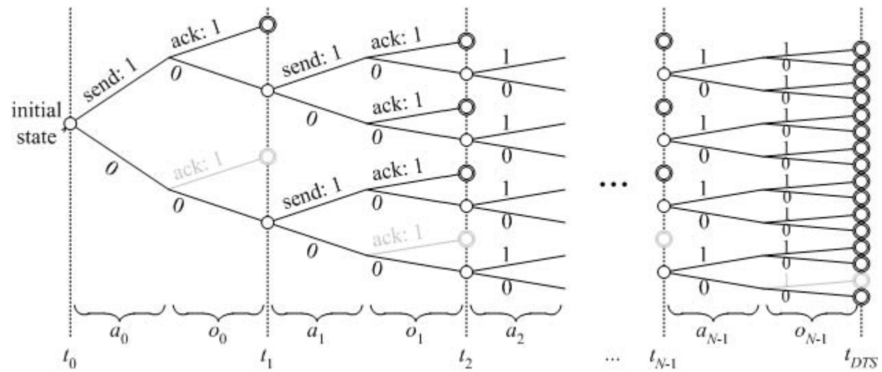
Palliative	Curative 1	Curative 2
< 3 days	< 14 days	< 28 days

Different possible approaches

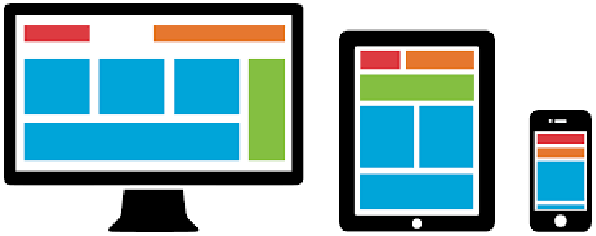
Stochastic Optimization

$$\begin{array}{lll} \min\limits_{x \in \mathbb{R}^n} & g(x) = c^T x + E[Q(x,\xi)] \\ \text{subject to} & Ax = b \\ & x \geq 0 \end{array} \qquad \begin{array}{lll} \min\limits_{y \in \mathbb{R}^m} & q(\xi)^T y \\ \text{subject to} & T(\xi)x + W(\xi)y = h(\xi) \\ & y \geq 0 \end{array}$$

Markov Decision Process



Online Optimization



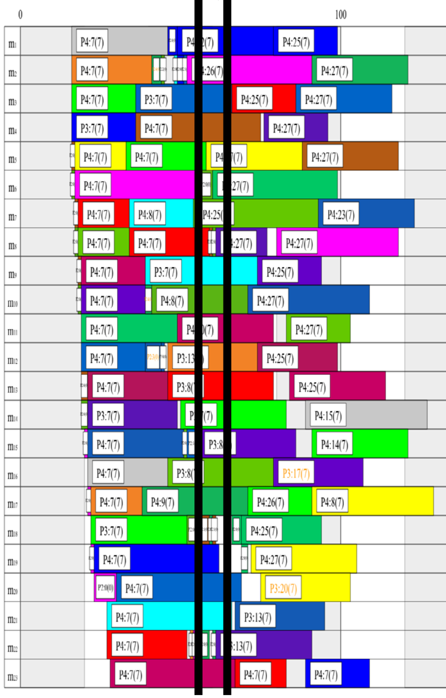
RT cancer patient booking

- Online stochastic combinatorial optimization:
  1. For each solution, we compute :
     1. A utilization cost (by day and by linac) for a time slot;
  2. We choose the appointment of minimum cost:
     1. Waiting time cost (depending of the priority) ;
     2. Expected utilization cost.

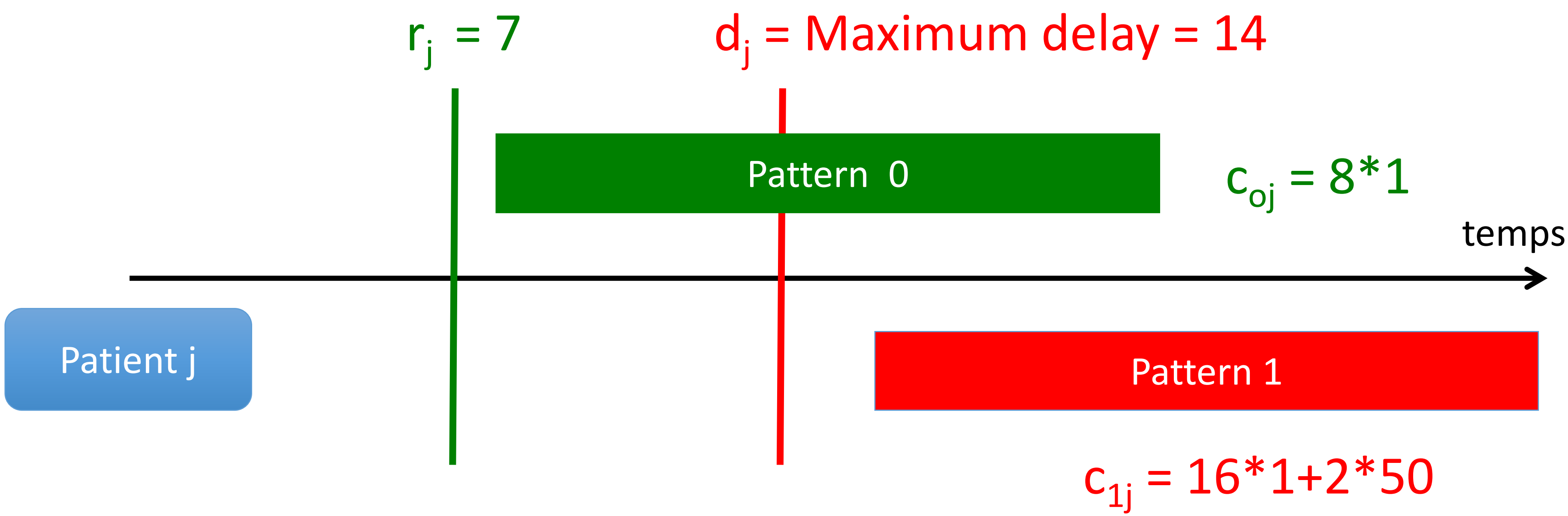
- Booking model -> Dantzig-Wolfe decomposition;

- Uncertainties -> Benders decomposition.

Utilization cost



Structure of the model



Treatment planning fix to 7 days … for now

Stochastic Programming Model

$$\min \sum_{i \in S_j} c_{ij} x_{ij} + \mathbb{E}_{\omega \in \Omega_j} [\sum_{l \in \mathcal{P}^\omega} \sum_{i \in S_l} c_{il} y_{il}^\omega + \sum_{k \in H} \sum_{m \in M} c^o z_{mk}^\omega]$$

subject to:

$$\sum_{i \in S_j} x_{ij} = 1$$

$$\sum_{i \in S_l} y_{il}^\omega = 1, \qquad \forall \omega \in \Omega_j, \forall l \in \mathcal{P}^\omega$$

$$\boxed{\sum_{i \in S_j} a_{ijk}^m x_{ij} + \sum_{l \in \mathcal{P}^\omega} \sum_{i \in S_l} a_{ilk}^m y_{il}^\omega \leq F_k^m + z_{mk}^\omega, \qquad \forall m \in M, \forall k \in H, \forall \omega \in \Omega_j}$$

$$\mathbb{1}_{\mathcal{P}_p}(j) \sum_{i \in S_j} a_{ijk}^m x_{ij} + \sum_{l \in \mathcal{P}_p^\omega} \sum_{i \in S_l} a_{ilk}^m y_{il}^\omega \geq z_{mk}^\omega, \qquad \forall m \in M, \forall k \in H, \forall \omega \in \Omega_j$$

$$\sum_{k=b}^{b+4} z_{mk}^\omega \leq O_{week}, \qquad \forall m \in M, \forall b \in \mathcal{B}, \forall \omega \in \Omega_j$$

$$z_{mk}^\omega \in [0, O_{day}], \qquad \forall m \in M, \forall k \in H, \forall \omega \in \Omega_j$$

$$x_{ij} \in \{0,1\}, \qquad \forall i \in S_j$$

$$y_{il}^\omega \in \{0,1\}, \qquad \forall l \in \mathcal{P}^\omega, \forall i \in S_l, \forall \omega \in \Omega_j$$

Approximated utilization cost of
a given initial treatment time slot

= dual variable of this constraint

Choose greedily the pattern
With best reduced cost

Pattern 1

Pattern 0

Initial Results

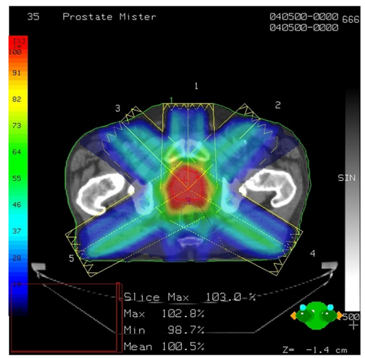
	Due date violations			Average waiting time			Utilization	Overtime
	>3	>14	>28	Palliative	Curative 1	Curative 2		
CICL	14	16	0	2,07	14,38	12,98	88,3%	44
OSCO - 1	9	6	0	1,05	10,57	15,98	88,0%	6

CICL real data:

- 170 patients ;
- 120 days;
- 2 linacs with 23 slots.

Legrain A, Fortin MA, Lahrichi N, Rousseau L-M (2015) "Online Stochastic Optimization of Radiotherapy Patient Scheduling", *Healthcare Management Science*, 18, 110-123.

(Q2) Will the patients be ready?

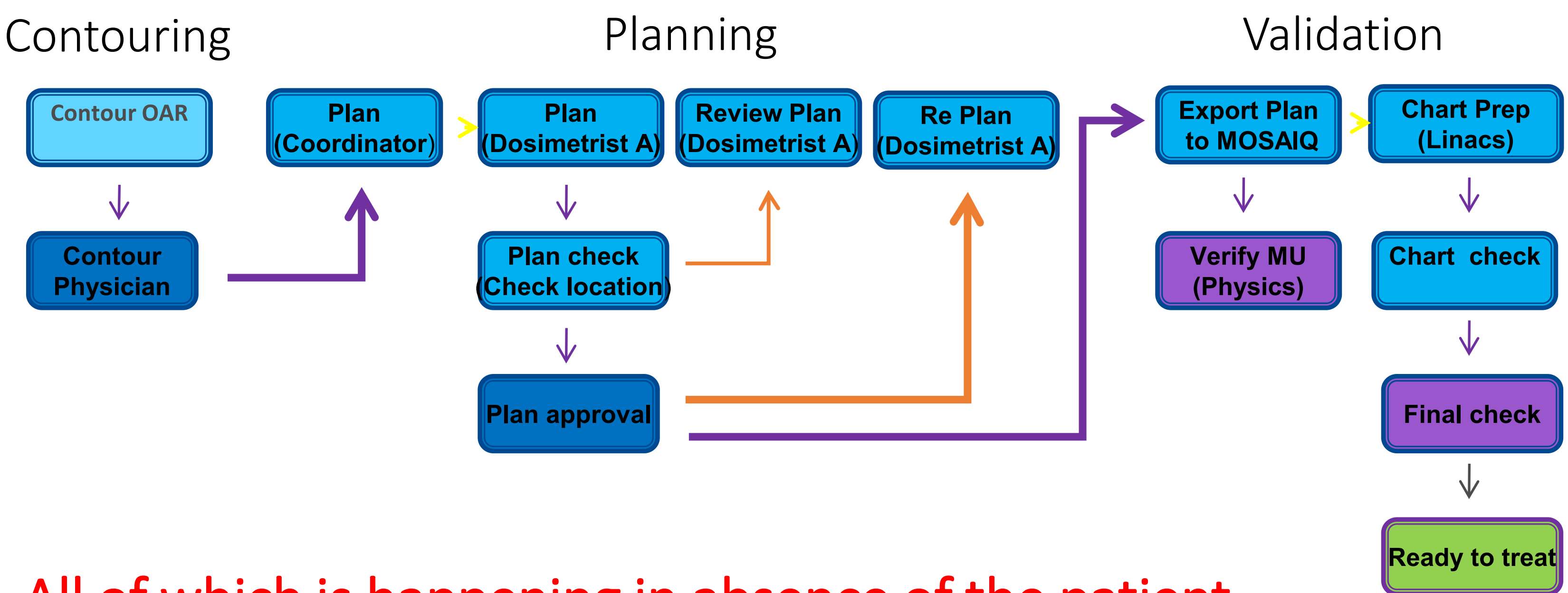


Appointment booking

Unknown dosimetry duration

Preparation completed

Preparation Tasks



All of which is happening in absence of the patient

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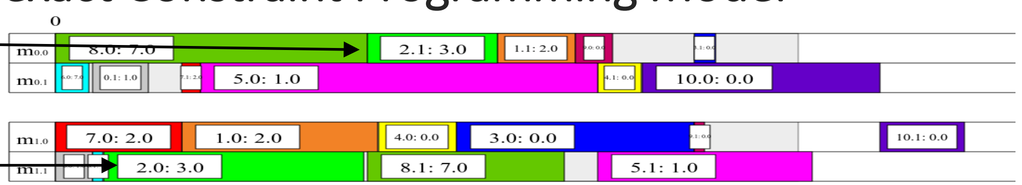
Best feasible appointment

Online stochastic optimization:

1. For each solution, we compute :
    1. A utilization cost (by day and by linac) for a slot;
    2. **A minimum day to start the treatment.**
        1. **with fast Genetic Algorithm**
        2. **with exact Constraint Programming Model**

Verification

Preparation



2. We choose the appointment of minimum cost:
    1. Waiting time cost (depending of the priority) ;
    2. Expected utilization cost.

New Results

	Cancellations	Due date (in days)			Average waiting time			Overtime
		>3	>14	>28	>3	>14	>28	
CICL	230	373	104	0	3,45	12,58	12,63	111
OSCO 1	107	335	67	0	1,05	10,57	15,98	19
OSCO 2	1	326	119	0	3,23	14,04	18,43	8

CICL real data:

- 1529 patients ;
- 248 days;
- 4 linacs with 29 slots.

A prediction-based approach for online dynamic radiotherapy scheduling

Tu-San Pham, Antoine Legrain,
Louis-Martin Rousseau

CHUM - CENTRE HOSPITALIER DE L'UNIVERSITÉ DE MONTRÉAL

10 linacs

5 generics

4 specialized

1 cyberknife

4400 consultations

3500 new patients

40.000 fractions

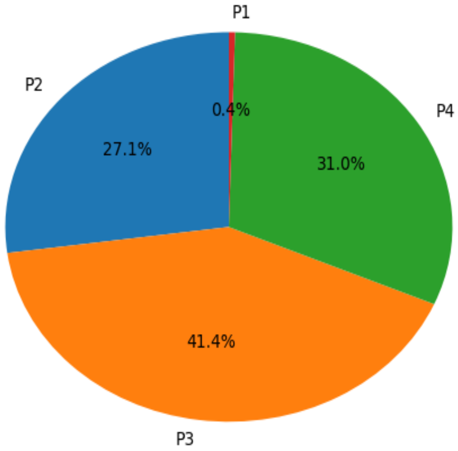
(2019)

GRAY

https://www.graysuite.com/

CHUM - 2019

	Category	Treatment deadline (days)	Percentage of overdue treatment (%)	Average waiting time (days)
Palliative	P1	1	14.29	1.09
	P2	3	79.89	6.91
Curative	P3	14	74.55	18.11
	P4	28	29.89	22.59

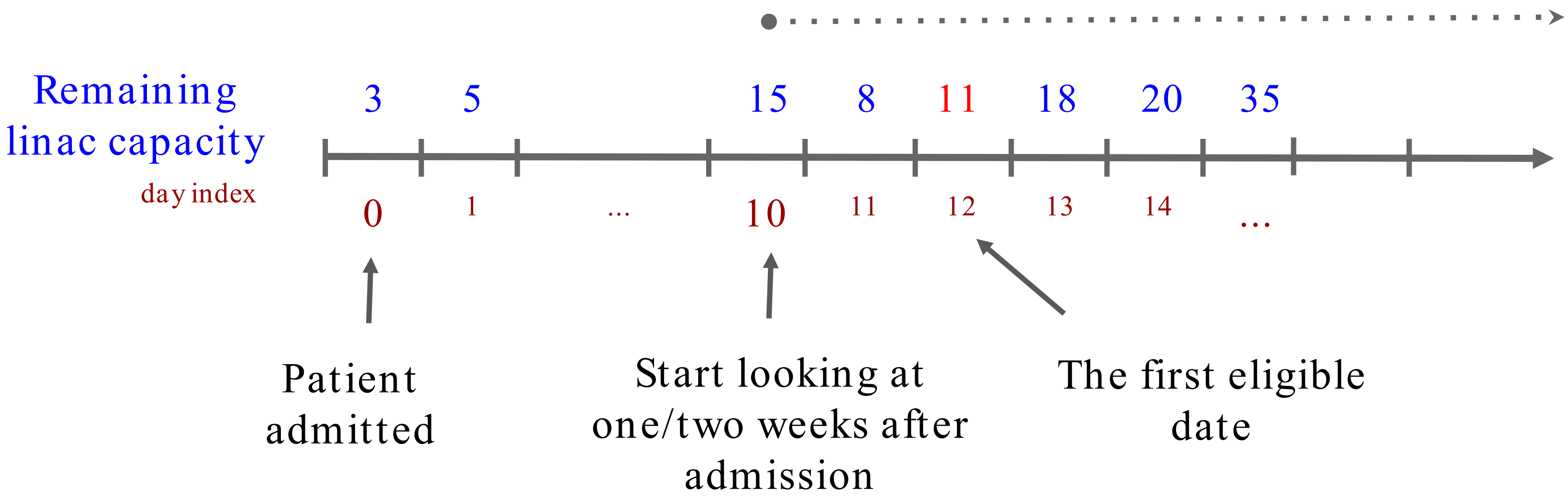


Objective: minimizing overdue treatment and waiting time

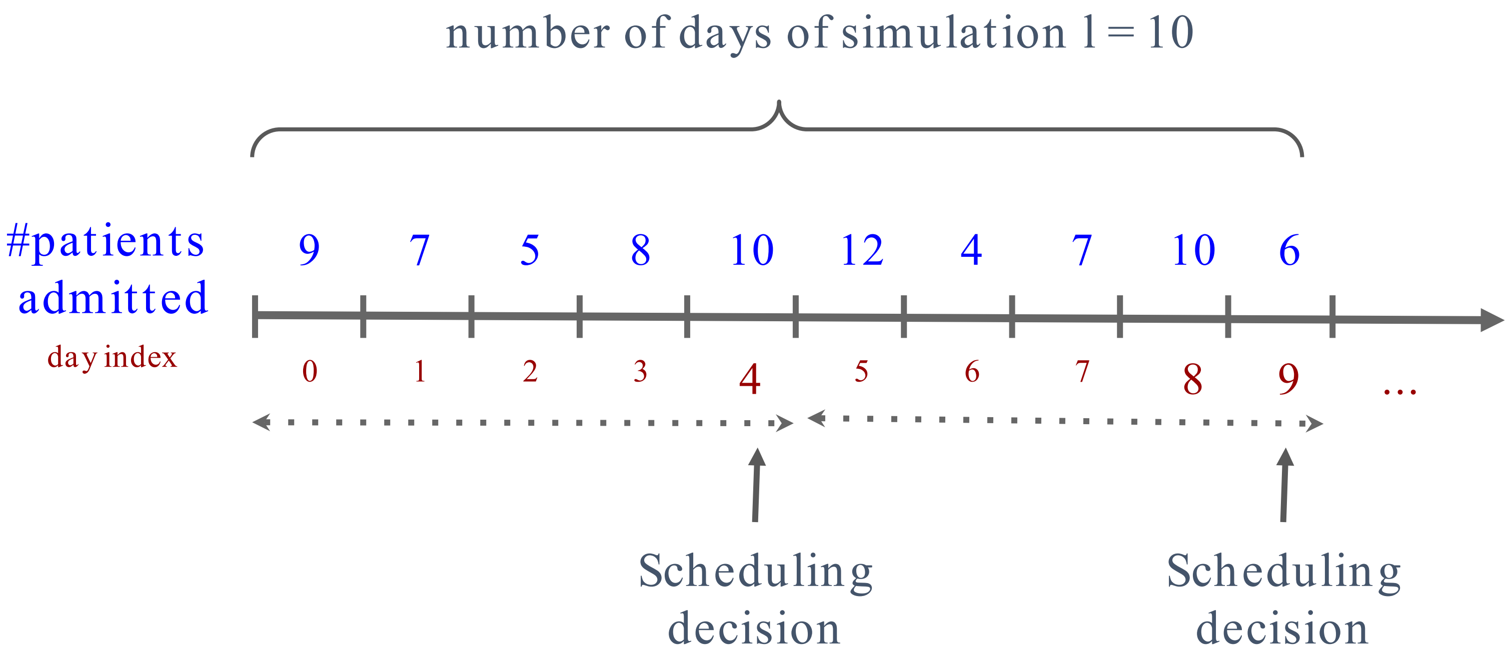
Online Scheduling with a Greedy Heuristic

- 1 linac, capacity 120 time slots
- a curative patient (P4) with 3 sessions, 10 time slots each

Looking for the first eligible date that can accommodate the whole treatment



Batch Scheduling



Palliative patients: schedule at arrival

A MIP Model for Batch Scheduling

$$x_{tl}^i = \begin{cases} 1 & \text{if patient } i \text{ receives their treatment on day } t\text{, linac } l \\ 0 & \text{otherwise} \end{cases}$$

$$\text{minimize} \sum_{i \in \hat{\mathcal{P}}} \sum_{t \in \mathcal{T}, t > a_i} \sum_{l \in \mathcal{L}} \omega_1 \boxed{(t - a_i) log(t - a_i + 1) x_{tl}^i}$$

waiting time

$$+ \sum_{i \in \hat{\mathcal{P}}} \sum_{t \in \mathcal{T}, t > d_i} \sum_{l \in \mathcal{L}} \omega_2 \boxed{(t - d_i) log(t - d_i + 1) x_{tl}^i}$$

overdue time

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MIP MODEL

$$\sum_{t\in\mathcal{T}}\sum_{l\in\mathcal{L}} x^i_{tl} = 1 \qquad \text{assignment constraint} \qquad \forall i \in \hat{\mathcal{P}}$$

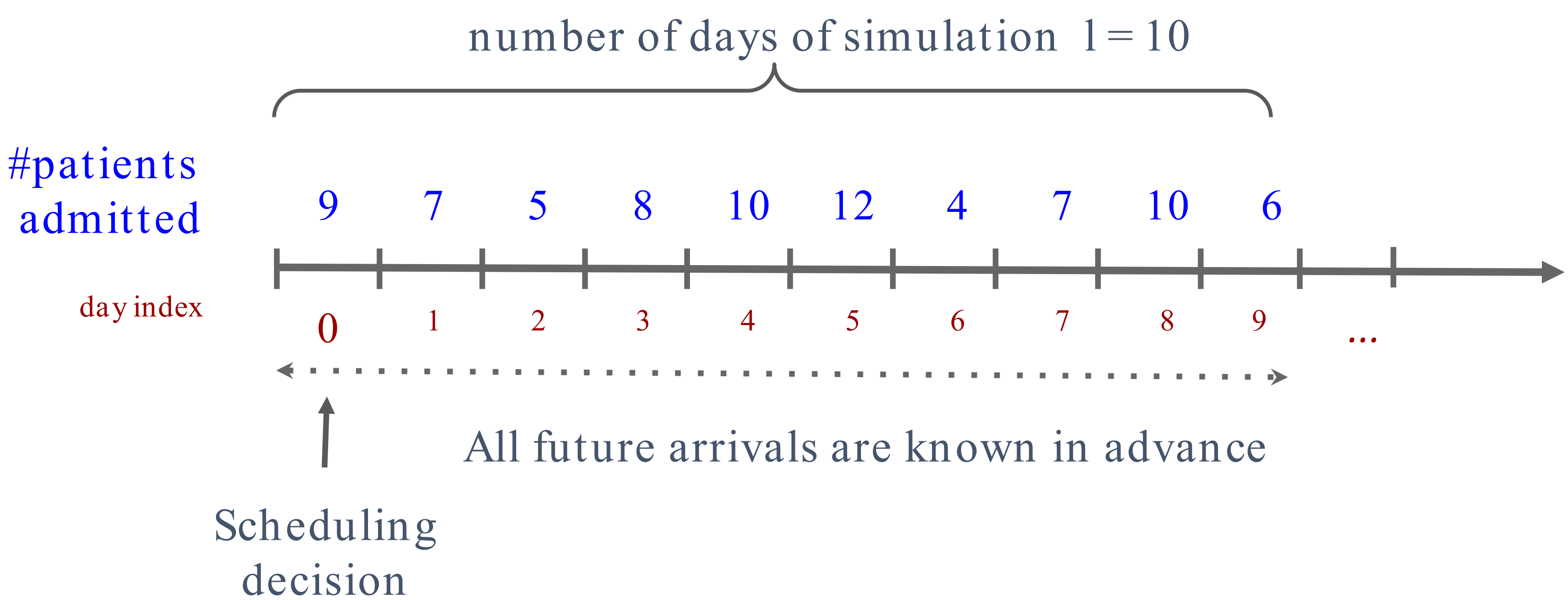
$$x^i_{tl} = 0 \qquad \text{ready date} \qquad \forall i \in \hat{\mathcal{P}}, l \in \mathcal{L}, t \in \{0, \ldots, r_i - 1\}$$

$$\sum_{i\in\hat{\mathcal{P}}}\sum_{t'=max\{0,t-I_i+1\}}^{t} p_i x^i_{t'l} \le \hat{C}^t_l \qquad \text{capacity constraints} \qquad \forall t \in \mathcal{T}, l \in \mathcal{L}$$

$$\sum_{i\in\mathcal{P}^C}\sum_{t'\in\{t-I_i+1,\ldots,t\}} p_i x^i_{t'l} \le max\{0, \hat{C}^t_l - \gamma C^t_l\} \qquad \text{reserved capacity} \qquad \forall t \in \mathcal{T}, l \in \mathcal{L}$$

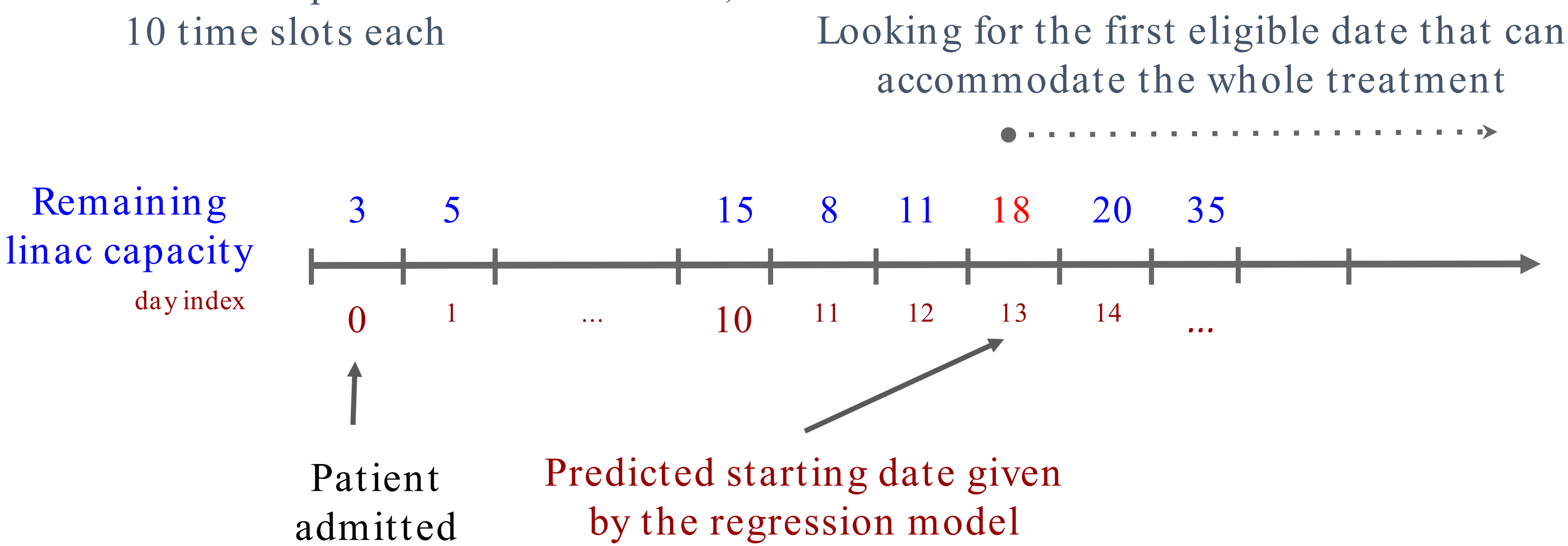
$$x^i_{tl} \in \{0,1\} \qquad \forall i \in \hat{\mathcal{P}}, t \in \mathcal{T}, l \in \mathcal{L}$$

Offline Scheduling – with Perfect Information



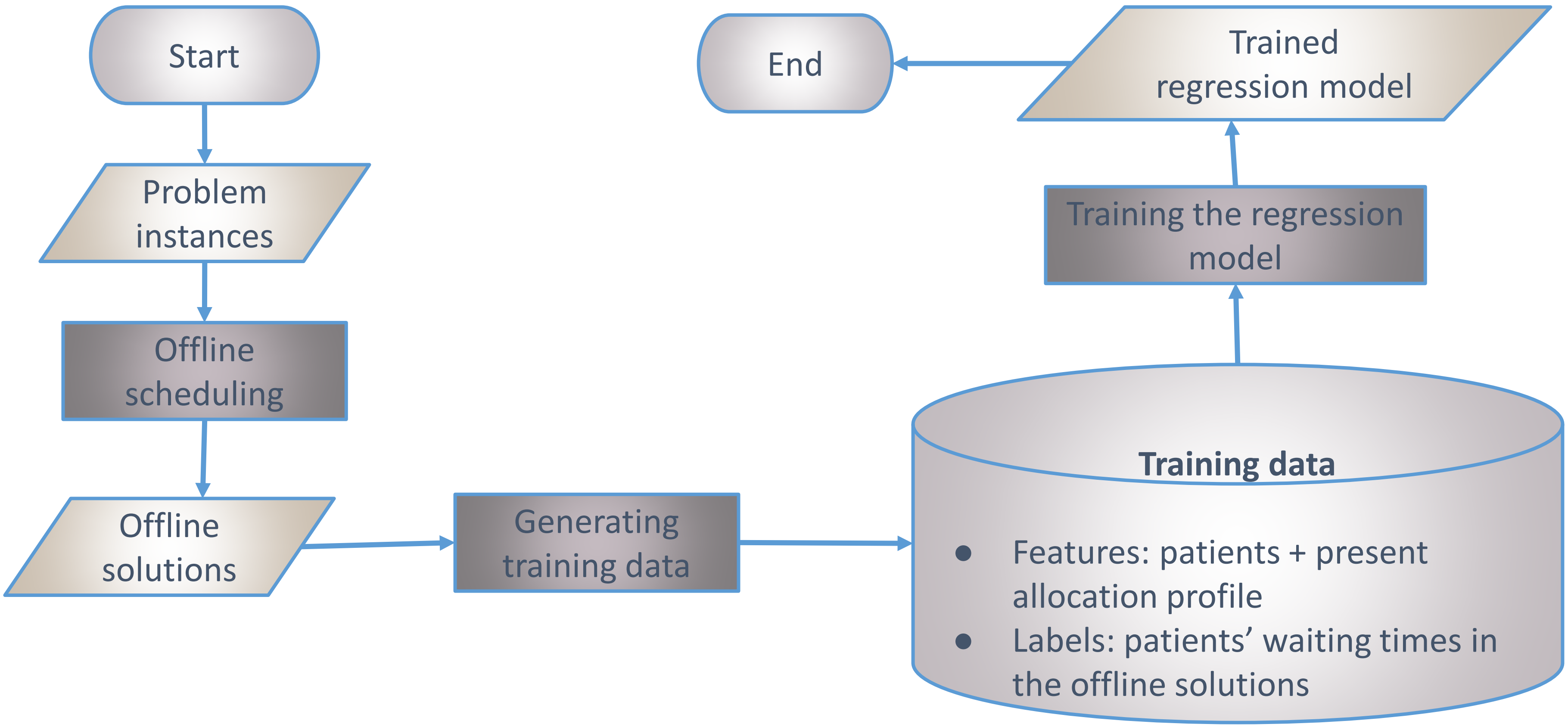
Prediction-based Scheduling

- 1 linac, capacity 120 time slots
- a curative patient with 3 sessions, 10 time slots each



How do we predict a “good” starting date for a patient?

Training the Regression Model for Scheduling



Data Generation

Patient arrivals: Poisson distribution

Treatment plans: based on historical data

Instance setting

- Number of linacs
- Arrival rate (average daily number of patients)

For each instance setting: 500 instances

- 400 for training the regression model
- 100 for testing

PREDICTIVE MODELS

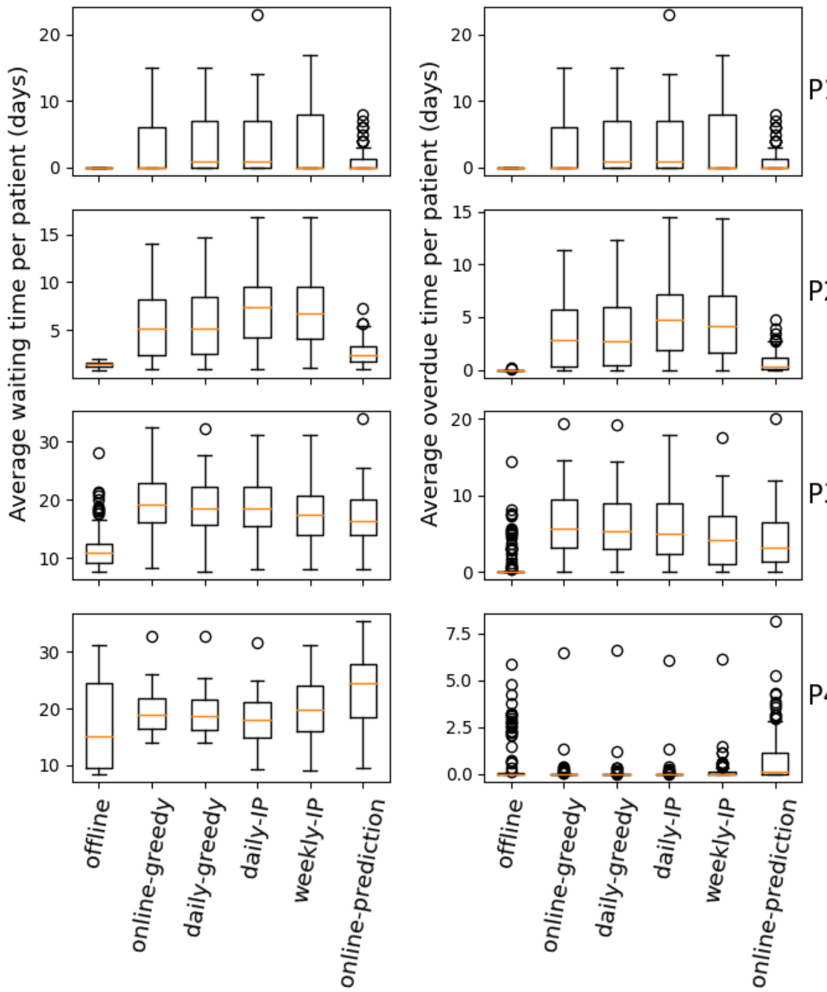
	Training time	Training		Testing	
		MSE	MAE	MSE	MAE
MLP	116.19	3.45	1.32	3.33	1.29
SGD	0.35	6.06	1.84	5.61	1.77
Lasso	0.44	5.97	1.81	5.52	1.74
ElasticNet	0.25	6.26	1.85	5.83	1.8
SVR	43.16	3.19	1.07	3.12	1.07
Decision Tree	0.84	2.41	0.48	6.59	1.4
Random forest	51	**0.38**	**0.39**	2.64	1.03
XGBoost	7.71	0.96	0.66	**2.44**	**0.97**

SCHEDULING STRATEGIES

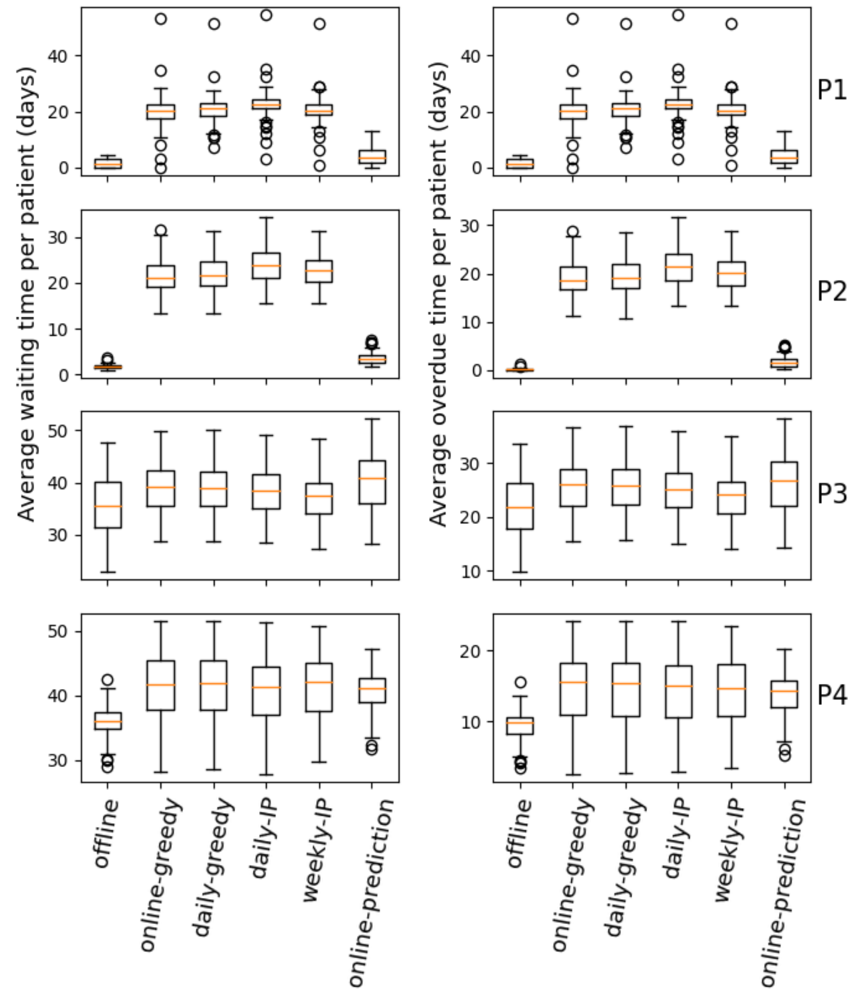
	Scheduling strategy	Scheduling palliative patients	Scheduling curative patients
Batch scheduling	Offline	Scheduling once with all future arrivals known in advance	
Batch scheduling	Daily	Every day	Every day
Batch scheduling	Weekly	Every day	Every Friday
Batch scheduling	Daily greedy	Every day	Every day
Online scheduling	Greedy	At admission	At admission
Online scheduling	Prediction-based	At admission	At admission

4 LINACS

Arrival rate of 5.0

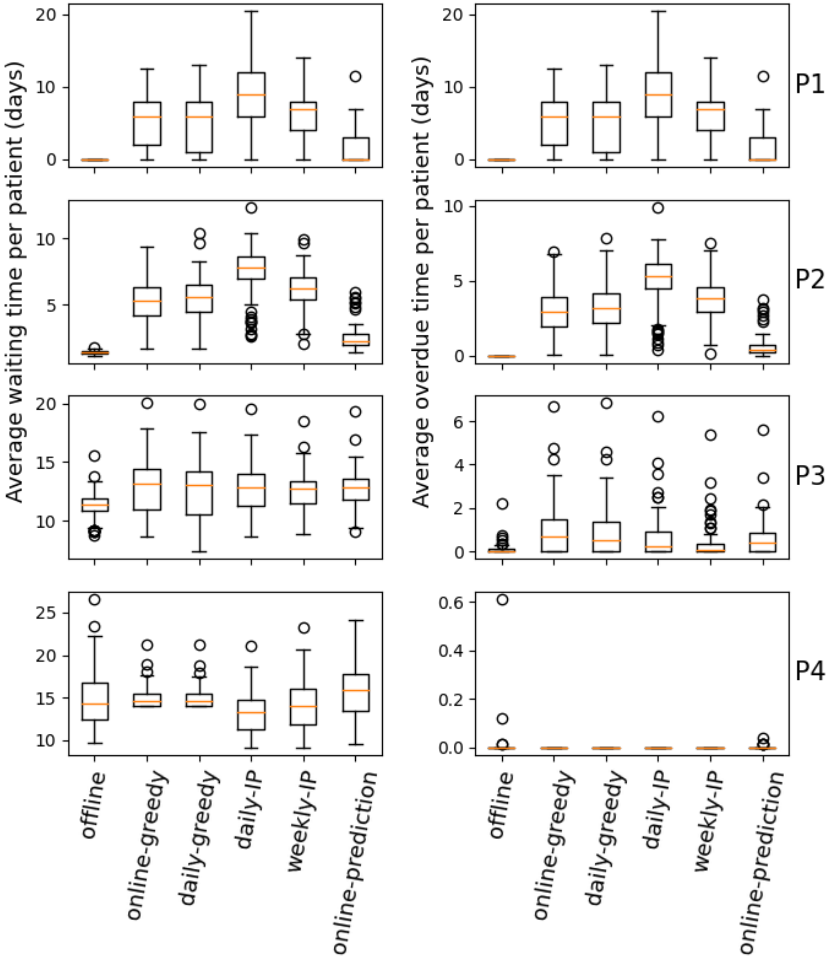


Arrival rate of 6.0

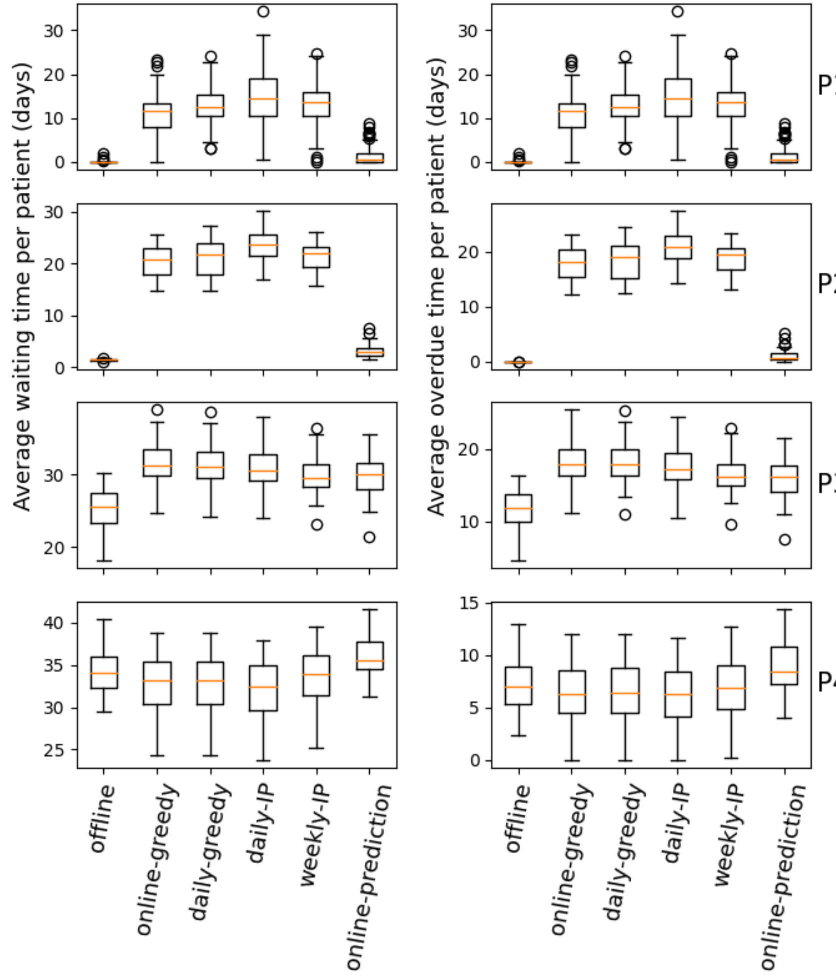


8 LINACS

Arrival rate of 10.0



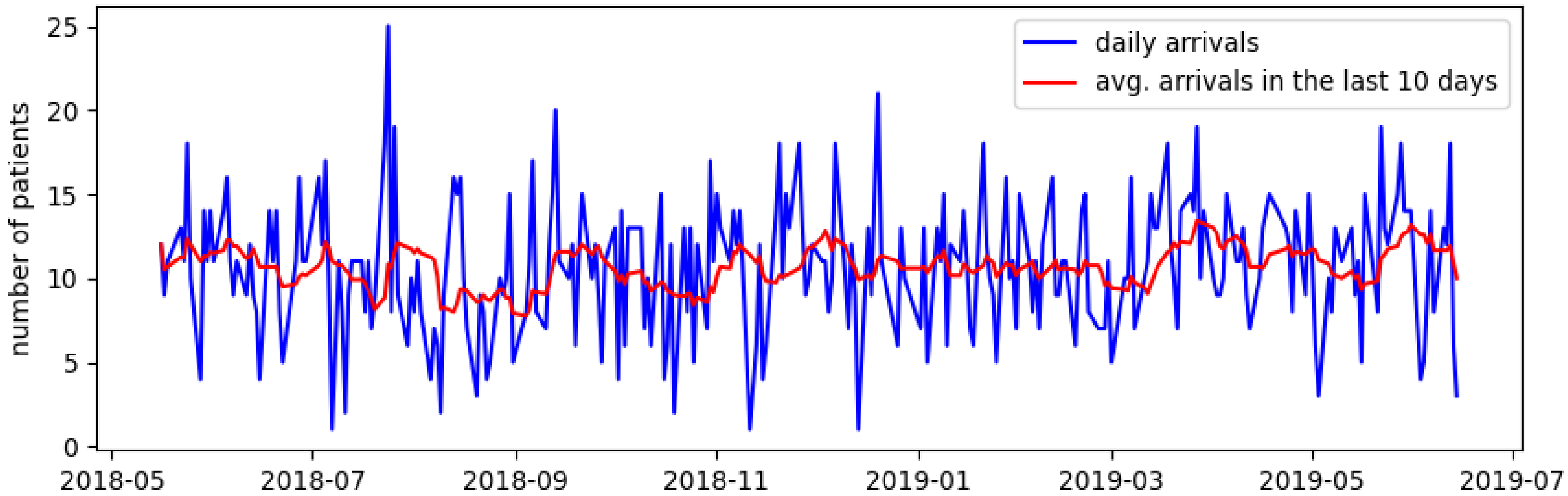
Arrival rate of 12.0



Experiment on a real CHUM data

7 linacs operating 8 hours/day
High fluctuation in arrival rate

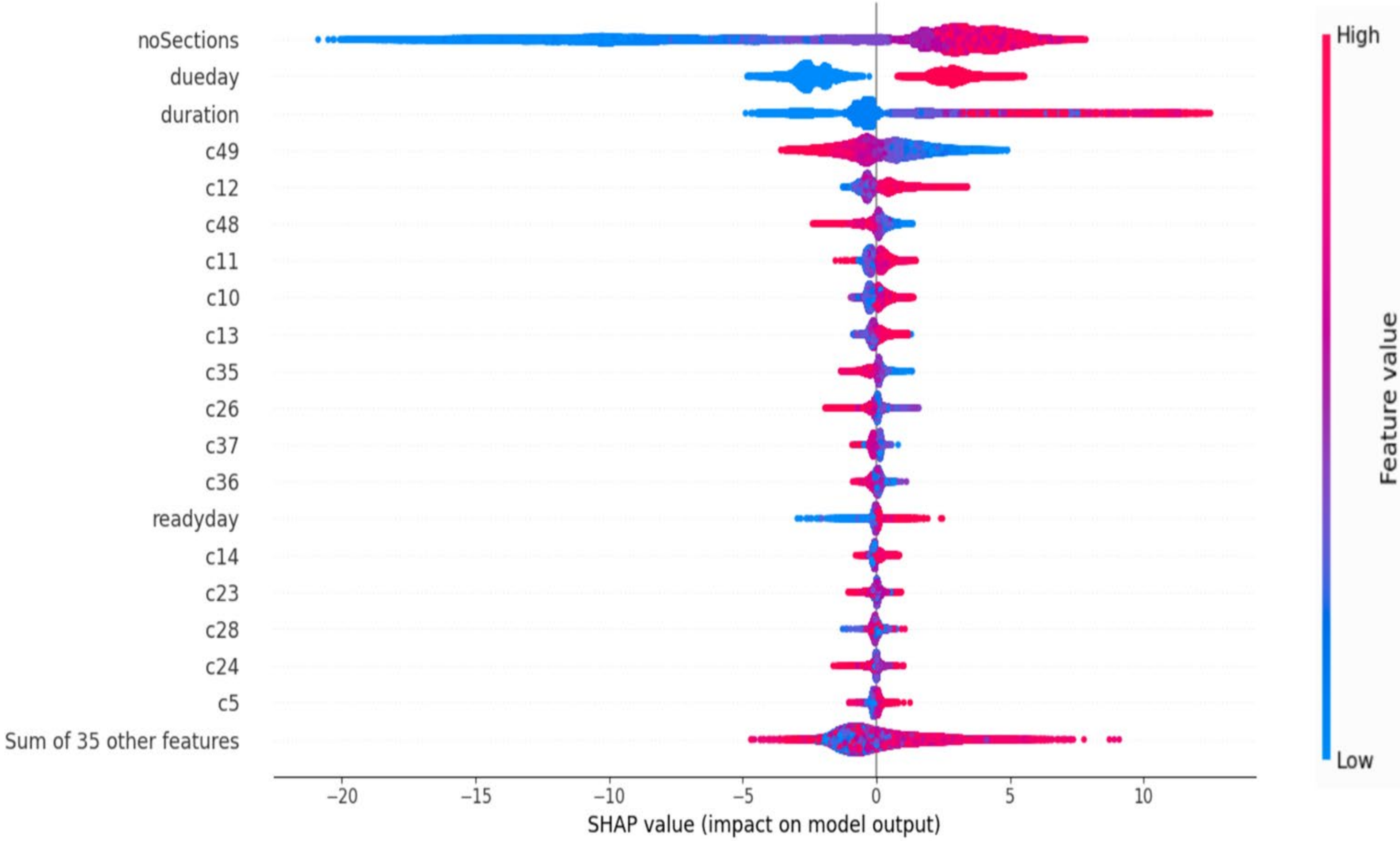
- Instance setting for training: arrival rate of 10.1 patients/day



RESULTS ON THE REAL INSTANCE

Scheduling strategy	Avg. occupancy (%)	Waiting time (days)					Overdue time (days)				
		overall	P1	P2	P3	P4	overall	P1	P2	P3	P4
online-greedy	97.45	33.02	5.14	6.13	43.67	44.02	44.02	5.14	3.91	29.74	16.18
daily-greedy	97.51	32.91	6.00	6.23	43.48	43.80	17.71	6.00	3.99	29.58	16.00
daily	97.72	33.53	9.79	9.63	42.87	43.44	18.25	9.79	7.15	28.93	15.65
weekly	97.61	33.04	7.86	7.72	42.42	44.10	17.76	7.86	5.37	28.51	16.19
prediction-based	97.14	32.93	3.29	4.05	44.21	44.94	17.69	3.29	1.99	30.22	16.96

Explainability



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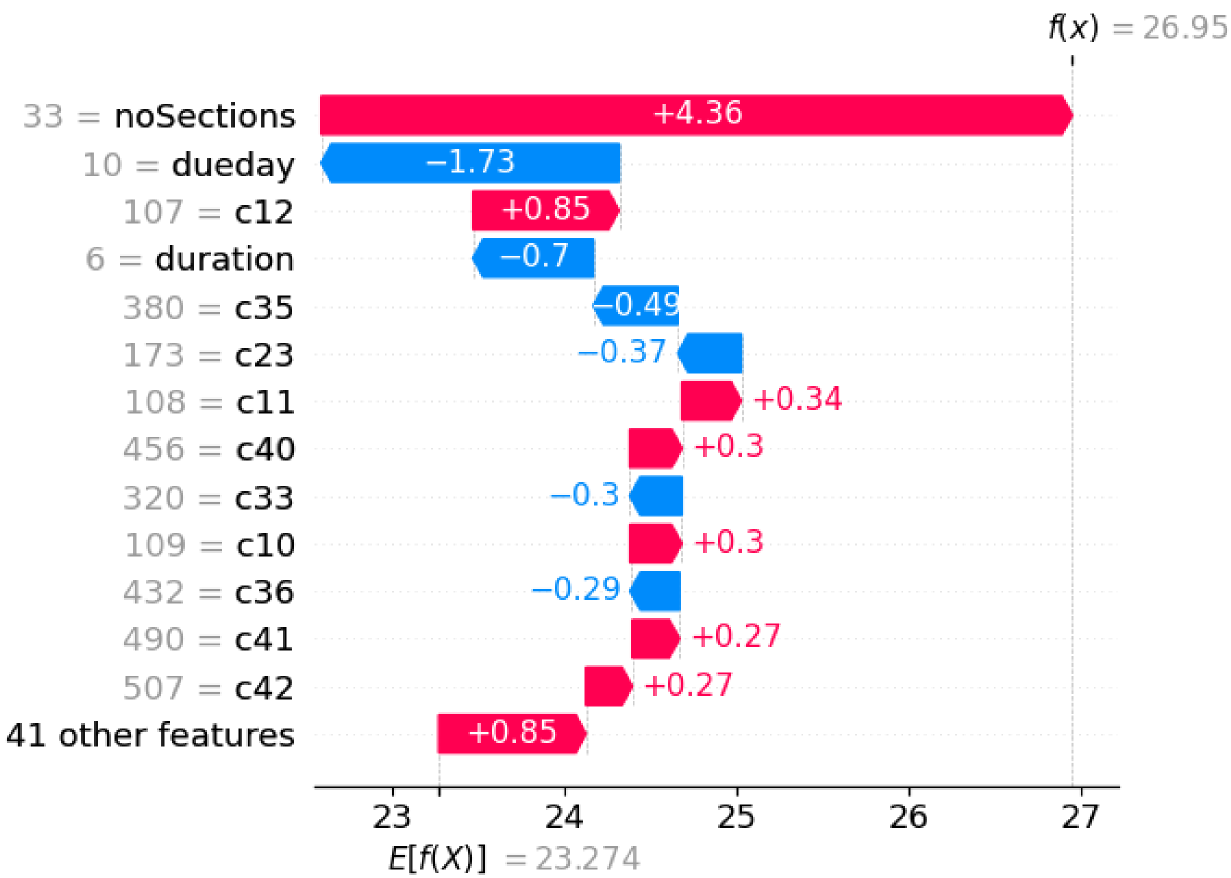

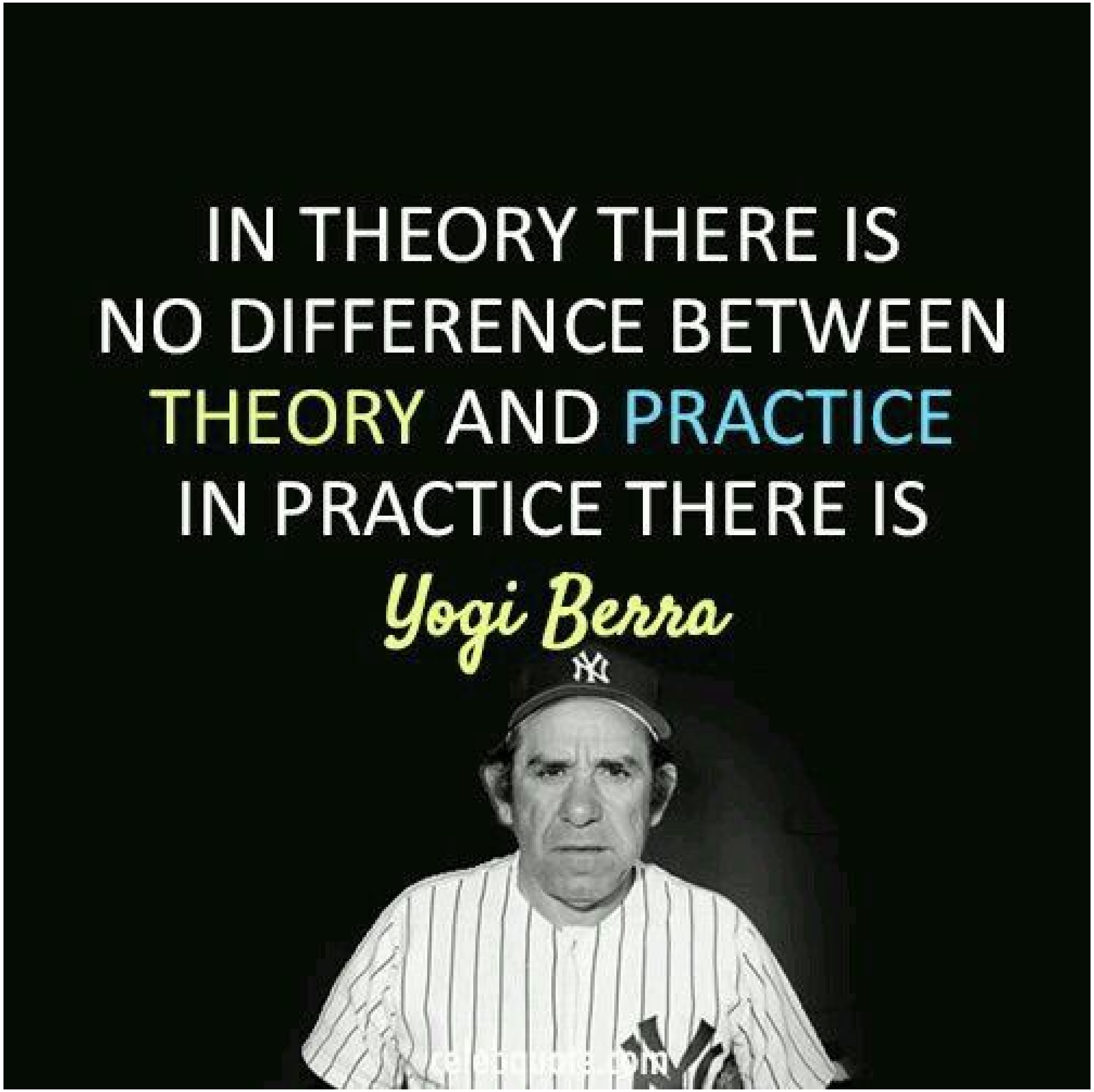
IN THEORY THERE IS
NO DIFFERENCE BETWEEN
THEORY AND PRACTICE
IN PRACTICE THERE IS
Yogi Berra
NY

Spin-out of Gray Oncology Solution