

Prescriptive Analytics in Health Care

International Summer School: Economic Modelling in Health Care

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City of Wuppertal



http://www.mygeo.info/landkarten/deutschland/Deutschland_in_Europa.png



City of Wuppertal

- Approx. 350,000 inhabitants
- Area of 168.41 km²
- Density: 2,100/km²
- Most famous for its suspension railway ("Schwebebahn")
- University funded in 1972



Source: https://upload.wikimedia.org/wikipedia/commons/thumb/3/30/Schwebebahn_G15.jpg/1200px-Schwebebahn_G15.jpg

- University funded in 1972
- 3 different locations in the city
- 7 different faculties
- 1,800 employees
- Around 22,000 students:
3,200 students in Business & Economics
- B.Sc. in Health Economics and
Management (M.Sc. programme in
preparation)



- **Education**

- M.Sc. in Management & Economics
- PhD on mathematical optimisation for operating room planning

- **Professional Appointments**

2013 - 2014 Consultant to Medical Director, Städtisches Klinikum Solingen, Germany

2014 - 2017 Postgraduate Research Associate, University of Exeter, UK

Since 2017 Assistant Professor of Operations Management, University of Wuppertal, Germany

- **Research Interests**

- Develop and apply optimisation & simulation models to solve healthcare problems
- Emergency Departments, inpatient wards, operating rooms, ambulance locations, ...

- **Lecture**

- Analytics – What is it and how can we use it?
- Models & Methods – Distinction and possible uses
- Application: Decision problems in location and operating room planning

- **Tutorial – Part I**

- Software R and R Studio
- Location analysis

- **Tutorial – Part II**

- Operating room planning
- Discussion/Presentations

Intended Learning Outcomes

- Distinguish different dimensions of Analytics
- Understand how prescriptive analytics can be applied to health care
- Understand existing mathematical optimisation models
- Independently develop simple optimisation models
- Solve optimisation models using software package R and solver
- Develop, solve and present case study results

Assessing prior knowledge

- Analytics: Can you give a definition?
- Optimisation: what is it?
- R and R Studio: Have you ever used it?
- Optimisation in MS Excel: Do you have any experience with it?

Analytics – What is it?

Descriptive Analytics



What did happen?

Predictive Analytics



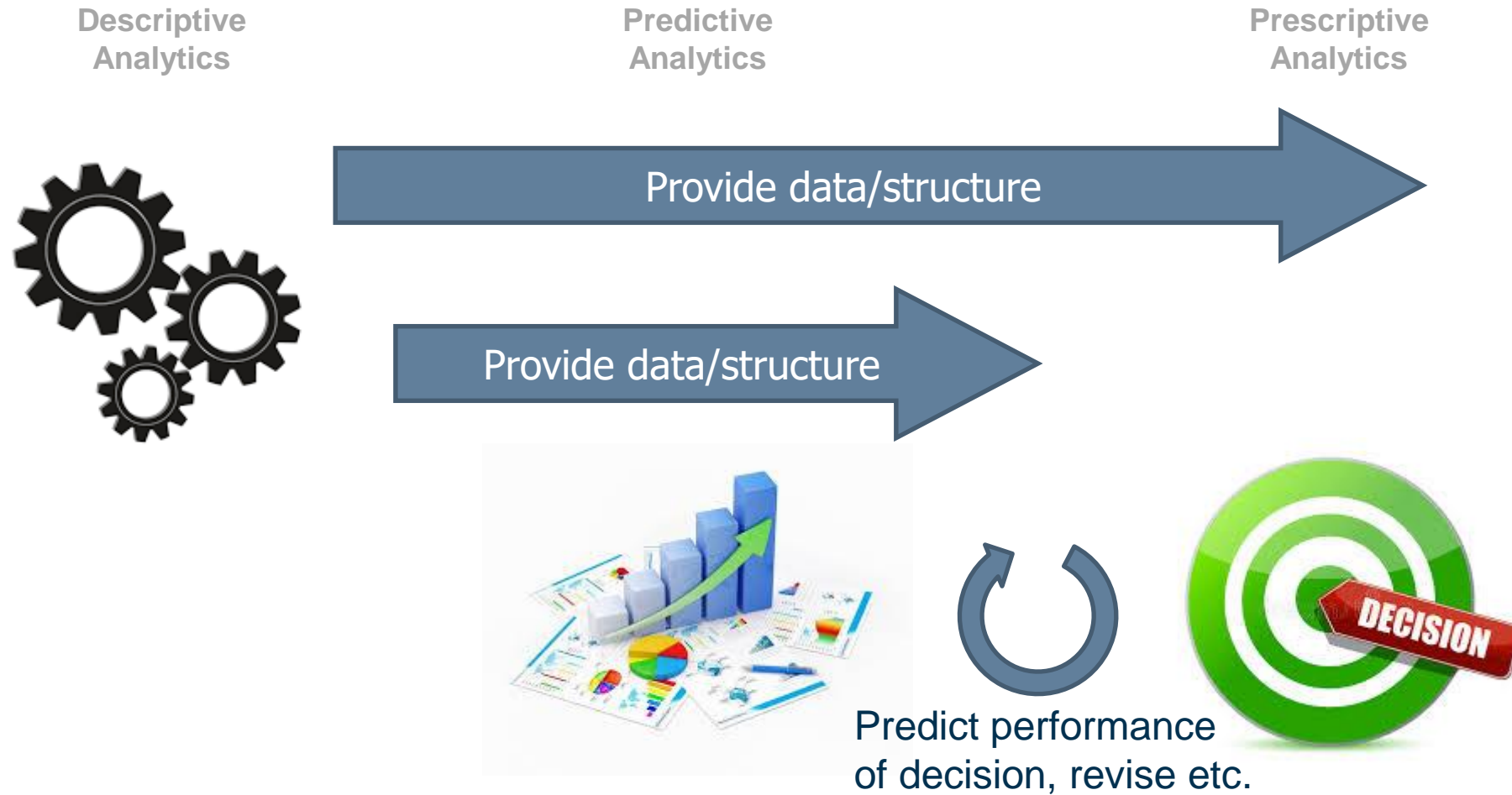
What will happen?

Prescriptive Analytics



What should we do?

Analytics – What is it?



- **Descriptive Analytics**

- Understanding current issues is key to any further analysis
- Solving real-world problems requires understanding real-world data

- **Predictive Analytics**

- How are current issues to develop?
- What will happen following changes?

- **Prescriptive Analytics**

- What should you do, given your objective
- Best possible solution (i.e. optimum) versus real-world setting

Descriptive Analytics



What did happen?

Predictive Analytics



What will happen?

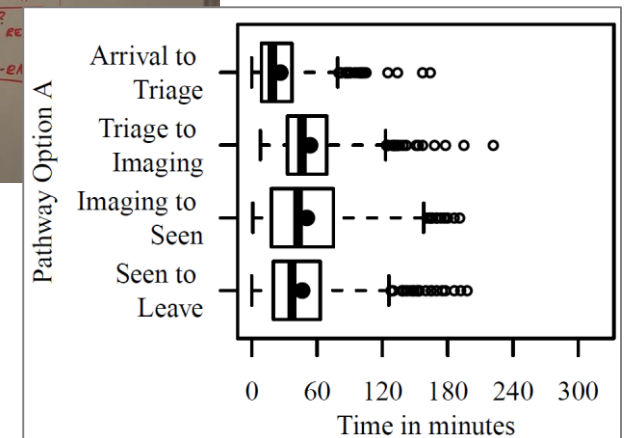
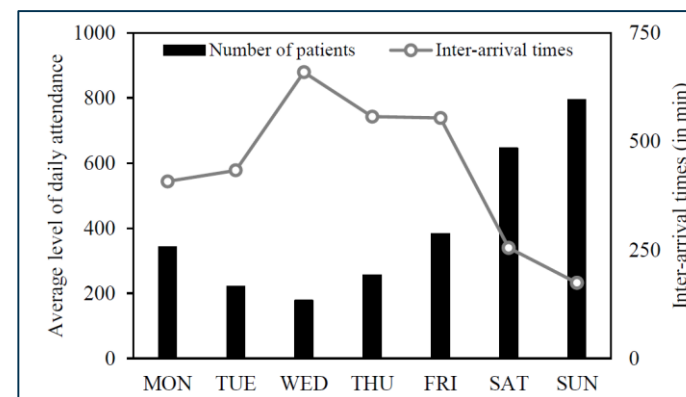
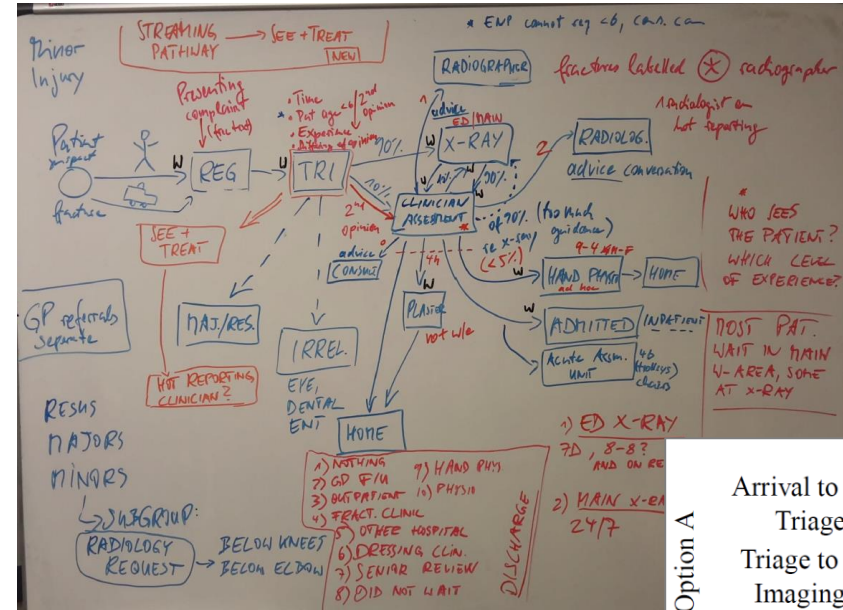
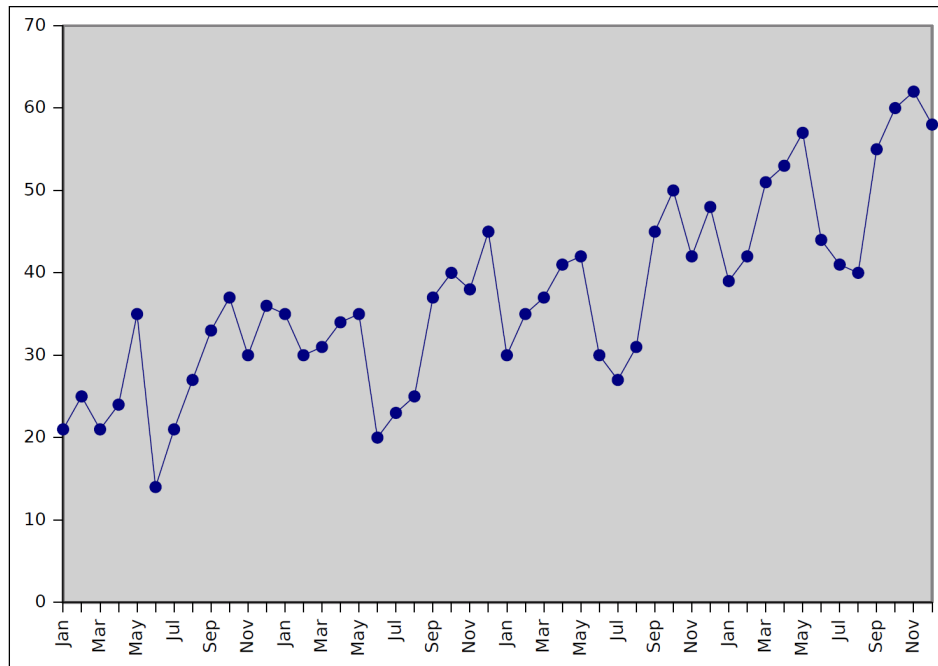
Prescriptive Analytics



What should we do?

Descriptive Analytics

- Typical examples could be:



Descriptive Analytics



What did happen?

Predictive Analytics



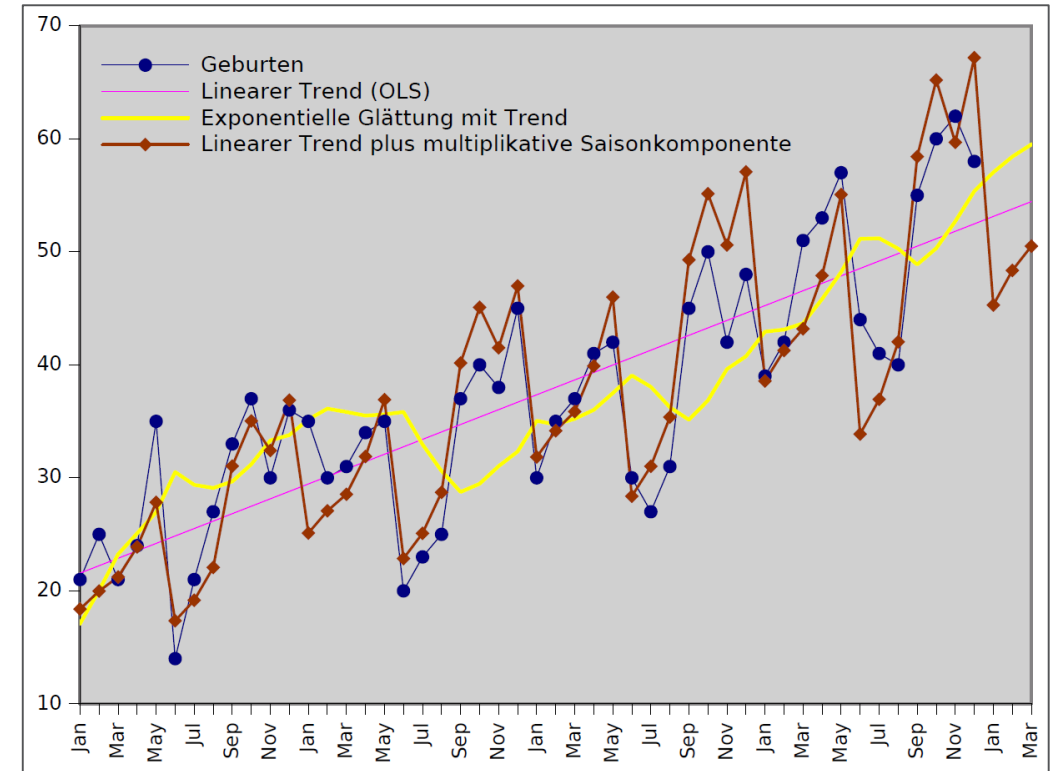
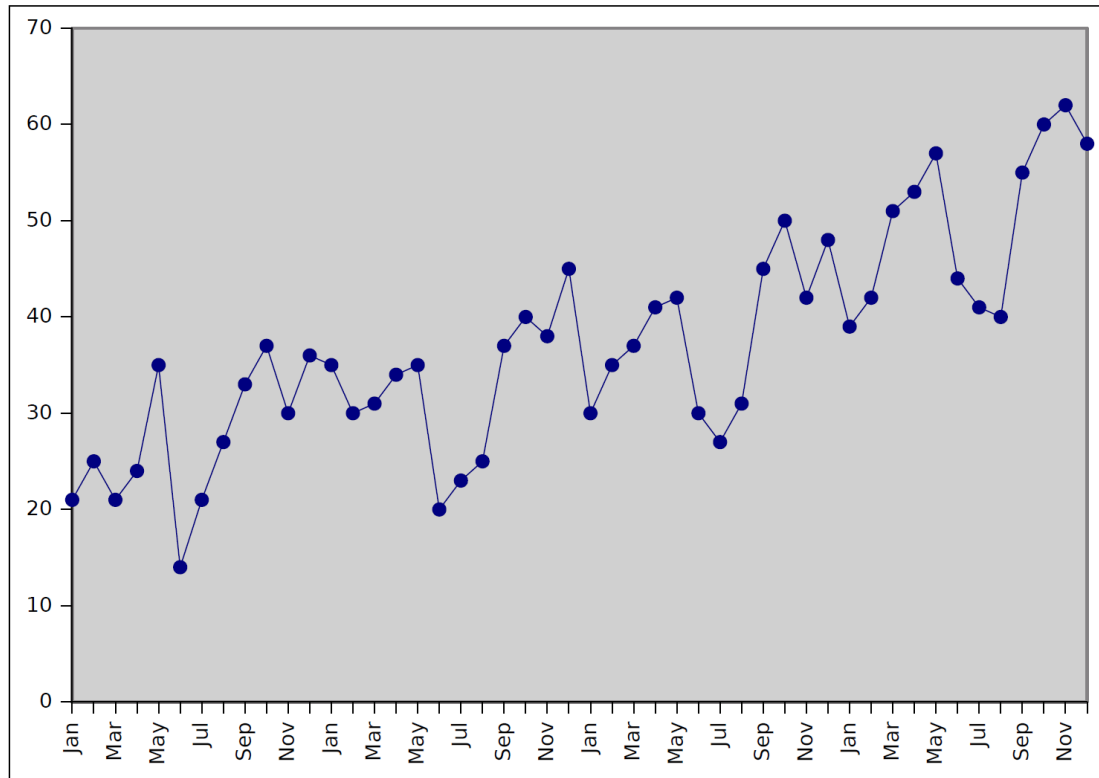
What will happen?

Prescriptive Analytics



What should we do?

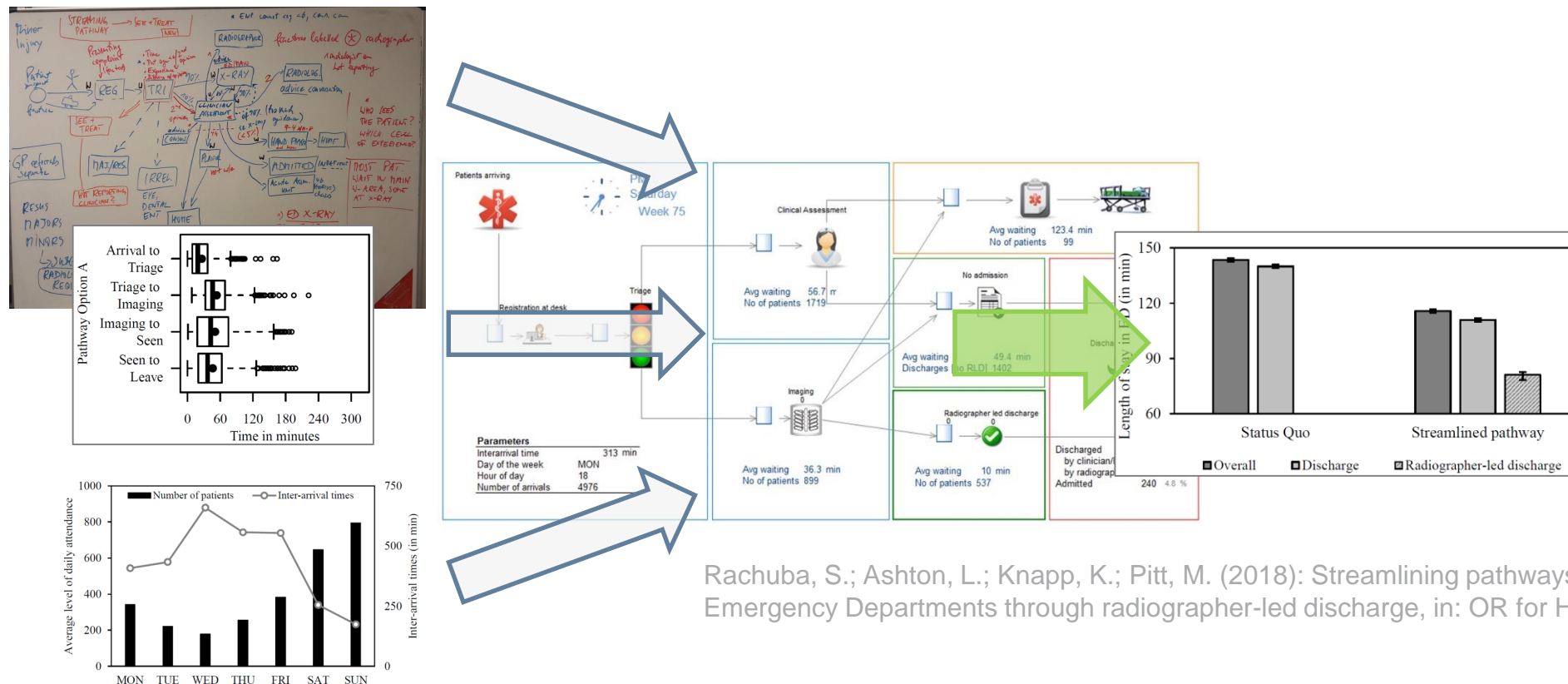
- (Likely) common example: Time series and prediction models



... other possible tool: Simulation

- Basic idea: replicate behaviour of “systems”
- Goals: (1) to explain how things work, (2) to predict likely effects of changes to the system
- Different paradigms:
 - System Dynamics
 - Agent-based Simulation
 - Discrete Event Simulation
 - Tool to replicate pathways and patient flows, e.g. in EDs
 - Dedicated software packages, such as Simul8, ARENA, etc.
 - Manually coded “from scratch”

- Example: Assess the likely impact of the introduction of radiographer-led discharge at a hospital in the South West of the UK
- Means: Computer simulation model built to replicate processes in ED



Rachuba, S.; Ashton, L.; Knapp, K.; Pitt, M. (2018): Streamlining pathways for minor injuries in Emergency Departments through radiographer-led discharge, in: OR for Health Care (in press)

Descriptive Analytics



What did happen?

Predictive Analytics



What will happen?

Prescriptive Analytics



What should we do?

What is it?

Answers questions such as:

“What is the best possible decision?”

“What should be done to achieve a goal?”



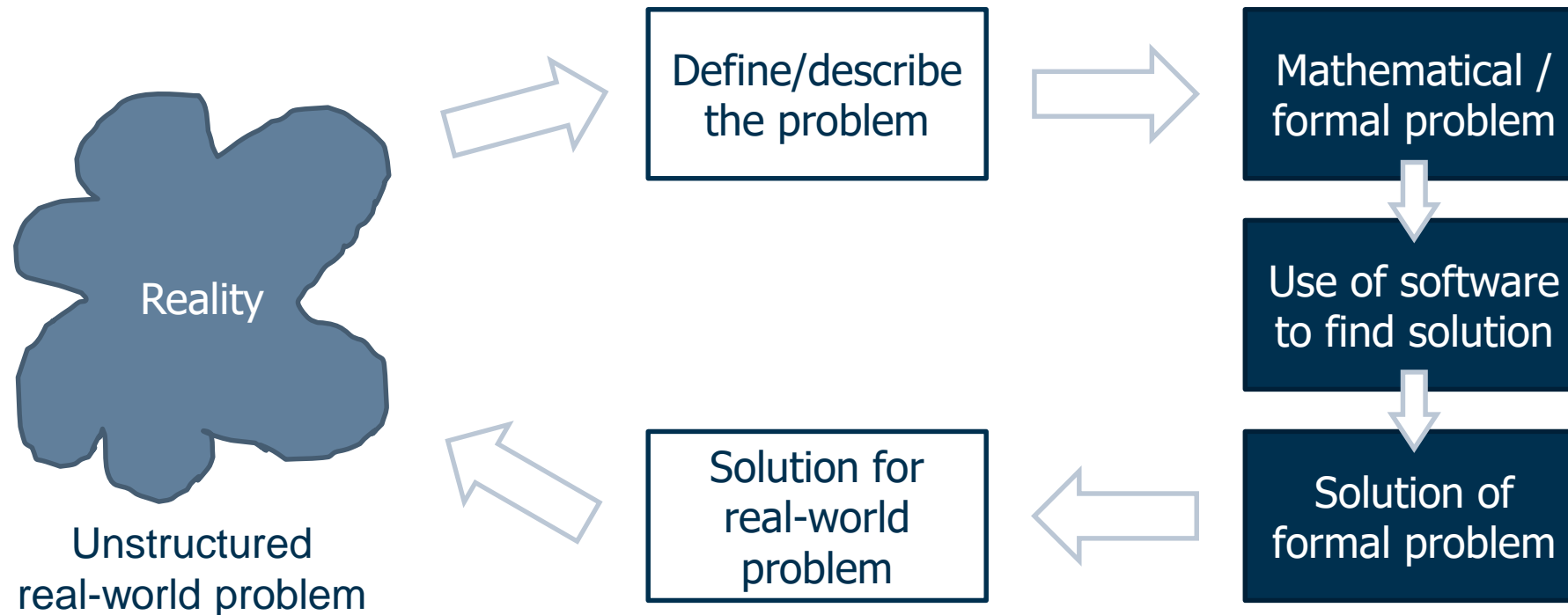


In what situation do we want to prescribe?

- Decisions are often complex because of multiple dependencies (hard to process in your head)
- Dependencies can lead to counter-intuitive decisions – one would normally not expect
- To see whether a decision is “good” is not always trivial (many “almost good” decisions)

Can you think of examples (in health care)?

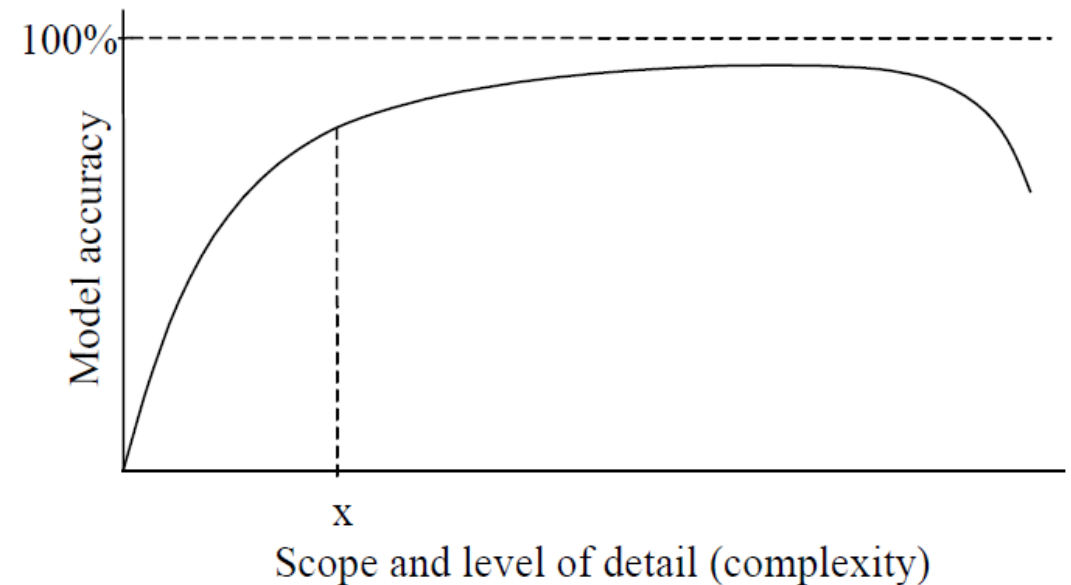
Model-based decision making:



A few characteristics of models:

- Models to describe, explain, or decide
- Given purpose / application
- Simplified version of reality
- As much detail as necessary
- As little detail as possible
- Structure is replicated

Example: mathematical optimisation models



Source: Robinson, S. (2008).

Optimisation models

- Three major parts:

1. Decision variables

What are possible decisions?

$$10x_1 + 10x_2 \rightarrow \max! \quad \mathbf{3}$$

2. Constraints

Are there any restrictions?

$$2x_1 + x_2 \leq 10 \quad \mathbf{2}$$

$$x_1 + 2x_2 \leq 8$$

3. Objective function

What is the overall goal?

$$x_1, x_2 \geq 0 \quad \mathbf{1}$$

- Three major parts:

1. Decision variables

What are possible decisions?

2. Constraints

Are there any restrictions?

3. Objective function

What is the overall goal?

$$\max \sum_{s \in \mathcal{S}} \sum_{j \in \mathcal{J}} \sum_{a \in \mathcal{A}} \sum_{h \in \mathcal{H}} w^s \cdot y_{ahj}^s \cdot \ln(p_{ah} + \varepsilon)$$

3

$$\text{s.t.} \quad \sum_{a \in \mathcal{A}} \eta_{ag} \sum_{h \in \mathcal{H}} y_{ahj}^s = x_{jg}^s \quad \forall j \in \mathcal{J}, g \in \mathcal{G}, s \in \mathcal{S}$$

$$\sum_{a \in \mathcal{A}} \sum_{h \in \mathcal{H}} y_{ahj}^s = 1 \quad \forall j \in \mathcal{J}, s \in \mathcal{S}$$

$$\sum_{j \in \mathcal{J}} \sum_{a \in \mathcal{A}} \sum_{h \in \mathcal{H}} y_{ahj}^s \cdot c_h = C \quad \forall s \in \mathcal{S}$$

$$\sum_{j \in \mathcal{J}} x_{jg}^s = d_g^s \quad \forall g \in \mathcal{G}, s \in \mathcal{S}$$

$$\sum_{g \in \mathcal{G}_k} \sum_{j \in \mathcal{J} \setminus \mathcal{J}_k} x_{jg}^s = 0 \quad \forall k \in \tilde{\mathcal{K}}, s \in \mathcal{S}$$

$$\sum_{h \in \mathcal{H}} z_{hj} = 1 \quad \forall j \in \mathcal{J}$$

$$y_{ahj}^s \leq z_{hj} \quad \forall a \in \mathcal{A}, h \in \mathcal{H}, j \in \mathcal{J}, s \in \mathcal{S}$$

$$z_{hj} \in \{0, 1\} \quad \forall h \in \mathcal{H}, j \in \mathcal{J}$$

$$x_{jg}^s \in \mathbb{N}_0 \quad \forall j \in \mathcal{J}, g \in \mathcal{G}, s \in \mathcal{S}$$

$$y_{ahj}^s \in \{0, 1\} \quad \forall a \in \mathcal{A}, h \in \mathcal{H}, j \in \mathcal{J}, s \in \mathcal{S}$$

1

2

Koppka et al. (2018): Optimal distribution of operating hours over operating rooms using probabilities.

- Standard form of optimisation model:

$$c_1 \cdot x_1 + c_2 \cdot x_2 + \dots + c_n \cdot x_n \rightarrow \max$$

$$\begin{array}{rcl} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n & \leq & b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n & \leq & b_2 \\ \vdots & & \\ a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n & \leq & b_m \end{array}$$

$$x_1, x_2, \dots, x_n \geq 0$$

Objective/constraints + task

Constraint matrix

Operator

RHS

Variables / types

- Standard form of optimisation model:

$$c_1 \cdot x_1 + c_2 \cdot x_2 + \dots + c_n \cdot x_n \rightarrow \max$$

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n \leq b_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n \leq b_2$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n \leq b_m$$

$$x_1, x_2, \dots, x_n \geq 0$$

Typical structure:

$$c^t x$$

$$Ax \leq b$$

$$x \geq 0$$

Prescriptive Analytics

Optimisation in a nutshell

- Optimisation solvers use existing structure of problems/models
 - Commercial solvers: very fast, very expensive
 - Open source solvers: freely available, not so fast
 - MS Excel's built-in solver: easy to access, limited in scope
- Apply solution techniques (i.e. algorithms) to provide optimal solution
- Interfaces
 - Programming languages
 - Data import/export (Excel, csv, etc.)



Prescriptive Analytics

Optimisation in a nutshell



- Transform models, if necessary
- Translate models: solver language
- Solve mathematical model
 - Use predefined algorithms, usually available through software package (such as simplex algorithm,
 - Develop new solution procedures
- Analyse solutions obtained for mathematical model
- Translate solutions to real-world problem

```
library(lpSolve, lpSolveAPI)
d <- data.frame(x=c(1,1,1,2,2,3,4,4),y=c(5,6,7,8,7,5,6,5),w=c(1,2,3,4,5,6,7,8))
ncol <- 8 #you have eight rows that can be picked or dropped from the solution set
lp_rowpicker <- make.lp(ncol=ncol)
set.type(lp_rowpicker, columns=1:ncol, type = c("binary"))
obj_vals <- d[, "w"]
set.objfn(lp_rowpicker, obj_vals)
lp.control(lp_rowpicker, sense="min")
#Add constraints to limit x values from repeating
add.constraint(lp_rowpicker, xt=c(1,1,1), #xt specifies which rows of the LP
              indices=c(1,2,3), rhs=1, type="<=")
add.constraint(lp_rowpicker, xt=c(1,1), #xt specifies which rows of the LP
              indices=c(4,5), rhs=1, type="<=")
add.constraint(lp_rowpicker, xt=c(1,1), #xt specifies which rows of the LP
              indices=c(7,8), rhs=1, type="<=") #x's in dataframe rows 7 & 8 are both '4'
#Add constraints to limit y values from repeating
add.constraint(lp_rowpicker, xt=c(1,1,1), #xt specifies which rows of the LP
              indices=c(1,6,8), rhs=1, type="<=") #y's in df rows 1,6 & 8 are all '5'
add.constraint(lp_rowpicker, xt=c(1,1), #xt specifies which rows of the LP
              indices=c(2,7), rhs=1, type="<=") #y's in dataframe rows 2&7 are both '6'
add.constraint(lp_rowpicker, xt=c(1,1), #xt specifies which rows of the LP
              indices=c(3,5), rhs=1, type="<=") #y's in dataframe rows 3&5 are both '7'
solve(lp_rowpicker)
get.objective(lp_rowpicker) #20
get.variables(lp_rowpicker)
lp_rowpicker
#[1] 0 0 1 1 0 1 1 0
#this tells you that from d you pick rows: 3,4,6 & 7 in your optimal solution.
#If you want to look at the full formulation:
rownames1 <- paste("one", c(1,2,4), sep="")
rownames2 <- paste("two", c(5,6,7), sep="")
colnames <- paste("pick_", c(1:8), sep="")
dimnames(lp_rowpicker) <- list(c(rownames1, rownames2), colnames)
print(lp_rowpicker)
#write it to a text file
write.lp(lp_rowpicker, filename="max_w.lp")
```

Console

```
Model name:
Minimize  C1 C2 C3 C4 C5 C6 C7 C8
R1        1  2  3  4  5  6  7  8
R2        1  1  1  0  0  0  0  0 <= 1
R3        0  0  0  1  1  0  0  0 <= 1
R4        1  0  0  0  0  0  1  0 <= 1
R5        0  1  0  0  0  0  1  0 <= 1
R6        0  0  1  0  1  0  0  0 <= 1
Kind      std std std std std std std
Type      Int Int Int Int Int Int Int
Upper     1  1  1  1  1  1  1  1
Lower     0  0  0  0  0  0  0  0
```

Prescriptive Analytics for Health Care

Classification of decision problems

- *Distinction by time horizon:*
 - Strategic
 - Tactical
 - Operational (online / offline)
- *Distinction by managerial area:*
 - Medical
 - Resources/Material
 - Finance



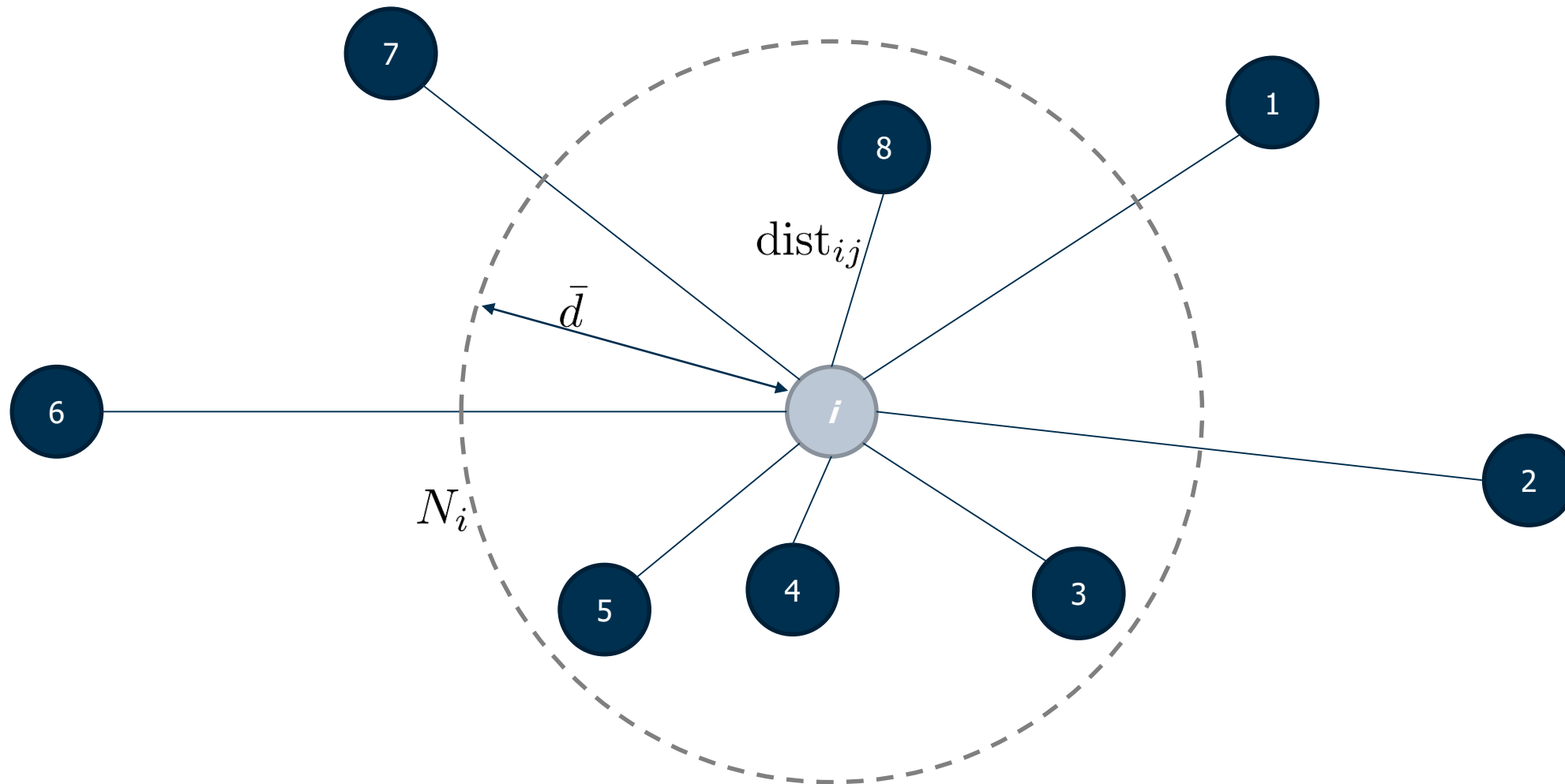
Prescriptive Analytics

| | <i>Medical planning</i> | <i>Resource capacity planning</i> | <i>Materials planning</i> | <i>Financial planning</i> | |
|--------------------------------|---|--|---|--|--------------------------------|
| Strategic | Research, development of medical protocols | Case mix planning, capacity dimensioning, workforce planning | Supply chain and warehouse design | Investment plans, contracting with insurance companies | ← hierarchical decomposition → |
| Tactical | Treatment selection, protocol selection | Block planning, staffing, admission planning | Supplier selection, tendering | Budget and cost allocation | |
| Offline operational | Diagnosis and planning of an individual treatment | Appointment scheduling, workforce scheduling | Materials purchasing, determining order sizes | DRG billing, cash flow analysis | |
| Online operational | Triage, diagnosing emergencies and complications | Monitoring, emergency coordination | Rush ordering, inventory replenishing | Billing complications and changes | |
| | ← managerial areas → | | | | |

Source: Hans/van Houdenhoven/Hulshof (2012), p. 311.

- Many possible applications:
 - Staffing (how many, rotas, emergency assignments, etc.)
 - Locations (where/how many, capacity allocation, re-allocation, etc.)
 - Operating room (size, departmental allocation, selection, sequence, etc.)
 - Blood Supply Chain
 - Hospital Layout
- Focus on two areas:
 1. Location analysis
 2. Operating room planning

- Set covering location problem (SCLP, Toregas et al. 1971)
- Idea: What is the minimum number of locations so that every demand area can be “reached”?
- Key parts of the model:
 - Possible supply sites (=locations): $J = \{1, 2, \dots, n\}$
 - Possible demand sites: $I = \{1, 2, \dots, m\}$
 - Distances between demand area and potential location: dist_{ij}
 - Neighbourhood: subset of all potential locations which can be reached within given limit



- Set covering location problem (SCLP)
- Idea: What is the minimum number of locations so that every demand area can be “reached”?
- Decision variable:

$$y_j = \begin{cases} 1 & \text{if location } j \text{ is chosen,} \\ 0 & \text{else.} \end{cases}$$

- Conditions to “reach” demand area: defined by neighbourhood set N_i
- Neighbourhood = close enough:

$$N_i := \{j \in J \mid \text{dist}_{ij} \leq \bar{d}\}$$

Set covering location problem (SCLP)

- Idea: What is the minimum number of locations such that every demand area can be “reached”?
- Optimisation model:

$$\sum_{j \in J} y_j \rightarrow \min!$$

Minimise number of locations

$$\text{s.t. } \sum_{j \in N_i} y_j \geq 1 \quad \forall i \in I$$

Cover every demand region at least once

$$y_j \in \{0, 1\} \quad \forall j \in J$$

Choose location j (1=yes, 0=no)

- Maximal covering location problem (MCLP, Church and ReVelle 1974):
 - Choose locations such that covered population is maximised (demand: a_i)
 - Limited number of locations: P
- Decision variables:

$$y_i = \begin{cases} 1 & \text{if demand in region } i \text{ is covered,} \\ 0 & \text{else.} \end{cases}$$

$$x_j = \begin{cases} 1 & \text{if location } j \text{ is chosen,} \\ 0 & \text{else.} \end{cases}$$

- Maximal covering location problem (MCLP):
 - Choose locations such that covered population is maximised
 - Limited number of locations: P

- Optimisation model:

$$\sum_{i=1}^m a_i \cdot y_i \rightarrow \max!$$

Maximise amount of covered demand

$$\text{s.t.} \quad \sum_{j \in N_i} x_j \geq y_i \quad \forall i$$

If location is chosen, demand is served

$$\sum_{j=1}^n x_j = P$$

Number of locations is limited

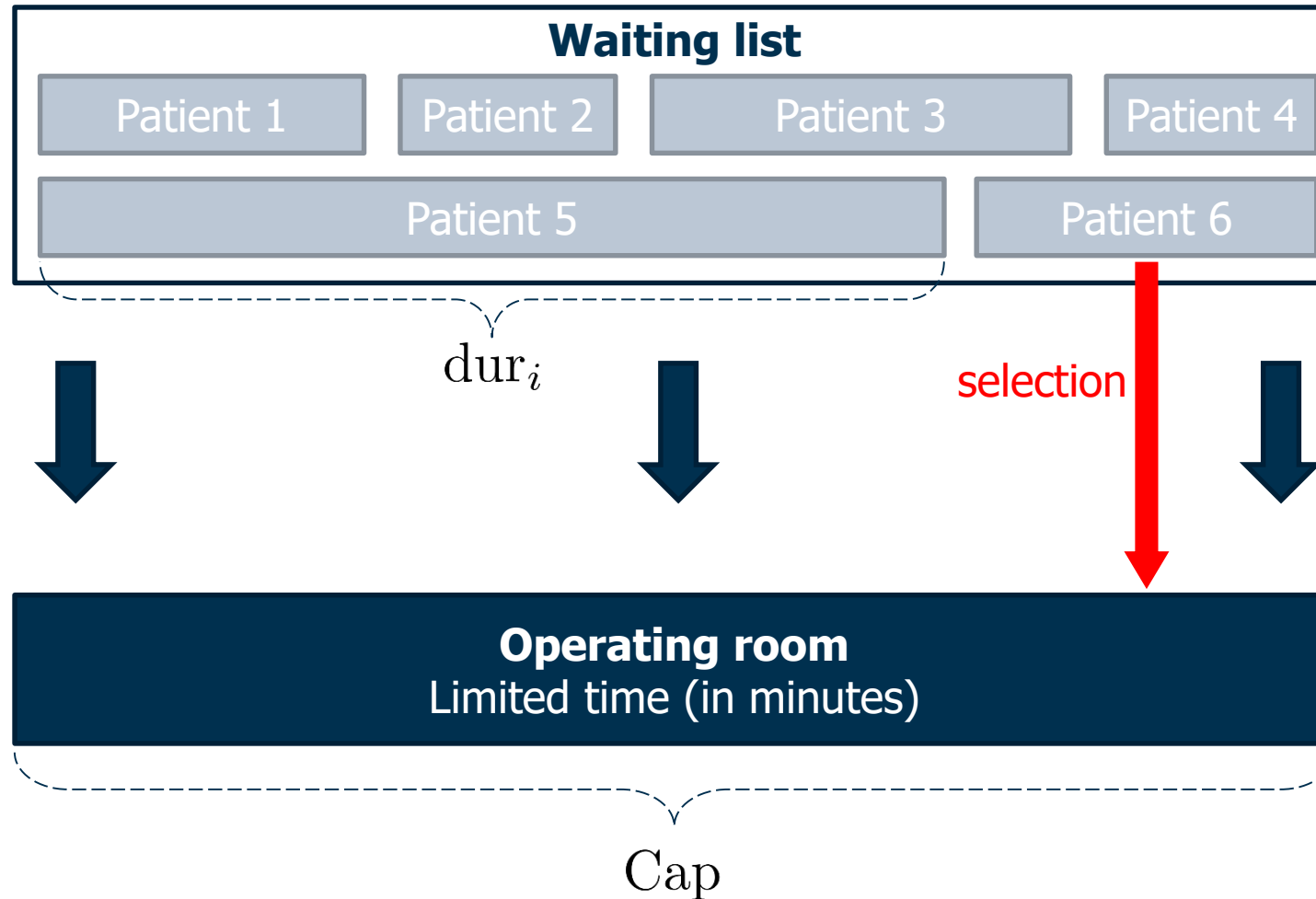
$$x_j \in \{0, 1\} \quad \forall j$$

$$y_i \in \{0, 1\} \quad \forall i$$

Binary decisions (area served, location chosen)

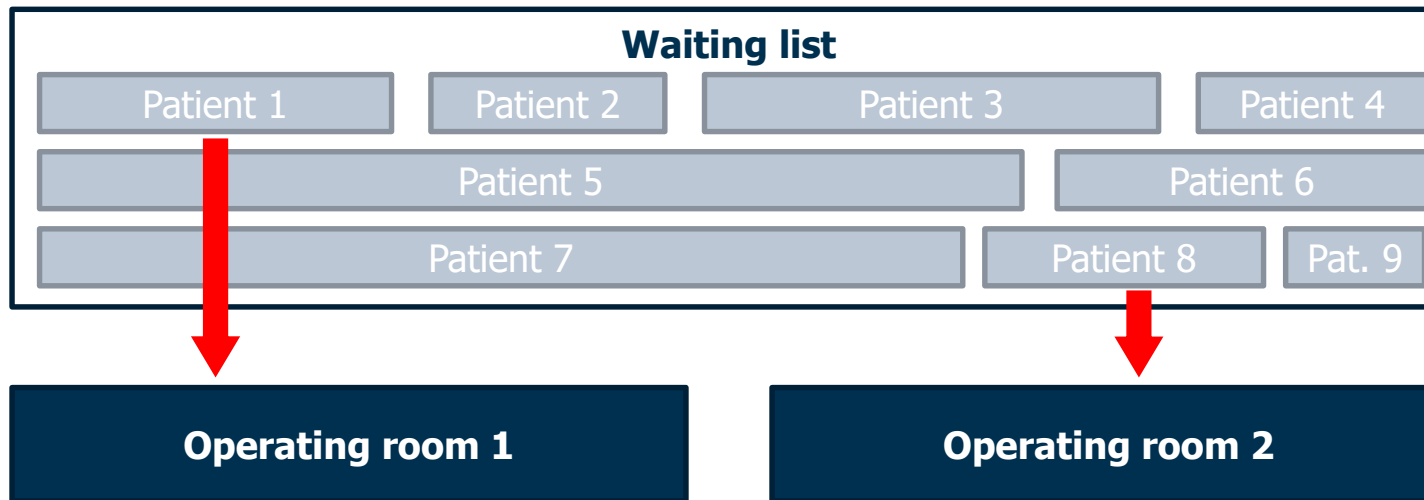
Prescriptive Analytics

Scheduling



- Select patients (index: i) from waiting list: $P = \{1, 2, \dots, \bar{p}\}$
- Criteria:
 - As many patients as possible
 - Minimize idle time – target utilisation
 - Patients with longest waiting time first
- Decision variable:
$$x_i = \begin{cases} 1 & \text{if patient is selected for surgery} \\ 0 & \text{else.} \end{cases}$$
- Surgery duration is known: dur_i
- Operating room has limited capacity: Cap

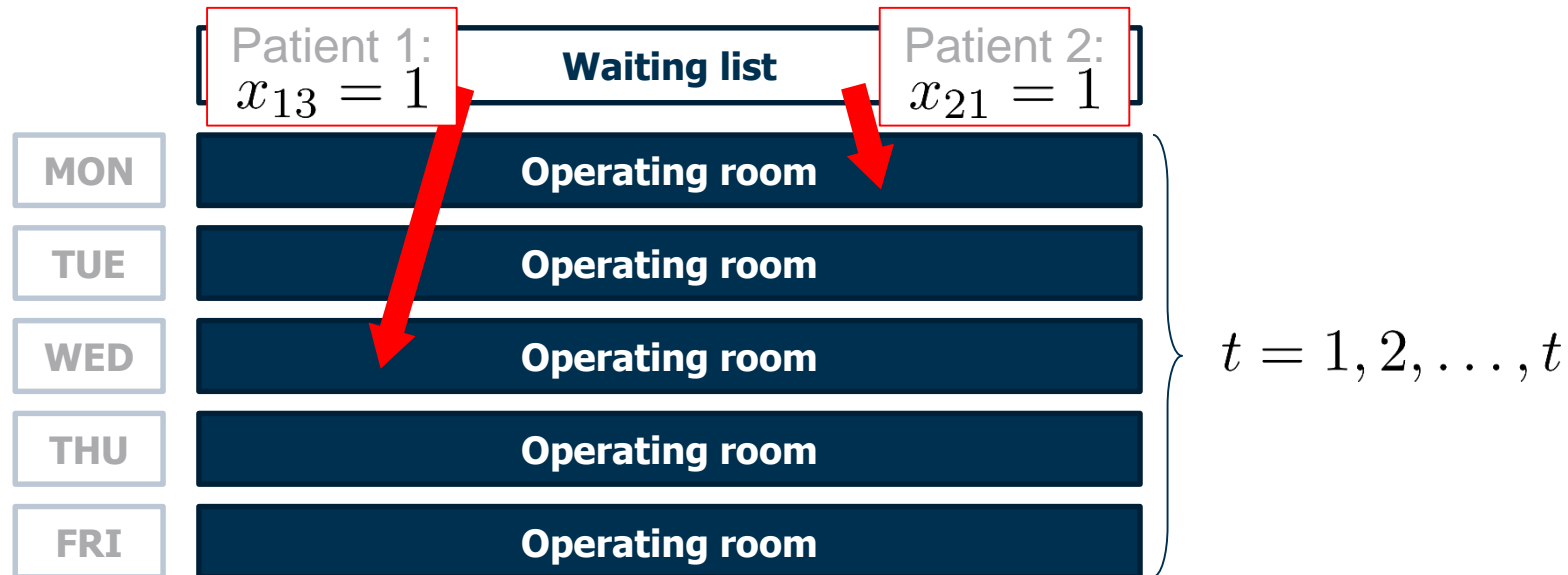
- Extension 1: Plan multiple operating rooms simultaneously



- Distinguish operating rooms: $J = \{1, 2, \dots, n\}$
- Potentially different capacities: Cap_j
- Decision variable:

$$x_{ij} = \begin{cases} 1 & \text{if patient } i \text{ is selected for room } j \\ 0 & \text{else.} \end{cases}$$

- Extension 2: Plan a full week at once, five working days



- Decision variable:

$$x_{it} = \begin{cases} 1 & \text{if patient } i \text{ is selected for day } t \\ 0 & \text{else.} \end{cases}$$

- Optimisation model: maximise number of patients in planning horizon

$$\sum_{i=1}^m \sum_{t=1}^T x_{it} \rightarrow \max!$$

Maximise #patients
for the week

$$\sum_{i=1}^m \text{dur}_i \cdot x_{it} \leq \text{Cap}$$

$$\forall t \in \{1, 2, \dots, T\}$$

Limited capacity, patients
consume time in the OR

$$\sum_{t=1}^T x_{it} \leq 1$$

$$\forall i \in \{1, 2, \dots, m\}$$

Schedule each
patient at most once

$$x_{it} \in \{0, 1\}$$

$$\forall i, t$$

Scheduled: yes/no

Which assumptions did we make?

- Ambulance locations:
 - Demand is known
 - Driving times are not changing
- Operating rooms:
 - Limited waiting list, equal importance of patients
 - Doctors are always available and can perform any surgery
 - Surgery duration is known, i.e. deterministic

What did we cover?

- Distinguish different types of Analytics
- Discuss potentials and limitations of optimisation
- Understand simple optimisation models
 - Ambulance location
 - Operating room planning

Textbooks

- Ozcan, Yasar A (2017): Analytics and Decision Support in Health Care Operations Management, 3rd Edition, Wiley.
- Brandeau, Margaret L.; Sainfort, Francois; Pierskalla, William P. (Eds.): Operations Research and Health Care: A Handbook of Methods and Applications, Springer.
- Hall, Randolph (2013): Patient Flow – Reducing Delay in Healthcare Delivery, Springer.
- Vissers, Jan; Beech, Roger (2005): Health Operations Management: Patient Flow Logistics in Health Care, Routledge.

Research articles

- Salmon, A.; Rachuba, S.; Briscoe, S.; Pitt, M. (2018): A structured literature review of simulation modelling applied to Emergency Departments, in: Operations Research for Health Care (in press)
- Rachuba, S.; Ashton, L.; Knapp, K.; Pitt, M. (2018): Streamlining pathways for minor injuries in Emergency Departments through radiographer-led discharge, in: OR for Health Care (in press)
- Rachuba, S.; Salmon, A.; Zhelev, Z.; Pitt, M. (2018): Redesigning the diagnostic pathway for chest pain patients in emergency departments, in: Health Care Management Science, 21(2):177-191.
- Rachuba, S.; Werners, B. (2017): A fuzzy multi-criteria approach for robust operating room schedules, in: Annals of Operations Research, 251(1):325-350.
- Rachuba, S.; Werners, B. (2014): A robust approach for scheduling in hospitals using multiple objectives, in: Journal of the Operational Research Society, 65:546-556.

Useful links

- Script: Optimisation with R:
http://www.is.uni-freiburg.de/resources/computational-economics/5_OptimizationR.pdf
- Using IpSolveAPI with R:
<https://www.r-bloggers.com/linear-programming-in-r-an-lpsolveapi-example/>
- Set Covering problem:
<http://mat.gsia.cmu.edu/classes/integer/node8.html>
- Knapsack problem:
<http://mat.gsia.cmu.edu/classes/integer/node6.html#SECTION00032000000000000000>
- Modeling and Solving LPs with R (free book):
<https://www.r-bloggers.com/modeling-and-solving-linear-programming-with-r-free-book/>
- Introduction to glpkAPI with R:
<https://cran.r-project.org/web/packages/glpkAPI/vignettes/glpk-gmpl-intro.pdf>
- Introduction to linear programming:
<https://www.math.ucla.edu/~tom/LP.pdf>



All models are wrong but some are useful!

George E.P. Box (1919 - 2013)