Health data Analytics: Making Sense of Health Data to improve health services

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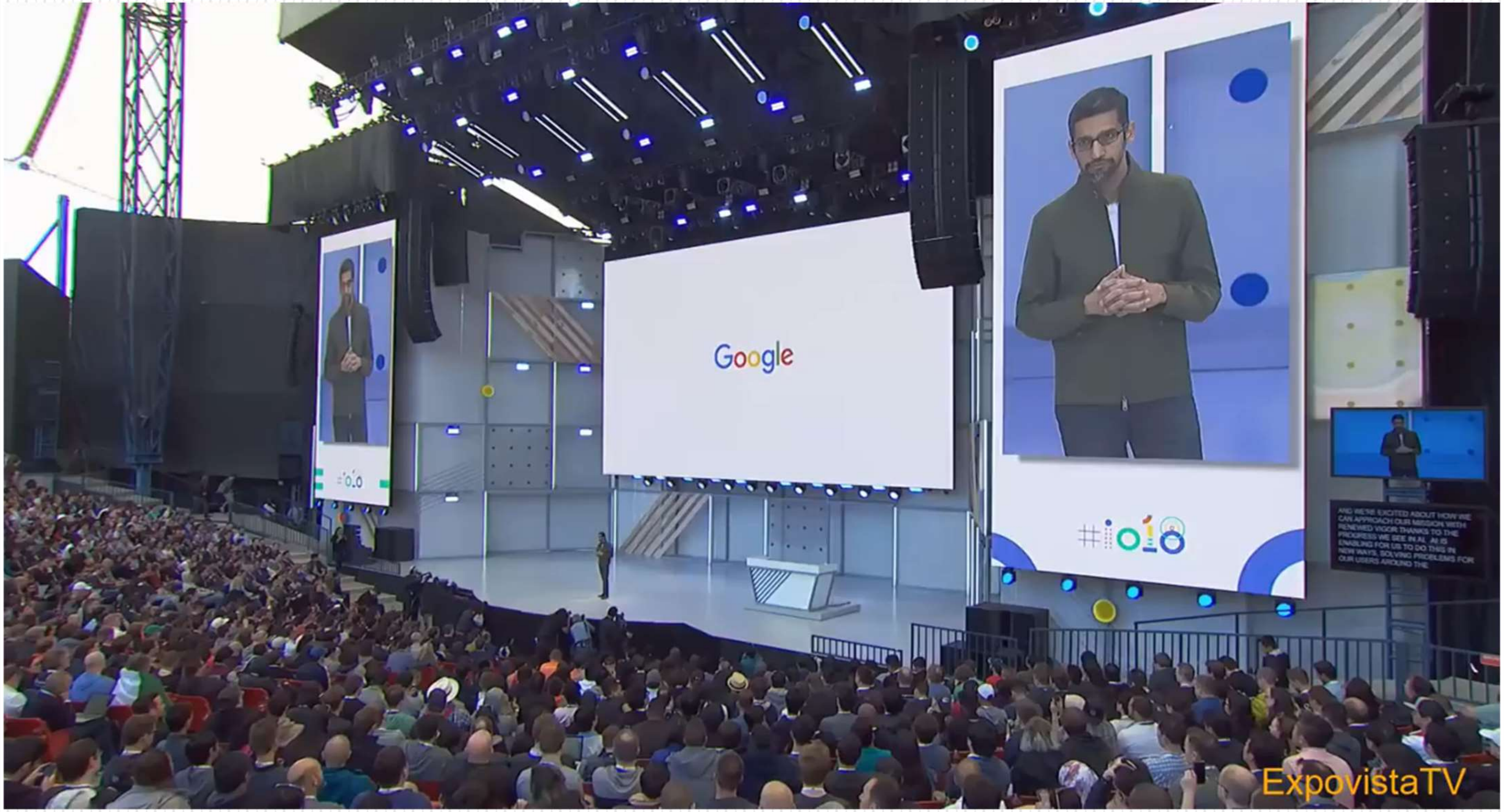

https://www.youtube.com/watch?v=DziXSfAOHhQ

Health data Analytics: Making Sense of Health Data to improve health services

https://www.youtube.com/watch?v=YFDgUpmCmGA

Health data Analytics: Making Sense of Health Data to improve health services

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Roadmap

- Introduction
  - Complex Systems
  - Some interesting problems and observations
- Background
  - Phase type distribution
  - Phase type distribution survival trees
- Applications
- Publications

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Introduction

- Life expectancy has increased with improvement in health services and standard of living.

Introduction

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- Higher demand to the healthcare resources

Introduction

- Life expectancy has increased with improvement in health services and standard of living.
- Higher demand to the healthcare resources
- Healthcare challenge is to continue providing the same quality of care

Introduction

- Healthcare system facing major problems

Introduction

- Healthcare system facing major problems
  - Lack of beds in hospitals

Introduction

- Healthcare system facing major problems
  - Lack of beds in hospitals and
  - Lack of other hospital resources.

Introduction

- To work with these problems the healthcare system needs :

Introduction

- To work with these problems the healthcare system needs :
  - An efficient way to forecast the resources required

Introduction

- To work with these problems the healthcare system needs :
  - An efficient way to forecast the resources required
  - To minimize the cost of care while maintaining the quality of care.

Introduction

- When modelling the healthcare system it would help:

Introduction

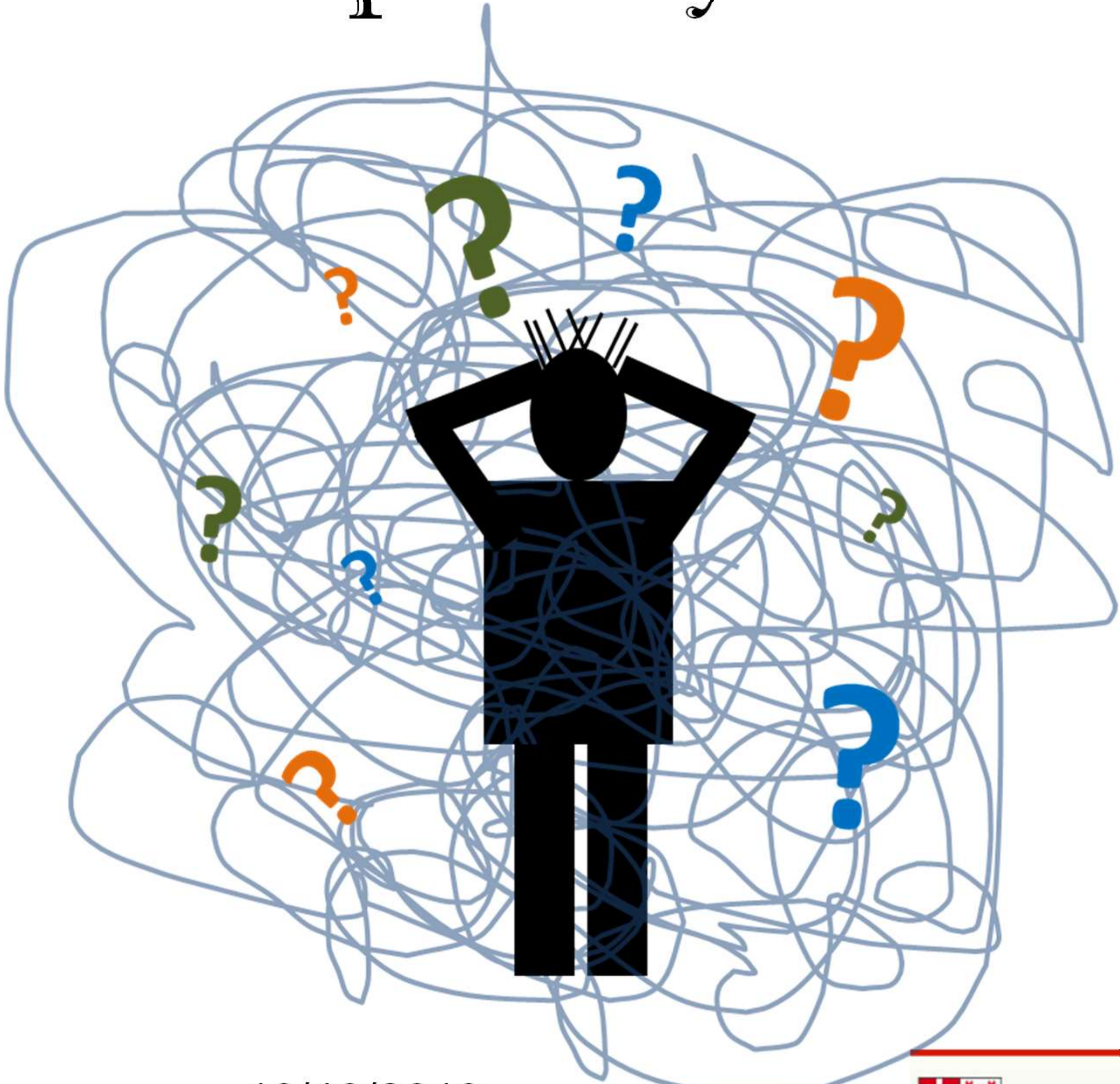
- When modelling the healthcare system it would help:
  - To better understand the process for the design of polices that can improve the quality of care

Introduction

- When modelling the healthcare system it would help:
  - To better understand the process for the design of polices that can improve the quality of care
  - To ensure the optimal utilization of the available resources

Background

Complex Systems



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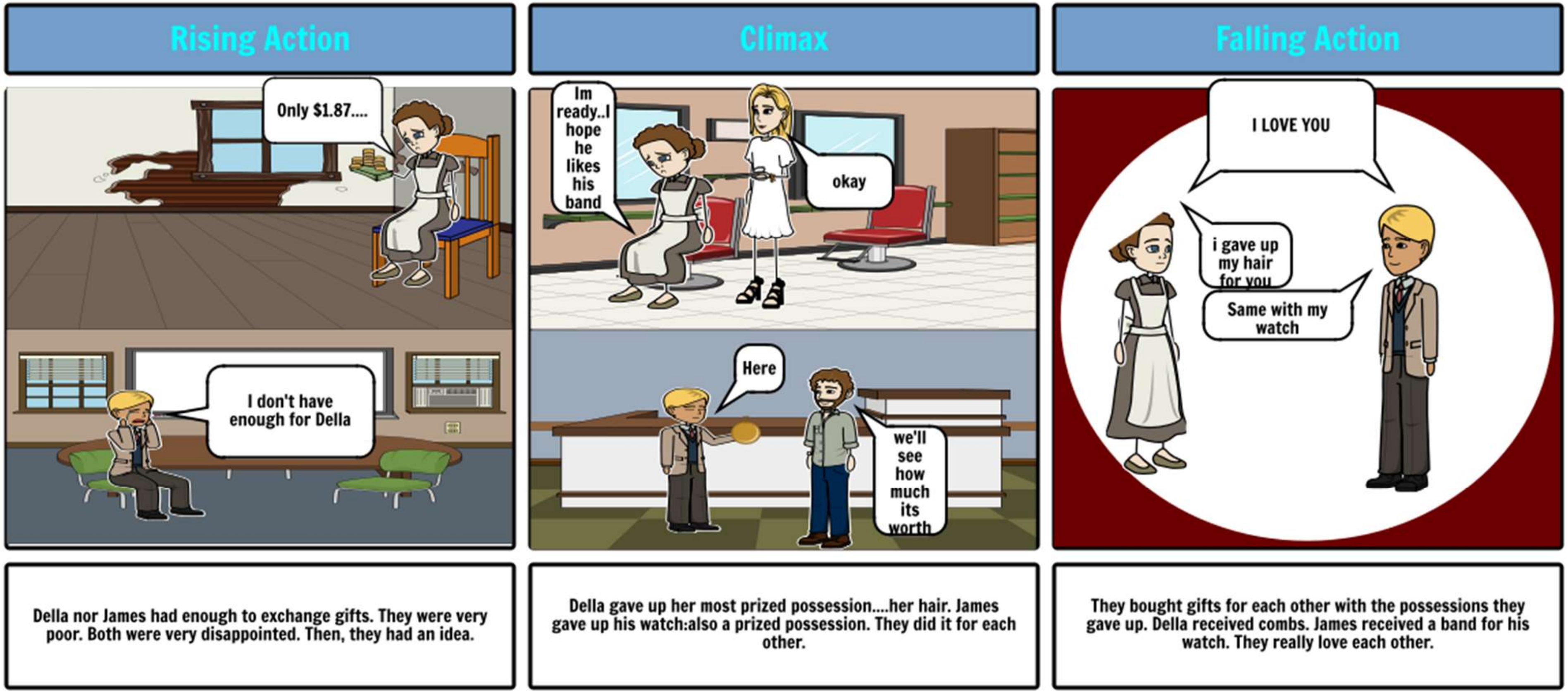
Our family system: One of the most complex systems



Create your own at Storyboard That

https://www.storyboardthat.com/storyboards/baptist_snniper/the-gift-of-the-magi-story-elements

Our family system: One of the most complex systems

Our family system: One of the most complex systems

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Our family system: One of the most complex systems

Requires

1. Human Behavioural Modelling

Our family system: One of the most complex systems

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2. Modelling the effect of others' Behaviour (using game theory),

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4. Most difficult: modelling spontaneous (uncorrelated) changes in sentiments,

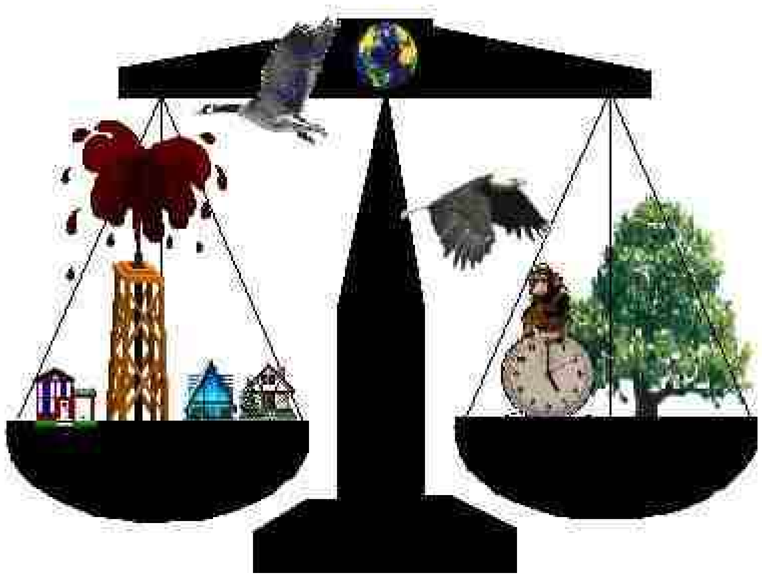
Our family system: One of the most complex systems

Requires

1. Human Behavioural Modelling
2. Modelling the effect of others' Behaviour (using game theory),
3. Modelling of cultural, social, economical, financial and environmental effects (Big data analytics),
4. Most difficult: modelling spontaneous (uncorrelated) changes in sentiments,
5. Reality vs perception.

Reality vs Perception

Our Economy:
A Complex System



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Our Economy:
A Complex System

With government intervention:

Our Economy:
A Complex System

With government intervention:

More demand than supply = More subsidy to the buyer

Our Economy:
A Complex System

With government intervention:

More demand than supply = More buyer subsidy

More buyer subsidy = More profit

Our Economy:
A Complex System

- **All buyer subsidy will go to supplier/ manufacturers**

Our Economy:
A Complex System

With government intervention:

More demand than supply = More buyer subsidy

More buyer subsidy = More profit

More profit = More attractive industry

Our Economy:
A Complex System

All grants will ultimately go to the buyers

Our Economy:
A Complex System

With government intervention:

More demand than supply = More buyer subsidy

More buyer subsidy = More profit

More profit = More attractive industry

= More players

Our Economy:
A Complex System

With government intervention:

More demand than supply = More buyer subsidy

More buyer subsidy = More profit

More profit = More attractive industry

= More players

= More supply than demand

Our Economy:
A Complex System

With government intervention:

More demand than supply = More buyer subsidy

More buyer subsidy = More profit

More profit = More attractive industry

= More players

= More supply than demand

= Less price = Less profit

Our Economy: A Complex System

With government intervention:

More demand than supply = More buyer subsidy

More buyer subsidy = More profit

More profit = More attractive industry

= More players

= More supply than demand

= Less price = Less profit

= Some will leave the market with loss

Our Economy: A Complex System

If these players are farmers: Suicide

Our Economy:
A Complex System

With government intervention:

More demand than supply = More buyer subsidy

More buyer subsidy = More profit

More profit = More attractive industry

= More players

= More supply than demand

= Less price = Less profit

= Some will leave the market with loss

= More demand than supply

Our Economy:
A Complex System

With government intervention:

More demand than supply = More grant to the supplier/manufacturer to ensure meeting the demand

Our Economy:
A Complex System

With government intervention:

More demand than supply = More supplier grant

More supplier subsidy = More profit

Our Economy:
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With government intervention:

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Our Economy:
A Complex System

Without government intervention:

More demand then supply = More profit

Our Economy:
A Complex System

Without government intervention:

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= More players

= More supply than demand

= Less price = Less profit

= Some will leave the market with loss

= More demand than supply

Our Economy:
A Complex System

For industries to solve the problem: One of the solution is **innovation**.

- ✓ Develop substitute products
- ✓ Make process more efficient
- ✓ Reduce production cost
- ✓ More efficient supply chain network
- ✓ Provide add-on services

Our Economy: A Complex System

For other industries to solve the problem: One of the methods is **innovation**

And **duration of stay in the market**

- ✓ How long an industry would be attractive
- ✓ When to leave the market/industry
- ✓ How to increase this duration
- ✓ Alternate product development through **innovation**
- ✓ Plan to leave the market/industry

Our Education System

According to MHRD:

- In 2015, there were more than 6000 engineering and technology institutes.
- Produced more than 2.9 million engineering graduates.
- Only 1.5 million got jobs in their engineering discipline.
- ????

Our Education System

- **The decision to pursue BE/BTech in their chosen discipline was taken 4 years back based on then current data.**

Food wastage

- **Should we reduce the food wastage or not?**

Food wastage

- **Should we reduce the food wastage or not?**
- Assume there is 35% food wastage
- Means we are producing 135% food than required.
- Are food producers (farmers) getting too much profit?
- Are food product prices are inflated?

Food wastage

- **Should we reduce the food wastage or not?**
- What if we reduce the food wastage by 50%?
- Then the demand will be 118% and supply will be 135%?
- What will be the food prices?
- What will happen with our farmers?

Our healthcare system: A complex system

Our healthcare system: A complex system

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Our healthcare system:
A complex system

Other complex systems: A complex system

Private healthcare:

- Some patients want cheap healthcare

Other complex systems: A complex system

Private healthcare:

- Some patients want cheap healthcare
- Some patients want best (luxurious) healthcare

Other complex systems:
A complex system

Private healthcare:

- Some patients want cheap healthcare
- Some patients want best (luxurious) healthcare
- Health providers want maximum profit

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A complex system

Private healthcare:

- Some patients want cheap healthcare
- Some patients want best (luxurious) healthcare
- Health providers want maximum profit
- maximum profit = maximum hospital visits

Other complex systems:
A complex system

Private healthcare:

- Some patients want cheap healthcare
- Some patients want best (luxurious) healthcare
- Health providers want maximum profit
- maximum profit = maximum hospital visits
- = maximum readmissions
- + maximum hospital duration of stay

Our healthcare system:
A complex system

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Other complex systems: A complex system

Public healthcare:

- Everyone gets the same healthcare

Other complex systems:
A complex system

Public healthcare:

- Everyone gets the same healthcare
- Health providers want minimum cost

Other complex systems:
A complex system

Public healthcare:

- Everyone gets the same healthcare
- Health providers want minimum cost
- Minimum cost

  = Limited resources

  = least duration in hospitals + minimum admissions

Other complex systems: A complex system

Public healthcare:

- Everyone gets the same healthcare
- Health providers want minimum cost
- Minimum cost
  - = Limited resources
  - = least duration in hospitals + waiting list

Other complex systems:
A complex system

Public healthcare:

- Everyone gets the same healthcare
- Health providers want minimum cost
- Minimum cost

    = Limited resources

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Other complex systems:
A complex system

Public healthcare:

- Everyone gets the same healthcare
- Health providers want minimum cost
- Minimum cost

  = Limited resources

  = more readmissions + waiting list

  = longer waiting list

Other complex systems:
A complex system

https://fineartamerica.com/featured/hospital-waiting-room-mark-thomasscience-photo-library.html

Other complex systems:
A complex system

Public healthcare:

- Everyone gets the same healthcare
- Health providers want minimum cost
- Minimum cost
  - = Limited resources
  - = longer waiting list
  - = **Poor healthcare**

Other complex systems: A complex system

Public healthcare:

- Everyone gets the same healthcare
- Health providers want minimum cost
- Minimum cost
  - = Limited resources
  - = longer waiting list
  - = **Poor healthcare**
  - **= Public outcry**
  - **= Preference**

Other complex systems: A complex system

Public healthcare:

- ~~**Everyone gets the same healthcare**~~
- Health providers want minimum cost
- Minimum cost
  - = Limited resources
  - = longer waiting list
  - = **Poor healthcare**
  - **= Public outcry**
  - **= Preference**

Other complex systems: A complex system

Public healthcare:

- **Corruption**
- Health providers want minimum cost
- Minimum cost
  - = Limited resources
  - = longer waiting list
  - = **Poor healthcare**
  - **= Public outcry**
  - **= Preference**

Other complex systems:
A complex system

Public healthcare:

- More resources

Other complex systems: A complex system

Public healthcare:

- More resources = More cost

Other complex systems: A complex system

Public healthcare:

- More resources = short waiting lists

Other complex systems:
A complex system

Public healthcare:

- More resources = short waiting lists
- Short waiting list = longer hospital stay

Other complex systems:
A complex system

Public healthcare:

- More resources = short waiting lists
- Short waiting list = longer hospital stay

  minimum readmissions

Other complex systems: A complex system

Public healthcare:

- More resources = short waiting lists
- Short waiting list = longer hospital stay

  minimum readmissions

  more patients

Other complex systems: A complex system

Public healthcare:

- Even more resources = no waiting lists
- Short waiting list = longer hospital stay

  minimum readmissions

  more patients

  underutilization

Other complex systems: A complex system

Public healthcare:

- Even more resources = no waiting lists
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  minimum readmissions

  more patients

  underutilization

  misuse

Other complex systems: A complex system

Public healthcare:

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minimum readmissions

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misuse

more cost

Other complex systems:
A complex system

Public healthcare:

- Even more resources = no waiting lists
- Short waiting list = longer hospital stay

minimum readmissions

more patients

underutilization

misuse

more cost

Some waiting lists

Other complex systems:
A complex system

Public healthcare:

- Optimum resources = optimum waiting time

Other complex systems: A complex system

Public healthcare:

- Optimum resources = optimum waiting time
- = Optimum hospital stay

Other complex systems: A complex system

Public healthcare:

- Optimum resources = optimum waiting time

  = Optimum hospital stay

  = minimum readmissions

Other complex systems:
A complex system

Public healthcare:

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  = Optimum hospital stay
  = minimum readmissions
  = **optimum patients' number**

Other complex systems: A complex system

Public healthcare:

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  optimum utilization

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A complex system

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  = **optimum patients' number**
  optimum utilization
  minimum misuse

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Other complex systems: A complex system

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  = **optimum patients' number**

  optimum utilization

  minimum misuse

  optimum cost

  Some waiting lists

Other complex systems: A complex system

Public healthcare:

- Optimum resources = Proper planning

  = Continuously adding resources (if population is increasing/changing)

  = Resource requirement forecasting

Other complex systems: A complex system

Public healthcare:

- Optimum resources = Proper planning

  = Continuously adding resources (if population is increasing/changing)

  = Resource requirement forecasting

  = Admission rate estimation

  = Length of stay estimation

Coxian phase type distributions

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Among popular choices to fit spell length of stay data.

Coxian phase type distributions

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Provide a simple interpretation of fit for the length of stay data.

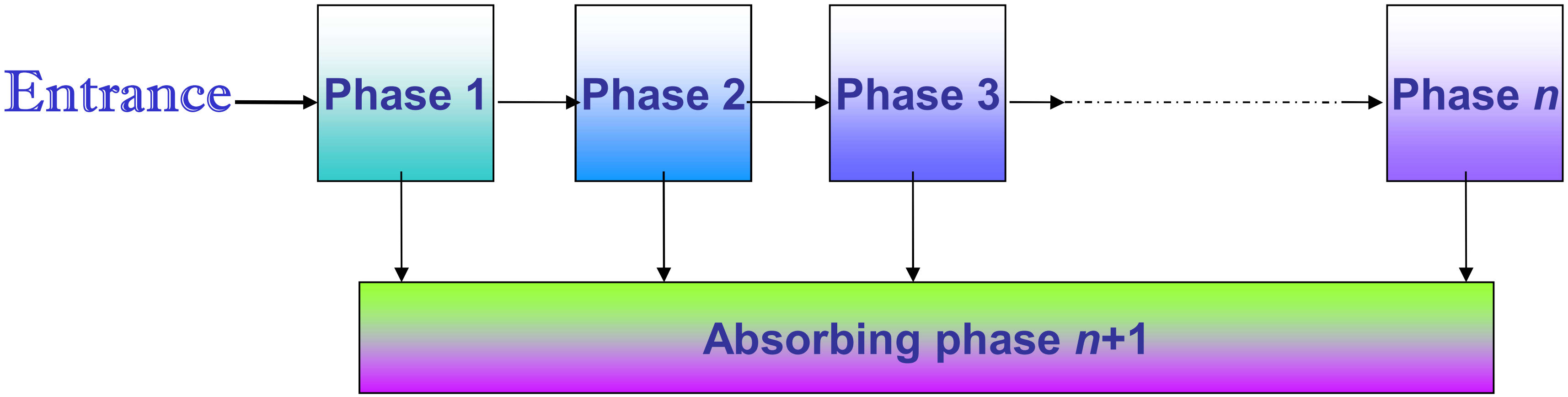
Coxian phase type distributions

Among popular choices to fit spell length of stay data.

Provide a simple interpretation of fit for the length of stay data.

Parameter estimation is easier than other phase type distributions.

A Markov chain



A Markov chain

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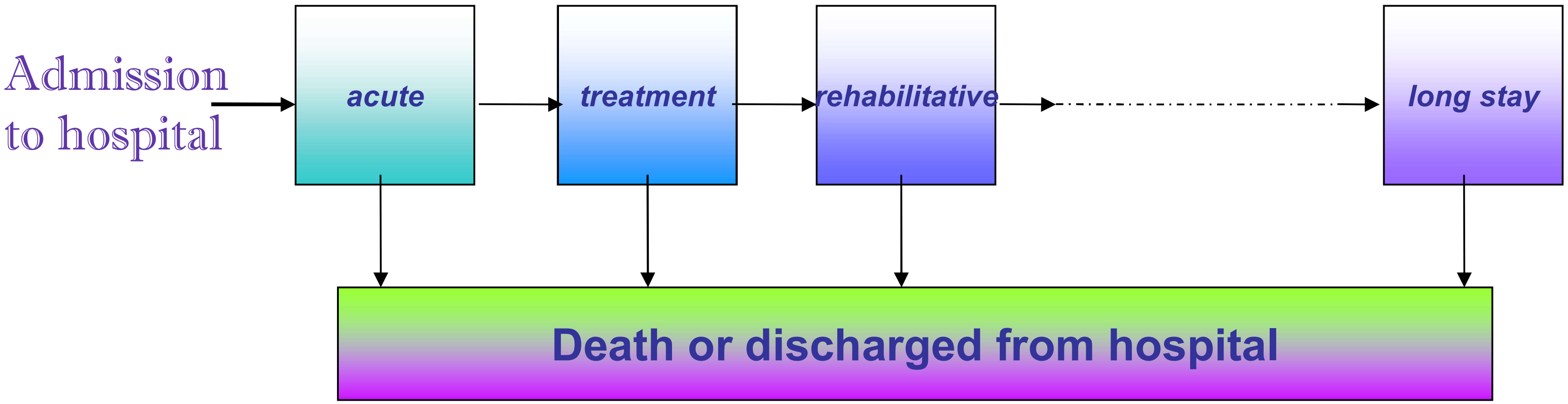
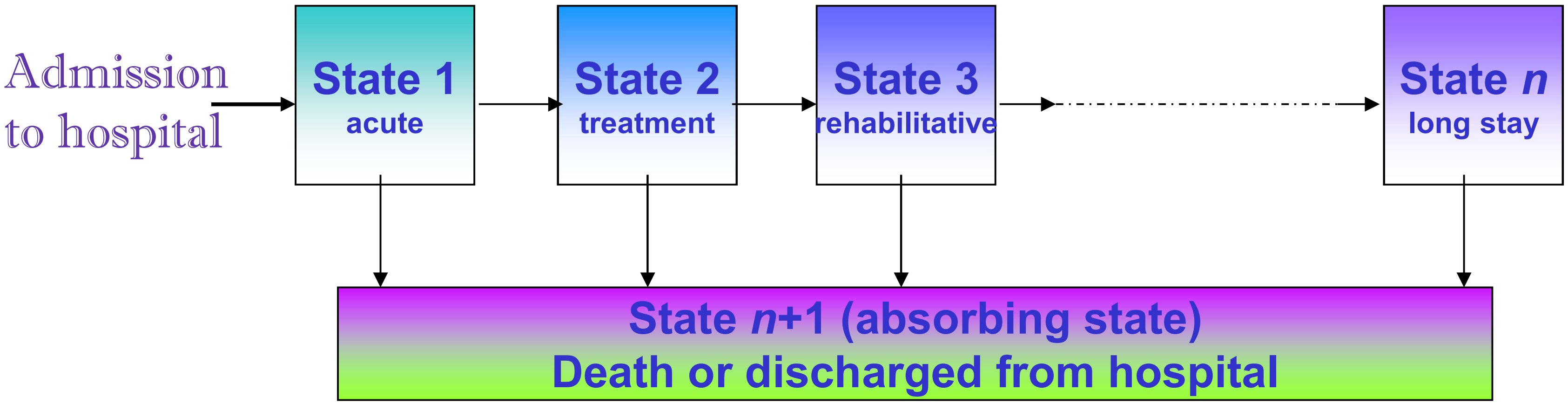
Hospital care system as a Markov chain

Patient flow in the stroke care system can be modelled as an *n* state Markov process with Coxian phase type distributions



Coxian phase type distributions



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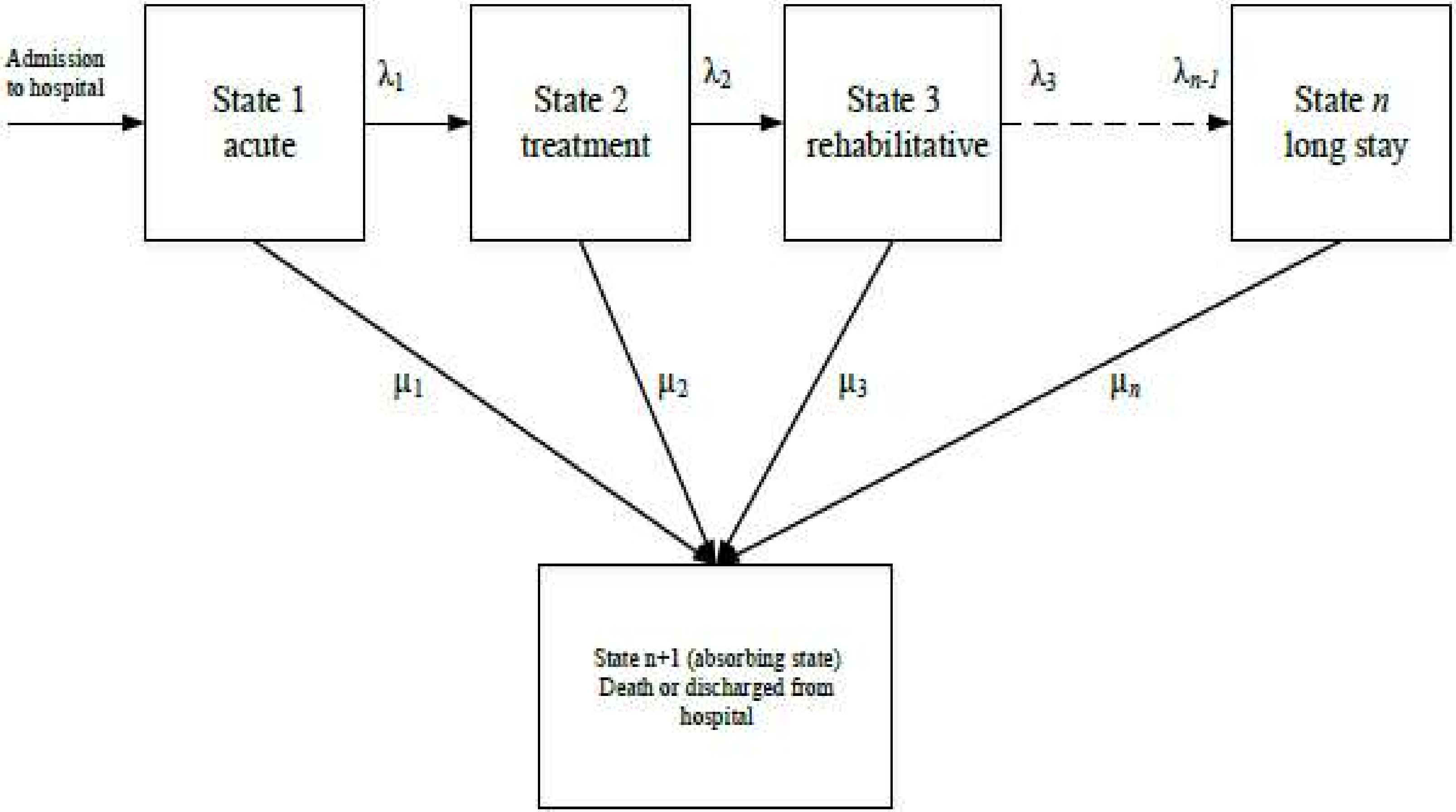

Coxian phase type distributions

A process can start only in the first state (state 1).

Sequential transition rate is λ_k.

Also transition rate from any state k to the absorbing state n+1 is μ_k.

Coxian phase type distributions

The PDF for the duration before absorption:

$$\mathrm{f}\left(t\right)=\mathbf{p}\exp\left(\mathbf{Q}t\right)\mathbf{q}$$

where the initial state probability distribution

$$\mathbf{p}=(1\ 0\ 0\ \ldots 0\ 0)$$

absorption probabilities

$$\mathbf{q}=\left(\mu_1\quad \mu_2\quad \ldots\quad \mu_{n-2}\quad \mu_n\right)^{\mathrm{T}}\ .$$

Coxian phase type distributions

And the transition matrix

$$\mathbf{Q} = \begin{pmatrix} -(\lambda_1+\mu_1) & \lambda_1 & 0 & \cdots & 0 & 0 \\ 0 & -(\lambda_2+\mu_2) & \lambda_2 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \cdots & 0 & 0 \\ 0 & 0 & 0 & 0 & -(\lambda_{n-1}+\mu_{n-1}) & \lambda_{n-1} \\ 0 & 0 & 0 & \cdots & 0 & -\mu_n \end{pmatrix}$$

Coxian phase type distributions

The likelihood function:

$$l = \prod_{i=1}^{N} \left(\mathbf{p} \exp\left\{ \mathbf{Q} t_i \right\} \mathbf{q} \right)$$

where *N* is the total number of patients in the care system.

Coxian phase type distributions

The loglikelihood function

$$L=\sum_{i=1}^{N}\left(\log\left(\mathbf{p}\exp\left\{\mathbf{Q}t_i\right\}\mathbf{q}\right)\right).$$

Or

$$L=\sum_{i=1}^{N}f(t_i)$$

where $f(t_i)=\log\left(\mathbf{p}\exp\left\{\mathbf{Q}t_i\right\}\mathbf{q}\right)$

Weighted-Average Information Criterion

WIC (Weighted-Average Information Criterion) is a weighted average of the Bayesian information criterion and the Akaike information criterion with a small sample size correction.

Weighted-Average Information Criterion

WIC (Weighted-Average Information Criterion) is a weighted average of the Bayesian information criterion and the Akaike information criterion with a small sample size correction.

The splitting criteria based on the WIC combines the strengths of both the AIC and the BIC it works well with small and large sample sizes and in the situation where sample size is not known.

Weighted-Average Information Criterion

The performance of WIC was compared with several other popular criteria in the study and the results showed that WIC is very reliable.

$$WIC = -2L + d + \frac{d(((\log(N) - 1)\ \log(N))(N - (d - 1))^2 + 2N(N + (d + 1)))}{(2N + (\log(N)(N - (d + 1))))(N - (d + 1))}\ .$$

Survival tree

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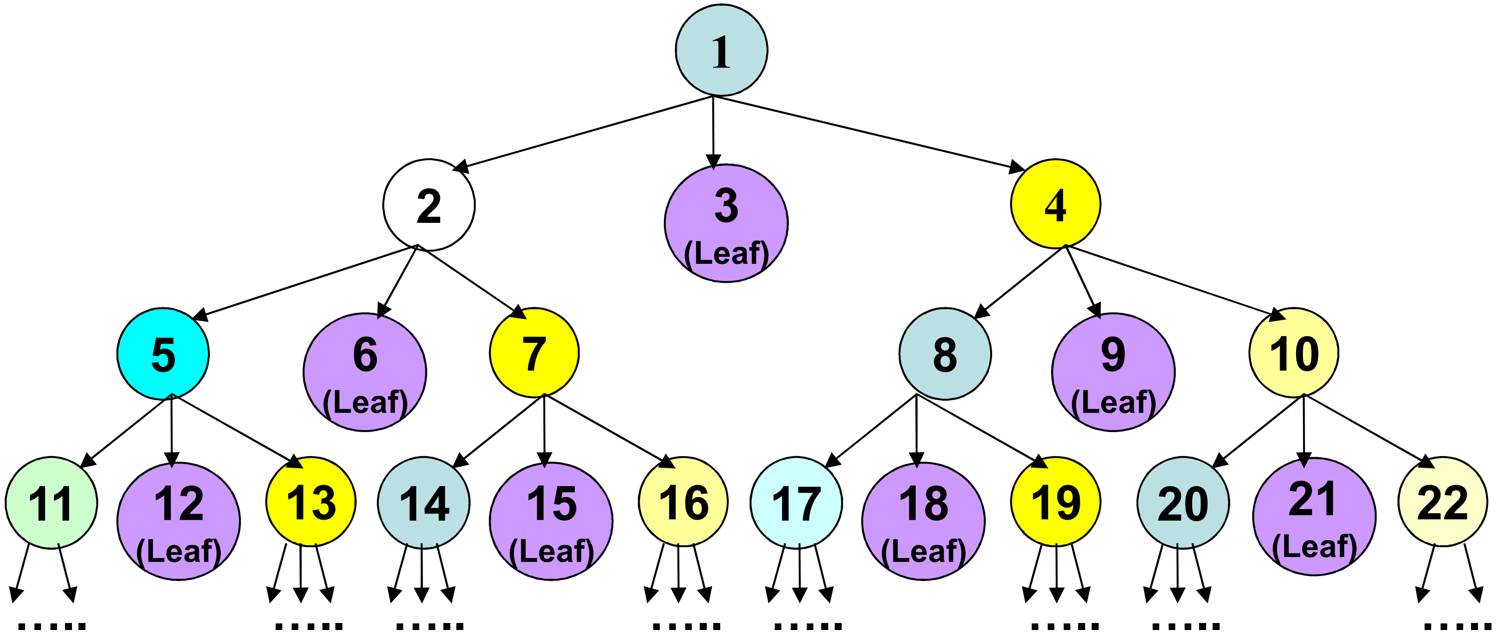
Survival tree



Survival trees

- Decision trees in survival analysis

Survival trees

- Decision trees in survival analysis
- A type of classification and regression trees

Survival trees

- Decision trees in survival analysis
- A type of classification and regression trees
- Constructed by recursively partitioning the given dataset in to subsets based on some splitting and selection criteria.

Phase type survival tree

Phase type survival trees

- A powerful non-parametric method of clustering survival data for prognostication

Phase type survival trees

- A powerful non-parametric method of clustering survival data for prognostication

  - To determine importance and effect of various covariates (such as patient's characteristics)

Phase type survival trees

- A powerful non-parametric method of clustering survival data for prognostication

  - To determine importance and effect of various covariates (such as patient’s characteristics)

  - Their interrelation on patient’s survival, treatment outcome, disease risk, disease progress or hospital length of stay

Phase type survival tree

- Each node of *the survival tree* is separately modeled by *phase type distributions*

Phase type survival tree

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- It combines the merits of both phase type distributions and survival trees.

Phase type survival tree

- Each node of *the survival tree* is separately modeled by *phase type distributions*

- It combines the merits of both phase type distributions and survival trees.

- Reduces the dimensionality of data and explains the variations in the data.

Tree construction

Two steps

Growing: splitting a node into child nodes

Tree construction

Two steps

Growing: splitting a node into child nodes

Selection: determining if a node is terminal node. If it is not then selecting the best possible partition by exploring all possible splits.

Tree growing

Growing: by recursively partitioning into sub groups by the covariates based on some splitting criteria.

At each node apply one covariate at a time and repeat this with other covariates.

Tree growing

Splitting criteria: maximizing either within node homogeneity or between node separation.

- We used splitting criteria to maximize within node homogeneity based on improvement of WIC functions

Tree growing

A covariate *a* can have any of the *l* values such that

$$N = N_{a1} + N_{a2} + \ldots + N_{al} = \sum_{i=1}^{l} N_{ai} \ .$$

The loglikelihood of node *a* is

$$L = \sum_{j=1}^{l} \sum_{i=1}^{N_{aj}} f(t_{iaj}) = \sum_{i=1}^{N_{a1}} f(t_{ia1}) + \sum_{i=1}^{N_{a2}} f(t_{ia2}) + \ldots + \sum_{i=1}^{N_{al}} f(t_{ial})$$

Or $$L = L_{a1} + L_{a2} + \ldots + L_{al} = \sum_{i=1}^{l} L_{ai} \ .$$

Tree growing

Similarly, WIC of node *a* is

$$WIC = WIC_{a1} + WIC_{a2} + \ldots + WIC_{al} = \sum_{i=1}^{l} WIC_{ai} \quad .$$

Node selection

For each possible split of a node, record the total WIC after the split.

The split which maximizes the total WIC of sub-groups is determined as follows:

$$WIC_{\max} = \max(WIC_a,\ WIC_b, \ldots\ldots\ldots, WIC_l)$$

Node selection

If WIC_{max} is greater than WIC of the node before the split, select the split with WIC equal to WIC_{max} else record the node as a terminal node.

Node selection

If *WIC*$_{max}$ is greater than WIC of the node before the split, select the split with WIC equal to *WIC*$_{max}$ else record the node as a terminal node.

Terminal node: A terminal node is the node at which within node homogeneity cannot significantly be improved by any possible split.

Dataset

To evaluate the model we used the discharge dataset from the Emergency department at the Mater Dei Hospital Malta of all patients discharged in 2011-2014.

Dataset

We used covariates that represent the patient characteristics:

Age

Gender

District

Source of Admissions

Dataset

For the length of stay :

The continuous covariate was the patient's age

Three categorical covariates Gender, District and Source of Admission.

Dataset

Categorical covariate data was divide in three groups.

The cut points of the age are:

1 to 40,

41 to 70 and

71 and over.

Patients with 0 age at admission were omitted from the data.

Dataset

The gender covariate has two different values that are Female and Male.

Dataset

The gender covariate has two different values that are Female and Male.

The district covariate has six different values that are the geographical districts of Malta.

Dataset

The gender covariate has two different values that are Female and Male.

The district covariate has six different values that are the geographical districts of Malta.

Source of admission is from where the patient was admitted and has five different covariates.

Dataset

The gender covariate has two different values that are Female and Male.

The district covariate has six different values that are the geographical districts of Malta.

Source of admission is from where the patient was admitted and has five different covariates.

Each cluster was given a group number for running the Coxian Phase fittings.

Dataset

For the admissions:

- The categorical covariate was the district of the patient and

Dataset

For the admissions:

- The categorical covariate was the district of the patient and
- The categorical covariates are the age and the gender.

Dataset

For the admissions:

The categorical covariate was the district of the patient and

The categorical covariates are the age and the gender.

Each value in the covariate is given a group number to run the Coxian phase fittings for each group.

LOS-Phase type Survival tree

Node	Covariate	Covariate Value	Total Number of Patients	WIC	Mean LOS	Number of phases	Total WIC	Gain in WIC
Level 1								
1 Root Node	All	Root Node	64439	351604.66	6.8411	6	351604.66	-
	Age	**1 to 40**	**20631**	**87222.35**	**4.1304**	**6**	**341295.6**	**10309.1**
		41 to 70	**22600**	**122877.8**	**6.7443**	**5**		
		71 +	**21208**	**131195.4**	**9.5813**	**5**		
	District	South	22237	121077.72	6.756	5	351775.15	-170.49
		Central	19480	107177.13	6.9864	4		
		West	8423	46460.1	7.0515	5		
		North	13542	72716.7	6.6032	4		
		Gozo	539	3227.25	8.3358	5		
		Unknown	218	1116.25	5.5	4		
	Source	Elderly Home	1925	11775.05	9.4732	6	351078.46	526.2
		Home	61356	332501.72	6.7339	6		
		Labour Ward	2	32.84	4.5	6		
		Other (Gov Hospital, Private, Mental and Abroad)	1060	6297.08	8.4632	6		
		Police Custody	96	471.77	4.7604	2		
	Gender	Female	32886	179393.48	6.8672	6	351637.51	-32.85
		Male	31553	172244.02	6.814	5		

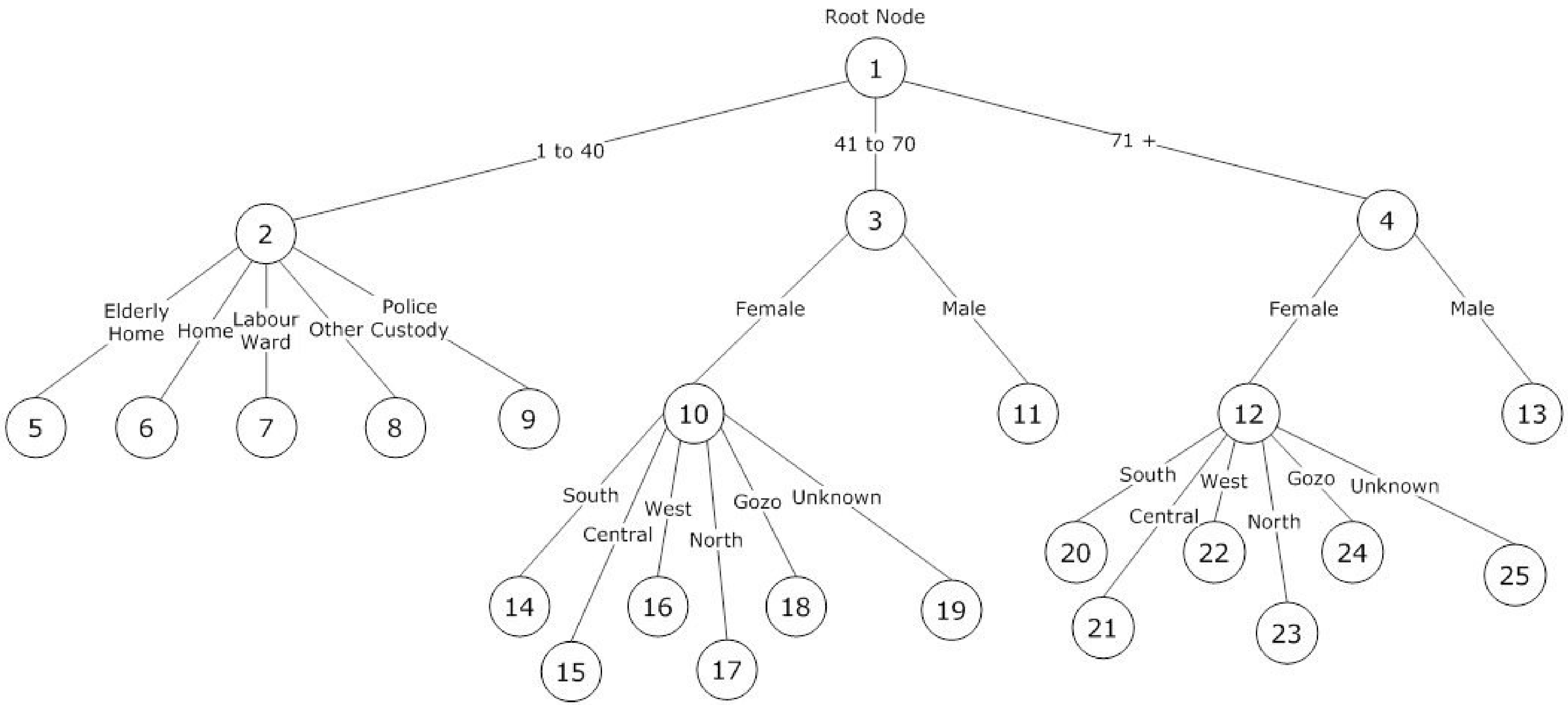
LOS-Phase type Survival tree

Node	Covariate	Covariate Value	Total Number of Patients	WIC	Mean LOS	Number of phases	Total WIC	Gain in WIC
Level 3								
10 (Age 41 to 70, Female)	All	Age 41 to 70, Female	9088	49410.24	6.817	4	49410.24	-
	District	**41 to 70, South, F**	**3164**	**17051**	**6.8587**	**6**	49148.34	261.9
		41 to 70, Central, F	**2782**	**15094.21**	**6.8724**	**5**		
		41 to 70, West, F	**1123**	**6118.53**	**6.9154**	**5**		
		41 to 70, North, F	**1933**	**10357.31**	**6.5525**	**3**		
		41 to 70, Gozo, F	**55**	**366.03**	**9.9454**	**1**		
		41 to 70, Unknown, F	**31**	**161.25**	**4.9678**	**3**		
	Source of Admission	41 to 70, Elderly Home, F	81	561.03	12.4445	3	49396.46	13.78
		41 to 70, Home, F	8835	47791.27	6.7268	4		
		41 to 70, Labour Ward, F	1	3.89	7	1		
		41 to 70, Other (Gov Hospital, Private, Mental and Abroad), F	170	1038.88	8.8529	4		
		41 to 70, Police Custody, F	1	1.39	2	1		

LOS-Phase type Survival tree

Node	Covariate	Covariate Value	Total Number of Patients	WIC	Mean LOS	Number of phases	Total WIC	Gain in WIC
Level 3								
12 (Age 71 +, Female)	All	Age 71 +, Female	11578	72543.24	9.9719	5	72543.24	-
	District	**71 +, South, F**	**3663**	**22859.81**	**9.8444**	**6**	**72219.66**	**323.58**
		71 +, Central, F	**3880**	**24104.55**	**9.8023**	**6**		
		71 +, West, F	**1736**	**11040.79**	**10.4919**	**4**		
		71 +, North, F	**2242**	**13837.2**	**10.0589**	**6**		
		71 +, Gozo, F	**40**	**287.23**	**12.825**	**1**		
		71 +, Unknown, F	**17**	**90.08**	**4.8235**	**1**		
	Source of Admission	71 +, Elderly Home, F	1257	7655.41	9.4121	4	72532.89	10.35
		71 +, Home, F	10093	63415.04	10.0396	6		
		71 +, Other (Gov Hospital, Private, Mental and Abroad), F	228	1462.44	10.057	4		

LOS-Phase type Survival tree



Admissions Phase-Type Survival Tree Construction

Node	Covariate	Covariate Value	Total Admissions	WIC	Mean	Number of Phases	Average WIC	Total WIC	Gain in WIC
Level 1									
1 (Root Node)	All	Root Node	32277	3171.43	89.43	22	3171.43	3171.43	-
	Age	1 to 40	10386	2561.57	29.45	10	853.86	2576.47	594.96
		41 to 70	11244	2590.39	31.81	10	863.46		
		71 +	10647	2577.45	30.17	10	859.15		
	Gender	Female	16510	2793.52	44.2	10	1396.76	2811.39	360.04
		Male	15767	2829.26	46.23	10	1414.63		
	District	**South**	**11211**	**2581.18**	**31.72**	**10**	**430.2**	**1756.39**	**1415.04**
		Central	**9690**	**2491.79**	**27.55**	**10**	**415.3**		
		West	**4270**	**2051.09**	**12.7**	**10**	**341.85**		
		North	**6774**	**2289.19**	**19.56**	**10**	**381.53**		
		Gozo	**289**	**895.58**	**1.79**	**6**	**149.26**		
		Unknown	**43**	**229.51**	**1.12**	**10**	**38.25**		

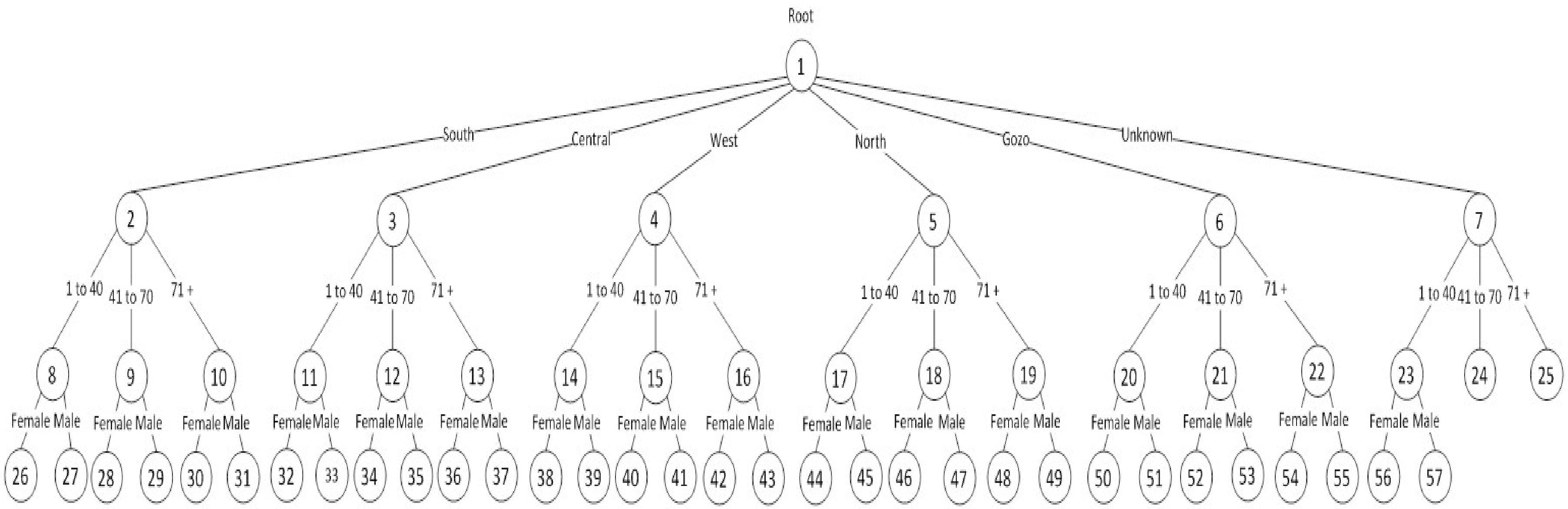
Admissions Phase-Type Survival Tree Construction

Node	Covariate	Covariate Value	Total Admissions	WIC	Mean	Number of Phases	Average WIC	Total WIC	Gain in WIC
Level 3									
8 (South, 1 to 40)	Gender	Female	2263	1817.71	7.2	5	50.49	94.97	17.71
		Male	1518	1601.38	5.16	5	44.48		
9 (South, 41 to 70)	Gender	Female	1602	1617.75	5.39	5	44.94	94.31	18.11
		Male	2413	1777.52	7.61	7	49.38		
10 (South, 71 +)	Gender	Female	1804	1680.7	5.94	5	46.69	91.78	17.34
		Male	1611	1623.45	5.41	5	45.1		
11 (Central, 1 to 40)	Gender	Female	1761	1719.87	5.82	5	47.77	89.34	16.18
		Male	1191	1496.32	4.26	5	41.56		
12 (Central, 41 to 70)	Gender	Female	1325	1565.73	4.63	5	43.49	91.16	17.21
		Male	1942	1716.2	6.32	6	47.67		
13 (Central, 71 +)	Gender	Female	1934	1725.28	6.3	5	47.92	92.36	18.68
		Male	1537	1599.83	5.21	5	44.44		
14 (West, 1 to 40)	Gender	Female	820	1357.36	3.25	4	37.7	69.44	18.49
		Male	506	1142.3	2.39	4	31.73		
15 (West, 41 to 70)	Gender	Female	565	1200.36	2.55	4	33.34	70.41	16.41
		Male	840	1334.26	3.3	4	37.06		

Admissions Phase-Type Survival Tree Construction

Node	Covariate	Covariate Value	Total Admissions	WIC	Mean	Number of Phases	Average WIC	Total WIC	Gain in WIC
Level 3									
16 (West, 71 +)	Gender	Female	908	1387.43	3.49	4	38.54	71.95	18.17
		Male	631	1202.62	2.73	4	33.41		
17 (North, 1 to 40)	Gender	Female	1304	1563.15	4.57	4	43.42	81.14	15.86
		Male	882	1357.83	3.42	4	37.72		
18 (North, 41 to 70)	Gender	Female	959	1411.44	3.63	4	39.21	84.06	17.54
		Male	1469	1614.66	5.02	5	44.85		
19 (North, 71 +)	Gender	Female	1125	1488.1	4.08	4	41.34	81.41	17.05
		Male	1035	1442.69	3.84	4	40.07		
20 (Gozo, 1 to 40)	Gender	Female	64	323.82	1.18	10	8.99	16.17	12.16
		Male	50	258.44	1.14	10	7.18		
21 (Gozo, 41 to 70)	Gender	Female	64	323.82	1.18	10	8.99	20.15	9.06
		Male	82	401.76	1.23	10	11.16		
22 (Gozo, 71 +)	Gender	Female	24	100.2	1.07	10	2.78	7.27	9.26
		Male	35	161.34	1.1	10	4.48		
23 (Unknown, 1 to 40)	Gender	Female	13	22.86	1.04	10	0.64	1.89	5.29
		Male	14	45.21	1.04	10	1.26		

Admissions Phase-Type Survival Tree Construction



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Phase-Type Survival Tree Construction

- The Length of Stay phase-type survival tree has 19 leaf nodes and has a total Gain in WIC of 12619.16.

Phase-Type Survival Tree Construction

- The Length of Stay phase-type survival tree has 19 leaf nodes and has a total Gain in WIC of 12619.16.
- The Admissions phase-type survival tree has 34 leaf nodes and a total Gain in WIC of 2111.41.

Prognostication

- Both phase-type survival trees are showing
  - Analysis of the determined patient groups from our dataset.

Prognostication

- Predictions can be made from the data used to construct the Phase-type survival tree
  - For the number of admissions by the patient grouping and

Prognostication

- Predictions can be made from the data used to construct the Phase-type survival tree
  - For the number of admissions by the patient grouping and
  - We can predict the LOS of a patient by his/her characteristics.

LOS-Prediction

Gender	Age	District	Source	Admission Date	Discharge Date	Actual LOS	Predicted LOS
M	1	South	Home	15/12/2012	19/12/2012	5	4.122102
M	67	Central	Home	21/12/2012	31/12/2012	11	6.744455
F	86	South	Home	18/12/2012	24/12/2012	7	9.960199
F	24	West	Home	22/12/2012	24/12/2012	3	4.122102
M	64	South	Home	15/12/2012	18/12/2012	4	6.744455
M	77	West	Elderly Home	26/12/2012	31/12/2012	6	9.189538
M	16	North	Home	20/12/2012	20/12/2012	1	4.122102
F	94	South	Home	18/12/2012	20/12/2012	3	9.960199
M	57	Central	Home	15/12/2012	19/12/2012	5	6.744455
F	49	Central	Home	20/12/2012	21/12/2012	2	6.916771

Admission Predictions

Admissions Date	Group	Actual Admissions	Predicted Admissions
31/12/2011	41 to 70 Unknown	0	0.04
28/12/2011	1 to 40, South, Male	3	4.15
24/12/2011	1 to 40, Central Males	2	3.28
28/12/2011	1 to 40, West, Males	1	1.39
26/12/2011	1 to 40, North, Males	1	2.45
27/12/2011	1 to 40, Gozo, Males	0	0.14
27/12/2011	1 to 40, Unknown, Males	0	0.04
19/12/2011	1 to 40, South, Females	7	6.30
29/12/2011	1 to 40, Central, Females	3	4.87
30/12/2011	1 to 40, West, Females	2	2.28
28/12/2011	1 to 40, North, Females	5	3.59
24/12/2011	1 to 40, Gozo, Females	0	0.18
24/12/2011	1 to 40, Unknown, Females	0	0.03
28/12/2011	41 to 70, South, Males	12	6.54
19/12/2011	41 to 70, Central, Males	7	5.30
26/12/2011	41 to 70, West, Males	5	2.27
15/12/2011	41 to 70, North, Males	6	2.61

Admission Predictions

Admissions Date	Group	Actual Admissions	Predicted Admissions
29/12/2011	41 to 70, Gozo, Males	0	0.22
23/12/2011	41 to 70, South, Females	7	4.39
29/12/2011	41 to 70, Central, Females	3	3.63
20/12/2011	41 to 70, West, Females	0	1.59
25/12/2011	41 to 70, North, Females	4	4.02
28/12/2011	41 to 70, Gozo, Females	0	0.18
24/12/2011	71 +, South, Males	8	4.41
30/12/2011	71 +, Central, Males	4	4.16
31/12/2011	71 +, West, Males	1	1.71
17/12/2011	71 +, North, Males	3	2.80
26/12/2011	71 +, Gozo, Males	1	0.10
17/12/2011	71 +, South, Females	4	4.87
16/12/2011	71 +, Central, Females	6	5.15
30/12/2011	71 +, West, Females	3	2.47
16/12/2011	71 +, North, Females	3	3.06
31/12/2011	71 +, Gozo, Females	0	0.07

Construction of Phase-Type Survival Tree showing Effect of Weather on LOS

Level	Covariate	Covariate Group	No. of Patients	Mean LOS	WIC	Total WIC	WIC Gain
1 (Root)	*All*	*Root*	*66166*	*6.88*	*361646.80*	*361646.80*	
	MinTemp	0°C-10°C (1)	16465	7.19	91916.01	361631.50	15.30
		11°C-20°C (2)	33516	6.76	181607.62		
		21°C-30°C (3)	16185	6.83	88107.87		
	MaxTemp	**0°C-10°C(1)**	**303**	**8.13**	**1786.56**	**349779.14**	**11867.67**
		11°C-20°C (2)	**28333**	**6.95**	**143924.01**		
		21°C-30°C (3)	**25205**	**6.83**	**137012.30**		
		31+°C (4)	**12325**	**6.82**	**67056.27**		
	AvgTemp	0°C-10°C (1)	4834	7.23	26828.01	361381.17	265.63
		11°C- 20°C (2)	34493	6.87	188586.75		
		21°C-30°C (3)	26090	6.83	141956.96		
		31+°C (4)	749	6.88	4009.44		
	MaxVar	x<-2°C (1)	4032	7.02	22086.49	361419.43	227.37
		-2°C $\leq$ x $\leq$ -1°C (2)	18199	6.78	99118.57		
		0°C (3)	19042	6.79	103741.30		
		1°C $\leq$ x $\leq$ 2°C (4)	21365	7.02	117284.96		
		x >2°C (5)	3528	6.88	19188.12		

Construction of Phase-Type Survival Tree showing Effect of Weather on LOS

Level	Covariate	Covariate Group	No. of Patients	Mean LOS	WIC	Total WIC	WIC Gain
2 (0°C-10°C Max)	*All*	*0° C-10° C (1)*	*303*	*8.13*	*1786.56*	*1786.56*	
	MinTemp	0°C-10°C (1)	303	8.13	1786.56	1786.56	0.00
		11°C-20 (2)	0	0.00	0.00		
		21°C-30°C (3)	0	0.00	0.00		
	AvgTemp	0°C-10°C (1)	303	8.13	1786.56	1786.56	0.00
		11°C-20°C (2)	0	0.00	0.00		
		21°C-30°C (3)	0	0.00	0.00		
		31+°C (4)	0	0.00	0.00		
	MaxVar	x<-2°C (1)	104	9.50	619.01	1809.80	-23.24
		-2°C $\leq$ x $\leq$ -1°C (2)	97	7.59	584.81		
		0°C (3)	102	7.25	605.99		
		1°C $\leq$ x $\leq$ 2°C (4)	0	0.00	0.00		
		x >2°C (5)	0	0.00	0.00		

Construction of Phase-Type Survival Tree showing Effect of Weather on LOS

Level	Covariate	Covariate Group	No. of Patients	Mean LOS	WIC	Total WIC	WIC Gain
2 (11°C-20°C Max)	*All*	*11° C-20° C (2)*	*28333*	*6.83*	*143924.01*	*143924.01*	
	MinTemp	0°C-10°C (1)	15983	7.19	88145.39	154784.63	-10860.62
		11°C-20°C (2)	12350	6.63	66639.23		
		21°C-30°C (3)	0	0.00	0.00		
	AvgTemp	0°C°C-10°C (1)	4531	7.17	25082.63	155610.36	-11686.34
		11°C-20°C (2)	23802	6.90	130527.73		
		21°C-30°C (3)	0	0.00	0.00		
		31+°C (4)	0	0.00	0.00		
	MaxVar	x<-2°C (1)	1818	6.98	10045.36	154715.89	-10791.88
		-2°C ≤ x ≤ -1°C (2)	8495	6.78	45964.04		
		0°C (3)	8287	6.72	44646.01		
		1°C ≤ x ≤ 2°C (4)	8551	7.23	47346.72		
		x >2°C (5)	1182	7.59	6713.75		

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Construction of Phase-Type Survival Tree showing Effect of Weather on LOS

Level	Covariate	Covariate Group	No. of Patients	Mean LOS	WIC	Total WIC	WIC Gain
2(21°C-30°C Max)	*All*	*21°C-30°C (3)*	*25205*	*6.83*	*137012.30*	*137012.30*	
	MinTemp	0°C-10°C (1)	179	6.13	967.79	136794.76	217.54
		11°C-20°C (2)	20347	6.83	110539.41		
		21°C-30°C (3)	4679	6.84	25287.56		
	AvgTemp	**0°C-10°C (1)**	**0**	**0.00**	**0.00**	**136265.41**	**746.88**
		11°C-20°C (2)	**10691**	**6.81**	**57269.63**		
		21°C-30°C (3)	**14514**	**6.84**	**78995.78**		
		31+°C (4)	**0**	**0.00**	**0.00**		
	MaxVar	x<-2°C (1)	1203	6.92	6576.60	136579.50	432.80
		-2°C ≤ x ≤ -1°C (2)	6861	6.77	36677.42		
		0°C (3)	7826	6.89	42694.92		
		1°C ≤ x ≤ 2°C (4)	8472	6.88	46191.76		
		x >2°C (5)	843	6.04	4438.80		

Construction of Phase-Type Survival Tree showing Effect of Weather on LOS

Level	Covariate	Covariate Group	No. of Patients	Mean LOS	WIC	Total WIC	WIC Gain
3(21°C-30°C Max, 11°C-20°C Avg)	*All*	*11°C-20°C (2)*	*10691*	*6.81*	*57269.63*	*57269.63*	
	MinTemp	0°C-10°C (1)	179	6.13	961.29		
		11°C-20°C (2)	10512	6.82	57122.54	58083.83	-814.20
		21°C-30°C (3)	0	0.00	0.00		
	MaxVar	x<-2°C (1)	397	5.66	2036.82		
		-2°C ≤ x ≤ -1°C (2)	2405	6.95	13061.90		
		0°C (3)	2666	6.88	14272.56	57493.12	-223.49
		1°C ≤ x ≤ 2°C (4)	4736	6.87	25550.60		
		x >2°C (5)	487	6.00	2571.25		
3(21°C-30°C Max, 21°C-30°C Avg)	*All*	*21°C-30°C (3)*	*14514*	*6.84*	*78995.78*	*78995.78*	
	MinTemp	**0°C-10°C (1)**	**0**	**0.00**	**0.00**		
		11°C-20°C (2)	**9835**	**6.85**	**52787.28**	**78354.56**	**641.22**
		21°C-30°C(3)	**4679**	**6.84**	**25567.28**		
	MaxVar	x<-2°C (1)	806	7.54	4555.23		
		-2°C ≤ x ≤ -1°C (2)	4456	6.68	23671.22		
		0°C (3)	5160	6.90	28290.46	78571.35	424.43
		1°C ≤ x ≤ 2°C (4)	3736	6.88	20163.21		
		x >2°C (5)	356	6.10	1891.23		

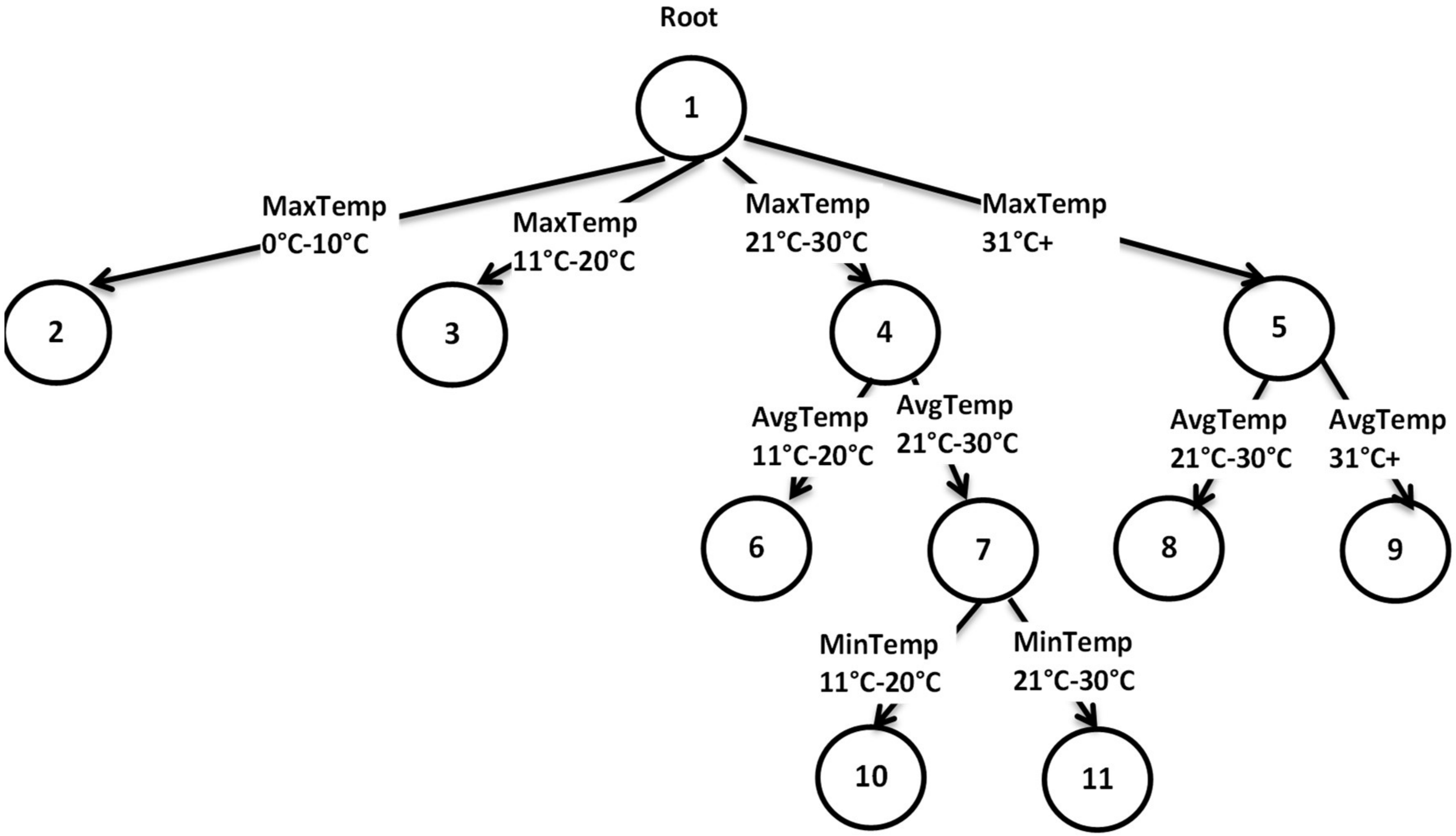
Construction of Phase-Type Survival Tree showing Effect of Weather on LOS

Level	Covariate	Covariate Group	No. of Patients	Mean LOS	WIC	Total WIC	WIC Gain
2(31+°C Max)	*All*	*31+°C (4)*	*12325*	*6.82*	*67056.27*	*67056.27*	
	MinTemp	0°C-10°C (1)	0	0.00	0.00	67053.54	2.73
		11°C-20°C (2)	820	6.70	4466.70		
		21°C-30°C (3)	11505	6.83	62586.84		
	AvgTemp	**0°C-10°C (1)**	**0**	**0.00**	**0.00**	**66238.27**	**818.00**
		11°C-20°C (2)	**0**	**0.00**	**0.00**		
		21°C-30°C (3)	**11576**	**6.82**	**62203.93**		
		31+°C (4)	**749**	**6.88**	**4034.35**		
	MaxVar	x<-2°C (1)	907	6.96	4967.36	66443.03	613.24
		-2°C ≤ x ≤ -1°C (2)	2746	6.79	14698.72		
		0°C (3)	2827	6.70	15140.27		
		1°C ≤ x ≤ 2°C (4)	4342	6.90	23535.51		
		x >2°C (5)	1503	6.80	8101.17		

Construction of Phase-Type Survival Tree showing Effect of Weather on LOS

Level	Covariate	Covariate Group	No. of Patients	Mean LOS	WIC	Total WIC	WIC Gain
3(31+°C Max, 21°C-30°C Avg)	*All*	*21° C-30° C (3)*	*11576*	*6.82*	*62203.93*	*62203.93*	
	MinTemp	0°C-10°C (1)	0	0.00	0.00		
		11°C-20°C (2)	820	6.70	4466.70	63023.76	-819.83
		21°C-30°C (3)	10756	6.83	58557.06		
	MaxVar	x<-2°C (1)	820	7.04	4489.42		
		-2°C ≤ x ≤ -1°C (2)	2546	6.80	13659.83		
						62465.66	-261.73
		0°C (3)	2827	6.70	15140.27		
		1°C ≤ x ≤ 2°C (4)	4243	6.90	23001.58		
		x >2°C (5)	1140	6.68	6174.55		
3(31+°C Max, 31+°C Avg)		**31+°C (4)**	**749**	**6.88**	**4034.35**	**4034.35**	
	MinTemp	0°C-10°C (1)	0	0.00	0.00		
		11°C-20°C (2)	0	0.00	0.00	4061.80	-27.45
		21°C-30°C (3)	749	6.88	4061.80		
	MaxVar	x<-2°C (1)	87	6.20	485.00		
		-2°C ≤ x ≤ -1°C (2)	200	6.62	1074.44		
		0°C (3)	0	0.00	0.00	4082.57	-48.23
		1°C ≤ x ≤ 2°C (4)	99	6.93	554.99		
		x >2°C (5)	363	7.17	1968.14		

Phase-Type Survival Tree showing Effect of Weather on LOS



Phase-Type Survival Tree showing Effect of Weather on LOS

- Most significant prognostic factor affecting the patients' length of stay (LOS) is the maximum temperature.

Phase-Type Survival Tree showing Effect of Weather on LOS

- Most significant prognostic factor affecting the patients' length of stay (LOS) is the maximum temperature.

- The average temperature affects the patients' length of stay only when the maximum temperature rises beyond 20ºC.

Phase-Type Survival Tree showing Effect of Weather on LOS

- The minimum temperature does not significantly affect the patients' length of stay.

Phase-Type Survival Tree showing Effect of Weather on LOS

- The minimum temperature does not significantly affect the patients' length of stay.

- Also, the maximum variability in the average temperature between one day and the next does not affect patients' length of stay as patients usually stay inside.

Phase-Type Survival Tree showing Effect of Weather on LOS

- These results might be different for different geographic regions due to different weather conditions and different genetic profile of inhabitants there.

Phase-Type Survival Tree showing Effect of Weather on LOS

Predictions and Accuracy Tests

Group	No. of Patients	Actual Mean LOS	Predicted Mean LOS	Forecast Error	Squared Error	Absolute Error	Percentage Error (%)
MaxTemp(0°C-10°C)	0	-	8.13	-	-	-	-
MaxTemp(11°C-20°C)	13406	7.19	6.83	-0.36	0.13	0.36	5.01
MaxTemp(21°C-30°C), AvgTemp(11°C-20°C)	6003	7.01	6.81	-0.20	0.04	0.20	2.85
MaxTemp(21°C-°C30),AvgTemp(21°C-30°C), MinTemp(11°C-20°C)	5850	6.78	6.85	0.07	0.00	0.07	1.03
MaxTemp(21°C-30°C),AvgTemp(21°C-30°C), MinTemp(21°C-30°C)	4520	6.47	6.84	0.37	0.14	0.37	5.72
MaxTemp(31+°C), AvgTemp(21°C-30°C)	0	-	6.82	-	-	-	-
MaxTemp(31+°C), AvgTemp(31+°C)	4471	6.72	6.88	0.16	0.03	0.16	2.38

Construction of Phase-Type Survival Tree showing Effect of Weather on Admissions

Level	Covariate	Covariate Group	No. of Records	Mean Admissions	WIC	Average WIC	Total Average WIC	WIC Gain
1 (Root)	*ALL*	*Root*	*721*	*91.04*	*6522.86*	*6522.86*	*6522.86*	
	Min	0°C-10°C (1)	174	94.63	1653.37	551.12	2249.21	4273.65
		11°C-20°C(2)	376	89.14	3421.33	1140.44		
		21°C-30°C (3)	181	89.41	1672.91	557.64		
	Max	0°C-10°C (1)	3	101.00	38.93	9.73	1690.81	4832.05
		11°C-20°C (2)	306	92.59	2848.41	712.10		
		21°C-30°C (3)	283	89.07	2580.33	645.08		
		31+°C (4)	139	88.67	1295.56	323.89		
	Avg	0°C-10°C (1)	49	98.65	495.38	123.84	1690.54	4832.32
		11°C- 20°C (2)	379	91.01	3490.43	872.61		
		21°C-30°C (3)	295	88.44	2685.31	671.33		
		31+°C (4)	8	93.62	91.04	22.76		
	MaxVar	**x<-2°C (1)**	**45**	**89.60**	**449.32**	**89.86**	**1369.18**	**5153.68**
		-2°C $\leq$ x $\leq$ -1°C (2)	**200**	**91.00**	**1867.44**	**373.49**		
		0°C (3)	**212**	**89.82**	**1956.63**	**391.33**		
		1°C $\leq$ x $\leq$ 2°C (4)	**236**	**90.53**	**2186.84**	**437.37**		
		x >2°C (5)	**38**	**92.87**	**385.68**	**77.14**		

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Construction of Phase-Type Survival Tree showing Effect of Weather on Admissions

Level	Covariate	Covariate Group	No. of Records	Mean Admissions	WIC	Average WIC	Total Average WIC	WIC Gain
2(MaxVar, x<-2°C (1))	*All*	*$x<$-2° C (1)*	*45*	*89.60*	*449.32*	*89.86*	*89.86*	
	Min	0°C-10°C (1)	11	91.64	121.58	40.53	161.37	-71.51
		11°C-20°C (2)	19	87.37	200.39	66.80		
		21°C-30°C (3)	15	90.93	162.15	54.05		
	Max	0°C-10°C (1)	1	104.00	7.07	1.77	120.11	-30.25
		11°C-20°C (2)	20	90.90	211.72	52.93		
		21°C-30°C (3)	14	85.93	150.35	37.59		
		31+°C (4)		90.70	111.31	27.83		
	Avg	0°C-10°C (1)	6	91.83	68.79	17.20	119.49	-29.63
		11°C-20°C (2)	20	88.40	210.66	52.66		
		21°C-30°C (3)	18	90.33	191.81	47.95		
		31+°C (4)	1	87.00	6.71	1.68		

Construction of Phase-Type Survival Tree showing Effect of Weather on Admissions

Level	Covariate	Covariate Group	No. of Records	Mean Admissions	WIC	Average WIC	Total Average WIC	WIC Gain
2(MaxVar,-2°C ≤ x ≤ -1°C (2))	*All*	*-2° C ≤ x ≤ -1° C (2)*	*200*	*91.00*	*1867.44*	*373.49*	*373.49*	
	Min	0°C-10°C (1)	44	96.32	454.40	151.47	650.97	-277.48
		11°C-20°C (2)	106	89.50	1003.42	334.47		
		21°C-30°C (3)	50	89.48	495.09	165.03		
	Max	0°C-10°C (1)	1	97.00	6.93	1.73	487.78	-114.29
		11°C-20°C (2)	92	92.34	896.50	224.12		
		21°C-30°C (3)	76	90.28	730.09	182.52		
		31+°C (4)	31	88.58	317.61	79.40		
	Avg	0°C-10°C (1)	1	99.63	175.32	43.83	484.97	-111.48
		11°C-20°C (2)	103	91.29	992.95	248.24		
		21°C-30°C (3)	79	88.63	761.01	190.25		
		31+°C (4)	2	100.00	10.59	2.65		

Construction of Phase-Type Survival Tree showing Effect of Weather on Admissions

Level	Covariate	Covariate Group	No. of Records	Mean Admissions	WIC	Average WIC	Total Average WIC	WIC Gain
2(MaxVar, 0°C (3))	*All*	*0°C (3)*	*212*	*89.82*	*1956.63*	*391.33*	*391.33*	
	Min	0°C-10°C (1)	60	93.87	593.16	197.72	682.65	-291.33
		11°C-20°C (2)	109	88.20	1025.83	341.94		
		21°C-30°C (3)	43	88.28	428.98	142.99		
	Max	0°C-10°C (1)	1	102.00	7.17	1.79	510.66	-119.34
		11°C-20°C (2)	90	92.08	864.84	216.21		
		21°C-30°C (3)	89	87.93	844.45	211.11		
		31+°C (4)	32	88.34	326.19	81.55		
	Avg	0°C-10°C (1)	14	100.79	154.78	38.70	507.59	-116.27
		11°C-20°C (2)	108	89.30	1021.80	255.45		
		21°C-30°C (3)	90	88.74	853.79	213.45		
		31+°C (4)	0	0.00	0.00	0.00		

Construction of Phase-Type Survival Tree showing Effect of Weather on Admissions

Level	Covariate	Covariate Group	No. of Records	Mean Admissions	WIC	Average WIC	Total Average WIC	WIC Gain
2(MaxVar, 1°C ≤ x ≤ 2°C (4))	*All*	*1°C ≤ x ≤ 2°C (4)*	*236*	*90.53*	*2186.84*	*437.37*	*437.37*	
	Min	0°C-10°C (1)	50	93.86	507.91	169.30		
		11°C-20°C (2)	128	89.68	1208.86	402.95	761.50	-324.13
		21°C-30°C (3)	58	89.56	567.72	189.24		
	Max	**0°C-10°C (1)**	**0**	**0.00**	**0.00**	**0.00**		
		11°C-20°C (2)	**92**	**92.95**	**896.15**	**23.24**	**369.35**	**68.02**
		21°C-30°C (3)	**95**	**89.18**	**899.29**	**224.82**		
		31+°C (4)	**49**	**88.61**	**485.15**	**121.29**		
	Avg	0°C-10°C (1)	10	99.00	113.07	28.27		
		11°C-20°C (2)	134	91.77	1271.13	317.78	563.66	-126.29
		21°C-30°C(3)	91	87.68	863.45	215.86		
		31+°C (4)	1	99.00	6.97	1.74		

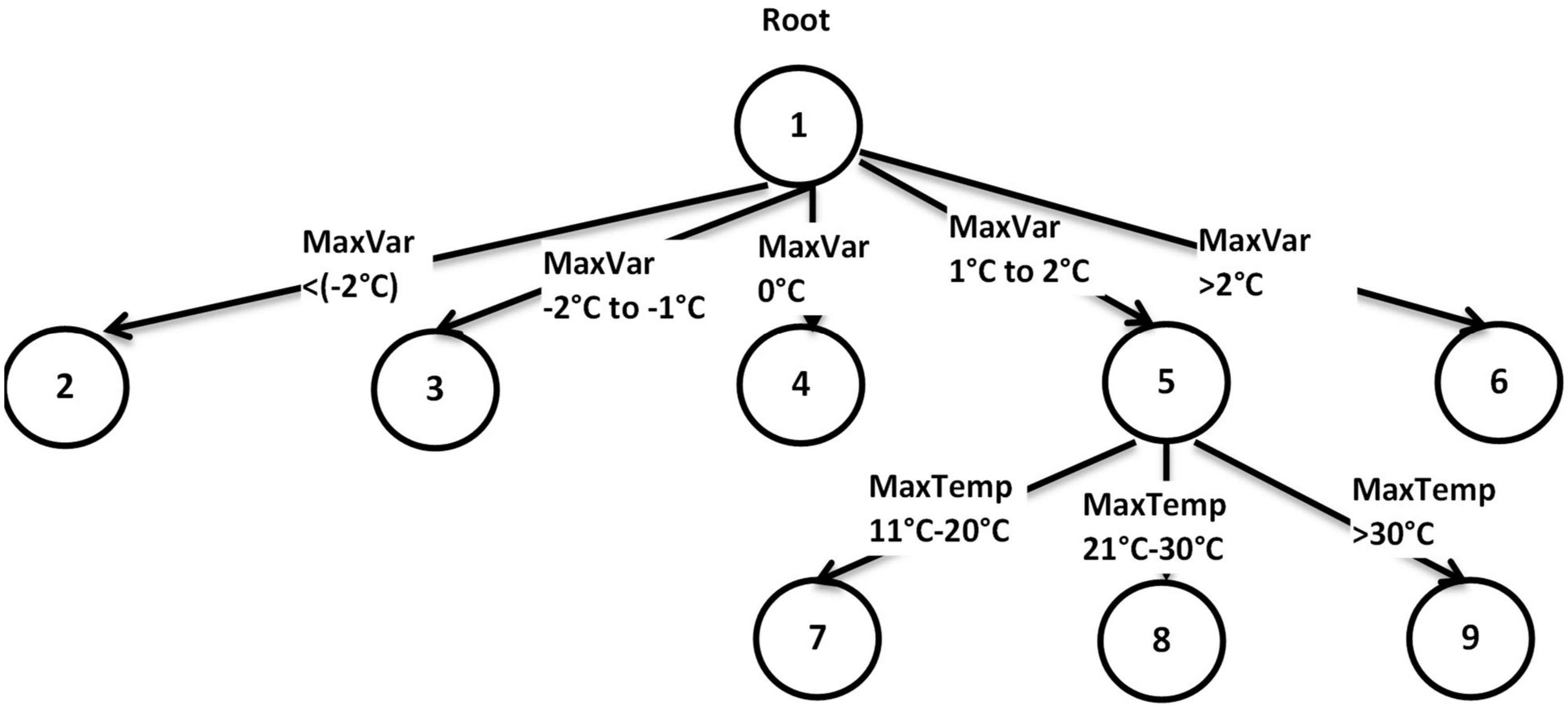
Construction of Phase-Type Survival Tree showing Effect of Weather on Admissions

Level	Covariate	Covariate Group	No. of Records	Mean Admissions	WIC	Average WIC	Total Average WIC	WIC Gain
3(MaxVar (4), Max (2))	*All*	*11- 20 (2)*	*92*	*92.95*	*896.15*	*23.24*	*23.24*	
	Min	0°C-10°C (1)	49	93.78	498.37	124.59		
		11°C-20°C (2)	43	92.00	434.78	108.69	233.29	-210.05
		21°C-30°C (3)	0	0.00	0.00	0.00		
	Avg	0°C-10°C (1)	49	93.78	498.37	124.59		
		11°C-20°C (2)	43	92.00	434.78	108.69	233.29	-210.05
		21°C-30°C (3)	0	0.00	0.00	0.00		
		31+°C (4)	0	0.00	0.00	0.00		
3(MaxVar (4), Max (3))	*All*	*21-30 (3)*	*95*	*89.18*	*899.29*	*224.82*	*224.82*	
	Min	0°C-10°C (1)	1		BAD WIC			
		11°C-20°C (2)	81	89.05	773.46	257.82	BAD WIC	BAD WI
		21°C-30°C (3)	13	89.31	141.15	47.05		
	Avg	0°C-10°C (1)	0	0.00	0.00	0.00		
		11°C-20°C (2)	52	91.08	512.81	128.20	235.24	-10.41
		21°C-30°C (3)	43	86.88	428.13	107.03		
		31+°C (4)	0	0.00	0.00	0.00		

Construction of Phase-Type Survival Tree showing Effect of Weather on Admissions

Level	Covariate	Covariate Group	No. of Records	Mean Admissions	WIC	Average WIC	Total Average WIC	WIC Gain
3(MaxVar (4), Max (4))	*All*	*31+ (4)*	*49*	*88.61*	*485.15*	*121.29*	*121.29*	
	Min	0°C-10°C (1)	0	0.00	0.00	0.00	164.93	-43.64
		11°C-20°C (2)	4	77.50	46.13	15.38		
		21°C-30°C (3)	45	89.60	448.66	149.55		
	Avg	0°C-10°C (1)	0	0.00	0.00	0.00	BAD WIC	BAD WI
		11°C-20°C (2)	0	0.00	0.00	0.00		
		21°C-30°C (3)	48	88.40	476.47	119.12		
		31+°C (4)	1		BAD WIC			
2(MaxVar, x >2°C (5))	*All*	*x >2°C (5)*	*38*	*92.87*	*385.68*	*77.14*	*77.14*	
	Min	0°C-10°C (1)	9	99.33	103.12	34.37	138.99	-61.85
		11°C-20°C (2)	14	91.29	151.95	50.65		
		21°C-30°C (3)	15	90.47	161.90	53.97		
	Max	0°C-10°C (1)	0	0.00	0.00	0.00	104.15	-27.01
		11°C-20°C (2)	12	98.50	133.30	33.32		
		21°C-30°C (3)	9	93.78	102.12	25.53		
		31+°C (4)	17	88.41	181.18	45.29		
	Avg	0°C-10°C (1)	3	96.00	38.63	9.66	105.29	-28.15
		11°C-20°C (2)	14	98.64	154.06	38.52		
		21°C-30°C (3)	17	88.06	181.07	45.27		
		31+°C (4)	4	90.75	47.39	11.85		

Phase-Type Survival Tree showing Effect of Weather on Admissions



Phase-Type Survival Tree showing Effect of Weather on Admissions

- Most significant prognostic factor affecting the number of admissions is the maximum variability in the average temperature between one day and the next.

Phase-Type Survival Tree showing Effect of Weather on Admissions

- Most significant prognostic factor affecting the number of admissions is the maximum variability in the average temperature between one day and the next.
- The maximum temperature affects the number of admissions only when the average temperature increases by 1ºC-2ºC than the previous day.

Phase-Type Survival Tree showing Effect of Weather on Admissions

- The minimum temperature and average temperature do not affect number of admissions.

Phase-Type Survival Tree showing Effect of Weather on Admissions

- The minimum temperature and average temperature do not affect number of admissions.

- These results might be different for different geographic regions due to different weather conditions and different genetic profile of inhabitants there.

Phase-Type Survival Tree showing Effect of Weather on Admissions

Predictions and Accuracy Tests

Group	No. of Records	Actual Mean Adm.	Predicted Mean Adm.	Forecast Error	Squared Error	Absolute Error	Percentage Error (%)
MaxVar(x<-2°C)	31	92.13	89.60	-2.53	6.40	2.53	2.75
MaxVar(-2°C≤x≤-1°C)	99	92.34	91.00	-1.34	1.80	1.34	1.45
MaxVar(x =0°C)	93	92.77	89.82	-2.95	8.70	2.95	3.18
MaxVar(x>2°C)	19	97.63	92.87	-4.76	22.66	4.76	4.88
MaxVar(1°C≤x≤2°C), MaxTemp (11°C-20°C)	42	100.95	92.95	-8.00	64.00	8.00	7.92
MaxVar(1°C≤x≤2°C), MaxTemp (21°C-30°C)	54	91.63	89.18	-2.45	6.00	2.45	2.67
MaxVar(1°C≤x≤2°C), MaxTemp (31+°C)	27	95.48	88.61	-6.87	47.20	6.87	7.20

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Accuracy test for all predictions

		MSE	RMSE	MAD	BIAS
LOS	*Weather*	0.08	0.28	0.26	-0.09
	Personal Characteristics	1.15	1.07	0.74	-0.69
Admissions	*Weather*	16.17	4.02	3.37	-3.37
	Personal Characteristics	1.38	1.17	0.96	-0.82

MSE: Mean Square Error,
RMSE: Root Mean Square Error,
MAD: Mean Absolute Deviation
BIAS: Bias

Conclusions

- We can use phase-type survival tree analysis to
  - Effectively prognosticate survival data and

Conclusions

- We can use phase-type survival tree analysis to
  - Effectively prognosticate survival data and
  - Cluster survival data into groups of patients following homogeneous patient pathways.

Conclusions

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Conclusions

- Our models can be used to forecast bed occupancy and the requirements.
- The LOS can be predicted at admission by the use of this model.
- The number of admissions can be forecasted by the patients' characteristics.

Conclusions

- These models can also be used to characterize the effect of weather on LOS and admissions.

Conclusions

- These models can also be used to characterize the effect of weather on LOS and admissions.
- We can also use these models to predict effect of other factors affecting LOS and admissions.

Conclusions

- These forecasts can help us better designing policies to ensure optimal utilization of scarce health resources.

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Meditec: Medical Informatics

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Why Medical Informatics

Why Medical Informatics

- **Provide an example of each.**

Provide an example of each.
Why Medical Informatics

- To Understand
  - Human body (anatomy),
  - Its mechanisms
  - Influencing factors
  - Diseases
  - Disease progression
  - Factors responsible and/or affecting
  - Factors preventing/curing
  - Medicine/treatment response
  - Patient psychology
  - Community psychology and care provider's psychology

Provide an example of each. Why Medical Informatics

- To Understand
  - Healthcare dynamics
    - Healthcare delivery processes
    - Hospital processes
    - Influencing factors
  - Disease network
  - Monitoring
    - Patient
    - Disease progression
    - Healthcare delivery processes
    - Hospital processes
    - Influencing factors

Provide an example of each.
Why Medical Informatics

- To Understand
  - Detecting
    - Diseases, disease episodes and disease state
    - Influencing factors
    - Health status
    - Disease spread
  - Predicting
    - Diseases, disease episodes and disease state
    - Treatment response
    - Policy effect/response
    - Infection spread
    - Influencing factors
    - Resource requirements

Provide an example of each.
Why Medical Informatics

- Simulating
  - Diseases
  - Disease progression
  - Healthcare delivery processes
  - Hospital processes
  - Treatment mechanism
  - Policy effect/response
  - Infection spread
  - Influencing factors
  - Resource utilization
  - Schedule
  - Disease spread
  - Disease Network

Provide an example of each.
Why Medical Informatics

- Drug development
    - Drug mechanism
    - Drug response
    - Influencing factors
- Training and Education
- Healthcare costing
- Healthcare economics
- Policy making
- Planing new healthcare delivery system/facility

Provide an example of each.
Why Medical Informatics

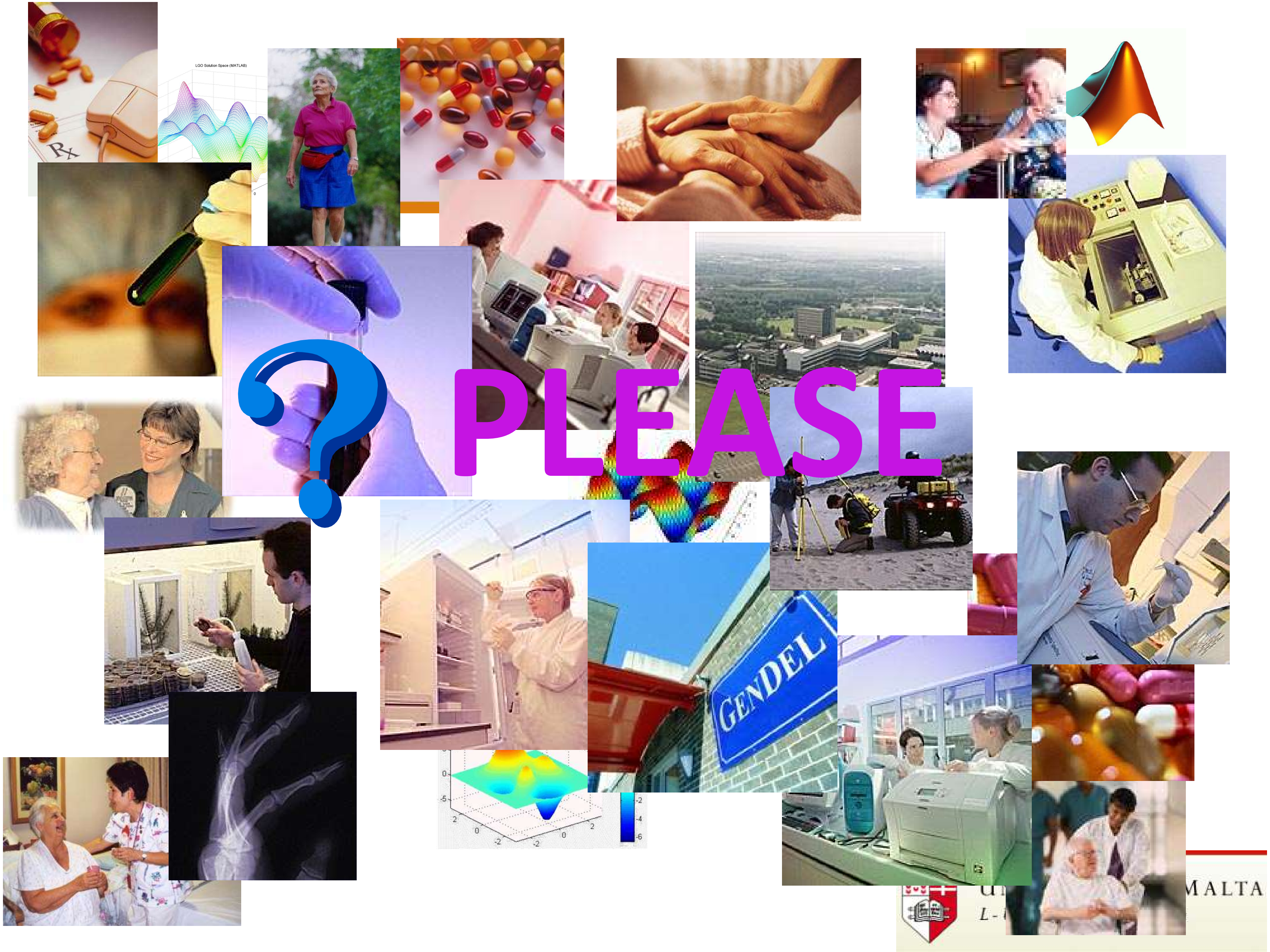
- Management/control
    - Disease management/control
    - Patient management /control
    - Healthcare resource management /control
    - Healthcare Service management /control
    - Health management
    - Information management/access control/data confidentiality/security
    - Health Data Management
    - Risk management (Health/disease/service delivery)

Evaluate the following Apps

- Diagnosis Medical App
- Prognosis: Your Diagnosis
- Medication reminder & Pill Tracker
- Ada – your health companion
- Medical Dictionary
- Medical Dictionary – Search offline
- Disorder & Diseases Dictionary 2019
- Arabic Medicine Dictionary
- Netmeds App- India's Trusted Online Pharmacy App

Evaluate the following Apps

- Full Code – Emergency Medicine Simulation
- Anatomy Learning – 3D Online Anatomy Atlas
- Pill Reminder and Medication Tracker by Medisafe
- Mediscape (WebMD, LLC)
- SastaSundar-Genuine Medicine, Pathology, Doctor App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