Artificial Health Intelligence-Making sense of health data

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Research Excellence Funds awarded to four UM academics

In Research   08:58, 04 Jan 2021

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More funding in support of the maritime field

RESEARCH 07:30, 07 Jan

Data Science Research Group

RESEARCH 08:57, 04 Jan

How do you teach behavioural economics using film?

RESEARCH 10:19, 22 Dec

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Global health challenges

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Global health challenges

1. Obesity and Chronic diseases
2. Aging
3. Drug resistance, Hospital acquired infections and medical errors
4. Global warming and pollution
5. Health inequality and healthcare finance
6. Infectious and/or zoonotic diseases and viruses
7. Stress and sleep aponia
8. Relationships and social health

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Future healthcare technologies

Future healthcare technologies

1. Artificial Intelligence in Healthcare: AI/ML predictive/prescriptive analytics and digital twin
2. Sensors: Smart wearables, cyborg, satellites, wireless sensor networks and IoTs
3. 5G/6G: Cloud computing, telemedicine and Mobile health
4. Robotics (computer vision and natural language processing)
5. Gene editing, genomics, epigenomics proteomics and metabolomic

Enabler: Globalization and economic growth

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Why Artificial Intelligence in Healthcare?

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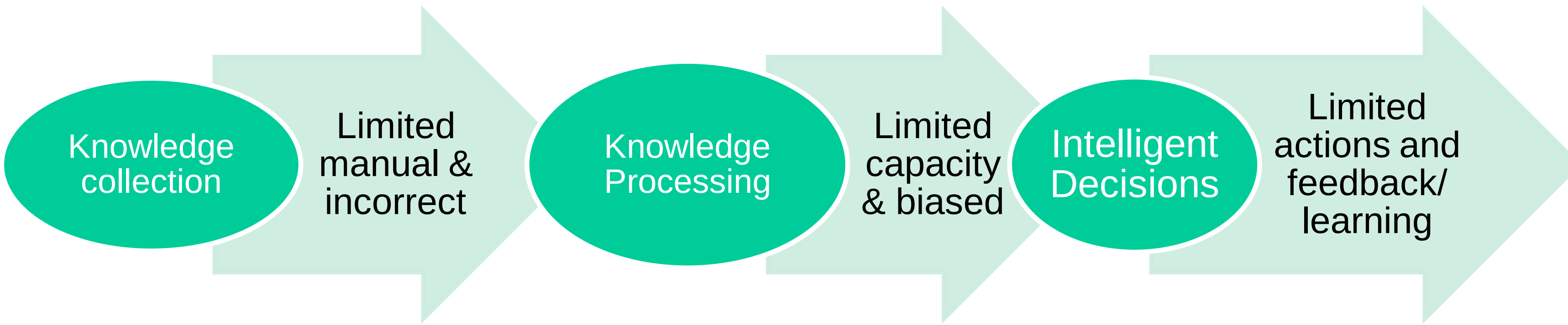
Human Intelligence



https://www.chirpbooks.com/audiobooks/paradise-lost-by-john-milton

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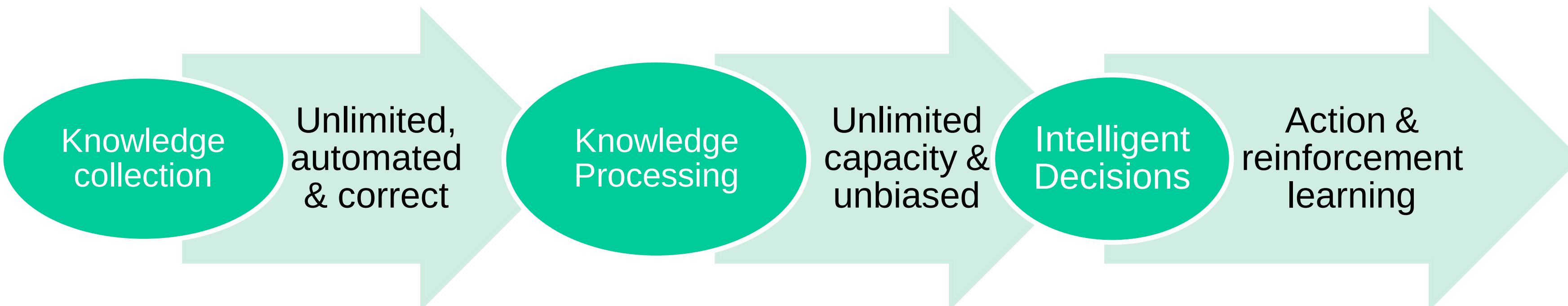
Artificial Intelligence



https://www.chirpbooks.com/audiobooks/paradise-lost-by-john-milton

Cognitive biases

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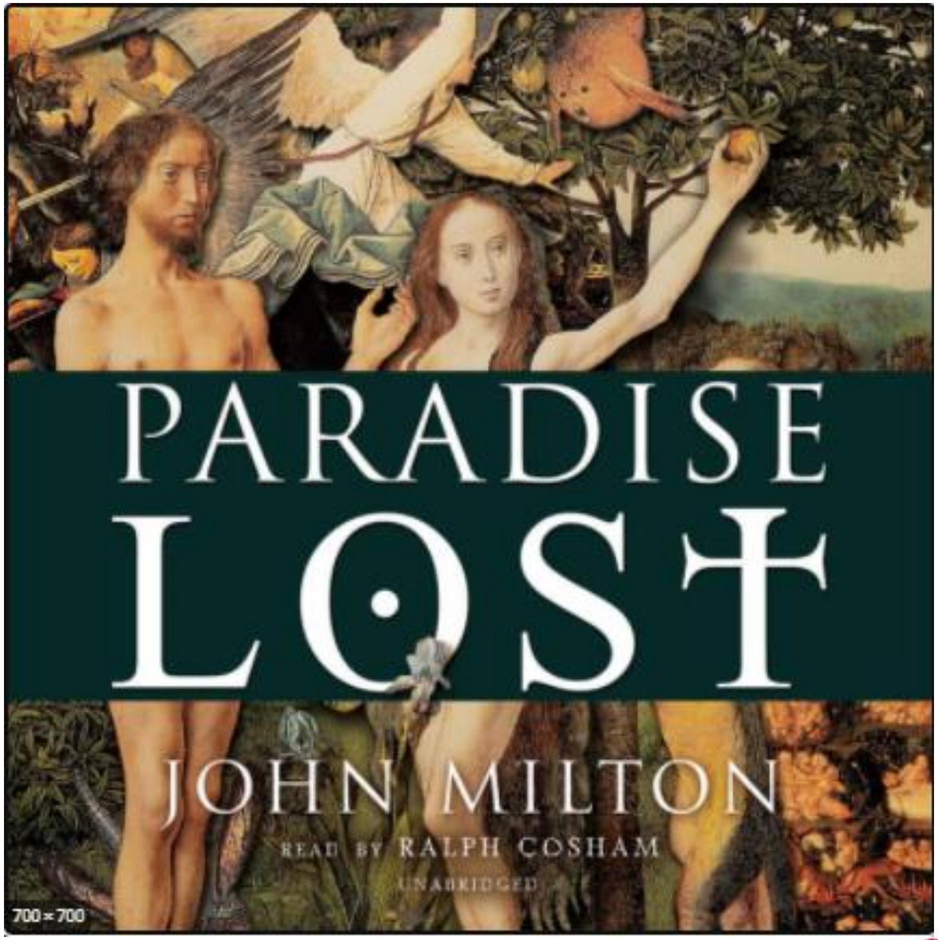
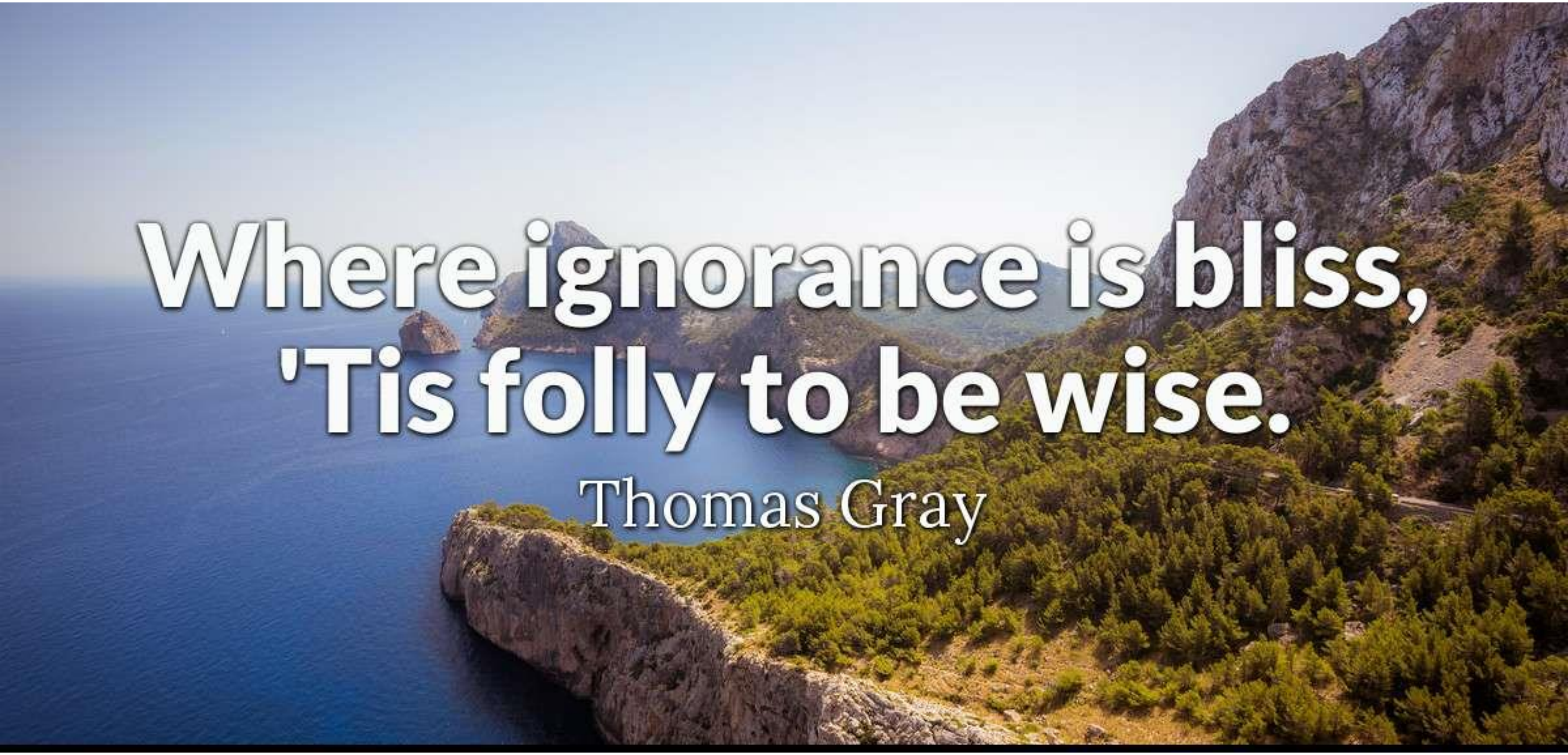
Forbidden fruit of the knowledge



https://www.chirpbooks.com/audiobooks/paradise-lost-by-john-milton

Forbidden fruit of the knowledge



https://www.brainyquote.com/quotes/thomas_gray_150669

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Forbidden fruit of the knowledge

https://www.pngkit.com/bigpic/u2q8t4r5r5q8r5r5/

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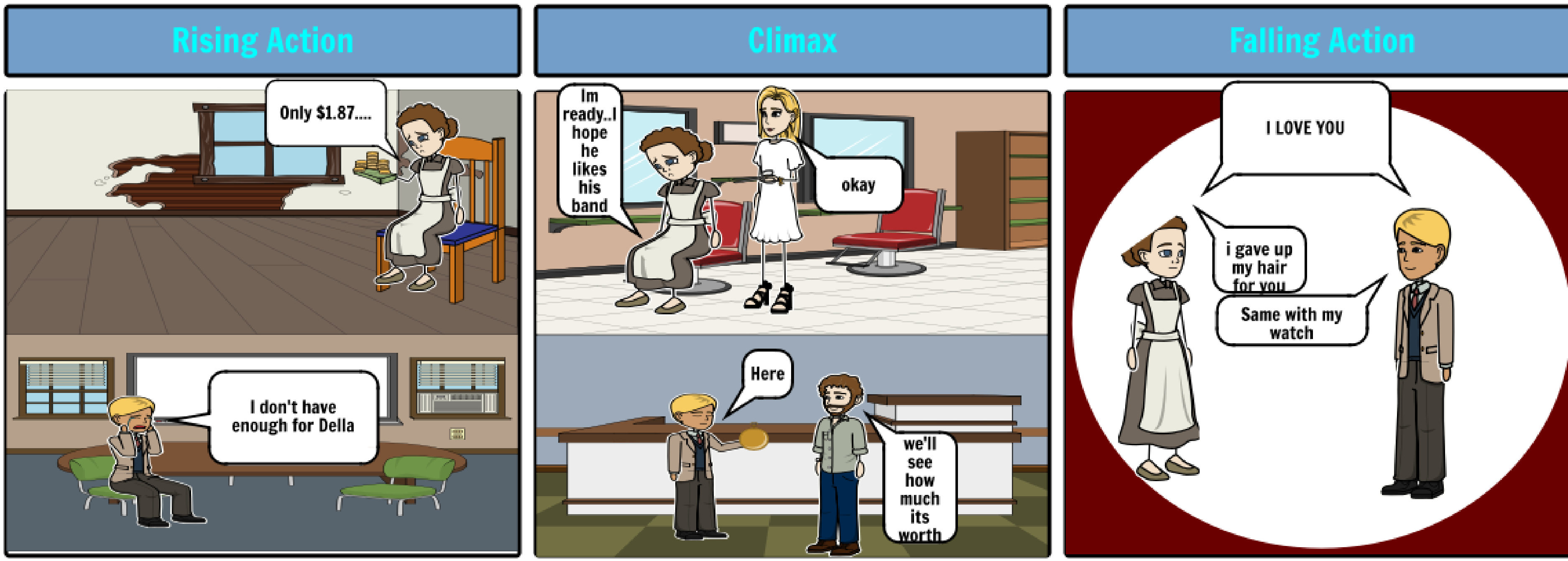
Forbidden fruit of the knowledge

http://www.hdwallpaperspulse.com/apple-logo-pictures.html

Our family system: One of the most complex systems



Della nor James had enough to exchange gifts. They were very poor. Both were very disappointed. Then, they had an idea.

Della gave up her most prized possession....her hair. James gave up his watch:also a prized possession. They did it for each other.

They bought gifts for each other with the possessions they gave up. Della received combs. James received a band for his watch. They really love each other.

Create your own at Storyboard That

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

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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

Requires

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

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),

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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,

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Our family system: One of the most complex systems

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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.

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Reality vs Perception

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Reality vs Perception

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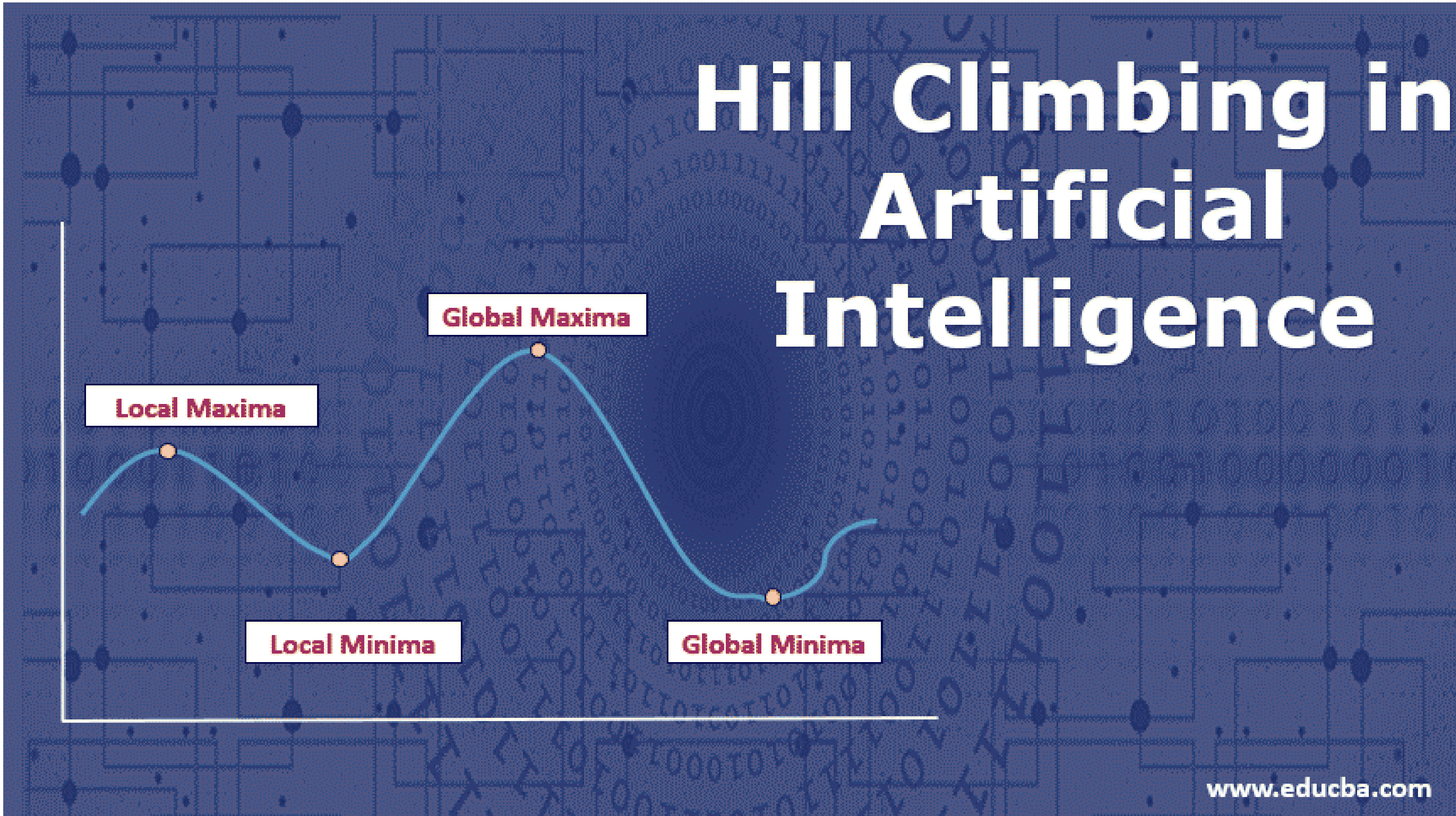
Reality vs Perception



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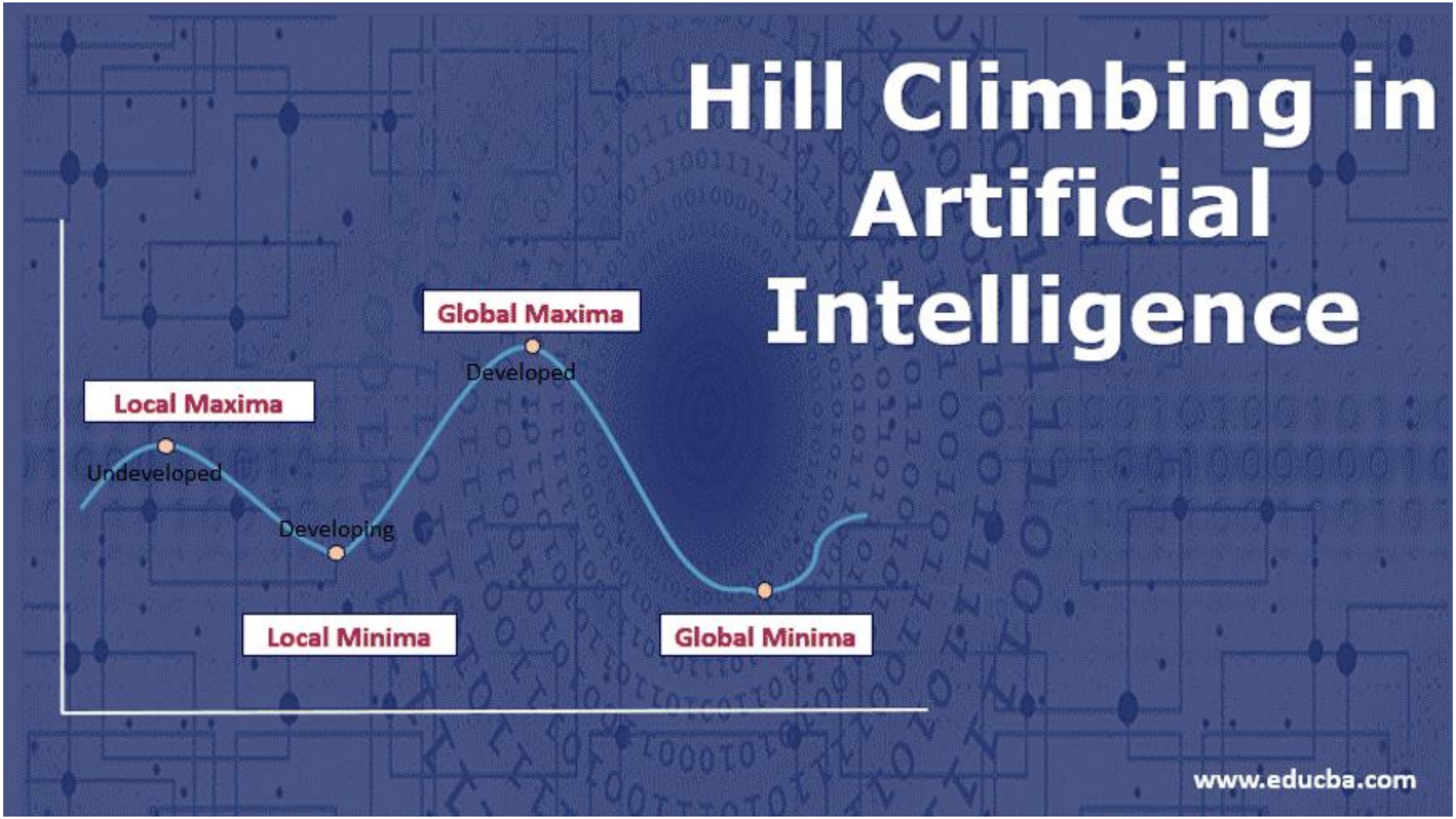
Reality vs Perception



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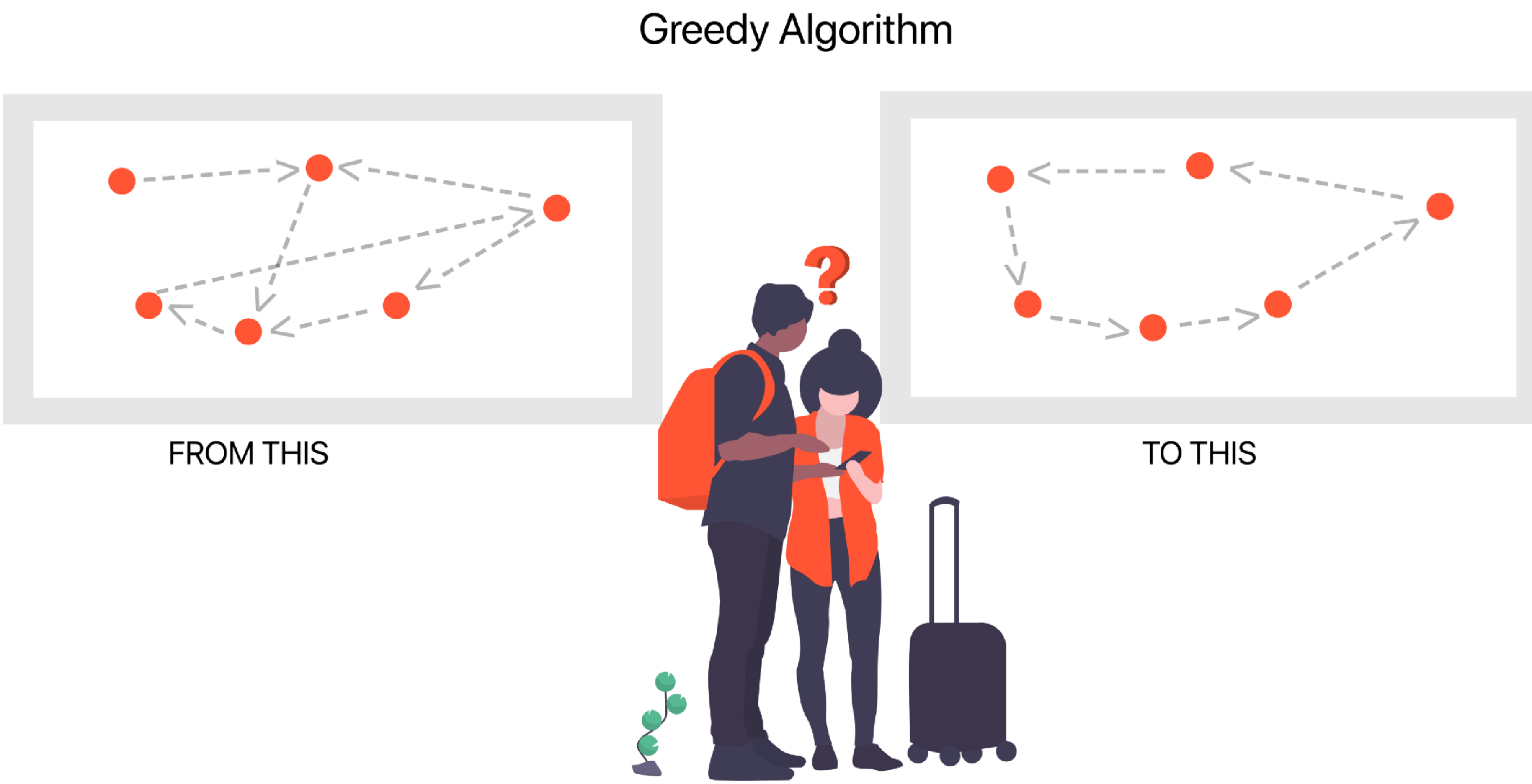
Reality vs Perception



Source: https://medium.com/ivymobility-developers/algorithm-a168afcd3611

Optimism bias in COVID-19

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Pessimism bias in COVID-19

23% migrant workers walked back to villages during coronavirus lockdown

Despite the hardships some optimism remains as 33 per cent respondents said they wanted to return to the city they worked in once the lockdown is lifted

BusinessToday.In | August 11, 2020 | Updated 08:41 IST

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Pessimism bias in COVID-19

Coronavirus lockdown: The Indian migrants dying to get home

By Vikas Pandey
BBC News, Delhi

20 May 2020

Coronavirus pandemic

Many migrants have also taken their families along on their difficult journeys

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Pessimism bias in COVID-19

Coronavirus: India's pandemic lockdown turns into a human tragedy

Soutik Biswas
India correspondent

30 March 2020

Coronavirus pandemic

Coronavirus: Heartbreaking scenes as India lockdown sparks mass migration

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Pessimism bias in COVID-19

FINANCIAL EXPRESS
Read to Lead

Covid-19 2.0: Migrant crisis returns! Indian Railways steps up special services

By: FE Bureau | April 22, 2021 2:30 AM

At present, the Indian Railways is running 1,512 mail/express and festival specials, on an average per day, up from the 1,490 such services last week.

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Other biases

Cognitive biases

- Confirmation bias
- Anchoring bias
- Bandwagon effect
- Halo effect
- Availability bias/heuristic
- Ostrich effect
- Recency/serial position effect
- Choice-supportive bias

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Cognitive biases

- Fundamental attribution error
- Outcome bias
- Illusory correlation bias
- Dunning Kruger effect
- Exponential-growth bias
- Magical Beliefs
- Conspiracy Theory Beliefs
- Overconfidence

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Cognitive biases

- Conformity bias
- Authority bias
- Loss-aversion bias
- False causality bias
- Action bias
- Self-serving bias
- Framing bias
- Ambiguity bias

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Cognitive biases

- Strategic misrepresentation
- Projection bias
- Pro-innovation bias
- Status-quo bias
- Feature positive effect
- Bounded Rationality
- Certainty Effect
- Cognitive Dissonance

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Cognitive biases

- Commitment
- Decision Fatigue
- Decoy Effect
- Time Discounting / Present Bias
- Diversification Bias
- Ego Depletion
- Elimination-By-Aspects
- Hot-Cold Empathy Gap

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Cognitive biases

- Commitment
- Decision Fatigue
- Decoy Effect
- Time Discounting / Present Bias
- Diversification Bias
- Ego Depletion
- Elimination-By-Aspects
- Hot-Cold Empathy Gap

Cognitive biases

- Endowment Effect
- Fear of Missing Out (FOMO)
- Gambler's Fallacy (Monte Carlo Fallacy)
- Habit
- Hedonic Adaptation
- Herd Behaviour
- Hindsight Bias (Knew-It-All-Along Effect)
- IKEA Effect

Cognitive biases

- Less-Is-Better Effect
- Licensing Effect
- Mental Accounting
- Naive Diversification
- Over justification Effect
- Pain of paying
- Partitioning
- Peak-End Rule

Cognitive biases

- Priming
- Procrastination
- Ratio bias
- Reciprocity
- Regret aversion
- Representativeness heuristic
- Scarcity
- Social proof

Cognitive biases

- Sunk Cost Fallacy
- Zero Price Effect

Our Economy:
A Complex System

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A Complex System

More demand then supply = More profit

Our Economy:
A Complex System

More demand then supply = More profit

More profit = More attractive industry

Our Economy:
A Complex System

More demand then supply = More profit

More profit = More attractive industry

= More players

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Our Economy:
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= More players

= More supply than demand

Our Economy:
A Complex System

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= Some will leave the market with loss

Our Economy:
A Complex System

More demand then supply = 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 healthcare system: A complex system

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Our healthcare system:
A complex system

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Our healthcare system:
A complex system

Our healthcare system:
A complex system

Private healthcare:

- Some patients want cheap healthcare

Our healthcare system:
A complex system

Private healthcare:

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

Our healthcare system:
A complex system

Private healthcare:

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

Our healthcare system:
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

Our healthcare system: 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

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Our healthcare system: A complex system

Private healthcare:

- At the time of COVID-19 pandemic:

Our healthcare system:
A complex system

Private healthcare:

- At the time of COVID-19 pandemic:
- Should they make more hospitals and employ more health professionals?

Our healthcare system: A complex system

Private healthcare:

- At the time of COVID-19 pandemic:
- Should they make more hospitals and employ more health professionals?
- Can they make more hospitals and employ more health professionals instantly?

Our healthcare system: A complex system

Our healthcare system: A complex system

Public healthcare:

- Everyone gets the same healthcare

Our healthcare system:
A complex system

Public healthcare:

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

Our healthcare system:
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

Our healthcare system: 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

Our healthcare system:
A complex system

Public healthcare:

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

    = Limited resources

    = more readmissions + waiting list

Our healthcare system: 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

Our healthcare system: A complex system

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

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Our healthcare system:
A complex system

Public healthcare:

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

Our healthcare system:
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

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Our healthcare system:
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**

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Our healthcare system:
A complex system

Public healthcare:

- **Corruption**
- Health providers want minimum cost
- Minimum cost

  = Limited resources

  = longer waiting list

  = **Poor healthcare**

  = Public outcry

  = Preference

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Our healthcare system: A complex system

Public healthcare:

- More resources

Our healthcare system: A complex system

Public healthcare:

- More resources = More cost

Our healthcare system:
A complex system

Public healthcare:

- More resources = short waiting lists

Our healthcare system: A complex system

Public healthcare:

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

Our healthcare system:
A complex system

Public healthcare:

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

Our healthcare system:
A complex system

Public healthcare:

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

  minimum readmissions

  more patients

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Our healthcare system: A complex system

Public healthcare:

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

  minimum readmissions

  more patients

  underutilization

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Our healthcare system: A complex system

Public healthcare:

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

minimum readmissions

more patients

underutilization

misuse

Our healthcare system: A complex system

Public healthcare:

- Even more resources = no waiting lists
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minimum readmissions

more patients

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more cost

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Our healthcare system:
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

Our healthcare system: A complex system

Public healthcare:

- Optimum resources = optimum waiting time

Our healthcare system:
A complex system

Public healthcare:

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

Our healthcare system: A complex system

Public healthcare:

- Optimum resources = optimum waiting time

  = Optimum hospital stay

  = minimum readmissions

Our healthcare system: A complex system

Public healthcare:

- Optimum resources = optimum waiting time

  = Optimum hospital stay

  = minimum readmissions

  = **optimum patients' number**

Our healthcare system: A complex system

Public healthcare:

- Optimum resources = optimum waiting time

  = Optimum hospital stay

  = minimum readmissions

  = **optimum patients' number**

  optimum utilization

Our healthcare system: A complex system

Public healthcare:

- Optimum resources = optimum waiting time

= Optimum hospital stay

= minimum readmissions

= **optimum patients' number**

optimum utilization

minimum misuse

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Our healthcare system:
A complex system

Public healthcare:

- Optimum resources = optimum waiting time

= Optimum hospital stay

= minimum readmissions

= **optimum patients' number**

optimum utilization

minimum misuse

optimum cost

Our healthcare system: A complex system

Public healthcare:

- Optimum resources = optimum waiting time

= Optimum hospital stay

= minimum readmissions

= **optimum patients' number**

optimum utilization

minimum misuse

optimum cost

Some waiting lists

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Our healthcare system:
A complex system

Public healthcare:

- Optimum resources = Proper planning

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

  = Resource requirement forecasting

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Our healthcare system:
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

Our healthcare system:
A complex system

Public healthcare:

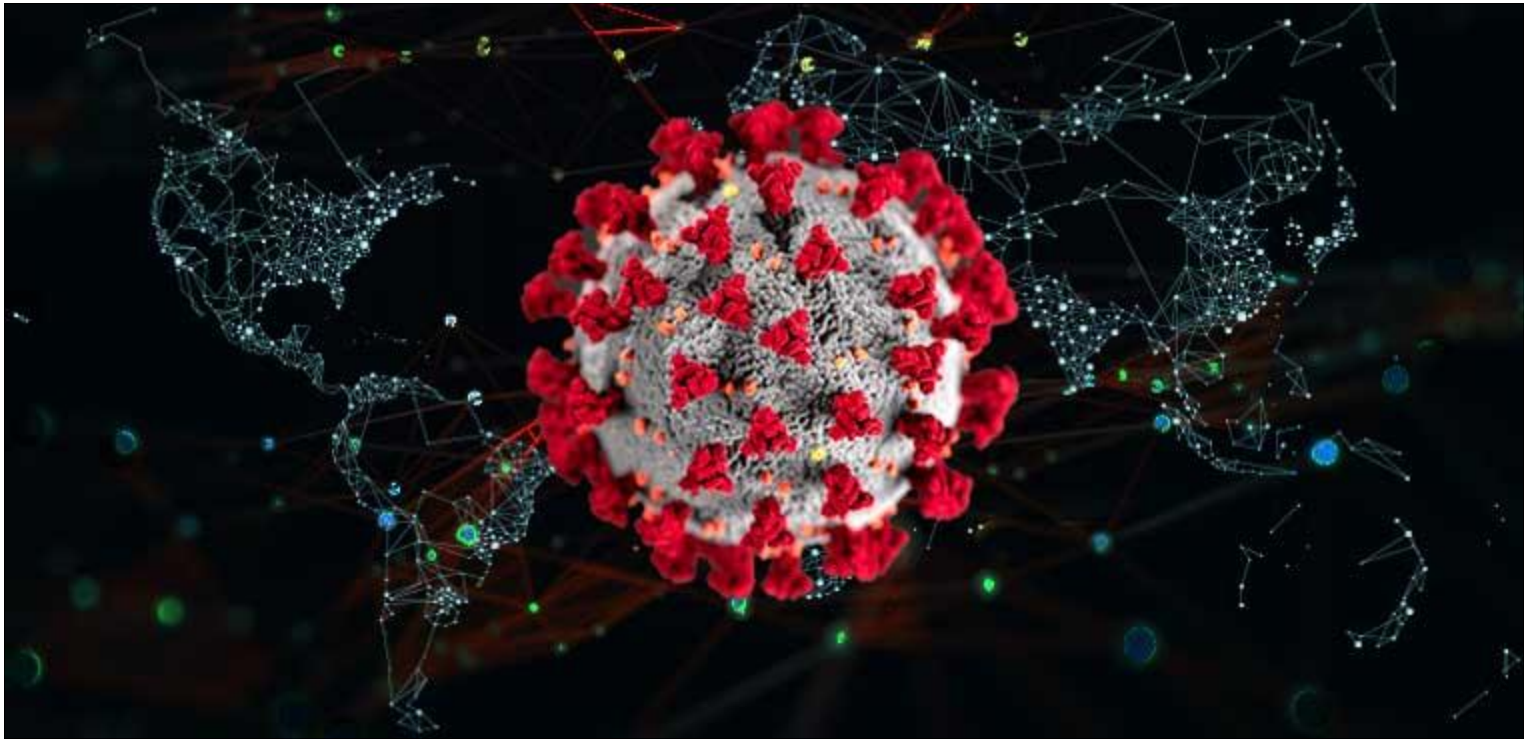
- At the time of COVID-19 pandemic:
- Should they make more hospitals and employ more health professionals?
- Can they make more hospitals and employ more health professionals instantly?

Our healthcare system: A complex system

Do we prepare ourselves for such a pandemic?

- Do we keep a hospital bed booked for us?
- Do we keep resources for homecare?

Covid-19



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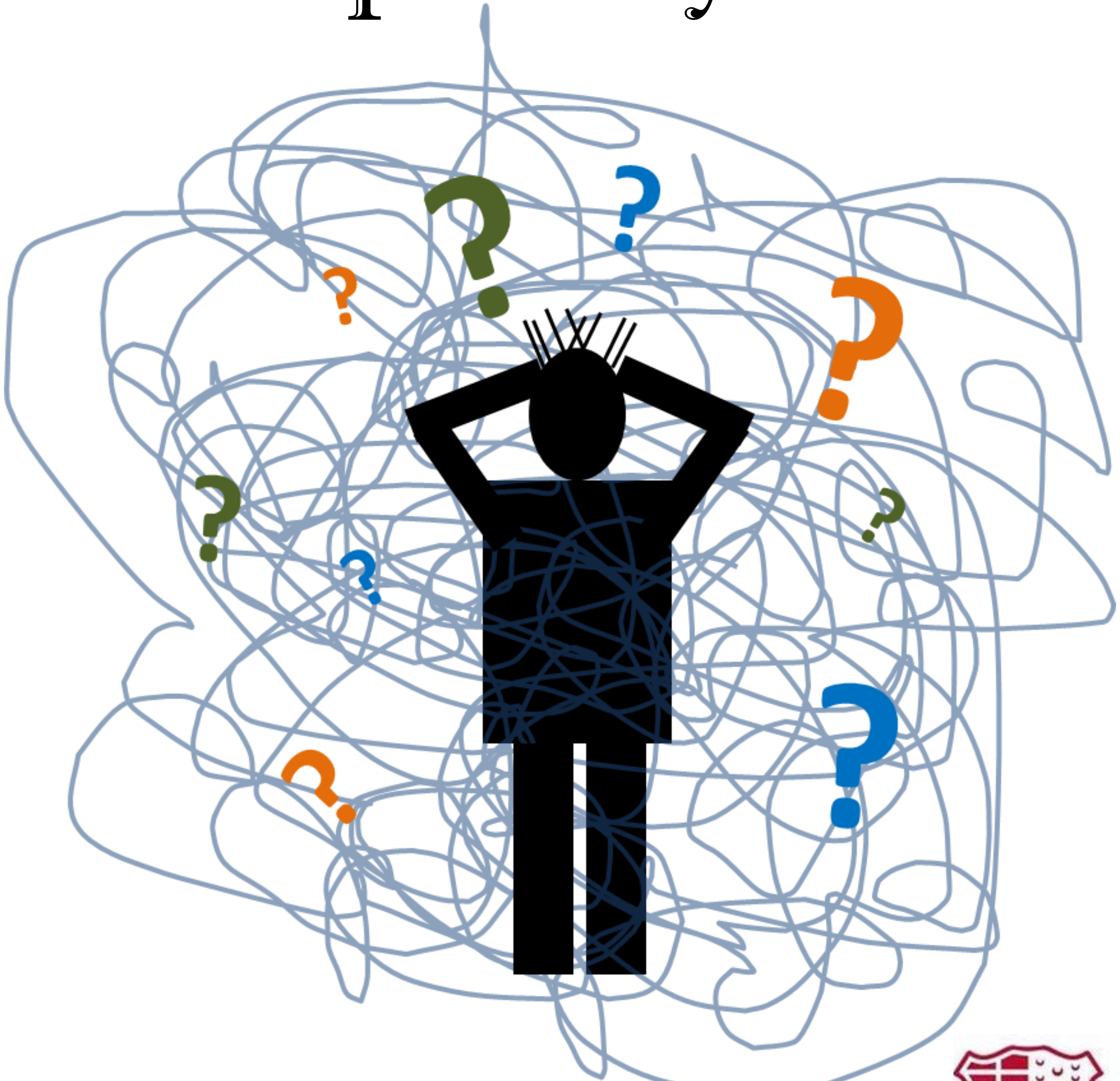
Complex Systems



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Covid-19

We need an efficient mechanism/system for

Acquiring/collecting, analysing, and sharing

information from different domains of the **complex system** for decision making

to fight COVID-19 and monitor the progress.

I.e. we need **Artificial Intelligence in Healthcare**.

Covid-19

Covid-19 is not just a medical problem but

It is also a

1. Social problem
2. Political problem
3. Cultural problem
4. Community problem
5. Communication problem
6. Transportation problem

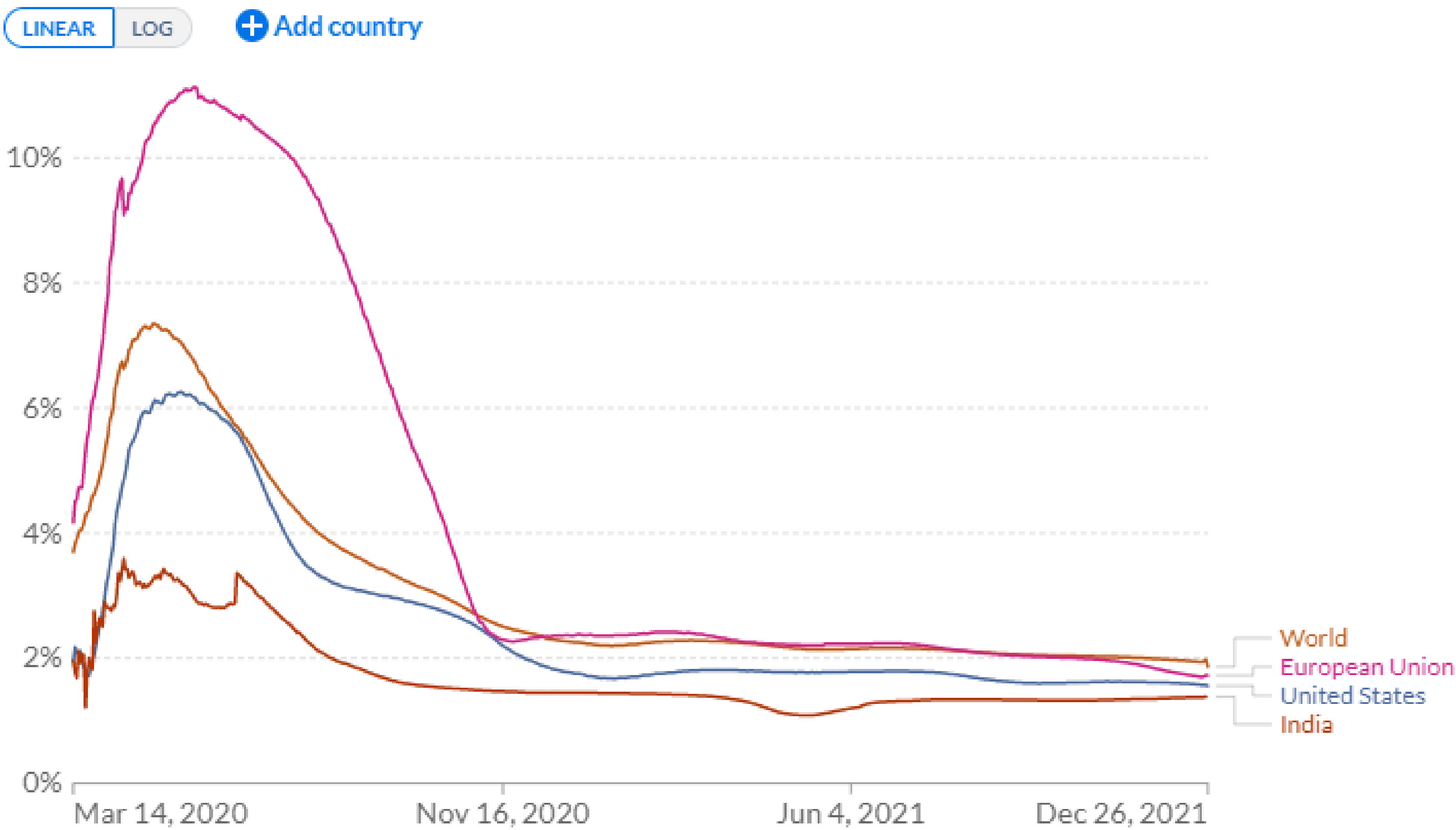
Covid-19

7. Management problem
8. Supply chain problem
9. Administration problem
10. Education problem
11. Financial problem
12. Economical problem
13. Behavioural/ psychological problem
14. Geological problem

Some COVID-19 Statistics

Case fatality rate of COVID-19

The case fatality rate (CFR) is the ratio between confirmed deaths and confirmed cases. The CFR can be a poor measure of the mortality risk of the disease. We explain this in detail at OurWorldInData.org/mortality-risk-covid



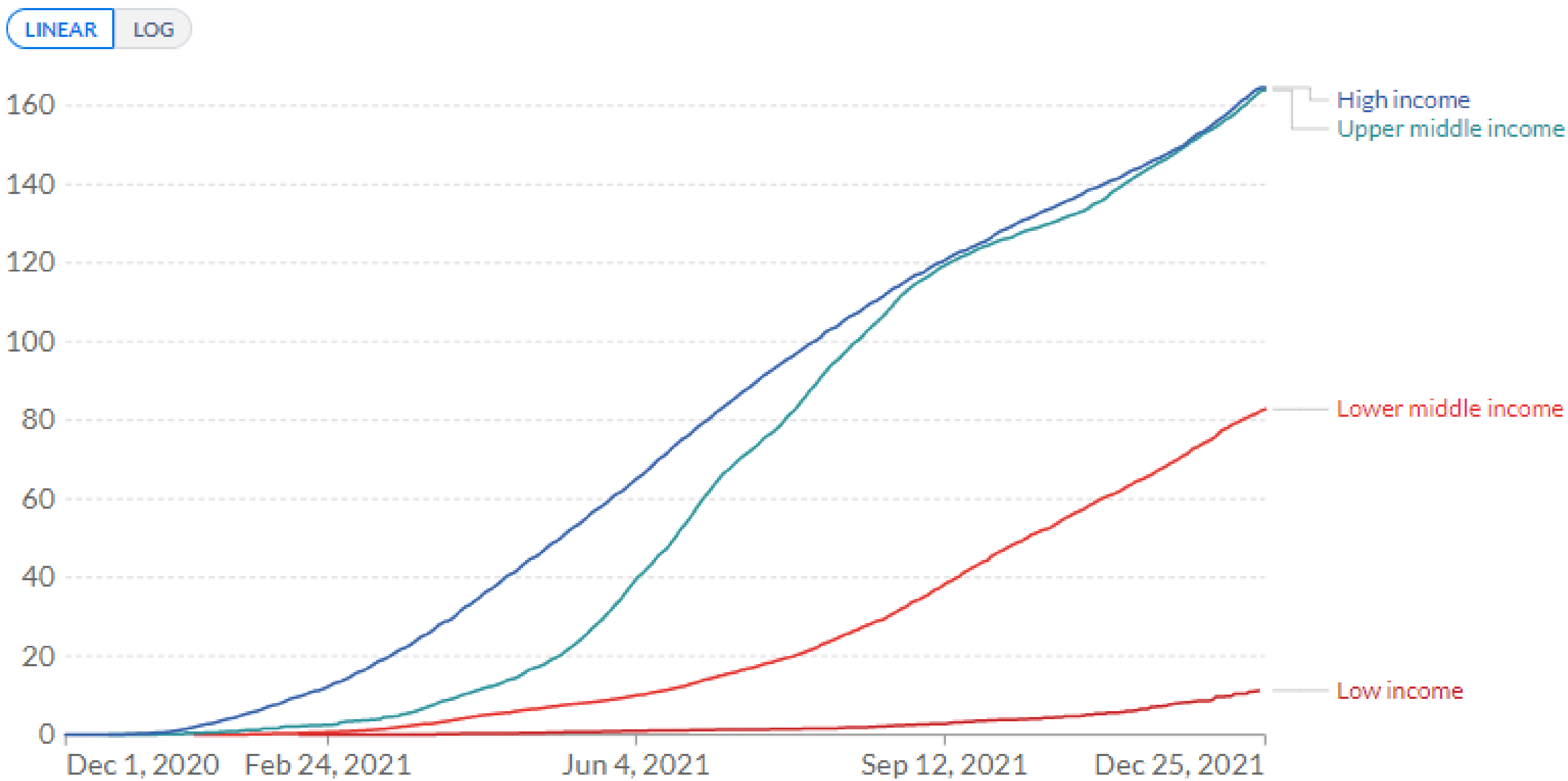
Source: Johns Hopkins University CSSE COVID-19 Data

HTTPS://OURWORLDINDATA.ORG/MORTALITY-RISK-COVID

COVID-19 vaccine doses administered per 100 people, by income group

Our World in Data

All doses, including boosters, are counted individually. As the same person may receive more than one dose, the number of doses can be higher than the number of people in the population.



Source: Official data collated by Our World in Data, World Bank
Note: Country income groups are based on the World Bank classification.

HTTPS://OURWORLDINDATA.ORG/COVID-VACCINATIONS

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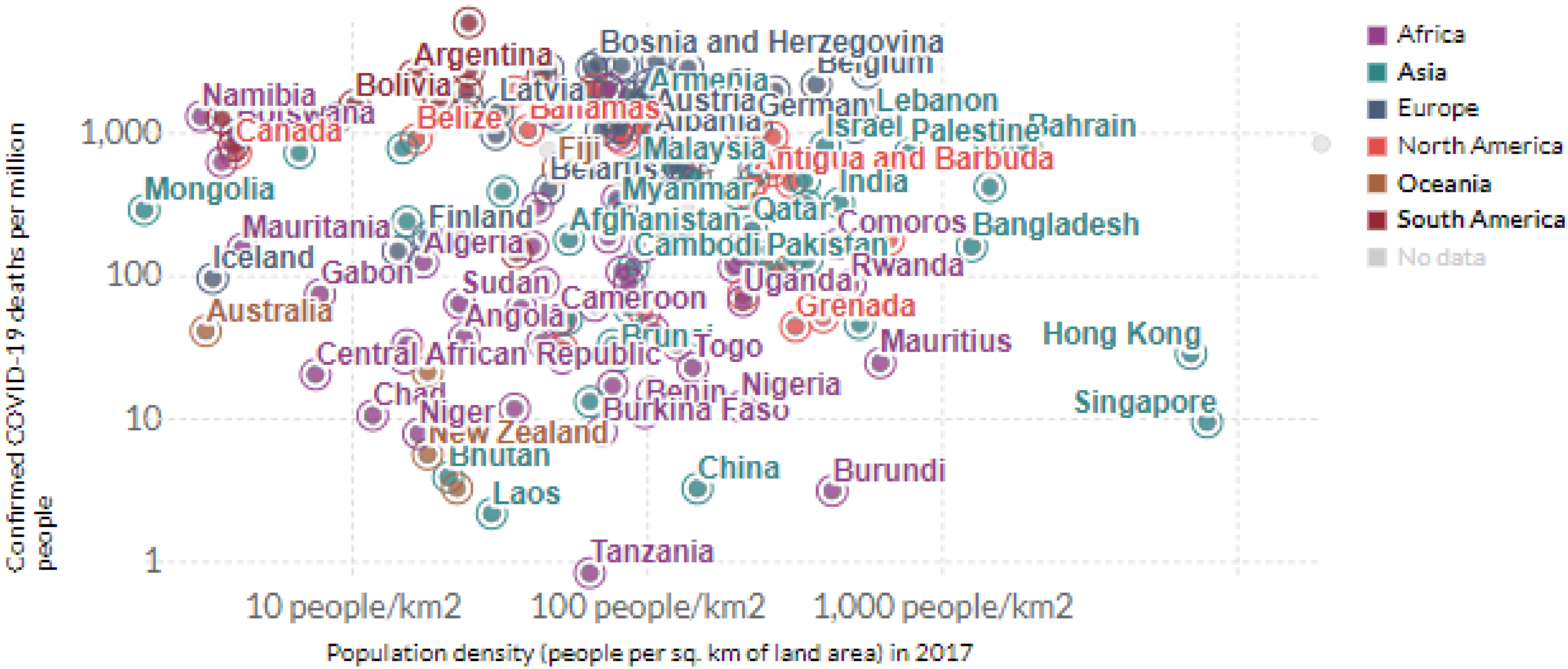
COVID-19 death rate vs. Population density, Sep 4, 2021

The death rate is the number of total confirmed deaths due to COVID-19 per million people.

Our World in Data

Y: LINEAR | Y: LOG | X: LINEAR | X: LOG | Select countries | Zoom to selection | More



Source: Johns Hopkins University CSSE COVID-19 Data – Last updated 5 September, 09:03 (London time), World Bank
OurWorldInData.org/coronavirus • CC BY

TOTAL CONFIRMED COVID-19 DEATHS PER MILLION VS GDP PER CAPITA, JAN 6, 2021
HTTPS://OURWORLDINDATA.ORG/GRAPHER/TOTAL-CONFIRMED-DEATHS-OF-COVID-19-PER-MILLION-PEOPLE-VS-GDP-PER-CAPITA?YSCALE=LINEAR&TIME=LATEST

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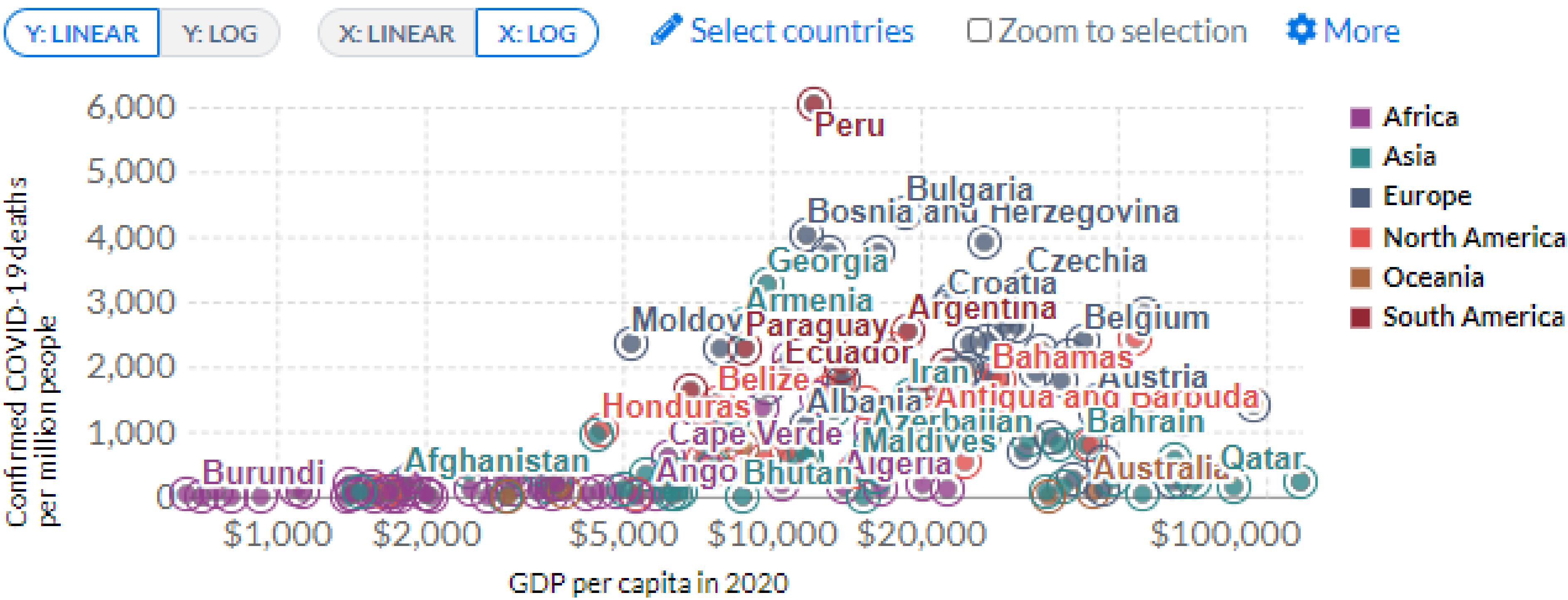
Total confirmed COVID-19 deaths per million vs GDP per capita, Dec 17, 2021

Due to limited testing and challenges in the attribution of the cause of death, confirmed deaths can be lower than the true number of deaths. GDP per capita is adjusted for price differences between countries (it is expressed in international dollars).



Source: Johns Hopkins University CSSE COVID-19 Data – Last updated 18 December, 05:05 (London time), World Bank
OurWorldInData.org/coronavirus • CC BY

TOTAL CONFIRMED COVID-19 DEATHS PER MILLION VS GDP PER CAPITA, JAN 6, 2021
HTTPS://OURWORLDINDATA.ORG/GRAPHER/TOTAL-CONFIRMED-DEATHS-OF-COVID-19-PER-MILLION-PEOPLE-VS-GDP-PER-CAPITA?YSCALE=LINEAR&TIME=LATEST

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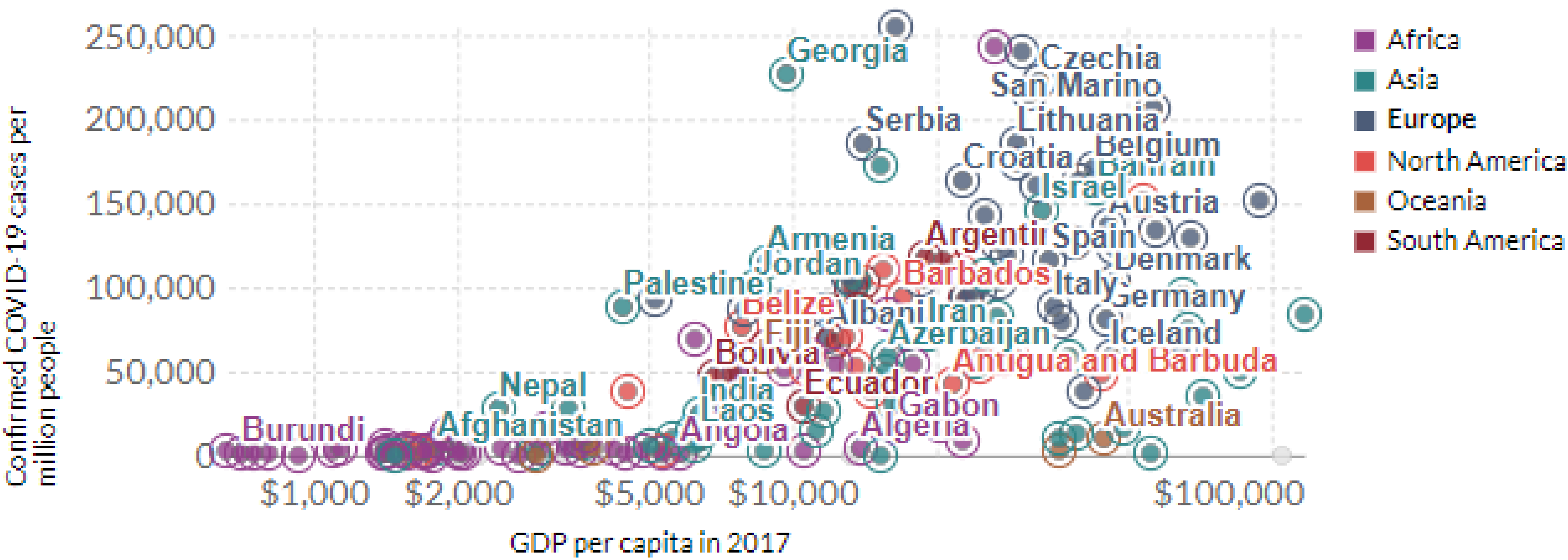
Cumulative confirmed COVID-19 cases per million vs. GDP per capita, Dec 17, 2021

Our World in Data

Due to limited testing, the number of confirmed cases is lower than the true number of infections. GDP per capita is adjusted for price differences between countries (it is expressed in international dollars).

Y: LINEAR | Y: LOG | X: LINEAR | X: LOG | Select countries | Zoom to selection | More



Source: Johns Hopkins University CSSE COVID-19 Data – Last updated 18 December, 05:05 (London time), World Bank
OurWorldInData.org/coronavirus • CC BY

CUMULATIVE CONFIRMED COVID-19 CASES PER MILLION VS. GDP PER CAPITA, JAN 6, 2021: REF: HTTPS://OURWORLDINDATA.ORG/GRAPHER/TOTAL-CONFIRMED-CASES-OF-COVID-19-PER-MILLION-PEOPLE-VS-GDP-PER-CAPITA

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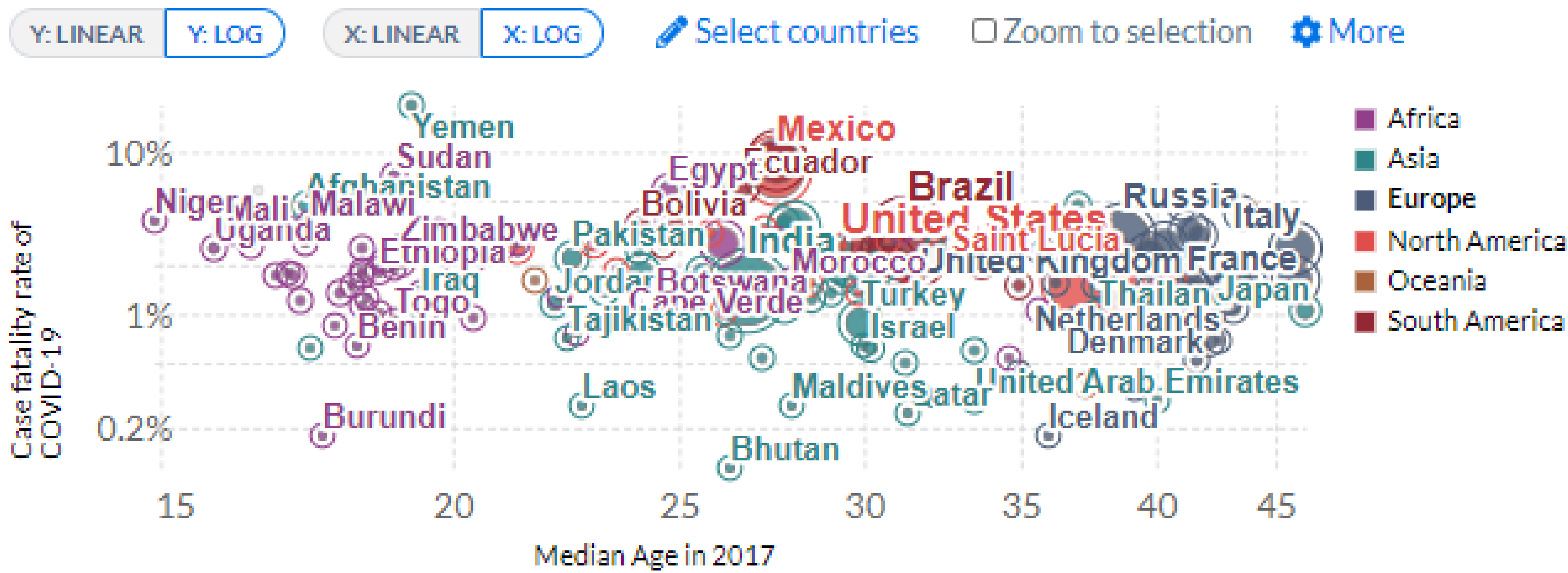
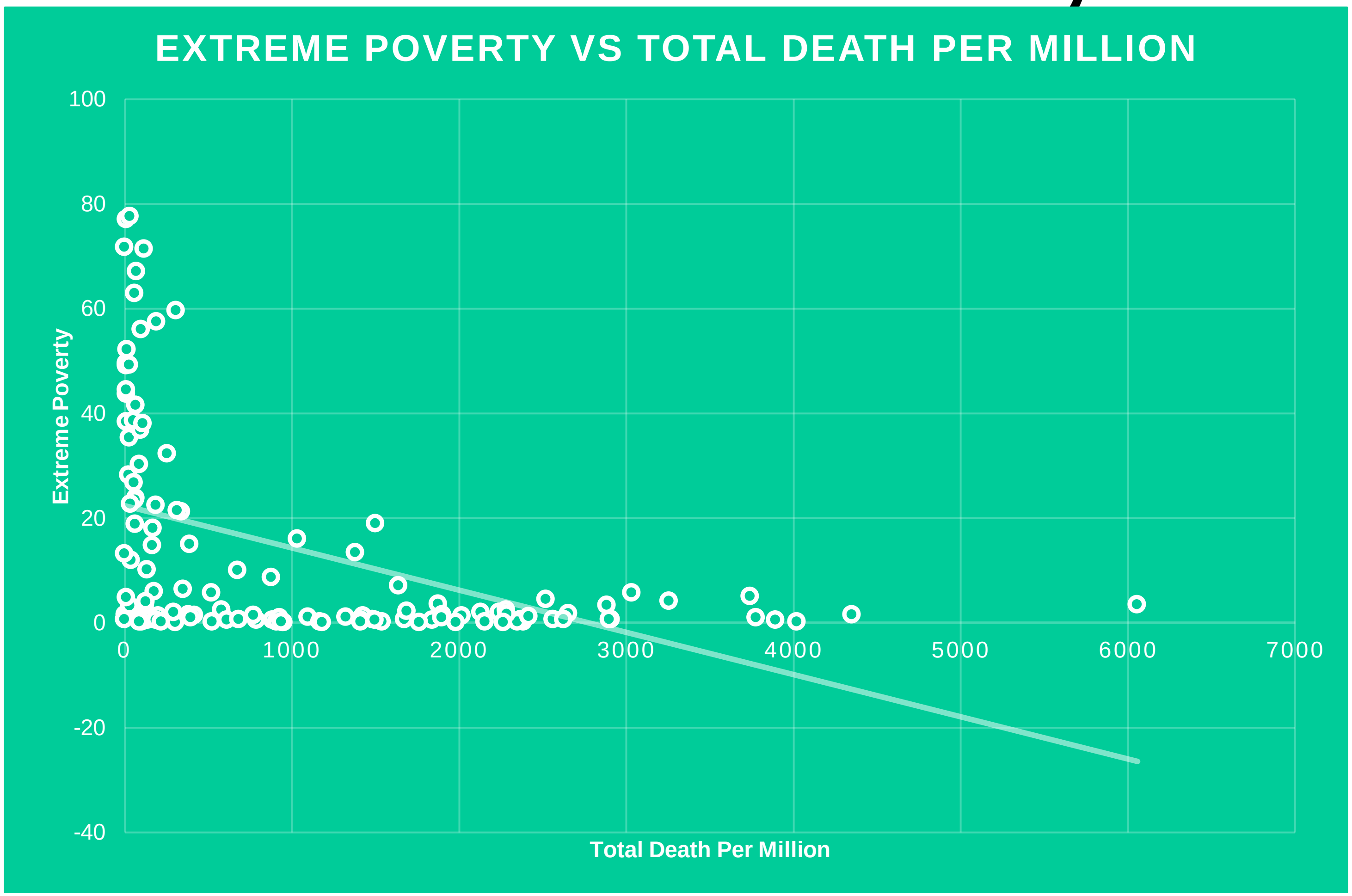
Case fatality rate of COVID-19 vs. Median age of the population

The Case Fatality Rate (CFR) is the ratio between confirmed deaths and confirmed cases.
During an outbreak of a pandemic the CFR is a poor measure of the mortality risk of the disease. We explain this in detail at OurWorldInData.org/coronavirus



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: REF: HTTPS://OURWORLDINDATA.ORG/GRAPHER/CASE-FATALITY-RATE-OF-COVID-19-VS-MEDIAN-AGE?XSCALE=LOG&YSCALE=LOG&COUNTRY=AFG~ALB~DZA~AGO~ARG~ARM~ATG~AUS~AUT~BHS~AZE~BHR~BGD~BRB~BLR~BEL~BLZ~LVA~LBN~LSO~LBR~LBY~LTU~LUX~MDG~MWI~MYS~MDV~MLI~MLT~MRT~MUS~MEX~BEN~BTN~BOL~BIH~BWA~BRA~BRN~BGR~BFA~BDI~KHM~CMR~CAN~CPV~CAF~TCD~CHL~CHN~COL~COM~COG~CRI~CIV~HRV~CYP~CZE~COD~DNK~DMA~DOM~ECU~EGY~SLV~GNQ~EST~SWZ~ETH~FJI~FIN~FRA~GAB~GMB~GEO~DEU~GHA~GRC~GRD~GTM~GIN~GNB~GUY~HTI~HND~HKG~HUN~ISL~IND~IDN~IRN~IRQ~IRL~ISR~ITA~JAM~JPN~JOR~KAZ~KEN~OWID_KOS~KWT~KGZ~LAO~MDA~MNG~MNE~MOZ~MAR~MMR~NAM~NPL~NLD~NZL~NIC~NER~NGA~MKD~NOR~OMN~PAK~PSE~PAN~PNG~PRY~PER~PHL~POL~PRT~QAT~ROU~RUS~RWA~KNA~LCA~VCT~SMR~STP~SAU~SEN~SRB~SYC~SLE~SGP~SVK~SVN~ZAF~KOR~SSD~ESP~LKA~SDN~SUR~SWE~CHE~TJK~TZA~THA~TLS~TGO~TTO~TUN~TUR~UGA~UKR~ARE~GBR~USA~URY~UZB~VUT~VNM~YEM~ZMB~ZWE

COVID-19: Deaths per Million vs. Extreme Poverty



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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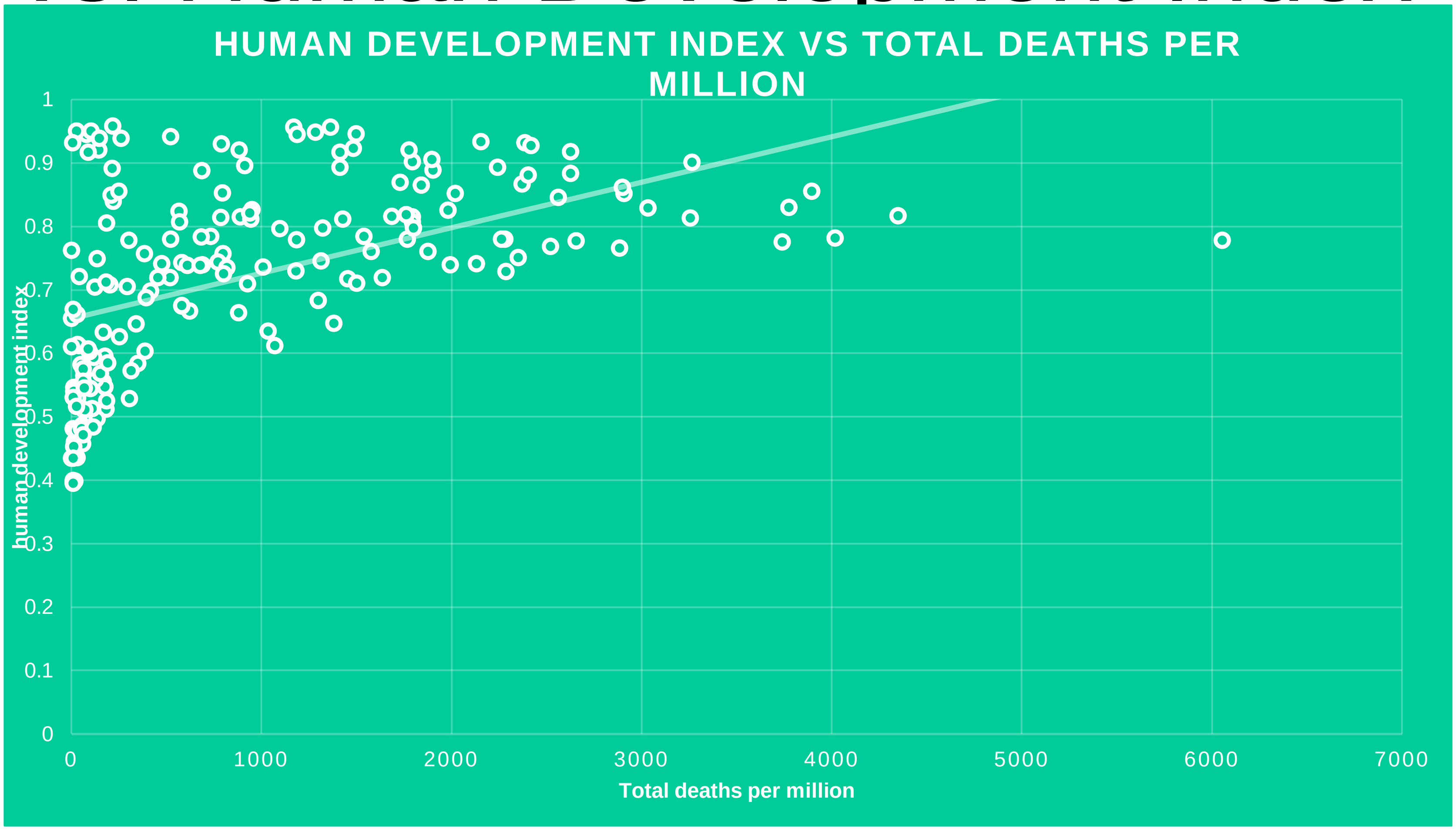
COVID-19: Deaths per Million vs. Human Development Index



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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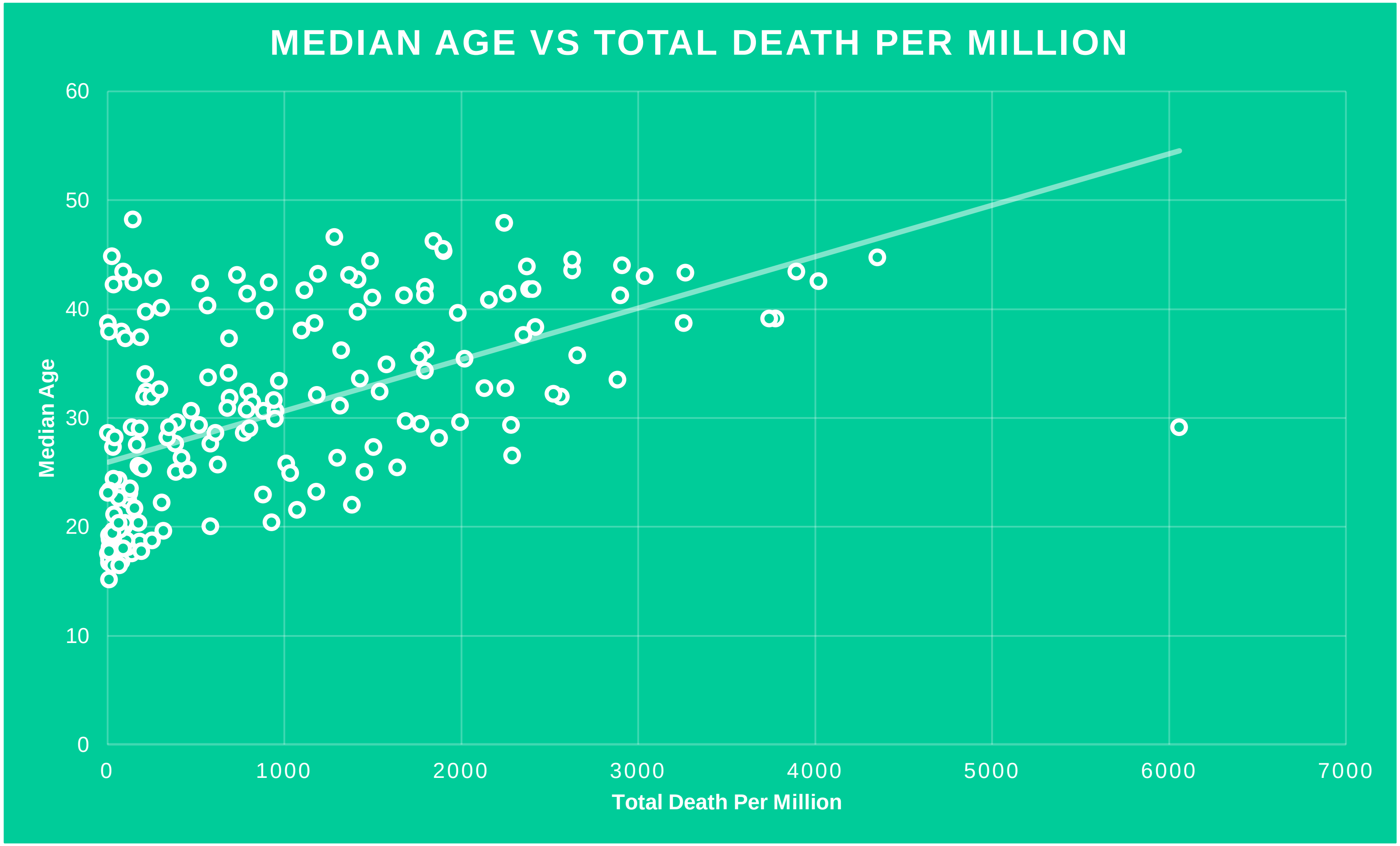
COVID-19: Median Age Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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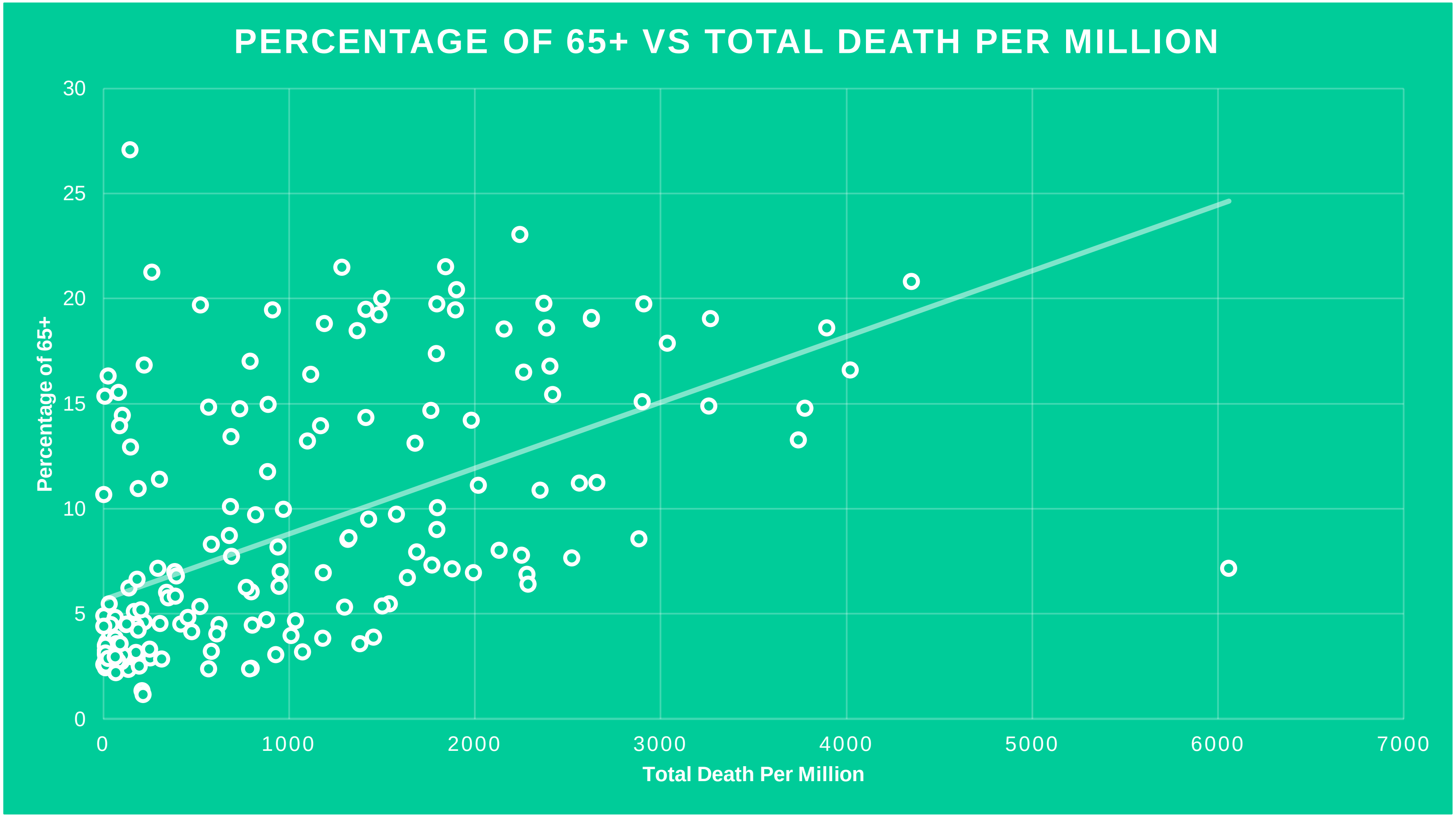
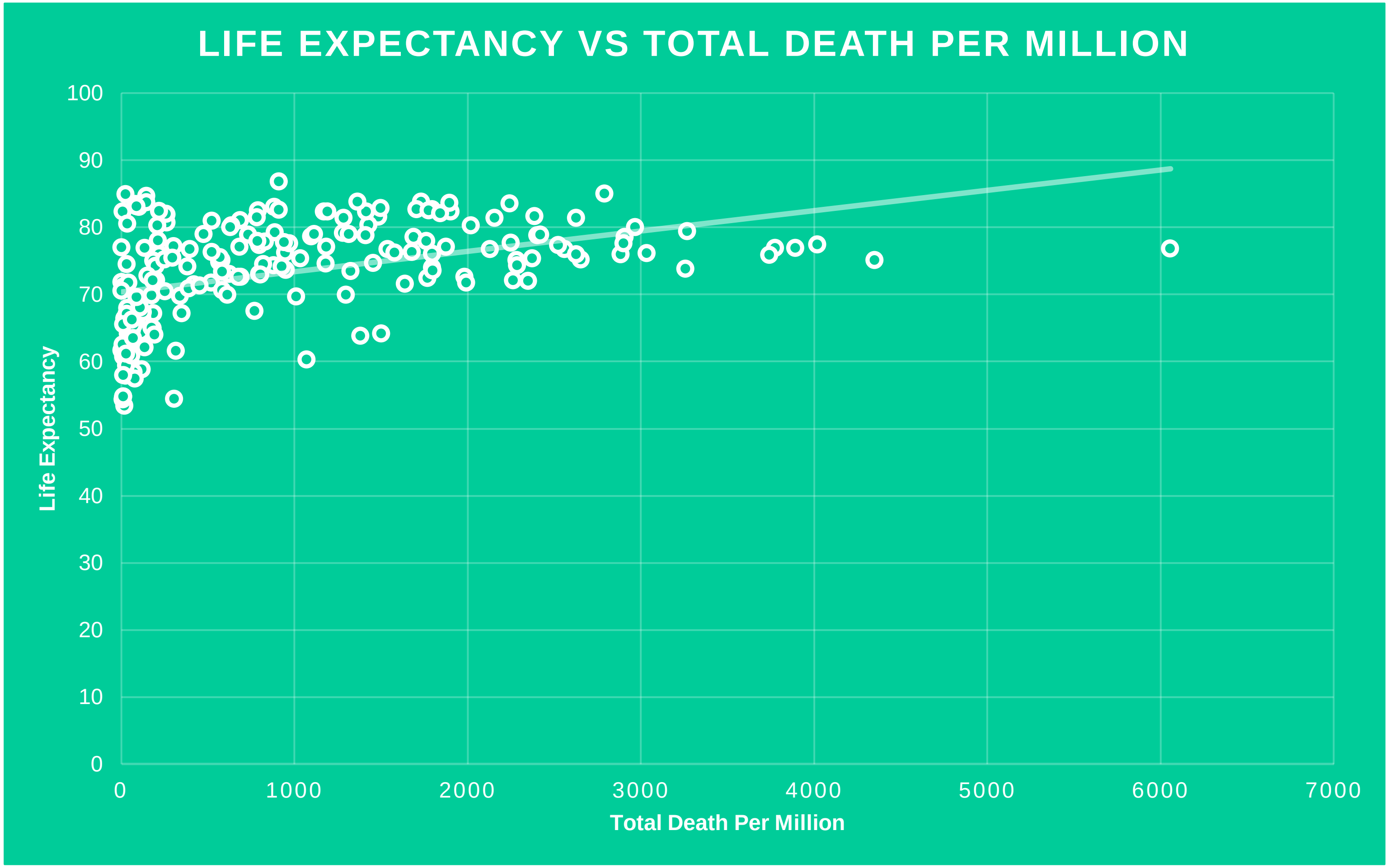
COVID-19: Percentage of 65+ Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

COVID-19: Life expectancy Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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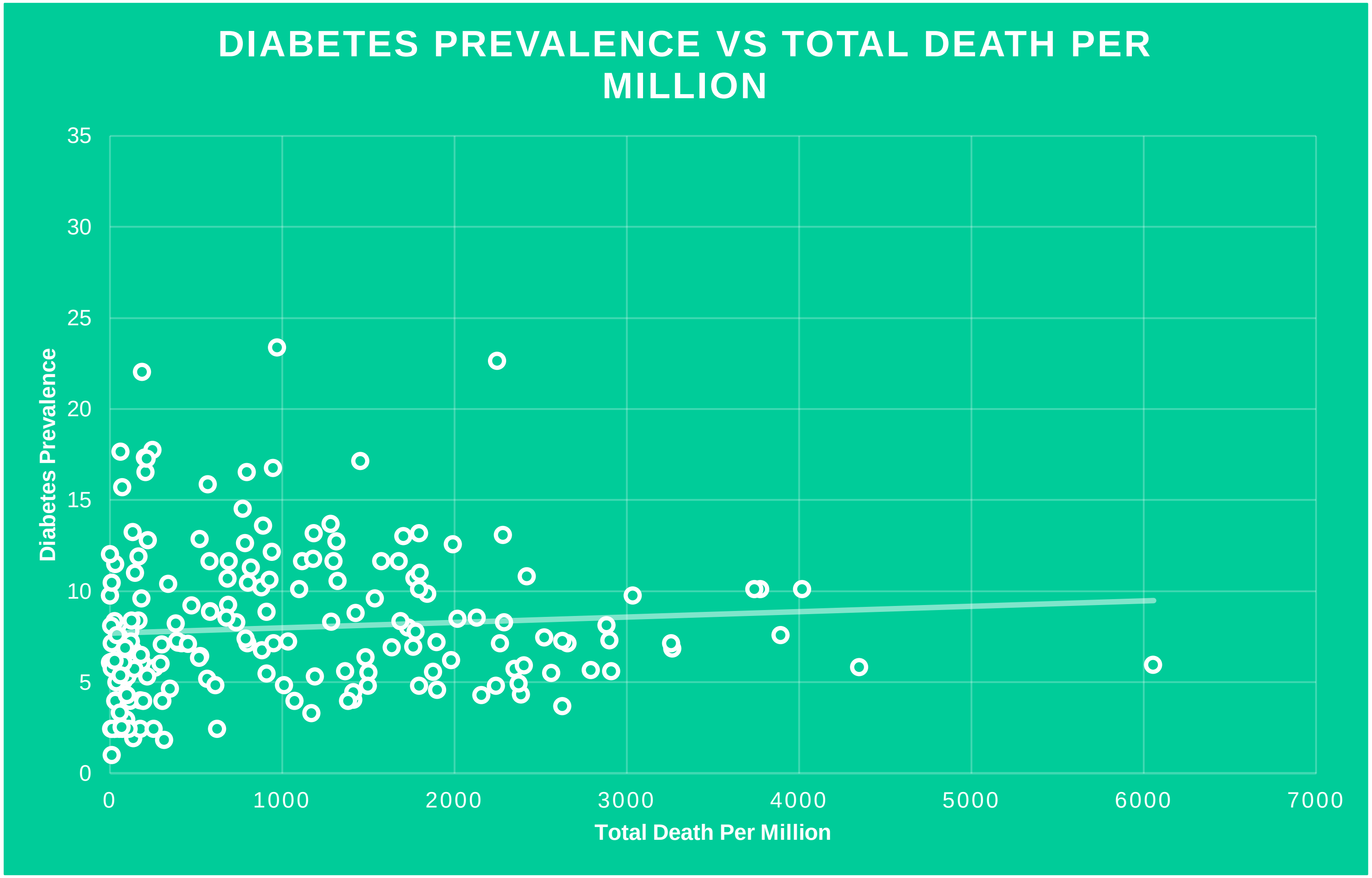
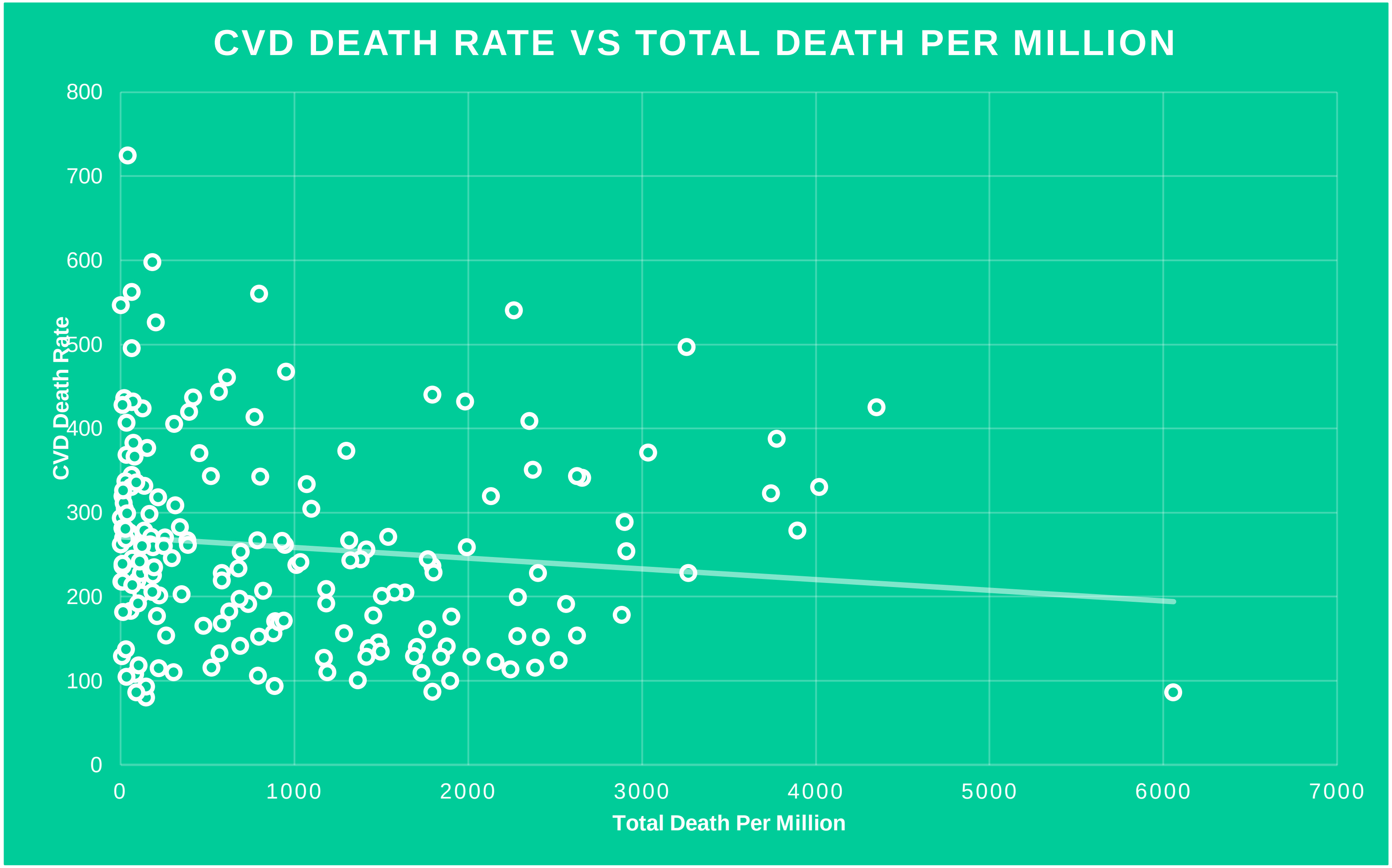
COVID-19: Diabetes Prevalence Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

COVID-19: Cardiovascular Death Rate Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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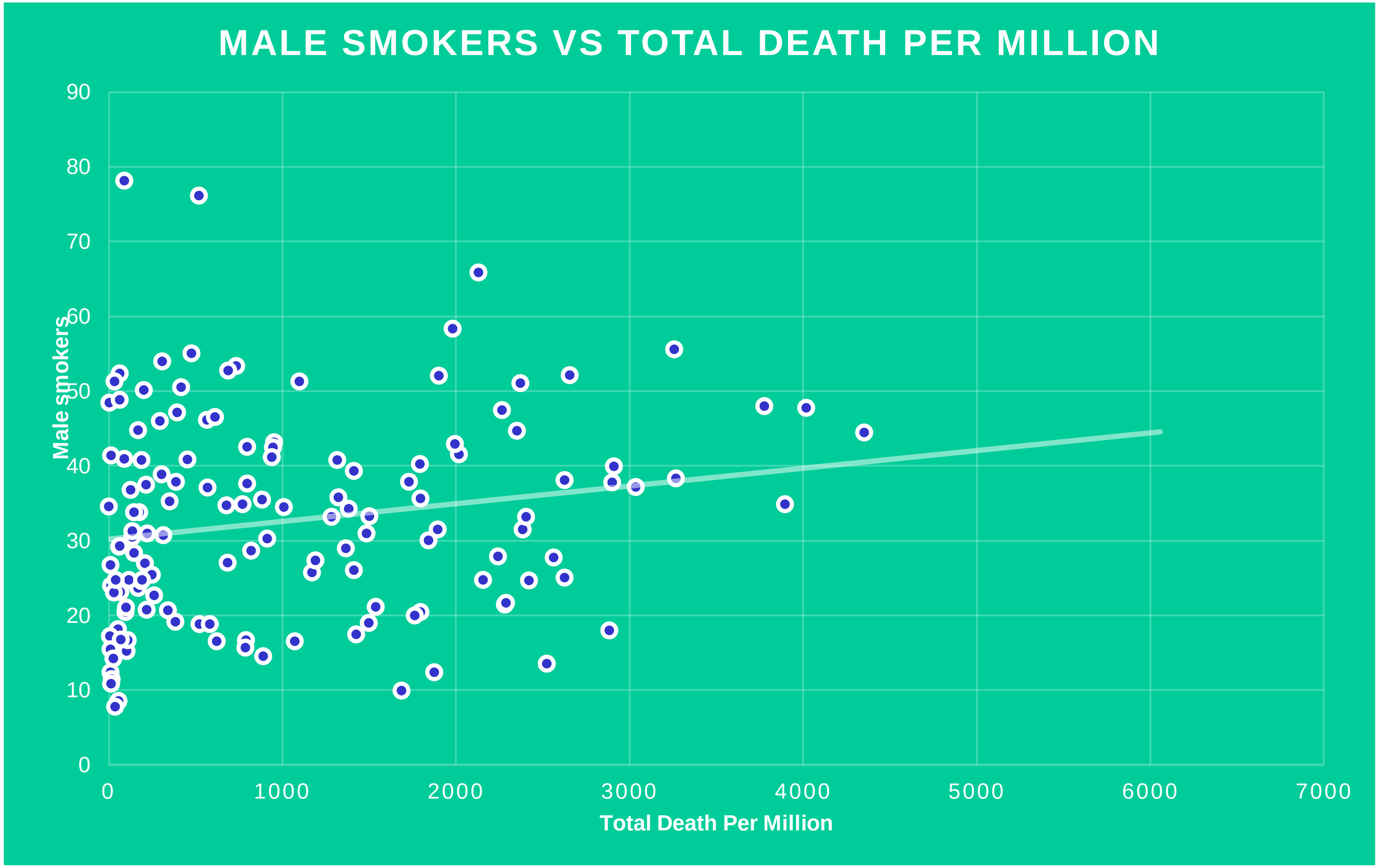
COVID-19: Male Smokers Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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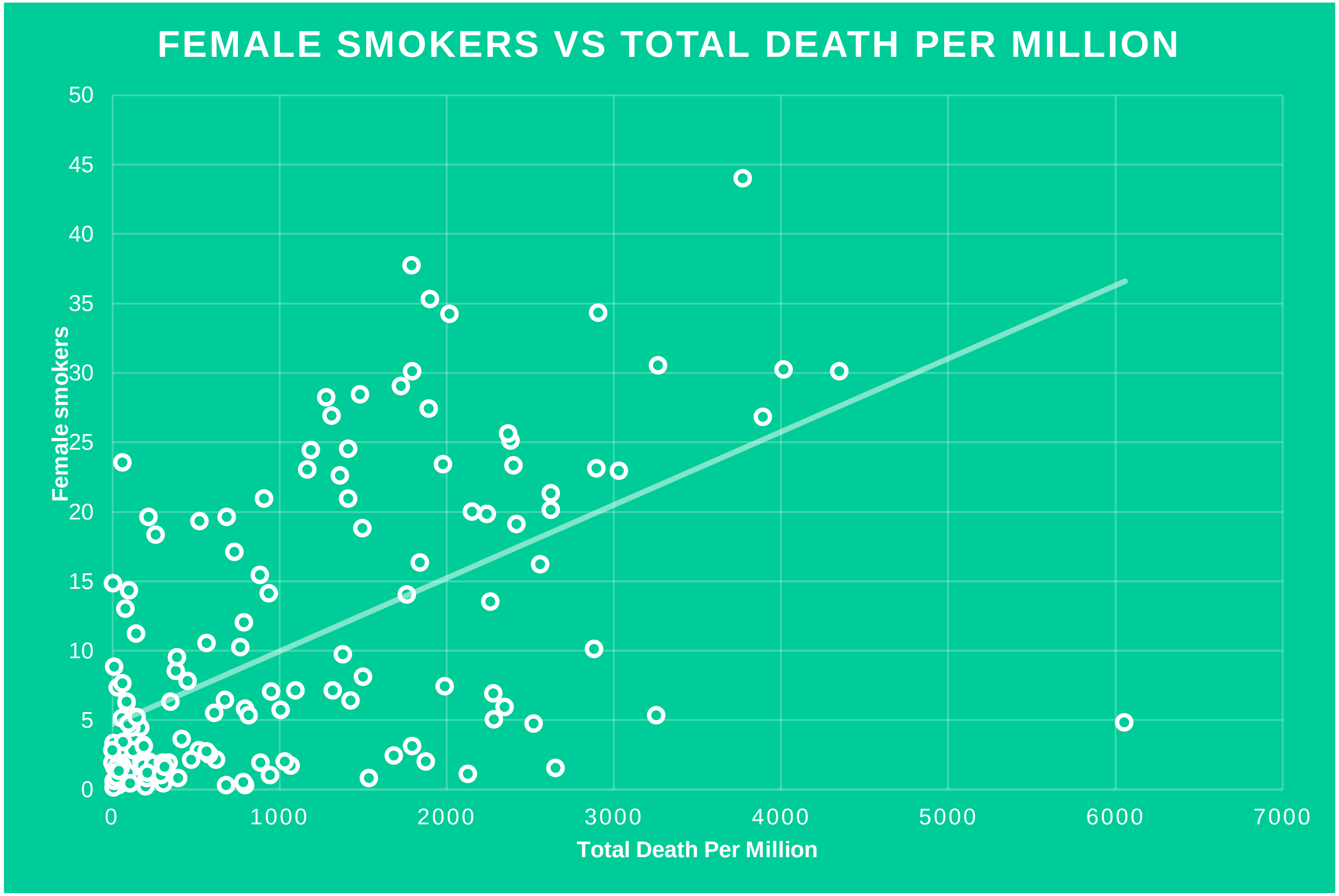
COVID-19: Female Smokers Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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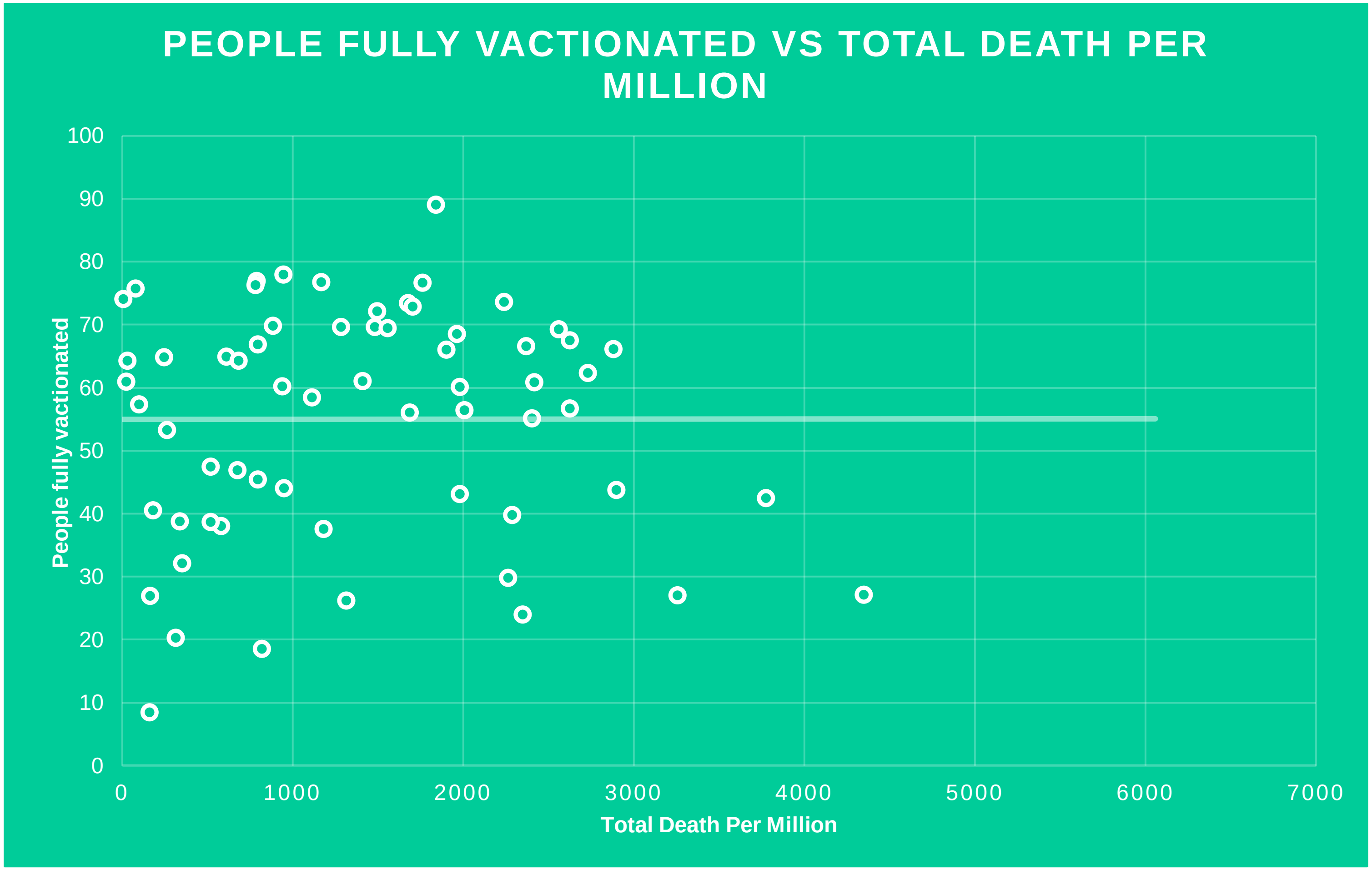
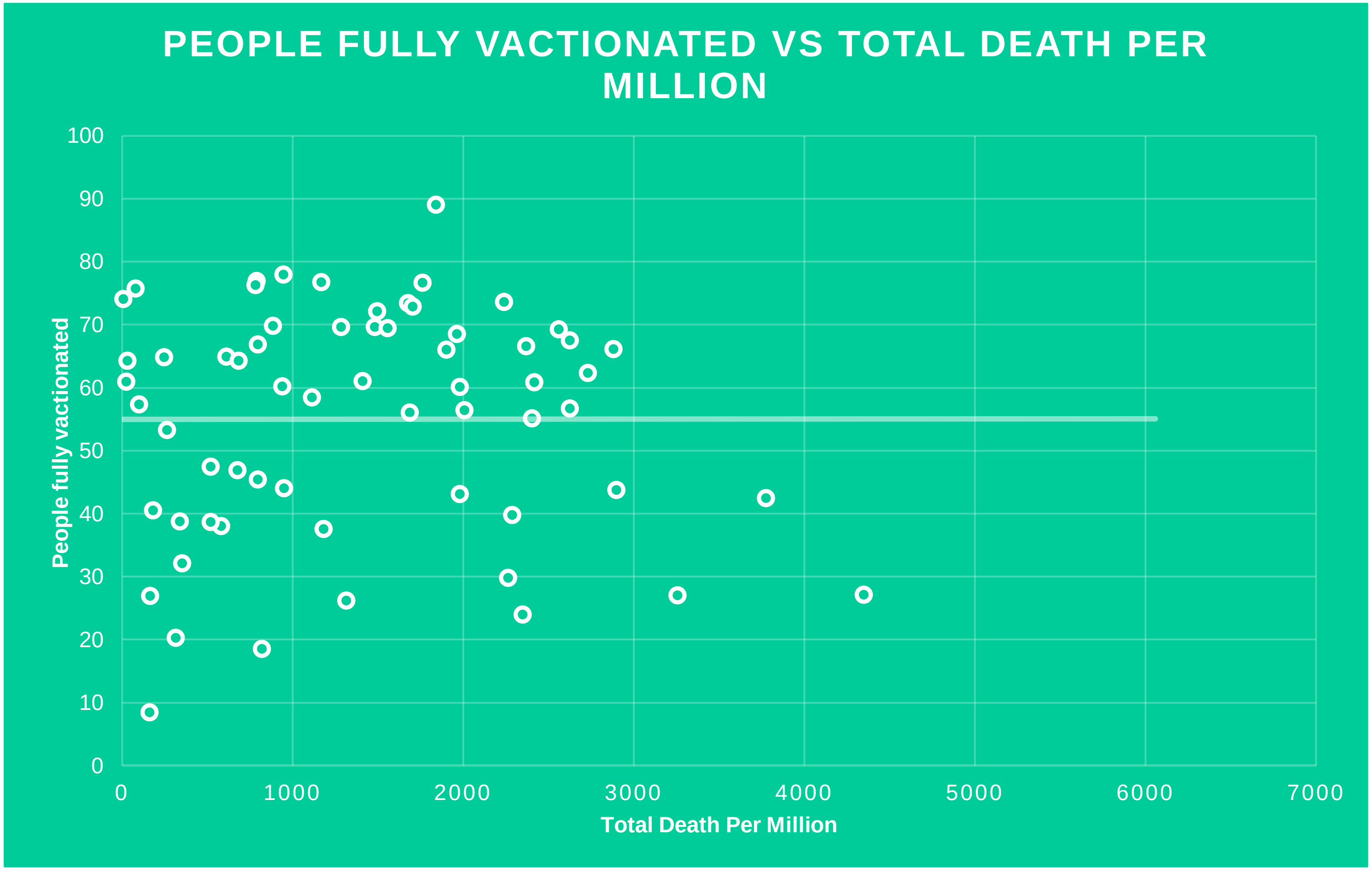
COVID-19: Vaccination rate Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

COVID-19: Fully Vaccination rate Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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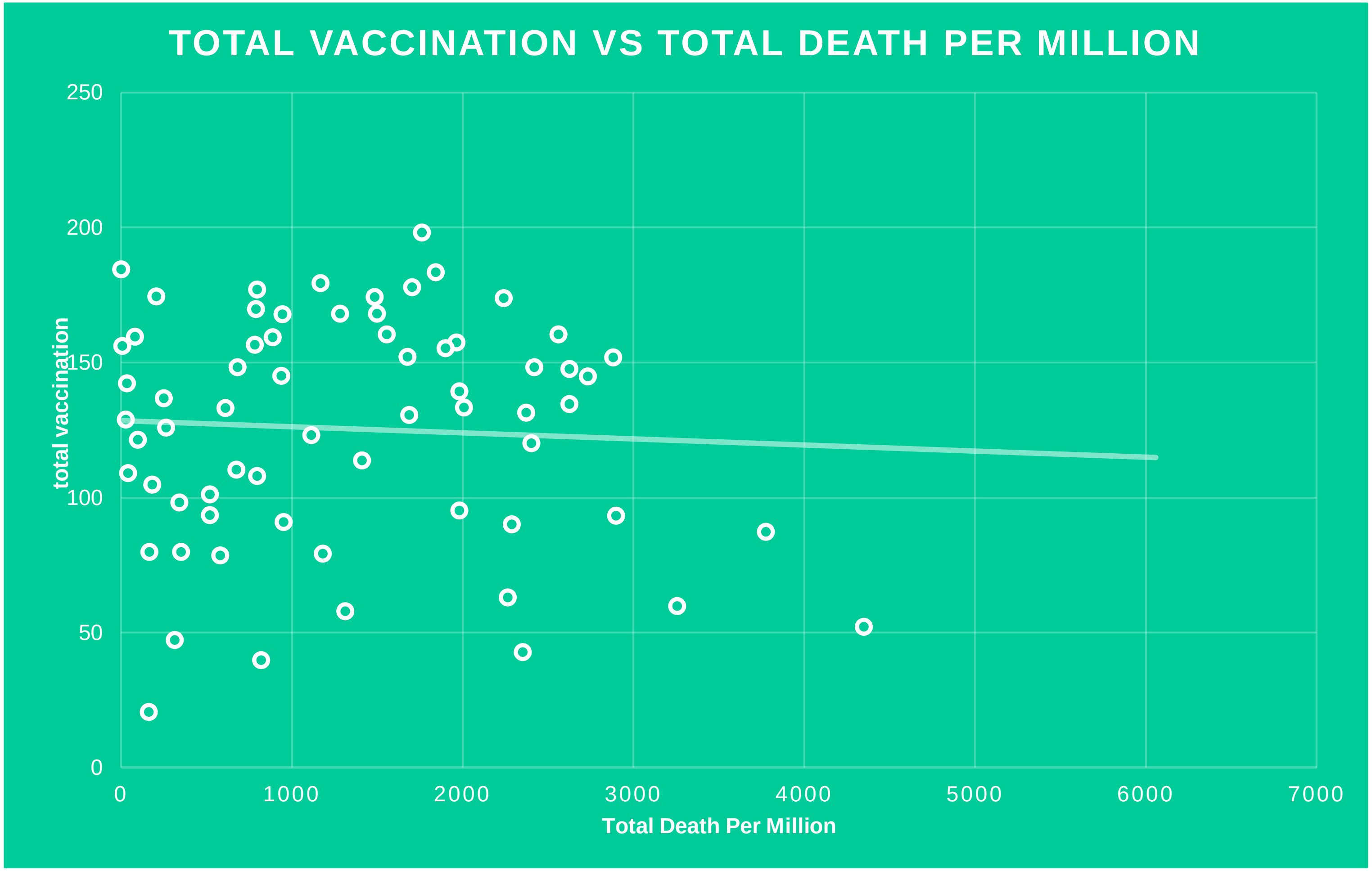
COVID-19: Total Vaccination rate Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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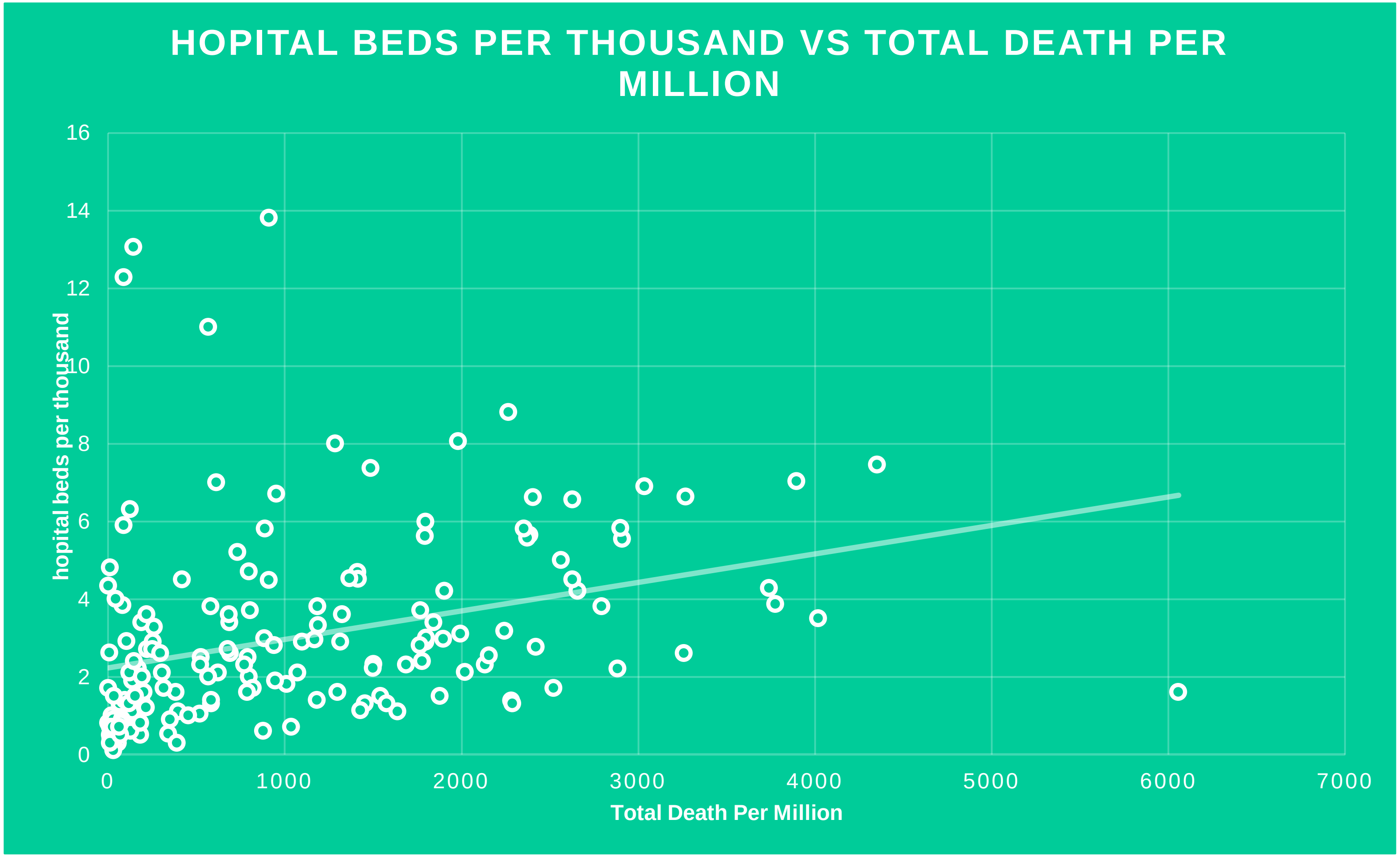
COVID-19: Hospital beds per thousand Vs Total Deaths Per Million



CASE FATALITY RATE OF COVID-19 VS. MEDIAN AGE OF THE POPULATION: SOURCE: HTTPS://OURWORLDINDATA.ORG/

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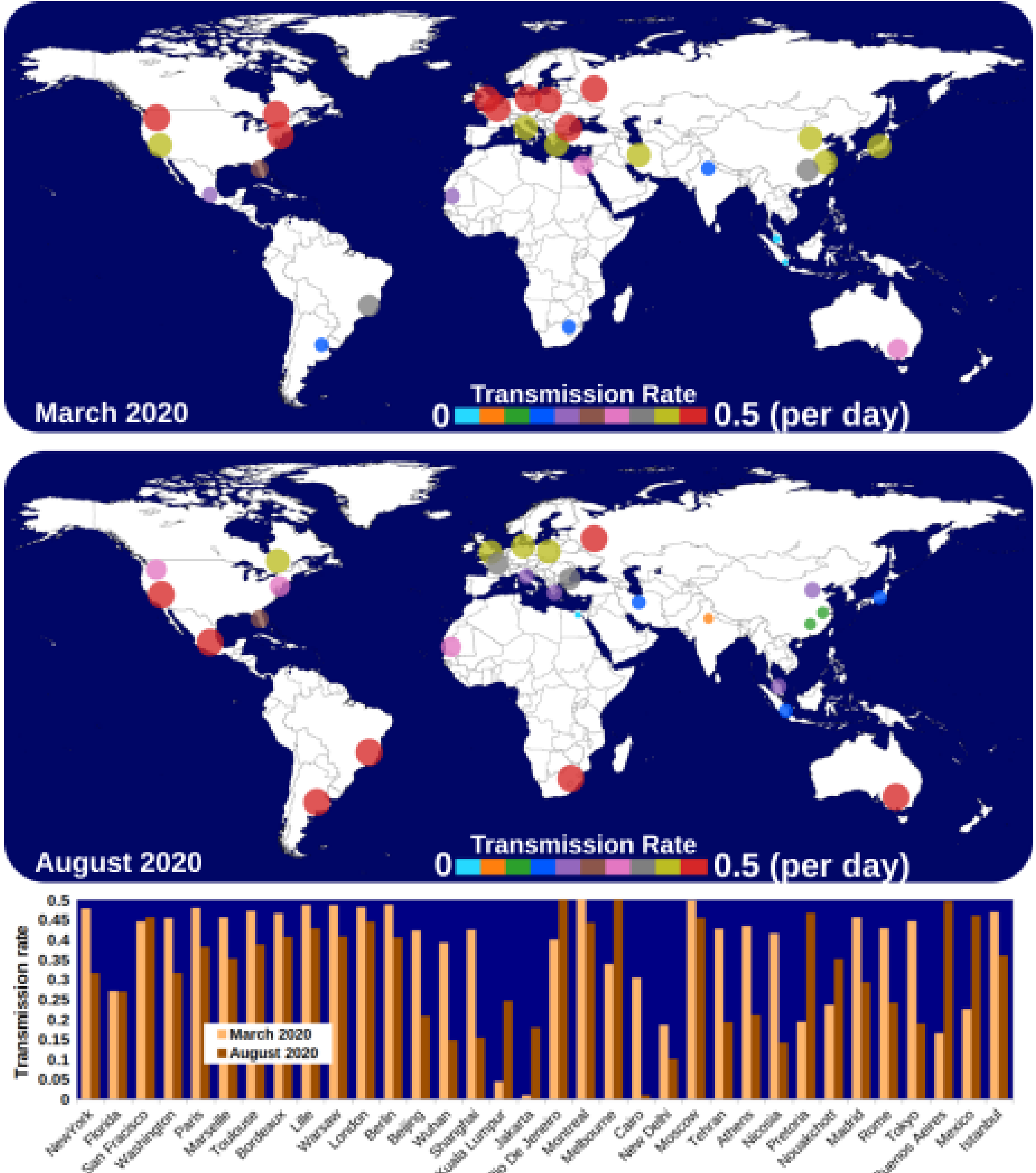
March 2020
Transmission Rate
0
0.5 (per day)
August 2020
Transmission Rate
0
0.5 (per day)
Transmission rate
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
March 2020
August 2020
NewYork
Florida
San Fracisco
Washington
Paris
Marseille
Toulouse
Bordeaux
Lille
Warsaw
London
Berlin
Beijing
Wuhan
Shanghai
Kuala Lumpur
Jakarta
Rio De Janeiro
Montreal
Melbourne
Cairo
New Delhi
Moscow
Tehran
Athens
Nicosia
Pretoria
Nouakchott
Madrid
Rome
Tokyo
Buenos Aires
Mexico
Istanbul

Why COVID-19 is dangerous

1. Low IFR (<1%) and CFR (<2%)
2. High incubation period (up to 14 days)
3. High number of asymptomatic cases
4. Spread by droplets (or airborne)
5. Global supply chain
6. The Aviation sector growth

Global Covid-19 Case Fatality Rates
HTTPS://WWW.CEBM.NET/COVID-19/GLOBAL-COVID-19-CASE-FATALITY-RATES/
WHO (2020):Transmission of SARS-CoV-2: implications for infection prevention precautions
https://www.who.int/news-room/commentaries/detail/transmission-of-sars-cov-2-implications-for-infection-prevention-precautions

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Economic impact and suicide

1. 5.2% contraction in global GDP in 2020.
2. Might result into 10-15% increase in depression, anxiety disorder and suicide rates
3. Might result in 2-5 million extra suicides in 2021
4. More than 10 million suicides in future due to COVID-19

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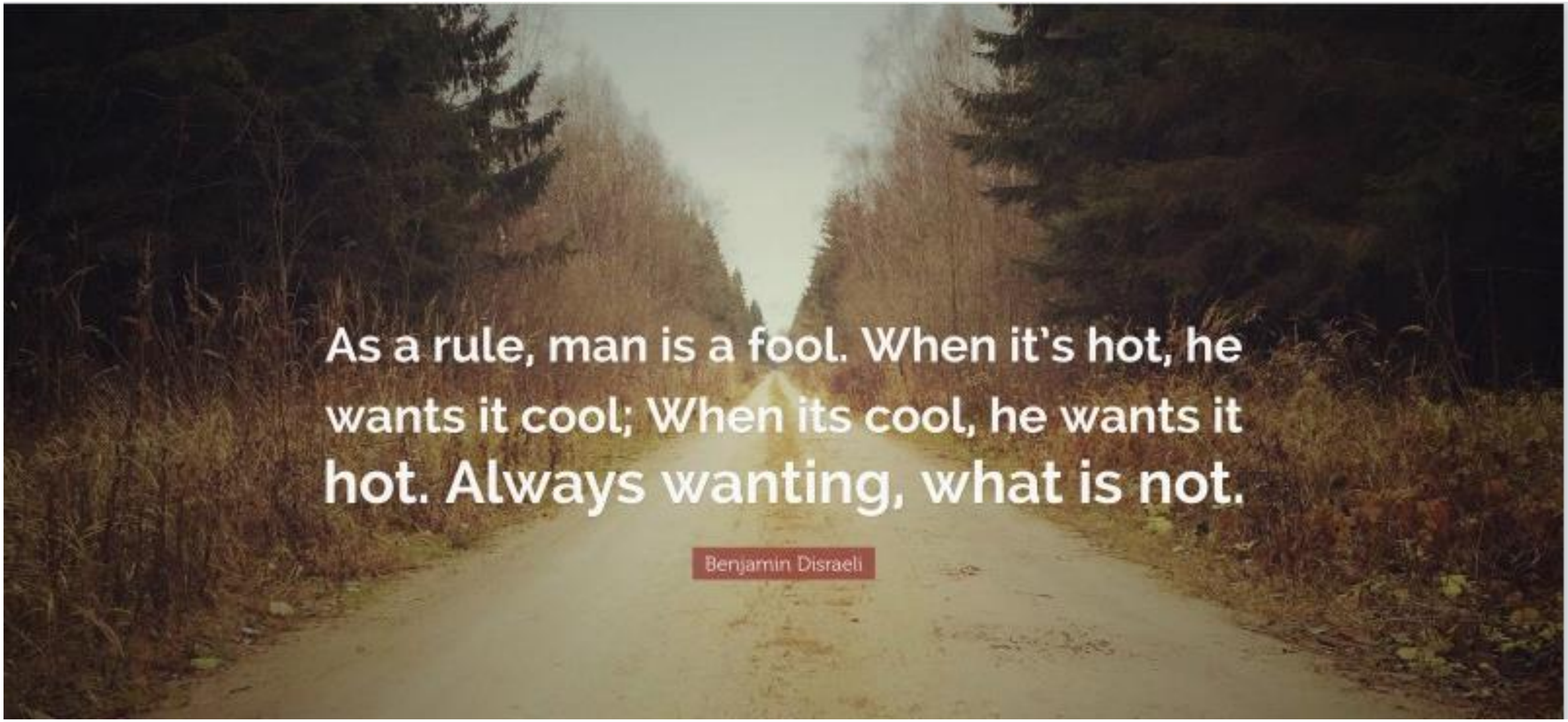
The problem

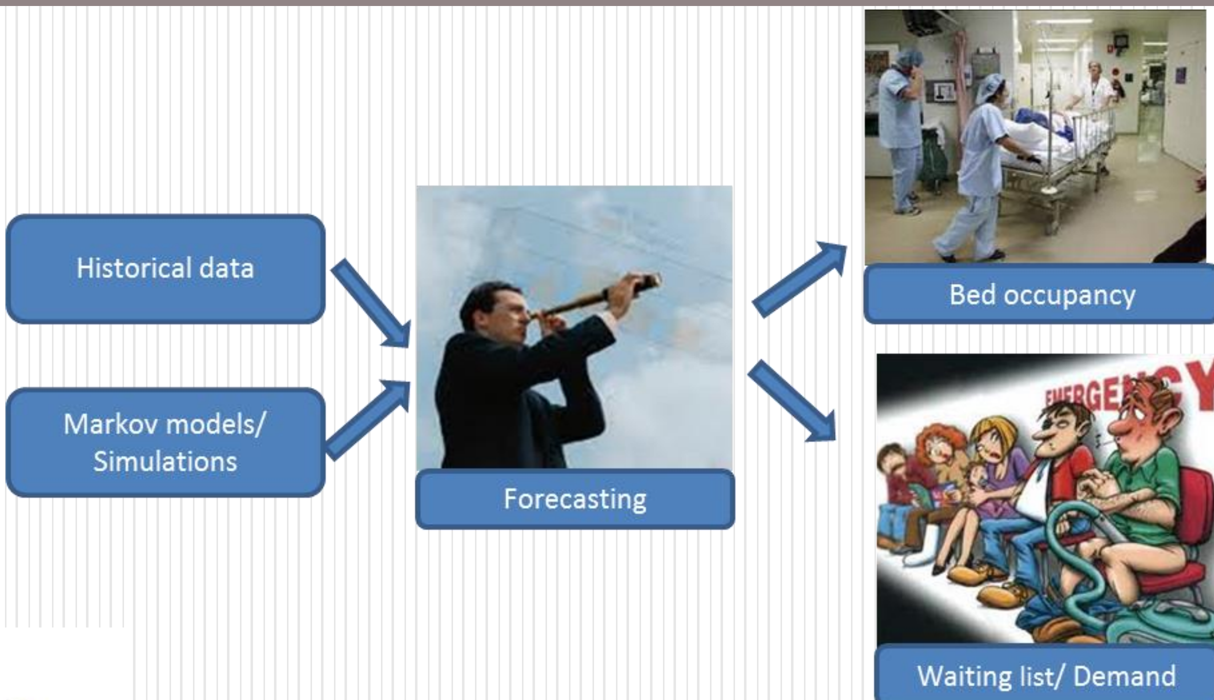

As a rule, man is a fool. When it's hot, he wants it cool; When its cool, he wants it hot. Always wanting, what is not.
Benjamin Disraeli

Who is spreading COVID-19

1. Those who do not know COVID-19 exists
2. Those who know but do not believe
3. Those who unknow about protection measures
4. Those who know but do not

Global Covid-19 Case Fatality Rates
HTTPS://WWW.CEBM.NET/COVID-19/GLOBAL-COVID-19-CASE-FATALITY-RATES/
WHO (2020):Transmission of SARS-CoV-2: implications for infection prevention precautions
https://www.who.int/news-room/commentaries/detail/transmission-of-sars-cov-2-implications-for-infection-prevention-precautions

Hospital bed occupancy and requirements forecasting



Intelligent Patient Management and Resource Planning for Complex, Heterogeneous, and Stochastic Healthcare Systems

Lalit Garg, *Member, IEEE*, Sally I. McClean, Maria Barton, Brian J. Meenan, and Ken Fullerton

***Abstract*—Effective resource requirement forecasting is necessary to reduce the escalating cost of care by ensuring optimum utilization and availability of scarce health resources. Patient hospital length of stay (LOS) and thus resource requirements depend on many factors including covariates representing patient characteristics such as age, gender, and diagnosis. We therefore propose the use of such covariates for better hospital capacity planning. Likewise, estimation of the patient's expected destination after discharge will help in allocating scarce community resources. Also, probable discharge destination may well affect a patient's LOS in hospital. For instance, it might be required to delay the discharge of a patient so as to make appropriate care provision in the community. A number of deterministic models such as ratio-based methods have failed to address inherent variability in complex health processes. To address such complexity, various stochastic models have therefore been proposed. However, such models fail to consider inherent heterogeneity in patient behavior. Therefore, we here use a phase-type survival tree for groups of patients that are homogeneous with respect to LOS distribution, on the basis of covariates such as time of admission, gender, and disease diagnosed; these homogeneous groups of patients can then model patient flow through a care system following stochastic pathways that are characterized by the covariates. Our phase-type model is then extended by further growing the survival tree based on covariates provide a stochastic approach to capacity planning across complex heterogeneous care systems. The approach is illustrated using a five year retrospective data of patients admitted to the stroke unit of the Belfast City Hospital.**

***Index Terms*—Capacity planning, cost, decision-making, forecasting, health information management, medical information systems, operations research, optimal control, prognostics and health management, stochastic systems.**

I. Introduction

EFFECTIVE resource requirement forecasting is necessary to minimize the escalating cost of care by ensuring optimum utilization and availability of scarce health resources [1]. Patient hospital length of stay (LOS) and thus resource requirements depend on many factors including covariates representing patient characteristics such as age, gender, and diagnosis [2]. It is therefore necessary to consider the effect of such covariates for better capacity planning. Information about the patient demography helps in making better allocation of scarce resources. Predicting different treatment outcome,

Health Care Manag Sci
DOI 10.1007/s10729-009-9120-0

A non-homogeneous discrete time Markov model for admission scheduling and resource planning in a cost or capacity constrained healthcare system

Lalit Garg · Sally McClean · Brian Meenan · Peter Millard

Received: 5 March 2009 / Accepted: 23 October 2009

Abstract Healthcare resource planners need to develop policies that ensure optimal allocation of scarce healthcare resources. This goal can be achieved by forecasting daily resource requirements for a given admission policy. If resources are limited, admission should be scheduled according to the resource availability. Such resource availability or demand can change with time. We here model patient flow through the care system as a discrete time Markov chain. In order to have a more realistic representation, a non-homogeneous model is developed which incorporates time-dependent covariates, namely a patient's present age and the present calendar year. The model presented in this paper can using a historical dataset from the geriatric department of a London hospital.

Keywords Resource management · Admission scheduling · Non-homogeneous Markov model · Stochastic optimal control

1 Introduction

Admission scheduling [1, 2] and resource planning [3] are fundamental problems which require complex strategies to effectively manage care services ensuring optimum utiliza-

INFORMATICA, 2011, Vol. 22, No. 1, 57–72

Phase-Type Survival Trees and Mixed Distribution Survival Trees for Clustering Patients' Hospital Length of Stay

Lalit GARG[1], Sally McCLEAN[1], Brian J. MEENAN[1], Peter MILLARD[2]

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12 Cornwall Road, Cheam, Sutton, Surrey, SM2 6DR, UK

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Received: October 2009; accepted: January 2011

Abstract. Clinical investigators, health professionals and managers are often interested in developing criteria for clustering patients into clinically meaningful groups according to their expected length of stay. In this paper, we propose two novel types of survival trees; phase-type survival trees and mixed distribution survival trees, which extend previous work on exponential survival trees. The trees are used to cluster the patients with respect to length of stay where partitioning is based on covariates such as gender, age at the time of admission and primary diagnosis code. Likelihood

IMA Journal of Management Mathematics (2009) **20**, 327–344
doi:10.1093/imaman/dpn030
Advance Access publication on November 20, 2008

Non-homogeneous Markov models for sequential pattern mining of healthcare data

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BRIAN MEENAN§
School of Engineering, University of Ulster, Jordanstown Campus, Newtownabbey, Co. Antrim, BT37 0QB, UK

AND

PETER MILLARD¶
St. George's Hospital Medical School, 12 Cornwall Road, Cheam, Sutton, Surrey SM2 6DR, UK

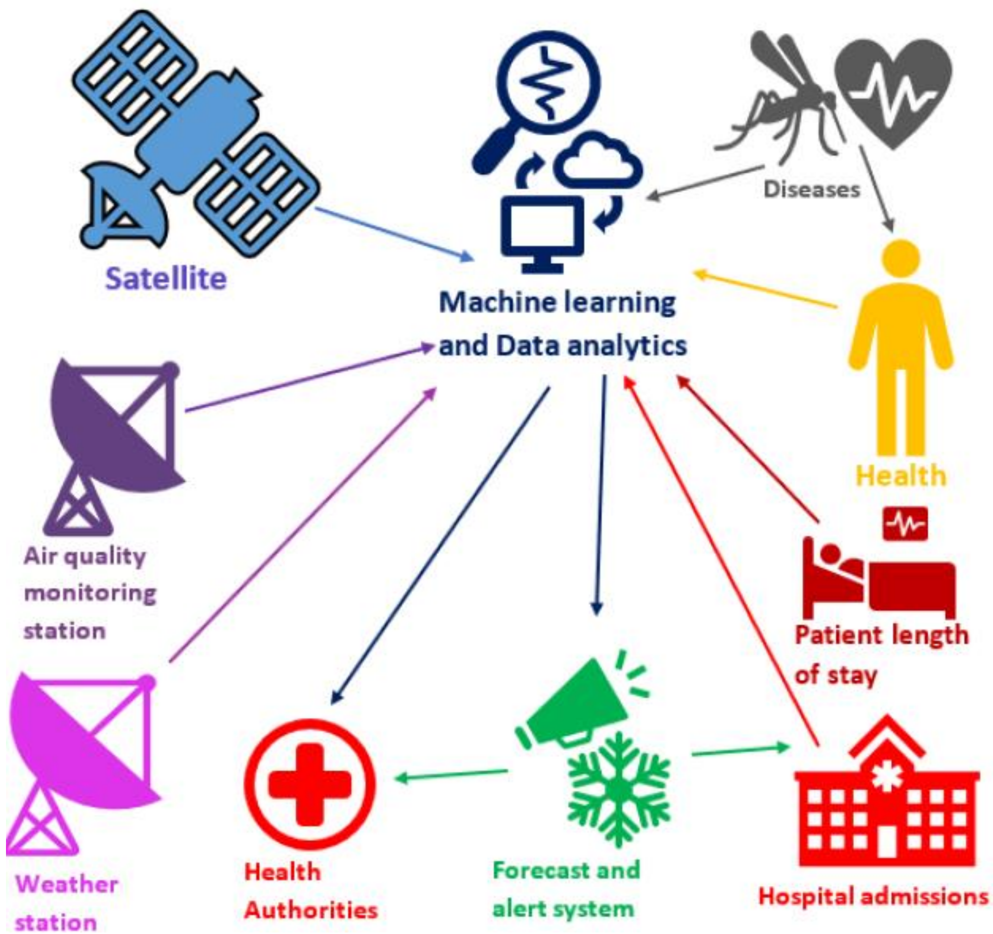
[Received May 2007; accepted May 2008]

Sequential pattern mining has been a popular data mining technique for extracting useful information from large databases and has successfully been used for numerous industrial and commercial problems. This paper presents a new mathematical modelling application to healthcare, providing important information to health service managers and policy makers to help them identify sequential patterns which require attention for efficiently managing scarce healthcare resources and developing effective healthcare management policies. In healthcare, these sequential patterns are analogous to the patient pathways. We present a non-homogeneous Markov model for identifying not only patient pathways which have high probability but also for identifying pathways which incur high cost or time. In order to have a more

Hospital bed occupancy and requirements forecasting

- **Collaborative partners:** Nanyang Technological University and Tan Tock Seng Hospital, Singapore.
- **Approach**: Markov modelling, reinforcement learning
- **Data**: Tan Tock Seng Hospital, Singapore.

Hospital bed requirements forecasting using satellite, weather & air quality data



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Introduction

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

Introduction

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

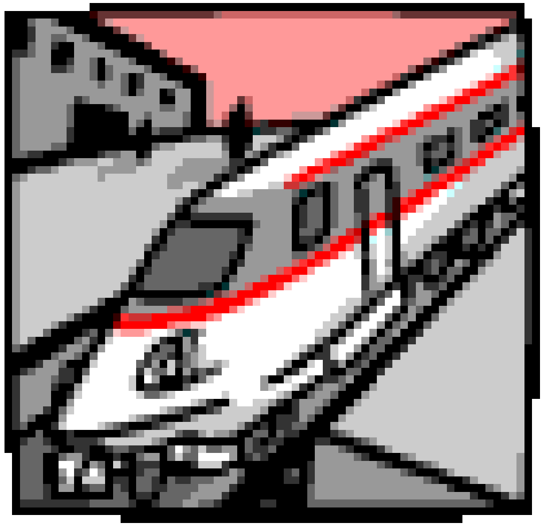
- When modelling the healthcare system it would help:

Introduction

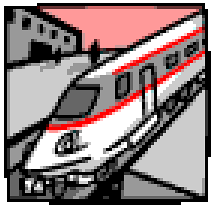
- When modelling the healthcare system it would help:
  - To better understand the process for the design of polices that can improve the quality of care

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

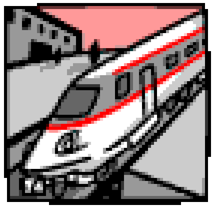


Coxian phase type distributions



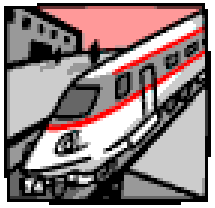
Coxian phase type distributions

- Among popular choices to fit spell length of stay data.



Coxian phase type distributions

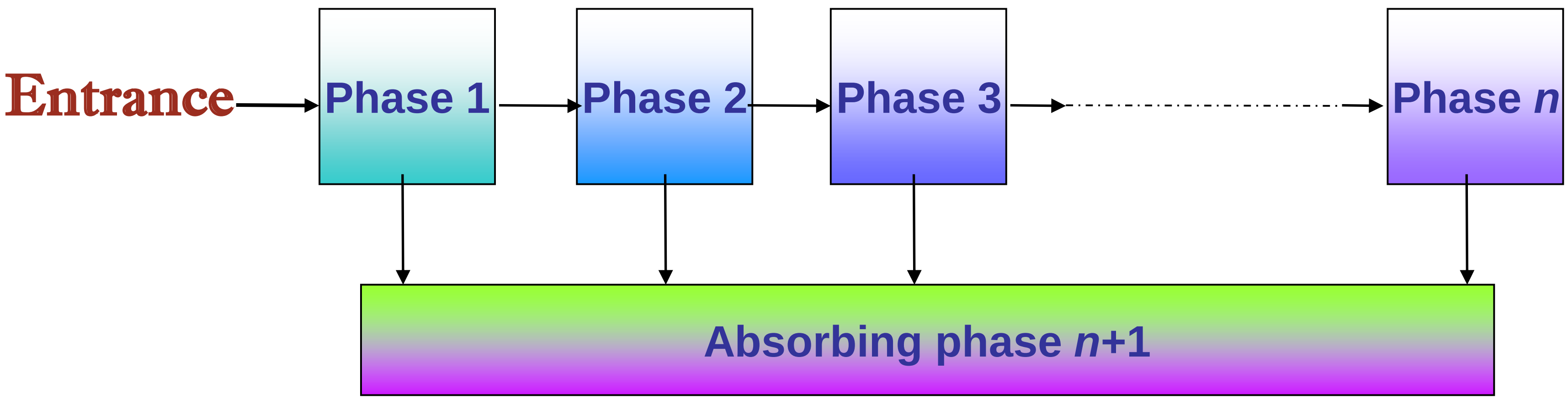
- Among popular choices to fit spell length of stay data.
- Provide a simple interpretation of fit for the length of stay data.



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



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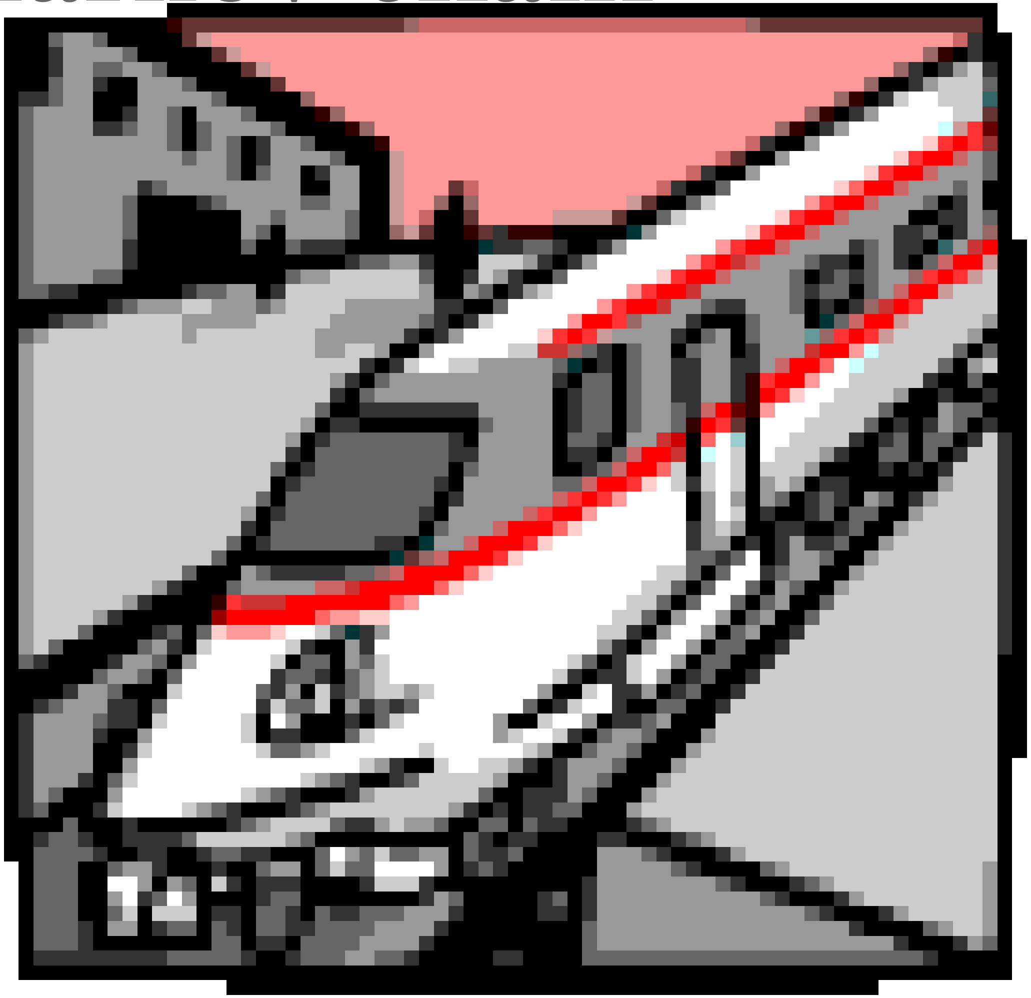
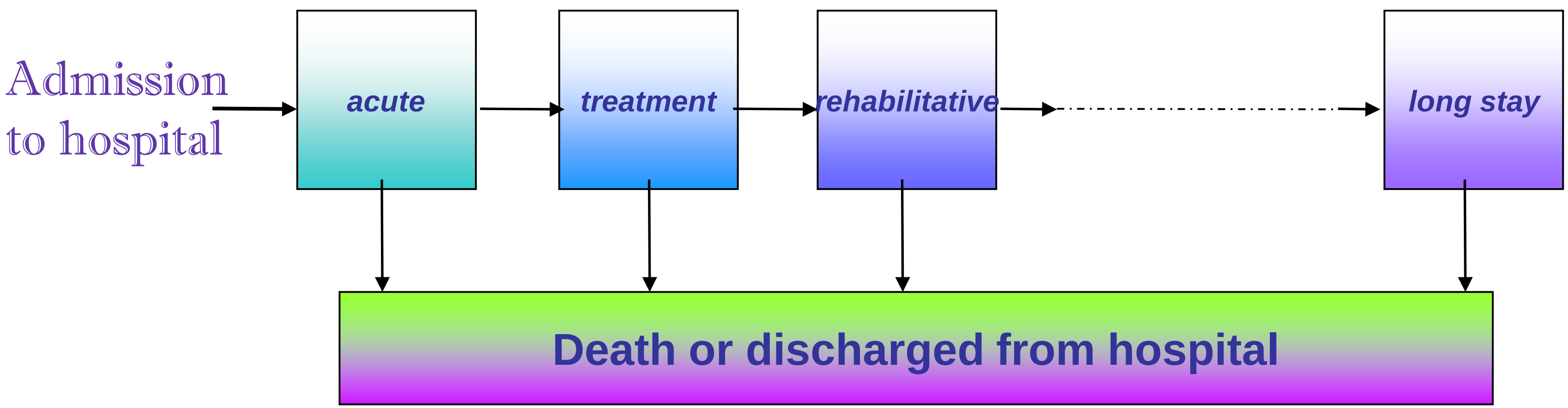
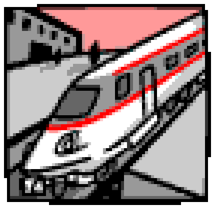


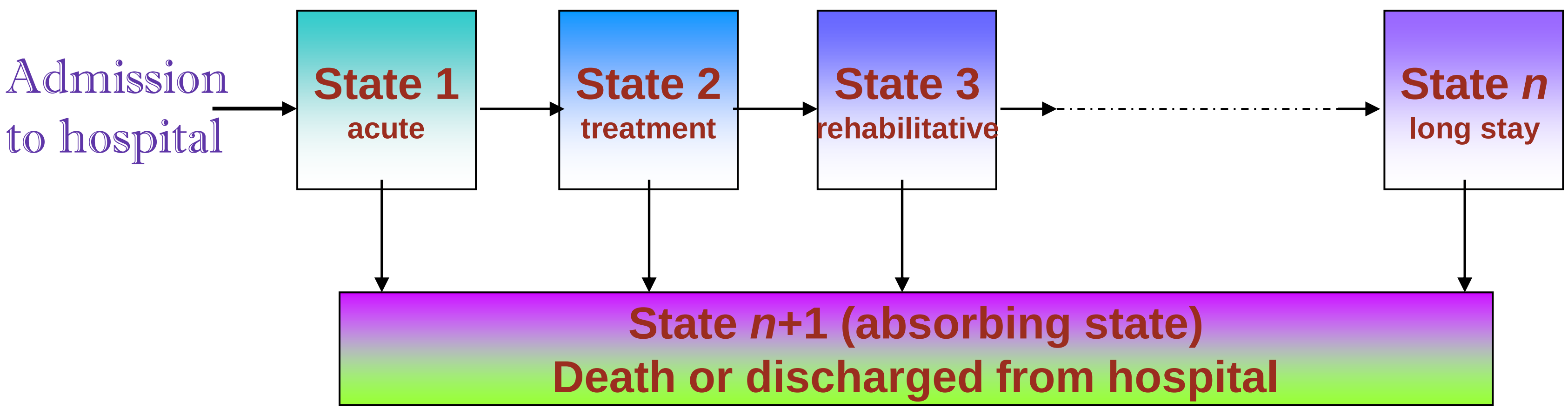
Hospital care system as a Markov chain

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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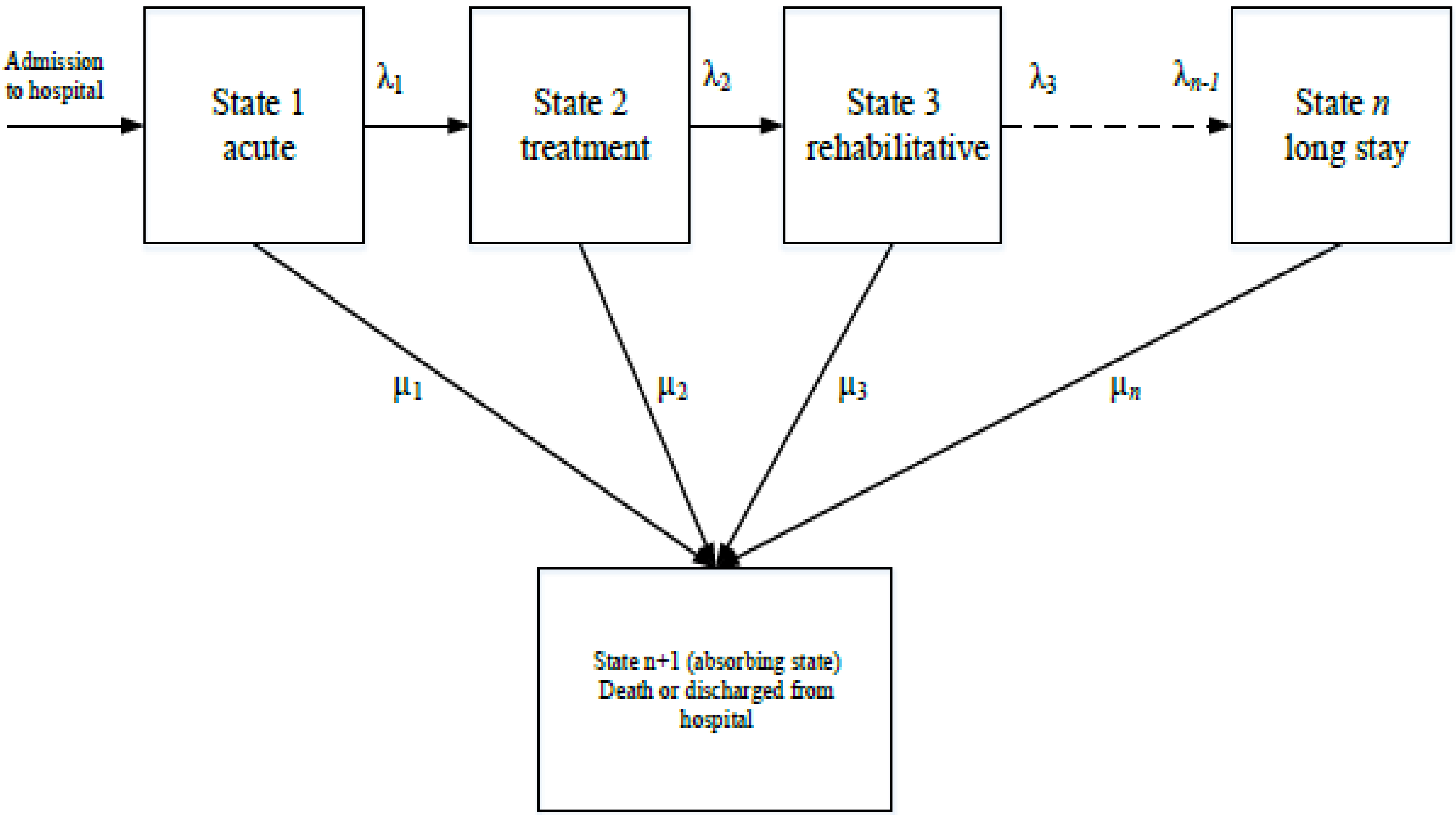
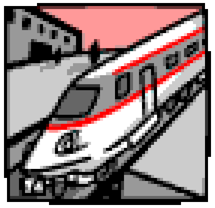




Coxian phase type distributions

- 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:

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

- where the initial state probability distribution

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

- absorption probabilities

$$\mathbf{q} = \begin{pmatrix} \mu_1 & \mu_2 & \ldots & \mu_{n-2} & \mu_n \end{pmatrix}^{\mathrm{T}} .$$

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.
-

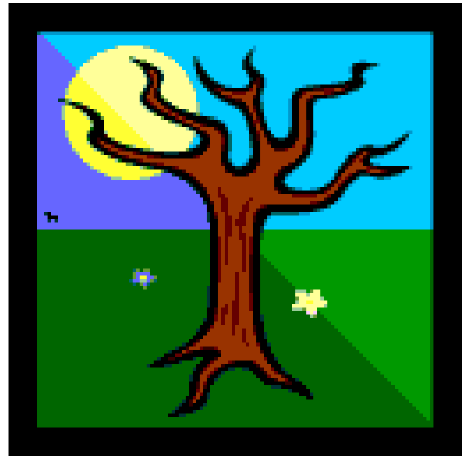
Weighted-Average Information Criterion

- 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

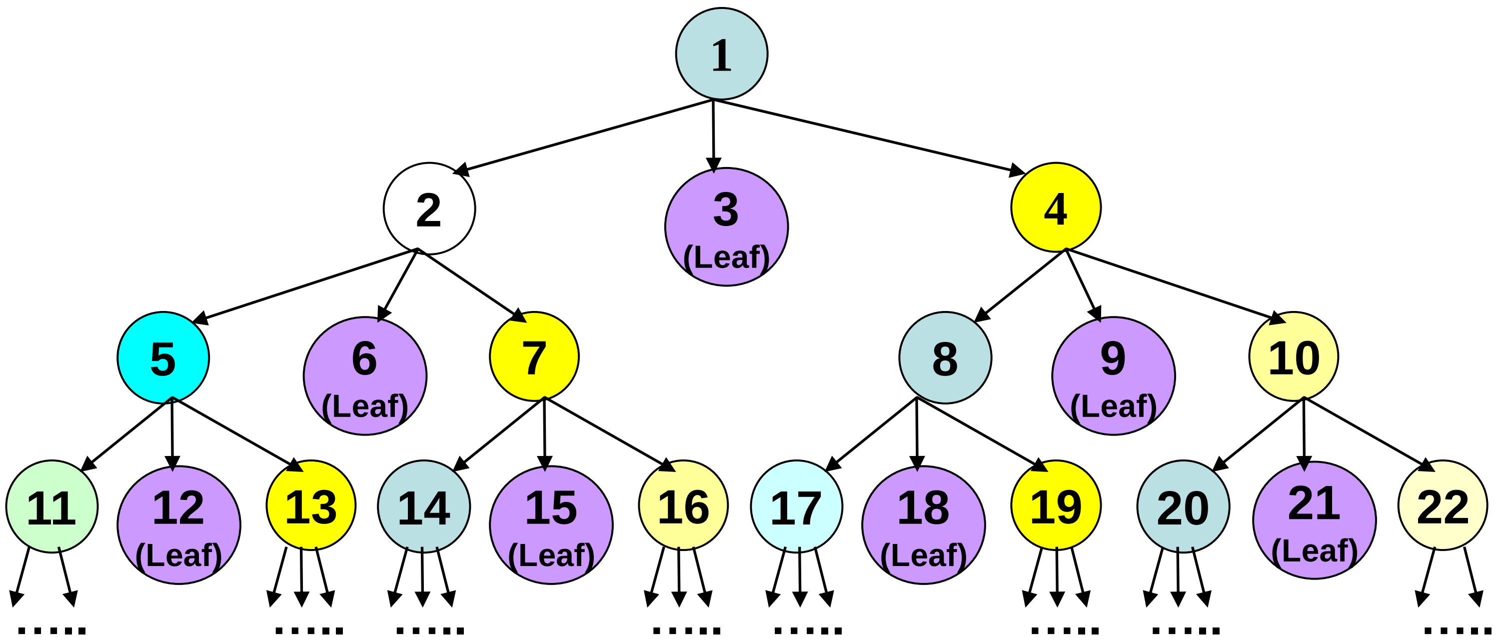
- The performance of WIC was compared with several other popular criteria in the study and the results showed that WIC is very reliable.

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



Survival tree

Survival tree



Survival trees

- Decision trees in survival analysis

Survival trees

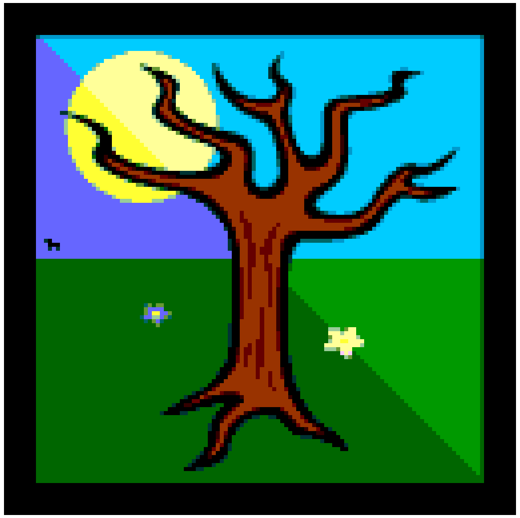
- Decision trees in survival analysis

- 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

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    - 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*

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- 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
- The loglikelihood of node *a* is

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

- Or

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

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

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 2011-2012.

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

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

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- 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

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  - 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.

Dataset

- Daily and Monthly Admission Values:

	Sun.	Mon.	Tues.	Wed.	Thurs.	Fri.	Sat.	Total
Jan.	1135	2423	1897	1837	1630	1650	1250	11822
Feb.	989	1942	1663	2013	1585	1518	1202	10912
Mar.	917	1855	1799	2010	1941	1851	1258	11631
Apr.	999	2179	1634	1783	1580	1555	1305	11035
May.	999	2064	1941	1994	1780	1621	1128	11527
Jun.	867	1835	1528	1888	1629	1731	1252	10730
Jul.	1113	2174	1873	1745	1528	1793	1222	11448
Aug.	849	2042	1779	2097	1802	1815	1112	11496
Sept.	934	1874	1623	1668	1756	1666	1189	10710
Oct.	973	2402	1947	2026	1683	1783	1394	12208
Nov.	946	1942	1971	2091	1891	1865	1278	11984
Dec.	894	1671	1404	1572	1469	1729	1262	10001
Tot.	11651	24403	21059	22724	20274	20577	14852	135504

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		

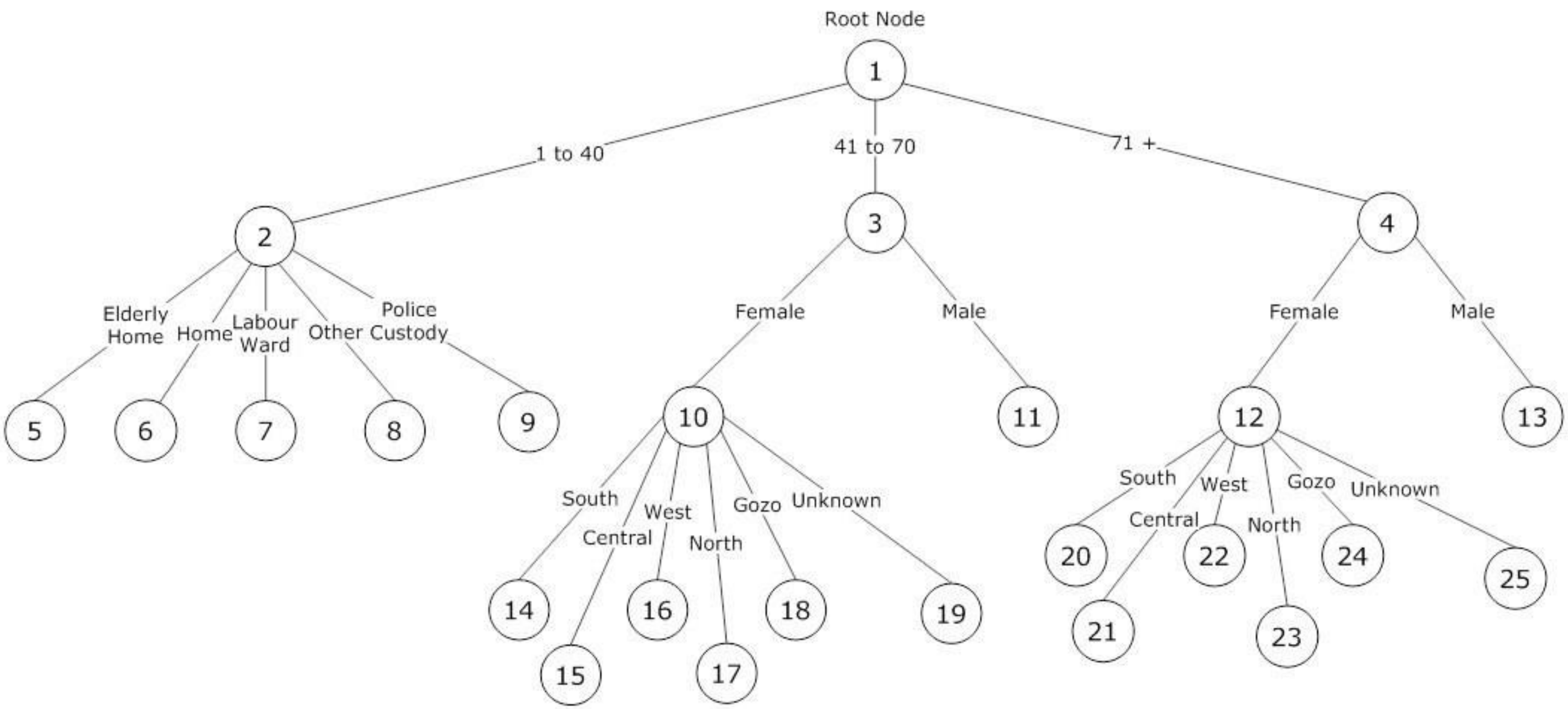
LOS-Phase type Survival tree

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

<table>
<tr><th>Node</th><th>Covariate</th><th>Covariate Value</th><th>Total Number of Patients</th><th>WIC</th><th>Mean LOS</th><th>Number of phases</th><th>Total WIC</th><th>Gain in WIC</th></tr>
<tr><td colspan="9">Level 3</td></tr>
<tr><td rowspan="10">12 (Age 71 +, Female)</td><td>All</td><td>Age 71 +, Female</td><td>11578</td><td>72543.24</td><td>9.9719</td><td>5</td><td>72543.24</td><td>-</td></tr>
<tr><td rowspan="6">District</td><td>71 +, South, F</td><td>3663</td><td>22859.81</td><td>9.8444</td><td>6</td><td rowspan="6">72219.66</td><td rowspan="6">323.58</td></tr>
<tr><td>71 +, Central, F</td><td>3880</td><td>24104.55</td><td>9.8023</td><td>6</td></tr>
<tr><td>71 +, West, F</td><td>1736</td><td>11040.79</td><td>10.4919</td><td>4</td></tr>
<tr><td>71 +, North, F</td><td>2242</td><td>13837.2</td><td>10.0589</td><td>6</td></tr>
<tr><td>71 +, Gozo, F</td><td>40</td><td>287.23</td><td>12.825</td><td>1</td></tr>
<tr><td>71 +, Unknown, F</td><td>17</td><td>90.08</td><td>4.8235</td><td>1</td></tr>
<tr><td rowspan="3">Source of Admission</td><td>71 +, Elderly Home, F</td><td>1257</td><td>7655.41</td><td>9.4121</td><td>4</td><td rowspan="3">72532.89</td><td rowspan="3">10.35</td></tr>
<tr><td>71 +, Home, F</td><td>10093</td><td>63415.04</td><td>10.0396</td><td>6</td></tr>
<tr><td>71 +, Other (Gov Hospital, Private, Mental and Abroad), F</td><td>228</td><td>1462.44</td><td>10.057</td><td>4</td></tr>
</table>

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**		

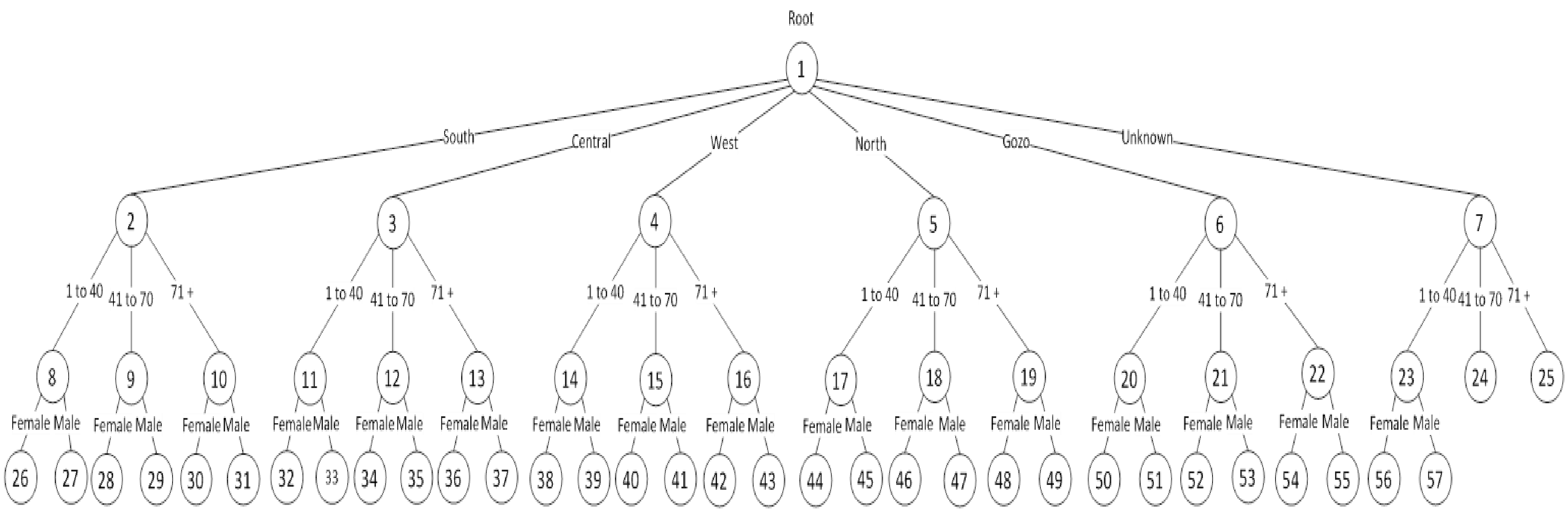
Admissions Phase-Type Survival Tree Construction

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



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 ≤ x ≤ -1°C (2)	97	7.59	584.81		
		0°C (3)	102	7.25	605.99		
		1°C ≤ x ≤ 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		

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	58083.83	-814.20
		11°C-20°C (2)	10512	6.82	57122.54		
		21°C-30°C (3)	0	0.00	0.00		
	MaxVar	x<-2°C (1)	397	5.66	2036.82	57493.12	-223.49
		-2°C ≤ x ≤ -1°C (2)	2405	6.95	13061.90		
		0°C (3)	2666	6.88	14272.56		
		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**	**78354.56**	**641.22**
		11°C-20°C (2)	**9835**	**6.85**	**52787.28**		
		21°C-30°C(3)	**4679**	**6.84**	**25567.28**		
	MaxVar	x<-2°C (1)	806	7.54	4555.23	78571.35	424.43
		-2°C ≤ x ≤ -1°C (2)	4456	6.68	23671.22		
		0°C (3)	5160	6.90	28290.46		
		1°C ≤ x ≤ 2°C (4)	3736	6.88	20163.21		
		x >2°C (5)	356	6.10	1891.23		

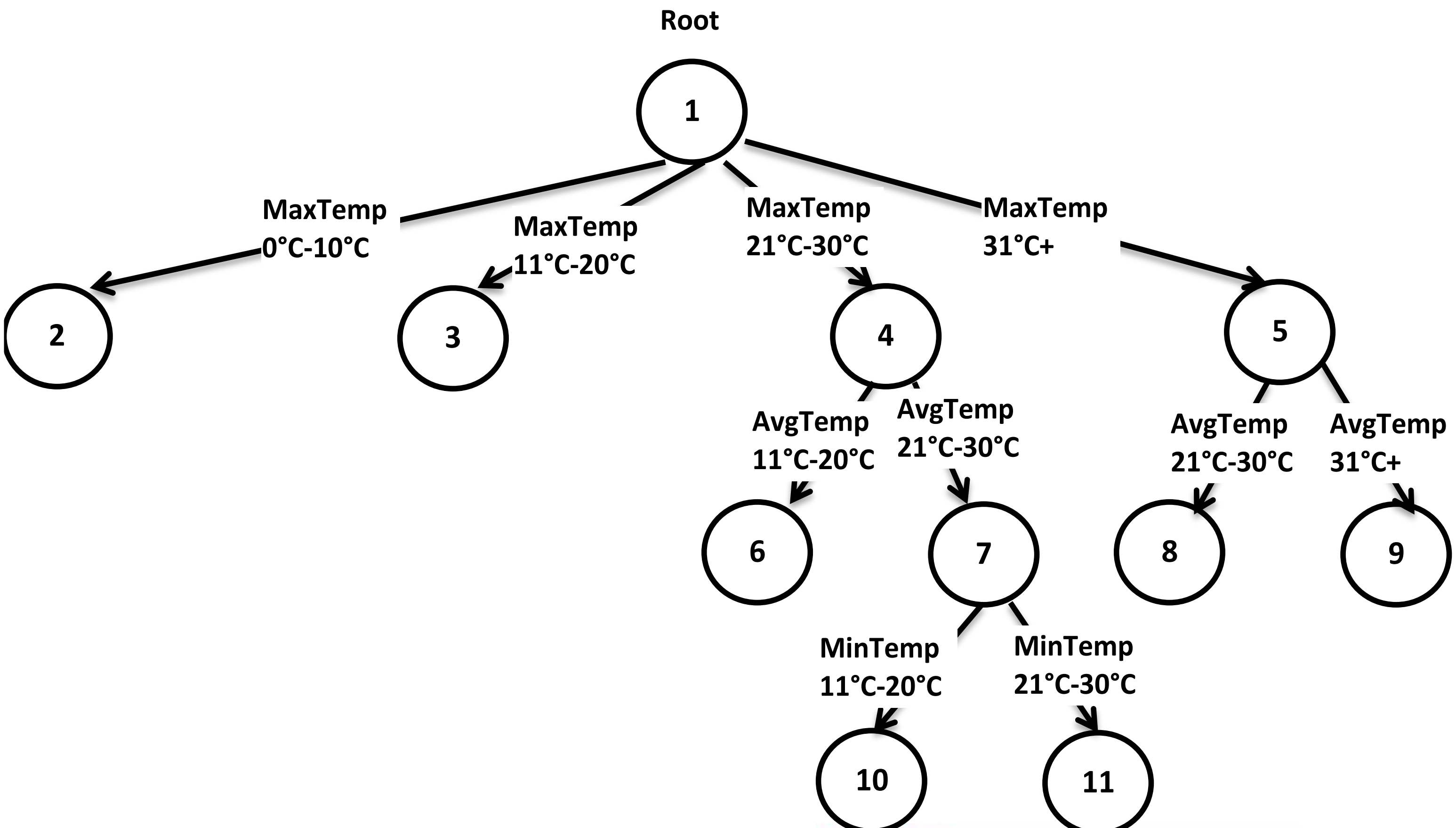
Construction of Phase-Type Survival Tree showing Effect of Weather on LOS

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 $\leq$ x $\leq$ -1°C (2)	2746	6.79	14698.72		
		0°C (3)	2827	6.70	15140.27		
		1°C $\leq$ x $\leq$ 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

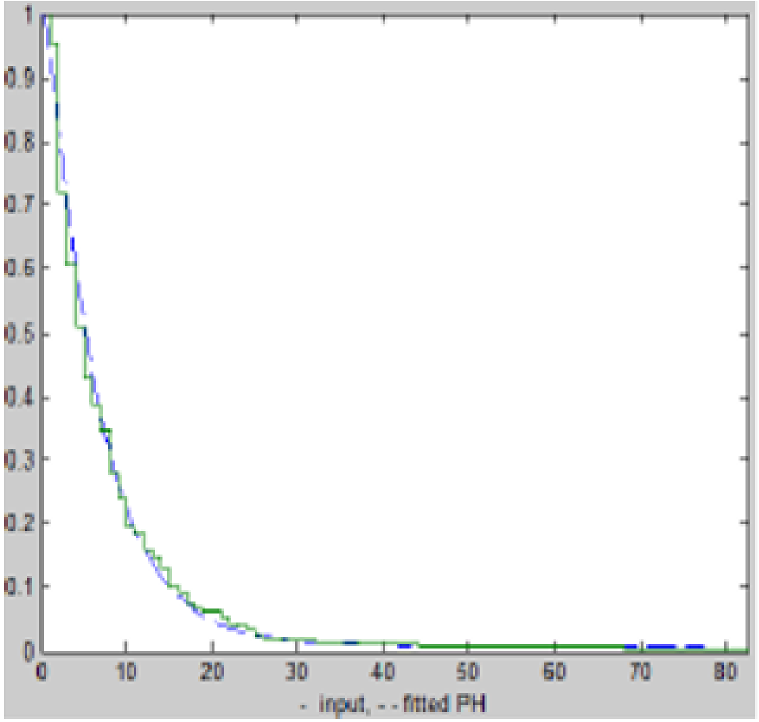
Level	Covariate	Covariate Group	No. of Patients	Mean LOS	WIC	Total WIC	WIC Gain
3(31+°C Max, 21°C-30°C Avg)	***All***	***21° C-30° C (3)***	***11576***	***6.82***	***62203.93***	***62203.93***	
	MinTemp	0°C-10°C (1)	0	0.00	0.00		
		11°C-20°C (2)	820	6.70	4466.70	63023.76	-819.83
		21°C-30°C (3)	10756	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		
		0°C (3)	2827	6.70	15140.27	62465.66	-261.73
		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		

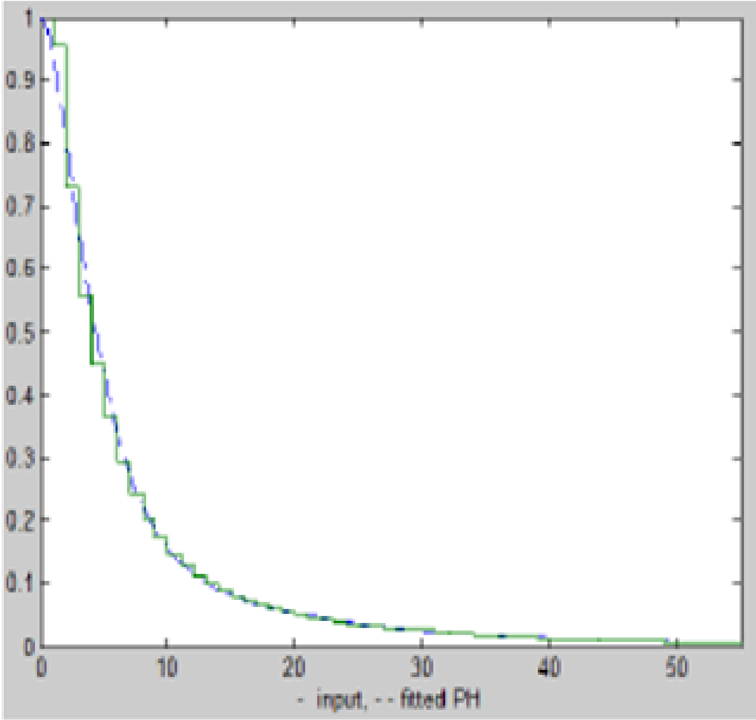
Phase-Type Survival Tree showing Effect of Weather on LOS



Phase-Type Survival Tree showing Effect of Weather on LOS

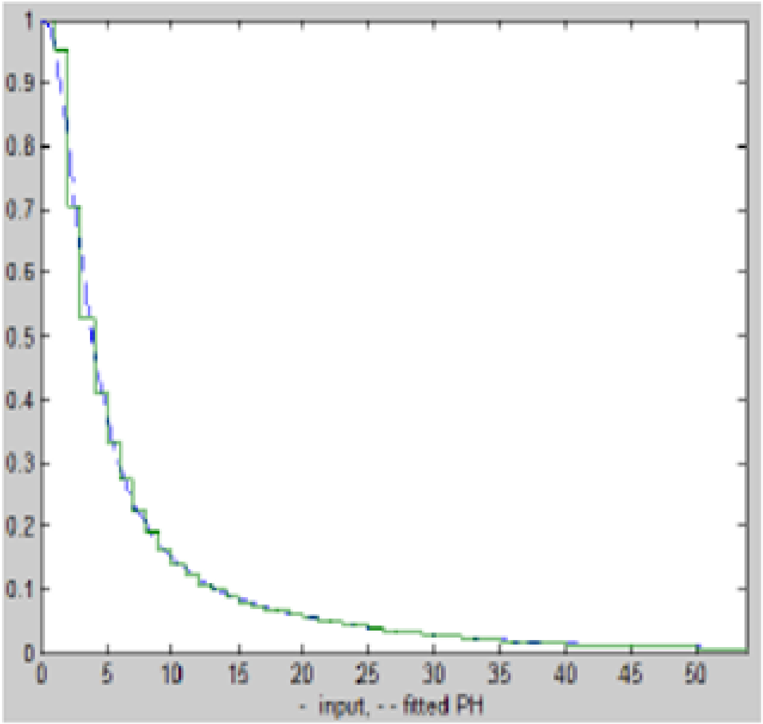
- Node 2 Node 3





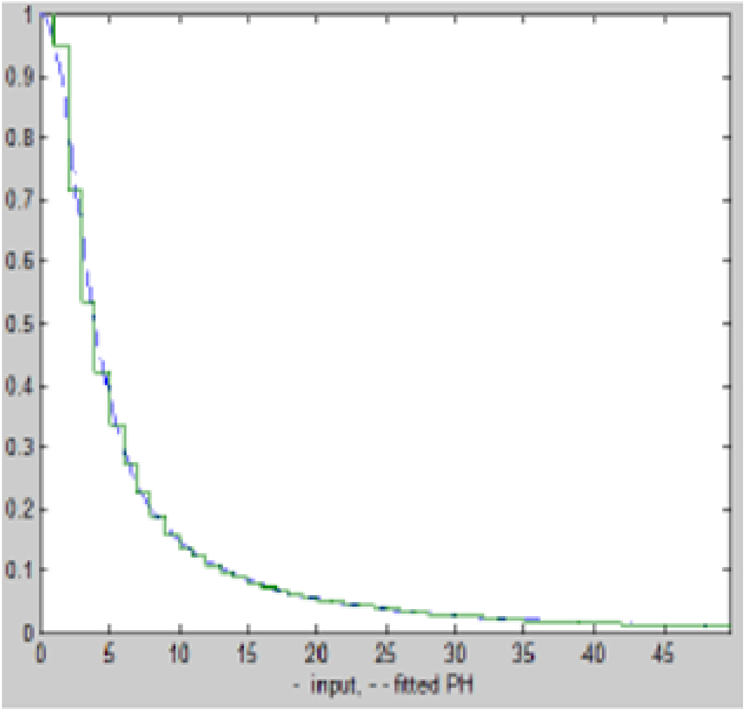
Phase-Type Survival Tree showing Effect of Weather on LOS

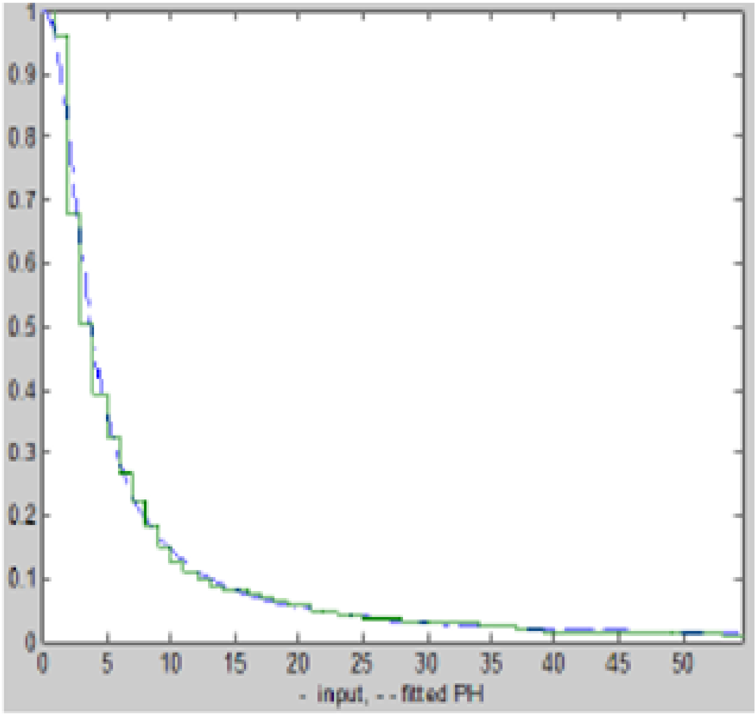
- Node 8 Node 9



Phase-Type Survival Tree showing Effect of Weather on LOS

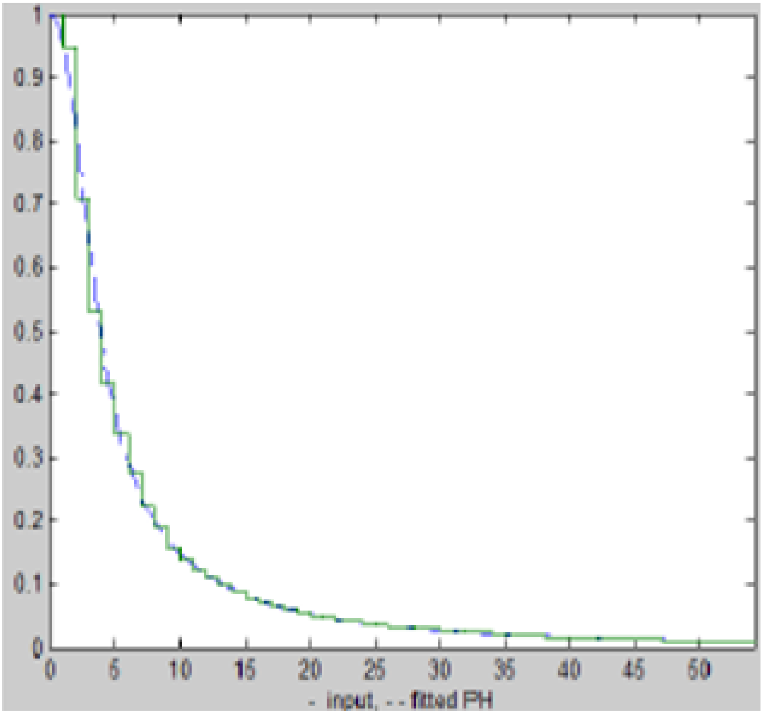
- Node 8 Node 9

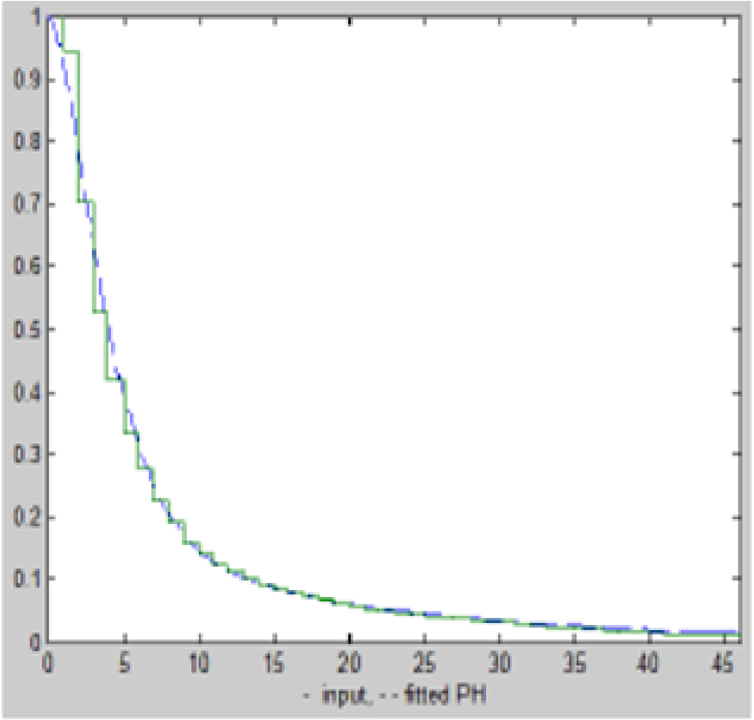




Phase-Type Survival Tree showing Effect of Weather on LOS

- Node 10 Node 11





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 ≤ x ≤ -1°C (2)	**200**	**91.00**	**1867.44**	**373.49**		
		0°C (3)	**212**	**89.82**	**1956.63**	**391.33**		
		1°C ≤ x ≤ 2°C (4)	**236**	**90.53**	**2186.84**	**437.37**		
		x >2°C (5)	**38**	**92.87**	**385.68**	**77.14**		

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,$-2°C \le x \le -1°C$ (2))	*All*	*$-2°C \le x \le -1°C$ (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, $1°C \le x \le 2°C$ (4))	*All*	*$1°C \le x \le 2°C$ (4)*	*236*	*90.53*	*2186.84*	*437.37*	*437.37*	
	Min	0°C-10°C (1)	50	93.86	507.91	169.30	761.50	-324.13
		11°C-20°C (2)	128	89.68	1208.86	402.95		
		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**	**369.35**	**68.02**
		11°C-20°C (2)	**92**	**92.95**	**896.15**	**23.24**		
		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	563.66	-126.29
		11°C-20°C (2)	134	91.77	1271.13	317.78		
		21°C-30°C(3)	91	87.68	863.45	215.86		
		31+°C (4)	1	99.00	6.97	1.74		

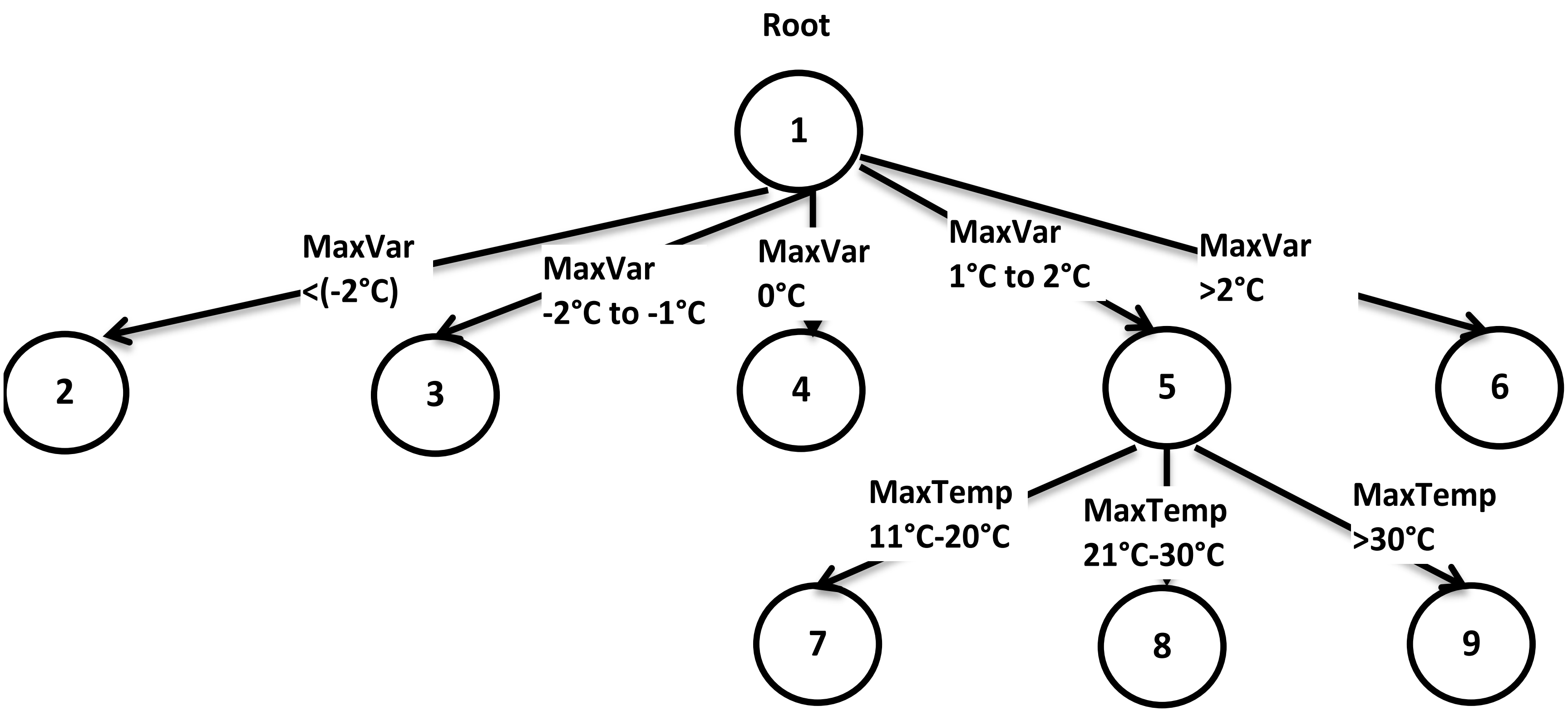
Construction of Phase-Type Survival Tree showing Effect of Weather on Admissions

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	233.29	-210.05
		11°C-20°C (2)	43	92.00	434.78	108.69		
		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	233.29	-210.05
		11°C-20°C (2)	43	92.00	434.78	108.69		
		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		BAD WIC	BAD WI
		11°C-20°C (2)	81	89.05	773.46	257.82		
		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	235.24	-10.41
		11°C-20°C (2)	52	91.08	512.81	128.20		
		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 1°C-2°C 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

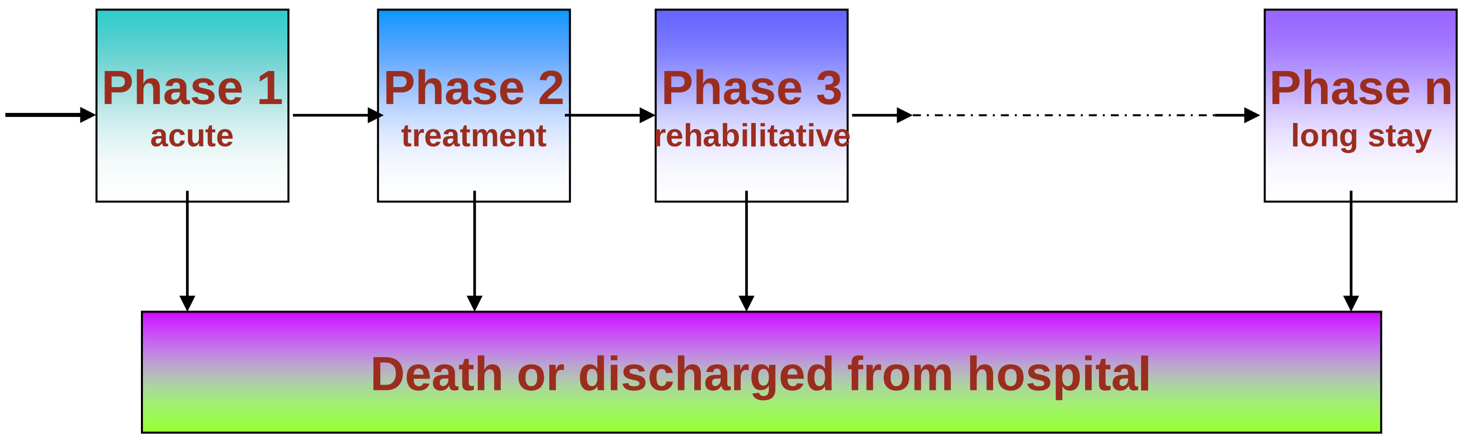
Group	No. of Records	Actual Mean Adm.	Predicted Mean Adm.	Forecast Error	Squared Error	Absolute Error	Percentage Error (%)
MaxVar($x<-2°C$)	31	92.13	89.60	-2.53	6.40	2.53	2.75
MaxVar($-2°C \leq x \leq -1°C$)	99	92.34	91.00	-1.34	1.80	1.34	1.45
MaxVar($x = 0°C$)	93	92.77	89.82	-2.95	8.70	2.95	3.18
MaxVar($x>2°C$)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

Accuracy test for all predictions

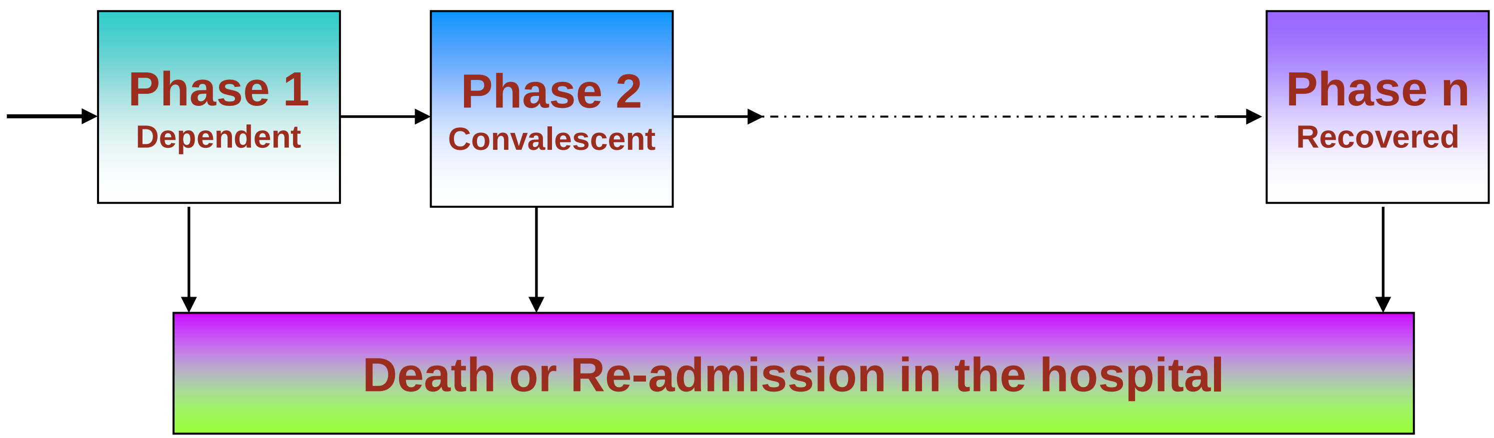
		MSE	RMSE	MAD	BIAS
LOS	*Weather*	0.08	0.28	0.26	-0.09
	Personal Characteristics	1.15	1.07	0.74	-0.69
Admissions	*Weather*	16.17	4.02	3.37	-3.37
	Personal Characteristics	1.38	1.17	0.96	-0.82

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

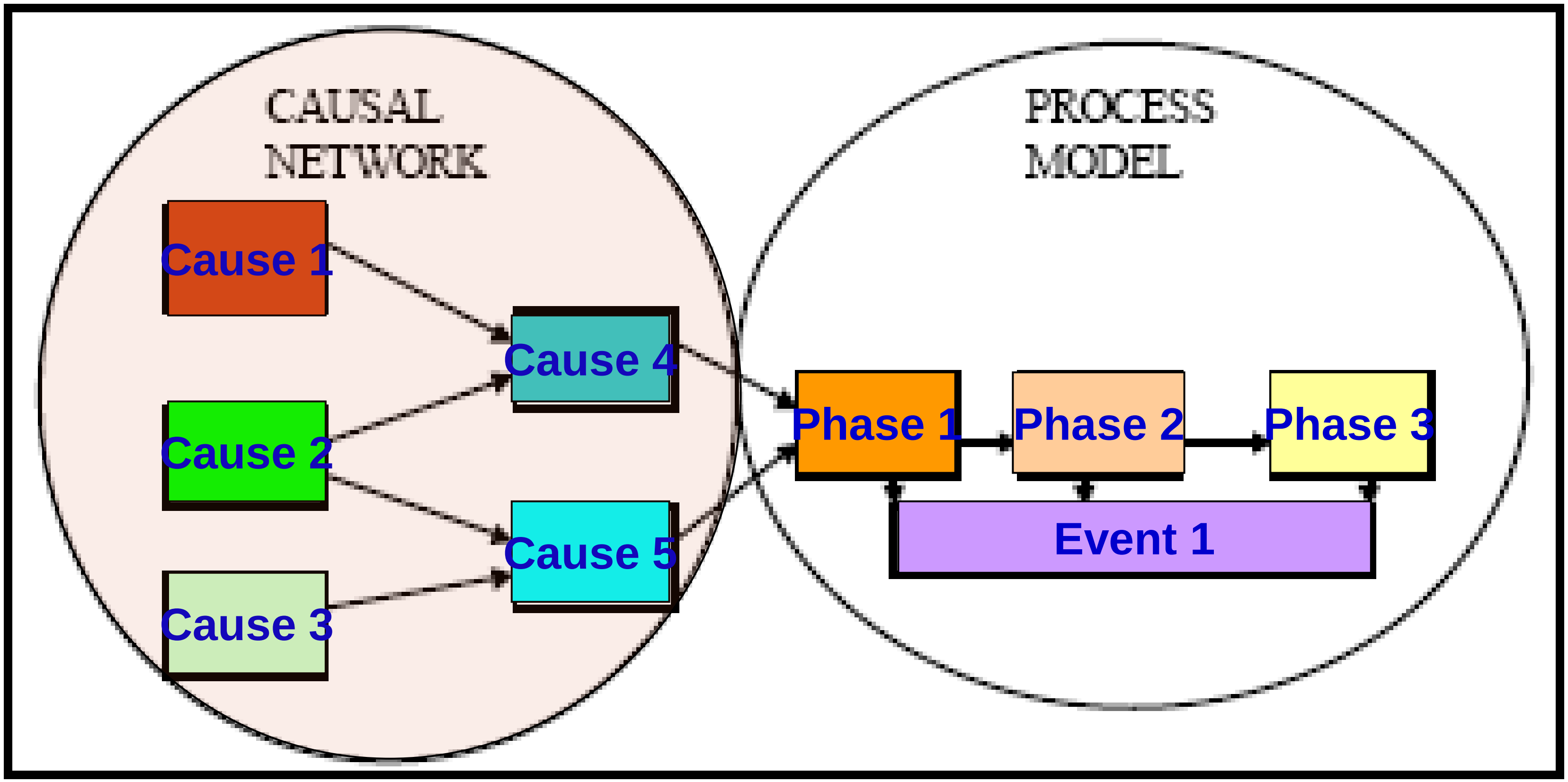
Hospital Care System as a Markov Chain



Community Care System as a Markov Chain

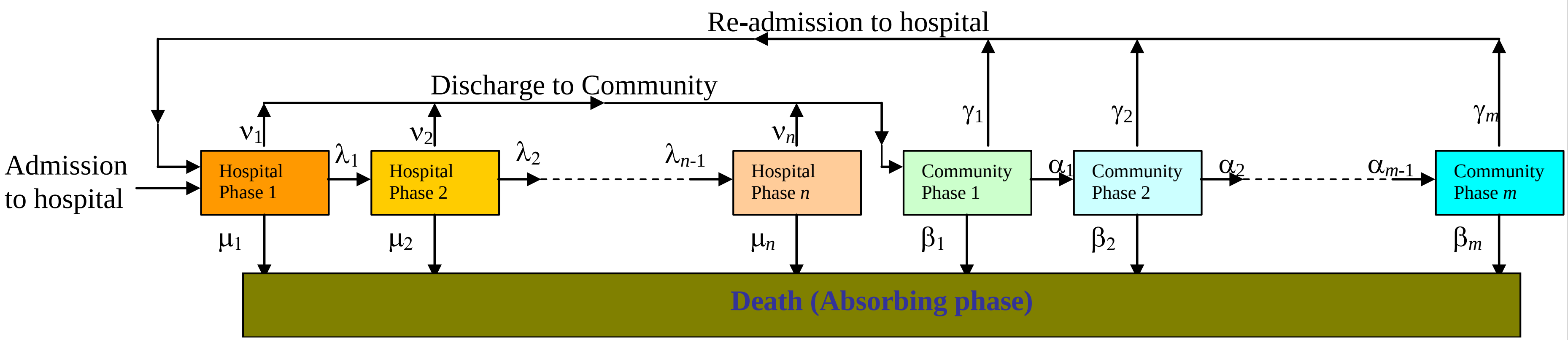


ONDITIONAL PHASE TYPE ISTRIBUTION

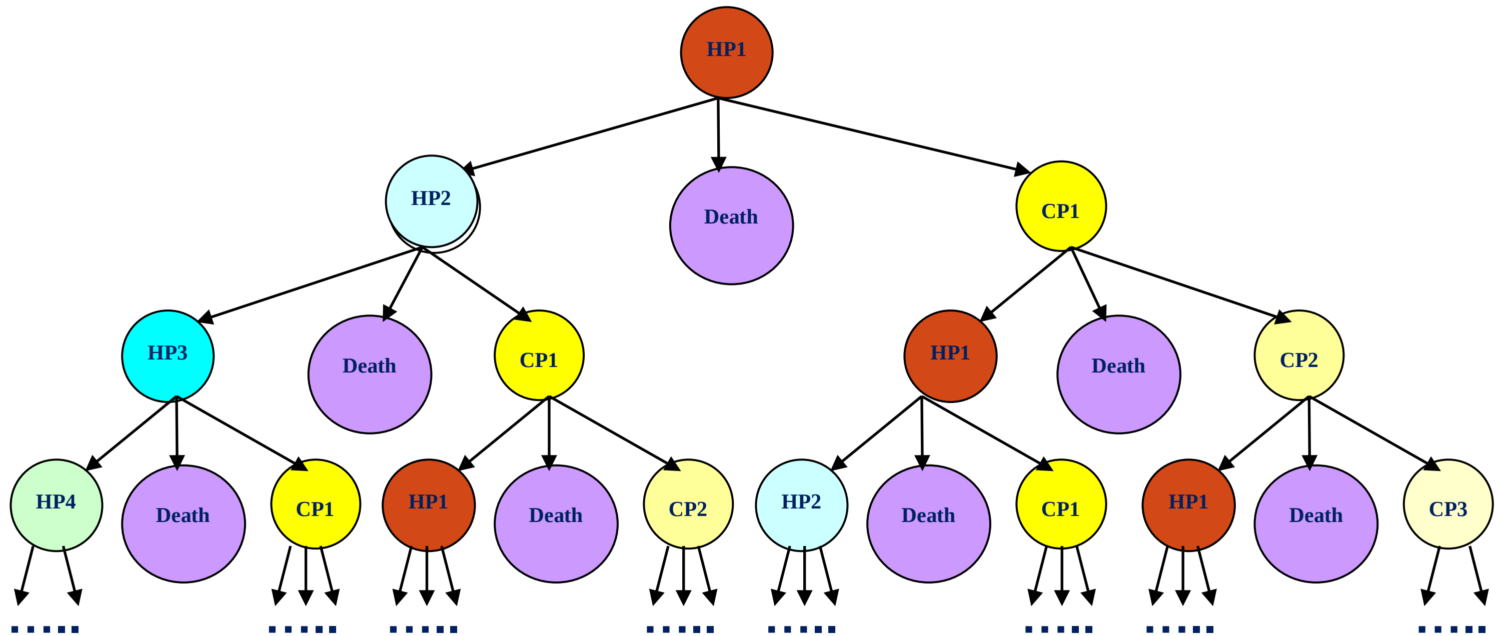


Conditional phase type distribution (taken from Marshall et al., 2000a)

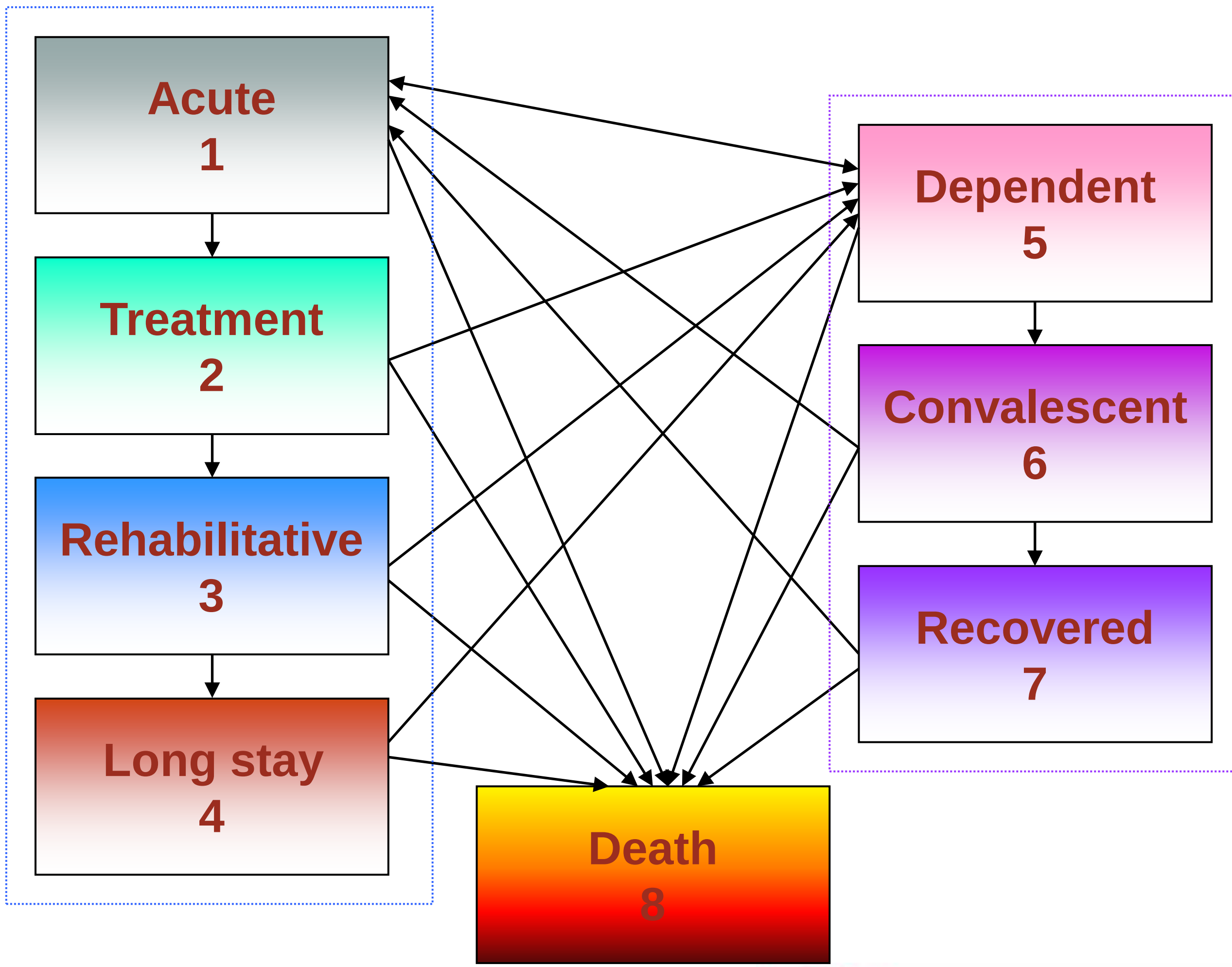
Elderly Care System as a Conditional Phase Type Distribution Model



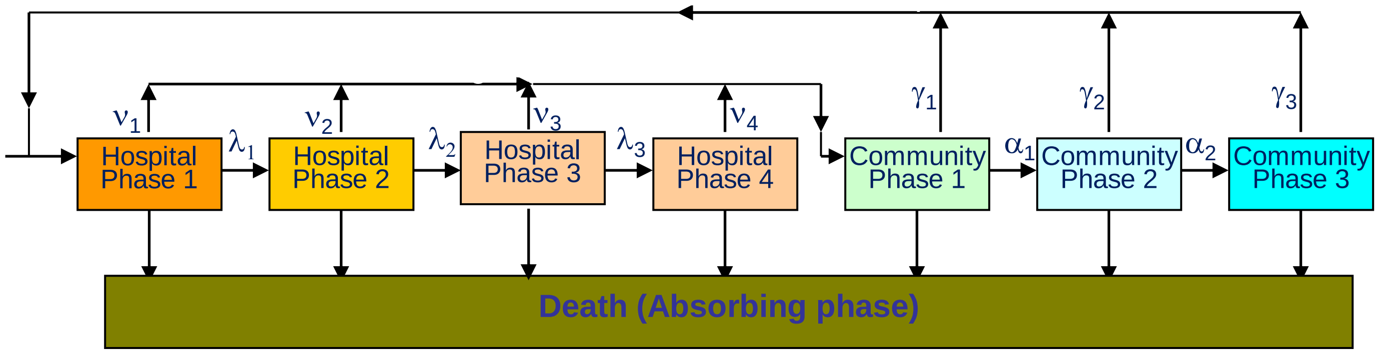
Sequential pattern mining: Patient pathways



8-Phase Markov Model



An Example: Eight-phase model



Transition matrix

Transition matrix Q = $\{q_{ij}\}$=Transition rate (next transition is to phase j | currently in phase i }

$$
Q=\left(\begin{array}{ccccc|ccccc|c}
-(\lambda_1+\mu_1+\nu_1) & \lambda_1 & 0 & \dots & 0 & \nu_1 & 0 & 0 & \dots & 0 & \mu_1 \\
0 & -(\lambda_2+\mu_2+\nu_2) & \lambda_2 & \dots & 0 & \nu_2 & 0 & 0 & \dots & 0 & \mu_2 \\
. & . & . & \dots & . & . & . & . & \dots & . & . \\
. & . & . & \dots & \lambda_{n-1} & . & . & . & \dots & . & . \\
0 & 0 & . & \dots & -(\mu_n+\nu_n) & \nu_n & 0 & 0 & \dots & 0 & \mu_n \\
\hline
\gamma_1 & 0 & 0 & \dots & 0 & -(\alpha_1+\beta_1+\gamma_1) & \alpha_1 & 0 & \dots & 0 & \beta_1 \\
\gamma_2 & 0 & 0 & \dots & 0 & 0 & -(\alpha_2+\beta_2+\gamma_2) & \alpha_2 & \dots & 0 & \beta_2 \\
. & . & . & \dots & . & . & . & . & \dots & . & . \\
. & . & . & \dots & . & . & . & . & \dots & \alpha_{m-1} & . \\
\gamma_m & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & -(\beta_m+\gamma_m) & \beta_m \\
\hline
0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 & 0
\end{array}\right)
$$

Transient probability matrix

Associated transient probability matrix A = $\{a_{ij}\}$, where a_{ij} = Probability {next transition is to phase j | currently in phase i } and,

$$
A=\left(\begin{array}{cccc:cccc:c}
0 & \frac{\lambda_1}{\lambda_1+\mu_1+\nu_1} & 0 & \ldots 0 & \frac{\nu_1}{\lambda_1+\mu_1+\nu_1} & 0 & 0 & \ldots 0 & \frac{\mu_1}{\lambda_1+\mu_1+\nu_1} \\
0 & 0 & \frac{\lambda_2}{\lambda_2+\mu_2+\nu_2} & \ldots 0 & \frac{\nu_2}{\lambda_2+\mu_2+\nu_2} & 0 & 0 & \ldots 0 & \frac{\mu_2}{\lambda_2+\mu_2+\nu_2} \\
. & . & . & .... & . & . & . & .... & . \\
. & . & . & .... & . & . & . & .... & . \\
0 & 0 & . & \ldots 0 & \frac{\nu_n}{\mu_n+\nu_n} & 0 & 0 & \ldots 0 & \frac{\mu_n}{\mu_n+\nu_n} \\
\hdashline
\frac{\gamma_1}{\alpha_1+\beta_1+\gamma_1} & 0 & 0 & \ldots 0 & 0 & \frac{\alpha_1}{\alpha_1+\beta_1+\gamma_1} & 0 & \ldots 0 & \frac{\beta_1}{\alpha_1+\beta_1+\gamma_1} \\
\frac{\gamma_2}{\alpha_2+\beta_2+\gamma_2} & 0 & 0 & \ldots 0 & 0 & 0 & \frac{\alpha_2}{\alpha_2+\beta_2+\gamma_2} & \ldots 0 & \frac{\beta_2}{\alpha_2+\beta_2+\gamma_2} \\
. & . & . & .... & . & . & . & .... & . \\
. & . & . & .... & . & . & . & .... & . \\
\frac{\gamma_m}{\beta_m+\gamma_m} & 0 & 0 & \ldots 0 & 0 & 0 & 0 & \ldots 0 & \frac{\beta_m}{\beta_m+\gamma_m} \\
\hdashline
0 & 0 & 0 & \ldots 0 & 0 & 0 & 0 & \ldots 0 & 1
\end{array}\right)
$$

Expected time

The expected time spent in a phase *i* (when next transition is to phase *j* / given that the patient has entered phase *i*)

$$t_{ij} = \begin{cases} (q_{ij}/q_{ij}) & \text{if } q_{ij} \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

Expected cost

The expected cost of care in phase *i* (when next transition is to phase *j* / given that the patient has entered phase *i*)

$$C_{ij} = \begin{cases} (b_i / t_{ij}) & \text{if } t_{ij} \neq \infty \\ 0 & \text{otherwise} \end{cases}$$

where, b_i is the average per day bed cost in phase i.

Probability of occurrence of a patient pathway

$$P_r(k) = \left(\prod_{h=1}^{k} p_h\right) * a_{l,(m+n+1)}$$

where, pathway *r* is having in total *k* transitions among various hospital and community phases and finally death in phase *l*

p_h *is* the transient probability for the h^{th} transition. (If the h^{th} transition is from phase *i* to phase *j* then $p_h = a_{ij}$),

$a_{l,(m+n+1)}$ is the probability of death in phase *l*

Expected duration of a patient pathway

$$\Delta_r(k) = \left(\sum_{h=1}^{k} t_h\right) + t_{l,(m+n+1)}$$

where,

t_h is the expected time spent in the phase before the h^{th} transition. If the h^{th} transition is from phase i to phase j then $t_h = t_{ij}$ = time spent in the phase l

$t_{l,(m+n+1)}$ is the time spent in phase l before death.

Expected total cost of a patient pathway

$$C_l(k) = \left(\sum_{h=1}^{k} c_h\right) + c_{l,(m+n+1)}$$

where,

c_h is the expected cost of stay in the phase before the h^{th} transition. If the h^{th} transition is from phase i to phase j then $c_h = c_{ij}$ = time spent in the phase l

$c_{l,(m+n+1)}$ is the cost of stay in phase l before death.

Daily resource requirements

On day *d:*

Number of patients in phase *i* =

η_i = (number of patients on the day *d*-1) + (number of patients entered in phase *I* on day *d*) – (number of patients left phase *i* on day *d*)

Daily resource requirements

In fact, we will calculate the number (η_i) of patients in phase i after every transition event.

For a transition from phase i to phase j with probability a_{ij}

$\eta_i = (1 - a_{ij})$*(the number of patients in phase i before the transition)

$\eta_j =$ (the number of patients in phase j before the transition) + (a_{ij})*(the number of patients in phase i before the transition)

Daily resource requirements

Total daily resource requirement for the given initial population of patients in various phases

$$\eta(t_{given}) = \sum_{i=1}^{n} \eta_i(t_0) * \eta_i(t_{given})$$

where, $\eta_i(t_0)$ = Given initial number of patients in phase i.

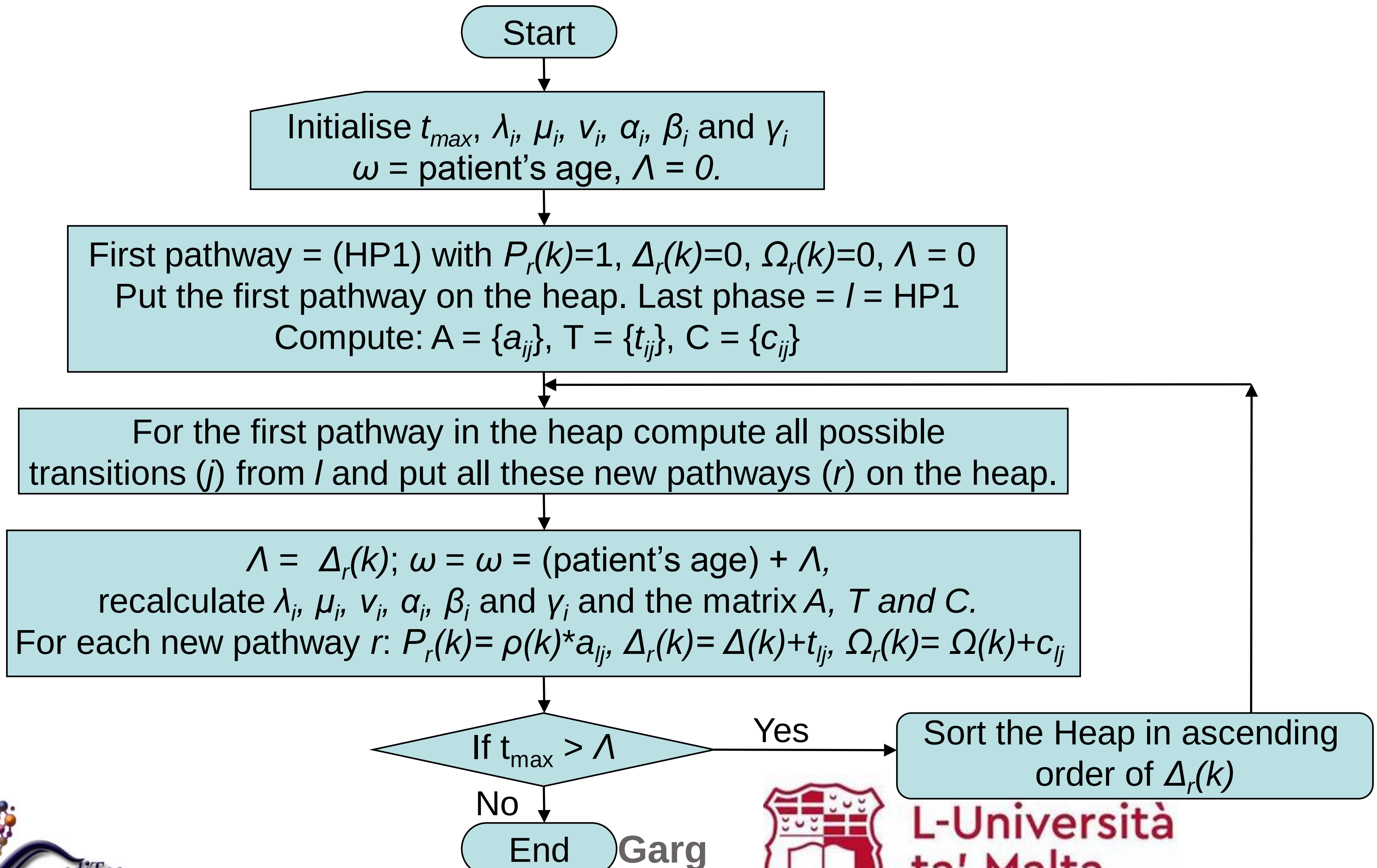
$\eta_i(t_{given})$ = daily resource requirement at time t_{given} for the care system starting with one patient in phase i (no new admissions).

Incorporating new admissions

Number of patients in phase 1 =

η_1 = 1 + (the number of patients in the hospital phase 1 before the new admission)

Enumerating the pathways



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Number of admissions required

For a new hospital

$$\text{Admissions required} = \frac{B(t_{given})}{\sum_{i=1}^{n} [\text{illegible}]} \; [\text{illegible}]$$

Where $B(t_{given})$ = number of beds available at time t_{given}

assuming that there are no patients in the hospital at $t = 0$.

Number of admissions required

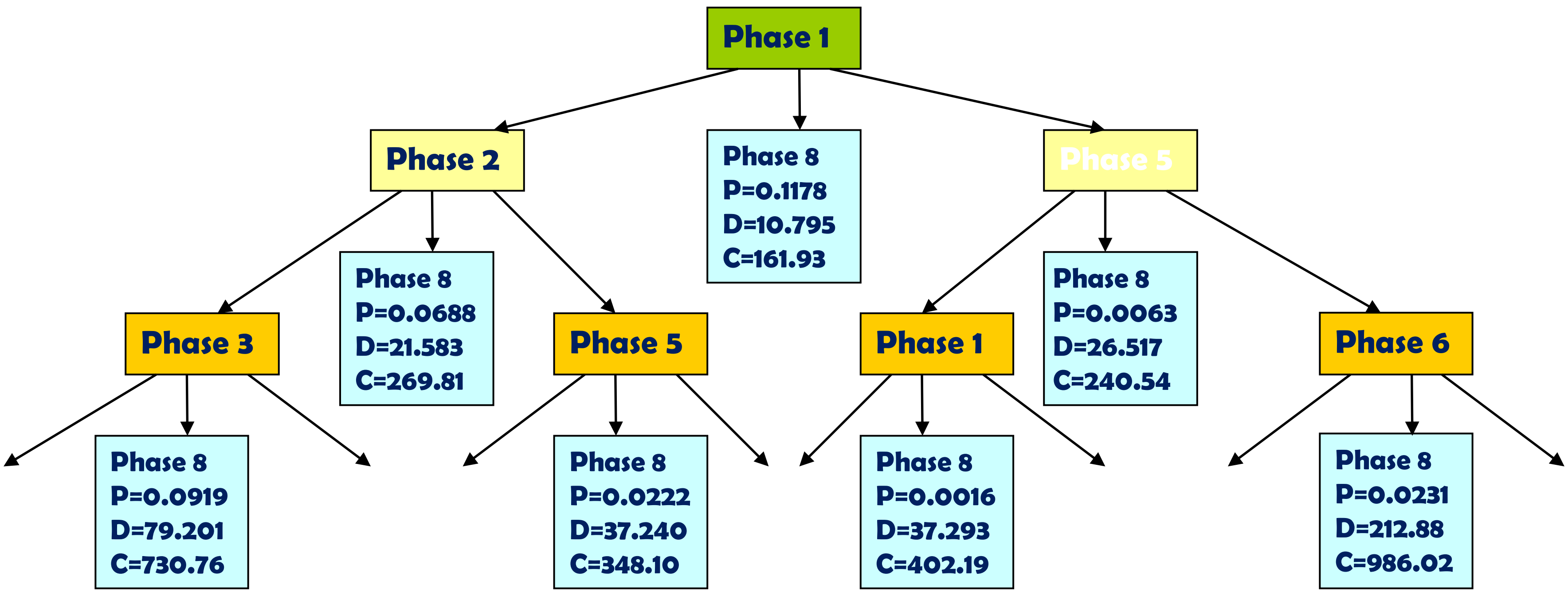
For a pre-existing hospital

$$\text{Admissions required} = \frac{B(t_{given}) - \eta(t_{given})}{\eta'(t_{given})} \text{ per day}$$

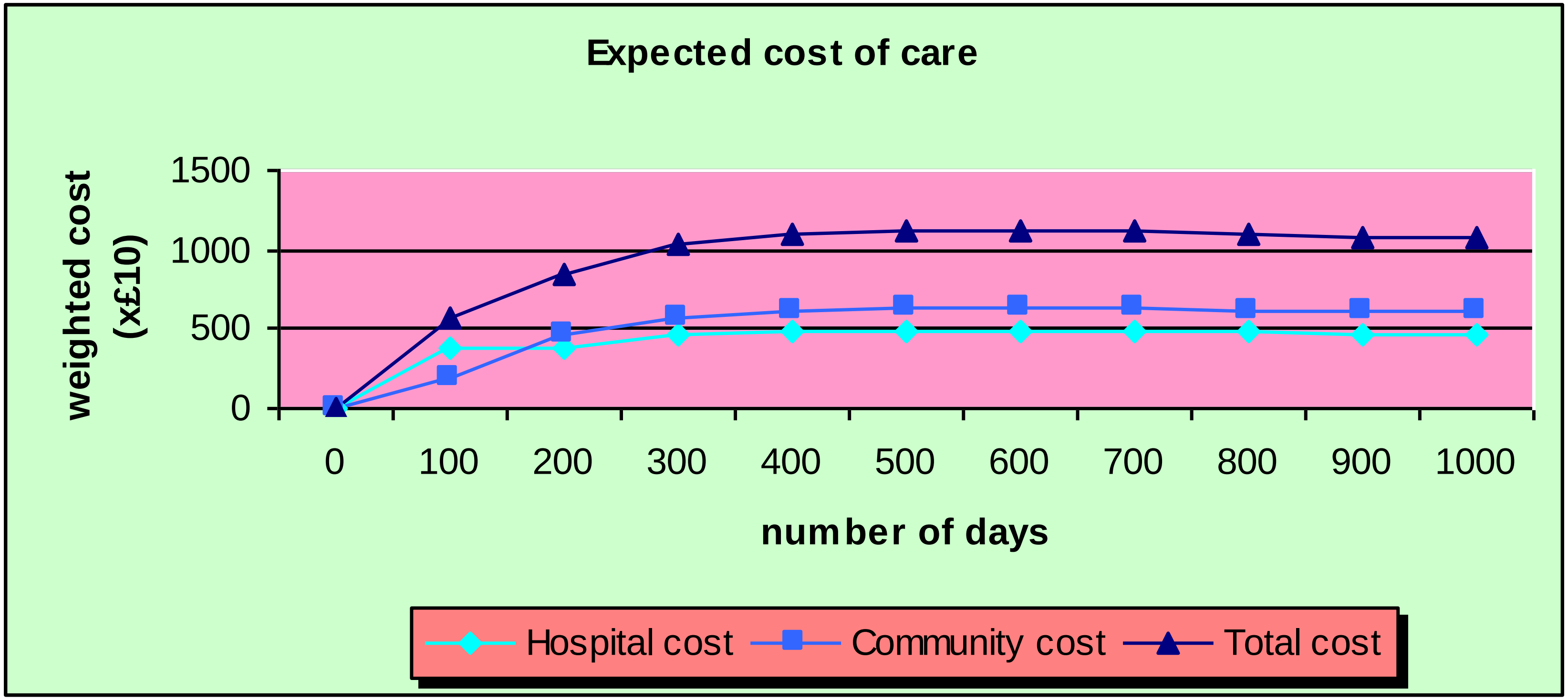
where, $\eta(t_{given})$ = the total number of patients still remaining at t_{given} for the initial population of patients in various phases (without any new admissions).

$\eta'(t_{given})$= the total number of patients remaining at t_{given} having been admitted before t_{given} (with one admission per day and no initial population)

INTERESTING PATIENT PATHWAYS

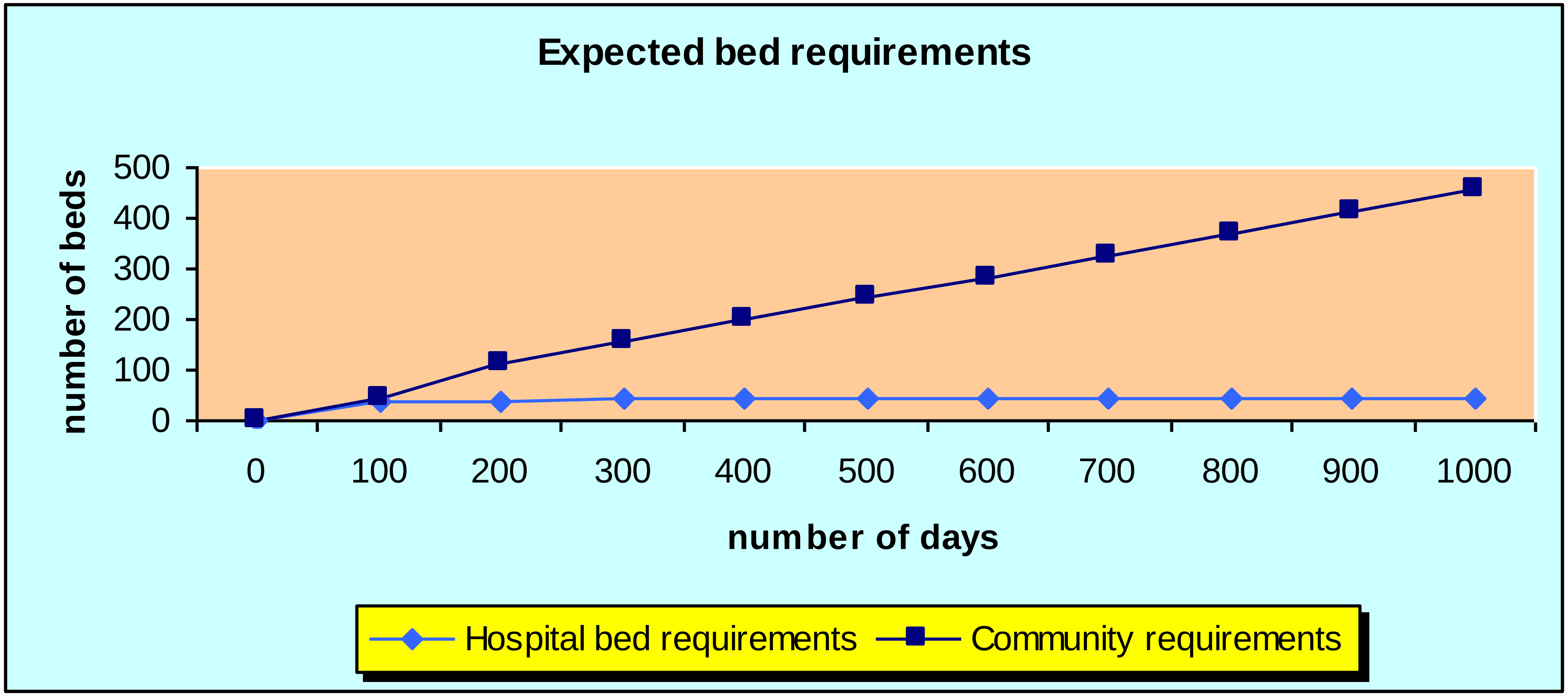


Expected cost of care



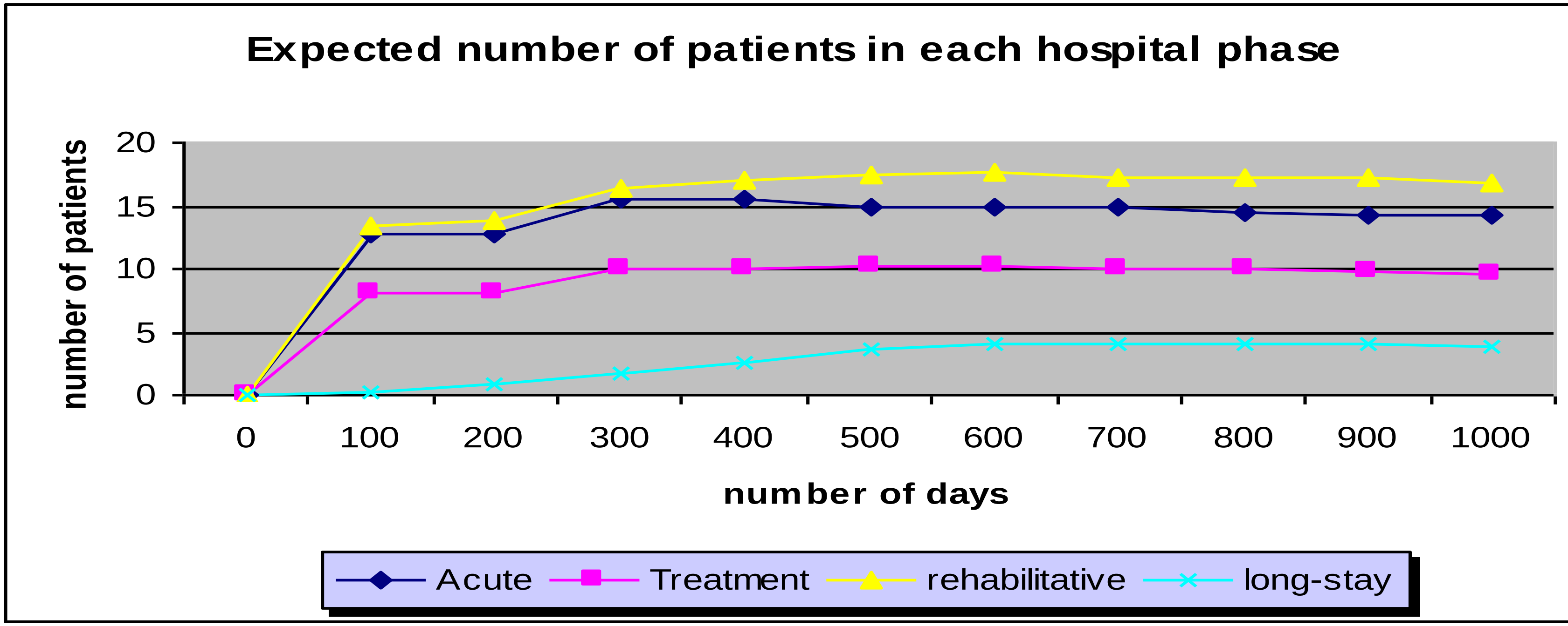
Data source: S.I. McClean and P.H. Millard, "Patterns of length of stay after admission in geriatric medicine: an event history approach", ***The Statistician*****, 42(3), 1993, pp. 263–274**

Expected bed requirements



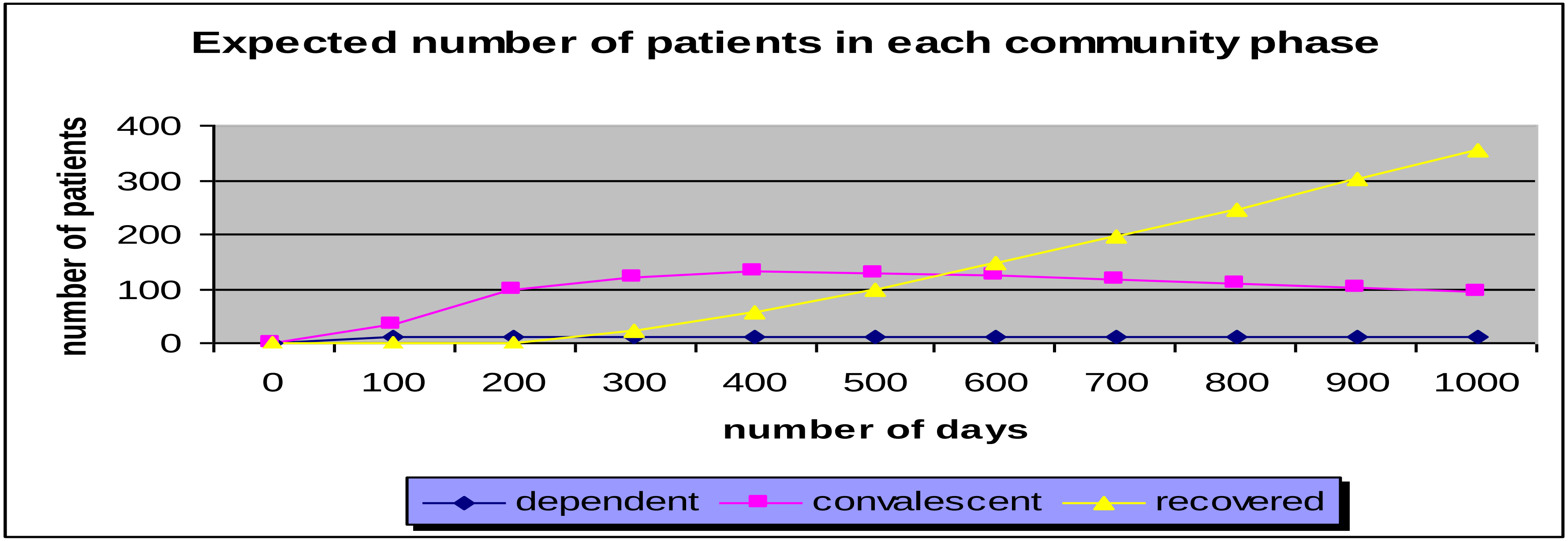
Data source: S.I. McClean and P.H. Millard, "Patterns of length of stay after admission in geriatric medicine: an event history approach", *The Statistician*, 42(3), 1993, pp. 263–274

Expected number of patients in each hospital phase



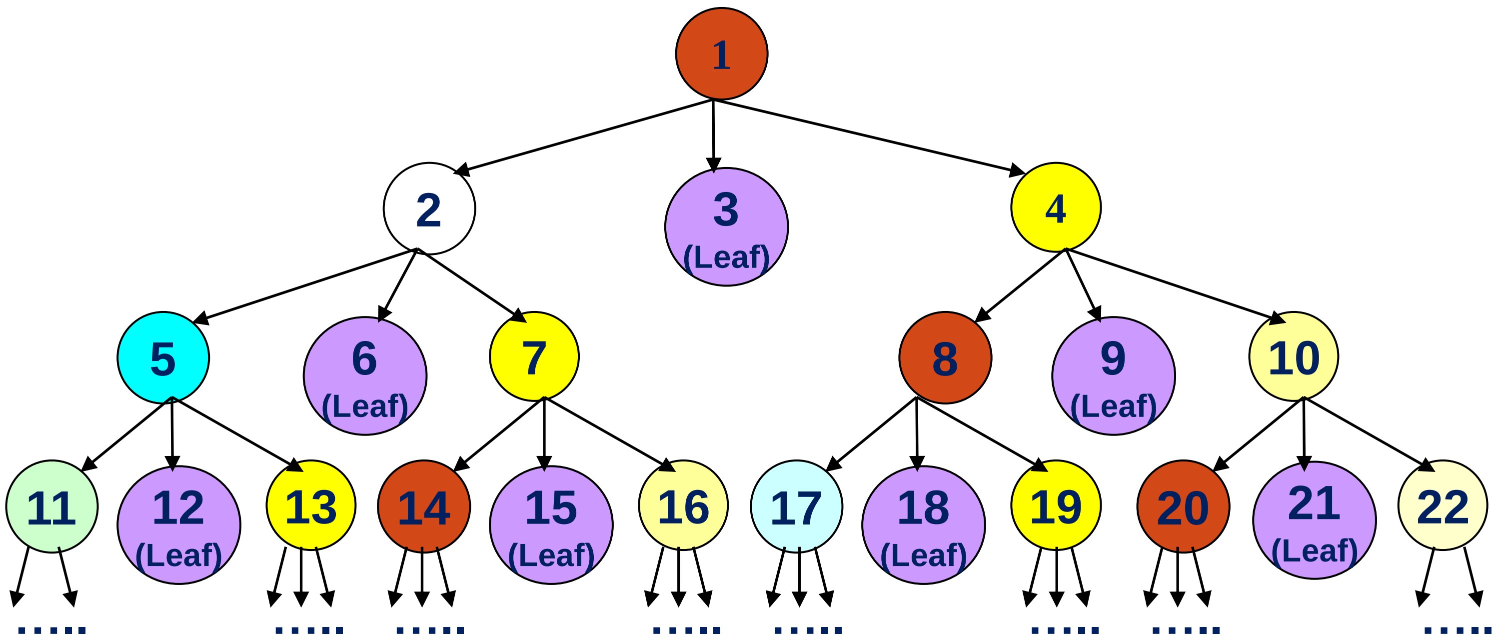
Data source: S.I. McClean and P.H. Millard, "Patterns of length of stay after admission in geriatric medicine: an event history approach", *The Statistician*, 42(3), 1993, pp. 263–274

Expected number of patients in each community phase

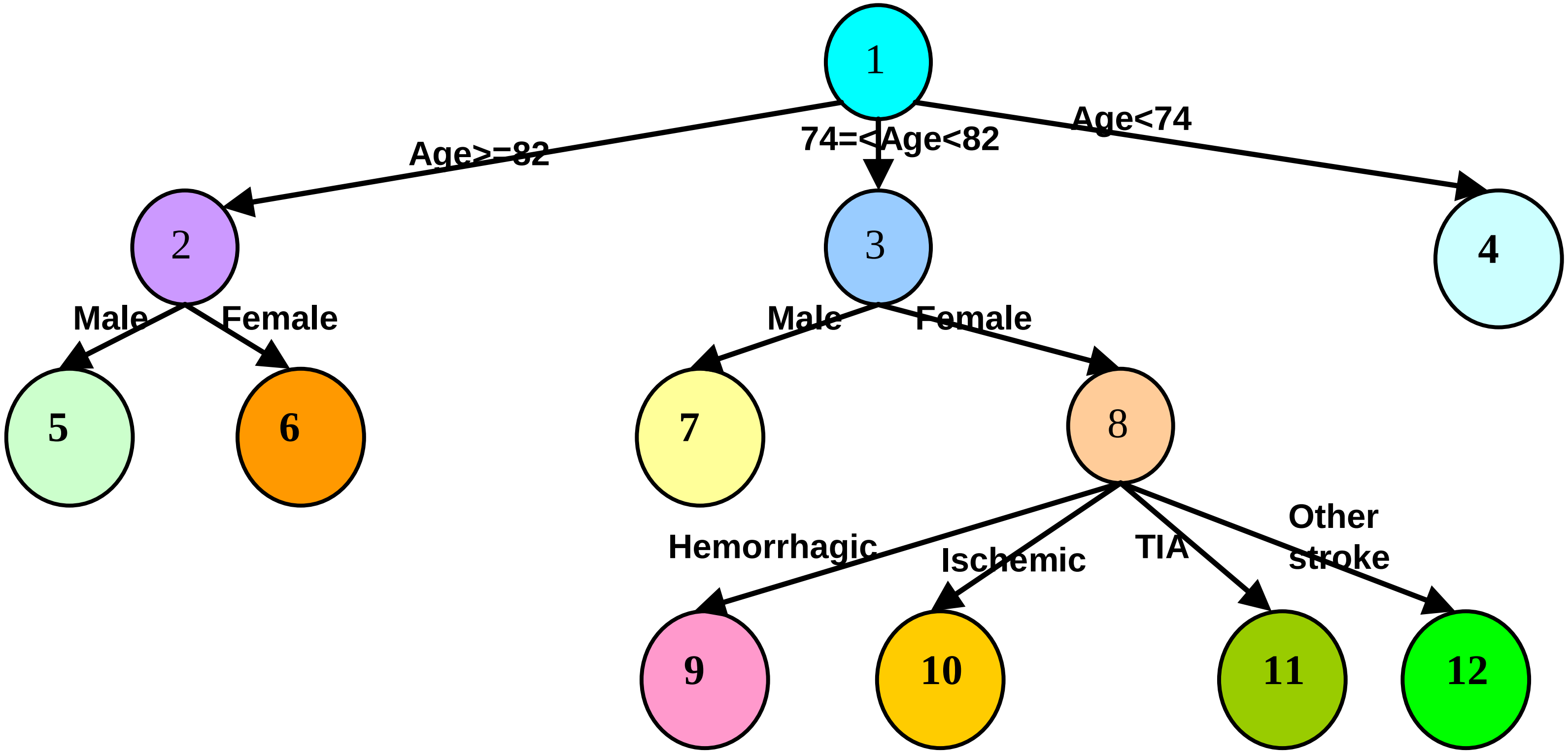


Data source: S.I. McClean and P.H. Millard, "Patterns of length of stay after admission in geriatric medicine: an event history approach", *The Statistician*, 42(3), 1993, pp. 263–274

SURVIVAL TREE

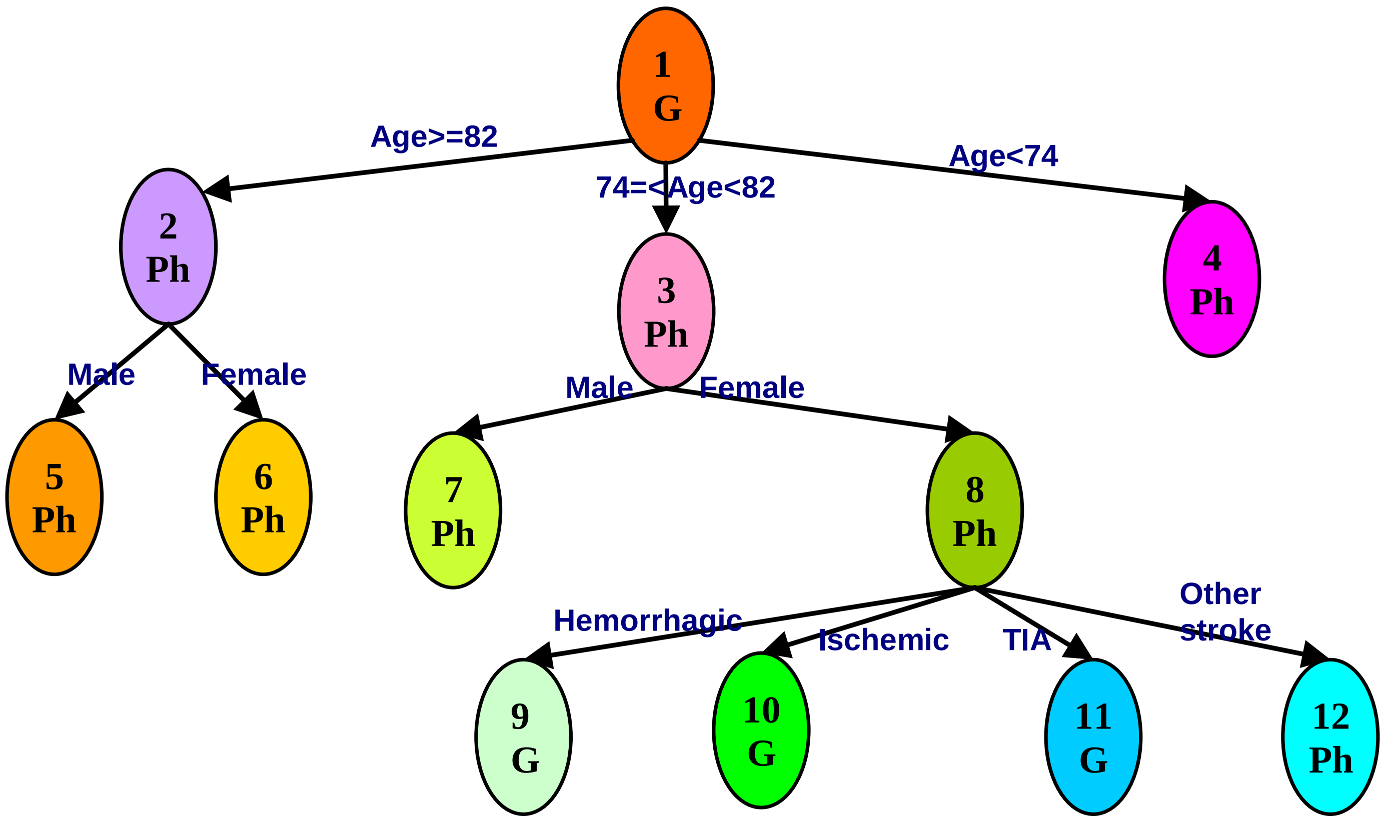


Phase Type Survival Tree



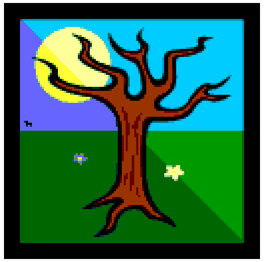
Details

MIXTURE DISTRIBUTION SURVIVAL TREE



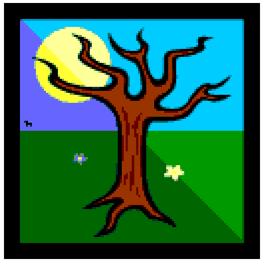
Ph: Coxian phase type distributions

G: Gaussian mixture distributions



Splitting criteria used

- MLIC (Maximum likelihood ratio criterion)
- AIC (Akaike Information Criterion)
- AICc (Corrected AIC)
- BIC (Bayesian Information Criterion)
- BICc (Corrected BIC)
- HQIC (Hannan and Quinn Criterion)
- WIC (The Weighted-Average Information Criterion)



Maximum likelihood ratio-based Splitting criteria

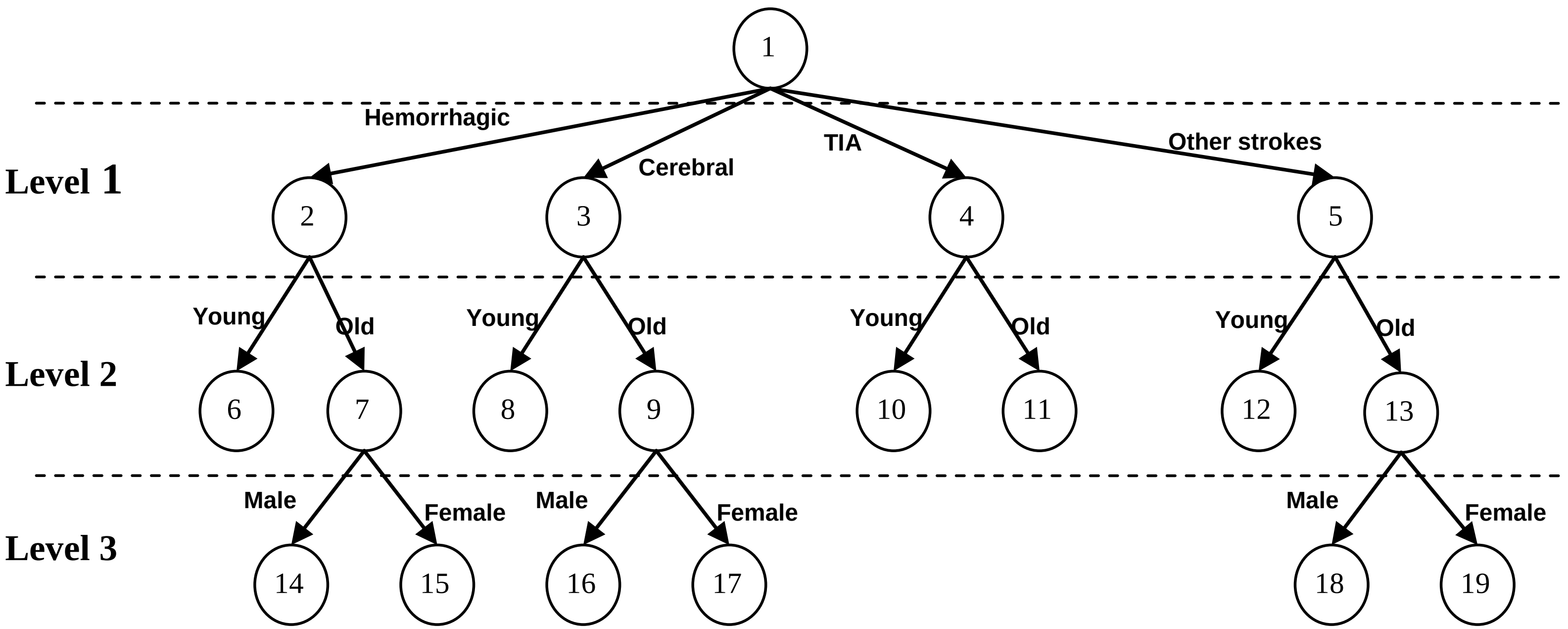
- Maximum likelihood ratio criterion

$$\text{MLIC}(df) = -2^{*}\text{Log likelihood.}$$

$$\text{MLIC}(df_1)\text{-MLIC}(df_2) \sim \chi^2_{df_1 - df_2}\,(p < \alpha)$$

- *df: number of free parameters required to be estimated

Maximum likelihood ratio based Splitting criteria

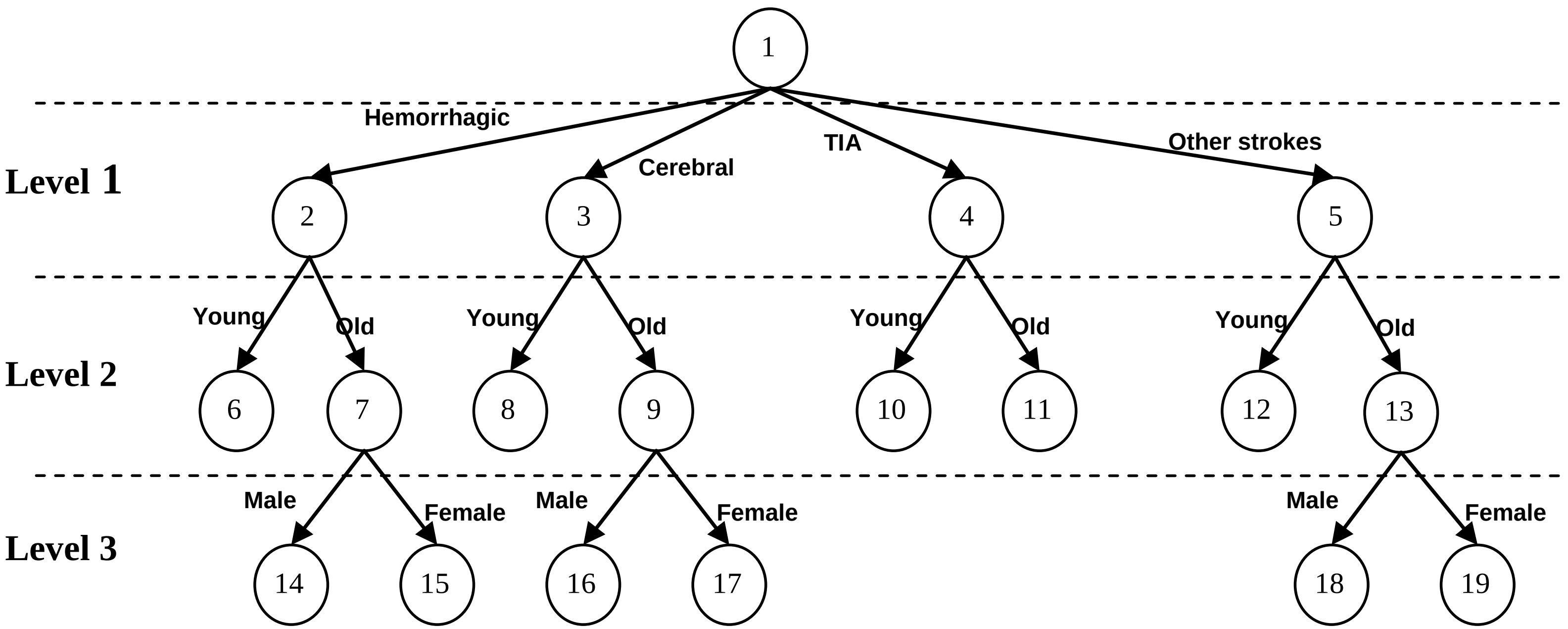


AIC based Splitting criteria

- Akaike Information Criterion

$$\mathrm{AIC}(df) = -2*\mathrm{Log\ likelihood} + 2*df.$$

AIC based Splitting criteria

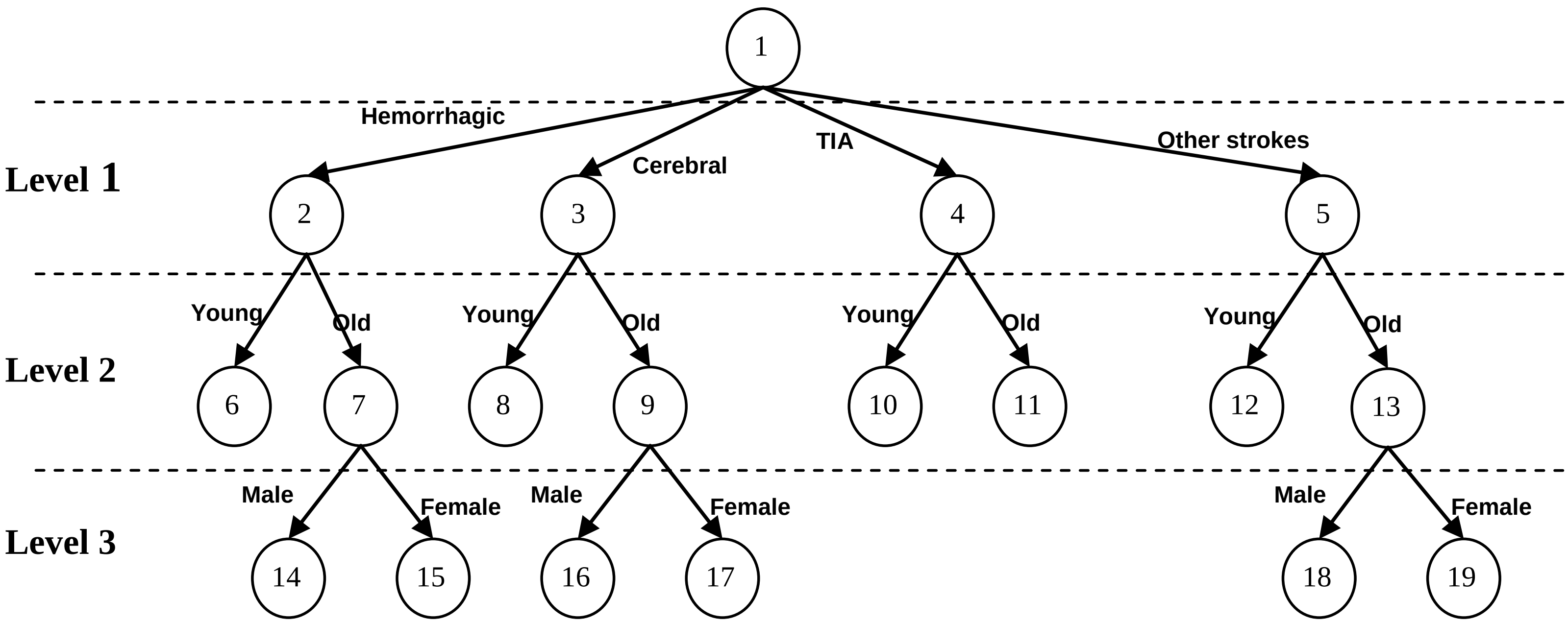


AICc based Splitting criteria

- Corrected AIC

$$\mathrm{AICc}(df) = -2 * \text{Log likelihood} + 2 * df + \frac{2 * df * (df + 1)}{(n - (df + 1))}$$

AICc based Splitting criteria



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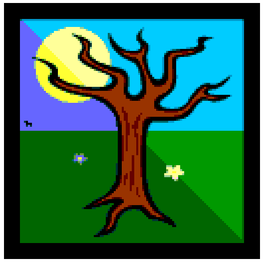
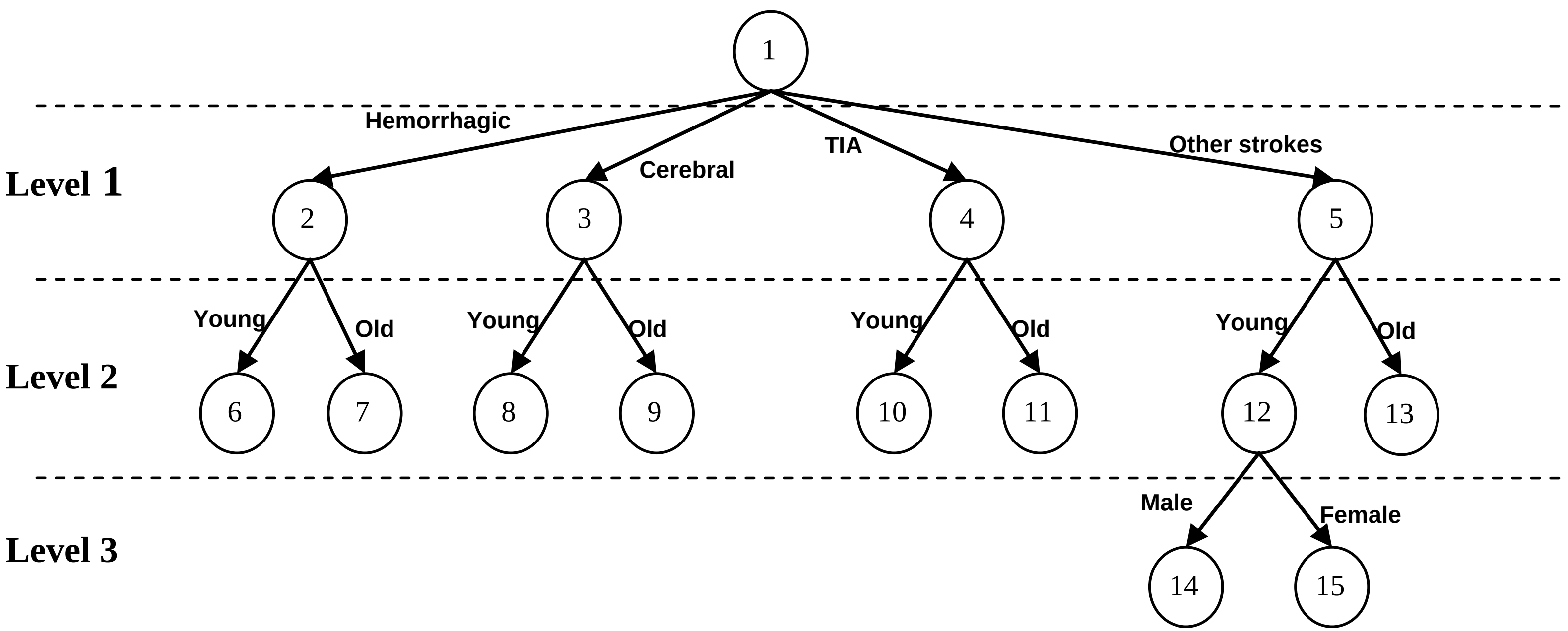


BIC based Splitting criteria

- Bayesian Information Criterion

$$BIC(df) = -2*\text{Log likelihood} + df * \log(n)$$

BIC based Splitting criteria

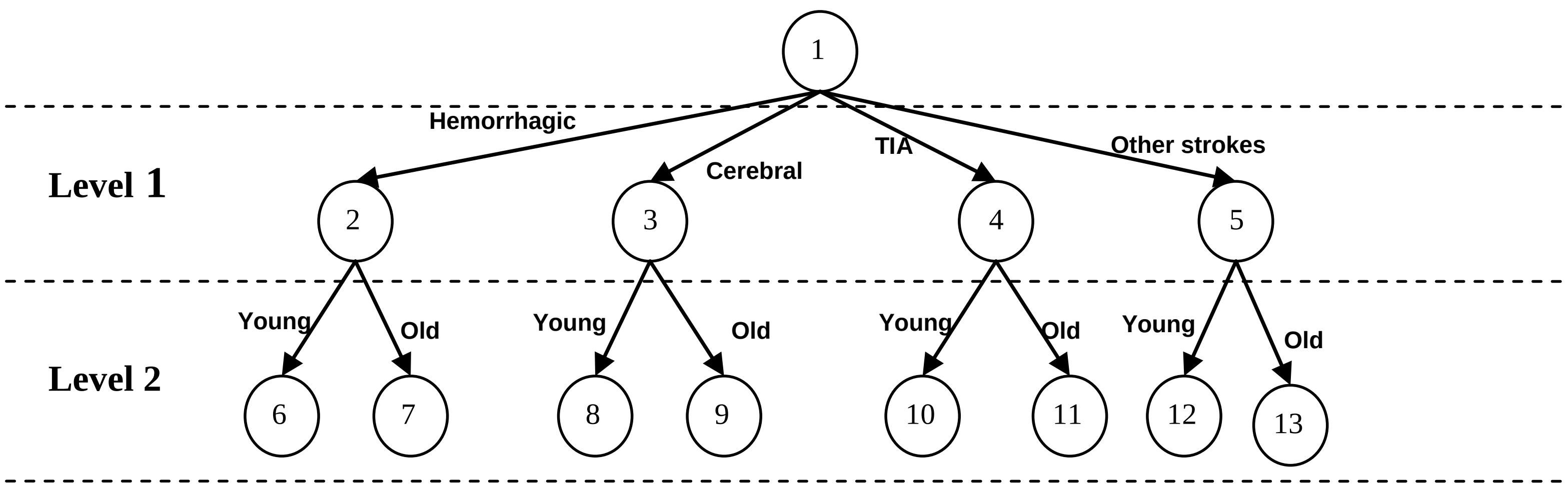


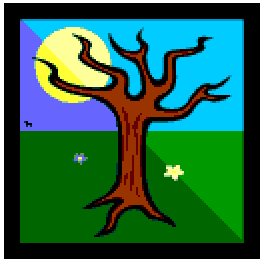
BICc based Splitting criteria

- Corrected BIC

$$\mathrm{BICc}(df) = \text{-}2\text{*Log likelihood} + df * \log(n) + \frac{2df * (df + 1)}{(n - (df + 1))}$$

BICc based Splitting criteria

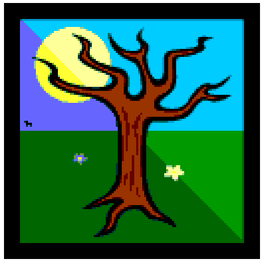




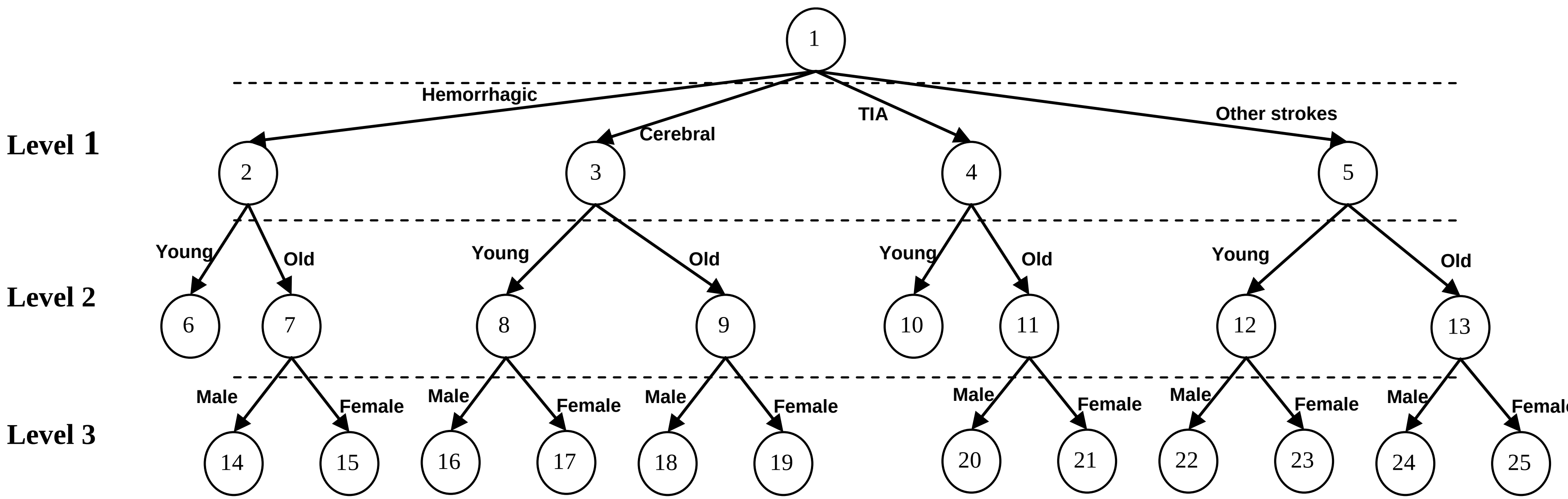
HQIC based Splitting criteria

- Hannan and Quinn Criterion

$$\mathrm{HQIC}(df) = -2*\mathrm{Log\ likelihood} + df * \log(\log(n))$$



HQIC based Splitting criteria

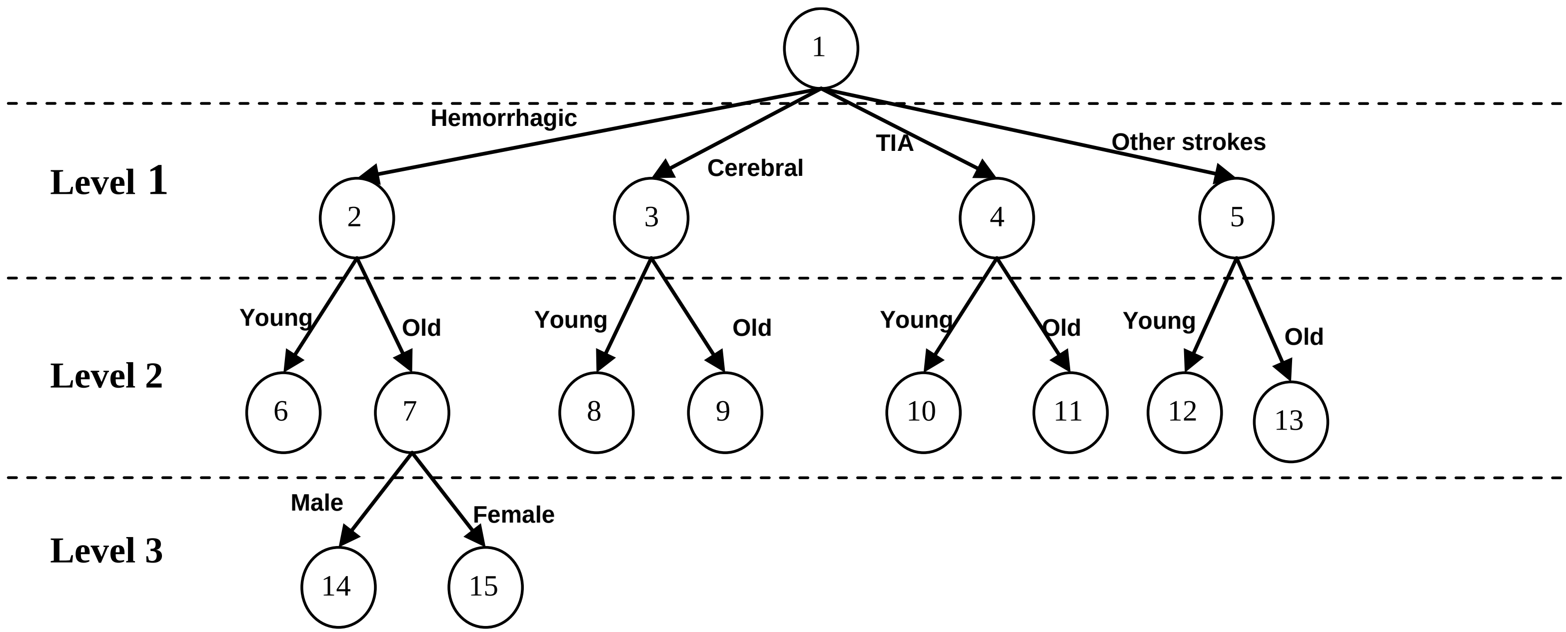


WIC based Splitting criteria

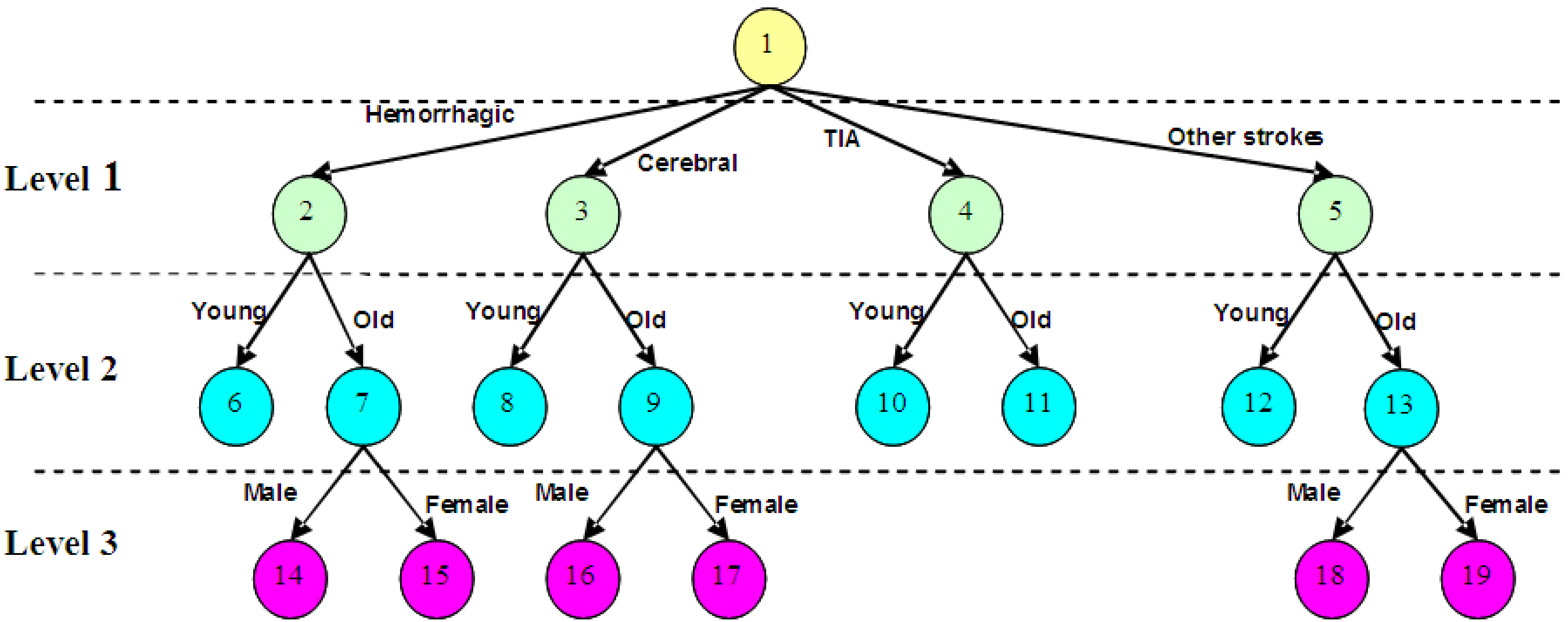
- The Weighted-Average Information Criterion:

$$\mathrm{WIC}(df) = \left(\frac{2*n}{2*n + (\log(n)*(n-(df+1)))} \right) * \mathrm{AICc} + \left(\frac{\log(n)*(n-(df+1))}{2*n + (\log(n)*(n-(df+1)))} \right) * \mathrm{BIC}$$

WIC based Splitting criteria



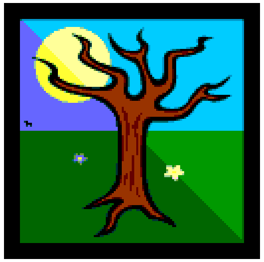
Phase type survival tree for the PAS dataset



Phase type survival tree for the PAS dataset

- The total gain in the with in node homogeneity

- The total gain in log-likelihood is 3793.651635 with 35 extra-free parameters (p=1)



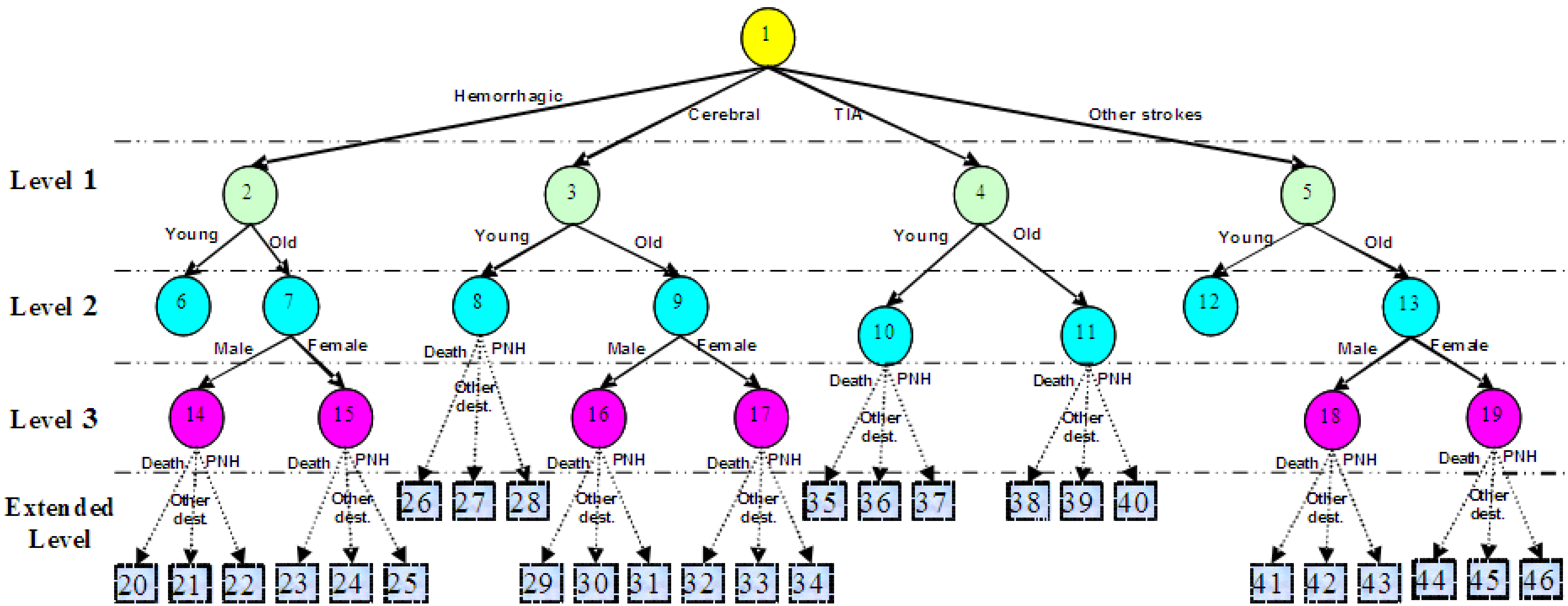
Extended Phase type survival tree

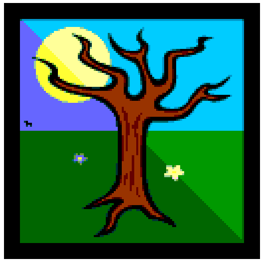
- The phase type survival tree approach can be extended by further growing the survival tree by partitioning the terminal nodes into subgroups with more homogeneous patient pathways based on covariates representing outcome measures such as discharge destination.

Extended Phase type survival tree

- Although the information about the discharge destination is not available at the time of admission, the probability of each discharge destination can be assigned using cohort analysis.

Extended Phase type survival tree for PAS dataset





Extended Phase type survival tree for PAS dataset

$$G_{Total} = 163.53$$

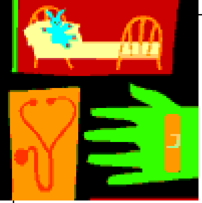
at the cost of 16 additional free parameters ($p<0.000001$).

Decision Support System

This DSS model has been further enhanced and now it can answer the questions like

- ✓ *Bed occupancy and resource allocation*: Resource requirements in various care units at various times
- ✓ *Survival Analysis*: Possibility of a patient to survive after a particular duration
- ✓ *Budgetary requirements*: The expected cost of care after a particular duration
- ✓ *What-if analysis*: Forecasting effects of various policies

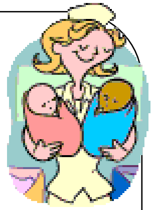
This model has been presented in **CBMS-2008**.



Hospital Capacity Planning

- The transition probability matrix

Hospital Capacity Planning



- The initial distribution of patients (at $t = 0$)

$$S_0 = \left\{ S_{0,1}, S_{0,2}, \ldots, S_{0,n}, S_{0,n+1} \right\}$$

Hospital Capacity Planning

- If there are no patient admissions, then the expected distribution of patients ($\mathbf{s}_t$)

$$\mathbf{s}_t = \mathbf{s}_0 * \mathbf{P}^t \; .$$

Hospital Capacity Planning

- If patient admissions (or arrivals) are modeled using a Poisson process with a mean arrival rate α.

$$S_t = S_0 * \alpha * \sum_{j=1}^{t} P_j \, .$$

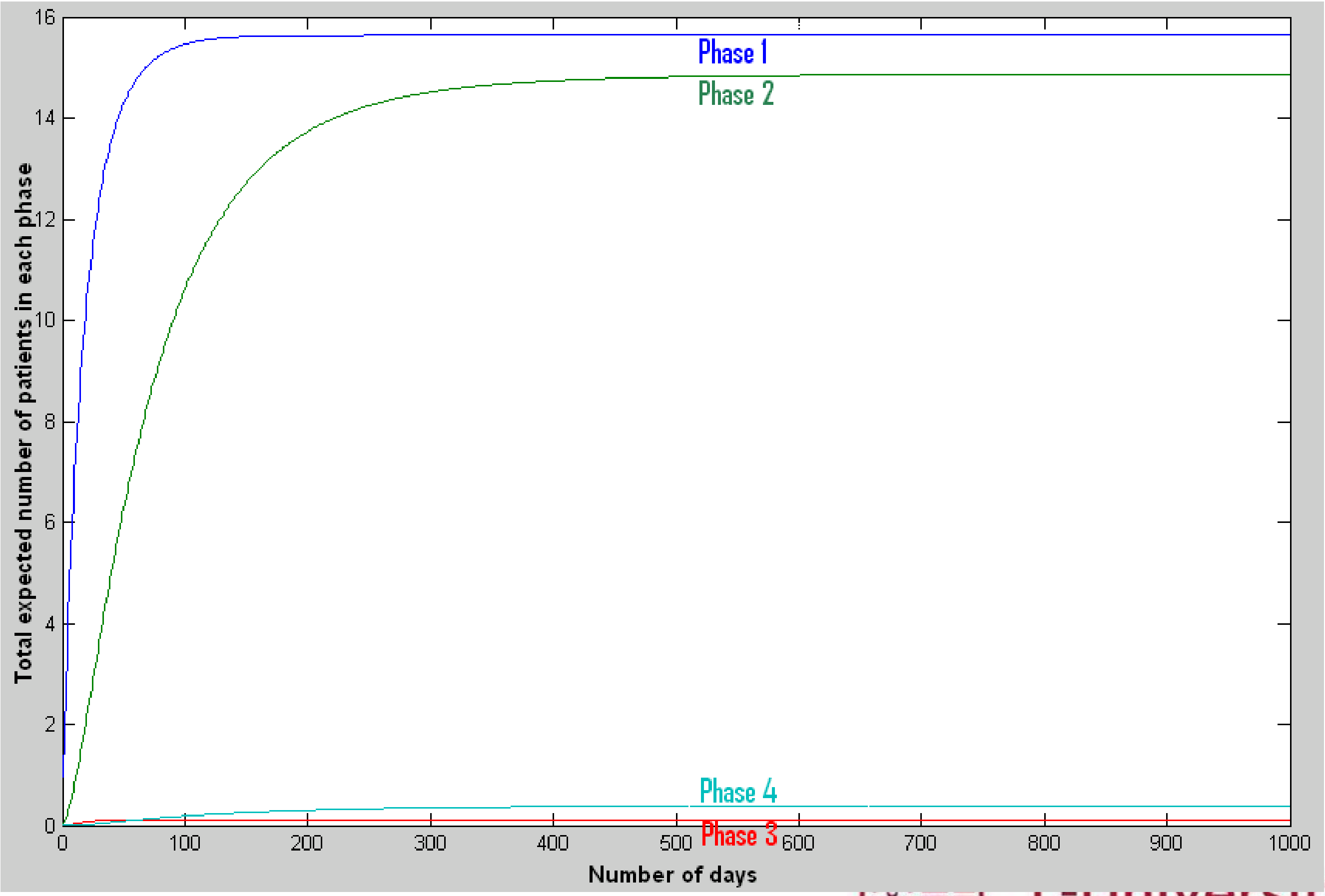
Hospital Capacity Planning

- For the whole care system with *R* clusters, patient distribution:

$$S_{v|t} = \sum_{r=1}^{R} S_{r|t} = \sum_{r=1}^{R} \left(S_{0r} * \sum_{j=1}^{t} P_{r,j} \right)$$

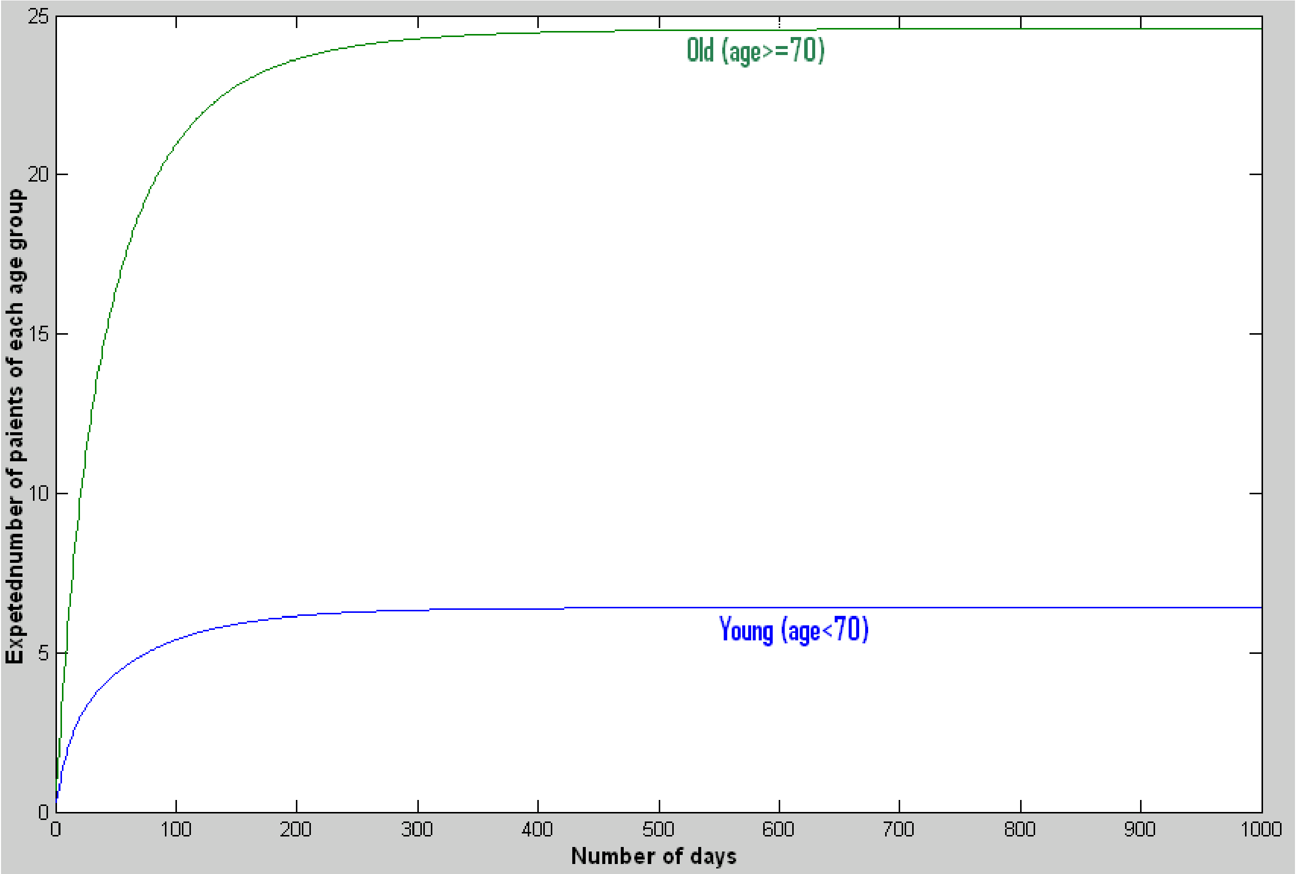
Hospital Capacity Planning

Total expected number of patients in each phase:



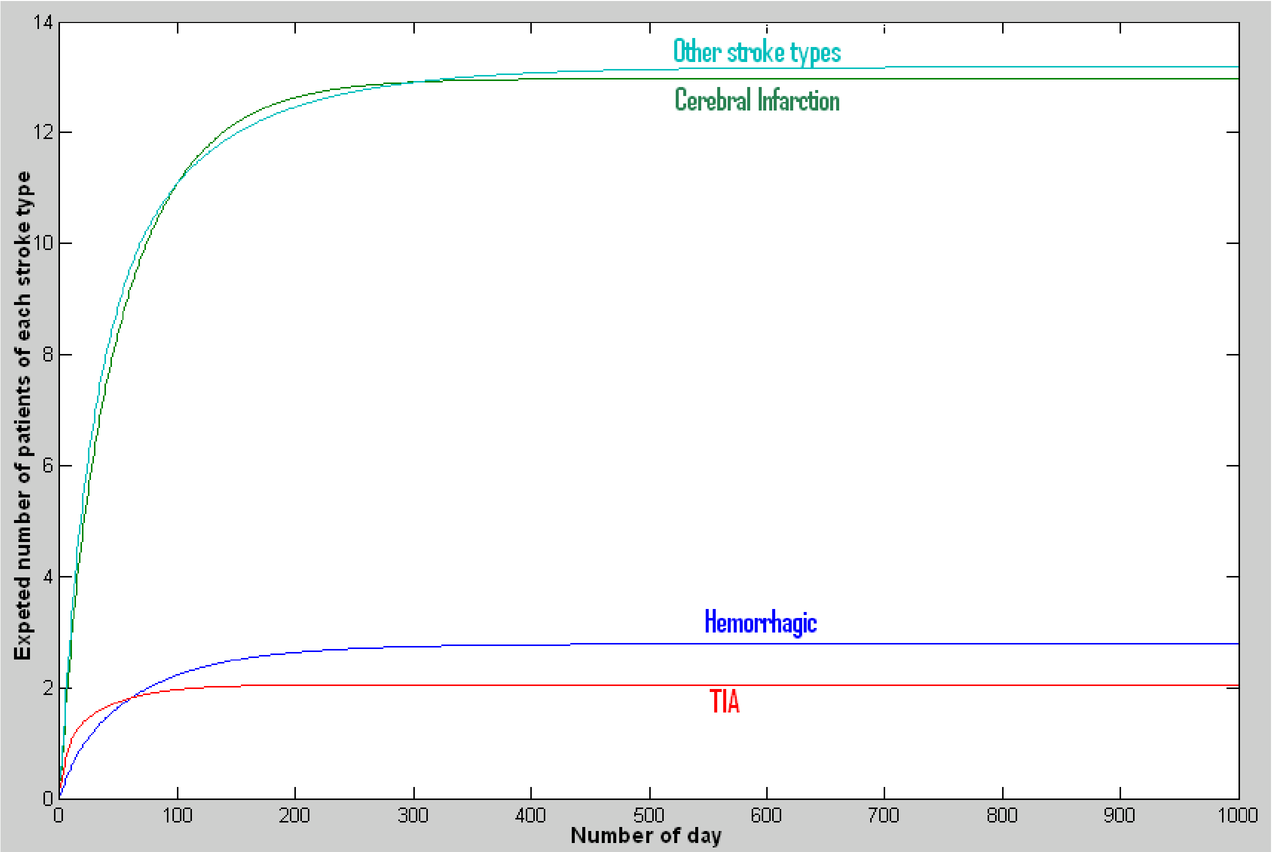
Hospital Capacity Planning

Expected number of patients of each age group



Hospital Capacity Planning

Expected number of patients of each stroke type



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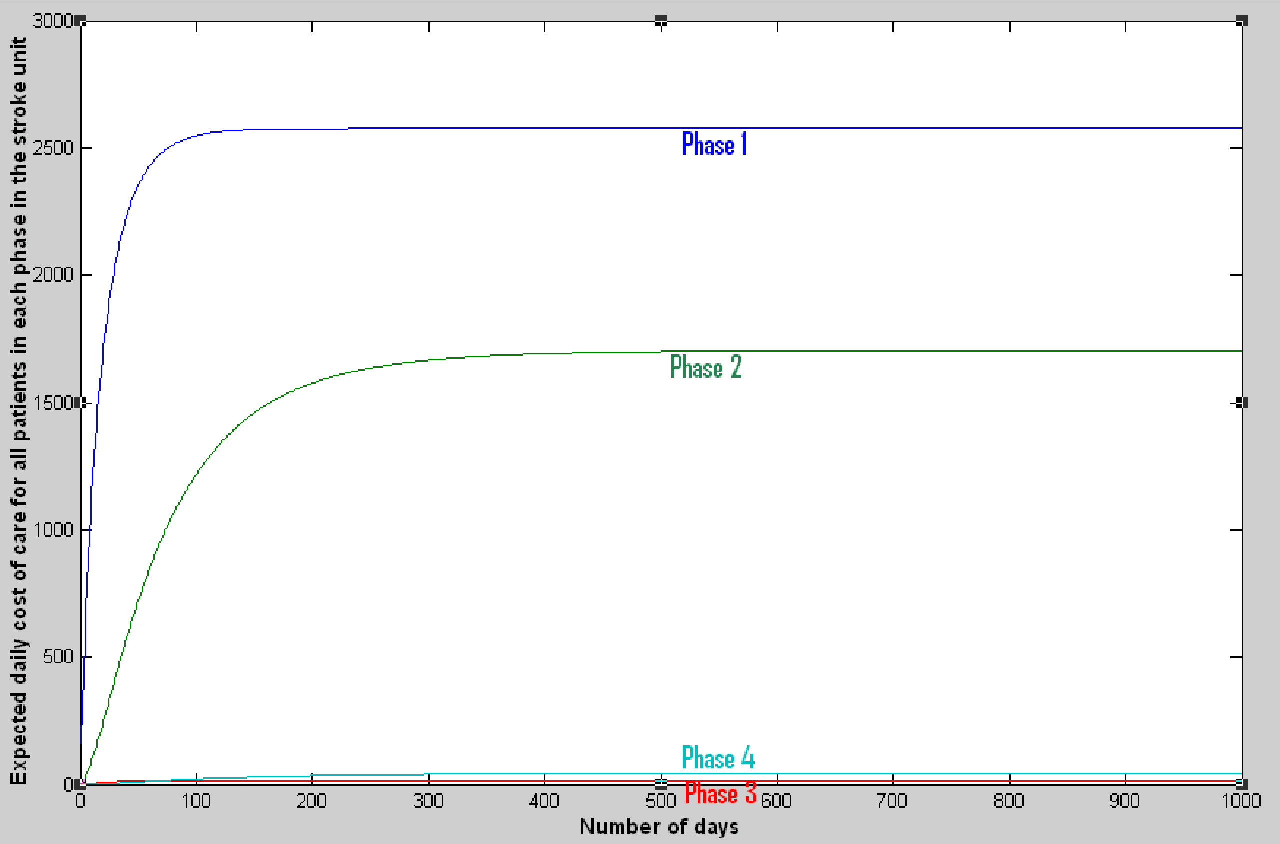
Hospital Capacity Planning

Expected daily cost of care (in £s) for all patients in each phase of the stroke unit



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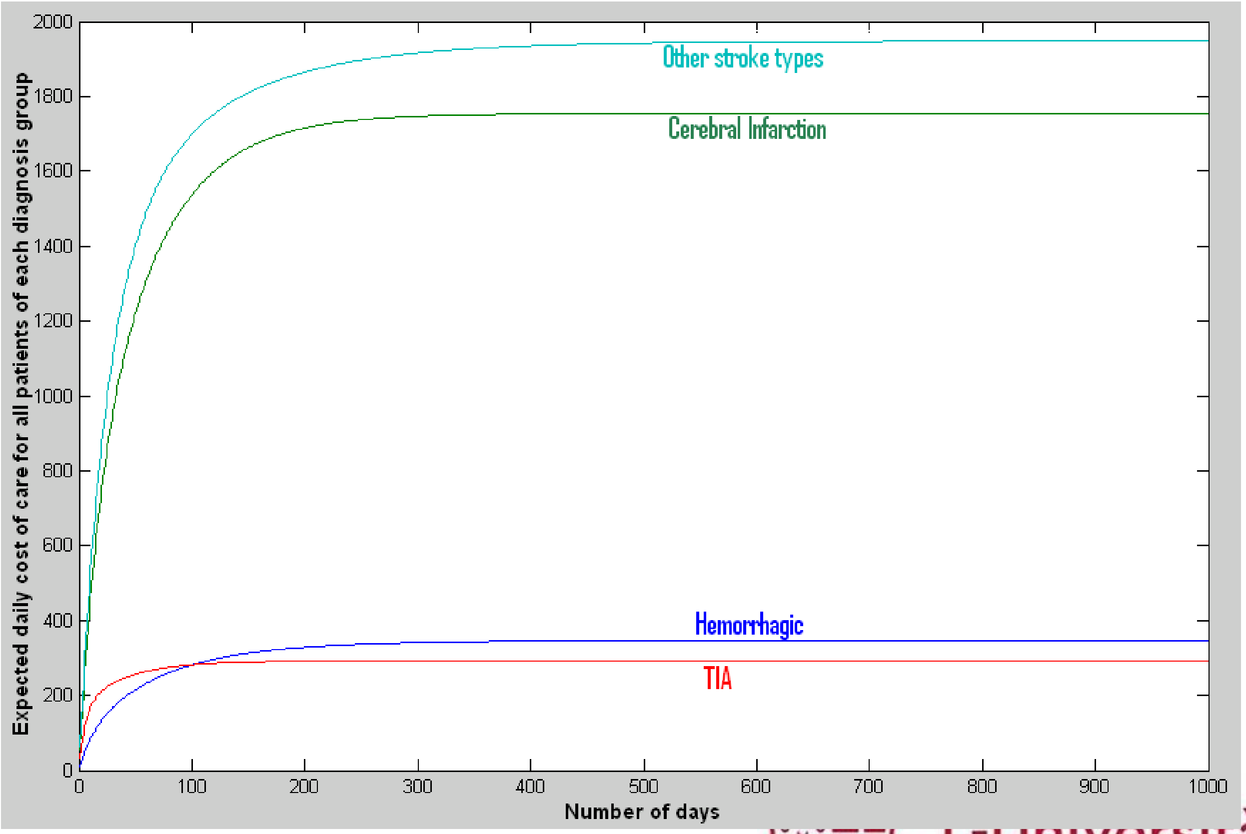
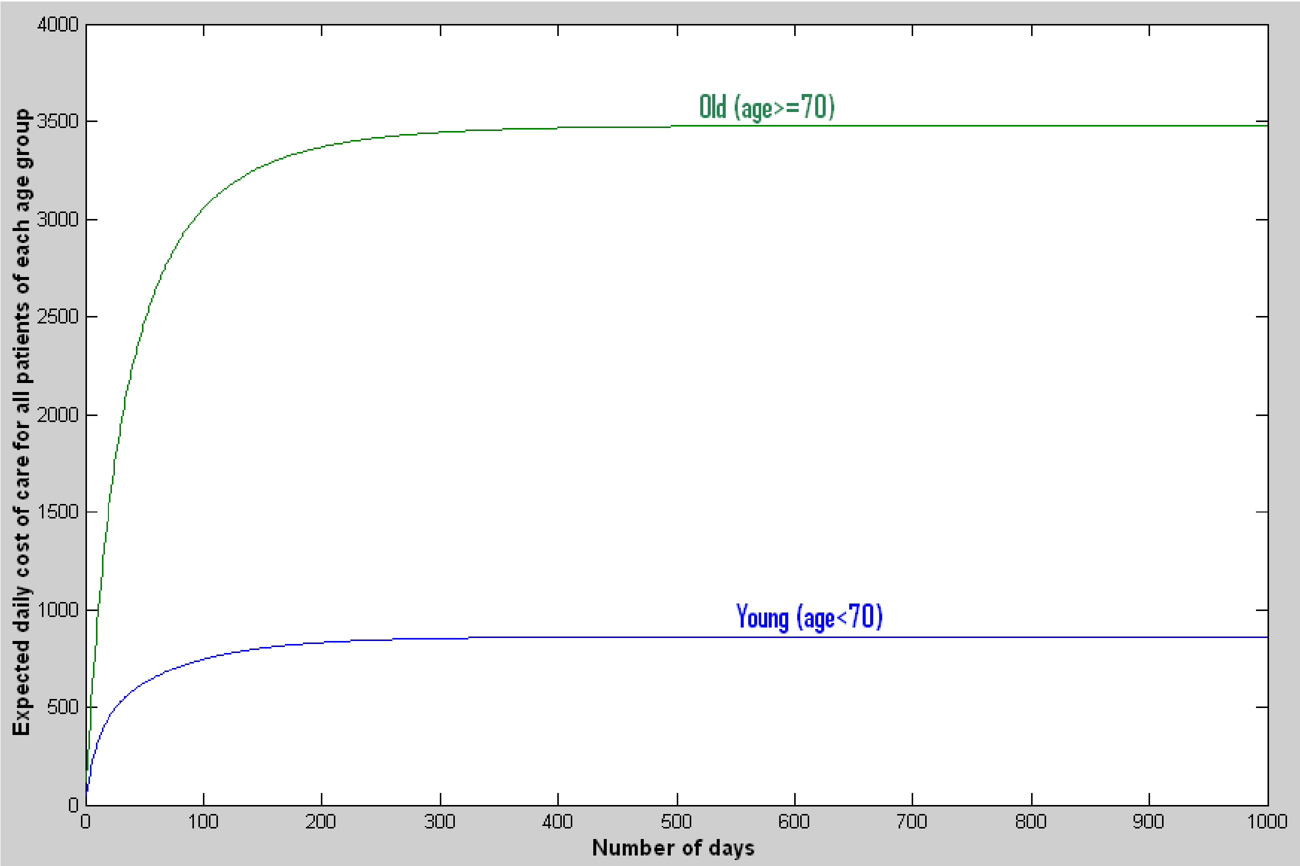
Hospital Capacity Planning

Expected daily cost of care (in £s) for all patients of each diagnosis group



Hospital Capacity Planning

Expected daily cost of care (in £s) for all patients of each age group



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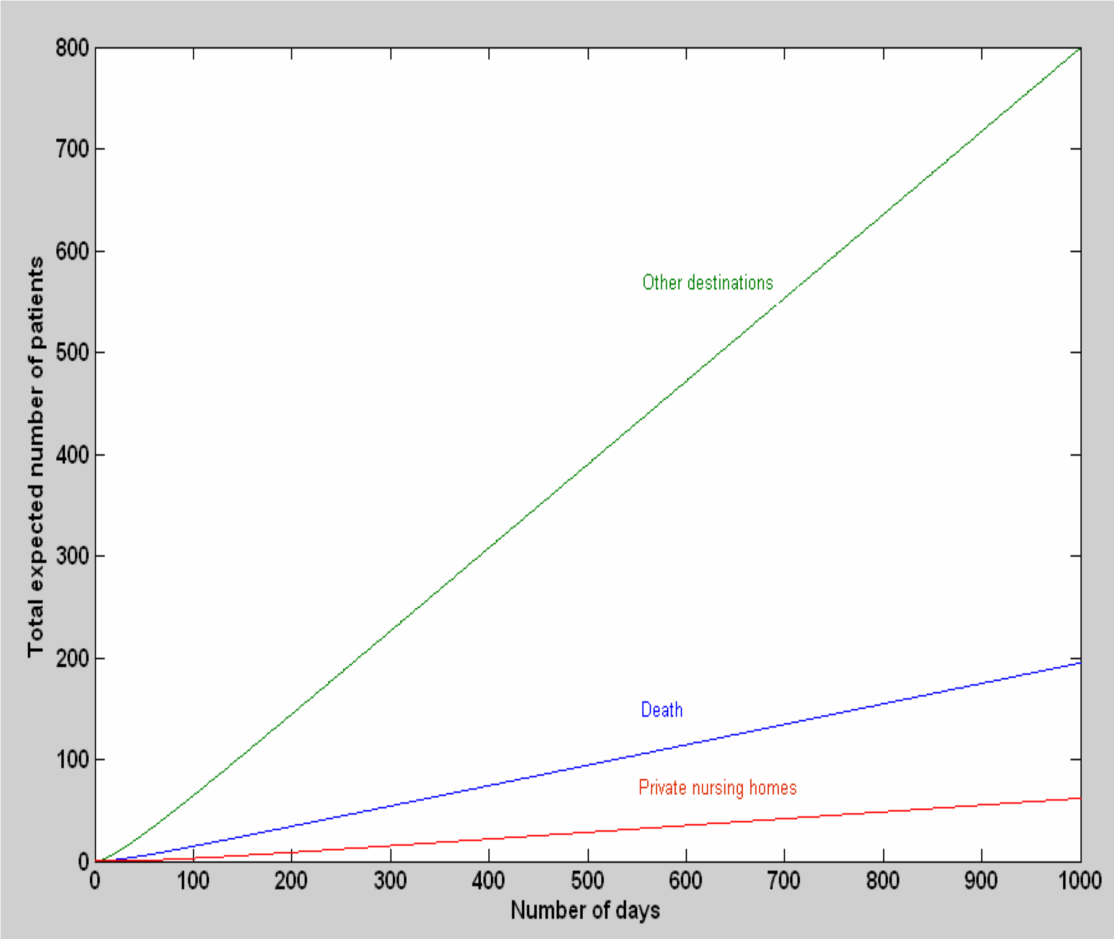
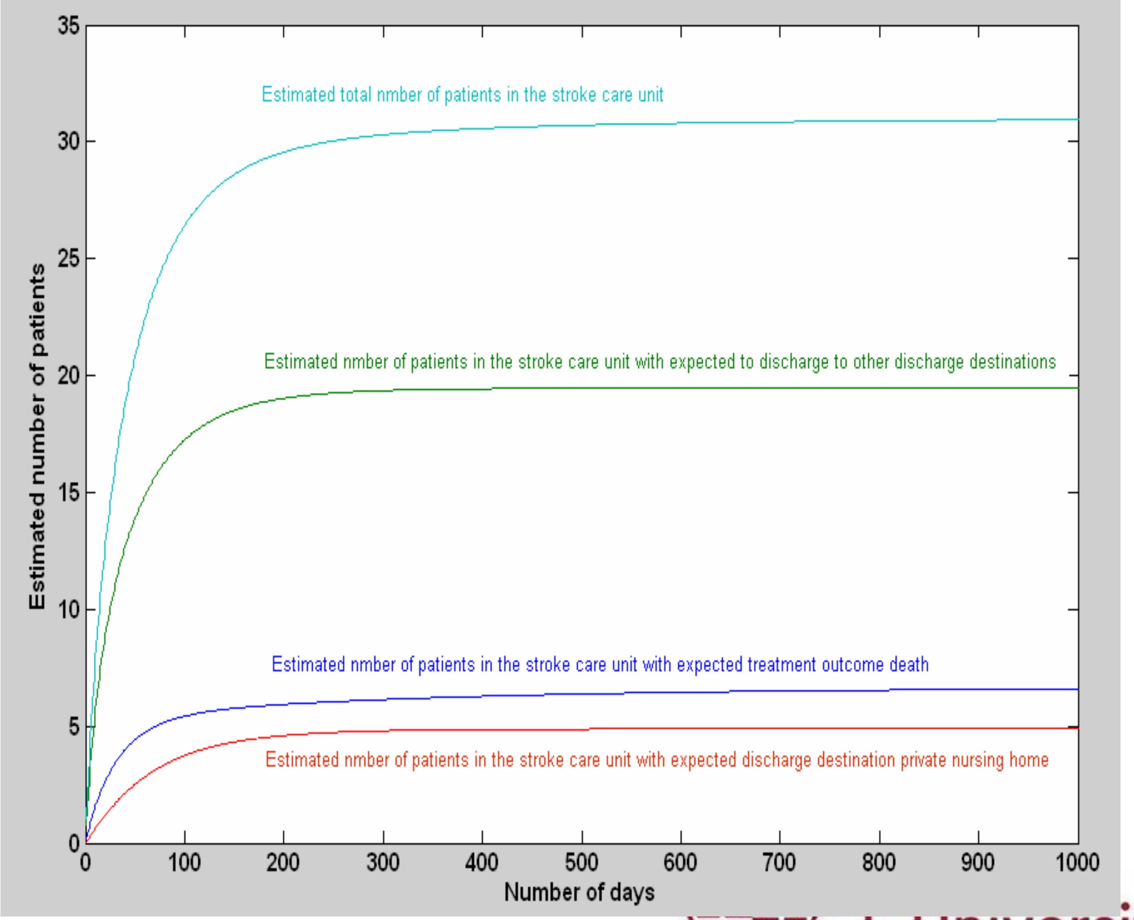
Hospital Capacity Planning

Total expected number of patients discharged to each discharge destinations



Hospital Capacity Planning

Distribution of patients based on their expected discharge destinations



Cost of care

- The total expected daily cost after k days:

$$\Omega_k = \mathbf{s}_{whole,k} * \mathbf{c}.$$

- Where cost vector

$$\mathbf{c} = \{c_1, c_2, c_3, \ldots, c_n, c_{n+1}, c_{n+2}, \ldots, c_{n+m}\}^T ,$$

- where c_i is the daily cost of care in state *i*.

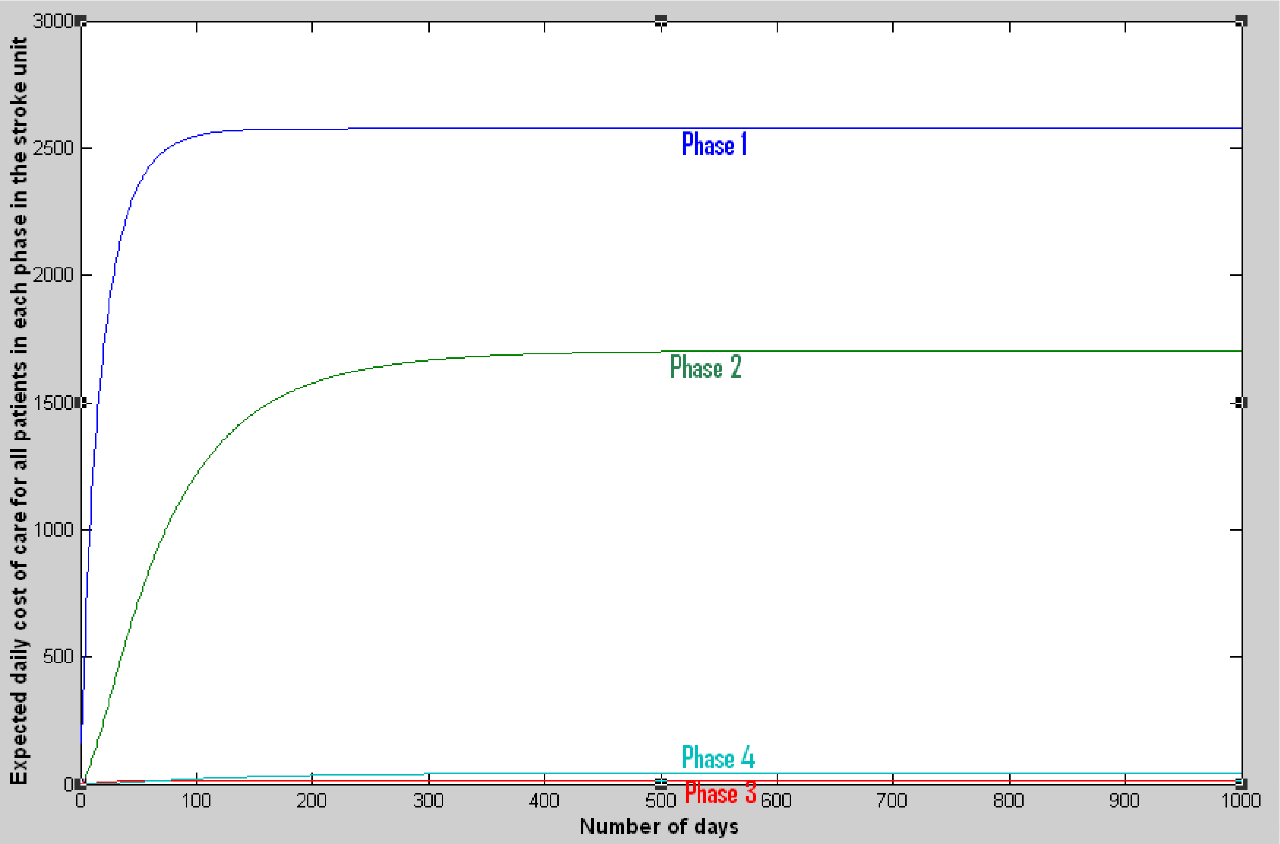
Cost of care

- We attach unit costs* of £164.80 per day for stay in acute care (phase 1) and £114.80 per day for stay in rehabilitative care or long stay care (phase 2, phase 3 and phase 4).

- *using estimates from Saka et al. (2009) which is adjusted from 2005.
- Saka O, McGuire A, Wolfe C (2009). Cost of stroke in the United Kingdom. Age and Aging. 38: 27-32.

Cost of care

Expected daily cost of care (in £s) for all patients in each phase of the stroke unit



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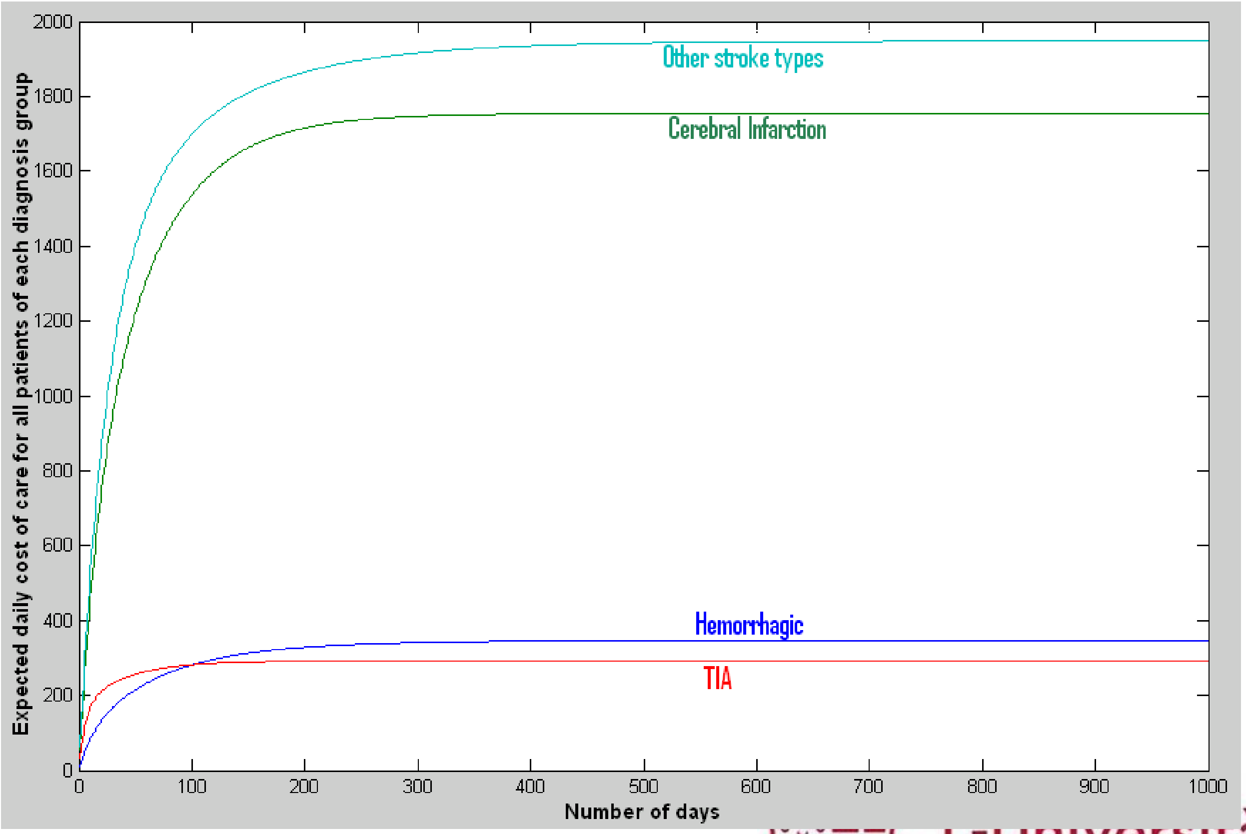
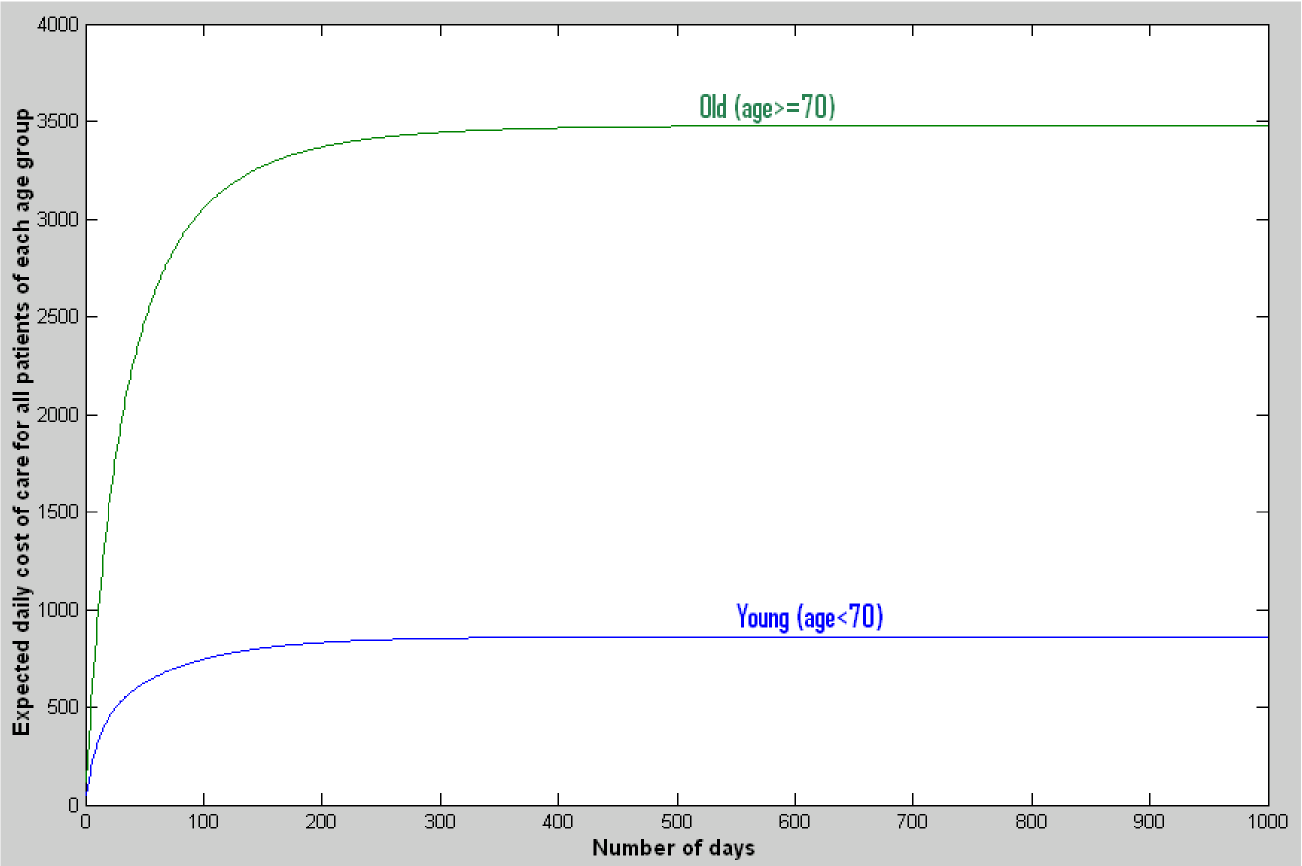
Cost of care

Expected daily cost of care (in £s) for all patients of each diagnosis group



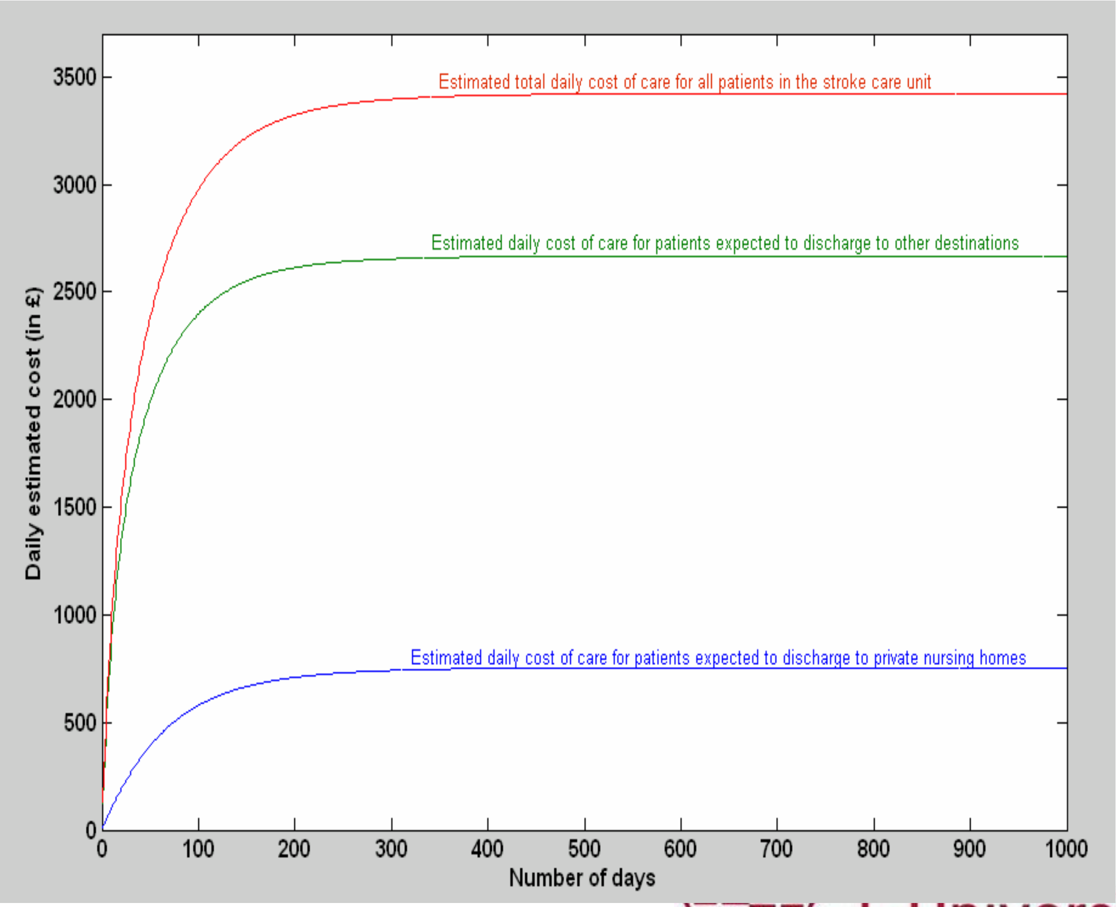
Cost of care

Expected daily cost of care (in £s) for all patients of each age group



Cost of care

Estimated daily cost (in £s) of care of patients for each discharge destination



Opportunities unlimited

- Discharge delay modelling
- Activity mining in sensor network
- Disease progression modelling (HIV)
- Mental state detection (using fMRI and EEG neuroimages)
- Behavioral analysis

Discharge delay modelling

- A challenge for healthcare managers and policy makers
- Negatively affects the hospital performance metrics
- Has other serious consequences for the healthcare system such as affecting patients' health

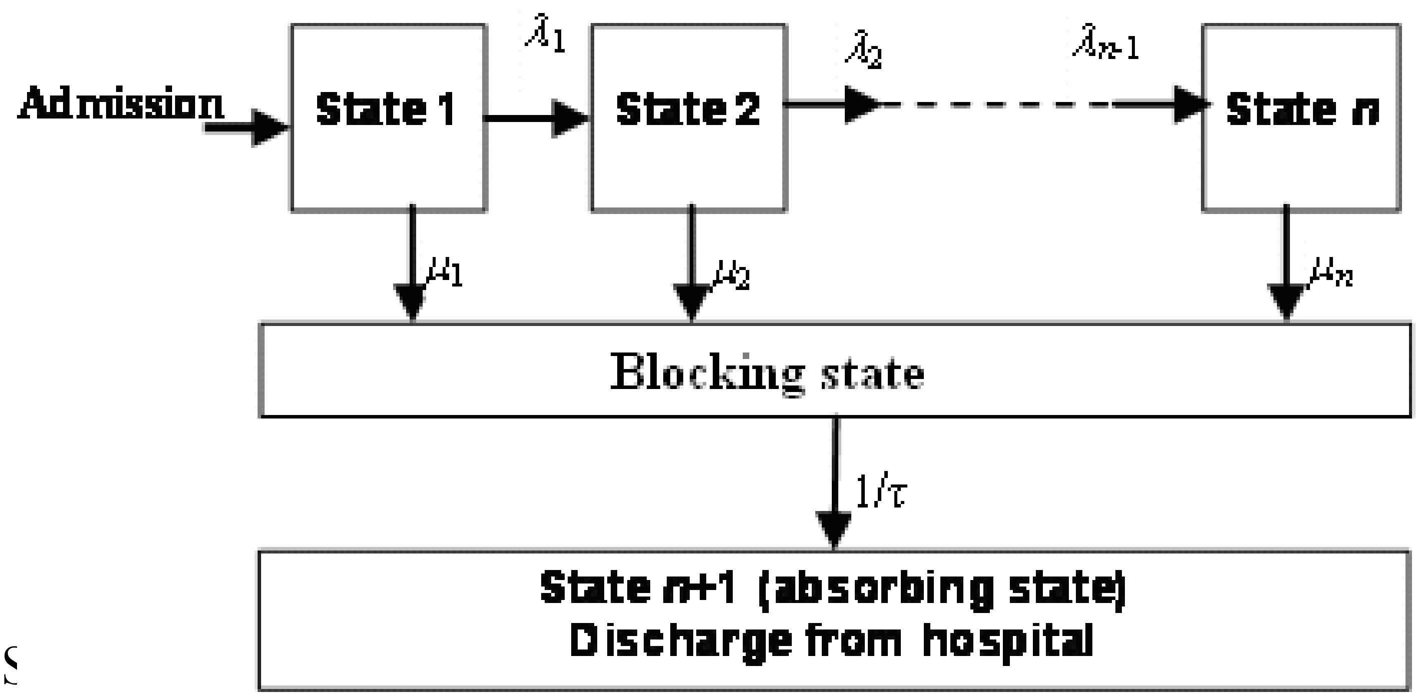
Discharge delay modelling

- Phase type distribution survival tree based clustering can be used for modelling delayed discharge and its effects

- Delayed discharge patients waiting for discharge can be modeled as a special state in the Markov chain called ‘blocking state’

- A model can be developed to recognize association between demographic factors and discharge delays and its effects, and to identify groups of patients who require attention in order to resolve the most common delays and prevent them from happening again.

Discharge delay modelling



- S

blocking state

Activity mining in sensor network

- A sensor network is deployed in the smart home environment to aid assistive living in self care of patients with Dementia (Alzheimer's disease).

- Sensors in the sensor network are placed such that each sensor detects and records (time and duration of) a particular activity each time it is performed by the user.

- In order to carry out a task, a user performs combination of these activities in a particular sequence.

Activity mining in sensor network

- Activity mining or exception mining from the sensor network data might help in monitoring patient condition, recognising alarming events, determining care needs, treatment effects and progress etc.

- The time spent in each activity can separately be modelled by Coxian Phase Type Distribution.

- A sequential pattern can be defined as a sequence of activities followed by a user in order to perform a task.

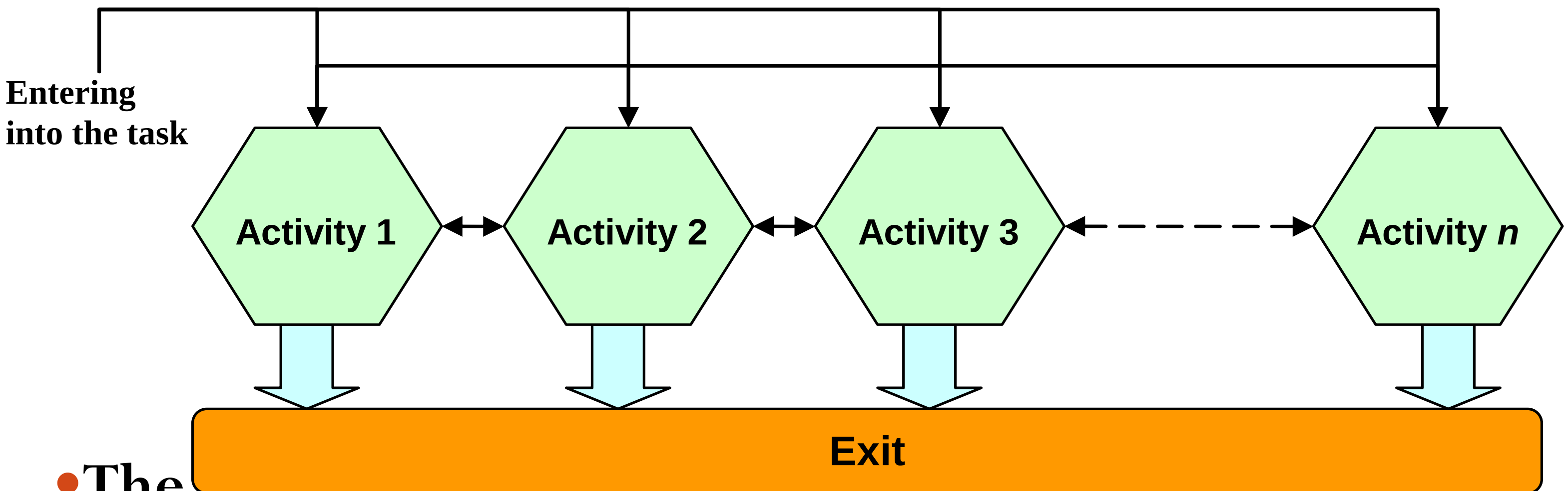
Activity mining in sensor network

- The values of fitting parameters and dependency parameters can be estimated using semi-supervised learning.

- Frequent sequential patters satisfying given criteria of interestingness can be enumerated using an algorithm based on global optimization (Falk and Soland, 1969, Garg et al. 2009a, Lawler and Wood 1966) or some other suitable algorithm based on the given criteria.

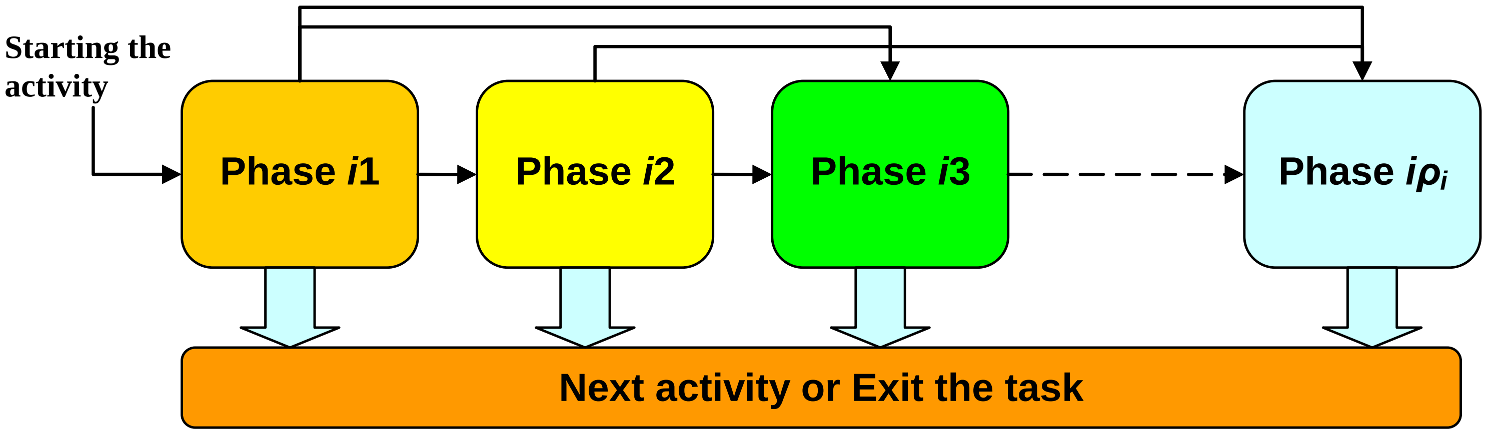
- We can use the model to recognise unexpected patterns based on given criteria such as patterns having likelihood less than the given threshold or pattern with duration more than the given threshold duration.

Activity mining in sensor network



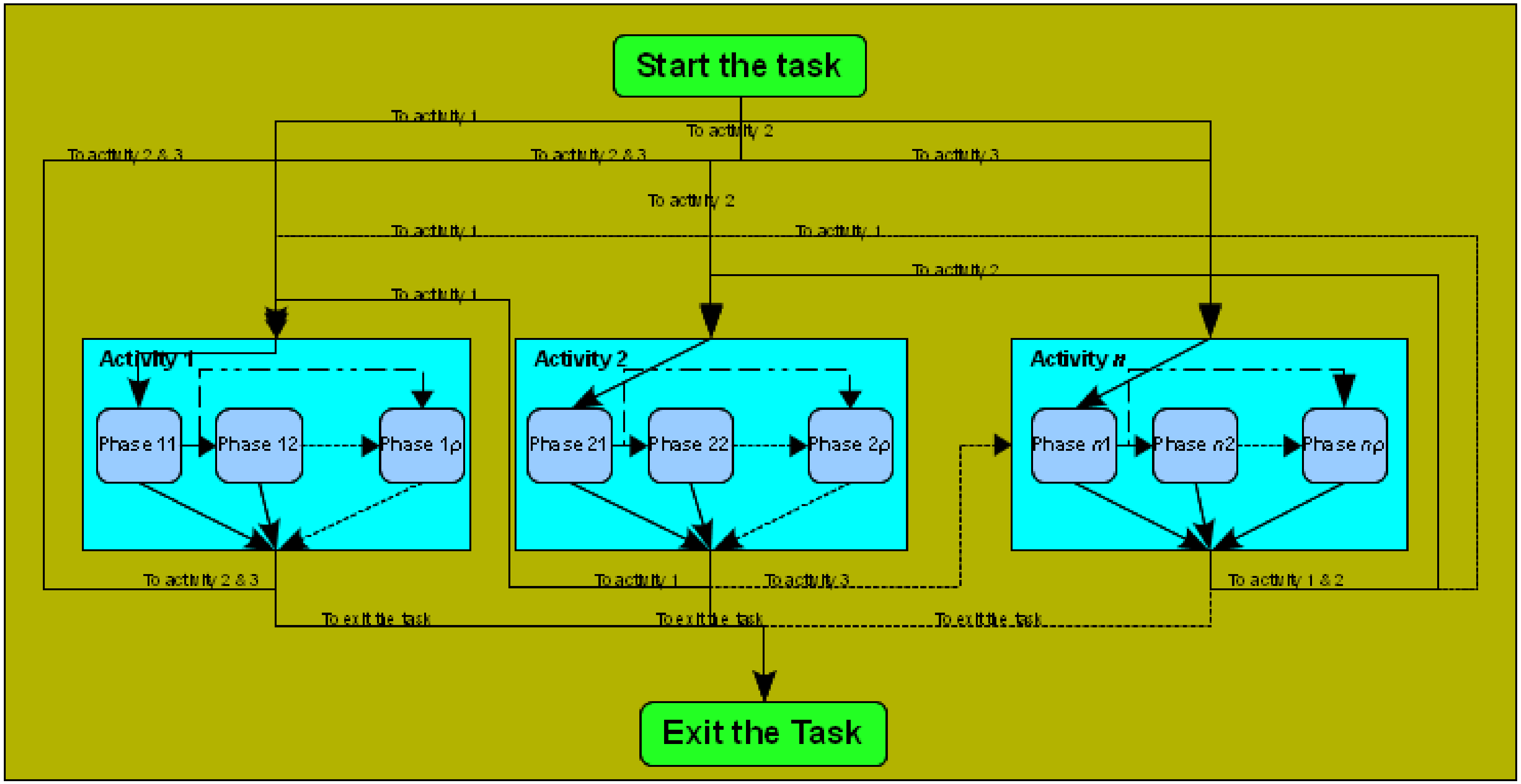
- The schematic representation of extracting possible (sequnece) dependencies among activities

Activity mining in sensor network



- The schematic representation of an activity as a Markov chain

Activity mining in sensor network



separately modelled by Coxian-Phase type distribution.

Disease progression modelling (HIV)

- Disease progression models can be useful tools for gaining a systems understanding of the transitions to disease states, clustering patients based on their disease progression rates and characterizing the relationship between disease progress and factors affecting it such as patients profile, treatment, stage at which disease was diagnosed or stage at which patient was first institutionalized.

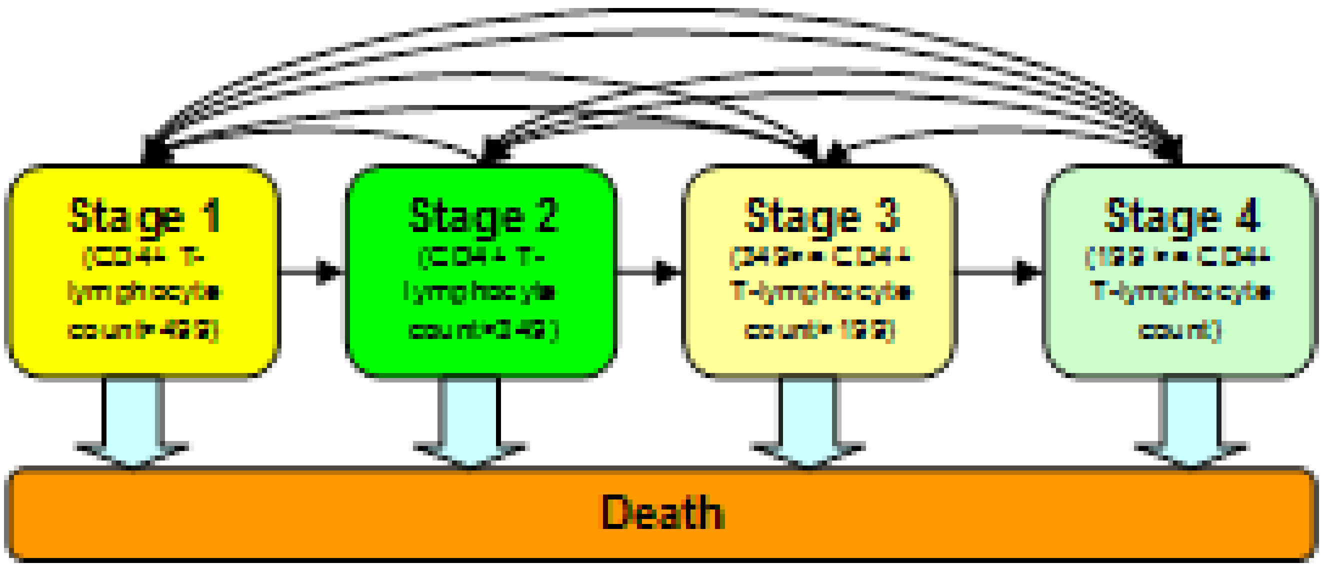
- WHO classifies the progression of HIV disease as a 4 stage bidirectional process in which a patient's disease progression stage is determined by his/her absolute peripheral blood CD4+ T-lymphocyte count.

Disease progression modelling (HIV)

- The patient's immunological status can not only progress sequentially from stage 1 to stage 4 but also regress or jump from one stage to the another stage.
-
- We are developing a novel approach of modelling progression of HIV disease using phase type distributions.

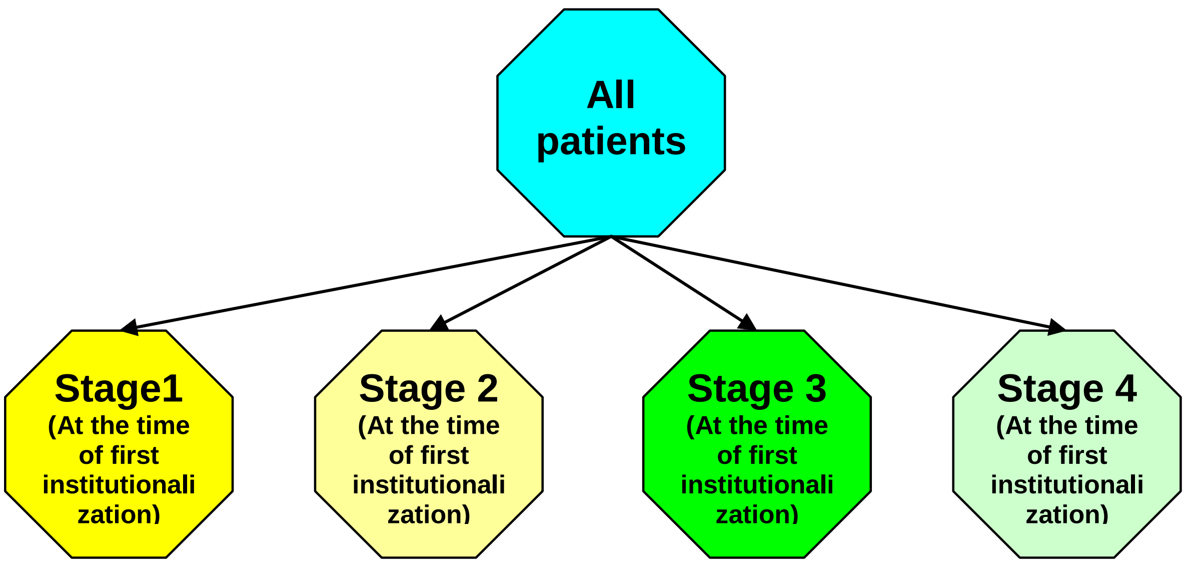
- Model can then be extended to illustrate how it can be used to model effects of the affecting factors such as stage at which disease was diagnosed or stage at which the patient was first institutionalized.

Disease progression modelling (HIV)



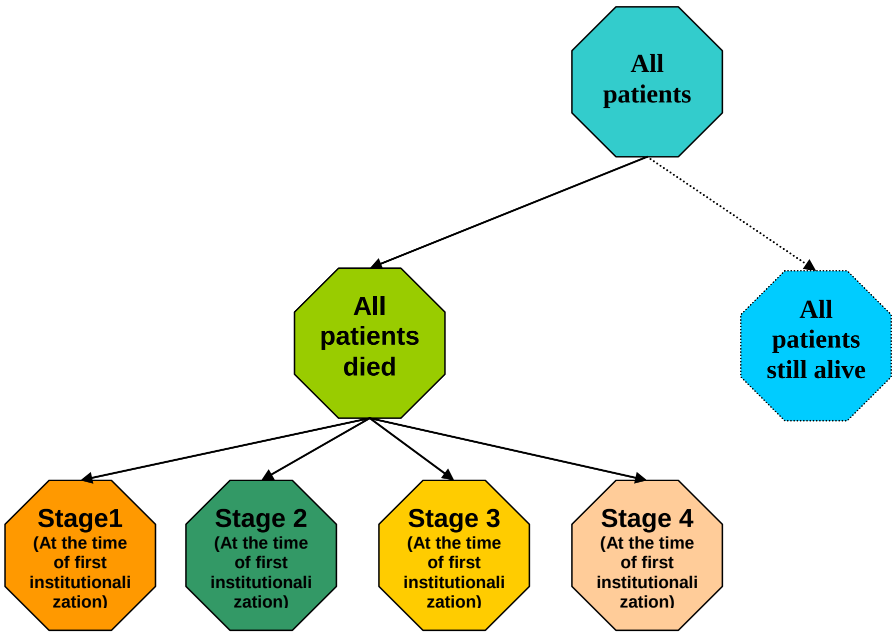
- Stages of HIV progression

Disease progression modelling (HIV)



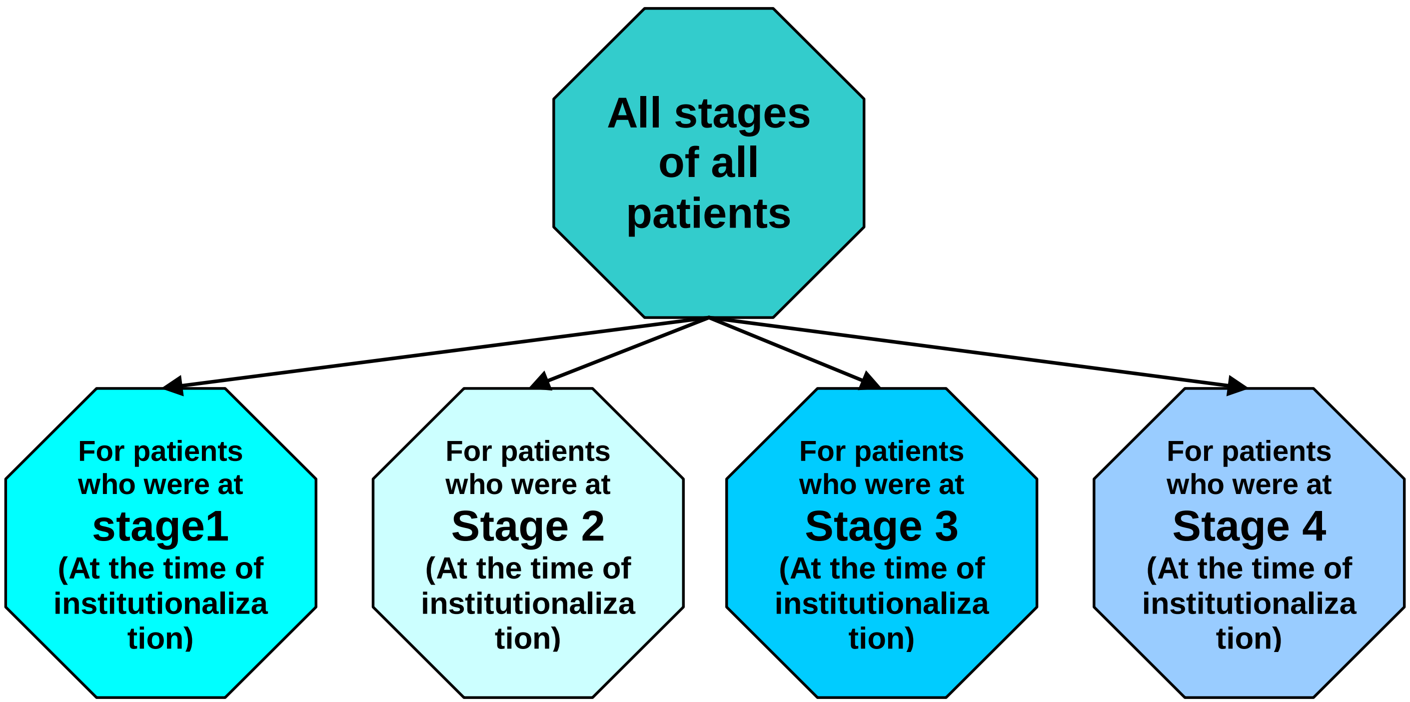
- Dendrogram of clustering durations of stay data of all patients based on the HIV disease progression stage at the time of first institutionalization of the patient

Disease progression modelling (HIV)



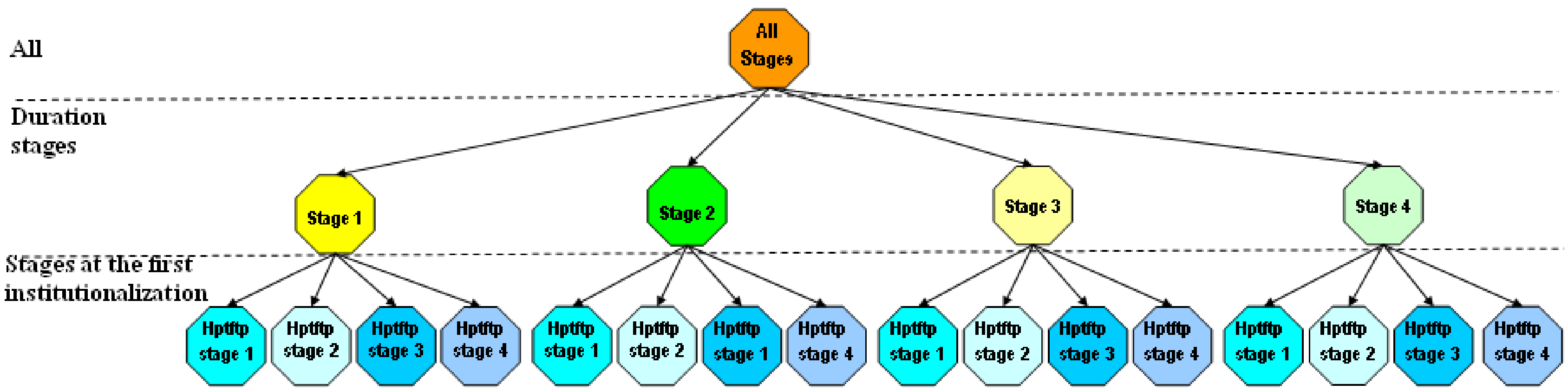
- Dendrogram of clustering durations of stay data of all died patients based on the HIV disease progression stage at the time of first institutionalization of the patient

Disease progression modelling (HIV)



- Dendrogram of clustering durations of stay in each stage data of all died patients based on the HIV disease progression stage at the time of first institutionalization of the patient

Disease progression modelling (HIV)



- Dendrogram of clustering time spent in each stage data of all patients first based on the HIV progression stage in which time is spent and then each such cluster in further sub-clustered based on the HIV disease progression stage at the time of first institutionalization of the patient

Mental state detection

- Mental state detection (using fMRI and EEG neuroimages)
- To identify the activation regions in fMRI data
- To model brain response to different activities using fMRI data

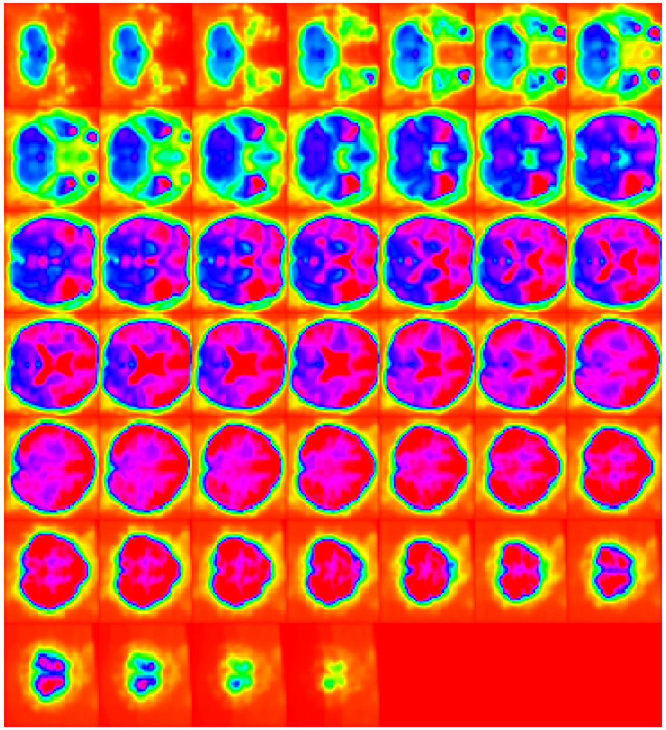
Mental state detection

- Repeating these with EEG data
- Characterising similar and complimentary information in fMRI and EEG data.
- To develop an integrated model for mental state detection using both fMRI and EEG data.

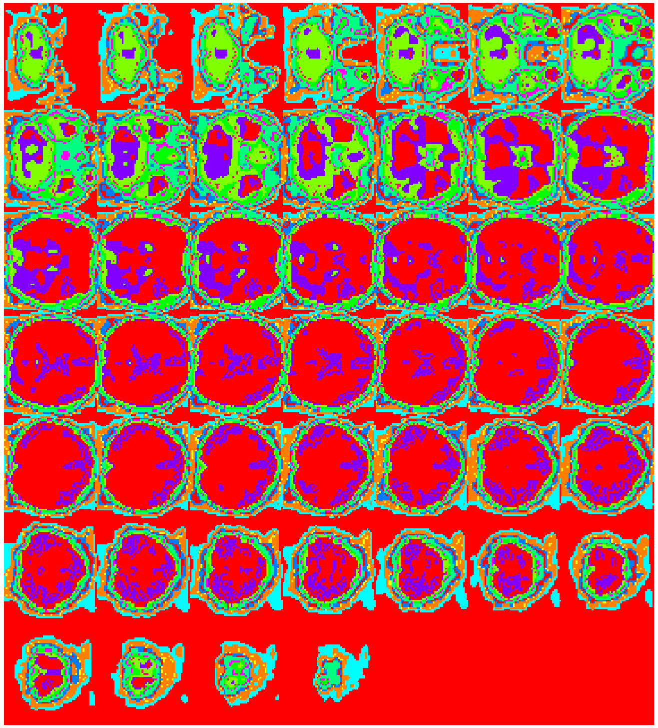
Mental state detection

- fMRI provides Blood Oxygen Level Dependent (BOLD) responses in brain.
- Clustering (pattern recognition) whole fMRI data using Gaussian Mixture Distributions
- Developing Gaussian Mixture Distribution tree using covariates such as subjects, Time, Slices and Regions

Mental state detection

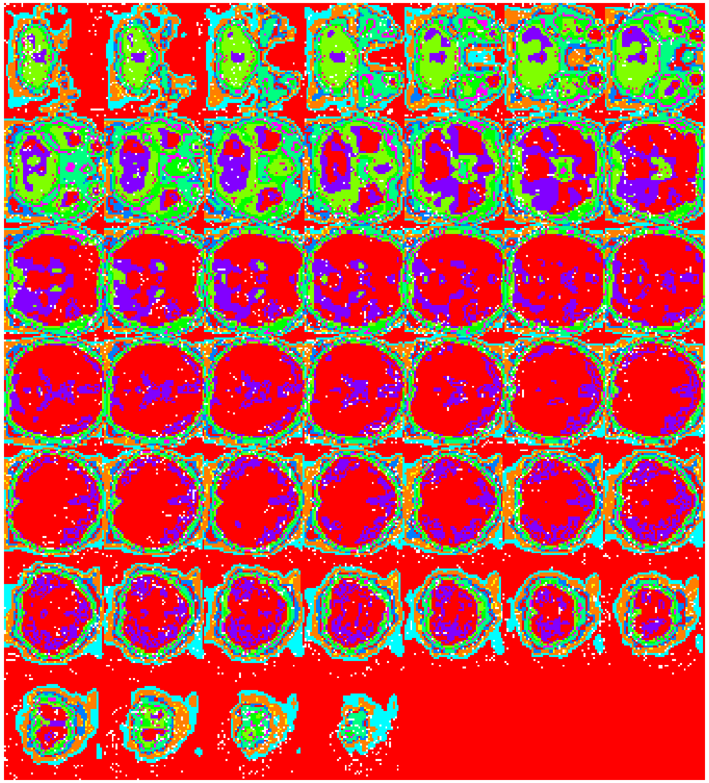


Different slices of a single scan before clustering

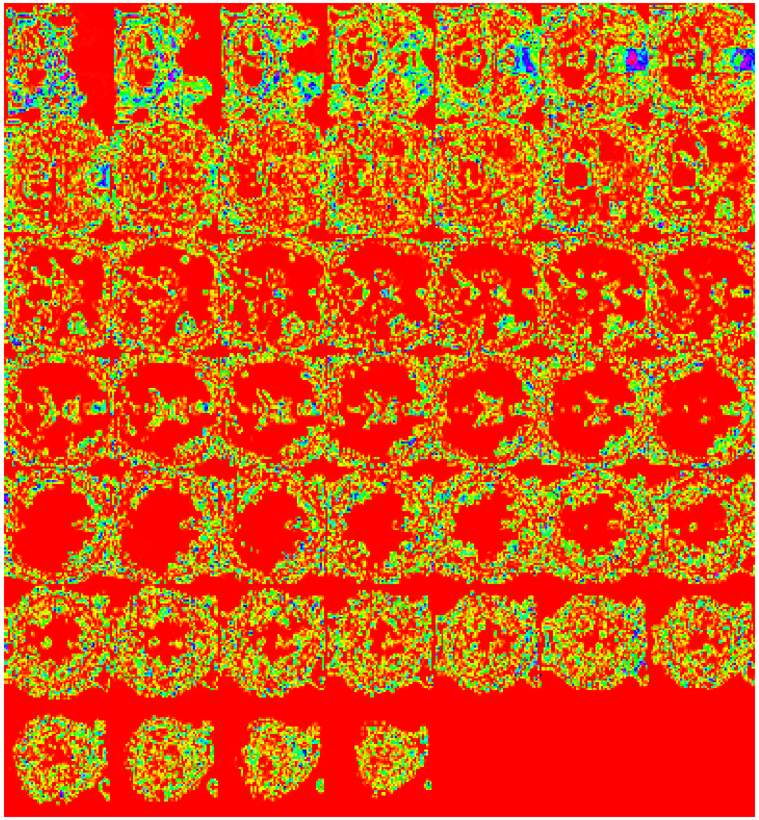


Different slices of a single scan after clustering

Mental state detection



Different slices of a single scan after clustering



Changes in time domain in different slices

Mental state detection

- Again Clustering whole fMRI data using Phase Type Distributions, which gives the phase changes in data on the time axis.

- Developing Phase Type Survival tree using covariates such as subjects, Slices and Regions

Mental state detection

- Dirichlet Mixture Model based analysis of probability of shift in the given cluster.

- Complete brain model for changes in Blood Oxygen Level Dependent (BOLD) activity.

Mental state detection

- Dirichlet Mixture Model based analysis of probability of shift in the given cluster.

- Complete brain model for changes in Blood Oxygen Level Dependent (BOLD) activity.

Conclusions

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

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  - Effectively prognosticate survival data and
  - Cluster survival data into groups of patients following homogeneous patient pathways.

Conclusions

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- 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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