



# **MODELLING PATIENT DATA IN HEALTHCARE**

BAM CONFERENCE 2014

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## AGENDA

Background

Patient Data – what is being captured?

Patient Data – what can we do with it?

**Demand Forecasting** – Aims

**Demand Forecasting** – Time Series Approach

**Demand Forecasting** – Challenges

**Capacity Planning** – Aims

**Capacity Planning** – Queuing Theory Approach

**Capacity Planning** – Simulation Approach

**Risk Stratification** – Aims

Questions?

# Hospital and health services have reservoirs of data that are often underutilised in hospital decision making.

- Hospitals always seek to optimise utilisation of resources.
  - Physical resources (e.g. Operating Theatres, Ward beds, etc.)
  - Manpower (e.g. nurses, surgeons, anaesthetists).
- Health Services around Australia are currently implementing Activity Based Funding (ABF).
  - Weighted activity units (WAUs) are attributed to each activity undertaken by a Hospital and Health Service (HHS)
  - Activities include hospital infrastructure spending, outpatient activities, and scheduled/unscheduled inpatient activities
- Discrepancy between available capacity and demands on its services can result in inefficiency in some areas – either in underutilised resources (and unnecessary costs) or unmet demand.
- Biarri has been working with Gold Coast Hospital and Health Service (GC HHS) to actively understand the capabilities of GC HHS' patient data in health service management and undertake resource optimisation.

# Hospitals and Health Services collect patient datasets from many sources, although they can be difficult to join together.

- GC HHS is currently implementing a “Shared Care Record.”
  - A single repository to contain patient HHS data stored in separate systems
- The types of patient data that are currently being captured includes:
  - Hospital Admission/Discharge Notification data
  - GP and OHP Event Summaries
  - Ambulance Service Admission/Discharge Notification data
  - Home Monitoring Service data
  - Maintenance and Rapid Response Clinic data
  - Patient Diary data
  - Holistic Assessment data
- These datasets are candidates for the Shared Care Record.

# Patient data can be used for demand forecasting, resource optimisation and other cost-minimising activities.

- Before undertaking resource optimisation, hospitals need to understand the volume of patients and associated costs that they will be dealing with.
  - Need to undertake Demand Forecasting for Patient admissions and WAUs.
- Once future demand is understood, resources can be optimally allocated
  - Capacity Planning (Operating Theatres, Ward Beds, Treatment spaces, etc.)
  - Manpower Planning/Workforce management
- Capacity Planning then helps resolve questions on whether a HHS requires CapEx on further facilities.
- A disproportionately large amount of costs for HHS' costs are attributed to Emergency admissions (relative to the total volume of admissions).
  - It is important to undertake interventions to prevent Emergency admissions.
  - Patient data can be used to model Emergency admission risks for candidate patients.
  - Modelling can lead to targeting out-of-hospital care for at-risk patients, preventing Emergency admissions and costs.

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# The aim of the Demand Forecast was to generate a projection on the number of admissions and WAUs.

- The aim of Demand Forecasting was to generate a prediction on the number of hospital admissions and WAUs for future years. Predictions were split across:
  - Service-Related Groups (SRGs)
  - Diagnosis-Related Groups (DRGs)
  - Urgency Categories.
- Patient Hospital admission data (HBCIS data) contains time-stamped admission events.
- GCUH opened in September 2013 to replace old Southport hospital (10min away)
  - Must use Southport admissions data to model new hospital.
  - Forecasting approach must take into account the jump in patient admissions with new hospital.
  - Approach must weigh recent data points more heavily than older data points.
  - Over time, various events have been undertaken by hospitals which change/spike admission rates. Need to select approach to deal with these events.

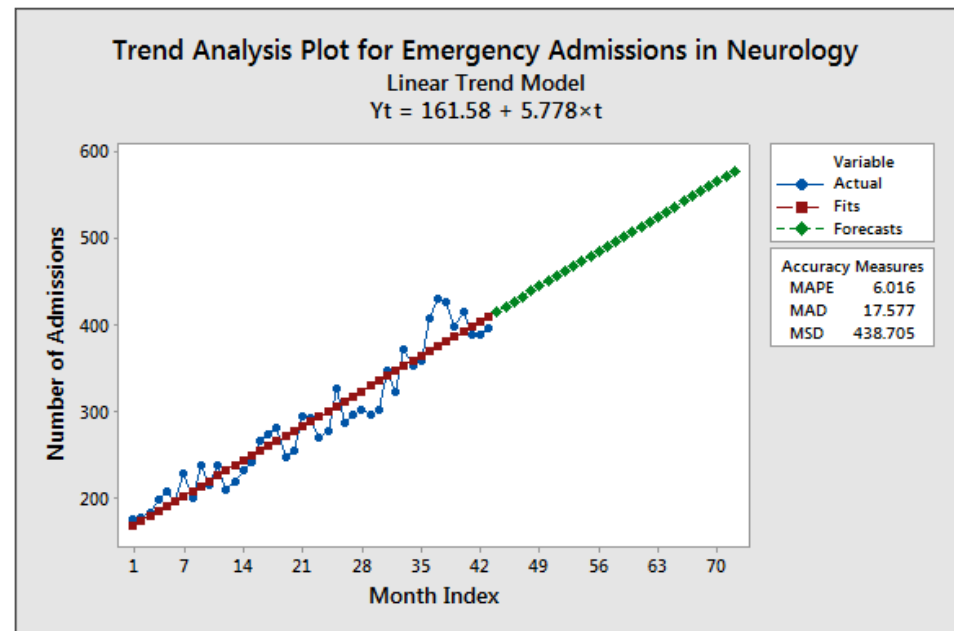
# Time Series Forecasting techniques were used to generate monthly forecasts for 2015 and 2016 FYs

- Initially, exploratory data analysis undertaken to visualise historical demand over time across categories.
- Several Time Series Forecasting Techniques were applied across all groups. These groups included:
  - Linear Trend
  - Exponential Smoothing
  - Trend-Adjusted Exponential Smoothing
  - Holt-Winter's Method
- The benefits of these forecasting methods are that they weigh recent data points more heavily than older data points. This allows spikes and jumps in admissions (i.e. from GCUH opening in September 2013) to be modelled accurately.



Linear Trend forecasts were used for categories with large numbers of admissions/WAUs following a reasonably linear growth rate over time.

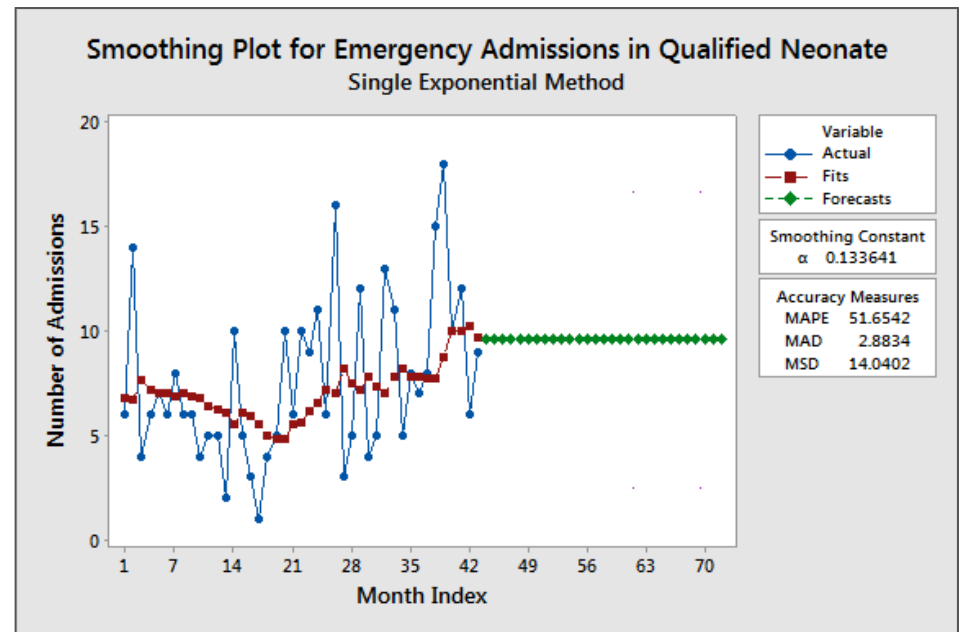
- For SRGs/High Volume DRGs/Surgical Specialities with reasonably linear trends, few outliers, large numbers of records and no seasonality, a simple Line Trend had the best fit of data.
- Although we may logically expect growth to follow exponential growth, it appears that, over a short period of time (e.g. 5 years), a linear rate fit data better than an exponential rate.
- E.g. Emergency Admissions in Neurology



Exponential Smoothing forecasts were made for categories with fewer data points or more relative variability, where little growth pattern is discernible.

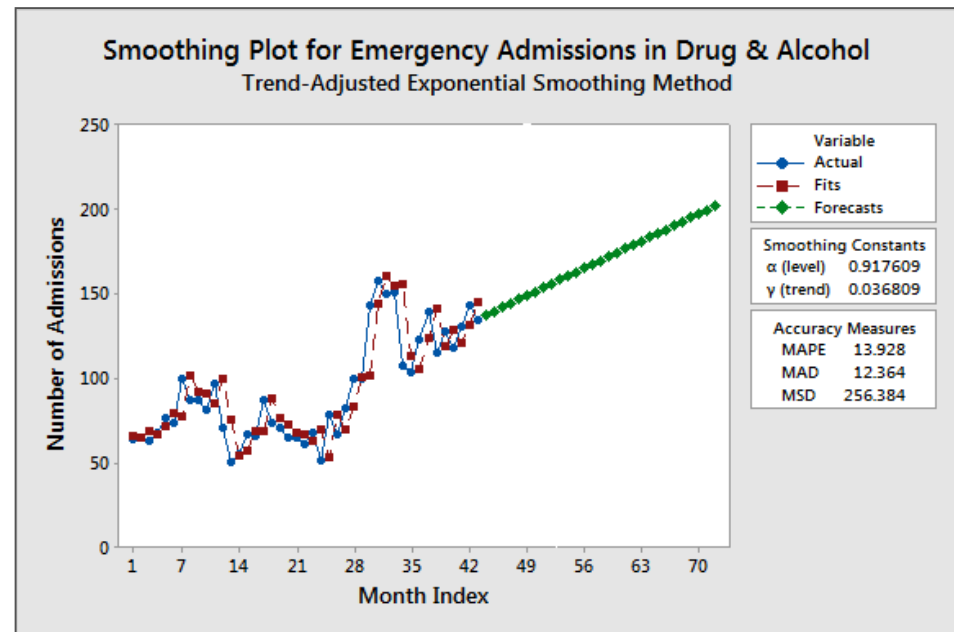
- For SRGs/High Volume DRGs/Surgical Specialities with fewer data points, more outliers, and more inherent relative variability, Exponential Smoothing was required to be used.
- Exponential Smoothing is the least desirable forecasting method as it generates a weighted average value as a forecast, where more recent entries have a higher weighting.
- E.g. Emergency Admissions in Qualified

Neonate



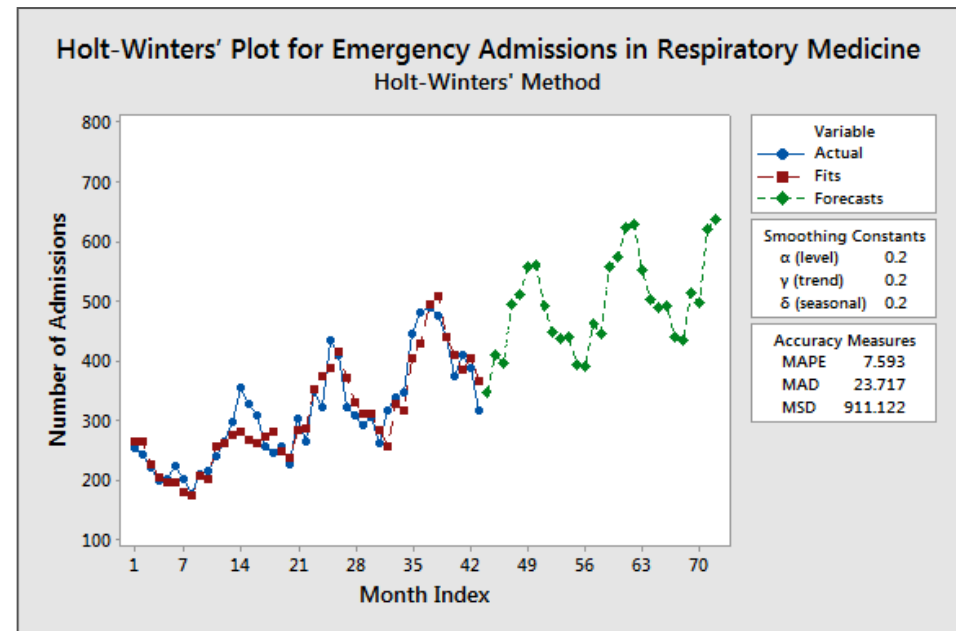
Trend-Adjusted Exponential Smoothing forecasting method was used when a trend was present, but skewed due to outliers/ large peaks of surgeries.

- For SRGs/High Volume DRGs/Surgical Specialities that show distinct linear growth rate, but is affected by outliers/large peaks of surgeries, Trend-Adjusted Exponential Smoothing forecasts were used.
- Trend-adjusted forecasts produce a linear growth rate, but the impact of values far outside of this growth rate are reduced. This removes the bias of outliers and large peaks of surgeries on the forecast. The main benefit of TAES is that it allows constant-gradient linear trends, even with marked jumps in the data (i.e. from GCUH coming online in September 2013)
- E.g. Emergency Admissions in Drug and Alcohol



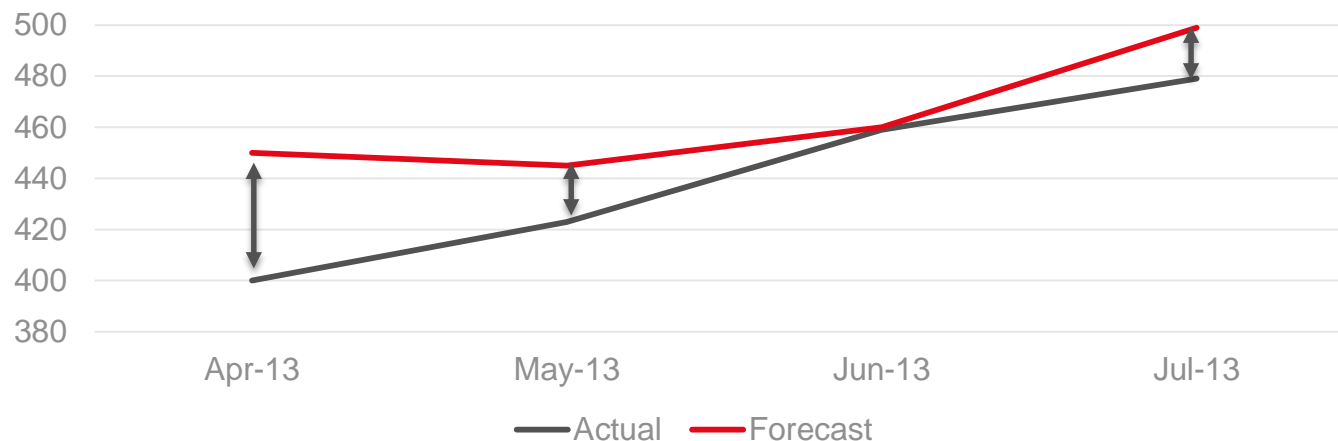
# Holt-Winters' forecasts was used on admissions/WAUs for a category where seasonal behaviour was present.

- In Holt-Winters' forecasts, the time periods are grouped into seasonal periods of a single year, and forecasts generated based on the behaviour within and between seasonal periods.
- E.g. Emergency Admissions in Respiratory Medicine



# Mean Absolute Percentage Errors (MAPEs) were used to report how well forecasts fit against the actual numbers.

- Measures of fit:
  - Mean Absolute Percentage Error (MAPE)
  - Mean Absolute Deviation (MAD)
  - Mean Squared Deviation (MSD)
- MAPE is the mean relative difference between actuals and forecasts.
- Under visual observation, MAPEs >40/50% seem to be poorly fitted forecasts.



# Several issues were faced in determining forecasts.

- For Inpatients, higher volume surgeries showed far better fits of forecasts against actuals for both admission numbers and QWAUs. On the other hand, Outpatients did not seem to show better fits for higher patient volumes. This was due to a concerted effort by GCUH to treat their Outpatient backlog in recent months, skewing all forecasts.
- GCUH only opened in September 2013, and therefore historical data from the decommissioned Southport hospital used to proxy historical data for GCUH. Is this a valid assumption to make? Modelling methods were chosen to minimise this impact.
- Emergency data was finely grained, so resulted in relatively good fits of forecasts vs. actuals. Elective wait list data very sparse and inconsistent/noisy, and only recorded for 2012 onwards. Far fewer data points resulted in far more worse fits of forecasts vs actuals.

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# With knowledge of forecasted demands for next Financial Year, GCUH undertook informed Capacity Planning.

- With knowledge of forecasted demands for the next Financial Year, GCUH could now plan capacity requirements for physical resources and staffing resources/workforce optimisation. Biarri and GCUH undertook capacity planning for treatment spaces, clinic spaces, beds and theatres across:
  - Inpatient/Outpatients
  - Scheduled/Unscheduled
  - SRG
  - Care Type
  - Triage Categories
  - Children (0-14)/Adults
  - Time of Day/ Day of week
- Two approaches were considered for Capacity Planning.
  - Queuing Theory Approach
  - Simulation Approach



# A Queuing Theory approach for Capacity Planning was initially implemented.

- In a Queuing Theory approach, each space (e.g. Operating Theatre, Ward Bed, Treatment space) is considered a “Server”, with patients considered as “Customers”.
- The aim of this approach is to determine the optimal number of servers that are required to reduce the probability of all servers “busy” and/or meet some target Utilisation.
- Hospital HBCIS data contains Transfer In/Out times when physical space was allocated to patients. For patients using a particular type of space
  - a Service distribution can be determined by the total time each patient spent using the space.
  - An Arrival distribution can be determined by the patient Admission rates.
- Using tests for distribution fits (e.g. Chi-Square and Kolmogorov-Smirnov tests), the best possible distributions can be fitted to the Admission and Service rates (e.g. Erlang distributions).
- Once best fits are known, proportion growths/decreases in arrival rates (driven by demand forecasting) can be applied to the arrival rate distribution.

# Once appropriate Arrival and Service rate distributions are fit, multiple criteria can be used to determine capacities.

- Once arrival and service rate distributions are calculated, Queuing Theory stationary analysis can be used to determine the optimal number of servers, using the criteria
  - Minimum number of servers required to reduce the probability of all servers busy to some target.
  - Maximum number of servers required to meet some Utilisation target.
- For example, for the M/M/c queue (Poisson distributed arrivals, Exponentially distributed service times and c number of servers), stationary Utilisation ( $\rho$ ) is given by

$$\rho = \frac{\lambda}{c\mu}$$

where  $\lambda$  is the Poisson arrival rate,  $\mu$  is the Exponential service rate parameter, and c is the number of servers.

- For this same queue, the probability of all servers being used is given by

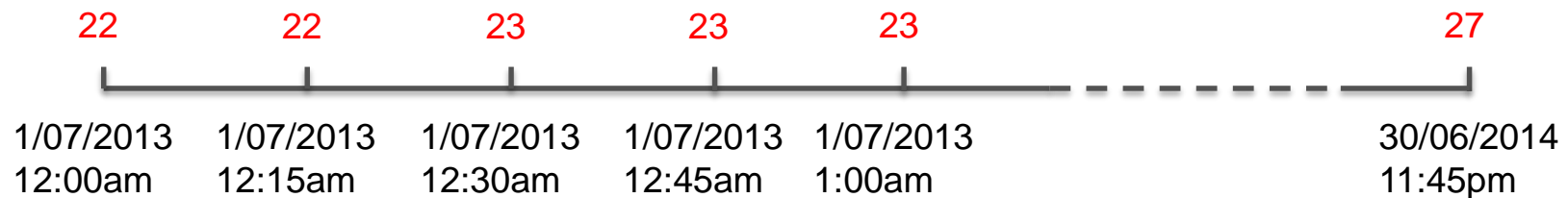
$$P(c \text{ occupied servers}) = \frac{\frac{(\lambda/\mu)^c}{c!}}{\sum_{k=0}^c \frac{(\lambda/\mu)^k}{k!}}$$

## Once appropriate Arrival and Service rate distributions are fit, multiple criteria can be used to determine capacities.

- A major downside of the Queuing Theory approach is the dependence on the fit of arrivals and service to distributions.
  - Different time periods (day/night, weekday/weekend, time of year) may have different distributions.
  - The effect can be mitigated by calculating separate capacity calculations at different points in time when arrival and service rate distributions may change.
  - Regardless, it is possible that no accurate distributions for arrivals and service can be fit.
- Therefore, a simulation approach will reduce the impact of poor distribution fits.

# A Simulation approach to Capacity Planning can be implemented to solve for poor distribution fits.

- A simulation approach determines space usage (i.e. beds, theatres, treatment and clinic spaces) based on historical patient admissions/discharges, with simulated growth.
- We begin by looking at distinct timesteps through the duration of a year (e.g. 15 minute timesteps). For each time step, we determine how many patients are occupying a space (which tells us how many of those spaces are being used).

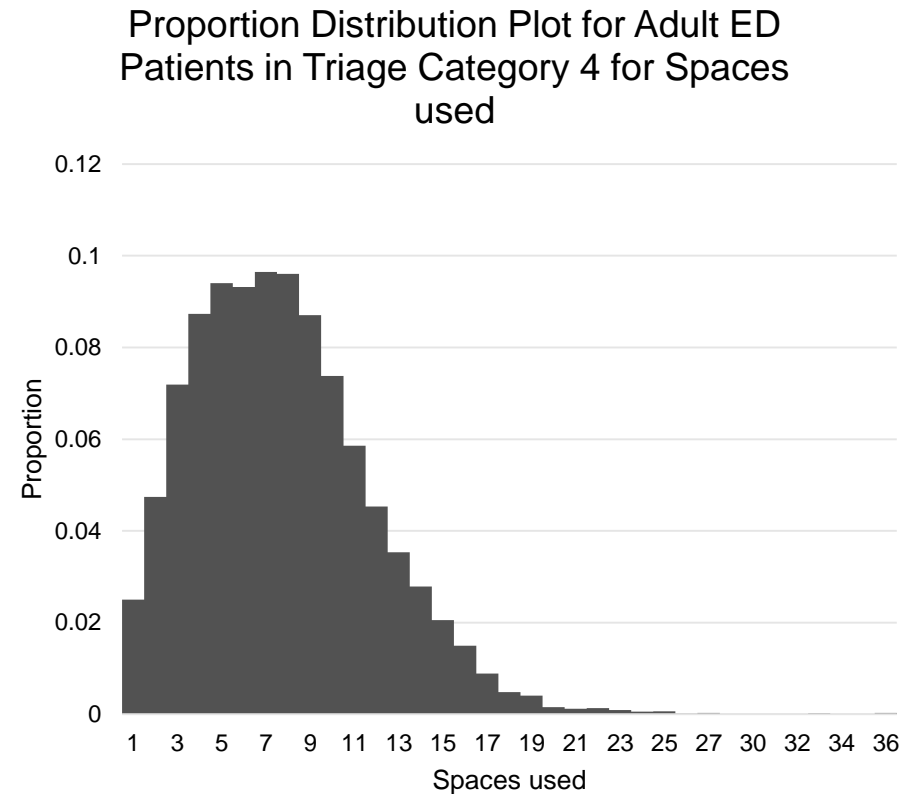
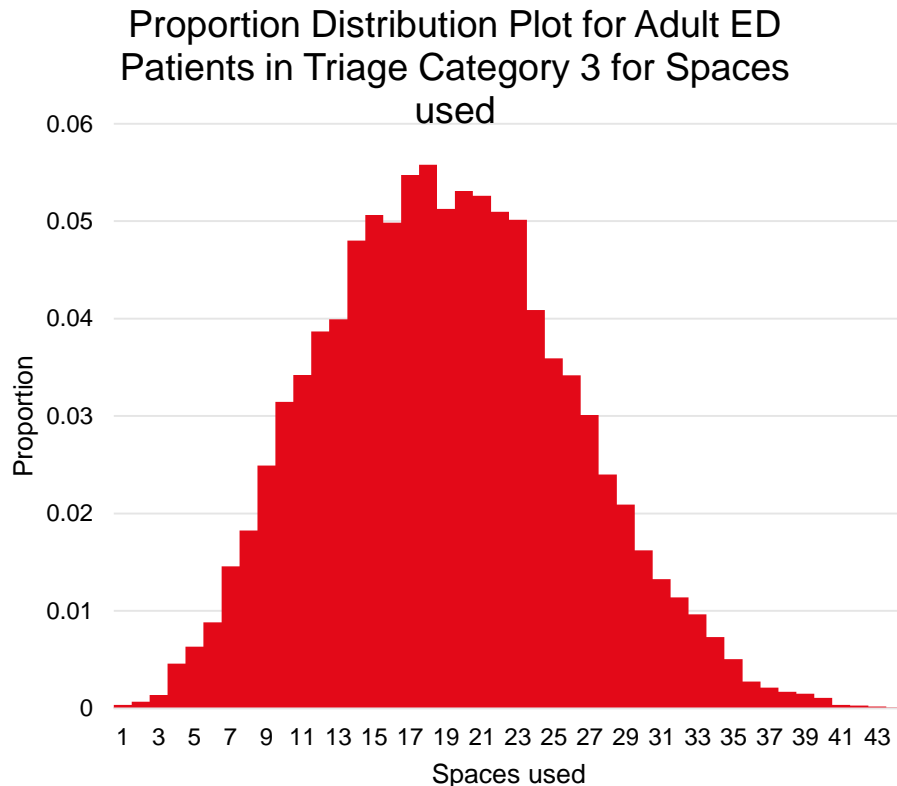


- So for a whole bunch of individual time steps in the year (~35,000 if we used 15min time steps for a year, we now know how many spaces of a certain type (e.g. Adult Overnight Inpatients for Obstetrics SRG) are being used.
- From this, we can determine the proportion of time that different numbers of spaces are being used (i.e. the space usage distribution) and idle time.

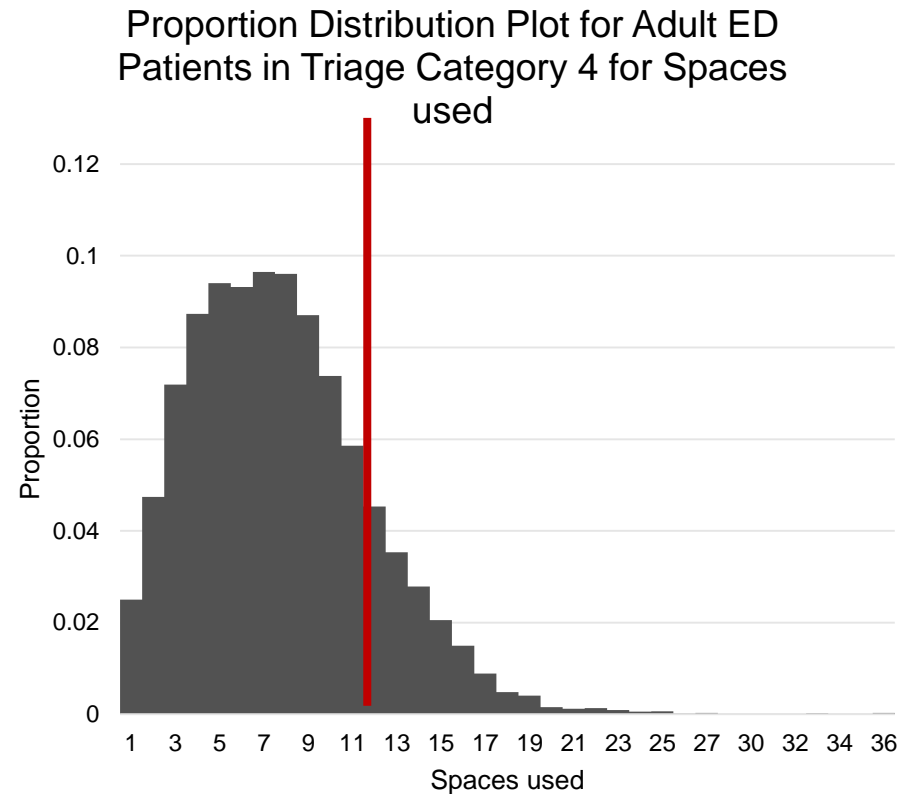
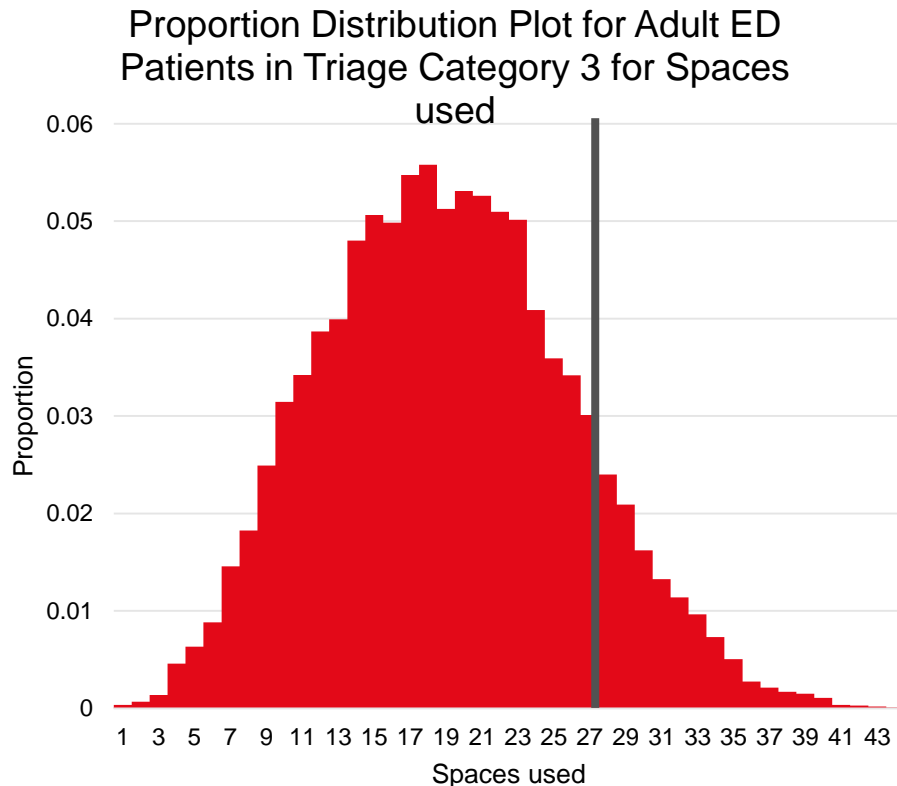
# A Simulation approach to Capacity Planning can be implemented to solve for poor distribution fits.

- Growth is then simulated using Monte Carlo to determine the increase/decrease in space usage distribution based on specified percentage growth.
  - For high patient volume spaces, simulated patients can be drawn from the historical dataset (as Idle time is not affected).
  - For low patient volume spaces, simulations are guided based on hospital criteria such as appropriate surgery times, time-of-year and forced idle time.
- The distribution of space usage (both historical and with simulated growth) can then be plotted, and capacity requirements derived from the distribution (e.g. how many spaces are required to meet space demand 90% of the time).

# A Simulation approach to Capacity Planning can be implemented to solve for poor distribution fits.

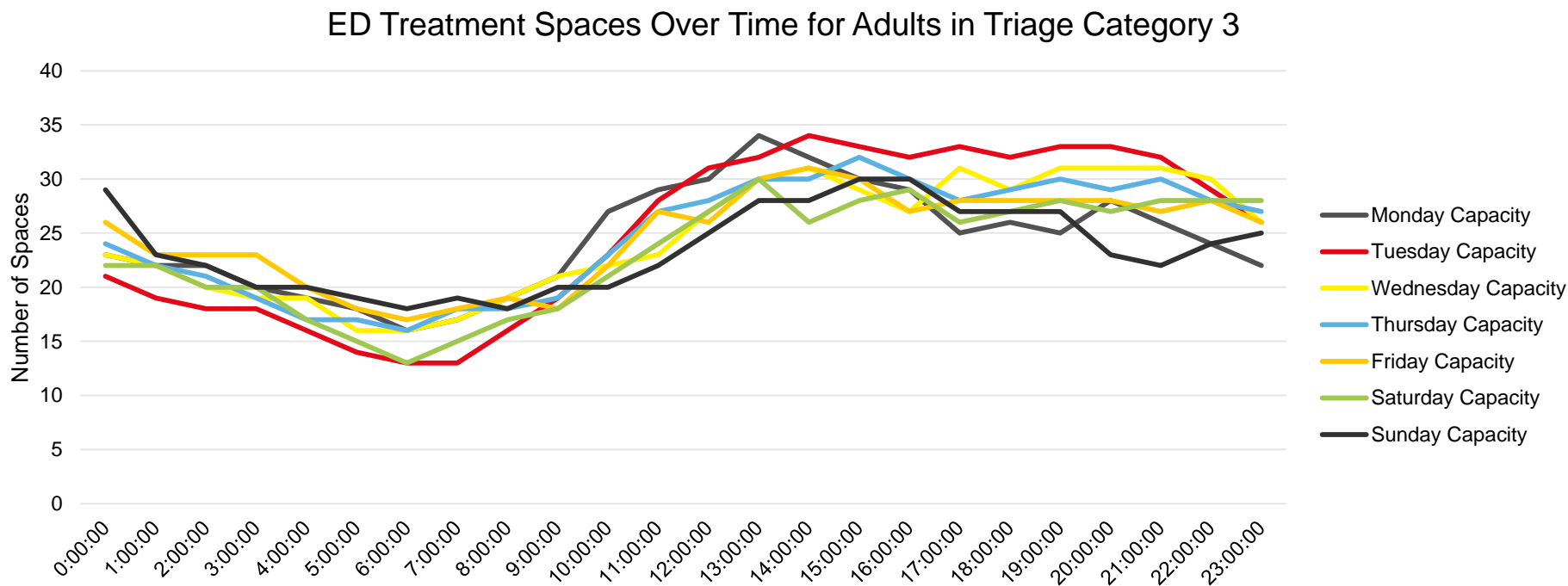


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# A Simulation approach to Capacity Planning can be implemented to solve for poor distribution fits.

- Resource usage over different days of the week and times of day bring up interesting results.





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# Risk Stratification allows identification of patients at risk of unscheduled hospitalisation.

- Gold Coast HHS aims to reduce the number of unscheduled presentations at hospital campuses.
  - Unscheduled presentations are costly.
  - Currently implementing Integrated Care procedures in the community.
  - Used mainly for patients with chronic illnesses.
- Gold Coast Integrated Care plans to develop and action targeted interventions to mitigate the impact of healthcare events.
  - Interventions are guided by identification and management of potential events before they require hospitalisation.
- Using GC HHS' Shared Care Record, real-time updates of patient data can be sourced from various disconnected sites (Hospitals, GPs, Home-monitoring, etc).
- Potential events could possibly be identified using forecasting from historical data and discrete event-driven algorithms.

# Questions?

