Abstract

Henry Ford Health System (HFHS) worked with Central Michigan University Research Corporation (CMURC) to investigate new approaches to forecasting patient bed requirements by physician specialty. The association-sequence analysis methodology developed for retail marketing and store layout design provided insight into forecasting future hospital admission distribution.

Introduction

HFHS is one of the nation's leading health care providers, offering a seamless array of acute, primary, tertiary, quaternary and preventive care backed by excellence in research and education. More than 12,700 full-time equivalent employees, including 3,000 nurses and more than 4,000 allied health professionals provide care during more than 2 million patient visits per year. HFHS providers perform more than 50,000 ambulatory surgery procedures each year. Nearly 65,000 patients are admitted to HFHS hospitals each year.

HFHS management met with CMURC representatives to initiate a project to investigate a novel approach to their forecasting problem, taking advantage of the data HFHS had been collecting in their proprietary systems. Improved forecasting should improve budgeting accuracy, support improved capital investments vs. operations decisions and also improve staffing and procurement activities for increased operational efficiency.

The project team included people from the HFHS Management Services department, staff of CMURC and several CMU faculties from the College of Health Professions and the Statistics department in the College of Science and Technology.

The goals set forth for the team were:

- Accurately predict inpatient volumes at Henry Ford Hospital (HFH) 3-6-9-12 months into the future based on HFHS current activity levels and historical trends. The level of detail is to the Nurse Unit, by date.
- The general principle is that outpatient activity and emergency department (ED) levels feed into the inpatient process and can be used to predict future inpatient levels in the short term.
- A more advanced model begins to understand the typical service paths which patients take through the system and to identify sub areas such as specific outpatient clinic services or diagnostic codes that translate into larger inpatient levels.

The duration of the project was scheduled to be 6 months.

Data Cleansing and preparation

In this project, as in most data mining projects, combining data from different tables presented significant hurdles. The hurdles could be addressed in this problem because the source tables shared a unique patient identifier, the MRN and this definition was consistently applied across HFHS. Complexity in the definitions of visits, admits, length-of-stay (LOS), etc. were the cause of most of the project time. This situation is not uncommon – in fact, HFHS data was useable only because of the unique MRN.

The HFHS data mining project consisted of three major datasets, namely Patient Encounters (Encounters), Inpatient Medical Record (Medical Record), and Inpatient (PEMS). The encounters table stores billing information for every patient encounter, outpatient or inpatient, including the site and date of service. The Medical Records table stores inpatient data for HFH, and includes Length of Stay (LOS) and primary DRG. The PEMS dataset includes unit level LOS and holds admit and discharge timestamps for each unit that the patient spent time on.

Roadmap

The scope of this project was to predict the bed occupancy of HFH, by nurse station, by day for a relatively short time (months) and also to forecast the admit rate by week for a period of a year. It had been observed that about 90% of admits to HFH are the result of prior visits to clinics and urgent care facilities of HFHS. Thus, set of patients with encounters in HFHS was split into the three groups:

1. Case A: Patients who have been admitted to HFH with prior encounters in the non-HFH environment (clinics and urgent care facilities);
2. Case B: Patients who have not been admitted to HFH, although they have had encounters in the non-hospital environment; and

3. Case C: Patients who have been admitted to HFH without any prior HFHS encounters.

All records have an associated doctor specialty code (specialty) to allow grouping patients into major sets of care requirements. Admitted patients with encounters in HFHS and with assigned specialty were analyzed to obtain pair-wise ‘rules’ connecting an outpatient (O) or emergency (E) visit to the later inpatient (I) event. These rules result in the frequency of occurrence (number of patients with this pair of events), the conditional probability that the admission follows the O/E event, and the time delay between the first encounter and the admit. (The set of time delays, per specialty, are well represented by the Weibull distribution function).

Patients who have been admitted to HFH without prior O/E encounters are forecasted by regression with trend, seasonality and holiday factors. The distribution of specialty associated with these patients (Case C) are calculated over the past two years and applied to the volume predicted by the regression model.

Patients admitted without a specialty assigned are accumulated and assigned specialties based on historical distribution. Predictions are obtained through regression of the total admits without specialty using trend, seasonality and holiday factors; then the factors are applied to the forecasted volumes to get the predicted admits by specialty.

The recent (prior 6-months) O/E visits were then used to generate a forecast of admits by specialty by week for the following 6 months. Likewise, the regression forecasts were generated with parameters for future weeks (number of week in the future, season, and holiday) to obtain the total expected admits by specialty by week.

The data from the Medical Records table were used to generate a table of percent of weekly admits for each day of the week for those weeks with no holiday. There were four rows to this table, one for each quarter of the year. An additional column was added to capture the percentage of admits on a holiday of a holiday week’s admits. In addition, the Medical Records data were used to generate a distribution of length-of-stay (LOS) by specialty in days.

The PEMS data were used to generate a table by specialty of the distribution of time spent by patients in various nurses’ stations (NURS_UNIT).

The weekly admits by specialty are then converted to admits per day, extended to bed requirements per day and then assigned to nurse stations. This completed the primary deliverable.

Unusual events, such as the power outage of August 14 and 15, 2003, were studied for impact on the patterns of activity and were found to be statistically insignificant. The average daily activity over a three week period (the week before, the week of, and the following week) was considered.

Operational decisions, such as expanding a wing, closing a section for renovations, etc., have significant impact on the detailed forecast. Any such planned activity can be easily incorporated as changes in the allocation tables and the forecasts can be re-run through that part of the system.

Association-Sequence process

The activities for each patient of Case A were organized in chronological sequence. Each encounter (visit or admit) was described by unique MRN+service date+patient type code+doctor specialty code+site code.

SAS Enterprise Miner 4.3 was used as a tool for the Sequence analysis. Patients from case A (at least one “I” and at least one “O/E”) were selected to relate admits (I) to preceding O and E visits, based on the service date. The O/E records covered from Jan 2000 – August, 2004 and the I-records were selected for Jan 2001 – August 2004. This range was used in the analysis to allow the admits of 2001 to have a history to look for O/E activity prior to the admit. Records identifying visits (unique MRN+service date+patient type code+doctor specialty code+site code) were used as input for the association node. The number of generated rules depends on the support levels requested. If rule had a support that was too low, the rules generated did not produce statistically significant time delay distributions. Different levels for support were used and it was found that a support of 0.5% seemed appropriate. The program produced 6,321 rules; of these, 206 rules described situations where “O/E” was followed by “I” (an admit). This subset contained the most active sites and major doctor specialty codes. The initial run used data from January, 2000 to March, 2004, where only O/E records were selected from the first year. For the final run, data were selected from 2001 through 2004, again restricting the first year to O/E visits. For each rule, the time lag (in weeks) was calculated between outpatient/emergency visits and admission to HFH.

The time lag distributions were fitted to parametric distributions such as Lognormal, Gamma and Weibull. Through an examination of the curves, it became evident that the two parameter Weibull distribution offered the best fit. For each rule, the two parameter values (for Weibull distribution): shape and scale, were calculated.

To create a forecast, the most recent O/E visit activities were collected over the prior twenty six weeks. O/E visits were taken from Encounters Case A and Case B datasets. The predictions of admits for the future twenty six weeks were based on the previous twenty six weeks. This timeframe was chosen because the peaks of
the Weibull distributions were contained within a twenty six week horizon, therefore capturing the majority of patients. The forecasting algorithm for the HFHS referrals uses the two parameter Weibull PDF (probability density function) for each rule.

The ‘raw’ forecast is obtained by considering the O/E activity for each of the preceding twenty six weeks and calculating the expected admits to result in each of the future twenty six weeks. The time between the previous week being considered and the forecasted future week is the primary variable needed to obtain the appropriate value from the Weibull distribution to get the probability that the admit will occur during the forecasted week. Thus, for each rule, the O/E visits for a previous week at a site for a doctor specialty code (the rule Left Hand Side, LHS) are multiplied by the conditional probability of the rule with that LHS to obtain the estimated admits for the Right Hand Side (RHS) doctor specialty code. The expected admits are then allocated to each future week based on the appropriate Weibull distribution for that rule and the time difference between the historical week’s activity and the forecasted week.

After a raw forecast is generated, the forecast series has to be scaled to by a factor, which is a linear function of time, to accommodate those O/E visits that do not yield an admit. The “scaling factor” is calculated per doctor specialty code in the following way: generate a forecast for a previous time period with known actual number of admits, then divide that forecasted value by the actual value, and use regression coefficients to create a scaling factor as a function of the week forecasted.

The above procedure provides a forecast of total HFHS referral admits per week by specialty. Actual admit date includes factors such as day-of-week, holiday, and season. Regression analysis indicates that on the average, the number of admits on Strict Holidays (New Year’s, Memorial Day, Independence Day, Labor Day, Thanksgiving, and Christmas) is somewhat lower than on regular days. The regression parameters are obtained for the forecasted period and normalized. They are then used to shift the specific week volumes for the expected admits.

Regression forecasts
Stepwise regression was applied to the following datasets:
- Residuals from rule-based forecasting (A Residuals)
- Admits from outside the HFHS (Case C)
- Admits with no specialty assigned
- Total forecast of admits for 6-months to one year in future

The application of stepwise regression allowed only the variables with specified significance to enter and stay in the model. The entry parameter significance was 25% and 15% significance was needed to keep the variable. The values obtained from regression were used as parameters for the prediction. The regression was based on weekly total admits for each of the above datasets.

Time variables were included to allow for changes in trends over time. These variables were created by first numbering the weeks in the model (history data) and the forecast. The number of weeks divided by two was subtracted from the weekly number. This formed the variable ‘T’. ‘T2’ was the square of ‘T’, and ‘T3’ was the cube of ‘T’. The ‘T’ variable permitted a linear trend in the forecast; ‘T2’ enabled a parabolic function; and ‘T3’ allowed the forecast to obtain an inflection point.

Binary variables were included in the stepwise regression to offer further adjustments in the prediction. These variables were: Strict Holiday, Lax Holiday, Season, and Season2. The Strict Holiday variable included the holidays: New Year’s, Memorial Day, Independence Day, Labor Day, Thanksgiving, and Christmas. The Lax Holiday marked the Easter holiday. The Season factor indicated the grade school calendar; Season2 designated the timeframe when snow was likely to be on the ground (December through February).

Since the prediction was calculated as number of admits per week, it was necessary to extrapolate to the specialties to obtain the required detail. Admits without a specialty (= blank) were modified in that the discharge doctor specialty code was then assigned to the specialty. The distribution of these codes was very similar to overall distribution. The distribution of specialties was also calculated for case C; and the case A residuals have a unique specialty distribution. After the regression forecasts were made for each group, the corresponding distribution was used to generate the weekly forecast by specialty.

Timelines of forecast techniques
An initial dataset starting with events from Jan 1, 2000 through March, 2004 was used. In October, 2004, another set of data (covering April 2004 through August 2004) was used for quality testing as well as for generating the 2005 (Oct. 2004-Sept. 2005) forecast. Research indicated that this method would offer the best results.3

In order to assess our techniques and generate a ‘scaling factor’ for the forecasting by rules, it was decided to first cut off the ‘calibration’ data at November 2003 and forecast to March 2004.

At the beginning of the data, an anomaly was anticipated in that admits very early in the data would show no (or inadequate) prior encounters in the outpatient or urgent care facilities, since they would have
occurred in 1999 or earlier. For this reason, the rules dataset was started with admits from 2001 and later; likewise for selecting the patients treated as non-HFHS referrals, we started with Jan 2001.

By comparing with the actual admits from Nov 2003 through Mar 2004, the rules’ scaling factors were calculated.

The rules and distribution functions were recalculated, and forecasts were generated for Mar 2004 through Aug 2004. The scaling factors were also recalculated using the more recent data – and these scaling factors were also used for generating the 2005 forecasts.

The base data was shifted up one year for the 2005 forecasting activity. Thus, regression started at 2002 and O/E activity for rules generation started at 2002.

By comparing the distributions and rules from those two periods, it was found that rules and distributions remained quite constant.

**Day of Week distribution**

It was observed that the percentage of weekly admits for each day of the week is very constant across weeks, unless there is a holiday in the week. A set of daily factors was kept for each quarter of the year and then applied to non-holiday-containing weekly forecasts.

For weeks that contain a holiday, a column was added to the table to store the percentage of the holiday-week admits that occurred on the holiday itself. Thus, there is a different ‘holiday factor’ for each quarter. Then, the weekly forecasts for a holiday week were expanded to daily forecasts by a set of factors dynamically calculated.

The holiday day factor was set to the statistical percentage for a holiday in that quarter. The factors for the other days of the week were copied from the row for that quarter. This holiday row was then re-normalized to 100%.

**Length of Stay**

The length-of-stay (LOS) distributions by SPECIALTY were building blocks (or compartments) of the model. “Compartmental models describe the flow of something, such as patients, through a system, where the system is comprised of a finite number of homogeneous subsystems known as compartments.”

The patient’s LOS had to be incorporated into the model to convert from admits to hospital census. An average length of stay (ALOS) was unsuitable for this prediction because the distribution of a length of stay is skewed. The peak of the distribution is usually around 4 to 5 days but can extend past a year. Secondly, the complexity of the integration of patient types is not captured by an average. Specifically, the length of stay distributions changes depending on specialty.

The distribution table used the length of stay (days), SPECIALTY, and total number of patients with that code as the basis for bed requirements. The bed requirement was calculated by subtracting the percentage of the patients who would have been discharged after that LOS (% patients) from the percentage of beds occupied at the start of that day (% beds). This number was the percentage of beds that would be occupied by those patients on the following day. Every specialty’s LOS table was calculated in this way. This table was applied to the predicted number of patients with specified specialty and the resulting number of required beds was used for the total model.

**Assignment of Admits to a Nurse Station**

To assign a predicted new admit by specialty to various Nurse Stations, a table was constructed based on how previous patients were admitted (within that specialty). The PEMS dataset contained information for each patient on the number of hours spent in the various nurse stations, including Intensive Care and Recovery Units. Matching PEMS with Medical Records was done in order to obtain more detailed information for each patient specialty. The final mapping table is a normalized list based on the number of hours spent in different Nurse Stations by all patients admitted with the specific specialty.

**Quality assessment**

The best test of forecast accuracy is to compare the results of a forecasted period with the results actually obtained after the forecast was completed. In February, 2005, the actual admits were compared with the forecasted admits for Sept, Oct, Nov, and Dec 2004 and the forecast was found to be 1.1% too high. Traditional aggregated budgeting methods used by HFH were typically within 3%. The model proved to be significantly more accurate than previously used forecasting methods.

Forecasting at the nurse unit level by day of the week proved to be less accurate, with an error reaching 25% in some cases. Such forecasting is not currently produced at this level of detail, thus no comparison with other methods was available. Forecasting at this level became more difficult as many specialties changed locations within the hospital during the prior five years. This should be resolved in future iterations by retroactively mapping units to their current configurations.

**Model Applications**

In addition to providing an accurate forecast for budgeting purposes, the forecasting tool can be used in
the future for multiple purposes. One key use is to use the tool for scenario testing and “what-if” analysis. In this application, capacity and patient volume can be changed at a given location and the effect on hospital admissions can be seen in a simulated environment. This can aid in deciding where to best allocate capital and human resources. Another major use of the model will be to analyze the flow of patients across the continuum. Because of the way the data was consolidated for this project, the value of the primary care network as well as the emergency department will be better understood as their role in hospital admissions months beyond the initial patient visit will become more apparent.

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Biographical Sketch

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Mike Meitzner has worked in the Management Services department at Henry Ford Health System for the last four years. He has worked on a number of projects for the health system including emergency department simulation modeling, capacity planning, physical space planning, and volume forecasting.

Mike has 10 years of experience in operations management and modeling in the automotive, beverage, retail, and health care industries.

Mike earned a Bachelor of Arts degree from Michigan State University where he majored in Materials and Logistics Management. Mike earned a Master of Business Administration degree from Eastern Michigan University and has received additional graduate level training in applied statistics.