

Forecasting patient outflow from wards having no real-time clinical data

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Abstract—Modelling patient flow is crucial in understanding resource demand and prioritization. To date, there has been limited work in predicting ward-level discharges. Our study investigates forecasting total next-day discharges from an open ward. In the absence of real-time clinical data, we propose to construct a feature set from patient demographics, ward data and discharge time series to derive a random forest model for forecasting daily discharge. Using data from a general ward of a large regional Australian hospital, we compared our random forest model with a classical auto-regressive integrated moving average (ARIMA) for 12,141 patient visits over 1826 days. Forecasting quality was measured using Mean Forecast Error, Mean Absolute Error, symmetric Mean Absolute Percentage Error and Root Mean Square Error. When compared to the baseline model, next day discharge forecasts using random forests achieved 17.4 % improvement in Mean Absolute Error, for all days in the year 2014.

I. INTRODUCTION

Healthcare services are becoming unsustainable [1]. This is largely due to increase in population and life expectancy, escalating costs, increased patient expectations and workforce issues [2]. Despite the increased demands, the number of inpatient beds in hospitals has come down by 2% since last decade [3]. Efficient bed management is crucial in meeting this rising demand and reducing health care costs.

Daily discharge rate can be a potential real-time indicator of operational efficiency [4]. From a ward level perspective, a good estimate of next day discharges will enable hospital staff to foresee potential problems, such as: changes in number of available beds and changes in number of required staff. Efficient forecasting reduces bed crisis and improves resource allocation. This foresight can help accelerate discharge preparation which has huge cost on clinical staff and educating patients and family, requiring post-discharge planning [5], [6].

Current methods in discharge forecasting resort to variations of auto-regressive moving average models [7], [8], [9] and estimating individual patient length of stay from clinical data [10], [11]. Forecasting discharges from general wards have received less attention than emergency and acute care discharges. The task is challenging due to the following reasons. First, ward discharges incorporate far greater hospital dynamics that are often non-linear [12]. For example, routine discharges from a regional hospital in Australia demonstrated significant variation for each day of the week (Fig. 1), and the weekly discharge pattern was highly irregular (Fig. 2). Second, such wards have little information on the patient medical

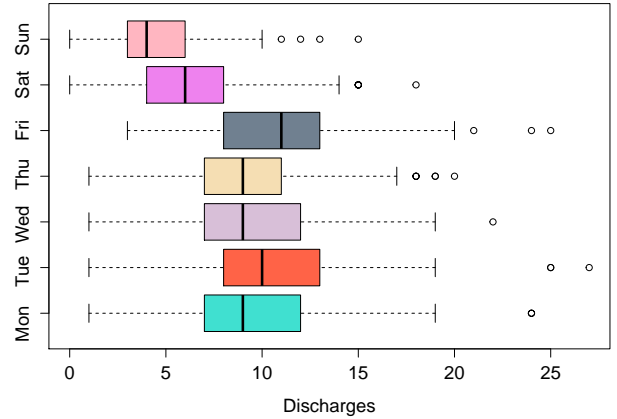


Figure 1. Distribution of daily discharges for each day of week

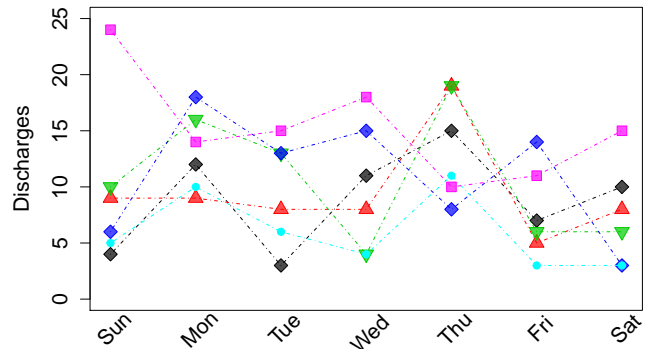


Figure 2. Daily discharges over 6 consecutive weeks. Each colour represents a week.

condition and variation in care quality. Since diagnosis coding for ward patients is done after discharge, real-time clinical information is often unavailable to make a good prediction. This problem is further aggravated by having a case-mix of patients. Patient admissions can be direct admissions from home, from emergency care, or from other wards.

In the absence of real-time clinical data, we employed feature engineering principles to build a predictor set from commonly available features stored in hospital records. We identified ward level and patient level features and time series components from daily ward discharges. The final set of features were used to train a random forest model that forecasts total number of next-day discharges from the ward. We compared our model with the classical auto-regressive integrated moving average (ARIMA) time-series modelling.

Our experiments were conducted on commonly available data from a surgical recovery ward (Heath Wing 5) in Barwon Health, a regional hospital in Victoria, Australia. Forecasting accuracy of our chosen methods was measured using mean absolute error (MAE), root mean square error (RMSE) and symmetric mean absolute percentage error (sMAPE) [13], [14]. For a held-out set of 2,511 patient visits in the year 2014, forecasts based on random forest were more accurate than the traditional ARIMA model. We demonstrate through our experiments that a random forest forecasting model that incorporates seasonality, statistics of past admissions and discharges, and ward occupancy details outperforms ARIMA forecasts by 17.4 % (as measured using MAE).

The significance of our study is in identifying the importance of foreseeing available beds in wards, which could help relieve emergency access block [15].

A. Related Work

Patient length of stay directly contributes to hospital costs and resource allocation. Reducing length-of-stay by one full day was found to decrease the average care cost by 3% or more [16]. Studies on understanding patient flow analyse metrics such as bed occupancy[2], [12], [17], [18], [19], [20], patient arrivals [21] and individual patient length of stay [11], [20], [22], [23], [24]. A host of techniques have been used for this purpose.

When looking at discharges as time series, auto regressive moving average models are the most popular [7], [8], [9]. Exponential smoothing techniques have also been used to forecast monthly [25] and daily patient flow [26]. Jones et al. [26] compared several time series forecasting methods and artificial neural networks to forecast daily patient volumes in emergency department. Mackay and Lee [2] advise modelling the patient flow in healthcare institutions for tactical and strategic forecasting. To this end, compartmental modelling [18], [27], queuing models [28], [29] and simulation models [20], [29], [30], [31] have been applied to analyse the patient flow.

A significant portion of forecast studies analyse emergency department (ED) patient flow, since ED length of stay is regarded as an important characteristic of hospital care quality [32], [33]. However, patient flow in wards are more complex. Patients are admitted from a variety of source: direct planned admissions, ED admissions, admissions from other wards or medical centres. Unlike ED, diagnosis coding for ward patients is done after discharge. Hence, clinical data is not available in real time. A recent work used random forests to predict in-patient length of stay in an acute ward from patient data containing demographic and clinical information [22]. In difference, our work focuses on a surgical recovery ward with minimum clinical information.

II. METHOD

A. Data

Our study used retrospective data collected from a surgical recovery ward in Barwon Health, a large public health provider in Victoria, Australia serving about 350,000 residents. Ethics

approval was obtained from the Hospital and Research Ethics Committee at Barwon Health (number 12/83) and Deakin University. Patient flow was collected for a period of 4 years. A total of 12,141 patients were admitted into the ward with a median discharge of 8 patients per day from January 1, 2010 to December 31, 2014. The physicians in the ward had no teaching responsibilities. Table. I summarizes the data. For each day, we analysed the number of admissions, discharges and occupancy level in the ward. Patient level details included age, gender, admission date and time, discharge date and time, previous wards visited, reference to speciality and patient class. Additional real-time data that described patient condition or disease progression were unavailable, since diagnosis coding using medical codes is done after discharge.

Table I
COHORT DETAILS

Total patient visits	12,141
Unique patients	10,610
Length of stay: mean, median	4.26, 3 days
Discharges per day: mean, median	8.7, 8
Admissions per day: mean, median	8.6, 8
Mean ward occupancy	30.9 patients/day
Gender	54.8% Female
Age: mean, median	66, 63.23

1) *Time series analysis*: A time series decomposition of our data revealed strong seasonal variations and high non-linearity in daily discharge patterns. There was a defined weekly pattern - discharges from ward peaked on Fridays and dropped significantly on weekends (Fig. 3). This seasonal nature is in tune with previous studies [9], [34]. Aggregating the daily discharges into a monthly time series revealed defined monthly patterns (Fig. 4). The data displayed no significant trend.

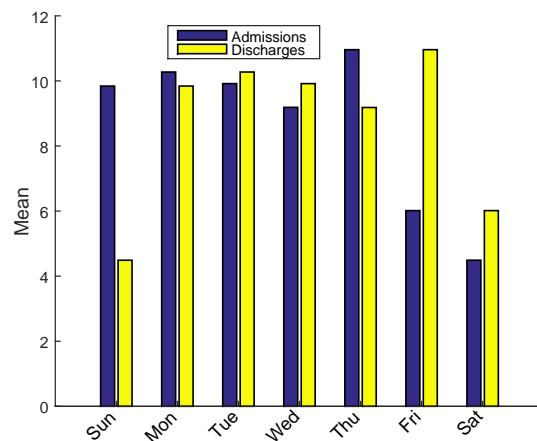


Figure 3. Mean Admissions and discharges per day from ward

We now describe two popular methods that are applicable to forecasting under complex data dynamics: *auto-regressive*

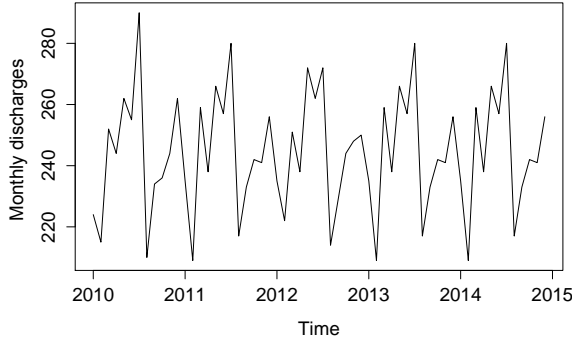


Figure 4. Time series of monthly discharge from ward

integrated moving average (ARIMA) and random forest. ARIMA is a standard forecasting method for time-series data. While ARIMA models the temporal linear correlation between nearby data nearby points in the time-series, random forest looks for a non-linear functional relationship between the future outcomes and descriptors in the past.

B. Auto-regressive integrated moving average (ARIMA)

Time-series forecasting methods analyse the pattern of past discharges and formulate a forecasting model from underlying temporal relationships [35]. Such models can then be used to extrapolate the discharge time series into the future. Auto regressive integrated moving average (ARIMA) models are widely used in time-series forecasting. Their popularity can be attributed to ease of model formulation and interpretability [36]. ARIMA models look for linear relationships in the discharge sequence to detect local trends and seasonality. But such relationships can change over time. ARIMA models are able to capture these changes and update themselves accordingly. This is done by combining Autoregressive (AR) and moving average (MA) models. Autoregressive models formulate discharge at time t : y_t , as a linear combination of previous p discharges. On the other hand, moving averages models characterize y_t as linear combination of previous q forecast errors. For ARIMA model, the discharge time series is made stationary using differencing. If ϕ denotes the autoregressive parameter, θ be moving average parameter, and ϵ be the forecast error, we can define an ARIMA model as:

$$y_t = \mu + \sum_{i=1}^p \phi_i y_{t-i} + \epsilon_t - \sum_{i=1}^q \theta_i \epsilon_{t-i} \quad (1)$$

By varying p and q , we can generate different models to fit the data. Box Jenkins method [37] provides a well-defined approach for model identification and parameter estimation. In our work, we choose the *auto.arima()* function in the forecast package [38] in R [39] to automatically select the best model.

C. Random forest

Here, we assume the next-day discharge as a function of historical descriptor (or feature) vector \mathbf{x} . We use each day in the past as a data point, where the next-day discharge is the outcome y , and the short-period prior to the discharge are

used to derive descriptors \mathbf{x} . The random forest used in this paper is currently one of the most powerful methods to model the function $y = f(\mathbf{x})$ [40]. A random forest is an ensemble of regression trees. A regression tree approximates a function $f(\mathbf{x})$ by recursively partitioning the descriptor space. At each region R_p , the function is approximated as

$$f(\mathbf{x}) = \frac{1}{|R_p|} \sum_{x_j \in R_p} y_j$$

where $|R_p|$ is the number of data point falling in region R_p . The random forest creates a diverse collection of random trees by varying the subsets of data points to train the trees and the subsets of descriptors at each step of space partitioning. The final outcome of random forest is an average of all trees in the ensemble. Since tree growing is a highly adaptive process, it can discover any non-linear function to any degree of approximation if given enough training data. However, the flexibility makes regression tree prone to overfitting, that is, the inability to generalize to unseen data. This requires controlling the growth by setting the number of descriptors per partitioning step, and the minimum size of region R_p .

The voting leads to great benefits: reduce the variations per tree. The randomness helps combat against overfitting. There is no assumption about the distribution of data, or the form of the function $f(\mathbf{x})$. There is controllable quality of fits. We now describe the process of building our descriptor set.

1) *Deriving Features for Random Forest:* We begin by extracting the following features from different tables in the hospital database: Admission id, Patient Id, Patient age and gender, Hospital admission date, Hospital discharge date, Name of admitted ward, Ward admission date, Ward discharge date, Patient class, Type of admission and Unit that the patient was referred to (Patient Referral). From this data, we derive three main types of descriptors: (i) Patient level features (ii) Ward level features (iii) Time series features. Table. II summarizes our main descriptors.

a) *Patient level features:* For each patient, we calculated the number of previous wards visited and type of last visited ward. The elapsed length of stay in the ward was calculated and updated daily for each patient. The data for age, patient class, patient referral medical unit and type of admission were divided into categories and updated for every admission and discharge.

b) *Ward level features:* For each day, we compute (i) number of admissions in the past 7 days (ii) number of discharges in the past 7 days (iii) number of discharges in the past 14th and 21st day (iv) number of patients in ward on the previous day (ward occupancy)

c) *Time series features:* A time series decomposition for the daily discharge pattern is done to obtain the seasonality component for each day of the week. Trend for next day forecast is calculated using locally weighted polynomial regression [41] from past discharges on the same weekday.

D. Validation protocol

The characteristics of the training and validation cohort are shown in Table III. Training data consisted of 1460 days from

Table II
FEATURES USED TO TRAIN THE RANDOM FOREST FORECASTING MODEL

Patient level	
Admission type	5 categories
Patient Referral	49 categories
Patient Class	21 categories
Age	8 categories
Number of wards visited	4 categories
Elapsed length of stay	Calculated daily for each patient in the ward
Ward level	
Admissions	Number of admissions during past 7 days
Discharges	Number of discharges during past 7 days, number of discharges in previous 14 th day and 21 st day
Occupancy	ward occupancy in previous day
Time-series	
Seasonality	current day-of-week, current month, seasonality statistic from time series decomposition [35]
Trend	calculated using locally weighted polynomial regression from past discharges on the same weekday

January 1, 2010 to December 31, 2013. Testing data consisted of 365 days in the year 2014. For each day, we analysed the patient flow in the ward using the features in Table. II. The majority of stays are short, around 65% of patients stayed for less than 5 days.

Table III
TRAINING AND VALIDATION COHORTS CHARACTERISTICS.

	Training (2010-2013)	Testing (2014)
Total days	1460	365
Mean discharges per day	8.47	9.17
Number of admissions	9630	2511
Gender:		
Male	4329 (44.9%)	1135(45.2%)
Female	5301 (55.1%)	1376 (54.8%)
Mean age (years)	63.65	61.62
Length of Stays:		
1-4 days	6377 (66.22%)	1636 (65.15%)
5 or more days	3253 (33.78%)	875 (34.85%)

The baseline was chosen to be the auto-regressive intensive moving average (ARIMA) model, which was derived from daily ward discharges. We compared the forecasts of our random forest model with ARIMA based on the measures of mean forecast error, mean absolute error, symmetric mean absolute percentage error and root mean square error [13], [14]. If y_t is the measured discharge at time t , and f_t is the forecast discharge at time t , we can define the following:

- Mean Forecast Error (MFE): is used to gauge model bias and is calculated as:

$$\text{MFE} = \text{mean}(y_t - f_t)$$

For an ideal model, $\text{MFE} = 0$. If $\text{MFE} > 0$ model tends to under-forecast, and if $\text{MFE} < 0$, model tends to over-forecast.

- Mean Absolute Error (MAE): is calculated as the average of unsigned errors:

$$\text{MAE} = \text{mean}|y_t - f_t|$$

MAE indicates the absolute size of the errors.

- Root mean square error (RMSE) is a measure of the deviation of forecast errors. It is calculated as:

$$\text{RMSE} = \sqrt{\text{mean}(y_t - f_t)^2}$$

Due to squaring and averaging, large errors tend to have more influence over RMSE. In contrast, individual errors are weighted equally in MAE. There has been much debate on the choice of MAE or RMSE as an indicator of model performance [42], [43]. In our work, we use both measures

- Symmetric mean absolute percentage error (sMAPE): is a form of percentage error which is scale independent and hence be used to compare models from different data. It is calculated as:

$$\text{sMAPE} = \text{mean}(200|y_t - f_t|/(y_t + f_t))$$

It overcomes the disadvantage of MAPE which penalizes positive errors more than negative errors. But sMAPE ranges from -200% to 200%, giving it an ambiguous interpretation [44].

III. RESULTS

A. Model Performance

A naive method of forecasting next day discharge is to take the mean of last week discharges. We compared a naive forecasting method, ARIMA time series model, and random forest model using metrics in Section II-D. The results are summarized in Table IV. Fig. 5 compares the distribution of actual discharges with different model forecasts.

Table IV
FORECAST ACCURACY OF DIFFERENT MODELS

Model	MFE	MAE	sMAPE	RMSE
Naive Forecast	0.02	3.57	41.68 %	4.42
ARIMA Forecast	0.06	3.27	38.32 %	4.15
Random forest	0.44	2.70	32.15 %	3.56

The naive forecast acts as a moving average, and is unable to capture the variations in the data. As expected, among all our models, the naive forecast showed the maximum error.

The variations in seasonality and trend are better captured in an ARIMA model. The time-series consisting of past 3 months discharges were used to generate the next day discharge forecast. When compared to naive forecast, this resulted in small improvements.

The random forest model was trained using a total of 329 features, where 22 features were related to ward level data and 307 features related to patient level data in the ward. The

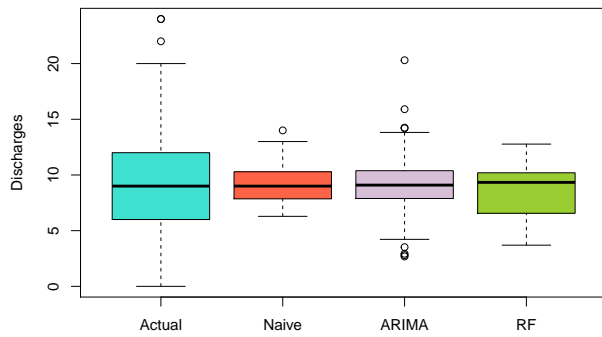


Figure 5. Comparison of actual discharges and model forecasted discharges from ward for each day in the year 2014

random forest forecast model returned the least error, with 17.4 % improvement in MAE when compared to ARIMA (Table. IV). When looking at forecast error for each day of week, RF was more accurate (Fig. 6).

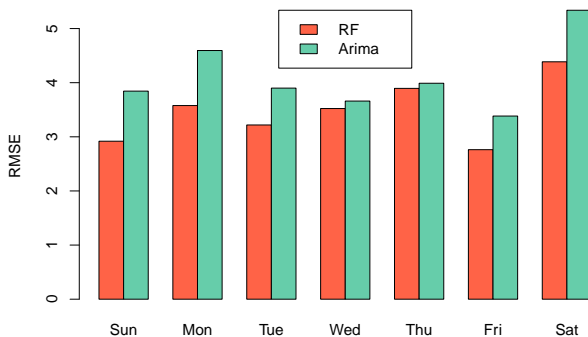


Figure 6. Forecast error in predicting each day of week in test data

B. Feature importance

Figure. 7 summarizes the most significant features, ordered by importance in the random forest model. The seasonality value from time series decomposition, day of week, and number of patients in the ward during the day of forecast were substantially important than the rest of the features. Other important features were: number of patients who had visited only one previous ward (Pre_Ward_Cnt_1), the number of males in the ward, number of discharges 14 days before (Discharges_d14), the trend of discharges measured using locally weighted polynomial regression, number of patients labeled as: “Public standard” (PatientClass_15), number of discharges 21 days before (Discharges_d21) and elapsed length of stay in hospital (HospitalLOS_1).

IV. DISCUSSION AND CONCLUSION

Improved patient flow and efficient bed management is key to counter escalating service and economic pressures in hospitals. Predicting next day discharges is crucial, but has been seldom studied for general wards. When compared to emergency and acute care wards, predicting next day discharges from a general ward is more challenging because of the non availability of real-time clinical information. The

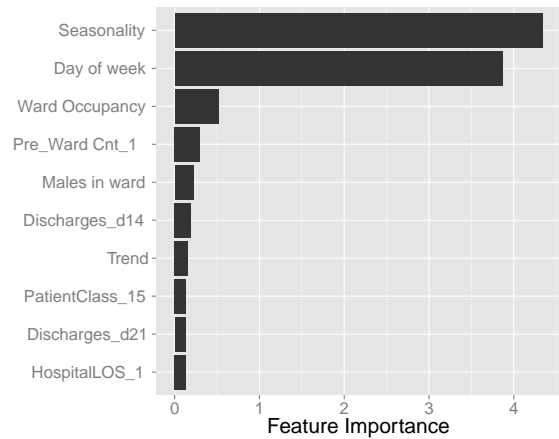


Figure 7. Top features (ranked by feature importance) from training random forest model

daily discharge pattern, though seasonal is highly irregular. This could be attributed to how hospital processes such as ward rounds, inpatient tests, and medication are managed. The nonlinear nature of these processes contribute to unpredictable length of stay even in patients with similar diagnosis.

In this paper, we attempt to forecast next day discharges from a general ward using ARIMA models and random forest model. We have compared the forecasting performance using MAE, RMSE and sMAPE. Our predictors are extracted from commonly available data in the hospital database. The random forest model can be implemented by the analytics staff in hospital IT department and can be easily integrated into existing health information systems.

A. Findings

In our experiments, forecast based on random forest model outperformed ARIMA model. Forecasting error rate is 32.5% (as measured by sMAPE) which is in the same ballpark as the recent work of [22], though we had no real-time clinical information. A random forest model makes minimum assumptions about the underlying data. Hence it is the most flexible, and at the same time, comes with great overfitting control. ARIMA models can adapt to linear changes in patterns, and fails to model the nonlinear relationships in daily discharge time series. As expected, a naive forecast of using the median of past discharges performed worst.

We noticed a weekly pattern (Fig. 3) and monthly pattern (Fig. 4) in discharges from the ward. Other studies have also confirmed that discharges peak on Friday and drop during weekends [34], [4], [45]. This “weekend effect” could be attributed to shortages in staffing, or reduced availability of services like sophisticated tests and procedures [46], [45]. This suggests discharges are heavily influenced by administrative reasons and staffing.

The seasonality values from discharge time series proved to be one of the most important features in the random forest model. Other important features included trend based on non linear regression of past weekdays, day of week of

discharge, ward occupancy in previous day, elapsed length of stay, distribution of number of wards visited.

When looking at forecasts for each day of the week, Friday had the least error in prediction for both models (Fig. 6), while Saturday proved to be the most difficult. Retraining the random forest model by omitting “day of the week” increased the forecast error by 1.39% (as measured by sMAPE).

B. Study limitations

We acknowledge the following limitations in our study. First, we focused only on a single ward. However, it was a ward with different patient types, and hence the results could be an indication for all general wards. Second, we did not use patient clinical data to model discharges. This was because clinical diagnosis data was available only for 42.81% of patients who came from emergency. In a general ward, clinical coding is not done in real-time. However, we believe that incorporating clinical information to model patient length of stay could improve forecasting performance. Third, we did not compare our forecasts with clinicians/managing nurses. Finally, our study is retrospective. However, we have selected prediction period separated from development period. This has eliminated possible leakage and optimism.

C. Conclusion

This study set out to model patient outflow from an open ward with no real-time clinical information. We have demonstrated that non-linear analysis of daily discharges outperforms the traditional auto-regressive method in forecasting next day discharge. Our proposed models are built from commonly available data and hence could be easily extended to other wards. By supplementing patient level clinical information when available, we believe that the forecasting accuracy of our models can be further improved.

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