

A Comparison of Multivariate SARIMA and SVM Models for Emergency Department Admission Prediction

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Abstract: A comparison of multivariate SARIMA model with a multivariate regression-based time series based on a Support Vector Machine model was performed for emergency department admissions prediction. The same input variables were used in both models. Both models were trained with consecutive daily samples of data corresponding to the January 2009 – August 2012 period (n=1339). Performance was evaluated on the September 2012 test dataset (n=30). The results obtained with the Support Vector Machine were found to be more accurate with a 46,53% RMSE improvement and a 48,89% MAE improvement on the train set. The experiment was repeated six times with varying time periods. The SVM approach produced better results in all cases. Error measurements on the test set were compared with a paired T test. The differences between all comparisons were found to be statistically significant in all cases with a 95% CI.

1 INTRODUCTION

Specialized emergency care volume is, by its very nature, hard to predict and requires a large amount of healthcare resources in all developed countries. A flexible and easily adaptable model for emergency department (ED) admission prediction would be of great use for healthcare managers.

Emergency care admission prediction has been a problem extensively studied by several approaches, although the predominant trend has consisted in the usage of autoregressive time series, such as SARIMA (seasonal ARIMA). These models are based on the constant variance assumption, which does not hold in emergency ward arrivals and admissions for long periods of time (Monte et al., 2002). Therefore, although short term predictions for total arrivals seem to be possible, long term predictions have unacceptably high errors. ARIMA models are also limited by linearity assumptions. A systematic review of regression-based, exponential smoothing and ARIMA time series models for ED prediction (Wargon et al., 2009) suggests a simple regression model called the “calendar method” (Batal et al., 2001) is preferable since it is one of the simplest and has been found to have similar

accuracy to more complex models. Also, ARIMA time series models have been found to be unreliable when hospital managers need them most – in times of high demand “bursts” (Jones et al., 2002). However, some recent multivariate models have been used to successfully predict short-term ED crowding and short-term ED census (Schweigler et al., 2009).

In order to improve predictive capabilities, research has been performed on environmental factors affecting emergency medical services demand of cardiovascular (Metzger et al., 2004) and respiratory pathologies (Stieb et al., 2009) as well as the effect of heat waves (Schaffer et al., 2011). However, including these variables in predictive models is problematic since weather forecasts have limited validity and often lack the exact variables used in these models. Also, environmental factors have not been found to be significant in models which try to predict overall admissions (Wargon et al., 2009); (Jones et al., 2002); (Sun et al., 2009). Machine learning techniques have been used to predict bed demand, which is a similar but harder to model phenomenon. A hybrid ARIMA and neural approach had promising results (Joy and Jones, 2005), although relatively little research has been

performed in this direction.

Our approach was to compare multivariate ARIMA and SVM-based time series prediction models.

2 MATERIALS AND METHODS

Our final goal was to build a model which allowed admission prediction, which would serve as a decision support system for hospital management.

Although an SVM-based approach was preferable, its performance had to be compared to the performance of ARIMA models, which had been widely used for ED admission prediction.

The SPSS Time Series Expert Modeler had been used in previous research with reasonable accuracy for a similar problem (Sun et al., 2009), hence we decided to replicate the approach. Weka software was chosen for the SVM time series modeling approach due to its ubiquity and flexibility. The same independent variables were used in both models.

2.1 Study Setting

2.1.1 Data Selection and Analysis

The Ramon y Cajal University hospital is a 1100-bed tertiary care referral center with all medical specialties excepting obstetrics. Its emergency department (ED) provides urgent care 24 hours a day in three shifts.

Notably, less than 13% percent of ED admissions were hospitalized in the January 2009 – September 2011 period. This is a relatively common pattern in Spanish hospitals (Palanca-Sánchez et al., 2010) and is a proxy for an inadequacy in ED usage, i.e. most patients could have received care in primary or secondary care. However, from a predictive point of view, a high affluence of low severity admissions is likely to be more seasonal and exhibit better memory, and hence might be easier to predict based on seasonality factors.

ED admissions data was obtained from the Central Hospital Information System, which, in the case of the Ramon y Cajal University Hospital, is the HP-HIS software. This HIS is a database-centric application based on the Solaris 8 operating system with an Informix database backend developed with the MULTIBASE tool. Although based on old technologies by current standards, this software is still widely used in many Spanish hospitals.

A total of 1369 daily samples were obtained. The

total number of admissions was obtained for each day. Independent variables were computed for each sample. 1339 samples were used for the train set in the January 2009 – August 2012 time period. The remaining 30 samples (September 2012) were used as the test set.

Descriptive statistics were obtained with SPSS version 15.

2.1.2 Dependent Variable Analysis

ED admissions follow an almost normal distribution (figure 1). The Shapiro-Wilk test yielded a significant result.

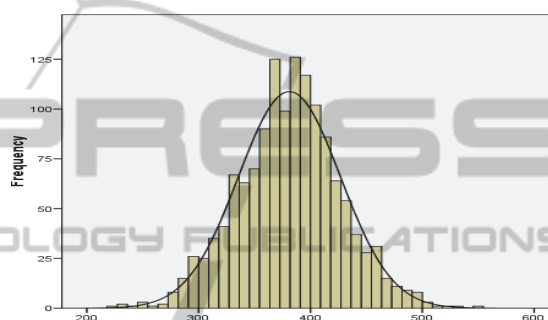


Figure 1: ED admissions distribution.

However, the admission time series exhibits seasonal trends and periods of high volatility (figure 2).

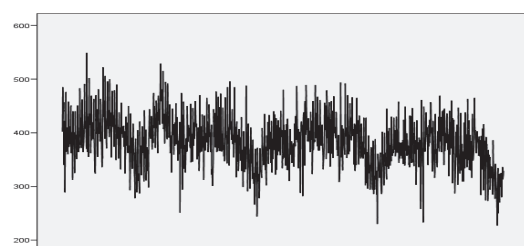


Figure 2: ED admissions time series.

However, admissions cluster in periods of high and low volatility and variance is not constant across the time series.

2.1.3 Independent Variable Selection

Environmental data was found to be of little use in previous research, however vacation days were found to be statistically significant (Jones et al., 2002); (Sun et al., 2009); (McCarthy et al., 2008); (Abraham et al., 2009), hence they were included in the model.

2.2 Model Adjustment

2.2.1 SARIMA Model Adjustment

Week number (52 weeks a year) and week day (7 days a week) seasonality levels were defined in SPSS. Automatic outlier detection was enabled and holiday days were introduced as an independent variable. An ARIMA (2,5,1) (1,0,1) model was fit to the data. The examination of residuals (figure 3) shows that the model fit is adequate.

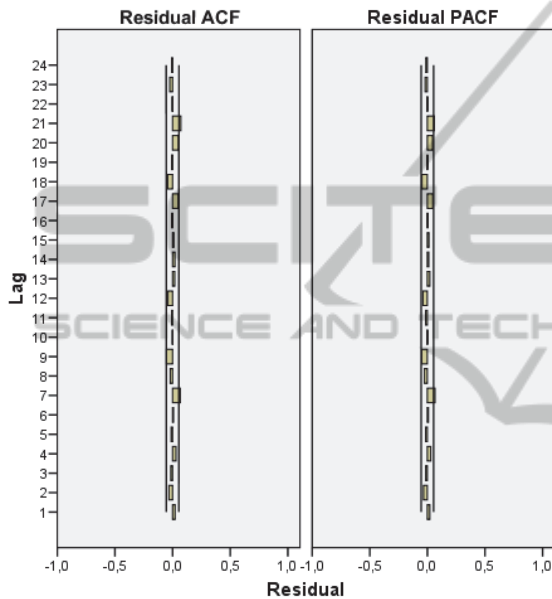


Figure 3: SARIMA PACF and ACF residuals.

Stationary R-squared on test data was 0.697.

Error statistics for the test set were computed using an Excel 2002 spreadsheet since SPSS does not allow for an automatic split between train and test sets.

2.2.2 SVM Model Adjustment

Weka uses a regression-based time series approach. This approach is considered more flexible by some authors (Darlington, 1990). Regression-based time series models easily allow the inclusion of cyclical factors and with the usage of SVMs non-linear trends can be better modelled (Mukherjee et al., 1997).

Year, week number, month, day of week variables were added to the model in order to add seasonality information.

Holiday and weekend independent variables were added to the model similarly to the SPSS

model.

The number of lag terms to be included in the regression was set at 60 as higher values were found to produce overfitting and hence worse results on the test set.

A radial basis function (RBF) kernel (Smola and Schölkopf, 2004) was selected for the SVM (Shevade et al., 2000). The software was configured to produce predictions with a 95% confidence interval.

Error statistics were computed for the test set (Table 1). A visual inspection of the series fit confirmed the adequacy of the approximation (Figure 4).

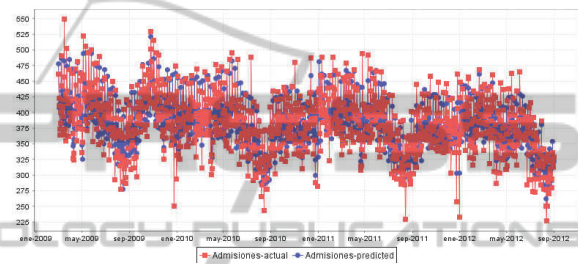


Figure 4: SVM model test set fit.

2.2.3 SARIMA and SVM Accuracy Comparison

The SVM model was deemed to be more accurate than the SARIMA model. These differences were higher on the test set.

Table 1: Train set model comparison.

	SARIMA	SVM	Δ%
MAE	20.405	16.253	20.35%
RMSE	26.242	23.312	11.17%
MAPE	5.440	4.540	16.54%

Table 2: Test set model comparison.

	SARIMA	SVM	Δ%
MAE	31.800	16.253	48.89%
RMSE	38.453	20.560	46.53%
MAPE	9.805	4.749	51.57%

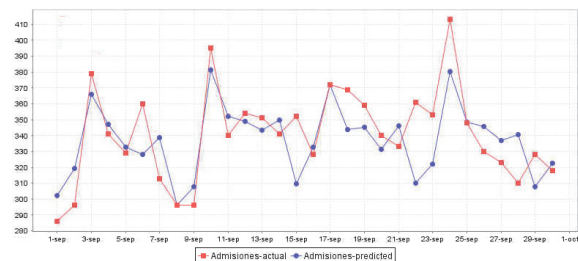


Figure 5: SVM model test set prediction.

To assess the differences between both approaches with varying time windows, the experiment was replicated 6 times calculating error indicators in all cases. With each new repetition, the latest month was removed and a new split between train and test sets was introduced using the latest remaining month as test set. In all cases, models were re-calculated with identical independent variables and input parameters for both SPSS and Weka. MAE, RMSE and MAPE were calculated in all cases for the test set for both approaches. The SVM approach produced better results in all cases.

Table 3: Model comparison.

	Mean	St.Dev.	St.Err.	p
Δ MAE	9.829	8.389	3.425	0.0349
Δ RMSE	10.759	9.055	3.697	0.0339
Δ MAPE	2.882	2.667	1.089	0.0456

A paired T-test was performed in order to compare the differences between the ARIMA and SVM approaches. The differences between all comparisons were found to be statistically significant in all cases with a 95% CI.

3 RESULTS

An evaluation of SARIMA and regression-based SVM prediction models for ED arrivals has been performed.

The SARIMA approach produced low error fits on the train set, however the errors on the test set were higher than with the SVM approach. In order to generalize this approach, testing on different hospital datasets is necessary; however our empirical evidence shows promising results.

Further development will lead to the construction of an automated ED admission prediction system based on the SVM approach. Due to the violation of stationarity conditions, ARIMA ED admission predictive models have to be regularly re-generated in order to be useful (Sun et al., 2009). This can be due to the frequent variability of factors which influence ED arrivals. Changing emergency care patterns, notably a higher percentage of medium and high clinical severity cases are likely to lower the time series accuracy. This variability would also affect the SVM model non short-term predictions. Hence, this system will automatically re-calculate the SVM model frequently and produce daily forecasts, as this is easily achievable with the Weka software package.

4 CONCLUSIONS

Roca and Vilardell have shown that for certain datasets, emergency ward arrivals do not follow a Poisson distribution, are self-similar and have a fractal nature (Monte et al., 2002) over long periods of time. Constant variance assumptions do not apply and therefore the process cannot be assumed to be stationary. Furthermore, the usage of queue and Markov chain models, which are widely used in ED computer simulations, is likely to yield inadequate results when compared with actual ED patient flow.

Although a reasonable accuracy has been achieved for short-term predictions in our dataset, the practical applicability of time of both ARIMA and SVM-based time series models presented in this paper is nevertheless problematic since neither of these is likely to successfully predict “burst” or periods of high demand, where predictions are most needed (Jones et al., 2002). However, the SVM approach is still more likely to yield better results as a “burst” mode may be included with extra independent variables and non-linear modeling.

Models able to stratify admission predictions in severity levels are more useful for healthcare management. An hourly model would also allow for better crowding management and prediction. Also, the SVM approach should be compared to more sophisticated time series models which can be fit to high volatility periods such as GARCH and its variations. Further research will try to address these issues.

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