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Predicting Blood Donations in a Tertiary Care Center Using Time Series Forecasting

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Abstract. The current algorithm to support platelets stock management assumes that there are always sufficient whole blood donations (WBD) to produce the required amount of pooled platelets. Unfortunately, blood donation rate is uncertain so there is the need to backup pooled platelets productions with single-donor (apheresis) collections to compensate periods of low WBD. The aim of this work was to predict the daily number of WBD to a tertiary care center to preemptively account for a decrease of platelets production. We have collected 62,248 blood donations during 3 years, the daily count of which was used to feed (standalone and ensemble versions of) six prediction models, which were evaluated using the Mean Absolute Error (MAE). Forecast models have shown better performances with a MAE of about 8.6 donations, 34% better than using means or medians alone. Trend lines of donations are better modeled by autoregressive integrated moving average (ARIMA) using a frequency of 365 days, the trade-off being the need for at least two years of data.

Keywords. forecasting, blood donations, data mining, time series

1. Introduction

Blood is a valuable product that we cannot afford losing or not having. Blood donation inflow is very irregular, and the demand for blood products follows a stochastic pattern [1]. Maintaining an optimal stock that meets requests efficiently is challenging, a fact aggravated by the reduced shelf life of these components. Also, blood platelets are perishable, and due to their reduced shelf life, the stock level has a very narrow window. Stock shortage of a given component results in increased costs for both the institution (which needs to replenish product stocks from other institutions) and the patients (if these products cannot be replenished). Outdating, however, is frowned upon, as donors are a scarce resource (only 5% of potential donor population will actually donate blood [2]), not to mention the ethical reasons involved and an inherent waste of resources.

Several factors can influence donors' visit to the blood bank. In our country, blood donation is voluntary, non-remunerated, and based on the loyalty of donors through social awareness, selfless spirit, and recognition of the importance of their role in helping patients who require blood and blood products. Empirically we observed periods where there is a higher influx of donors, particularly during extended holidays, following a long weekend or as result of blood donation campaigns. There is also the possibility of climate having an influence on the influx of donors. The blood bank at our university hospital has recently implemented an algorithm to support platelets stock management [3], so we tried to optimize this process, since the current algorithm assumes that there are always sufficient whole blood donations to produce the required number of pooled platelets, not

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taking into account the periods of scarce donations. We can compensate for this by increasing the single-donor (apheresis) platelets collections during the periods when the influx of whole blood donors is low. Fortsch et al. have shown that there is no need for distinct models for each blood type, and a single forecast technique can be used [4]. Such works addressing donor arrival and blood supply forecasting have studied yearly forecast of supply vs. demand [5], donor arrival after scheduling [6] or hourly donor flow for resource allocation [7]. Likewise, many blood centers use weekly or monthly moving average models for their inventory planning [8]. However, time series analysis shows good performances with monthly demand forecasting for red blood cell (RBC) transfusions using autoregressive integrated moving average (ARIMA), Holt-Winters exponential smoothing and neural networks [9]. Thus, the primary objective of this work was to apply time series prediction models optimized for blood donation inflow forecast within a period of 120 days, in order to later support the apheresis donor recruitment.

2. Materials and methods

In order to allow further application of a rolling horizon planning [10], we have assessed the overall forecasting for 120 days, 30 days and 7 days, using both an increasing-size training set as well as a fixed-size training set. We used the data available at the Blood Bank and Donors Management System at our hospital, from October 1st, 2012 to September 30th, 2015. We obtained public data from a weather station located within 600m from the hospital site, available through Weather Underground [11]. Data were sampled daily, including the *date* and *total* number of valid donations. There is no redundancy and the donation data set is 100% complete, while climate data had some missing readings which were imputed by interpolation. Data were grouped by day of the week, and anomaly detection was performed using box-plot. Holidays, long weekends and days next to festive events that could bias the analysis were also labeled and tested for anomaly detection with two-tailed Grubb's test (alpha = 0.01). Instead of removed, anomalies were labeled as such, as they could be used for the prediction of specific events such as the absence of blood donations on January 1st, Easter and Christmas. If filtered, anomalies were replaced by homologous values (e.g. same weekday in the previous week). We aligned and grouped the data by year and then divided it into quarters. The distributions were evaluated by Fligner-Killeen test, for homogeneity of variances, and analyzed with ANOVA. Next, we used the TukeyHSD test to identify similarities and differences among the quarters. Both quarterly and per day of the week distributions were tested for kurtosis and skewness through the Anscombe-Glynn and D'Agostino tests, respectively. Time series were tested for stationarity with augmented Dickey Fuller test, for their dependence with Box-Ljung test, and decomposed using Seasonal-Trend based on Loess (STL). Six kinds of prediction models were evaluated: Autoregressive Neural Networks (NNETAR), STL with Exponential Smoothing (ETS), Holt-Winters (HW), Autoregressive Integrated Moving Average (ARIMA), Double-Seasonal Holt-Winters (DSHW) and Exponential smoothing state space model with Box-Cox transformation, ARMA errors, Trend and Seasonal components (TBATS). We have also evaluated ensembles with the best compositions of previous methods. Evaluation focused on Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), following a chain cross-validation approach for time series forecasting. Our chain validation method uses the first section of time series as training set and the second section of 120 days as test set. Two designs were used: ten-fold progressive chain validation and ten-fold fixed-size chain validation. On the former, the training set is composed by a small sample and each fold adds more data to the training set; on the latter, the training set has a fixed size using different samples from the data. In this study, a model that underestimate the forecast is preferred over an overestimation as we need to be prepared for low donation periods. All analysis was performed using R software with the *forecast* library [12].

3. Results

A total of 62,248 donations with a mean of 20,749 donations per year and 56.85 donations per day were collected. Donations by day of the week show a normal distribution wherein the skewness and kurtosis are not substantially large. Fig. 1 shows a box-plot for each day of the week where we can confirm the seasonal frequency of 7 days, being Sunday the most active with a median of 84 donations, and Friday the less active with a median of 46 donations. Annual distribution shows a half-year seasonality, wherein the first and third quarters are similar to each other, as are the second and fourth quarters (ANOVA p=0.023) with homogeneous variances (p=0.175), also confirmed by TukeyHSD test. Fig. 2 shows a graphic representation of the distributions where we can see two peaks of donation in March and August and a later peak at the end of the year. Time series is shown to be stationary (p=0.01) and there is dependence between the observations (p<0.001). These are primary requisites for a good forecasting since most models assume data stationarity and interdependencies are the basis for auto-regression analysis. Assuming that the data has a homogeneous variance, and the time series is stationary, no transformation was needed prior to the application of the prediction models.

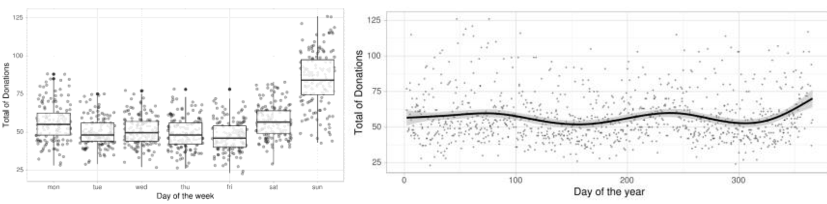
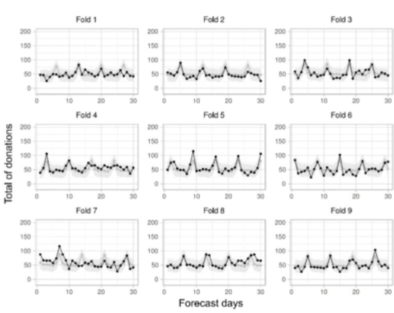
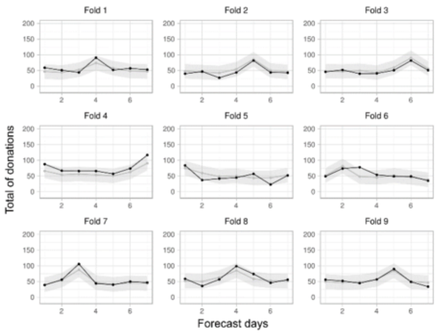


Figure 1. Donations distribution per day of the week (left) and distribution of 3 years of blood donations over 365 days, trend with 95% CI for smoothing (right).



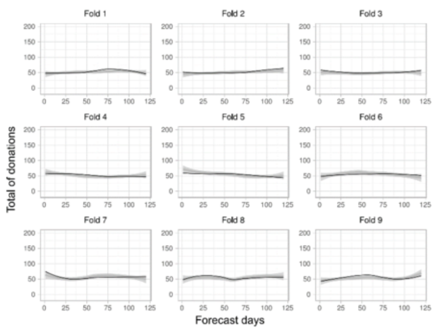
Model	Freq	ME	MAE	RMSE	H
TBATS	7	-0.10	8.98	11.54	30
HW	7	-0.11	9.72	12.40	30
ETS	182	-0.10	9.86	12.72	30
DSHW	7;182	-0.76	10.28	13.40	30
NNETAR	7	-2.55	10.56	13.54	30
ARIMA	7	-0.71	11.92	14.95	30
medians	-	-0.65	13.13	17.29	30
means	-	-4.11	14.12	17.57	30
TA	7	-0.40	9.69	12.33	30

Figure 2. TBATS forecast for 30 days horizon with frequency of 7 days. Black lines are the real data, gray lines are forecasts with 95% confidence intervals. Table presents forecast results for all tested approaches.



Model	Freq	ME	MAE	RMSE	H
HW	7	0.93	8.39	10.57	7
TBATS	7	1.26	8.51	11.14	7
ETS	7	-0.05	9.00	11.03	7
DSHW	7;182	0.44	9.27	12.71	7
ARIMA	7	0.40	9.98	13.58	7
NNETAR	7	-0.76	10.18	12.90	7
medians	-	0.81	13.38	18.68	7
means	-	-2.69	14.51	18.71	7
TA	7	0.83	8.63	11.35	7

Figure 3. Holt-Winters forecast for 7 days horizon with frequency of 7 days. Black lines are the real data, gray lines are forecasts with 95% confidence intervals. Table presents forecast results for all tested approaches.



Model	Freq	LME	LMAE	LRMSE
ARIMA	365	1.73	2.54	3.13
TBATS	7	1.51	2.65	3.52
ETS	365	2.54	2.86	3.70
HW	365	2.40	3.08	4.04
NNETAR	182	2.09	3.57	4.56
DSHW	7;182	2.55	4.20	5.11
medians	-	3.66	4.34	5.05
means	-	7.24	7.41	8.03
TA	365	2.04	3.08	4.10

Figure 4. ARIMA forecast for 120 days horizon trending with frequency of 365 days. Black lines are real data, gray lines are forecasts with 95% confidence intervals for smoothing. Table presents forecast results for all tested approaches.

Figures 2 and 3 present visual comparisons of the best forecast with the real data from progressive chain validation folds for horizons of 30 and 7 days, respectively, and the results for all tested approaches. It shows samples of TBATS and HW predictions where we can see the almost complete coverage of the real data by predictions plus confidence interval. Fig. 4 shows the visual comparison of real and forecasting trending lines for 120 days using ARIMA. TBATS and HW have a good MAE and RMSE for both 30 and 7 days horizon, clearly overcoming means and medians. Simulations were performed using frequencies of 7 days, 182 days and 365 days, when allowed by the training dataset size, in order to account for larger or multiple seasonality. ARIMA was the best model for forecasting the trend for 120 days using Loess smoothing: again, overcoming means and medians. Cross-correlations and clustering analysis for climate data did not return any correlation with donations.

4. Discussion

Forecast models have shown better performances than using means or medians alone, even when limited data is available. TBATS is a versatile model that yields the best performance across several scenarios, only being surpassed by HW when compared with 7 days forecast in progressive chain validation. TBATS also yields the best performance with limited data (70 days), only being surpassed by ETS for 7 days forecast. Some ensembles may have similar performances and may be useful since ensembles tend to minimize the probability of overfitting. Using a forecast model for 30 days, we have a MAE of about 8.98 donations, at least 31.6% better, when compared to using means or medians alone. For a long-range perspective, the trend line of donations is better modeled by ARIMA using a frequency of 365 days. We suggest using ARIMA for long-range trend analysis, TBATS for 30 days and HW for 7 days forecast using the available training data or ETS for 30 days forecast when the available data is below 120 days. The forecast models presented in this research do not intend to exactly predict the number of donations for a single day (although it might give us a hint) but to provide a trend we can follow in order to assess the number of pooled platelets we might be able to produce, providing us with a decision support to back up with apheresis collection, which is, in our department, currently scheduled using expert decision, without a supporting algorithm. This research may improve our platelet stock management enhancing the current pooled platelets production algorithm. Further work needs to be done in forecasting platelets demand to integrate both supply and demand forecasts in one apheresis schedule solution.

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