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Risk Modelling Framework for Emergency Hospital Readmission, Using Hospital Episode Statistics Inpatient Data

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***Abstract*—The objective of this study was to develop, test and benchmark a framework and a predictive risk model for hospital emergency readmission within 12 months. We performed the development using routinely collected Hospital Episode Statistics data covering inpatient hospital admissions in England. Three different timeframes were used for training, testing and benchmarking: 1999 to 2004, 2000 to 2005 and 2004 to 2009 financial years. Each timeframe includes 20% of all inpatients admitted within the trigger year.**

The comparisons were made using positive predictive value, sensitivity and specificity for different risk cut-offs, risk bands and top risk segments, together with the receiver operating characteristic curve. The constructed Bayes Point Machine using this feature selection framework produces a risk probability for each admitted patient, and it was validated for different timeframes, sub-populations and cut-off points. At risk cut-off of 50%, the positive predictive value was 69.3% to 73.7%, the specificity was 88.0% to 88.9% and sensitivity was 44.5% to 46.3% across different timeframes. Also, the area under the receiver operating characteristic curve was 73.0% to 74.3%. The developed framework and model performed considerably better than existing modelling approaches with high precision and moderate sensitivity.

***Keywords*-Hospital Episode Statistics, Emergency Hospital Readmission, Inpatient, Bayes Point Machine, Feature Selection, Framework**

I. Introduction

Costs of care are increasing at a rate that is unsustainable, due to the impact of ageing population, population growth, deprivations, rise in emergency admission, increased expectations and cost of treatment and technology [1]–[3].

Inappropriate care support for high-risk patients has been the main contributor to derived emergency readmission rise [4]. It is estimated that £11 billion per year is the cost of emergency admissions to the National Health Service (NHS) [3]. As reported by the Nuffield Trust report in 2012 [5], about 8% of patients are readmitted within 30 days, and it is costing an estimated £2.2 billion a year. Also, based on a Clarke et al. [6] study, about half of the emergency readmissions within 30 days between 2004 and 2010 were potentially preventable.

Four principal contributing risks to increase in emergency (or unplanned) readmission to hospitals [3], [4] are ageing population, premature discharge and unpredictable accidents, patients with long-term conditions and unpredictable emergency. Discharging patients presents a way of freeing beds in healthcare systems, but still premature discharge could increase emergency readmission risk. Often hospital admissions can be avoided by providing appropriate care [7].

Therefore, development and implementation of robust predictive risk models for admitted patients are critical. Predictive models can help patients and carers to get the appropriate support services in clinical decision-making. Also, they can improve care quality and reduce the cost of inappropriate admissions to hospital and accident and emergency (A&E).

In 2005, the UK Department of health commissioned to develop the Patients at Risk of Re-hospitalisation (PARR) [8] algorithm for Primary Care Trusts. The aim of PARR was to identify patients in high-risk of 1-year emergency readmission using the inpatient data from the Hospital Episode Statistics (HES) database. Then, in 2006 the Combined Predictive Model (CPM) was released using a combination of the general practices (GPs) records and the HES database [9].

Thereafter, in 2011 the patients at Risk of Readmission within 30 days (PARR-30) model was developed as an upgrade. The PARR-30 was based on a wide range of parameters used in the PARR [10].

Most of the existing predictive risk models [11] that used hospital administrative data were based on logistic regression or Coxian Phase-type Distribution models. Although, they are uncomplicated and powerful, they are bounded by algorithms shortfalls, restricted assumptions and limited parameters. In healthcare risk modelling, there have been many successful implementations of machine learning methods, but, there are a few numbers of literature that applied a Bayesian approach.

The aim of this research was to develop, validate and benchmark a framework and a risk model for 1-year emer-

gency readmission to England's hospitals using Bayes point machine (BPM) approach and inpatient data from the HES. Firstly, a large set of features was constructed, filtered and sorted. Then, the model was trained, tested and benchmarked using three different timeframes.

In this paper, firstly, the data and the process of selection of a minimal amount of features is clarified. Then, the applied BPM algorithm is defined. Finally, results of training, validation and benchmarking of the developed model against CPM [9], PARR [8] and Billings et al. (2013) [12] models are discussed.

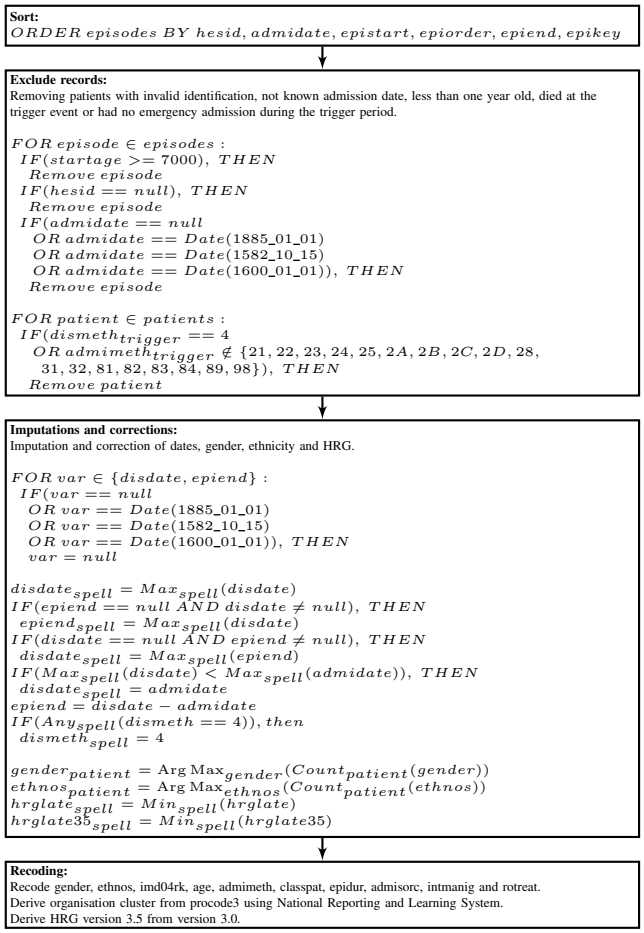

Figure 1. The summary of data preprocessing.

II. Data

Administrative databases are used in the monitoring of healthcare systems in the UK, the USA and other countries. And, healthcare data, such as inpatient, A&E, outpatient attendance and records from GPs are used in predictive modelling problems.

In this research, only inpatient data from the HES database was used. The queried snapshot of the HES database includes records from April 1995 until April 2010. The inpatient table consists of 206,528,432 episodes, that excludes 39,403 episodes with *null admidate* and 11,212,871 episodes with *null hesid*.

In terms of data quality, there are parameters, associations and timeframes that are missing from HES due to confidentiality, different practices and limitations of defined fields. For instance, inconsistency in data due to changes in policies, care services and facilities, and large missing attendance records in A&E records [13].

Similar to the PARR model, each sample covers about 20% of unique patients (10% training, 10% testing) within the trigger year of the selected timeframe (Table I). The first three years was regarded as the prior history, the fourth year was used as the trigger year and the 12-month follow-up was accounted as the prediction period. Also, *superspells* were constructed and regarded as the unit of care for each patient.

Moreover, before the modelling stage, four stages of data preprocessing have been carried out. The steps are presented in Fig. 1.

III. Features

Based on previous studies [11] and additional exploratory analyses, four main groups of features were initially generated from the inpatient database: three years cross-sectional, one year cross-sectional, 90 days cross-sectional and trigger-point features. In total 738 summary features were generated, which the main categories are presented in Table II.

Usually, Kernel classifiers, such as BPM and Support Vector Machine (SVM) are resistant to over-fitting, because of weight regularisation. However, since the number of generated features was very high, a feature reduction framework was needed. Hence, four feature filtering steps were carried out to capture the underlying structure better.

Firstly, highly stationary features were withdrawn (constant count $\geq$ 95%, since linear correlation to 1-year readmission was ¡ 50%). Thereafter, features with high linear correlation to 1-year readmission were excluded (linear correlation coefficient $\geq$ 80%). Then, in relation to the average of importance, initially the three years cross-sectional features were included, and after that other features were added. And, based on importance across samples, the features were sorted using random-forest importance score (sample sizes of 100,000, the number of trees equals to the features, and selected features at each node equals to 10) and an SVM importance ranking (sample sizes of 10,000). Finally, a forward-selection BPM procedure was developed using the micro-average precision $\geq$ 0.01%.

At the end, 100 features were selected and sorted using average random-forest scoring across samples.

IV. Model

Bayes Point Machines (BPMs) [17], [18] are parametric linear classification algorithms, which identify an average classifier (Bayes point) in a version space. BPMs, similar

Table I
SELECTED SAMPLES FROM HES INPATIENT

Samples	Timeframe	Population size	Sample size		Filtered patients		
		Patients	Episodes	Patients	Total	No prior spell	No post spell
Sample-1	1999-2004	7,206,133	6,347,067	1,441,227	1,157,873	492,458	148,950
Sample-2	2004-2009	8,104,748	11,394,152	1,615,347	1,410,923	395,522	110,961
Sample-3	2000-2005	7,370,830	6,449,169	1,474,166	1,324,712	671,919	194,097

Table II
MAIN CATEGORIES OF ALL THE INITIALLY DEFINED FEATURES.

Category	Sub-category
Administrative	Admission: patient classification; number of episodes and spells; admission, readmission and discharge times; source and methods of admission and discharge. Bed days: duration of spells; preoperative and post-operative durations. Geographical: provider code; region of treatment. ID: patient identification, and admission timeframe number. Speciality: speciality of consultant; palliative cares. Waiting time: admission waiting time.
Clinical	Diagnosis: Charlson comorbidity groups; Elixhauser comorbidity groups [14]; frequent categories of diagnoses; Charlson comorbidity index version that is developed by Dr Foster unit and adapted by the HSCIC [15]; PARR's HRGs *reference* conditions, using version 3.5 [16]. Operation: operation groups; number of operations; frequent categories of operations.
Patient	Demographic: age; deprivations; ethnicity; gender.

Table III
THE REPORTED PERFORMANCE OF THE PREVIOUS MODELS.

Statistic	PARR			CPM	Billings-13 (IP)	Billings-13 (IPAEOPGP)
Threshold	**0.50**	**0.60**	**0.70**	**0.50**	**0.50**	**0.50**
TP+FP[a]	17,455	4,810	2,011	NR[b]	8,743	10,545
TP	NR	NR	NR	NR	4,627	5,669
Sensitivity	0.543	0.178	0.081	NR	0.049	0.060
Specificity	0.722	0.950	0.986	NR	NR	NR
Precision	0.653	0.774	0.843	0.538	0.529	0.538
Emer. admi. post 12 m. per TP	1.47	2.23	3.0	NR	NR	NR
Emer. admi. prior 12 m. per TP	2.22	3.43	4.59	NR	NR	NR
Emer. admi. prior 13-24 m. per TP	0.93	1.84	2.80	NR	NR	NR
Emer. admi. prior 25-36 m. per TP	0.73	1.48	2.25	NR	NR	NR
AUC of ROC	0.69			0.780	0.73	0.78
Total number of patients	42,778			281,617	1,836,099	1,836,099

[a] True Positive (TP) and False Positive (FP).

[b] Not Reported (NR).

to SVMs, are more geometrically motivated and the soft margin SVM can be thought of an approximation to BPMs [17]. BPMs sample the Bayesian posterior for linear classification in a kernel space and approximate the centre of the version space. They minimise the generalisation error over a set of hypothesis according to a prior probability, unlike SVMs, which maximise the classification boundary margin explicitly.

In this research, Microsoft's Infer.Net library [19] was used as the core development package to construct the BPM model. The applied algorithm uses the original version of the BPM with two main modifications: a mixture of Gamma-Gamma priors for the precision of weights and features and Expectation Propagation (EP) message passing for inference of posteriors.

V. RESULTS

Profiling was done using independent test samples across different timeframes based on a number of main characteristics and indicators. The developed model was benchmarked using the reported performance of three previous models: CPM [9], PARR [8] and Billings et al. [12] models, which includes the inpatient submodel (IP) and the full model (IPAEOPGP). Also, three sub-populations were selected after running the model, in order to make the comparisons as close as possible:

- *Sub_PARR-2-Settings*: Including age 65+
- *Sub_IPAEOPGP*: Including age 18 to 95
- *Sub_Any-Acute*: Including all

The reported performance of the previous models are presented in Table III and similarly the outputs of the profiling are presented in Table IV. The selected cut-off points for the predicted probability are 50%, 60% and 70%,

Table IV
THE BENCHMARK OF THE BPM MODEL FOR DIFFERENT SUB-POPULATIONS.

Statistic	**Sub_PARR-2-Settings**			**Sub_IPAEOPGP**			**Sub_Any-Acute**		
Threshold	**0.50**	**0.60**	**0.70**	**0.50**	**0.60**	**0.70**	**0.50**	**0.60**	**0.70**
Train: train sub-sample of *Sample-1*; Test: test sub-sample of *Sample-1*									
TP	12,739	6,955	3,266	35,789	20,952	7,692	36,700	21,383	7,869
FP	9,489	4,046	1,371	15,289	6,592	2,068	15,987	6,973	2,182
TN[a]	36,418	53,113	63,217	135,163	167,917	191,793	159,908	193,839	218,378
Sensitivity	0.415	0.227	0.106	0.463	0.271	0.100	0.445	0.259	0.095
Specificity	0.760	0.898	0.965	0.880	0.948	0.984	0.893	0.953	0.985
Precision	0.573	0.632	0.704	0.701	0.761	0.788	0.697	0.754	0.783
Emer. admi. post 12 m. per TP	1.145	1.384	1.744	1.542	1.798	2.227	1.538	1.788	2.223
Emer. admi. prior 12 m. per TP	0.403	0.518	0.645	0.350	0.444	0.626	0.349	0.443	0.624
Emer. admi. prior 13-24 m. per TP	0.353	0.459	0.566	0.319	0.412	0.568	0.317	0.410	0.565
Emer. admi. prior 25-36 m. per TP	0.005	0.005	0.007	0.004	0.005	0.008	0.004	0.005	0.008
AUC of ROC	0.663			0.736			0.743		
Total number of patients	70,147			204,672			231,755		
Train: train sub-sample of *Sample-2*; Test: test sub-sample of *Sample-2*									
TP	15,544	9,033	4,397	41,347	24,114	9,228	42,381	24,628	9,419
FP	10,839	5,074	1,852	17,533	7,746	2,723	18,221	8,111	2,816
TN[a]	34,026	51,570	63,914	143,986	181,189	207,809	161,137	199,791	227,079
Sensitivity	0.459	0.267	0.130	0.474	0.277	0.106	0.463	0.269	0.103
Specificity	0.725	0.871	0.953	0.872	0.943	0.980	0.880	0.947	0.981
Precision	0.589	0.640	0.704	0.702	0.757	0.772	0.699	0.752	0.770
Emer. admi. post 12 m. per TP	1.235	1.442	1.754	1.596	1.863	2.292	1.590	1.852	2.287
Emer. admi. prior 12 m. per TP	0.420	0.521	0.635	0.367	0.467	0.632	0.366	0.466	0.632
Emer. admi. prior 13-24 m. per TP	0.360	0.450	0.563	0.329	0.423	0.571	0.328	0.422	0.570
Emer. admi. prior 25-36 m. per TP	0.007	0.009	0.011	0.005	0.007	0.010	0.005	0.007	0.010
AUC of ROC	0.664			0.721			0.730		
Total number of patients	73,315			224,001			243,712		
Train: train sub-sample of *Sample-1*; Test: test sub-sample of *Sample-3*									
TP	15,251	7,743	3,282	42,941	22,287	7,082	44,039	22,803	7,260
FP	10,482	4,114	1,324	16,662	6,497	1,826	17,424	6,913	1,965
TN[a]	51,918	72,992	84,507	188,075	230,439	256,811	221,760	265,541	292,706
Sensitivity	0.371	0.188	0.080	0.421	0.218	0.069	0.404	0.209	0.067
Specificity	0.791	0.918	0.974	0.900	0.961	0.989	0.911	0.965	0.990
Precision	0.593	0.653	0.713	0.720	0.774	0.795	0.717	0.767	0.787
Emer. admi. post 12 m. per TP	1.213	1.475	1.871	1.607	1.881	2.392	1.606	1.876	2.401
Emer. admi. prior 12 m. per TP	0.447	0.565	0.688	0.367	0.492	0.691	0.365	0.489	0.687
Emer. admi. prior 13-24 m. per TP	0.371	0.472	0.568	0.323	0.441	0.593	0.321	0.437	0.588
Emer. admi. prior 25-36 m. per TP	0.005	0.005	0.007	0.004	0.005	0.007	0.004	0.005	0.008
AUC of ROC	0.661			0.739			0.743		
Total number of patients	91,369			268,575			304,888		

[a] True Negative (TN).

Table V
THE MOST IMPORTANT VARIABLES.

Sum of number of operations (90-day, trigger).
Count of main speciality: 'Maternity' (3-year, trigger).
Count of main speciality: 'Gynaecology' (3-year, trigger).
Count of main speciality: 'General' (3-year, trigger).
Average of post-operative durations (trigger).
Count of the emergency admissions (90-day, 1-2-year).
Average of spells durations (past, trigger).
Average of gaps between admissions (3-year).
Average of Dr Foster Charlson Index (3-year).
Age (trigger).
Gender: 'Female'.
Ethnicity: 'NA'.

and it may be optimised with help of a cost function, like estimated readmission and intervention costs, to determine the trade-off between sensitivity and specificity.

Firstly, the effects of complexity levels based on the number of features were investigated using F-score versus the number of features. Adding up to 18 features (Table V) improves the performance extensively. But, the gains became smaller afterwards, about 0.005 change on average in Area Under Curve (AUC) of Receiver Operating Characteristic (ROC).

Moreover, the model converged very fast, and after 40 iterations the weights differences become very small across all samples (≤ 0.01). Also, based on the generated learning-curve and the complexity plots, the performance was consistent across all samples. In addition, the model was stable in cross-validations testing, and it exhibited very small standard deviations in accuracy (average 0.005), mean of negative log-probability (average 0.004) and AUC (average 0.001).

Overall, the model performs considerably better than the CPM [9], PARR [8] and Billings et al. [12] models using

inpatient data.

Moreover, in healthcare risk modelling research area, there have been many successful implementations of machine learning methods. But, there are a few number of literatures that used a Bayesian approach to address emergency hospital readmission problems [3], [13], [20]–[29].

Furthermore, methods like logistic regression or Coxian Phase-type Distribution models are simple and powerful, but they do not update prior probabilities, can handle small number of input variables and can not account for small probabilities in appropriate way. On the other hand, BPM addresses these issues, and probably its main issue is the complexity of the algorithm and the inference approximation.

Finally, in comparison to SVMs, the BPM approach is demonstrated [17] to provide better solution for asymmetric version space, to efficiently handle large datasets and to provide smoother decision boundary. In empirical studies [17], [30]–[32] have been shown that BPMs usually outperform SVMs.

VI. Conclusion

A framework and a predictive model were built with an optimal subset of generated features from England's HES inpatient. The model was developed using a BPM algorithm with a mixture of Gamma-Gamma priors and EP message passing for inference. The developed model estimates the risk of emergency readmission to NHS hospitals in England within 12 months of discharge. Finally, the model benchmarked against PARR, CPM and Billings et al. (2013) models with very similar settings.

The model outperforms for the sub-population of 18 to 95-year-old patients, as well as all emergency readmissions population. The specificity was 88.0% to 88.9%, the positive predictive value was 69.3% to 73.7%, and sensitivity was 44.5% to 46.3% across different timeframes. Also, the AUC of ROC was 73.0% to 74.3%. On the other hand, the reported AUC of ROC of PARR, CPM and the IP and the IPAEOPGP sub-models of Billings et al. (2013) models were 69%, 78%, 73% and 78%. Moreover, the developed model proved to be robust to changes and be stable with high precision across different timeframes.

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