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To cite this version:

Catherine Combes, Farid Kadri, Sondès Chaabane. PREDICTING HOSPITAL LENGTH OF STAY USING REGRESSION MODELS: APPLICATION TO EMERGENCY DEPARTMENT. 10ème Conférence Francophone de Modélisation, Optimisation et Simulation- MOSIM'14, Nov 2014, Nancy, France. hal-01081557

HAL Id: hal-01081557

https://hal.science/hal-01081557v1

Submitted on 9 Nov 2014

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PREDICTING HOSPITAL LENGTH OF STAY USING REGRESSION MODELS: APPLICATION TO EMERGENCY DEPARTMENT

Catherine COMBES[1]

[1]*PRES Lyon, Hubert Curien Laboratory - University Jean-Monnet, Saint-Etienne, France*
catherine.combes@univ-st-etienne.fr

Farid KADRI[2,3], **Sondès CHAABANE**[2,3]

[2]Univ. Lille Nord de France, F-59000 Lille, France
[3]TEMPO Lab., PSI Team, F-59313 Valenciennes, France
Farid.kadri@univ-valenciennes.fr
sondes.chaabane@univ-valenciennes.fr

ABSTRACT: *Increasing healthcare costs motivate the search for ways to increase care efficiency. In this paper, we present a novel methodological framework based on predictive data mining approach to estimate the LOS (Length Of Stay) in an emergency department (ED). We use supervised learning that the goal is to build concise models in terms of predictor features. The aim is to identify the factors (variables) characterizing the LOS in EDs in order to propose models to predict the LOS. We identified two models based on linear regression. These models are validated and were successfully applied to the classification and prediction of the LOS in the pediatric emergency department (PED) at Lille regional hospital centre, France.*

KEYWORDS: *Emergency department, healthcare modelling, regressions, LOS forecast*

1 INTRODUCTION

Nowadays, with the growing demand for emergency medical care (Kadri et al., $2014_{a,b}$), emergency departments (EDs) need information to manage this patient influx and make decisions (Kadri et al., 2014_c). The objective is to propose a Decision Support System (DSS) based on a data mining approaches, in order to support operational and tactical decisions. For planning and logistic purposes, it is of interest to see prediction estimates, to forecast the class of new clients; to have time-based forecasts and to find the variables that explain the ED behavior. For management, it is relevant to find patterns among care consumption, available from the care services. Organizations must systematically acquire the information needed to make decisions and to evaluate the effects and consequences of these decisions. To fully explore the opportunities for our approach, we propose a modelling environment based on data warehousing and data mining approaches (Figure 1). This allows one to manage the resources, to elaborate medico-social resource planning and to eventually simulate them in order to evaluate their performances.

The main aim of the proposed DSS is to improve the decisional performances by discovering some links between data and checking hypotheses (observations).

The objective is to prove the contribution of data mining approach for health care management. The application concerns the prediction of the length of stay (LOS) for patients admitted to hospital emergency department.

Data are been collected from the database of Pediatric Emergency Department in Lille regional hospital centre, France, The dataset includes 12,498 patients on a period of 6 months.

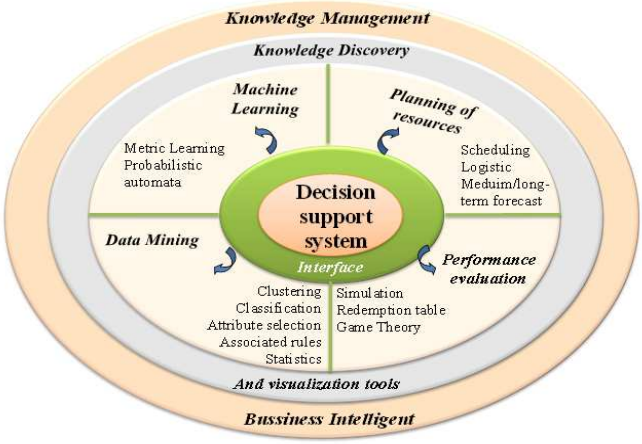


Figure 1: Modelling environment.

During the last decades, several applications for Machine Learning (ML) are used and the most significant of which is predictive data mining and concerns classification problems. Classification is one of the most common learning models in data mining. The aim is to identify a model in order to predict future behaviors through classifying database records into a number of predefined classes/groups based on certain criteria. The resulting classifier is then used to assign class labels to the testing instances where the values of the predictor features are known, but the value of the class label is unknown. The most common tools used for classification are linear regression, neural networks, decision trees, if-then-else rules, Bayesian networks, Naive Bayes classifiers, neural networks, Super vectors machines and regression (tree regression, logistic regression, support vector regression…).

Using regression includes curve fitting, prediction (forecasting), modeling of causal relationships, and testing

scientific hypotheses about relationships between variables.

Regression analysis is a method for investigating functional relationships among variables that is expressed in the form of an equation or a model connecting the response or dependent variable and one or more explanatory or predictor variables.

The structure of the rest of this paper is as follows. Section 2 gives an overview of the contribution of data mining and presents related works. The methodological approach is described in section 3. We test the different algorithms based on regressions from data and identify the relevant variables. The proposed models and the experiments with a real case study from French Emergency Department are described. Conclusions and an outlook are finally presented in Section 4.

2 RELATED WORK

Data mining allows finding models and patterns from the available data. Data mining is a discipline at the interface of statistics and information technologies: databases, artificial intelligence, machine learning. Data mining includes descriptive data mining algorithms for finding interesting patterns in the data, like associations, clusters and subgroups, but also predictive data mining algorithms, which result in models that can be used for prediction and classification.

The aim of data mining is to automatically find useful information in large quantities of data. Data mining can be both predictive and descriptive: in the first case, the objective is to predict the value of a particular attribute given existing data, in the latter case the objective is to derive patterns that summarize the underlying relationships in the data. Data mining hence is an integral part of knowledge discovery, which is the overall process of converting raw data into knowledge through obtaining useful information from the data.

In (Tan, 2007), four core data mining tasks are identified:

1. *Predictive modelling*. The task is to build a predictive model for a target variable, based of explanatory variables. Classification and regression are methods to predict a discrete outcome (eg. whether or not somebody will do something) cq. an extrapolation of continuous output (eg. what the future value of a measurement will be).
2. *Attribute selection*. Most machine learning algorithms allows us to learn which are the most appropriate attributes (predictor variables) to use for making their decisions. Most methods for attribute selection involve the space of attributes for the subset that is most likely to predict the class best.
3. *Association analysis*. The goal is to discover patterns that describe strongly associated features in the data. Typically, one tries to find implication rules. An example application is the understanding relationships between different goods bought simultaneously in a supermarket, e.g. the pattern that people buying milk also buy bread, or people buying beer also buy snacks.
4. *Cluster analysis*. The goal is to group similar observations such that observations within one group are more similar to each other, and observations of different groups are less similar to each other. For example, this way it is possible to find groups of customers with related behavior.
5. *Anomaly detection*. The task is to detect outliers, i.e. whose characteristics are significantly different from the rest of the data. A good anomaly detector should have a low error rate and a high detection rate. An example application domain is the detection of spam email.

Since last decade, many works deals with the contribution of implementing information systems in health care organizations (Berg, 2001; Duan et al., 2011) in order to analyze healthcare quality indicator (Chae et al., 2003; Kadri et al., 2013).

Theoretical models are based on statistical pattern recognition well-described in (Jain et al., 2000; Kotsiantis, 2007; Kotsiantis et al., 2006) present interesting reviews of classification methods and combining techniques.

Recently, (Esfandiari et al., 2014) present a state of art concerning 291 papers published between 1999 and 2013 from wide variety of journals such as data mining and medicine. The authors clarify medical data mining and its main goals. Five data mining approaches are considered: classification, regression, clustering, association and hybrid. We observe regarding this article that there is wide variety of applications that covered most of the medicine field but the authors focused only on a structural data.

Our paper focuses on predictive modelling. The objective is to predict the LOS in the emergency department. But what are the “best” methods?

Decision Trees are considered to be one of the most popular approaches and easily understood tools for representing classifiers. They can handle both nominal and numeric input attributes. Most of the algorithms (like ID3 and C4.5) require that the target attribute will have only discrete values and are less appropriate for estimation tasks where the goal is to predict the value of a continuous attribute.

Regression tree also works in a very similar fashion than classification tree. But regression trees are needed when the response variable is numeric or continuous (case of surgery duration or LOS in the emergency department). Thus regression trees are applicable for prediction type of problems as opposed to some classification tree. It might be interesting is to compare different methods (regression trees, SVM regression, logistic regression) regarding other approaches (such that decision tree, multi-layer perceptron, Bayesian networks, neural networks…) and to study the limits of each of them regarding the data raw. In fact, the approach concerns the class of nonlinear predictive model which at first seems too simple to possible work, namely prediction trees. Predictors like linear or polynomial regression are global mod-

els, where a single predictive formula is supposed to hold over the entire data space. When the data has lots of features which interact in complicated, nonlinear ways, assembling a single global model can be very difficult and hopelessly confusing when you do succeed.

In (Austin et al., 2010), the authors compare the performances of classification techniques in order to predict the presence of coronary artery disease (CAD). The authors compared performances of logistic regression (LR), classification and regression tree (CART), multilayer perceptron (MLP), radial basis function (RBF), and self-organizing feature maps (SOFM). Performances of classification techniques were compared using ROC curve, Hierarchical Cluster Analysis (HCA), and Multidimensional Scaling (MDS). The results of the classification of the top of 5 (best to worst) are:

1. MLP,
2. LR,
3. CART,
4. RBF,
5. SOFM.

Many applications show that the logistic regression gives excellent results.

(Mazzocco and Hussain, 2012) proposed prediction models based on logistic regression algorithm (Landwehr et al., 2003) to predict the diagnosis of dementia using variables selected either by domain experts or by a statistical driven procedure. The aim of this study is to improve on the performance of a recent application of Bayesian belief networks using an alternative approach based on logistic regression.

In (Kurt et al., 2008), the authors compared the predictive accuracy of regression trees with that of logistic regression models for predicting in-hospital mortality in patients hospitalized with heart failure. The main conclusion is that Logistic regression predicted in-hospital mortality in patients hospitalized with heart failure more accurately than did the regression trees. Regression trees grown in random samples from the same data set can differ substantially from one another. The authors underline logistic regression can take into account for the underlying linear relationships between key continuous covariates and the log-odds of in-hospital mortality.

The state of the art shows that logistic regression is a good model. In fact, logistic regression models produce probabilities rather than predictions. For each class value, this technique estimates the probability that a given instance belongs to that class. It can be interesting but the main problem is the target variable should be discrete.
But in our case, the target variable is continued. Consequently if we want to use logistic regression for example, we should discretize the target variable. But our objective is to predict length-of-stay in the ED and not an interval of LOS.
Regression analysis methods allows investigating functional relationships among variables that is expressed in the form of an equation or a model connecting the response or dependent variable and one or more explanatory or predictor variables. But the problems caused by noisy data or outliers have been known in linear regression for years. In the case of linear regression, outliers can be identified visually but it is never completely clear whether an outlier is an error or a correct value (for example in our study, the patient absconded of the Emergency department, and we do not have this information in our data).
Although outliers dramatically affect the usual least-squares regression because the squared distance measures accentuates the influence of points far away the regression line, we decide to explore ordinary least squares (OLS) regression in order to obtain a very simple model. In fact, one way of making regression more robust is to use an absolute-value measure instead of usual squared one.
However, we will explore all the classification/prediction techniques in order to identify what is the "best" technique.

3 METHODOLOGY

The proposed methodological framework is based on predictive modelling to approximate the LOS of a new patient at the ED. The goal is to enable prediction with a very useful model, easily understandable and usable by the hospital staff. The methodology adopted to achieve this objective is outlined Figure 2. Each step is described in the next subsections.

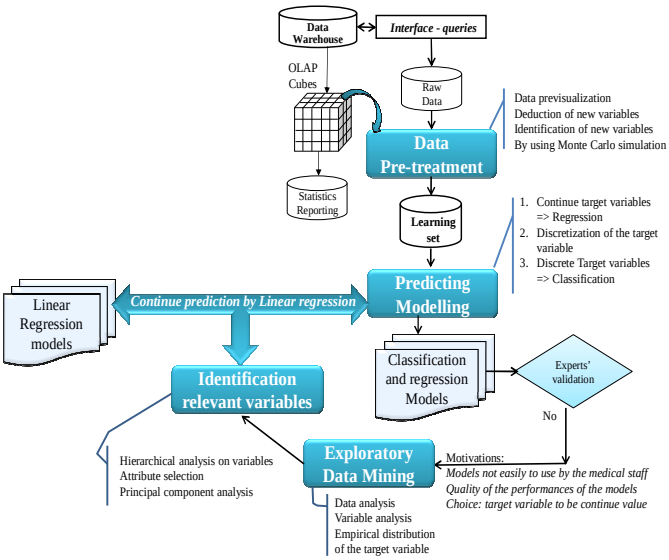


Figure 2: Proposed methodology.

3.1 Data description

First, the data is collected, prepared in the right format, eventually pre-visualized and fit to appropriate dimensions. Based on objective, we use discrete event simulation in order to create new variable such as "the number of patient in the system when a new patient arrived". We want to prove the contribution in coupling simulation

and data mining in order to discover new variable that it can explain the explicative variable.

3.1.1 Raw data

The table 1 describes the raw data. The data come from the PED data base and concern 12, 498 patients (period January-June, 2012).

Variables	Meaning	Type	Definition
X_1	Arrival Date	Date	Date of patient arrival
X_2	Arrival time	Hours	Hour of patient arrival
X_3	Arrival mean	Numeric	Arrival mean of patients (personal, fireman, mobile emergency)
X_4	Adressed by	Character	Who addressed the patient to the emergency department (attending physician, internal emergency, SAMU, Centre 15...)
X_5	Destination	Numeric	Destination/Orientation of patient at the end of emergency management (come back at home, hospitalization…)
X_6	Age	Numeric	Age of patients (in months)
X_7	Sex	Numeric	Sex of patients (1 = boy, 2 = girl)
X_8	Statut	Numeric	1=medical, 2= surgery
X_9	CAC	Numeric	3091: external care 3092: Short-term Hospitalization Unit
X_{10}	CCMU	Numeric	Clinical classification of emergency patients called CCMU (1-6)
X_{11}	GEMSA	Numeric	Multicentric Emergency Department Study Group called GEMSA (1-6)
X_{12}	Accident	Boolean	1 = yes, 0 = no
X_{10}	Echography	Boolean	1 = an echography and 0 = no echography
X_{11}	Scanner	Boolean	1= a scanner and 0 = No scanner
X_{12}	X-Ray	Boolean	1 = radiology and 0 = no radiology
X_{13}	Comp. X-ray	Boolean	1 = yes, 0 = no
X_{14}	Biology	Boolean	1 = biology test and 0 = no biology test
X_{15}	AvisSpe	Boolean	Specialised advice
X_{16}	Departure Date	Date	Date of patient leaving the PED
X_{17}	Departure time	Hours	Time (hour of day) of Patient leaving the PED

Table 1. Variable description from data records coming from the emergency data base

From the raw data, we deduce news variables:

- X_{18}: Day on the week (Monday, Tuesday….),
- X_{19}: Month of the year,
- X_{20}: Season regarding the date,
- X_{21}: Period of the day (morning, afternoon, night…)
- X_{22}: Patient's Length of stay in the PED including the waiting times (in minutes): LOS calculate with the variables (X_1,X_2) and (X_{14},X_{15}).

3.1.2 Monte Carlo simulation

In using Monte Carlo simulation, a model computes the number of patients present in the emergency department allowing us to deduce a new variable:

- X_{23}: the number of patients inside of PED when a new patient arrives.

If we directly used data mining approach without previously data analysis, we observe in the next paragraph that the classification by using regression methods is not easy.

3.2 Classification analysis

Our objective is to identify linear correlation between variable regarding a target variable called LOS (corresponding to X_{22}).

Robust estimation of LOS fluctuations is a challenging problem. The accuracy of statistical extrapolation is fairly sensitive to both model and sampling error.

3.2.1 Techniques for continue target value

Only regression allows us to use continue variable of the target variable. Nine methods available in Weka[1] (Hall et al., 2009) are used:

1. LR: Linear regression
2. DS (Decision Stump): Class for building and using a decision stump. Usually used in conjunction with a boosting algorithm regression (based on mean-squared error) or classification (based on entropy)
3. M5P: Induction of model trees for predicting continuous classes
4. REPTree: Builds a decision/regression tree using information gain/variance and prunes it using reduced-error pruning (with backfitting).
5. SMOreg: SVM Regression
6. IRM: Isotonic regression model
7. MLP: MultiLayer perceptron
8. PRLM: Pace regression linear models
9. KStar: K-nearest neighbors classifier (lazy)

The results are given table 2.

Methods	Correlation coefficient	Mean absolute error	Root mean squared error	Relative absolute error (%)	Root relative squared error (%)
LR	0.5823	143.932	250.372	77.83%	81.29%
DS	0.5092	155.126	265.057	83.88%	86.06%
M5P	0.5893	141.762	249.004	76.66%	80.85%
REPTree	0.5664	144.869	254.27	78.34%	82.56%
SMOreg	0.5777	129.776	270.472	70.17%	80.56%
IRM	0.5092	155.126	265.057	83.88%	86.06%
MLP	0.4993	180.291	281.782	97.49%	91.49%
PRLM	0.5824	143.945	250.357	77.84%	81.29%
KStar	0.5438	138.687	259.180	74.99%	84.15%

Table 2: Comparisons of classifier methods with continue target variable. Total Number of Instances 12,498

[1] But others free softwares can be used such as R [R, 2008], Tanagra [Rakotomalala, 2005]…

Classification models are not very useful when the target values are continuous. We also observe that independently of the used algorithms, we obtain quasi the same performances, but how to improve theses performances?

3.2.2 Classification with methods needing discrete target variable

Although many interesting real world domains demand for regression tools, machine learning researchers have traditionally concentrated their efforts on classification problems. They showed that it is possible to obtain excellent predictive results by transforming regression problems into classification ones.

Classification algorithms only deal with nominal variable and cannot handle ones measured on a numeric scale. To use them, numeric attributes must first be "discretized" into smaller number of distinct ranges.

Discretization processes exist to convert continuous target values into a discrete set of classes. There are different popular discretization methods, e.g. equal-width, equal-frequency...(Dougherty et al., 1995; Filzmoser, 2008) and new methods such as Extreme Randomized Discretization (Ahmad et al., 2012).

The obtained intervals are not realistic for the medical staff. So we decide to take into account the intuitive staff's experience in order to estimate the intervals.

We discretize with intervals of 1 hour 30 minutes (with all LOS > 12h are in the same class) more realistic than the values obtained by Weka tools for discretization.

Eight methods are compared in order to identify the most appropriate approach:

1. Logistic Model Tree (LMT)
2. Multi-class alternating decision tree using the LogitBoost strategy (LADTree)
3. Decision tree (C4.5 - J48),
4. Decision tree with naive Bayes classifiers at the leaves (NBTree)
5. Random Forest (RF),
6. Decision/regression tree using information gain/variance and prunes it using reduced-error pruning (REPTree)
7. Multilayer Perceptron (MP),
8. SVM (SMO).

For these eight methods, the first step corresponds to the discretization of the target variable LOS in order to apply some of these methods. The model valuation is carried out using 10-fold cross validation on the PED data set. The software is Weka (Hall et al., 2009). The corresponding results are presented in table 3. We obtain the best performances in using logistic regression.

Methods	Correctly classified instances	Incorrectly classified instances	Kappa
LMT	47.2316 %	52.7684 %	0.2744
LADTree	46.4314 %	53.5686 %	0.2765
C4.5	40.9185 %	59.0815 %	0.2249
NBTree	42.6388 %	57.3612 %	0.2387
RF	43.447 %	56.553 %	0.2483
REPTree	45.6233 %	54.3767 %	0.2663
MP	43.2869 %	56.7131 %	0.2272
SMO	42.1267 %	57.8733 %	0.1723

Table 3: Comparisons of classifier methods

We note that when we get an important number of variables and observations, data mining tools for classification are not able to extract knowledge on all of the data therefore a prior step of data analysis is essential. In fact, the model can predict the correct interval of LOS in less than one case over 2.

3.2.3 Synthesis

The directive such as to discretize the target variable in order to use the methods is tested in the previous paragraph. We observe that logistic regression model obtains the best percentage of correctly classified instances (47.2316 %) such as described in the related works (paragraph 2). We reminder logistic regression models produce probabilities rather than predictions. Our objective is to identify a very useful model easy to use by the medical staff.

3.3 Exploratory data mining by using data analysis

In the previous paragraph, we show that if we use all the variables, it is impossible to identify very simple model (for example, with C 4.5, the tree size is 227 levels). So it is necessary to propose a methodology based on data analysis.

Figure 3 propose a methodological framework permitting to initiate the data mining analysis process.

We present the contribution of our approach on a real case study concerning 12,499 patients (the six first months of 2012).

The objective is to predict the LOS regarding the available data.

The first step, it could be interesting to analyze the distribution of the LOS in the PED (Figure 4) and after, the similarities between the variables. The objective is to determine what are the variables most correlated to the LOS variable. The main challenge in high-dimensional regression is to identify the relevant variables.

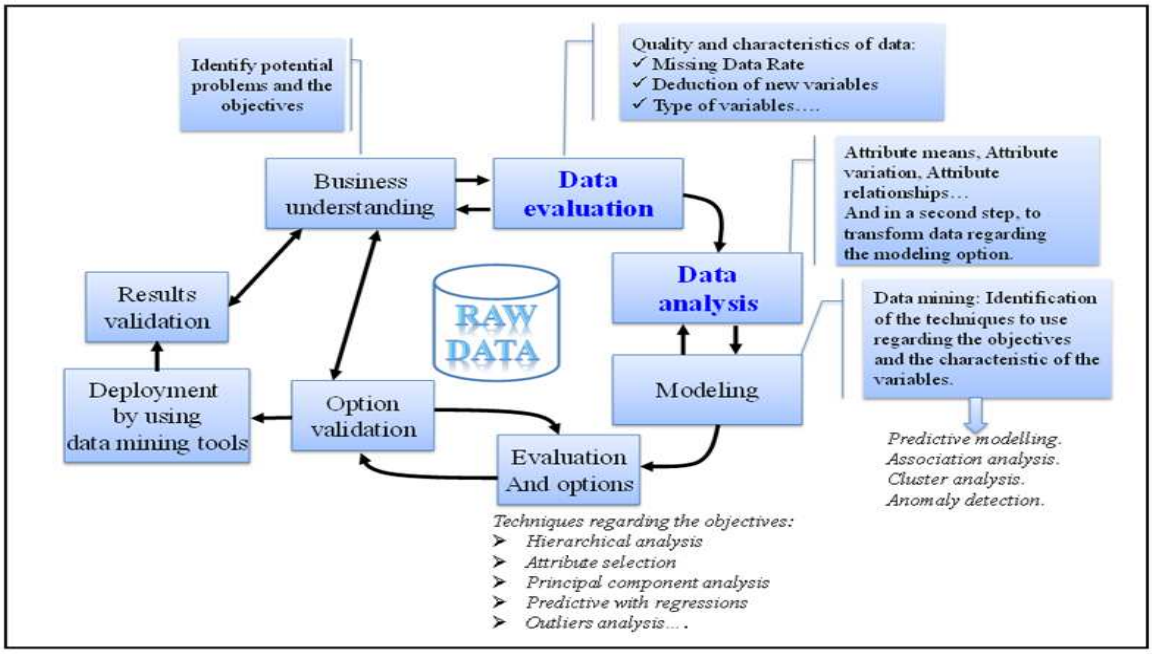
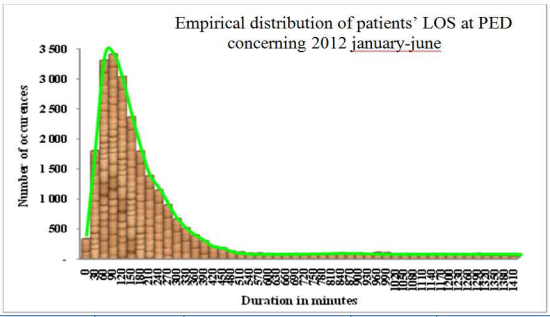


Figure 3. Explanatory data mining processes

The technique used is the hierarchical variable analysis, the attribute selection, and/or the Principal Component Analysis (PCA) in order to reduce the number of variables.



2012	Mean	Standard deviation	Min	Max
In minutes	252,20	305,93	0	4190
In Day/hours	4:12	5:06	0:00	2 days and 0:22

Figure 4: LOS at the Emergency department in 2012

The empirical probability distribution of LOS is leptokurtic, i.e. the shape is asymmetrical, with on the one hand, a center peak much higher than Normal law and, on the other hand, "heavy" or "long" tail. When we observe this, the predicted models are not easy to identify because there are many outliers (Data points that diverge in a big way from the overall pattern).

3.4 Identification of the relevant variables

We explore three approaches:

1. Hierarchical cluster analysis on the variables,
2. Attribute selection,
3. Principal component analysis.

3.4.1 Hierarchical cluster analysis on variables

It is possible to cluster variables in terms of their correlations, or distances based on their correlations.

Two variables have a pair of values for each sample, and we can consider measures of distance and dissimilarity between these two column vectors. More often, however, the similarity between variables is measured: this can be in the form of correlation coefficients or other measures of association.

The results of a cluster analysis is a binary tree, or dendrogram, with n–1 nodes (see Figure 5). The branches of this tree are cut at a level of similarities obtained in our case by using correlation.

From Figure 5, we observe that the LOS is linked with biology tests. After three variables linked to the couple (LOS, Biology) are X-ray, Comp X-ray and echography.

With data analysis, it is possible to deduce the variables that explain a predictive model for the target variable, in the study: LOS.

With a cut to 64.84 of similarity level, the retained variables regarding the LOS are:

- Comp X-Ray,
- X-Ray,
- Echo (echography),
- Biology,
- LOS.

But also, with a cut to 60.71 of similarity level, the following variables can explained the target variable LOS:

- Age,
- Statut,
- AvisSpe,
- Scanner.

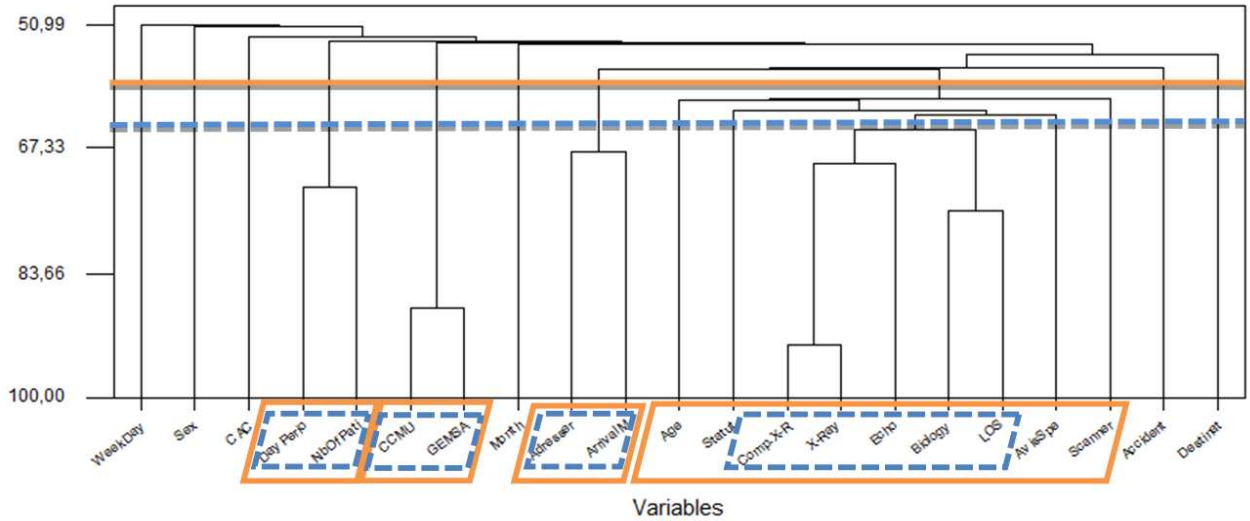


Figure 5: Similarities between the variables observed

3.4.2 *Attribute selection*

Now we verify if we obtain the same variable by using attribute selection methods with LOS as target variables.

In Weka, regarding the target attribute type (continue), the used methods can be "CFS Subset Evaluator" (see Witten et al., (2011) for more information) with search methods:

1. BestFirst,
2. LinearForwardSelection (Extension of BestFirst),
3. ExhaustiveSearch,
4. Random search.

The selected attributes are:

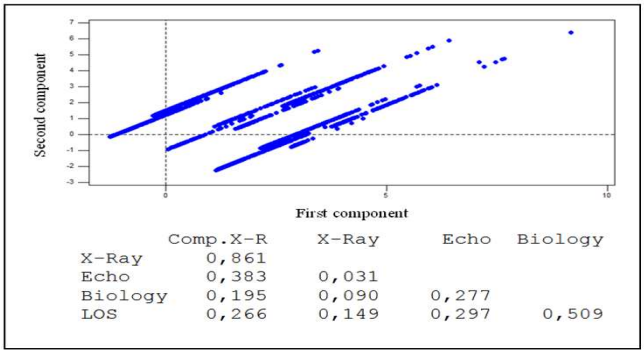
- NbOfPatients
- AdressedBy
- CAC
- Echo
- Scanner
- X-Ray
- AvisSpe
- Biology

3.4.3 *Principal component analysis*

Principal Component Analysis (PCA) is a powerful tool for analyzing data. It is a common technique for finding patterns in data of high dimension.

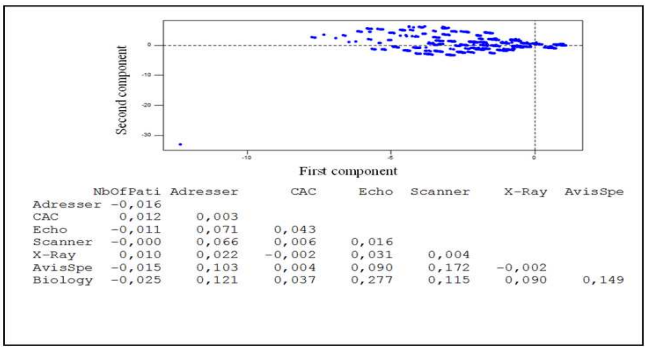
If we use PCA on the retained variables, and we observe that we have important link between the five variables: Comp X-Ray, X-Ray, Echo (echography), Biology, LOS (see the Pearson's correlation matrix presented in Figure 6).

For the selected attribute by using Weka, the contribution of the first two components is given Figure 7.



	Comp.X-R	X-Ray	Echo	Biology
X-Ray	0,861			
Echo	0,383	0,031		
Biology	0,195	0,090	0,277	
LOS	0,266	0,149	0,297	0,509

Figure 6: Contribution of the first two components of PCA and the corresponding Pearson's correlation matrix



	NbOfPati	Adresser	CAC	Echo	Scanner	X-Ray	AvisSpe
Adresser	-0,016						
CAC	0,012	0,003					
Echo	-0,011	0,071	0,043				
Scanner	-0,000	0,066	0,006	0,016			
X-Ray	0,010	0,022	-0,002	0,031	0,004		
AvisSpe	-0,015	0,103	0,004	0,090	0,172	-0,002	
Biology	-0,025	0,121	0,037	0,277	0,115	0,090	0,149

Figure 7: Contribution of the first two components of PCA and the corresponding Pearson's correlation matrix

We observe that the linearity is stronger on the first two principal components with the four variables selected (Figure 6) than the seven attributes identified by Weka (Figure 7).

3.4.4 *Synthesis*

We observe that there exist linear links between the five variables and it can be interesting to see the contribution of linear regression with:

- The target variable: LOS,

- The four predictor variables: Comp X-Ray, X-Ray, Echo (echography), Biology.

But also, the predictor variables obtained from selection attribute methods, can be:

- NbOfPatients,
- AdressedBy,
- CAC,
- Echo,
- Scanner,
- X-Ray,
- AvisSpe,
- Biology.

The second approach based on attribute selection identifies 3 against 4 attributes identified by using hierarchical clustering analysis on the variables. Other attributes are identified such that "number of patients inside of PED", CAC…

3.5 The proposed models

When the outcome or class is numeric and all the attributes are numeric, linear regression is a natural technique to consider.

3.5.1 Linear models

The classic way of dealing with continuous prediction is to write the outcome as a linear sum of attribute value with appropriate weights such that:

$y_{pure} = w_0 + w_1x_1 + w_2x_2 + \ldots + w_nx_n$

where

- ✓ y_{pure} is the class
- ✓ $x_1, x_2, \ldots, x_n$ are the attribute values of the variable $X_1, X_2, \ldots$ and X_n
- ✓ $w_1, w_2, \ldots, w_n$ are the weights of each variable $X_1, X_2, \ldots$ and X_n

We obtain a formula called regression equation and the objective is to determine the corresponding weights for each variable, a well-known procedure in statistics.
The weights are calculated from the training data.
The methods for calculating w_j ($j=1..n$) is based on the minimization of the sum of the squares of the difference between observed y_{pure} and the observed value called y_{obs} over all the training set instances.
Suppose that you have n variables and k training instances. Denote the ith one with a superscript (i), the sum of the squares of the differences is the following:

$$\sum_{i=1}^{k}\left(y_{obs}^{(i)} - \sum_{j=0}^{n} w_j x_j^{(i)}\right)^2$$

Where

- ✓ $\sum_{j=0}^{n} w_j x_j^{(1)} = w_o^{(1)}x_0^{(1)} + w_1^{(1)}x_1^{(1)} + w_2^{(1)}x_2^{(1)} + \cdots + w_n^{(1)}x_n^{(1)}$ corresponds to the predicted for the first instance class with $w_o^{(1)}x_0^{(1)}$ is in fact w_0.
- ✓ $y_{obs}^{(1)}$ is the first actual instance which corresponds the first observation.

The model minimizes this sum of squares by choosing the coefficients appropriately.
Linear is an excellent, simple method for numeric prediction and it has been widely used in statistical applications but very sensitive to outliers.

3.5.2 Model 1

The variable is LOS (continue values) and the four explained variables: Comp X-Ray, X-Ray, Echo (echography), and Biology.

The corresponding equation of regression through the Origin is

$$\textit{LOS} = 153 + 127\ \textit{Comp.X-Ray} + 133\ \textit{Echo} - 41.1\ \textit{X-Ray} + 347\ \textit{Biology} \qquad (1)$$

In order to validate the *model 1*, we propose Figure 8 the error rate regarding the observed LOS and the LOS estimated with the equation (1).

The difference between the observed value of the dependent variable (y_{obs}) and the predicted value ($\hat{y}_{pure}$) is called the residual (e). Each data point has one residual.

Residual = Observed value - Predicted value

$$e = y_{obs} - \hat{y}_{pure}$$

Both the sum and the mean of the residuals are equal to zero. That is, $\Sigma\, e = 0$ and $e = 0$.

With an error interval (residual values) of ± 2 hours, the model 1 "correctly" estimates 75% of the observations. But only 24.96% are correctly estimated and 62.16% for an error interval less than ± one hour.

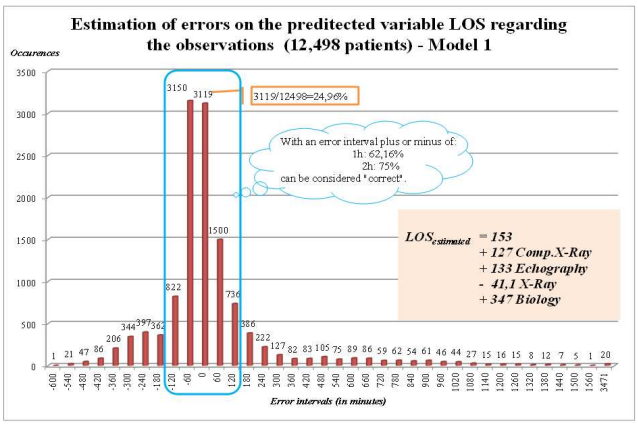


Figure 8: Errors between Estimated LOS and Observed LOS – *Model 1*

If we consider that the residual values is less than 4 hours, we have to analyze 25% of the observations. The-

se Data points (called outliers) diverge in a big way from the overall pattern and we have to identify it.

The main problem is that outlier greatly affects the slope of the regression line. It is absolutely necessary to test the influence of outliers; one way is to compute the regression equation without the outliers.

1) All the observations generating residual greater than ±180 minutes,
2) Analysis of all the observations considered outliers.

The regression equation through the Origin without outliers is:

$$LOS = 126 + 135\ Comp.X\text{-}Ray + 91.6\ Echo - 71.7\ X\text{-}Ray + 323\ Biology \quad (2)$$

In this case, we guarantee that with a residual ±3h, we can found the duration of the 4 exams in minutes and we can estimate the LOS with an error of ± 3h. The sample is constituted of 9,719 patients (77.66% of the observed population).

With respect to regression, outliers are influential only if they have a big effect on the regression equation. The difference between equation 1 and equation 2 shows that the substantial number of outliers has a relatively minor influence:

- 153-126, 27 minutes,
- 127-137, -10 minutes,
- 133-96.6, 36.4 minutes,
- 41.1-71.7, -30.6 minutes,
- 347-323, 24 minutes,

This is meaning that the *model 1* overestimates at most than two hours compared to the *model 2*.

Sometimes, outliers do not have big effects when the data set is very large. It depends on the number of outiliers. The outliers represent 22.34% of the population but should be analyzed in order to try to identify patterns explaining the LOS.

3.5.3 Model 2

The target variable is LOS (continue values) and the eight predictor variables are:

- NbOfPatients
- AdressedBy
- CAC
- Echo
- Scanner
- X-Ray
- AvisSpe
- Biology

$$LOS = -2436 + 3.59\ NbOfPatients + 17.8\ AdressedBy + 0.816\ CAC + 206\ Echo + 171\ Scanner + 75.2\ X\text{-}Ray + 176\ AvisSpe + 322\ Biology \quad (3)$$

Figure 8 presents the error rate regarding the observed LOS and the LOS estimated with the equation (3).

With a residual of ± 2 hours, the *model 2* "correctly" estimates 73.76% of the observations.

But only 28.24% are correctly estimated and 61.83% for an error interval less than ± one hour.

For this model, the influence of outliers is not presented.

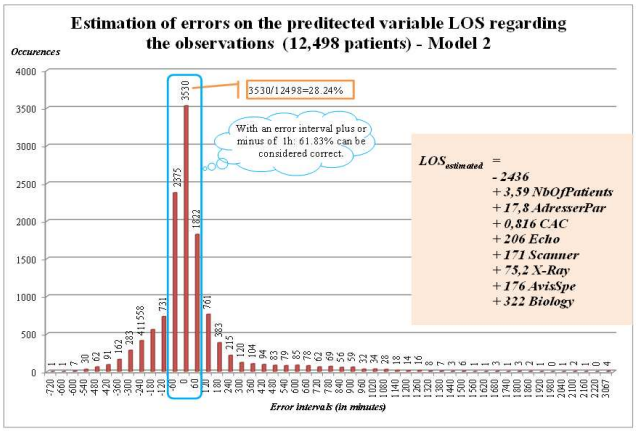


Figure 9: Errors between Estimated LOS and Observed LOS – Model 2

3.5.4 Discussion

Two different models can predict the LOS. The first one is very easy to use for the medical staff. In fact it explains the factor (corresponding to the variable) which increase or decrease the LOS.

The meaning of the equation 1 (***LOS = 153 + 127 Comp.X-Ray + 133 Echo – 41.1 X-Ray + 347 Biology***) is the following regarding that the explained variables are Boolean:

If the patient does not need ***Comp.X-Ray, Echo, X-Ray and Biology***, the LOS is around 153 minutes.

If the patient only needs ***Biology*** the LOS around 153 minutes increases of 347 minutes...

The second model allows us to be more accurate in LOS estimation (28.24% regarding 24.96% for the *model 1*).

But the use of the *model 2* is more complex because it requires counting the number of people present in the PED for example, and requires taking into account more variables (8 against 4 for the *model 1*).

The *model 2* gives information such that the multiplicative factor of crowd whose value is 3.59 and corresponds to the weight of the variable NbOfPatients regarding LOS. We also observe that the weight of the variable Biology is quasi the same (323 for the *model 1* without outliers and 322 for the *model 2*).

With the proposed approach, we illustrate that is possible to identify a very simple model. In this case, contrary to what is advocating in data mining, it is not always easy to discretize the variable target for classification and prediction.

Probably, these two models are dedicated to the PED of Lille's Hospital, because the results are linked to the management of the hospital. It is not possible to generalize to all the hospital Emergencies.

4 CONCLUSIONS AND FUTURE WORKS

We showed that different data mining techniques can be used beneficially in classification and prediction by using linear regression and we obtain a very "simple" model that it can easily use by the medical staff in order to estimate the LOS.

We experiment and validate the approach on real data concerning 12,498 patients. Data are collected from the database of the Pediatric Emergency unit located in France.

Given the presented care system and the methodological framework based on linear regression methods have been presented for LOS prediction. We identify two models. We retain the *model 1* because it is very simple to understand and to use by the medical staff.
We observe that the variable "*number of patients inside of PED*" deduced by using Monte-Carlo simulation does not have an important linear relationship with the LOS. Consequently, it is possible to estimate the LOS without taking into account "number of patients inside of PED" in the *model 1*. Only four variables allow us to explain LOS: The predictor variables are: Comp X-Ray, X-Ray, Echo (echography) and Biology. At the present time, we have to analyze the outliers representing approximately 25% of the observations for the *model 1*.

Of course, linear regression suffers from the disadvantage of, well, linearity. Maybe the data exhibits a non-linear dependency, the best-fit straight line will be found, where "best" is interpreted as the least mean-square difference. So we analyze the interval error committed with the obtained linear regression equation.
In 75% of cases, we correctly fit with an error of ± 2 hours.

But the basic regression method is not able to discover nonlinear relationships between the others variables.
Three issues are interesting to proceed in advancing this direction: a practical one, and two research issues.
Firstly, it could be interesting to identify if there exist correlations but not necessary linear between the variables. Secondly, we have to test the contribution of probabilistic view of the problem. Thirdly, we have to propose a probabilistic model taking into account the non-linearity between variables.

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