



RESEARCH ARTICLE

APPLICATION OF DATA MINING TECHNIQUES FOR OUTLIER MINING IN MEDICAL DATABASES

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ABSTRACT

Outlier detection has been a very important concept in the realm of data analysis and the complex relationships that appear with regard to patient symptoms, diagnoses and behavior are the most promising areas of outlier mining. This paper elaborates how the outliers can be detected by using statistical methods. The importance of outlier detection is due to the fact that outliers in data predict significant (and often critical) information in a wide variety of application domains. There are numerous different formulations of an outlier detection problem which have been explored in diverse disciplines such as statistics, machine learning, data mining and information theory. In fact, the study with medical data by using the DM techniques is virtually an unexplored frontier which needs extraordinary attention. In this study, the pima data set was used in the simulation carried out by TANAGRA. A total of 193 outliers were detected for the statistics namely leverage, R-standard, R-student, DFFITS, Cook's D and covariance ratio. The results of the present investigation suggested that the extraordinary behavior of outliers facilitates the exploration of the valuable knowledge hidden in their domain and help the decision makers to provide improved, reliable and efficient healthcare services.

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INTRODUCTION

Outlier detection is one of the most important tasks in data analysis. An outlier is an extreme observation. Typically points farther than, say, three or four standard deviations from the mean are considered as "outliers". In regression however, the situation is somewhat more complex in the sense that some outlying points will have more influence on the regression than others. Outlier detection has been suggested for numerous applications, such as credit and fraud detection, clinical trials, voting, irregularity analysis, network intrusion, severe weather prediction, geographic information system, and other data mining tasks (Barnett and Lewis, 1995; Fawcett and Provost, 1997; Hawkins, 1980; and Penny and Jolliffe, 2001). Outliers in a data may be due to recording errors or system noise of various kinds, and as such needs to be cleaned with regard to extract, transform, clean and load phase (ETCL) of the data mining/KDD process. On the other hand an outlier or small group of outliers may be quite error-free recordings that represent the most important part of a data that deserve further careful inspection, e.g., an outlier might represent an unusually high response to a particular advertising campaign, or an unusually effective dose-response combination in a drug therapy (Ben-Gal I, 2005). Either way, it is quite important in data mining to detect outliers in large amounts of highly

multi-dimensional data. The multidimensional aspect of the data makes this task particularly challenging. This is because highly important and influential outliers can be completely hidden in one-dimensional views of the data, which renders ineffective one-dimensional outlier detection based on scanning one field (variable, attribute) at a time. There are three fundamental approaches to the problem of outlier detection:

- Type 1 - Determines the outliers with no prior knowledge of the data. This is essentially a learning approach analogous to unsupervised clustering. The approach processes the data as a static distribution, pinpoints the most remote points, and flags them as potential outliers.
- Type 2 - Models both normality and abnormality. This approach is analogous to supervised classification and requires pre-labeled data, tagged as normal or abnormal.
- Type 3 - Models only normality (or in a few cases models abnormality). This is analogous to a semi-supervised recognition or detection task. It may be considered semi-supervised as the normal class is taught but the algorithm learns to recognize abnormality.

Outlier detection methods can be divided into univariate and multivariate methods.

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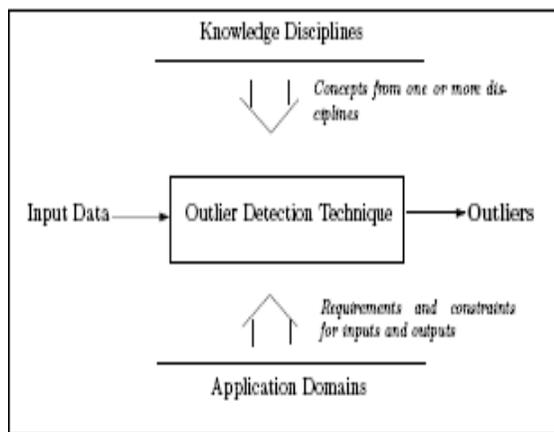


Fig 1. A general design of an outlier detection technique

The combination of data warehousing and data mining technology with evidence-based medicine as a new direction in modern health care introduces an innovative application field of information technology in healthcare industry (Kristin B. DeGruy, 2000). As a result of this transformation, all parties are demanding greater and more detailed information on the effectiveness of the healthcare systems. More and more entities place data demands on other entities, and many healthcare organizations find themselves overwhelmed with data, but lack truly valuable information (Varun Kumar, 2008).

MEDICAL AND PUBLIC HEALTH DATA

Outlier detection in the medical and public health domains typically work with patient records. The data can have outliers due to several reasons such as abnormal patient condition or instrumentation errors or recording errors. Thus the outlier detection is a very critical problem in this domain and requires high degree of accuracy. The data typically consists of records which may have several different types of features such as patient age, blood group and weight. The data might also have temporal as well as spatial aspect. Most of the current outlier detection schemes aim at detecting outlying records (Type I outliers). Typically the labeled data belongs to the healthy patients; hence most of the schemes adopt novelty detection approach (Kristin B. DeGruy, 2000).

DIABETES

Diabetes is an immune affecting disorder in which the body does not properly produce insulin. It is one of the most common chronic diseases, which can lead to serious long term complications. In diabetes there are two major types: Type I diabetes is caused by the failure of pancreas, in which case sufficient insulin will not be produced. Type I diabetes is usually diagnosed in children and young adults and was previously known as Juvenile diabetes (Siti Farhanah *et al.*, 2005). In Type II diabetes, the body will be resistant to the insulin it makes, which leads to an uncontrolled increase of blood glucose level that is elevated for a long period can result in metabolic complications such as kidney failure, blindness, and an increased chance of heart attacks. To prevent or postpone such complications strict control over the diabetic

blood glucose level is needed. Numbers of computer-based systems are available to diagnose the disease. Type II diabetes is the most common form of diabetes. Diabetes mellitus is now a big growing health problem as it is the world's fourth biggest cause of death particularly in the industrial and developing countries (Rajeeb Dey *et al.*, 2008). It is one of the most common chronic diseases, which can lead to serious long-term complications and death.

LITERATURE SURVEY WITH REGARD TO PIMA INDIAN DIABETES DATA SET (PIDD)

Most of the work related to machine learning in the domain of diabetes diagnosis has concentrated on the study of the Pima Indian Diabetes data set in the UCI repository. This particular Pima data set has been widely used in machine learning experiments and is currently available through the UCI repository of standard data sets. This population has been studied continuously by the National Institute of Diabetes, Digestive and Kidney Diseases owing to the high incidence of diabetes. To study the positive as well as the negative aspects of the diabetes disease, Pima data set can be utilized, which contains 768 data samples. Each sample contains 8 attributes which are considered as high risk factors for the occurrence of diabetes, like

- Plasma glucose concentration
- Diastolic blood pressure (mmHg)
- Triceps skin fold thickness (mm)
- 2-hour serum insulin (mu U/ms)
- Body mass index (weight in kg/(height in m))²
- Diabetes pedigrees function
- Age (years)

All the 768 examples were randomly separated into a training set of 576 cases (378, non-diabetic and 198, diabetic) and a test set of 192 cases (122 non-diabetic and 70 diabetic cases). In the above data set 268 patients are diabetic, which can be interpreted as "1" and the remaining patients are non-diabetic which can be interpreted as "0". A brief description of the DM technique "Regression" is presented below:

REGRESSION

Regression is a data mining (machine learning) technique used to fit an equation to a data set. There are two kinds of linear regression: 1) simple linear regression, and 2) multiple linear regressions (also known as multivariate linear regression). In Simple linear regression there is only one dependent variable (also known as an outcome, or response variable) and one independent variable (also known as a predictor or explanatory variable). In the case of Multiple linear regression there is one dependent variable and two or more independent variables. The simplest form of regression i.e., linear regression, uses the formula of a straight line ($y = mx + b$) and determines the appropriate values for m and b to predict the value of y based upon a given value of x . It is possible to fit more complex models by using advanced techniques which allow more than one input variable. Regression models are tested by computing various statistics that measure the difference between the predicted values and the expected values. The historical data for a regression project is typically divided into two data sets: one for building the model, the other for testing

the model. Regression modeling has many applications in trend analysis, business planning, marketing, financial forecasting, time series prediction, biomedical and drug response modeling, and environmental modeling. To statisticians, unusual observations are generally either outliers or 'influential' data points. In regression analysis, the unusual observations are categorized as: outliers, high leverage points and influential observations. Outlier is an observation in a data set which appears to be inconsistent with the remainder of the set of data (Johnson and Wichern, 2002). In other words, an outlier is an observation that deviates so much from other observations as to create suspicion such that it was generated by a different mechanism (Hawkins 1980).

Statistical outlier detection techniques are essentially model-based techniques; i.e. they assume or estimate a statistical model which captures the distribution of the data, and the data instances are evaluated with respect to how well they fit the model (V. Barnett and T. Lewis, 1994). If the probability of a data instance to be generated by this model is very low, the instance is deemed as an outlier. The need for outlier detection was experienced by statisticians as early as 19th century. The presence of outlying or discarding the observations in a data encouraged statistical analysis being performed on the data (Johnson, 2002). This led to the notion of *accommodation or removal of outliers* in different statistical techniques. Regression model based on outlier detection techniques typically analyze the residuals obtained from the model fitting process to determine how outlying is an instance with respect to the fitted regression model.

Grubbs' test is also called as ESD method (extreme studentized deviate). The first step is to quantify how far the outliers is from the others. Then the second step is to calculate the ratio Z as the difference between the outlier and the mean divided by the SD. If Z is large, the value is far from the others. Finally, the mean and SD are calculated from all values, including the outlier.

$$Z = \frac{|\text{mean} - \text{value}|}{SD}$$

TREATMENT OF OUTLIERS

The key point to be stressed is that the above procedure can only serve to identify points that are *suspicious* from a statistical perspective. It does *not* mean that these points should automatically be eliminated! The removal of data points can be dangerous. While this will always improve the "fit" of regression, and it may end up with destroying some of the most important information in data.

Methods to detect outliers

- ▶ Eyeball Method – look at what falls away from the line
- ▶ Standardized or Studentized Residual Scores – look at error scores such as those that are 2+ SD's away from mean
- ▶ Leverage Statistics (Hat Values) – difference of a data point from the pooled mean.
- ▶ Distance D as in Cook's D – how much an observation affects a change in a parameter estimate

(a or b weight). The correlation coefficient, r , is calculated using:

$$r = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$$

where,

$$\text{Var}(X) = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}$$

is the variance of X .

$$\text{Var}(Y) = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n-1}$$

is the variance of Y .

The covariance of x and y is given by,

$$\text{Cov}(X, Y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n-1}$$

Cook's distance for points i & j is :

$$D_i = \frac{\sum_{j=1}^n (\hat{y}_j - \hat{y}_j(i))^2}{(k+1)s^2}, i=1, \dots, n$$

Where,

D_i is the normalized measure of the influence of the point i on all predicted mean values;

y_i and y_j are the regression estimates for the conditional mean at the points

i and j , and s is the estimated root mean square error.

DFFITs

DFFITs is a diagnostic that shows how influential a point is in a statistical regression and is defined as the change ("DFFIT"), in the predicted value for a point, obtained when that point is left out of the regression, "Studentized" by dividing by the estimated standard deviation of the fit at that point:

$$DFFITs = \frac{\hat{y}_i - \hat{y}_i(i)}{s_{(i)} \sqrt{h_{ii}}}$$

where \hat{y}_i and $\hat{y}_i(i)$ are the predictions for the cases (i) with the point i and (ii) without the point i ; $s_{(i)}$ is the standard error estimated without the point in question, and h_{ii} is the leverage for the point.

EXPERIMENTAL RESULTS AND DISCUSSION:

Performance of a multiple linear regression analysis for a large set of data would be immensely time-consuming. Hence statistical analysis software could be used to quickly perform the test. The results obtained by using such a software clearly predicts: (i) R^2 value (ii) p-value. The results are presented in the figures 2 to 15.

Data set description

Workbook information

Number of sheets	1
Selected sheet	diabeticdata
Sheet size	769 x 9
Data set size	769 x 9

Datasource processing

Computation time	156 ms
Allocated memory	38 KB

Fig 2. Workbook information Data set description 9 attribute(s), 768 example(s)

Attribute	Category	Information
PR	Continue	-
PG	Continue	-
DBP	Continue	-
TRICEPS	Continue	-
SERUM	Continue	-
BMI	Continue	-
PEDI	Continue	-
AGE	Continue	-
CLASS	Continue	-

Fig 3. Data set description Global results

Endogenous attribute	CLASS
Examples	768
R ²	0.303253
Adjusted-R ²	0.295909
Sigma error	0.400210
F-Test (8,759)	41.2935 (0.000000)

Fig 4. Global results

The coefficient of determination R² is a valuable tool to evaluate the fit of a model. The regular R² always increases with the number of factors included in the model while the adjusted R² takes the complexity of the model into account. One reasonable criterion for a good model is to maximize the adjusted R². R² is a measure of how well future outcomes are likely to be predicted by the model. Adjusted R² is a modification of R² that adjusts for the number of explanatory terms in a model. Unlike R², the adjusted R² increases only if the new term improves the model beyond the expectation. The adjusted R² can be negative, and will always be less than or equal to R².

An F-test is any statistical test in which the test statistic has the F-distribution under the null hypothesis. The F-test in one-way analysis of variance is used to assess whether the expected values of a quantitative variable within several pre-defined groups, differ from each other. The alpha value arising from a test gives the p-value. Degrees of freedom is an integer value measuring the extent to which an experimental design imposes constraints upon the pattern of the mean values of data from various meaningful subsets of data.

Analysis of variance

Source	xSS	d.f.	xMS	F	p-value
Regression	52.9113	8	6.6139	41.2935	0.0000
Residual	121.5678	759	0.1602		
Total	174.4792	767			

Fig 5. Analysis of variance

If the p-value is lower than the significance level of test α (probability of the outcome under the null hypothesis), then the model is considered to be significant.

Coefficients

Attribute	Coef.	std	t(759)	p-value
Intercept	-0.853894	0.085485	-9.988825	0.000000
PR	0.020592	0.005130	4.014026	0.000066
PG	0.005920	0.000515	11.492938	0.000000
DBP	-0.002332	0.000812	-2.873049	0.004179
TRICEPS	0.000155	0.001112	0.138930	0.889542
SERUM	-0.000181	0.000150	-1.205020	0.228571
BMI	0.013244	0.002088	6.343656	0.000000
PEDI	0.147237	0.045054	3.268030	0.001132
AGE	0.002621	0.001549	1.692707	0.090922

Fig 6. Coefficients

Residuals analysis

It is to be noted that **residuals** is the predicted value minus the actual value and it is the predicted error.

Att. name	Full statistics		Histogram			
	Statistics		Values	Cou nt	Perce nt	Histogr am
Err_Pred_lm eg_1	Average	0.0000				
	Median	-0.0954	x<_-0.7880	6	0.78%	
	Std dev. [Coef of variation]	0.3981 [99999.0000]	-0.7880 =< x<_-0.5625	31	4.04%	
	MAD [MAD/STD DEV]	0.3322 [0.8344]	-0.5625 =< x<_-0.3370	119	15.49%	
	Min * Max [Full range]	-1.01 * 1.24 [2.26]	-0.3370 =< x<_-0.1114	217	28.26%	
	1st * 3rd quartile [Range]	-0.30 * 0.32 [0.62]	-0.1114 =< x<_0.1141	128	16.67%	
	Skewness (std-dev)	0.3957 (0.0882)	0.1141 =< x<_0.3396	82	10.68%	
	Kurtosis (std-dev)	-0.5881 (0.1762)	0.3396 =< x<_0.5651	87	11.33%	
			0.5651 =< x<_0.7906	85	11.07%	
			0.7906 =< x<_1.0161	11	1.43%	
			x>=1.0161	2	0.26%	

Fig 7. Residual analysis

From the above figure it was observed that the kurtosis is of subGaussian type.

Outliers and influential points detection for regression

Statistic	Lower bound	Upper bound	# detected
Leverage	-	0.0234	64
RStandard	-	-	0
RStudent	-2.0000	2.0000	19
DFFITs	-0.2165	0.2165	36
Cook's D	-	0.0053	34
COVRATIO	0.9648	1.0352	40

Fig 8. Outliers and influential points detection

Outlier detection evaluates the overall influence of each observation.

Regression Assessment:

Parameters:

Used data set : selected examples

Results:

Data set size : 768

		Error Sum of Squares		
Observed	Predicted	Default (Mean)	Model	Pseudo-R2
CLASS	PR	174.4792	17723.0000	-100.5766
CLASS	PG	174.4792	11933313.0000	-68392.9133
CLASS	DBP	174.4792	3917295.0000	-22450.3624
CLASS	TRICEPS	174.4792	507470.0000	-2907.4848
CLASS	SERUM	174.4792	15023744.0000	-86105.2343
CLASS	BMI	174.4792	815175.5503	-4671.0509
CLASS	PEDI	174.4792	228.1407	-0.3076
CLASS	AGE	174.4792	935085.0000	-5358.2931

Fig. 9. Regression Assessment

In the above table, a glance of the values pseudo-r2 revealed that there existed lot of internal inconsistencies in the data set. This clearly suggested that the data set corresponded to diabetic patients.

C-RT Regression tree:

Parameters:

Tree Parameters	
Max Number of leaves	100
Min. size for split	5
Max. depth	10
x-SE Rule	1.0000
Pruning set size	33 %
Show all tree sequence	0
Rnd generator	1

Fig. 10. Parameters for C-RT Regression tree
Global results

Endogenous attribute	CLASS
Examples	768
R ²	0.2725

Fig. 11. Global results-C-RT regression
Trees sequence (# 38) -- Mean Squared Error

N ^o	# Leaves	mse (growing)	mse (pruning)	se (mse)	x
38	1	0.2239	0.2341	0.0098	4.2087
34	5	0.1585	0.1791	0.0139	0.6732
30	9	0.1427	0.1686	0.0156	0.0000
1	75	0.0307	0.2797	0.0269	-

Fig. 12. Tree sequence

Tree description

Number of nodes	9
Number of leaves	5

Fig. 13. Tree description

Tree

- PG < 144.5000
 - BMI < 28.8500 then **avg(CLASS) = 0.0701** (std-dev = 0.2561, with 157 examples [30.54%])
 - BMI >= 28.8500
 - AGE < 29.5000
 - PG < 127.5000 then **avg(CLASS) = 0.1495** (std-dev = 0.3583, with 107 examples [20.82%])
 - PG >= 127.5000 then **avg(CLASS) = 0.5882** (std-dev = 0.5073, with 17 examples [3.31%])
 - AGE >= 29.5000 then **avg(CLASS) = 0.4737** (std-dev = 0.5015, with 114 examples [22.18%])
- PG >= 144.5000 then **avg(CLASS) = 0.6975** (std-dev = 0.4613, with 119 examples [23.15%])

Regression algorithm splits the data set into growing and pruning set. Here a two step algorithm was used. In the first step, a maximal tree was built that fits the possible growing set. In the second step, nested sub-trees were tested according to the cost-complexity principle, and RE was evaluated on the pruning set. It was noted that the optimal tree was selected on the pruning set and the simplest sub-tree was selected that had a performance near to the optimal tree.

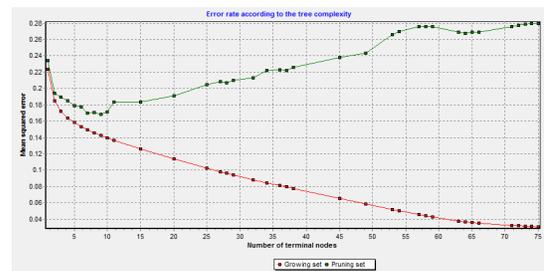


Fig 14. Error reduction curve for growing set and pruning set

CONCLUSION

In almost all of the developed countries, routine health tests are commonplace and are widespread among adults. Hence, precautionary measures which are less expensive than treatment and the detection of any disease in its earlier stages of development give the patient a better chance of treatment than discovering the disease at an advanced stage of development. Even if we do not know how to heal the patients, the treatment will be helpful and will provide life comfort. It is interesting to note that the clinical databases that store a huge amount of information about the patient's diagnosis, lab-test results, patients treatments etc., are a gold mine of medical

information for medical researchers and doctors. In fact, the study with medical data by using the DM techniques is virtually an unexplored frontier which needs extraordinary attention. The results of the present investigation suggest that (i)the extraordinary behavior of outliers facilitates the exploration of the valuable knowledge hidden in their domain and help the decision makers to provide improved, reliable and efficient healthcare services (ii)medical doctors can use the present experimental results as a tool to make sensible predictions of the vast medical databases and finally(iii)a thorough understanding of the complex relationships that appear with regard to patient symptoms, diagnoses and behavior is the most promising area of outlier mining. In order to carry out this experiment on outlier detection, the Pima data set was used in the simulation carried out by TANAGRA. A total of 193 outliers have been detected for the statistics namely leverage, R-standard, R-student, DFFITS, Cooks'D and covariance ratio.

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