RatingScaleReduction package: stepwise rating scale item reduction without predictability loss

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Abstract

This study presents an innovative method for reducing the number of rating scale items without predictability loss. The “area under the receiver operator curve method” (AUC ROC) is used to implement in the RatingScaleReduction package posted on CRAN\footnote{https://cran.r-project.org/web/packages/RatingScaleReduction/index.html}. Several cases have been used to illustrate how the stepwise method has reduced the number of rating scale items (variables).

Keywords: rating scale, receiver operator characteristic, ROC, AUC, scale reduction.

1 Introduction

Rating scales (also called assessment scale and ”the scale” in this study) are used to elicit data about quantitative entities. Often, predictability of rating scales (also called “assessment scales”) can be improved. Rating scales often use values “1 to 10” and some rating scales may have over 100 items (questions) to rate. Sometimes, the scale is called a survey or a questionnaire. A questionnaire is a tool for data collection while a survey may not necessarily be conducted by questionnaires since some surveys may be conducted by interviews or by data gathered from web pages. In fact, the main and very important distinction between the scale and both questionnaires and surveys is that the scale is used for assessment (as in “the scale of disaster”) while questionnaires and surveys may be used to only collect data. In other words, some kind of “summation procedure” must be provided for questionnaires or surveys to become rating scales.

The recent popularity of rating scales is due to various “Customer Reviews” on the Internet where five stars are often used instead of ordinal numbers. However, the most important examples of rating scales are questionnaires used in examinations. We may risk a statement that the accelerated progress of granting academic degrees can be linked to a better use of rating scales.
Rating scales are predominantly used to express our subjective assessments such as “on the scale 1 to 5 express your preference”: “strongly agree to strongly disagree” (with 3 as ‘neutral” preference). The importance of subjectivity processing probably inspired introduction of the idea of *bounded rationality*, proposed by Herbert A. Simon (the Nobel Prize winner), as an alternative basis for the mathematical modeling of decision making. It is often expressed as “good enough is perfect” and gained popularity in the software industry where frequent updates are common. Objective data are more commonly used in so called “strict sciences” while processing subjectivity is still under development. It is worth noticing that the objectivity is illusive. Often, the difference between subjectivity and objectivity is a matter of an arbitrary decision. For example, an item listed for sale for, let us say, 100,000 monetary units, will be very likely sold for 99,999 of such units if such an offer is made. If so, one may also not resist accepting 99,998 monetary units and so on. Setting a limit (so called, “the bottom line”) is often a highly subjective decision. Scales help in many cases, but a large number of items (questions) is often a discouragement for its use.

It seems that one of the first successful rating scale reduction (RSR) took place in [13]. The 17-item Hamilton Rating Scale for Depression (HAM-D17) was used to derive even a more reduced version (Ham-D7) with seven items. According to [10], “The clinical utility of the HAM-D17 is hampered, in part, by the length of time required to administer the interview and by the lack of inter-rater reliability.”

## Heuristic algorithm

A heuristic is, in essence, a simplified method for solving a problem more quickly when well-established methods fail to find a sound algorithm. Usually, this is achieved by the “good enough is perfect” approach, mentioned in the introduction, as characterization of the heuristic solution. Heuristics are expected to produce a reasonable solution when a time frame and accuracy are a problem. The “good enough” solution for an urgent problem is commonly practiced in computer science. It is usually not the best solution to our problem but it may still be of great value. For example, the traveling salesman problem (TSP), often formulated as “find the shortest possible route to visit each city exactly once and return to the origin city”, cannot be solved for 50 or more cities by verifying all possible combinations since the total number of such combinations would easily exceeds the number of atoms in the entire Universe. Using heuristics, we can solve TSP for millions of cities with the accuracy of a small fraction of 1%. Most heuristics produce results by themselves but many are used in conjunction with optimization algorithms to improve their efficiency (e.g., differential evolution).

In our case, the number of possible combinations for a rating scale with 100 items (which is not uncommon) is a “cosmic number” hence the complete search must be ruled out. Computing the area under the receiver characteristic curve for all items is the basis for our heuristic. Common sense dictates that
the contribution of the individual items to the overall value of the area under the receiver characteristic curve needs to be somehow utilized. We have decided on a stepwise heuristic. Certainly, the results need to be verified and used only if the item reduction is substantial.

3 The package description

Rating scales are used to elicit data about qualitative entities (e.g., research collaboration). This study presents an innovative method for reducing the number of rating scale items without predictability loss. The “area under the receiver operator curve method” (AUC ROC) is used. The presented method has reduced the number of rating scale items (variables) to 28.57% (from 21 to 6) making over 70% of collected data unnecessary.

Results have been verified by two methods of analysis: Graded Response Model (GRM) and Confirmatory Factor Analysis (CFA). GRM revealed that the new method differentiates observations of high and middle scores. CFA proved that the reliability of the rating scale has not deteriorated by the scale item reduction. Both statistical analysis evidenced usefulness of the AUC ROC reduction method.

Rating scales (also called assessment scale) are used to elicit data about quantitative entities. Often, the predictability of rating scales (also called “assessment scales”) could be improved. Rating scales often use values: “1 to 10” and some rating scales may have over 100 items (questions) to rate. Other popular terms for rating scales are: survey and questionnaire, although a questionnaire is a method of data collection while survey may not necessarily be conducted by questionnaires. Some surveys may be conducted by interviews or by analyzing web pages. Rating itself is very popular on the Internet for “Customer Reviews” where five stars (e.g., Amazon.com) are often used instead of ordinal numbers. One may regard such rating as a one item rating scale.

In computer science and mathematical optimization, a heuristic is a technique designed for solving a problem for finding an approximate solution when classic methods fail to find any exact solution. Often, finding such methods is achieved by trading completeness, accuracy, or optimality, for speed.

The main objective of a heuristic is to produce a solution that is good enough to solve our problem. The solution may not be the “best” solution and it may only approximate the solution since the optimal solution may require a prohibitively long time. The traveling salesman problem and virus scanning are probably the most recognized problems where the need for using heuristics is evident. In both cases, the complete search for the optimal search would take thousands of years using the fastest computers built. One of the shortest heuristics may be “22/7” as an approximation of Π constant with two decimal points (3.14), as it is easier to remember and sometimes easier to use.

Herbert A. Simon originally was the proponent of bounded rationality. In practice, it means that human judgments are based on heuristics. He is the only person who received both the Nobel prize and the Turing prize.
Data collected by a rating scale with a fixed number of items (questions) are stored in a table with one decision (in our case, binary) variable. The parametrized classifier is usually created by total score of all items. The outcome of such rating scales is usually compared to external validation provided by assessing professionals (e.g., grant application committees).

Our approach not only reduces the number of items, but also sequences them according to the contribution to predictability. It is based on the Receiver Operator Characteristic (ROC), which gives individual scores for all examined items. The term “receiver operating characteristic” (ROC), or “ROC curve” was coined for a graphical plot illustrating the performance of radar operators (hence “operating”). A binary classifier represented absence or presence of an enemy aircraft. It was used to plot the fraction of true positives out of the total actual positives (TPR = true positive rate) vs. the fraction of false positives out of the total actual negatives (FPR = false positive rate). Positive instances (P) and negative instances (N) for some condition are computed and stored as four outcomes of a 2 contingency table or confusion matrix, as follows:

| True Positives | False Positives |
|----------------|-----------------|
| False Negative | True Negative   |

Each patient either has or does not have the disorder. The screening outcome can be positive (classifying a patient as having the disorder) or negative (classifying the patient as not having the disorder). The screening results for each patient may or may not match the subject’s actual status.

In means that in the medical terminology we may have:

- TP = true positive: patient is correctly identified as having the disorder,
- FP = false positive: patient is incorrectly identified as having the disorder,
- TN = true negative: patient with no disorder is correctly identified as not having the disorder,
- FN = false negative: patient with the disorder is incorrectly identified as not having the disorder.

In simple terms, positive = identified and negative = rejected hence:

True positive = correctly identified examples
False positive = incorrectly identified examples
True negative = correctly rejected examples
False negative = incorrectly rejected examples

In assessment and evaluation research, the ROC curve is a representation of a “separator” (or decision) variable. The decision variable is usually: “has a property” or “does not have a property” or has some condition to meet (pass/fail).
The frequencies of positive and negative cases of the diagnostic test vary for the “cut-off” value for the positivity. By changing the “cut-off” value from 0 (all negatives) to a maximum value (all positives), we obtain the ROC by plotting TPR (true positive rate also called sensitivity) versus FPR (false positive also called specificity) across varying cut-offs, which generate a curve in the unit square called an ROC curve.

According to [2], the area under the curve (the AUC or AUROC) is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one (assuming the ‘positive’ rank higher than ‘negative’).

This can be seen as follows: the area under the curve is given by (the integral boundaries are reversed as large T has a lower value on the x-axis)

\[
A = \int_{-\infty}^{\infty} y(T)\xi'(T)dT = \\
\int_{-\infty}^{\infty} TPR(T)FPR'(T)dT = \\
\int_{-\infty}^{\infty} TPR(T)P_0(T)dT = \langle TPR \rangle
\]

The angular brackets denote average from the distribution of negative samples. AUC is closely related to the Mann-Whitney U test which tests whether positives are ranked higher than negatives. It is also equivalent to the Wilcoxon test of ranks.

ROC method is implemented by many R packages including: pROC [11] and ROCR [12]. There is also one interesting web application easyROC [3] giving possibility to compute the confusion matrix and plot the curve on-line. The RatingScaleReduction package expands this analysis to carry out the procedure of rating scale reduction.

A package for preprocessing “messy” data into a form is easily analyzed within R is presented in [8]. In [15], the new R package sbtools enables users direct access to the advanced online data functionality provided by ScienceBase, the U.S. Geological Survey’s online scientific data storage platform. It can be used for harvesting other data sets.

4 Rating scale stepwise reduction procedure

The procedure follows the heuristic algorithm represented by Fig. 2. Technically, it is an algorithm since the flowchart, represented by Fig. 2, shows the finite number of steps. It is, however, a heuristic algorithms since the optimality of the presented approach cannot be guaranteed (as pointed out in Section 2). However, the common sense dictates to select the “best” attribute and keep adding to it the next “best” attribute where the “best” has the meaning of the area under the curve (AUC) value since it is the universally accepted criterion.
for classifiers (in statistical classification and machine learning). A rating scale total is a classifier. The classification in this study is regarded as an instance of supervised learning. Briefly, it requires a training set of correctly identified examples (observations) with the external evaluation. In our case, a trained professional is needed to determine if a subject (a screened psychiatric patient) had a mental disorder or not). An algorithm that implements a concrete classification is called as a classifier. The most common way of doing it by a rating scale is using the total of all items. Some of them may be negative (e.g., in the Oxford Happiness Questionnaire, see [4]).

![Figure 1: Rating scale stepwise reduction heuristic algorithm](image)

In the **RatingScaleReduction**, the implemented algorithm (when reduced to its minimum) uses a loop for all attributes (with the class excluded) to compute AUC. Subsequently, attributes are sorted in the ascending order by AUC. The attribute with the largest AUC is added to a subset of all attributes (evidently, it cannot be empty since it is supposed to be the minimum subset \( S \) of all attributes with the maximum AUC). We continue adding the next in line (according to AUC) attribute to the subset \( S \) checking AUC. If it decreases, we stop the procedure. There are a lot of checking (e.g., if the dataset is not empty or full of replications) involved. These steps are implemented in `startAuc`, `totalAuc` oraz `rsr` functions of the package.

Before running the RSR procedure the data set should be analysed to detect replicated examples and so-called ”gray” examples. One example may be replicated \( m \) times, where \( m \) is the total number of examples, so that there are no
other examples. Such situation would deviate computations and should be early detected. Ideally, no example should be replicated but if the replication rate is small, we can proceed to computing AUC. There is no generally acceptable “golden rule” for the level or replication rate. Moreover the data may contain gray examples which should also be detected, gray example is an example for which there are another examples in the data set having identical values on all attributes but different decision. This analysis of data set can be carry out using functions: diffExamples and grayExamplesN, grayExamples.

The important problem after the scale reduction by RSR procedure is to check for the possible inclusion of the next attribute in the reduced rating scale by maximizing AUC of all included items. In a highly unlikely scenario, all attributes will be included in the reduced (that is, non reduced) set of items. The reduced rating scale of one attribute may be created if there is an identifying attribute. To test the inclusion the function CheckAttr4Inclusion is available in the package.

5 RatingScaleReduction: overview of the package functions

The RatingScaleReduction package implements the above-stated stepwise procedure using two functions of the pROC package: roc and roc.test. It works on the data as the matrix or data.frame containing columns of attributes and one decision column with two categories, e.g. (0,1). The rows in data.frame represents examples in the sample. All attributes and the decision vector must be numeric. There are to groups of functions available in the package. Because the essence of the procedure is to set the attributes in the correct order good practice is to enter their name using e.g. colnames in R. The first group are dedicated to carry out the RSR procedure:

1. startAuc(attribute, D) – compute the AUC values of every single attribute in the rating scale.

2. totalAuc(attribute, D, plotT=FALSE) – sort AUC values in the ascending order and compute AUCs of running total of first k attributes, k = 1, ..., n, where n is the number of attributes. Setting the argument plotT as TRUE the plot of new AUC values is created. The horizontal line marks the max new AUC.

3. rsr(attribute, D, plotRSR=FALSE) – the main function of the package reducing the rating scale according the procedure illustrated by Fig. 1. Setting the argument plotRSR as TRUE the plot of ROC curve of the sum of attributes in reduced rating scale is created.

Additionally, the package provides second group of functions to support the reduction procedure:
1. CheckAttr4Inclusion(attribute, D) – carry out a statistical tests for a difference in AUC of two correlated ROC curves: ROC1 of the sum of attributes from reduced rating scale and ROC2 of this sum plus the next ordered attribute. The function uses The function roc.test from the pROC is used and all implemented tests are available, in particular delong and bootstrap.

2. diffExamples(attribute) – search replicated examples in the data and return the number of different examples and the number of duplicates.

3. grayExamples(attribute, D) – produce the list of pairs of examples having identical values on all attributes. The decision value and attributes are produced for every pair in the data set, so the list clearly shows all gray examples.

4. grayExamplesN(attribute, D, N) – produce a list of examples and the numbers of examples $j$ in the data set having identical values on all attributes for the given example $N$.

5.1 Data sets used for verification and working with the package

The examples presents the capabilities of the RatingScaleReduction package. The full code is available for download from https://github.com/woali/RatingScaleReduction/example_Rj.r.

5.2 The first demonstration example: rating scale reduction

We consider the data BDI data set used in [7]. It is a rating scale for depression BDI (Beck Depression Inventory) with 21 attributes in our relational database. The goal in this example is to show how to reduce the BDI rating scale in the use of three main functions of the package. The data.frame we work on contains 21 columns with attributes and one additional column as a decision (reality). The sample is represented with 561 examples (instances).

We start with analysis of the AUC of all 21 individual attributes of BDI scale by the use of the function totalAuc setting the argument plotT as TRUE.

> tauc.bdi <- totalAuc(attribute, D, plotT=TRUE)

> tauc.bdi$summary

| attribute | AUC one variable | AUC running total |
|-----------|-----------------|-------------------|
| BDI_1     | 0.7250092       | 0.7250092         |
| BDI_14    | 0.7074013       | 0.7765412         |
| BDI_7     | 0.7014889       | 0.7945490         |
| BDI_9     | 0.7004614       | 0.8095300         |
| BDI_10    | 0.6972253       | 0.8131352         |
| Attribute | AUC          | Running Total |
|-----------|--------------|---------------|
| BDI_15    | 0.6920635    | 0.8221689     |
| BDI_17    | 0.6742833    | 0.8205426     |
| BDI_8     | 0.6679833    | 0.8192322     |
| BDI_20    | 0.6669989    | 0.8198782     |
| BDI_5     | 0.6584779    | 0.8211333     |
| BDI_3     | 0.6556663    | 0.8210840     |
| BDI_4     | 0.6511874    | 0.8211394     |
| BDI_13    | 0.6489172    | 0.8210779     |
| BDI_12    | 0.6367909    | 0.8195583     |
| BDI_2     | 0.6312046    | 0.8186908     |
| BDI_19    | 0.6292851    | 0.8181125     |
| BDI_18    | 0.6100283    | 0.8160699     |
| BDI_6     | 0.6100037    | 0.8138489     |
| BDI_16    | 0.6059370    | 0.8116525     |
| BDI_11    | 0.5973422    | 0.8110680     |
| BDI_21    | 0.5874677    | 0.8117263     |

The *R* output shows the `tauc.bdi$summary` AUC of every single attribute in the second column, sorted in the ascending order. The running total of AUCs is in the third column. The initially selected variable (BDI_1) for the first row is the attribute with the largest AUC. Subsequently, we add to it the variable with the largest AUC of the remaining attributes. The process continues while the last attribute of the scale is added.

Values in the running total (from the top to the current variable) are checked for growing. Evidently, the value 0.725 in the first row is the same for the running total as for the single variable (BDI_1). However, the value in the third row (0.795) is not for variable 7 but the total of variables BDI_1, BDI_14, and BDI_7. In particular, the value (0.812) in the last row is for the total of all variables. Their line plot can be easily created by setting the `totalAuc` parameter `plotT` as `TRUE`. The plot for our BDI scale is illustrated by Fig. 2. The curve peak is for variable #6 which is 15.
Figure 2: A stepwise AUC reduction method (example)

Printing the value `tauc.bdi$item` we receive the attribute labels in an ascending order.

```r
> tauc.bdi$item

"BDI_1" "BDI_14" "BDI_7" "BDI_9" "BDI_10" "BDI_15"
"BDI_17" "BDI_8" "BDI_20"
"BDI_5" "BDI_3" "BDI_4" "BDI_13" "BDI_12" "BDI_2"
"BDI_19" "BDI_18" "BDI_6"
"BDI_16" "BDI_11" "BDI_21"
```

As illustrated by Fig. 2, the value of AUC of the selected subset of attributes is increasing by adding the first six attributes labeled DBI_1, DBI_14, DBI_7, DBI_9, DBI_10, and DBI_15. There is a slight decline by adding the variable DBI_16. For this reason, the reduction procedure is terminated after the first six attributes are added. The function `rsr` reduce the scale automatically assuming the truncation point as the attribute that first reaches the maximum AUC. AUC is a real value between 0 and 1. It is 0.5 for random data but hardly ever reaches 1 since, in reality, there are always “gray examples” in sizable data.
> rsr.bdi <- rsr(attribute, D, plotRSR=TRUE)
The criteria: Stop first MAX AUC
> rsr.bdi$rsr.auc

[1] 0.7250092 0.7765412 0.7945490 0.8095300 0.8131352 0.8221669

$rsr.label
[1] "BDI_1" "BDI_14" "BDI_7" "BDI_9" "BDI_10" "BDI_15"

$summary
AUC one variable AUC running total
BDI_1  0.7250092 0.7250092
BDI_14 0.7074013 0.7765412
BDI_7  0.7014889 0.7945490
BDI_9  0.7004614 0.8095300
BDI_10 0.6972253 0.8131352
BDI_15 0.6920635 0.8221669

Setting the rsr parameter plotRSR as TRUE the function generate plot illustrated by Fig. 3.

We assume that by selecting the “best” attribute in a loop, we are able to reduce the number of attributes for the best preventiveness. In our case, having the largest AUC is the “best” criterion. Adding the next “best” attribute to the selected attribute from the subset of the remaining attributes until AUC of all selected attributes decreases is the main idea of our heuristic. So far, each and every rating scale has been reduced.

5.3 Second illustrative example: using the entire RSR procedure

Let us consider the data set Hepatitis analyzed in [9] and located at http://archive.ics.uci.edu/ml/. It has 20 attributes and 312 examples used in [1]. The goal is to illustrate how our entire RSR procedure may be used. To reduce Hepatitis data set, we use the following attributes hepato:

> names(att[, -d3])
"time" "status" "trt" "age" "sex"
"ascites" "spiders"
"edema" "bili" "chol" "albumin" "copper"
"alk.phos" "ast"
"trig" "platelet" "protime" "stage"
Figure 3: AUC of $BDI_1 + BDI_{14} + BDI_7 + BDI_9 + BDI_{10} + BDI_{15}$, for DBI scale
The following steps are needed:

- detect duplicates and gray example in data,
- reduce rating scale,
- check possible inclusion.

By executing this code:

```r
> diffExamples(att[, -d3])
$total.examples
[1] 276

$dif.examples
[1] 276

$dup.examples
[1] 0
```

we detect no duplicate in data set.

Subsequently, we analyze the data set to detect gray examples for \((status, sex, spiders, stage)\) attributes. Gray examples are located by the use of `data.frame` and a function called \(gray.ex\).

Working on a full data set is a time-consuming process since it requires all pair comparisons to be analyzed. A short optimization procedure is used for attributes in two categories. The code below shows how to list by gray examples by comparing the subset of attributes \((status, sex, spiders, stage)\) using the function `grayExamplesN`. The key issue is to properly modify the data.
```
> gray.ex <-c()
> df1 <-unique(data.frame(hepato, status, sex, spiders, stage))

> for (i in 1:nrow(df1)){
> ex <-grayExamplesN(df1[,2:ncol(df1)], df1[,1], i)$examp
> if (nrow(ex)>1){
> gray.ex <-rbind(gray.ex, ex[1,])}
> }
> colnames(gray.ex) <-names(df1)
> gray.ex

   hepato status sex spiders stage
 1      1     1   1     1     4
 2      1     0   1     1     3
 3      0     0   2     0     4
 6      1     0   1     0     3
 7      0     0   1     0     3
 8      0     0   1     1     2
 9      0     0   1     1     4
15     1     0   1     0     4
22     1     0   2     0     2
23     0     0   1     0     2
29     1     0   1     0     2
42     0     0   2     0     3
48     1     0   1     1     2
53     0     0   1     0     4
54     0     0   1     1     3
57     1     0   2     0     3
70     1     0   2     0     4
80     0     0   2     0     2
93     1     1   1     0     3
98     0     1   1     0     3
111    1     1   1     0     4
139    0     1   1     0     2
253    1     1   1     0     2
256    0     1   1     0     4
```

The R print the list of gray examples. It means that every example from list corresponds to (not listed) examples having identical attributes, but different decision.

To reduce this rating scale, we execute the functions: totalAuc and rsr:

```
> totalAuc(att[-d3], hepato, plotT=TRUE)
```

14
After reduction, the scale contains two attributes: *stage*, *bili*. The plot in Fig. 4 illustrates AUC of the reduced rating scale and the proper ROC curve.

![Graphs illustrating AUC and ROC curves](image)

**Figure 4:** Left panel: AUC of individual attributes of *Hepatitis* data set; Right panel: AUC of *stage+bili* for *hepato* scale

Finally, we examine the scale for possible inclusion using deLong and bootstrap tests as in the function *roc.test* from the *pROC*.
ROC1 <- CheckAttr4Inclusion(att[,,-d3], hepato, 
   + method=c("delong"), alternative=c("two.side"))

ROC2 <- CheckAttr4Inclusion(att[,,-d3], hepato, 
   + method=c("bootstrap"), alternative=c("two.side"))

summ
   Z statistics  p-value
DeLong      1.986207  0.04701039
bootstrap   1.945672  0.05169413

The p-value = 0.04701 shows that according to deLong test the null hypothesis “H0: true difference in AUC is equal to 0" should not be rejected in favor of the alternative. Fig. 5 illustrates two tested ROC curves.

6 The potential application targets

Rating scales are by far more important contributors to science that we can address them by this study. Most examinations for granting scientific degrees are rating scales of various shapes and forms. Simplifying them (or reducing in size) is needed since we are subjected to more and more examination for so needed certifications.

In bioinformatics, reporting trade-off in sensitivity and specificity, by using a Receiver Operating Characteristic (ROC) curve, is becoming a common practice. ROC plot has the sensitivity on the y axis, against the false discovery rate (1-specificity) on the x axis. ROC curve plot provides a visual tool to determine the boundary limit (or the separation threshold) of a subset (or a combination) of scale items for the potentially optimal combination of sensitivity and specificity. The area under the curve (AUC) of the ROC curve indicates the overall accuracy and the separation performance of the rating scale. It can be readily used to compare different item subsets. As a rule of thumb, the fewer the scale items used to maximize the AUC of the ROC curve, the better.

World Health Organization estimates are included behind selected rating scales for mental disorder. Rating scales are of considerable importance for psychiatry where they are predominately used for screening patients for mental disorders such as:

- depression (see [7]) which affects 60 million people worldwide according to [14],
- bipolar affective disorder (60 million people),
- dementia and cognitive impairment (47.5 million people)
Figure 5: ROC curves for the original and reduced rating scales for the Hepatitis data set

- schizophrenia (21 million people),
- autism and autism spectrum disorder (e.g., [5])
- mania and bipolar disorder,
- addiction,
- personality and personality disorders,
- anxiety,
- ADHD;

and many other disorders.
Usually, there are many scales for each mental disorder. The most important for screening are global scales. Reducing these global rating scales makes they more usable as indicated in [7]. World Health Organization Media Centre reports that “depression and anxiety disorders cost the global economy US $1 trillion each year” and it is no longer a local problem.

7 Conclusions

The presented method has reduced the number of the rating scale items (variables) to 28.57% from the original number of items (from 21 to 6). It means that over 70% of collected data was unnecessary. It is not only an essential budgetary saving, as the data collection is usually expensive and may easily go into hundreds of thousands of dollars, but the excessive data collection may contribute to the data collection error increase. The more data are collected, the more errors may occur since a lack of concentration and boredom are realistic factors.

By using the proposed AUC ROC reduction method, the predictability has increased by approximately 0.5%. It may seem insignificant. However, for a large population, it is of considerable importance. In fact, [14] states that: “Taken together, mental, neurological and substance use disorders exact a high toll, accounting for 13% of the total global burden.”

The proposed use of AUC for reducing the number of rating scale items, as a criterion, is innovative and applicable to practically all rating scales. System R code is posted on the Internet (RatingScaleReduction) for the general use as a R package. Certainly, more validation cases would be helpful and the assistance will be provided to anyone who wishes to try this method using his/her data.

Future plans include using the presented method for financial data analyzed but the real aim our collaborative effort is towards psychiatric scales. The reduced scales can be further enhanced by the method described in [5] and [6].

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