HS Steyn

and

Johann L van der Walt

North-West University

Setting a cut-off score for a placement test at tertiary level

Abstract

In many placement tests, cut-off scores are determined once results become available. Various methods have been used to determine these scores. They are often also established arbitrarily by, for example, taking teaching capacity into account. This article illustrates how a cut-off point can be established my means of an objective statistical method. A test of Academic Literacy, TAG, is used to illustrate the method, which is based on historical data, an adjustment of scores to conform to the same norm, and a Receiver-Operating Characteristic (ROC) curve to generate a sensitivity/specificity report. An optimal cut-off score is then fixed. We suggest that a statistical procedure such as the ROC method can play a role in setting standards and cut-off scores in a responsible and accountable manner.

Keywords: academic literacy test; validation; cut-off score; test objectivity, test fairness

ISSN 0259-9570. http://dx.doi.org/10.4314/jlt.v51i2.5

1. Introduction

Cut-off scores are widely used in testing and assessment. A cut score can be defined as a "reference point, usually numerical, derived by judgement and used to divide a set of data into two or more classifications" (Cohen, Swerdlik & Sturman, 2013: 7). Some inferences can be made on the basis of this score. Cut-off scores are employed in a variety of situations, ranging from professional and academic tests to practical situations such as a test for a driving licence. They are employed to ensure that candidates have an appropriate minimum level of knowledge and skill for a particular purpose. Any pass or fail score on a summative, an admission or a placement test in an academic environment implies that there is a cut-off point. These points are often determined in advance, such as a minimum percentage of 50 per cent in an examination, or a specific number or band level achieved in a test.

In many cases, however, cut-off scores are only determined once test results become available. This often happens in the case of placement tests, where students are placed in an appropriate courses designed to address their specific needs. Cut-off scores always involve some kind of judgement, but this should always be done with the best interests of students and stakeholders involved in mind. The problem is that cut-off scores are often established arbitrarily (Messner & Liu, 1995: 39), which may result in students not being placed in a course they actually require. Determining cut-off scores is a difficult issue, and there often is no ideal solution in practice (cf. Feast 2002: 83), but this does not mean that the rationale for setting such scores should not be theoretically sound.

The process of establishing cut-off scores amounts to standard setting, i.e. a performance standard that indicates the minimally adequate level of performance for a given purpose. Cohen et al. (2013: 235) point out that academics and statisticians "have spent countless hours questioning, debating, and ... agonizing about various aspects of cut scores". The question we would like to address in this article is the following: Is there an objective method by which a cut-off score can be determined? We illustrate our argument with reference to a widely-used test of Academic Literacy, the *Toets van Akademiese Geletterdheid* (TAG), but the method we propose can be used in any situation where a cut-off score is required and where there is a criterion such as pass/fail in a first-year university course. We suggest that this method can result in a fair and consistent way of determining a cut-off score.

2. Types of cut-off scores

Cohen et al. (2013: 233) distinguish among norm referenced, fixed and multiple cut scores. A norm-referenced cut score, also referred to as a relative cut score, makes use of a specific reference point that is determined with reference to the performance of a class as a whole. A teacher may decide, for instance, that only the top 10% will be awarded an A symbol. A fixed cut score takes a minimum level of proficiency into account in setting a cut score. It is thus criterion-referenced – the only criterion is whether a candidate can perform a specific task competently or not (e.g. driving a car). Cohen et al. (2013: 233) differentiate between multiple cut scores and multiple hurdles. Multiple cut scores involve two or more cut scores based on performance on one predictor. Grading in schools is a typical example of this. Grades ranging from 1 to 7 are allocated using six cut scores. Multiple hurdle scores involve several "hurdles" that a candidate needs to overcome, i.e. a cut score is employed for each predictor. A final decision is made only after a series of performances (e.g. in a beauty pageant where aspects such as talent, responses to interviews and so on are all taken into account).

3. Methods for determining a cut-off score

Cut-off scores are often arrived at very informally and are thus somewhat arbitrary. There are also a number of formal methods, but it is notable that no one method has won universal acceptance (cf. Cohen et al., 2013: 236). Methods often employed include the following:

3.1. The known groups method

Cohen et al. (2013: 236) state that the known groups method entails "collection of data on the predictor of interest from groups known to possess, and *not* to possess, a trait, attribute, or ability of interest". The data are analysed and a cut-off score that distinguishes between the two groups is established.

3.2. IRT-based methods

Cut-off scores are usually based on classical test theory where such scores are based on the performance of candidates on all items in a test (cf. Van der Walt & Steyn, 2008: 195). Some proportion of items must be answered correctly in order to pass. In Item Response Theory (IRT), each test item represents a particular level of difficulty, which is determined by expert judgement. The level of difficulty serves as the cut score – the candidate must answer the items that are deemed above some minimum level of difficulty correctly in order to pass. IRT methods include the item mapping method, which involves arranging items of equivalent difficulty together in a histogram. This method also involves expert judgement. Assessors are trained in assessing the necessary skills that a learner should possess in order to pass a test. The bookmark method also depends on the judgements of experts. Assessors are given a book of test items arranged in order of difficulty and they place a bookmark between two items that are thought to distinguish between candidates that possess the necessary skills or abilities and those that do not.

Other methods for setting cut-off scores include the Angoff method for setting fixed cut scores (Angoff, 1971), the method of predictive yield for personnel selection (Thorndike, 1949), and using discriminant analysis (Cohen et al., 2013: 238).

These methods depend on subjective criteria or expert judgement. The question that arises is whether there is a more objective way in which a cut-off score can be determined than the methods currently used. Such a method has to be based on historical data of total scores of participants and need not be part of the standard-setting process where individual items are involved.

4. TAG as a case study

The TAG test is usually administered to first-year students at university, and the results are used to place them in an appropriate Academic Literacy course. It is then expected that students who take such a course would at least pass their first-year at university. Students below the cut-off score must typically take an additional course in Academic Literacy. This not only means an extra subject in their curriculum, but also involves an extra financial burden. It is therefore in the interests of students that cut-off scores are established in an objective manner.

5. Arguments for setting TAG cut-off scores

In our experience, two arguments are often advanced for determining TAG cut-off points:

- The average mark for a group is calculated, and the cut-off point is established at, say, 10% below this. (Ten per cent may be the percentage that has historically been used, but it remains an arbitrary number.)
- The capacity to teach the number of students below a specific cut-off point is taken into account, and this determines the point. (This does not take the needs of students into account and is also arbitrary.)
- These methods tend to be rather informal. We acknowledge that practical issues may often play a role in these decisions, but argue that an independent measure based on a scientific rationale should always be the point of departure in any such decision. Such an objective measure ultimately ensures the fairness of the test, enabling test administrators to treat candidates in a consistent manner.

6. Determining a cut-off score

The suitability of the particular test should be spelled out before any cut-off point is established. This should include aspects such as the purpose of the test, its format, its reliability, its validity and administration. The purpose of TAG is to determine first-year students' skills in Academic Literacy and to place them in appropriate module. It consists of about 80 multiple choice items. As cut-off scores involve standard setting, the appropriateness, validity and reliability of the test should ideally be supported by empirical data. In the case of TAG, a number of studies have been conducted that testify to its appropriateness, reliability and validity. The test has proved to be an appropriate one for assessing academic literacy skills, as it is based on a blueprint of what the construct of Academic Literacy entails (Blanton, 1994; Van Dyk & Weideman, 2004) and samples typical academic tasks at university (Van der Walt & Steyn, 2014). Reliability figures for TAG have consistently been above 0.80, the minimum Weir (2005: 29) sets as criterion for a language test. A validation study by Van der Walt and Steyn (2007) concludes that the test can be regarded as a valid one: correlation coefficients between the various subsections of the test and between each section and the whole test are as good as can be expected from a rich construct as Academic Literacy, and there is a good fit between test items and candidate ability. The test can therefore be considered a valid and fair one. Van Dyk (2010) performed a further validation study of the test and arrived at similar results.

Cut-off scores are either performance-related or group-related. Performance-related scores are established by making a judgement about the test scores, while group-related scores are set relative to the performance of candidates in a reference group (Public Service Commission of Canada 2011). The approach we adopt in this article is the group-related one, as we use the performance of students on *anchor* (historical) results in order to compute a cut-off point by means of statistical methods.

Any cut-off score involves two aspects of statistical measures, viz. sensitivity and specificity. Sensitivity (also called the recall rate) involves the number of true positives. Students who score above a cut-off point on a test should therefore perform adequately in their first year at university[1]. This figure should ideally be high. Sensitivity is here defined as the proportion (or percentage) of students above a cut-off point who pass their first year.

Specificity, on the other hand, involves the number of true negatives. These are the students who scored below the cut-off point; in this case they are predicted not to pass the first year. This figure should ideally also be high. Specificity is here defined as the proportion (or percentage) of students below a cut-off point who fail their first year.

The results of an ideal test would deliver results with 100% sensitivity and 100% specificity. In practice, of course, it is impossible to achieve this.

In determining a cut-off score, one needs to control both sensitivity and specificity. One way of doing this is by calculating the sum of the sensitivity and specificity for each possible cut-off point using receiver-operating characteristic (ROC) analysis (cf.

1 In this regard, we would like to point out the following: The aim of TAG is to identify students who need to take an additional course in Academic Literacy in addition to the compulsory one in order to assist them in passing their first year; we could have used the marks for the Academic Literacy courses in our analysis, but they were only available for the past few years, and a ROC analysis based on these results gave similar results as the first year pass/fail; TAG is only a case study in order to illustrate our method.;

Krzanowski & Hand, 2009). The cut-off point resulting in the maximum sum of sensitivity and specificity can then be viewed as the optimum one. But the question always is: high sensitivity or high specificity? This question has serious implications, as it implies that students can be misclassified and thus treated unfairly. Low sensitivity means many students who pass their first year were wrongly classified below the cut-off point. Also, low specificity results in misclassification of many students who fail their first year to be above the cut-off point.

7. A cut-off score for TAG

The complete available results of the TAG tests for 2005 to 2014 were obtained for first-year students at a certain campus of a South African university. Statistica (StatSoft Inc., 2016) was used to obtain the descriptive statistics per year and for the whole period 2005 – 2014 (displayed in Table 1).

8. Table 1

Table 1: *All available TAG scores (in %) – descriptive statistics*

Year	n	Mean	Standard deviation	Median	Min	Max	Skew-ness	Kurtosis
2005	2521	62.56	14.82	63	13	98	-0.16	-0.46
2006	2650	54.07	15.23	53	13	92	0.09	-0.50
2007	2707	51.14	15.56	50	5	94	0.21	-0.41
2008	2711	48.05	14.60	48	4	93	0.14	-0.27
2009	2921	53.18	13.35	53	13	92	0.01	-0.32
2010	3314	56.30	15.93	57	7	98	-0.33	-0.10
2011	3125	47.03	12.96	46	8	85	0.23	-0.34
2012	3096	42.84	12.17	42	1	84	0.33	0.04
2013	3108	44.65	11.69	44	2	84	0.23	0.09
2014	3316	54.69	14.37	54	1	95	-0.14	0.26
2005-2014	29469	51.28	15.16	51	1	98	0.16	-0.32

For each student who wrote the TAG test, the following academic records were obtained, where available:

- mean mark for all subjects in the first year;
- percentage of subjects passed in the first year;
- whether or not the student passed the first year.

Table 2 gives the descriptive statistics of the TAG scores for the students for which the academic information was available – a smaller group than that of Table 1.

Table 2: TAG scores – descriptive statistics for students with academic information

Year	n	Mean	Standard deviation	Median	Min	Max	Skew-ness	Kurtosis
2005	2351	62.67	14.72	63	13	98	-0.15	-0.46
2006	2069	54.30	15.12	54	13	92	0.05	-0.52
2007	2116	51.39	15.61	51	14	94	0.21	-0.42
2008	2109	47.75	14.14	47	4	91	0.10	-0.36
2009	2284	53.62	13.18	54	16	92	-0.01	-0.37
2010	2411	57.01	15.38	58	11	98	-0.30	-0.12
2011	2254	47.48	12.88	47	8	84	0.20	-0.33
2012	2086	43.00	12.26	42	9	84	0.35	-0.04
2013	2979	44.80	11.63	44	2	84	0.25	0.08
2014	2481	55.01	14.06	55	1	94	-0.03	-0.03
2005-2014	23140	51.67	15.05	51	1	98	0.17	-0.36

9. Adjusting the TAG scores

The next step was to ensure that the test results adhered to a uniform norm. To ensure this, the marks had to be adjusted to conform to the norm or standard based on historical data for test results (e.g. three or more years). Van der Walt and Steyn (2016) propose a formula with which this can be done. To adjust the test scores (x) of any group (with mean $\bar{x}$ and standard deviation (SD) of S) to an adjusted scores y, so that they have the same mean ($\bar{x}_S$) and SD (S_s) as the standard, the formula is as follows:

$$y = (S_s/S)\,(x - \bar{x}) + \bar{x}_S$$

Using this method, we adjusted the TAG scores for each year to have the same norm. The mean and standard deviation of the scores of all the students from 2005 to 2014 with available academic records were used to serve as the norm, viz. 51.67 and 15.05 respectively (see Table 2). For example, scores for 2014 were adjusted by using the formula:

Adjusted score = (**15.05/14.06) x** (score - **55.01**) + **51.67**

The remaining years' scores were adjusted in the same way.

Table 3 displays the Pearson correlations between the mean marks and percentage of subjects passed with the raw TAG scores and their adjusted counterparts. While these correlations are small to medium (cf. Cohen, 1988), those with the adjusted scores are somewhat larger.

Table 3: *Correlations between academic measures and TAG scores for all students 2005 to 2014*

	TAG scores	Adjusted TAG scores
Mean academic marks	0.27	0.31
Percentage subjects passed	0.20	0.24

10. The ROC curve (Krzanowski & Hand, 2009)

The next step was to consider the populations of the students who passed (P) and failed

(F) their first year. For each cut-off point t in the adjusted scores of the TAG test, we can construct a 2x2 table of proportions (Table 4).

Table 4: *Proportions in populations when cut-off point is t*

TAG test (adjusted scores)	P	F
Above and equal to cut-off *t*	tp(t)	fn(t)
Below cut-off *t*	fp(t)	tn(t)

The proportion of true positives when t is the cut-off point is denoted by tp(t), i.e. the sensitivity is at t. The false negatives are denoted by fn(t), i.e. 1 – specificity. Likewise, fp(t) and tn(t) are the proportions of false positives and true negatives at cut-off t. The values of tp(t) can be plotted on a graph against fn(t) for the sequence of all possible cut-off values t. The resulting plot is known as *Receiver-Operating Characteristic* curve, or ROC curve. This curve creates a sensitivity/specificity report. Figure 1 displays the ROC curve for TAG.

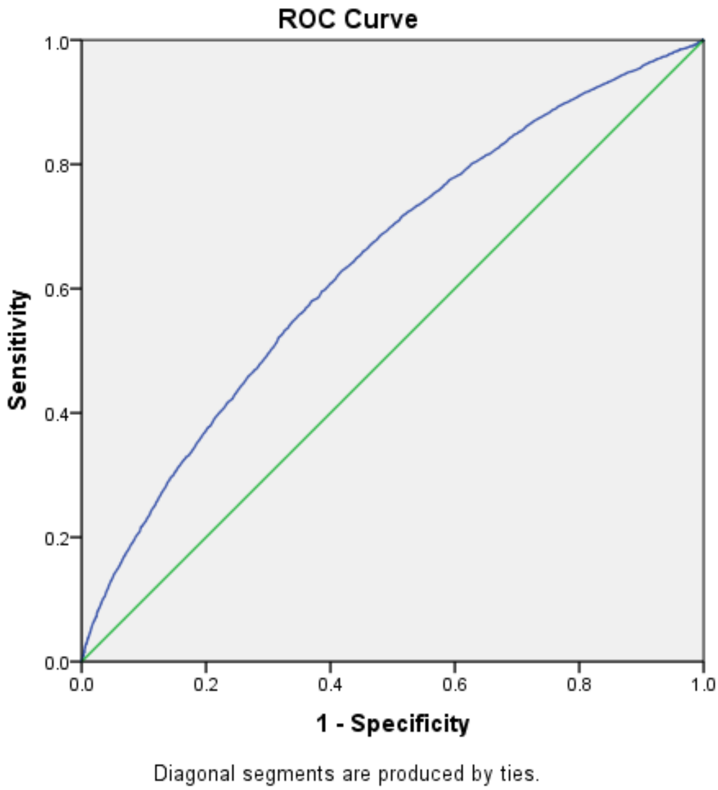

Figure 1*: ROC-curve for adjusted TAG scores of students 2005 - 2014*

11. Area Under the ROC curve (AUC)

The following results of a ROC analysis on the adjusted TAG scores of the 2005 to 2014 students were obtained, using SPSS (SPSS Inc., 2016):

If one considers the ROC-curve in Figure 1, it is clear that the area under the ROC curve lies between 0,5 and 1 in the case of the curved line (for the adjusted TAG scores), and at exactly 0,5 in the case of the diagonal line. This “Area Under the Curve” is denoted by AUC and is used as *a measure of the ability to discriminate between the distributions* of the adjusted TAG scores of the P and F populations. Larger values of AUC indicate a greater discriminatory ability. The AUC value 0,5 indicates that one is unable to distinguish between P and F.

For the adjusted scores of TAG the AUC is 0.642, which suggests a substantial discrimination between P and F students.

12. Choice of the optimal cut-off point

The ROC curve shows, for a sequence of cut-off values (*t*), the relationship between the proportion of true positives (*tp*) versus the proportion of false negatives (*fn*). The question is now whether or not there is an optimal value for t. In this regard we can consider the Youden Index (YI):

$$\mathrm{YI} = \max_t \left(tp(t) - fn(t) \right)$$

$$= \max_t \left(tp(t) + tn(t) - 1 \right)$$

i.e. YI is the maximum value of the sum of the sensitivity (tp) and Specificity (tn) minus 1, over all possible values of t. This index, like the AUC, is a descriptive measure of the

ROC curve. The optimal value of the cut-off point t is thus obtained when the sum of the sensitivity and specificity is at its maximum. Table 5 gives a selection of the possible cut-off values for the adjusted TAG-scores for all the students from 2005 – 2014, together with the values of tp(t), tn(t) and their sum.

Table 5: *A selection of the possible cut-off values for the adjusted TAG scores for all the students from 2005 – 2014 with sensitivities, specificities and their sum.*

t: Positive if greater than or equal to[a]	tp(t): Sensitivity	fp(t): 1-Specificity	tn(t): Specificity	tp(t) + tn(t)
1.17	1.000	1.000	0.000	1.000
3.01	1.000	1.000	0.000	1.000
4.83	1.000	1.000	0.000	1.000
5.32	1.000	1.000	0.000	1.000
5.59	1.000	1.000	0.000	1.000
6.13	1.000	.999	0.001	1.000
6.64	1.000	.999	0.001	1.000
6.67	1.000	.999	0.001	1.000
6.97	.999	.999	0.001	1.000

t: Positive if greater than or equal to[a]	tp(t): Sensitivity	fp(t): 1-Specificity	tn(t): Specificity	tp(t) + tn(t)
49.76	.642	.436	0.564	1.206
49.81	.640	.433	0.567	1.207
49.88	.637	.430	0.570	1.207
49.95	.634	.426	0.574	1.208
50.15	.632	.423	0.577	1.209
50.35	**.630**	**.421**	**0.579**	**1.210**
50.41	**.629**	**.418**	**0.582**	**1.210**
50.52	**.626**	**.415**	**0.585**	**1.210**
50.61	.622	.413	0.587	1.209
50.66	.618	.409	0.591	1.208
50.78	.615	.407	0.593	1.207
50.92	.613	.405	0.595	1.208
98.42	.001	0.000	1.000	1.001
99.16	.001	0.000	1.000	1.001
100.29	.000	0.000	1.000	1.000
			Max	1.210

a. The smallest cut-off value is the minimum observed test value minus 1, and the largest cut-off value is the maximum observed test value plus 1. All the other cut-off values are the averages of two consecutive ordered observed test values.

From the table, the values of 50.35, 50.41 and 50.52 correspond to the maximum of the sum of sensitivity and specificity, i.e. 1.21, and therefore the middle one of 50.41 is chosen as cut-off value, as displayed in Table 6:

Table 6: *Optimum cut-off value for Adjusted TAG scores for all students from 2005 – 2014.*

Optimal cut-off point	Sensitivity (% true positives)	Specificity (% true negatives)	% scores below cut-off
50.4	62.9	58.2	49

The sensitivity and specificity for the optimum cut-off value do not differ much and imply that more or less 37% of the students who passed their first year scored under this cut-off value. Likewise, also about 42% of the students who failed their first year scored above this cut-off value. Almost half of the students (49%) would have failed the TAG test with this cut-off value.

Table 7 gives the same information as Table 4 for adjusted TAG scores per year, including the AUC values.

Table 7: *Optimum adjusted cut-off values for adjusted TAG scores for each year.*

Year	Optimal Adjusted Cut-off	Sensitivity (% true positives)	Specificity (% true negatives)	% scores below cut-off	Area under ROC curve (AUC)
2005	54.6	58.6	66.1	59	0.668
2006	50.9	63.6	61.9	51	0.667
2007	50.8	63.2	60.9	46	0.652
2008	63.1	61.4	64.7	55	0.670
2009	43.5	61.7	63.8	46	0.663
2010	33.6	68.2	49.0	38	0.621
2011	50.5	61.7	63.8	46	0.663
2012	46.1	69.1	47.6	40	0.617
2013	50.0	60.0	56.9	47	0.612
2014	52.2	56.2	62.6	56	0.611

Table 8: *Available adjusted actual cut-off values of TAG scores, per year*

Year	Adjusted Actual cut-off	Sensitivity (%true positives)	Specificity (%true negatives)	% scores below cut-off
2010	40.4	44.5	69.8	49
2011	40.0	84.3	32.1	34
2012	41.2	80.9	33.5	27
2013	40.9	80.9	31.7	38
2014	38.3	85.9	24	41

The adjusted actual cut-off values were available for the years 2010 – 2014 and are displayed in Table 8. It is clear that these values as well as the sensitivities, specificities and percentage scores below cut-off differ substantially from those in Table 7. The low specificities for 2011 – 2014 mean that a large percentage of students who failed their first year erroneously passed the TAG test. Also, the low percentages of students who failed the TAG test show that the cut-offs were probably determined by taking teaching capacity of courses into consideration.

13. Conclusion

Our case study indicates that the cut-off points determined for TAG did not reflect success in the first year at university. In setting a cut-off score, a clearly documented process for standard-setting and determining these scores is required, as it allows all stakeholders to see that a systematic approach has been adopted. This process forms part of the evidence that enables one to defend the standard, maintain good practice and illustrate the fairness of the outcomes to all stakeholders.

While there are multiple methods for establishing cut-off scores, none of these has found general acceptance. As a result, teaching capacity – the seats and teachers available – is often used as the only criterion for setting cut-off scores. While this may be a practical solution, it does not take into account the needs of students involved. Cut-off points that are arbitrary, subjective or convenient do no serve the interests of students or stakeholders, and it is clear that an objective standard using a method such as the one illustrated in this article should be used to establish cut-off points. Further research in using ROC is warranted, but we suggest that is a fruitful method that can be applied in academic setting where placement tests are used.

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ABOUT THE AUTHORS

HS (Faans) Steyn

Statistical Consultation Services, Potchefstroom Campus,
North-West University, Potchefstroom

Email: Faans.Steyn@nwu.ac.za

HS (Faans) Steyn is a part-time statistical consultant at North-West University after his retirement. He assists researchers at the university in the planning of their research and doing sound statistical analyses. His research interests include practical statistics to develop new methods of analysing data.

Johann L van der Walt

School of Languages, Potchefstroom Campus, North-West University, Potchefstroom

Email: Johann.VanDerWalt@nwu.ac.za

Johann L van der Walt is an emeritus professor of English at North-West University and currently manages short courses and research in languages at the Potchefstroom campus. His research interests include language testing, second language acquisition and language teaching.