Game time: statistical contests in the classroom

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Abstract

We describe a contest in variable selection which was part of a statistics course for graduate students. In particular, the possibility to create a contest themselves offered an additional challenge for more advanced students. Since working with data is becoming more important in teaching statistics, we greatly encourage other instructors to try the same.

Keywords: teaching statistics, curriculum, holistic training, statistics education, student engagement
1 Introduction

Nowadays, teaching statistics through data application is essential (ASA 2014; Cobb 2015; Horton and Hardin 2015; Wagaman 2016). The ASA guidelines for undergraduate programs in statistical science emphasize the importance for students to have data applications as part of their curriculum (ASA 2014). Similarly, curriculum guidelines for teaching data science also stress that working with data is key (De Veaux et al. 2017). In his discussion on statistics education, Cobb (2015) puts forth five imperatives for successful teaching, of which he considers the most important to be “teaching through research”.

Not only is data work beneficial for students, it’s also an excellent opportunity to make the learning experience interesting and engaging. The idea to motivate students to learn statistics by creating a fun experience is certainly not new (Goldstein 1969; Selkirk 1973), but novel and creative ways of teaching are always well-received by students: Gerds (2016) teaches survival probabilities of the Kaplan-Meier estimate by students performing a ride on the Titanic when it sinks. As students “drown”, individual survival times are generated by measuring how long students can hold their breath, and from the collective data, the Kaplan-Meier estimate is calculated. Wierman (2016) describes how he uses jokes in the classroom to teach statistics, which students find to be very appealing. As data science courses are quickly gaining popularity, Hardin et al. (2015) point out that data applications can be exciting for students and relevant to their interests.

In a graduate course taught at a university, we sought creative ways to engage students to work with data and make the experience challenging and motivating. The overall course goal was to introduce the theoretical basis of concepts and methods in statistical learning alongside with practical exercises on real and simulated datasets. That meant students should not only gain a theoretical background, but also learn how to distinguish between appropriate and inappropriate methods and assess the performance of a method. The theoretical aspects of the course were mainly covered by the textbook *The Elements of Statistical Learning* (Hastie et al. 2009) and the accompanying *An Introduction to Statistical Learning* (James et al. 2013) is an excellent source for the corresponding practical exercises in R. Topics of the course included: regression, classification, model assessment and selection, regularization, random forests, neural nets and unsupervised clustering.
As part of the coursework we implemented several exercises in form of a contest, where teams suggest different methods and compete against each other. For an example of such a contest, see also [Pers et al. (2009)]. This format has become very popular in recent years and there is a growing global community comparing their methods on the platform Kaggle (www.kaggle.com), where participants can compete in predicting and analyzing datasets [Martinez and Walton (2014)]. When analyzing a datasets, it is difficult to know beforehand which technique will be most effective, but the broad spectrum of strategies used in Kaggle competitions has led to many successful models [Taieb and Hyndman (2014); Narayanan et al. (2011); Lloyd (2014)].

The goal of the classroom contests was to motivate students by the competition between teams and rewarding symbolic prizes for the best efforts. In addition, one of the graduate participants suggested to create a classroom competition, related to his research. As part of the coursework he implemented an exercise in variable selection in the form of a contest. This contest strongly contributed to the learning experience, since it allowed students of different levels to gain valuable insights within the same course. In this article we would like to describe the created contest, share our experience and encourage other instructors of statistics courses to integrate games and contests into their course.

2 The contest

The objective of the contest was fairly simple. Given a dataset with 20 independent binary variables $X$ and a binary outcome variable $y$, students had to use selection methods in order to identify variables which had an influence on the outcome. The dataset was simulated and the simulation mechanism was kept from the students. Selections made by contestants were rated based on number of true positive and true negative selections using a scoring rule that was previously announced.

The simulated dataset was inspired by the case-control study by [Orriols et al. (2010)] who investigated the relationship between drug prescriptions (risk factors $X$) and road traffic accidents (outcome $y$) in a large cohort of about 70,000 French drivers between 2005 and 2008. Students were given a presentation on the real dataset to learn about the background and context of the problem. To make the contest computationally more
feasible for students, the simulation comprised only 4,000 observations (2,000 cases and controls each) with 20 risk factors of interest. All variables were binary, with 1 indicating that a drug was prescribed to a driver at the time of the accident and 0 indicating that it was not.

A main challenge of the case-control study by Orriols et al. (2010) was the low prevalence of risk factors, meaning that many of the investigated drugs were prescribed only to a small fraction of drivers. Accordingly, prevalences in the simulation ranged from 3% (1 in 33.3) to 0.1% (1 in 1,000) uniformly on a log scale, making the data very sparse. Correlation between drugs was kept low.

Ideally when studying a dataset, there is some subject-matter knowledge involved. To imitate this in the contest, it was decided to disclose to the students that the number of risk factors with an influence on the outcome would be randomly between 3 and 7 inclusive. In a real setting, an investigator might have some sense about which results are plausible and which are not. Giving students a range of how many variables could have an influence also allows them to judge the plausibility of their submissions. The instruction given to students is shown in figure 1.

Effect sizes of risk factors were randomly either protective (log odds ratio between -1.5 and -0.5) or harmful (log odds ratio between 0.5 and 1.5). The simulation also used two confounders with a prevalence of 1%. Essential to a contest is the scoring rule that is used to compare submissions. The scoring rule was chosen to reflect the rational of a frequentist approach, meaning that a higher emphasis is placed on keeping the false positive rate low compared to the false negative rate. Accordingly, we chose a scoring rule which penalizes false positives errors more heavily than false negative, displayed in figure 1. Students formed teams of up to three people. As an extra incentive, there were three statistics textbooks awarded as prizes for the winning team.

3 Submissions

Team A used a best subset approach. They split the data into a train set (75% of observations) and test set (25% of observations) and fit logistic regression models with variable sizes between 3 and 7 on the train set. They chose the model which had the lowest prediction
You are given a dataset which simulates the relationship between the intake of drugs (risk factors $X$) and causing a road traffic accident (outcome $y$) in a large cohort.

The objective is to study the 20 risk factors to decide which have an influence on the outcome and which do not - in other words: perform a variable selection. There are no specifications, every approach and every method is admissible. Your method has to be reproducible, however, and lead to a justifiable selection.

Between 3 and 7 (inclusive) risk factors have an influence, the exact number is chosen randomly and secret.

Your selection per risk factor will be scored as follows:

| Risk factor         | Effect present | No effect present |
|---------------------|----------------|-------------------|
| selected            | +10 points     | -10 points        |
|                     | (true positive)| (false positive)  |
| not selected        | -3 points      | +3 points         |
|                     | (false negative)| (true negative)   |

For example, assume that 5 variables have an influence.

- If all risk factors are selected, the total score is $5 \times 10 + 15 \times (-10) = -100$ points
- If no risk factors are selected, the total score is $5 \times (-3) + 15 \times 3 = 30$ points
- If a perfect selection is made, the total score is $5 \times 10 + 15 \times 3 = 95$ points

If you decide to select variables based on the p-values from a logistic regression model, the method and the accompanying selection may look as follows in R:

```r
fit <- glm(y ~ X, family = binomial)
as.numeric(summary(fit)$coefficients[-1, 4] < 0.05)
[1] 0 0 1 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0
```

Figure 1: Task description
error in the test set.

Team B took a holistic approach. They first fitted penalized models with lasso and ridge regression and selected risk factors based on which models had the lowest deviances under cross-validation. Parallel to this, they graphed the number of drugs taken compared between cases and controls. Using these two pieces of information, they made an informed decision on which variables to select. The decision was influenced by a conservative attitude given that the scoring rule penalizes false positive errors heavily which lead the team to select only the 3 most obvious candidates.

Team C used the leaps algorithm [Furnival and Wilson 1974] to perform an exhaustive search for the best subsets of the variables. They chose the model which had the lowest prediction estimated by 4-fold cross-validation.

Team D used a resampling approach, fitting logistic regression models to 100 resamples of the data and gathering the resulting p-values. Using the fact that under the null hypothesis p-values are uniformly distributed, they plotted the p-values for every risk factor and visually looked for strong deviances from the uniform distribution. See figure 2 for an illustration.

Table 1 summarizes the selections made by every team.

4 Discussion

The contest was a rewarding and fun exercise for both the instructor and the students. The contest was designed by one of the graduate students who is working on problems of sparse data for his PhD and was thus able to provide most of the preparatory work without extra effort by the teacher. Given that the instructions were broad, teams were able to come up with very different approaches. The participants seemingly enjoyed the contest and liked being able to independently work on data without many restrictions. Although the levels of experience varied, the contest setup allowed all participants to use methods that they felt most comfortable with. Students had to explain their approaches and reasoning to the rest of the class. The way the simulated data was generated also allowed the creator to participate in the contest without knowing the correct risk factor selection.

Many scoring rules are conceivable, but all should be strictly proper scoring rules [Gneit-
Figure 2: The selection done by Team D. Shown are the boxplots for 100 p-values from a logistic regression model using resampling, sorted by their medians. The diagonal line represents the uniform distribution of p-values if no variables have an influence. From this plot, Team D decided to select risk factors 3, 6, 12, 17 and 5. The highlighted boxplots identify the relevant variables (highlighting not visible for relevant risk factors 3 and 6).
Table 1: Result overview. “Effect” is the regression coefficient (i.e. log odds ratio) used in simulating the outcome. As all variables were binary, their prevalences (i.e. frequencies) are also listed. The 7 relevant variables are highlighted, and the checkmarks indicate the selections by each team.

| Variable | Effect  | Prevalence (%) | Team A | Team B | Team C | Team D |
|----------|---------|----------------|--------|--------|--------|--------|
| 1        | 3.0     |                |        |        |        |        |
| 2        | 2.5     |                |        |        |        |        |
| 3        | -0.9    | 2.1            | ✓      | ✓      | ✓      | ✓      |
| 4        | 1.8     |                |        |        |        |        |
| 5        | 1.5     |                |        | ✓      | ✓      | ✓      |
| 6        | -0.72   | 1.2            | ✓      | ✓      | ✓      | ✓      |
| 7        | 1.0     |                |        |        |        |        |
| 8        | 0.9     |                | ✓      | ✓      |        |        |
| 9        | 0.7     |                |        |        |        |        |
| 10       | 0.53    | 0.6            |        |        |        |        |
| 11       | 0.5     |                |        |        |        |        |
| 12       | -1.26   | 0.4            |        | ✓      | ✓      |        |
| 13       | -0.64   | 0.3            |        |        |        |        |
| 14       | -0.8    | 0.2            | ✓      |        |        |        |
| 15       | -1.13   | 0.1            |        |        |        |        |
| 16       | -1.13   | 0.1            | ✓      |        |        |        |
| True positives | | | 57% | 29% | 57% | 43% |
| True negatives | | | 85% | 92% | 85% | 85% |
| Score    | 44 31 44 31 | | | | | |
such as the Brier score and logarithmic score for binary outcomes and continuous ranked probability scores for continuous outcomes. This ensures that a submission which corresponds to the truth scores higher than any other submission. For this contest, a simple rule was chosen in order for the scoring to be intuitive and clear to all participants. However, one weakness of the scoring rule that was noticed only afterwards was that the symmetric scoring would lead more easily to teams having the same score. An alternative would be to use Youden’s index \cite{Youden1950}. For repeating our contest, we suggest a scoring scheme as proposed in the appendix table “Proposed scoring”.

Since the dataset was created from a participant of the course, students could work in a setting similar to potential PhD projects at the university. In addition the background of the simulated data was shown, such that students felt responsible for delivering meaningful results. Since the parameters of the simulation were hidden, students were able to compete with the approaches of the creator and the instructor. Many of the students were thus eager to beat those solutions.

In courses without contests created by advanced students, we recommend to use readily available datasets. As an example, an introductory contest also carried out as part of the course, conducted similarly to the one described here, used the titanic survival dataset from Kaggle to compare classification trees, random forests and neural nets. Since the prediction variables are easy to interpret in this well-known example it encouraged students to improve their methods using their own hypotheses.

When repeating the contest game in the classroom, some points we would stress are:

1. Carefully choosing a scoring rule that is in line with the objective of the contest and makes it easier to identify a unique winner team.

2. Emphasize to students that their submissions have to be explainable and should be presented to the classmates.

3. Use a contest related to students’ interests or research of local groups.

Overall, the contest format was a very rewarding learning experience for both the teacher and the students, and we greatly encourage other instructors to try the same.
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Appendix

Table "Proposed scoring"

|                    | Effect present | No effect present |
|--------------------|----------------|-------------------|
| Risk factor selected | a              | b                 |
| Risk factor not selected | c            | d                 |

Let

- $TP =$ number of true positive selections
- $FP =$ number of false positive selections
- $TN =$ number of true negative selections
- $FN =$ number of false negative selections
- $P =$ number of risk factors with effect present ($= TP + FP)$
- $N =$ number of risk factors with no effect present ($= TN + FN)$

The score of a submission then is

$$Score = aTP + bFP + cFN + dTN$$

$$= (b - d)FP + (c - a)FN + aP + dN$$

From this, it is easier to see how the weighting might be chosen. In our case, since we wanted to punish false positive selections more heavily than false negative selections, it should follow that $b - d < c - a$. With the inclusion of further preferences, e.g. $b < c$ and $d < a$, one can start to limit the range of whole numbers that could make up a sensible score. If repeating our contest, the score we would chose would be $a = 3$, $b = -5$, $c = -2$, $d = 2$. 