Predictive modelling of alcohol-associated risks in College students

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Goals

Develop a predictive model of alcohol related risks in college students using information readily available to schools, in order to help:

1. identify students at risk and allocate support ressources as effectively as possible;
2. determine if additional information could help identify students at risk.

Assumption: alcohol-related risks are an important issue that a school wants to address on its own through supporting students in need.

Challenges

What we deal with:

1. **Meaningfulness.** We predict a "student need" score which is a function of student awareness and alcohol-related risks.
2. **Reliability.** We provide interval predictions with exact frequentist coverage. This communicates uncertainty in the prediction and could help mitigate issues related to over-confidence in the model.

Challenges

Things we don't deal with (but that we should):

1. **Interpretability.** It is difficult to summarize the model and explain the predictions.
2. **Fairness.** Non-discrimination (title IX). Issues using race, gender, age as predictors. Suitability of the "student need" response across these groups and quality of the data among them.
3. **Data representativeness.** The data may not represent a given school's student population and post-stratification would be necessary.

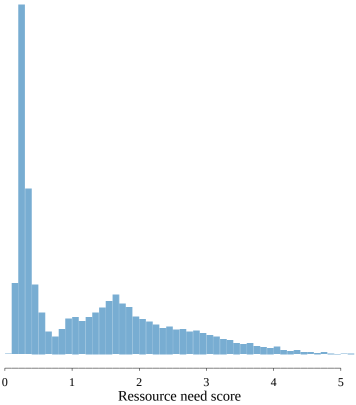
Response variable

- Student awareness score in $[0,1]$: school policy awareness and information received at school.
- Risk scores in $[0,1]$:
  - **Consumption risk**: "binge" drinking and self description.
  - **Behavioural risk**: drunk driving, missing classes, hangover, regret, medical issues, trouble with police, etc.
  - **Situational risk**: insulted, assaulted, damaged property, etc.

$$\text{need score} = (\text{2-awareness})(\text{consumption} + \text{behaviour} + \text{situational})$$

Better approach would use expert advice... this is a coarse approximation to it.

Response variable



consumption_risk	0.55	0.29	−0.13
0.55	behavioural_risk	0.38	−0.086
0.29	0.38	situational_risk	−0.17
−0.13	−0.086	−0.17	awareness

Random forest predictive models

Base model predictors:

- Demographic information (age, gender, year in program, race, marital status, etc)
- Living accomodation (living in dorm, alone, with roommates, spouse or parents; type of dorm, part of a fraternity or sorority).
- GPA.

Augmented data model predictors:

- Same as above, plus:
- Ratings of importance of different aspects of student life (athletics, arts, partying, etc)
- Time doing various activities (tv, study, work etc)
- Satisfaction with education and life; friendships and mentorship.

Predictive models fit

Base model: About 20% "variance explained".

- Most important predictors: race, part of fraternity or sorority, having roommates or not, etc.

Augmented model: About 40% "variance explained".

- Most important predictors: how much the student likes partying, and the above.

Conformal Prediction

Conformal prediction (to be defined) allows us to:

1. Quantify uncertainty associated with predicted values and limit issues associated with overconfidence.
2. Compare the fit of the two models from the point of view of the predictive error distribution.

Conformal Prediction

Prediction intervals that are

- valid at a given significance level for *finite* sample (Vovk, 2005)
- distribution-free
- universal
- individualized (Papadopoulos, 2009)
- only assume exchangeability
- cheap (Papadopoulos, 2002)

Inductive Conformal Prediction

Given a labeled training set $\{z_i = (x_i, y_i)\}_{i=1}^{n}$ and an unlabeled test observation x_{n+1},

1. partition training set into a *proper training* set $\{z_j\}_{j=1}^{l}$ and a *calibration* set $\{z_k\}_{k=l+1}^{n}$
2. fit predictive model on proper training set
3. compute predictions $\hat{y}_k$ on calibration set and anomaly scores

$$a(z_k) = |\hat{y}_k - y_k|, \quad k = l+1, \ldots, n$$

4. identify a_ϵ, the ϵ^{th} percentile of the $\{a\}_{k=l+1}^{n}$
5. compute prediction on test observation and set the prediction interval to be

$$\{y : |\hat{y}_{n+1} - y| < a_\epsilon\}$$

Set up

- Test set is 10% of data set
- Calibration set is 30% of training set.
- Repeat 100 times to obtain the expected width of prediction intervals
- Predictive model: Random Forest with $1,500$ trees, $m = p/3$ and default pruning.

Results - Coverage

	Significance	Set of Predictors	Mean Width	Coverage
1	0.500	Extensive	1.134	0.499
2	0.500	Restricted	1.367	0.505
3	0.750	Extensive	1.806	0.753
4	0.750	Restricted	2.112	0.754
5	0.900	Extensive	2.511	0.906
6	0.900	Restricted	2.808	0.900
7	0.950	Extensive	2.902	0.954
8	0.950	Restricted	3.218	0.951

Table: Coverage and Mean Width of Prediction Intervals

Results - Width

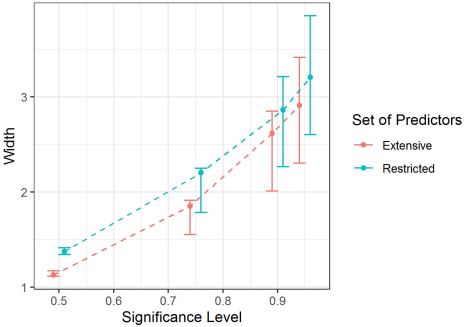


Figure: Median and inter-decile interval width across significance levels.

Conclusions

- Baseline student information provides some but limited information about the student "ressource need" variable.
- The random forest model does not perform much better than a linear regression in terms of R^2 value (18% in this case; 37% for the augmented model). Interpretable models would be more appropriate.
- Asking students about how they spend their time, what they value the most at college, and how satisfied they are with their education considerably improves predictive accuracy.

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