# 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.

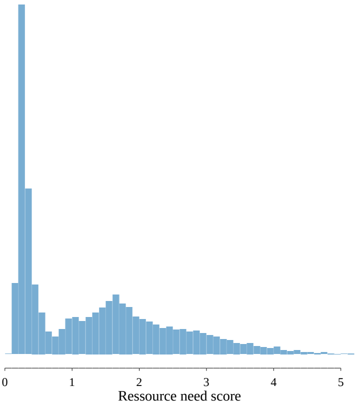
# Response variable

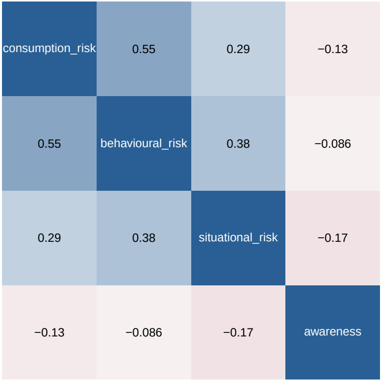
- Student awareness score in $[0,1]$: school policy awareness and information received at school.
- Risk scores in $[0,1]$:
  - **Consumption risk**: "binge" drinking and self description.
  - **Behavioural risk**: drunk driving, missing classes, hangover, regret, medical issues, trouble with police,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

# 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 $a_\epsilon$, the $\epsilon^{\text{th}}$ 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

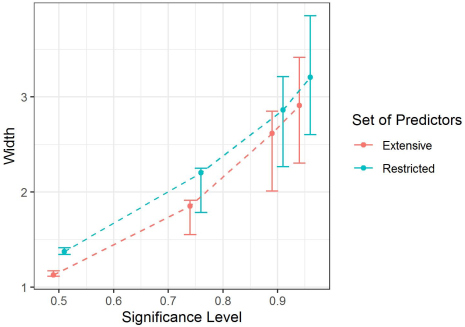


Figure: Median and inter-decile interval width across significance levels.

# Conclusions

- Student demographics, living accomodation and GPA provides are associated with the "ressource need" variable.
- Asking students about how they spend their time, what they value the most at college, and how satisfied they are with their education improves accuracy of "ressource need" predictions.
- 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). Such an interpretable model might be more appropriate.

# Appendix - Variable Importance

| | Variables | Importance |
|---|---|---|
| 1 | race | 123.5 |
| 2 | roommates | 91.2 |
| 3 | greek_life | 90.2 |
| 4 | marital_status | 72.4 |
| 5 | religion | 67.6 |
| 6 | age | 67.1 |
| 7 | location | 65.1 |
| 8 | live_parents | 64.9 |
| 9 | hispanic | 42.9 |
| 10 | transfer | 38.9 |

Table: Variable importance for predictive model with restricted set of predictors

# Appendix - Variable Importance

| | Variables | Importance |
|---|---|---|
| 1 | parties | 268.0 |
| 2 | religion | 77.0 |
| 3 | race | 72.2 |
| 4 | roommates | 62.1 |
| 5 | greek_life | 46.4 |
| 6 | marital_status | 40.9 |
| 7 | socialize | 40.3 |
| 8 | live_parents | 38.5 |
| 9 | friends | 29.3 |
| 10 | location | 28.1 |

Table: Variable importance for predictive model with extensive set of predictors

# References

Papadopoulos, H., Proedrou, K., Vovk, V., & Gammerman, A (2002)
Inductive confidence machines for regression
*European Conference on Machine Learning, pp. 345-356*

Papadopoulos, H., Vovk, V., & Gammerman, A. (2011)
Regression conformal prediction with nearest neighbours
*Journal of Artificial Intelligence Research, pp. 815-840*

Vovk, V., Gammerman, A., & Shafer, G. (2005)
Algorithmic learning in a random world
*Springer Science & Business Media.*