Using random forests to study physics graduate school admissions

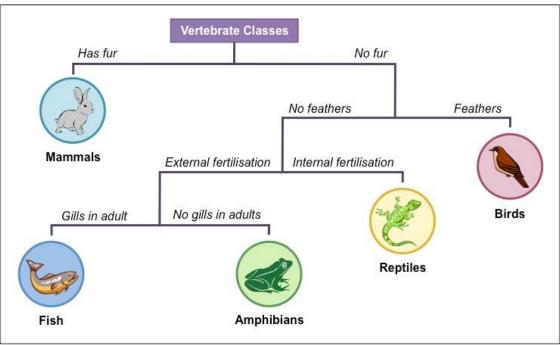
Nicholas T. Young

Center for Academic Innovation, University of Michigan





Dichotomous keys



Source: <u>BioNinja</u>



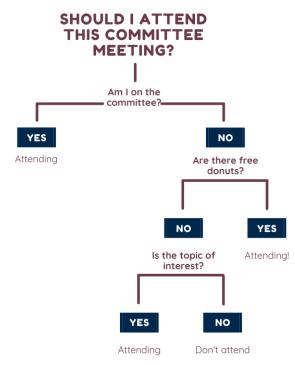


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Decision trees



Decision tree example







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Determining the split





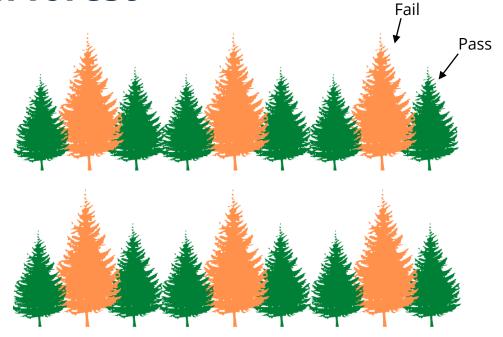
The random forest

	Run 1	Run 2	Run 3	Run 4	Run 5	
•	V1	V3	V1	V3	V2	
	V2	V4	V2	V5	V4	
	V3	V7	V6	V7	V5	
	V4	V8	V8	V9	V6	
	V5	V9	V10	V10	V8	





The random forest







Why use Random Forest

No assumptions on the shape of the data





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- No assumptions on the shape of the data
- Scaling of continuous variables is irrelevant





Why use Random Forest

- No assumptions on the shape of the data
- Scaling of continuous variables is irrelevant
- Interested in predicting outcomes





What Random Forest cannot do

Be a magic solution to the problem





What Random Forest cannot do

Be a magic solution to the problem

How do we know if random forest is working as intended?





The confusion matrix





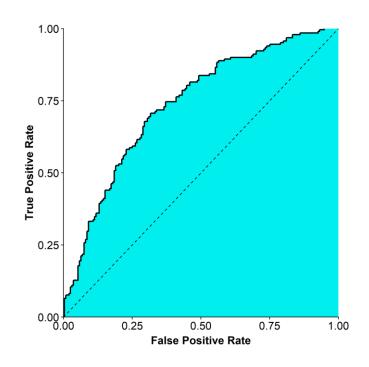
The confusion matrix

$$Accuracy = \frac{N_{TT} + N_{FF}}{N_{TT} + N_{TF} + N_{FT} + N_{FF}}$$





Receiver Operating Characteristic (ROC) Curve





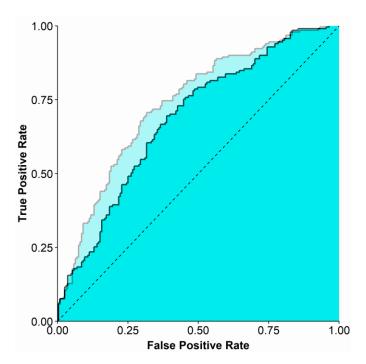


Use variable importance to determine what is useful in making a prediction





Order by the change in some metric







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Let's try it out!





Data

GRE scores
GPA
Undergrad school

Research interest

N=512 applications 2014-2017





Results

<u>All Variables</u>

Average Testing Accuracy:

75.6% ± 0.6%

Null accuracy: 52.7%

Average Testing
Area Under the Curve (AUC):
0.756 ± 0.006

Representative Run

	Is applicant admitted to the physics graduate program?		Actual Decision		
			Not Admitted	Admitted	
			Admitted		
	Model Prediction	Not Admitted	40.3%	14.9%	
		Admitted	9.1%	35.7%	





Results

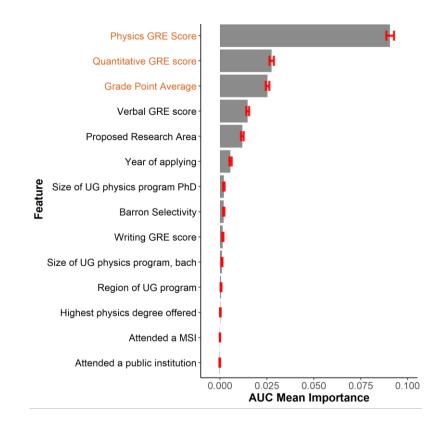
All Variables

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How do we know what matters?





Results

<u>All Variables</u>

Average Testing Accuracy:

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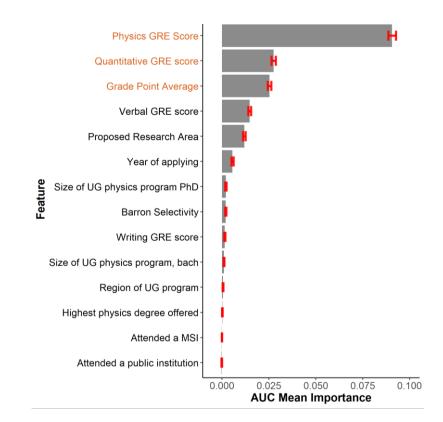
Only Selected Variables

Average Accuracy:

75.4% ± 0.6%

Average Area Under the Curve:

 $.754 \pm 0.006$

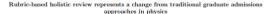






Learn more





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[Content of Computation of Content of Computer 1, 2021]

table, possibly helping to address the historical and ongoing inequities in the U.S. physics graduate school admissions process that have often excluded applicants from minoritized races, ethnicities genders, and backgrounds. Yet, no studies have examined whether rubric-based admissions methods represent a fundamental change of the admissions process or simply represent a new tool that achieves the same outcome. To address that, we developed supervised machine learning models of graduate admissions data collected from our department over a seven-year period. During the first four years, our department used a traditional admissions process and switched to a rubric-based process for the following three years, allowing us to compare which parts of the applications were used to drive admissions decisions. We find that faculty focused on applicants' physics GRE score and grade point averages when making admissions decisions before the implementation of the rubric While we were able to develop a sufficiently good model whose results we could trust for the data before the implementation of the rubric, we were unable to do so for the data collected after the implementation of the rubric, despite multiple modifications to the algorithms and data such as implementing Tomek Links. Our inability to model the second data set despite being able to model the first combined with model comparison analyses suggests that rubric-based admissions does change the underlying process. These results suggest that rubric-based holistic review is a method that could make the graduate admissions process in physics more equitable.

I INTRODUCTION

While graduate school has historically been seen as a route for students to begin careers in academia, graduates are increasingly pursuing careers across inclustry, government, and academia. The National Science Foundation's Survey of Doctorate Recipients finds that iese than half some properties of the properties of

Yet, the data suggests that isn't always the case. Only 3 out of 5 playsies students who erroll in a PhD program will successfully complete their program [2, 3]. As unfertaking graduate study involves a significant time and financial investment from both the student and institution, failing to resure students graduate leads to a wester to be considered to the student and investment from the student and institution of the student and retention sides to this problem. In this paper, we will focus out the former.

As the Council of Graduate Schools notes in one of its reports, "Better selection [of graduate students] can result in higher completion rates" [4]. Historically and continuing to today, graduate school admissions in the

vors certain groups over others. Previous research into the graduate admissions process in physics has found that the process relies heavily on the quantitative metrics such as grade point average (GPA) and General and Physics GRE scores [5–10]. These metrics have been found to benefit groups already overrepresented in higher education. For example, prior work has shown students from groups underrepresented in higher education (e.g., first generation, low income, Black, Latinx, Native) suffered a grade penalty relative to their more privileged peers with students from minoritized racial groups suffering the largest penalties [11]. Other work has shown that the General and Physics GREs are biased against women and students from minoritized racial and ethnic groups [2, 12] as well as against students from smaller or less prestigious universities [13]. Furthermore, the high costs associated with these often-required tests, despite limited evidence that these tests serve a predictive purpose [2, 14, 15], prevent some students from applying [16, 17].

US have tended to be an exclusionary process that fa-

The inequities in the admissions process and the fact that traditional admissions methods "miss may talented students" [18] have led various programs and organizations to consider alternative admission approaches such as holistic admissions, which considers a "broad range of candidate qualities including 'monospitive' or personal attributes" [19]. These efforts are often supported by publicis to ensure that all anonlicents are assessed on the

arxiv:2112.06886





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Recap

Random forest is a good technique if you know the outcome of your data, the data has a complex relationship to outcome (non-linear), and you are interested in predicting the outcome





Recap

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- Can also determine what features are most predictive of the outcome





Recap

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- Will always get an answer; want to make sure it is a reasonable answer





Recap

- Random forest is a good technique if you know the outcome of your data, the data has a complex relationship to outcome (non-linear), and you are interested in predicting the outcome
- Can also determine what features are most predictive of the outcome
- Will always get an answer; want to make sure it is a reasonable answer

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Resources & Recommended readings

- Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32. https://doi.org/10.1023/A:1010933404324
- Breiman, L. (2001). Statistical modeling: The two cultures (with comments and a rejoinder by the author). *Statistical science*, *16*(3), 199-231. https://doi.org/10.1214/ss/1009213726
- Janitza, S., Strobl, C., & Boulesteix, A. L. (2013). An AUC-based permutation variable importance measure for random forests. *BMC bioinformatics*, 14(1), 1-11. https://doi.org/10.1186/1471-2105-14-119
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 https://doi.org/10.1103/PhysRevPhysEducRes.15.020120



