

Testing for over- and under-dispersion in physics degree outcomes



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BACKGROUND:

With larger datasets available than ever, it is important—and possible!—to check if standard statistical assumptions apply in PER contexts.

METHODS

I used **population-level data** [1] to test if the **binomial assumption** holds for the **academic attainment** of UK physics students.

I achieved this by comparing the **year-on-year variance** with the **expected variance** for each physics degree programme in the data.

43 Institutions; 7 Years
26,960 Physics Graduates

From all accredited UK physics degree programmes that ran 2012/13–2018/19.

Split by Programme Type
Most institutions offer two main types of physics programme.

3-Year “Non-enhanced” (BSc)

4-Year “Enhanced” (MSc)

Calculate the Good Degree Rate for each year of each programme.

The % of students graduating with the top grades: a 1st class or a 2:1. (approx. GPA > 3.3)

Dispersion Analysis

Compare the observed year-on-year variance for each programme to the expected variance under the binomial assumption.

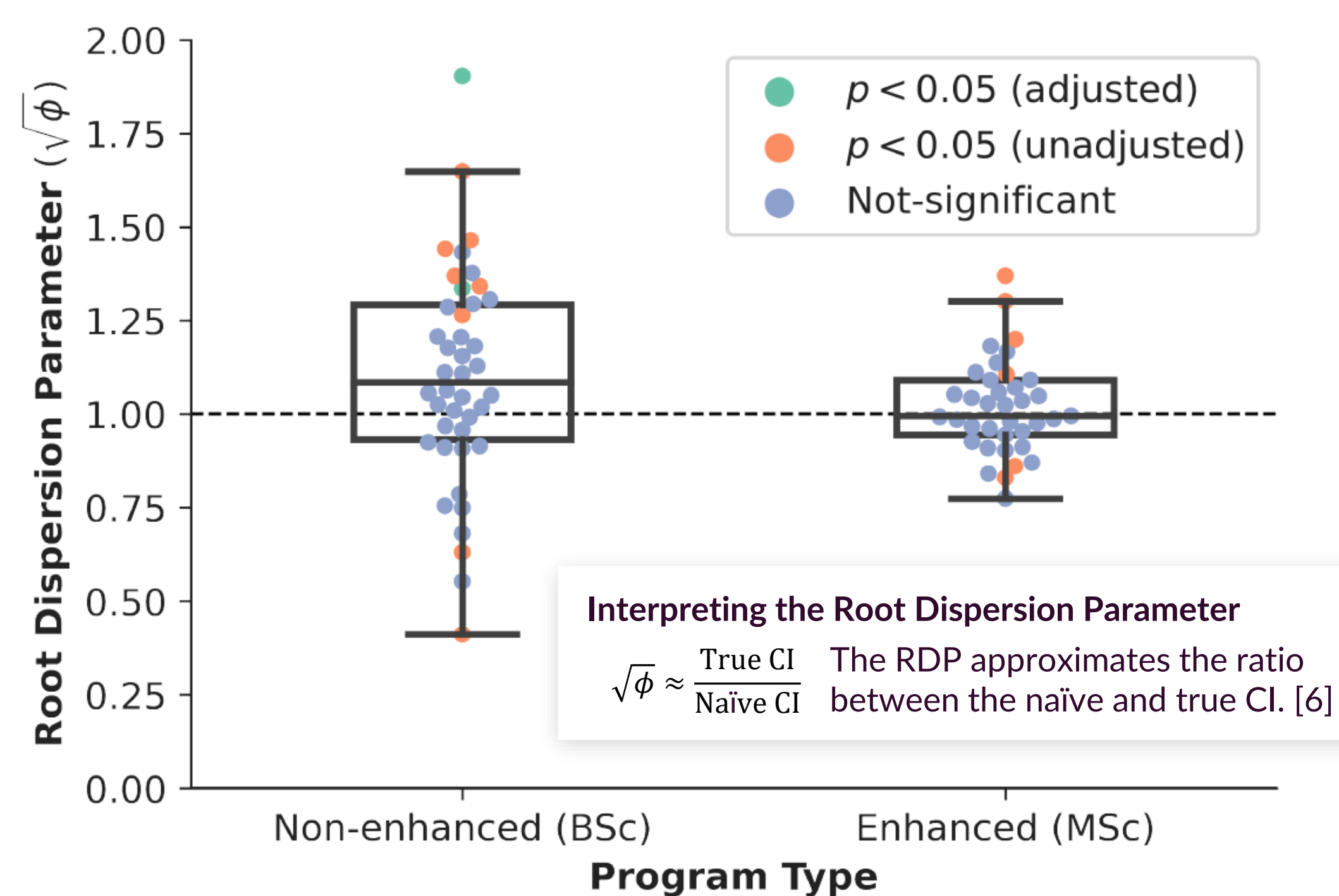
$$\text{Root Dispersion Parameter} = \sqrt{\phi} = \sqrt{\frac{\text{Observed Variance}}{\text{Expected Variance}}}$$

Calculate significance using the simulation-based approach implemented in the R package DHARMA [2] with $H_0: \sqrt{\phi} = 1$; $\alpha = 0.05$.

Post-hoc adjustment for false discovery: Benjamini-Hochberg [3] (FDR=0.05)

RESULTS

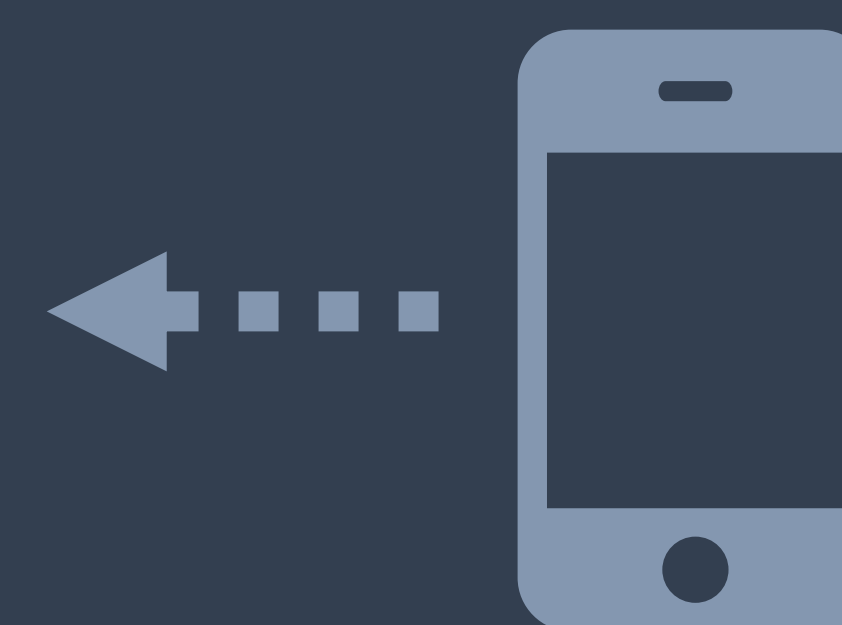
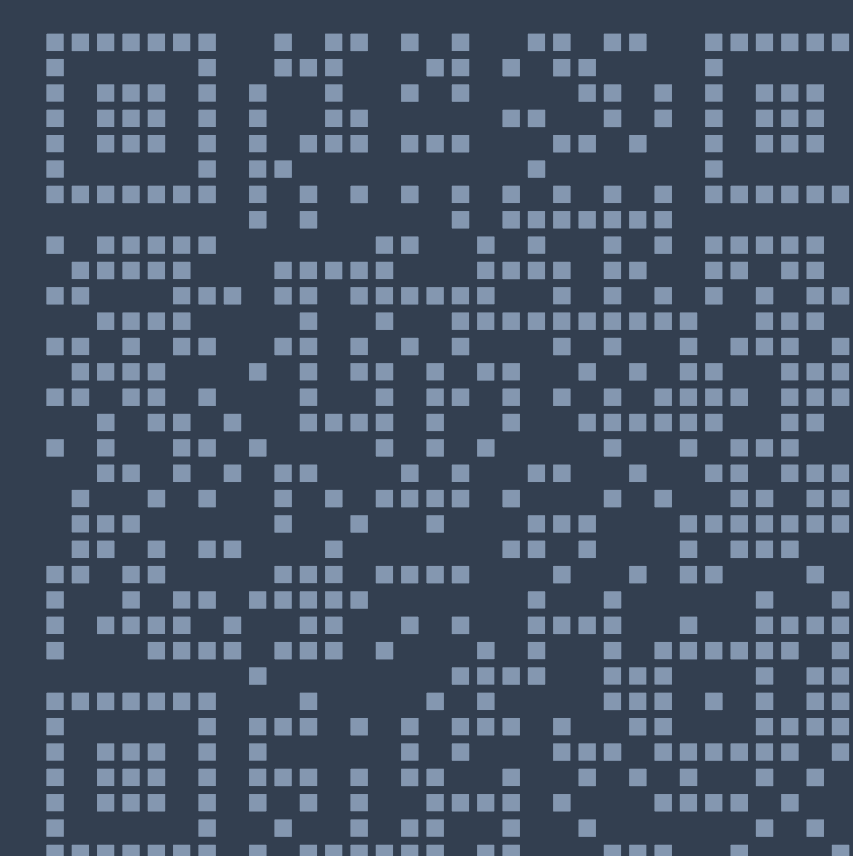
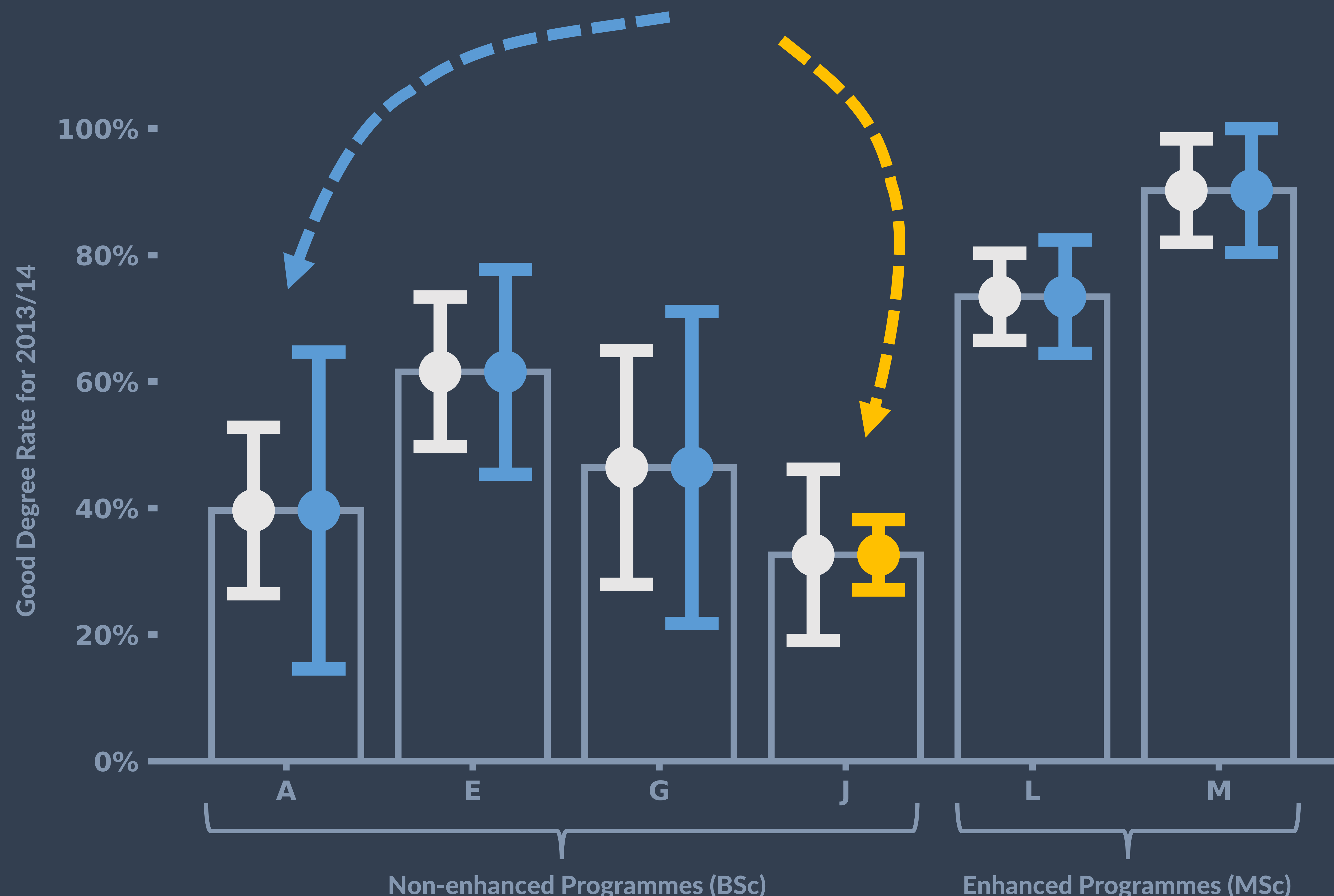
10 non-enhanced, and 6 enhanced degree programmes showed significant non-binomial dispersion ($p < 0.05$).



After controlling the False Discovery Rate (FDR) at 5% this number dropped to 2 programmes with a further 3 being “near misses,” significant at $p < 0.051$.

To illustrate, 2013/14 good degree rates for these programmes are shown on the right!

Error bars for proportion data using standard statistical assumptions can be wrong by a factor of 2 for **real PER data**.

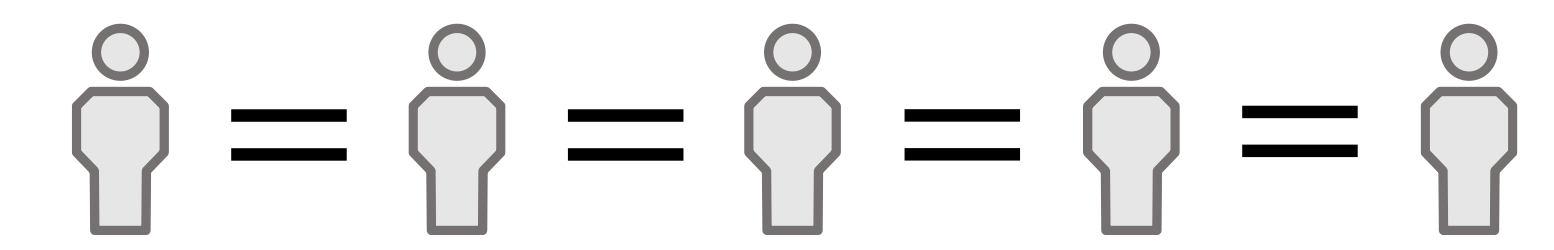


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astrasword.github.io/posters/dispersion

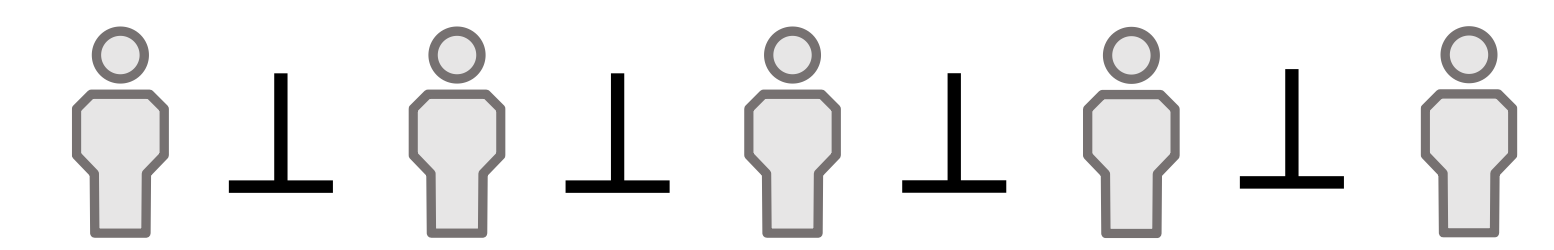
WHAT IS THE BINOMIAL ASSUMPTION?

In this context, that the chance of a student succeeding is:

1. Identical for all students.

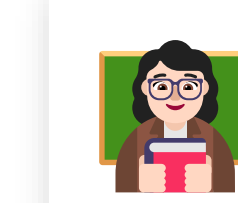
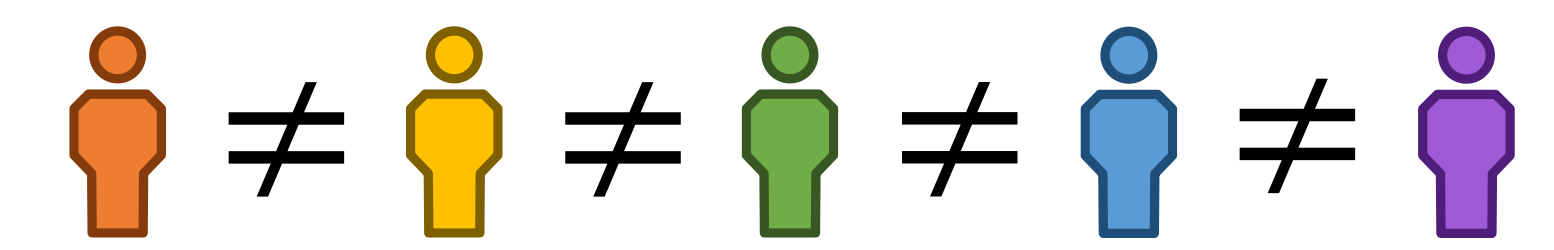


2. Statistically independent.



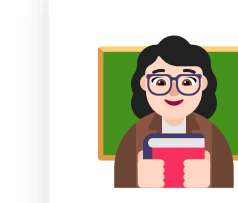
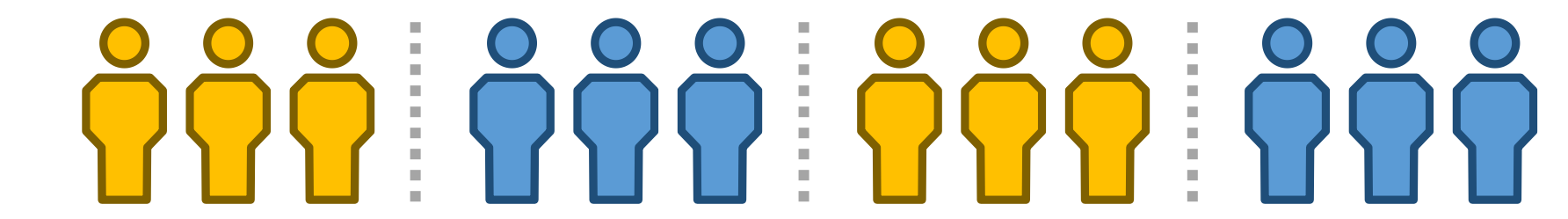
HOW CAN IT FAIL?

1. Diverse chances of success will lead to **overdispersion**. [4]



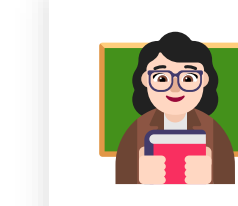
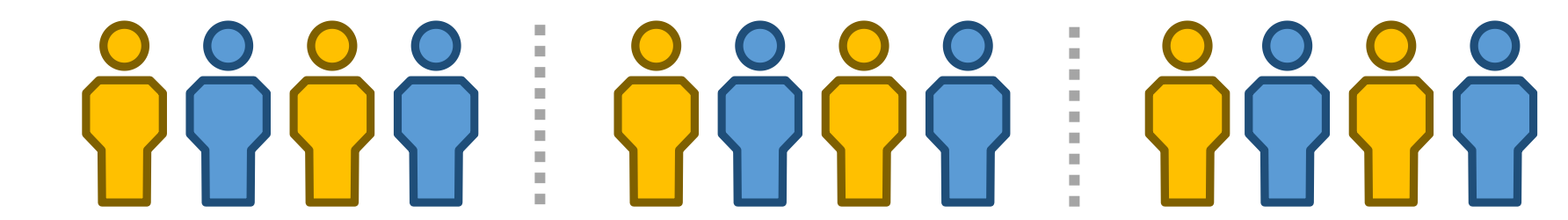
In the classroom:
Students are usually diverse, so this effect will be in play most of the time!

2. Correlated outcomes within cohorts also leads to **overdispersion**. [4]



In the classroom:
Happens when one student's success supports other students to succeed, e.g., collaborating on homework.

3. Anti-correlated outcomes within cohorts leads to **under-dispersion**. [4]



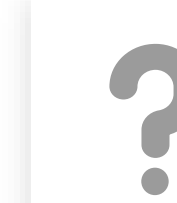
In the classroom:
Occurs whenever students must compete for access to learning resources or marks, e.g., grading on a curve.

Physics education is a complex social process so, in the real world, it's likely all three of these factors will be in play at once.

Tug of war:
How these forces balance out in practice is an empirical question.



WHAT CAN WE DO ABOUT IT?



Is it really a problem?: Non-binomial dispersion only matters for most statistical tests if it is present in the dependent variable *after conditioning* on the independent variables used in the model! [5]



Interpret Binomial Tests with Caution
If a statistical models makes the binomial/multinomial assumption, e.g., the χ^2 -test or logistic regression, consider how much non-binomial dispersion would be needed to alter interpretation.



Use Dispersion-Aware Statistical Models

Quasi-likelihood models account for both over- and under-dispersion with some downsides. If dealing with overdispersion only, a parametric or mixed effects approach may be better. [5][6]



Measure It!

Non-binomial dispersion is a feature, not a bug! Its size and direction is a clue about what is happening in the classroom. The R package DHARMA has a simulation-based approach for this [2].

REFERENCES

- [1] <https://www.hesa.ac.uk/services/custom/data>
- [2] Hartig, Florian. DHARMA: Residual Diagnostics for Hierarchical (Multi-Level / Mixed) Regression Models. 2022. <https://florianhartig.github.io/DHARMA/>
- [3] Benjamini, Yoav, and Yoel Hochberg. "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing." *Journal of the Royal Statistical Society: Series B (Methodological)* 57, no. 1 (January 1995): 289–300. <https://doi.org/10.1111/j.2517-6161.1995.tb0031.x>
- [4] Jurez-Colunga, Elizabeth, and C. B. Dean. "Analysis of Over- and Underdispersed Data." In *Methods and Applications of Statistics in Clinical Trials*, edited by N. Balakrishnan, 1–9. Hoboken, NJ, USA: John Wiley & Sons, Inc., 2014. <https://doi.org/10.1002/9781118594333.ch1>
- [5] Davison, A. C. *Statistical Models*. Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge: Cambridge University Press, 2003. <https://doi.org/10.1017/CBO9780511518350>
- [6] Agresti, Alan. *Categorical Data Analysis*. 3rd ed. Wiley Series in Probability and Statistics 792. Hoboken, NJ: Wiley, 2013.