

A Semi-Frivolous Attempt to Mathematize Grade Adjustments

Mike Price

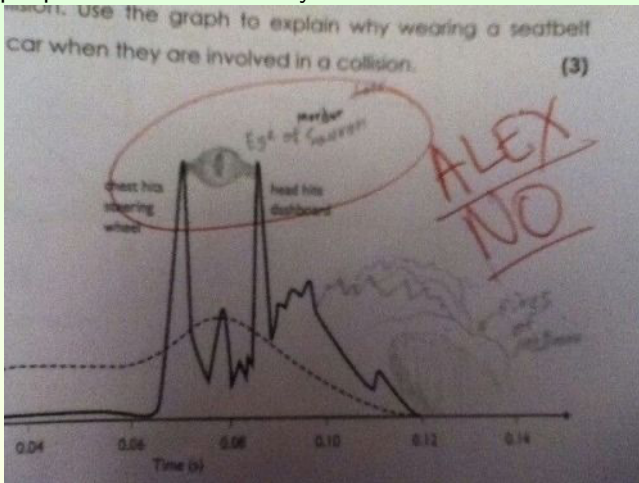
April 22, 2022

The Setup

“Use the graph to explain why wearing a seatbelt is important for the people in a car when they are involved in a collision.”

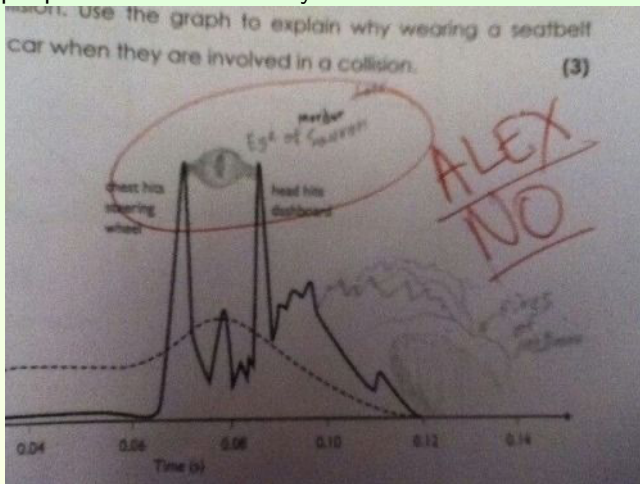
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Let's explore!

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- The basic mapping has no requirement that we make student grades better than their raw scores.

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Your Turn: Devise a verbal description, in terms of raw and adjusted scores, of each of the properties in the “responsible grading adjustment” function definition.

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The Constant Shift

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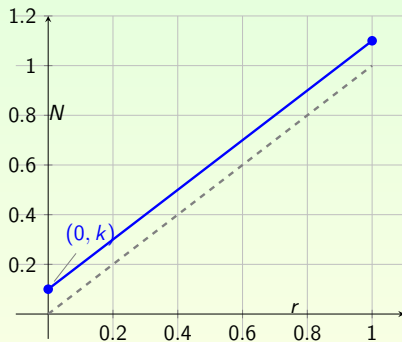
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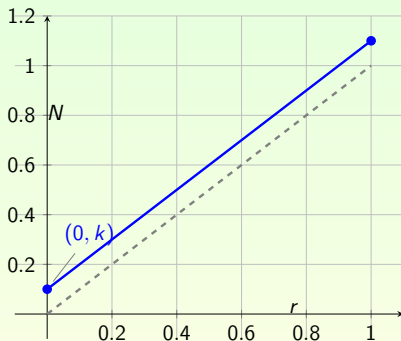
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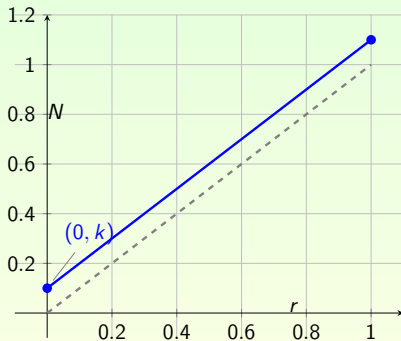


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Each score adjusted exactly the same; preserves the overall spread; creates scores above 100% (good/bad?).

The “Best Student” Scaling

The “best student” scaling is the constant shift, except the new 100% is based on the highest grade that any student earned, such that the highest grade is capped at 100%. Now the adjusted grade, N , is simply the raw grade, r , plus a constant that depends on the highest grade H .

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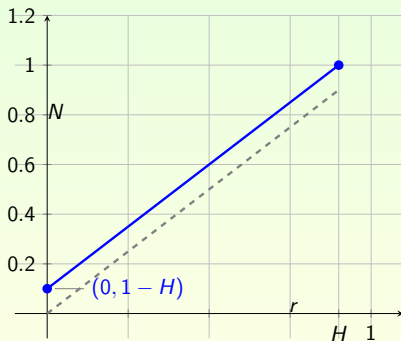
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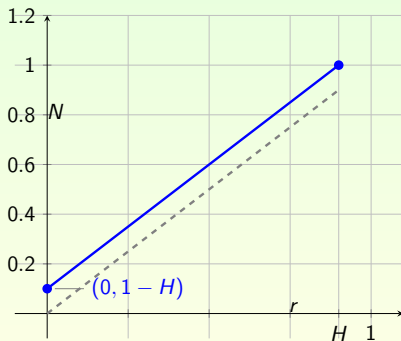
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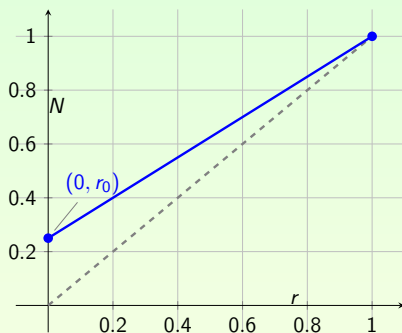
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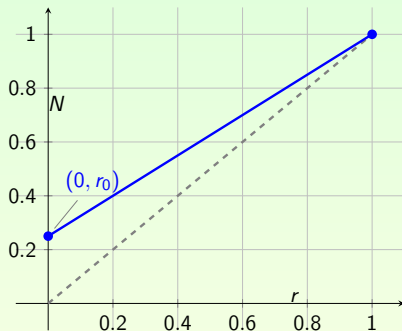
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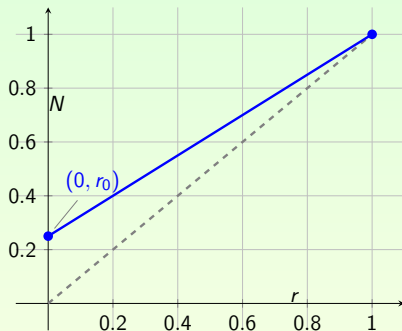
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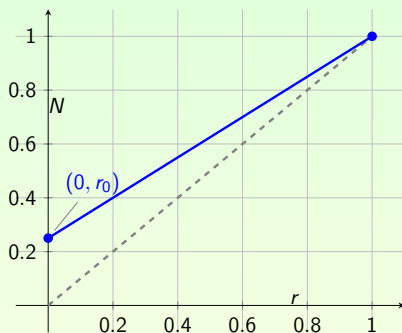


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Your Turn: Can you quickly convince yourself that condition #3 of the responsible grading adjustment definition is met for $L(r) = (1 - r_0)r + r_0$?

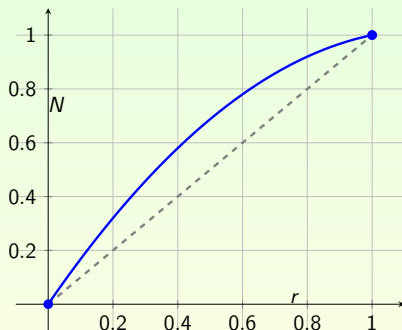
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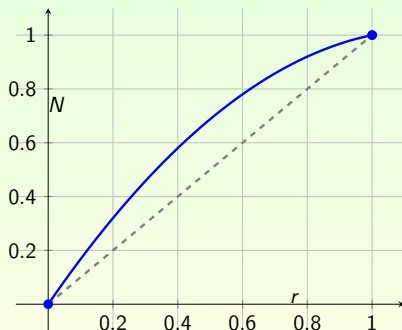
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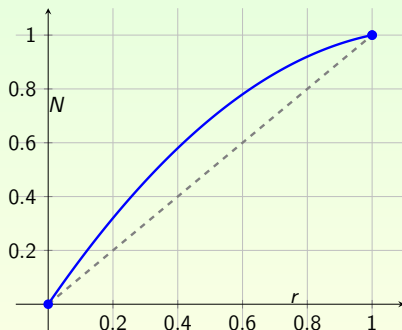


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Your Turn: Why do we need the given restriction on the value of k ?

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
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Choose a value of $0 < k < 1$, then raw scores are scaled by

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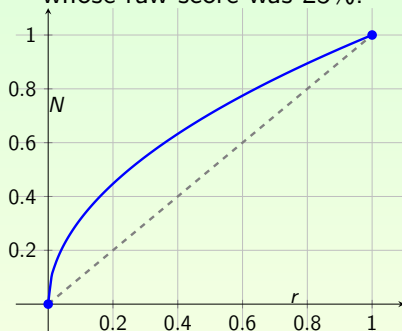
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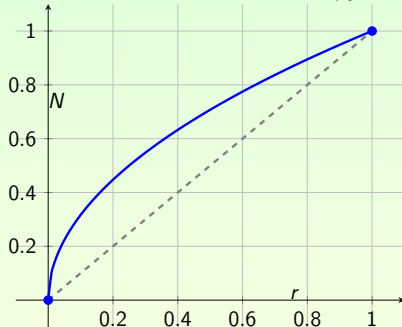
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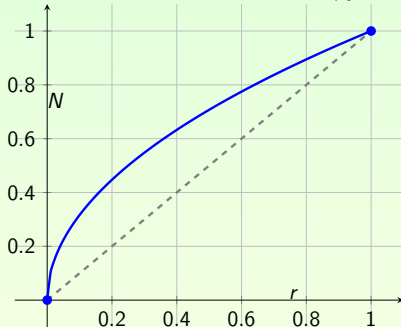


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Like the linear scaling, a power transformation pushes score more into the range of actual letter grades, without pushing anyone over 100%. Choosing a value of k closer to 1 implies a greater benefit to students with slightly higher raw scores, but with a limit.

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Bonus question: Under the power scaling $G(r) = r^k$, what is the largest raw score that you can prioritize (i.e. provide greatest benefit in adjusted grade) using your choice of k ?

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Your Turn: Come up with your own $N = G(r)$ responsible grading adjustment as a table and share with the group!