# How is math used outside academia?

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# Answers:

- Climate modeling
- Financial modeling
- Medical research
- Biology modeling
- Sports modeling
- Healthcare costs modeling

# Answers:

- Cryptography
- Advertising (purchase/click prediction)
- Recommendation engines
- Fraud detection of all kinds
- Geophysics (predicting oil accumulation)
- Defense modeling

# Answers:

- Image processing
- Handwriting recognition
- Language recognition
- Materials simulation
- Teacher evaluations
- The h-score for published researchers

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- I’m focusing on predictive models
- Is this math?
- What mathematicians in industry do
- Public face of math (besides calculus)

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- Incredibly sensitive to manipulation

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- Conflict of interest or disinterest?
- Largely used to manipulate politics
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- We shouldn't let this happen

# Salient properties

- Name
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# Example: EWMA for variance depends on "decay factor" s

Next, assume we have the current variance estimate as

$$V_{old} = (1-s) \cdot \sum_i r_i^2 s^i$$

and we have a new return $r_0$ to add to the series. Then it's not hard to show we just want

$$V_{new} = s \cdot V_{old} + (1-s) \cdot r_0^2.$$

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- Do this 1000 times, find 95th or 99th percentile

# Ex 1: VaR

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- Underlying model: Monte Carlo engine, ranking by P&L loss, percentile
- Underlying assumptions: Normal distributions, consistent correlations
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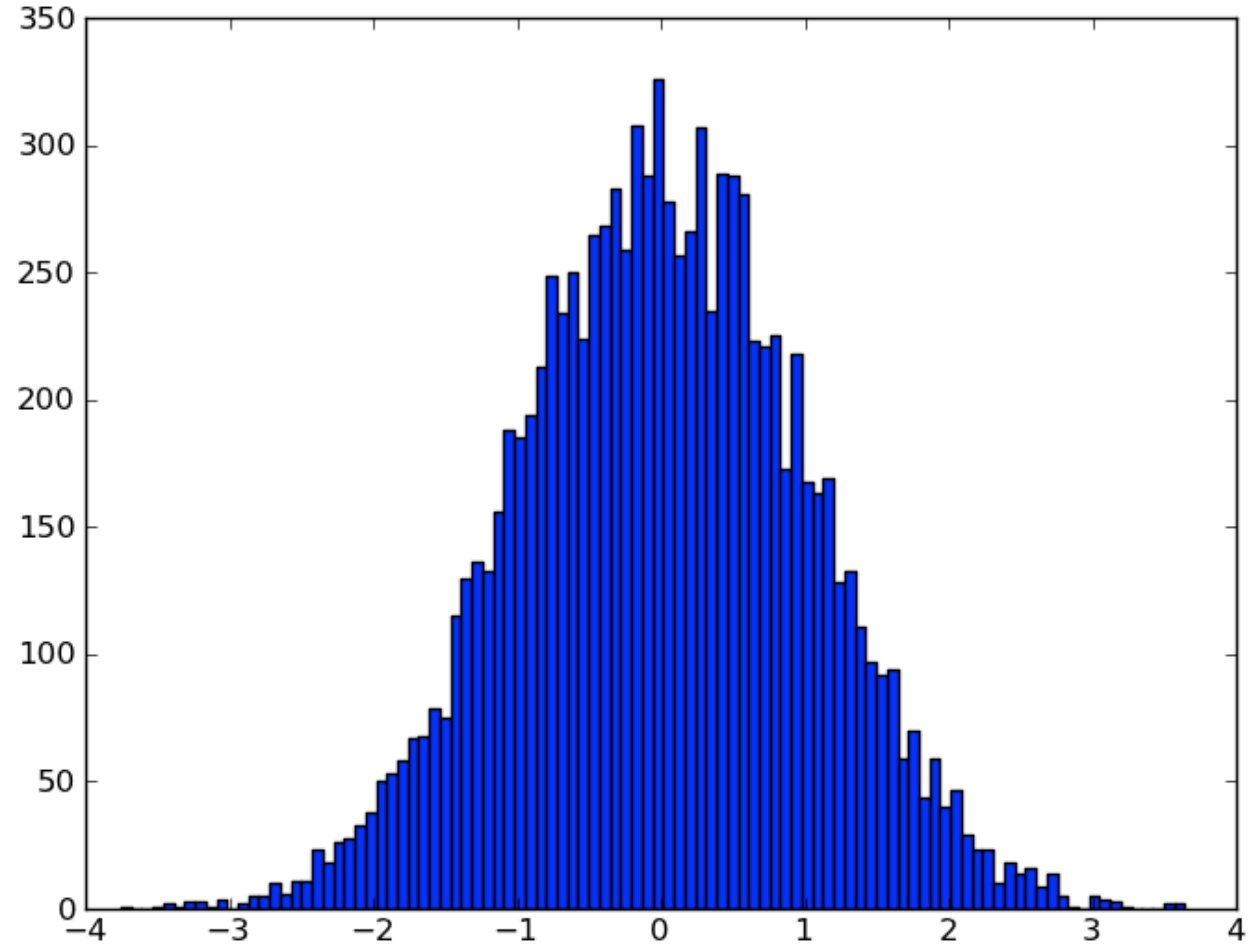
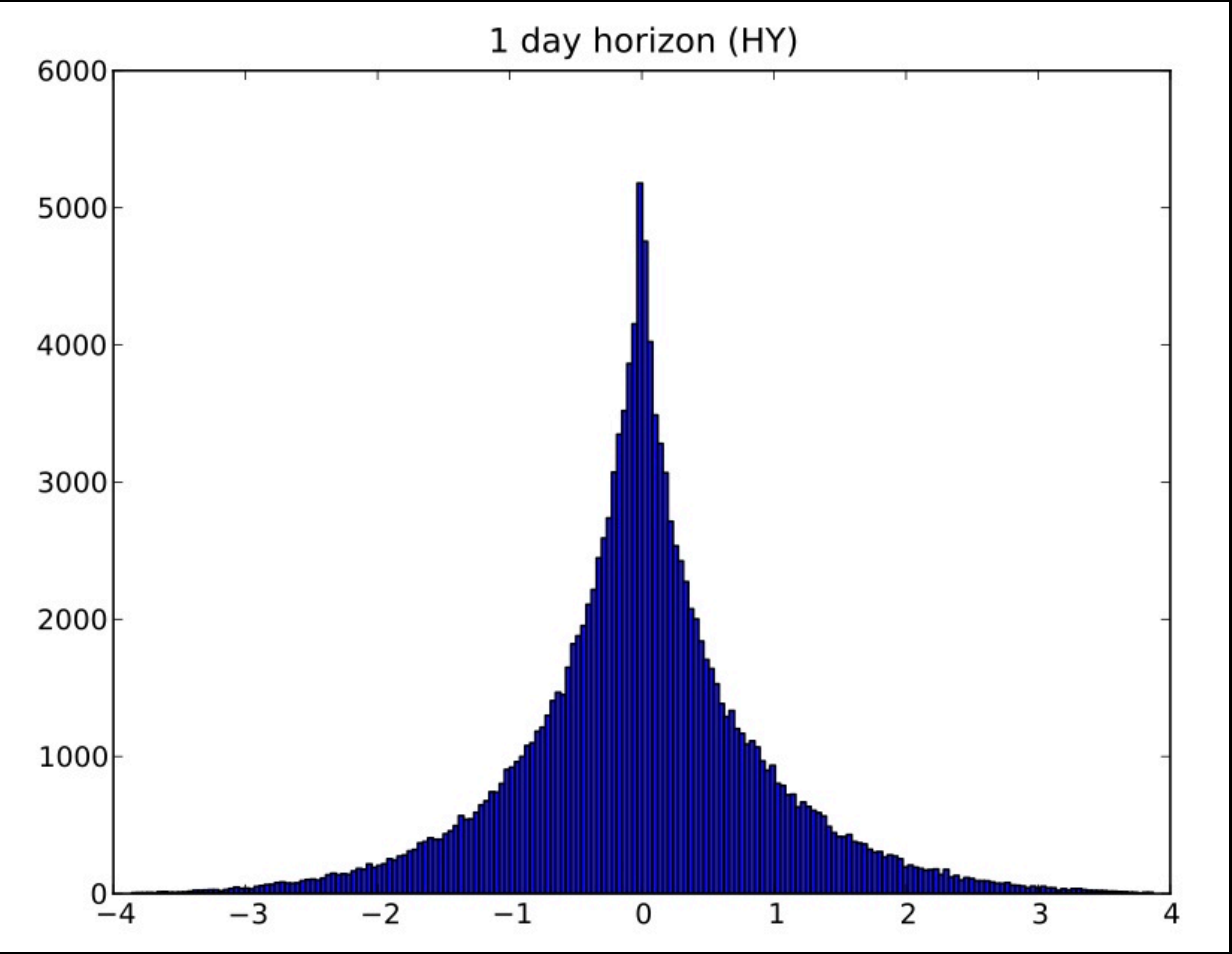

350
300
250
200
150
100
50
0
−4
−3
−2
−1
0
1
2
3
4


1 day horizon (HY)
6000
5000
4000
3000
2000
1000
0
−4
−3
−2
−1
0
1
2
3
4

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- Reach: The entire financial system

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# This is called "Counterfactual"

- In other words, the underlying model tries to predict what the score of a given student would be in a "random" class
- Takes into account student-level, classroom-level, and teacher-level attributes
- Hard to know how accurate this is!

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# Short list of sources of errors in VAM

- Need to score test
- Some problems harder than others?
- Some years smarter than others?
- Some tests harder than others?
- Normalized differently for different years
- Correlation of errors
- Model error
- Bayesian “shrinkage”

# Accounting for externalities in VAM

- Account for what is “under control”
- Tests better at testing middle than ends
- % of free school lunches very fat tailed
- Summer vacation loss
- “no child left behind” mindset
- Punishes teachers at tough schools

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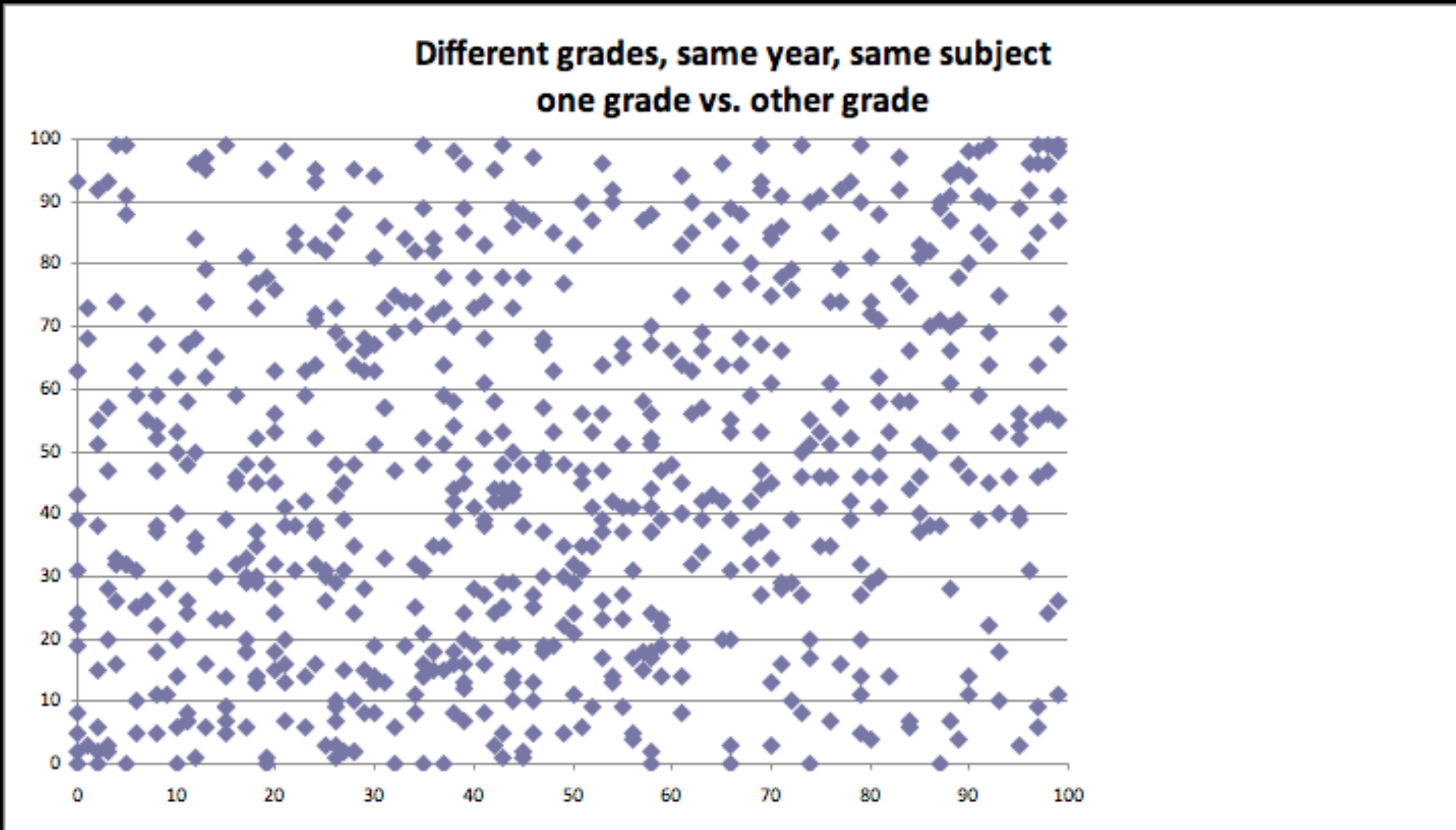
# The underlying model

- Linear regression with multiple sub-models
- Opaque correction terms and techniques
- Small samples (by grade, subject, year)
- Lots of missing data
- 14% correlation on NYC teachers


Different grades, same year, same subject
one grade vs. other grade
100
90
80
70
60
50
40
30
20
10
0
0
10
20
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- Reach: LA, NY, Chicago public school systems...

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- Reach: National, possibly international

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- Philosophically, what do we want our culture to be?

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- Reach: As far as h-score reaches

# Others

- Education - who will graduate
- Debt collectors - who will pay
- Political ads - uberpersonal targeting
- Health and DNA models

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- "People models" ≠ "statistical models"

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- What are we *not* quantifying for each ex?
- Should we be?

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- Anticipate gaming
- Require transparent evaluation methods
- Let’s not become economists though

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- Effort to make models “simple”
- Effort to educate public
- Panels of mathematicians (& others)
- Don’t take money from industry for this