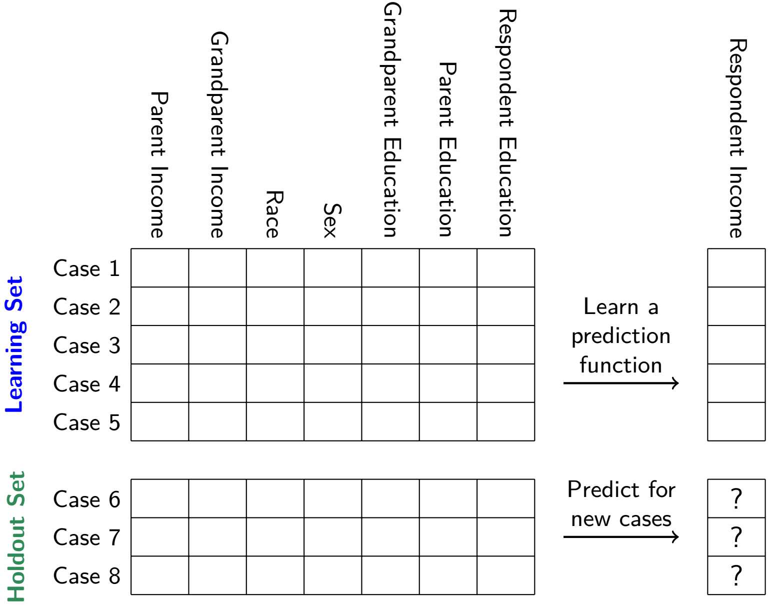
Social
Data Science

Soc 114
Winter 2026

Are complex models better?
The Fragile Families Challenge

Equality Opportunity and Prediction



A past study motivated this problem set.

Measuring the predictability of life outcomes with a scientific mass collaboration

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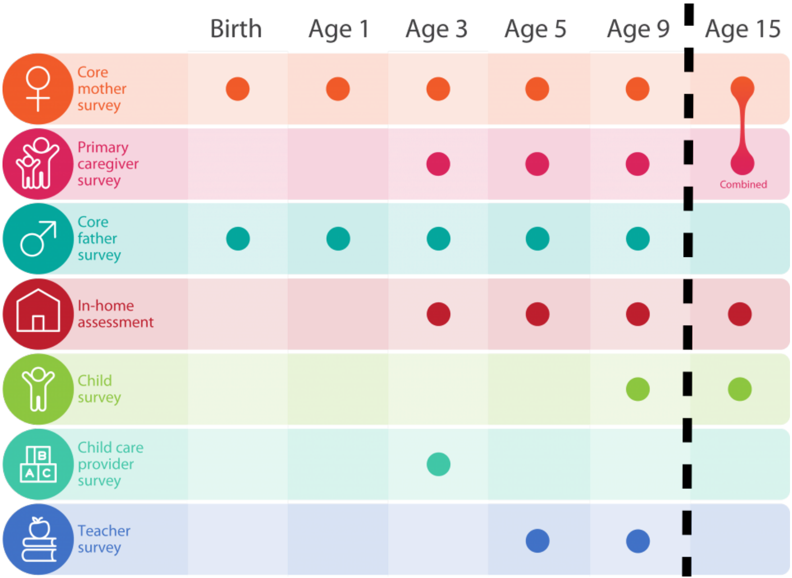
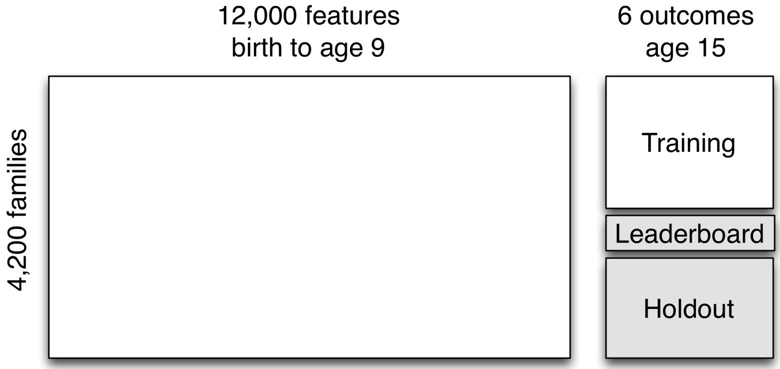
	Birth	Age 1	Age 3	Age 5	Age 9
Core mother survey	●	●	●	●	●
Primary caregiver survey			●	●	●
Core father survey	●	●	●	●	●
In-home assessment			●	●	●
Child survey					●
Child care provider survey			●		
Teacher survey				●	●


Birth
Age 1
Age 3
Age 5
Age 9
Age 15
Core mother survey
Primary caregiver survey
Combined
Core father survey
In-home assessment
Child survey
Child care provider survey
A B C
Teacher survey

Six age 15 outcomes:

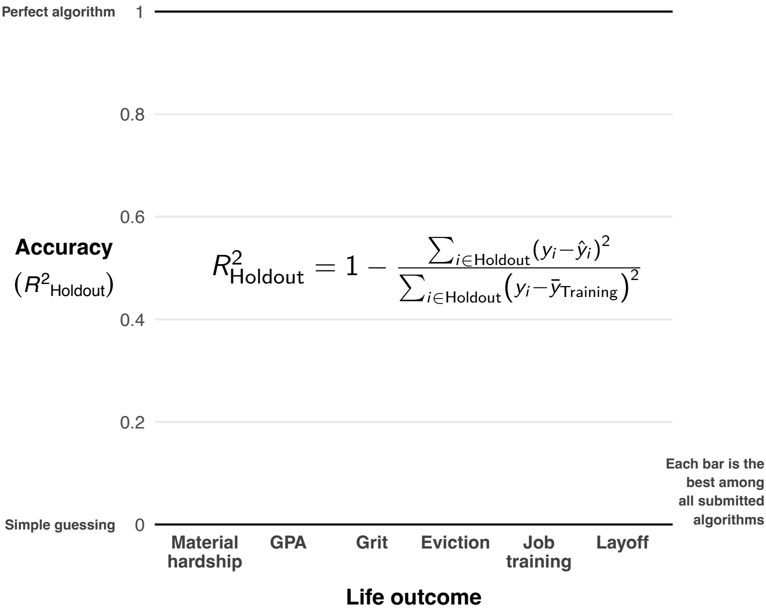
- GPA
- Material Hardship
- Grit
- Evicted
- Job training
- Job loss


12,000 features
birth to age 9
6 outcomes
age 15
4,200 families
Training
Leaderboard
Holdout

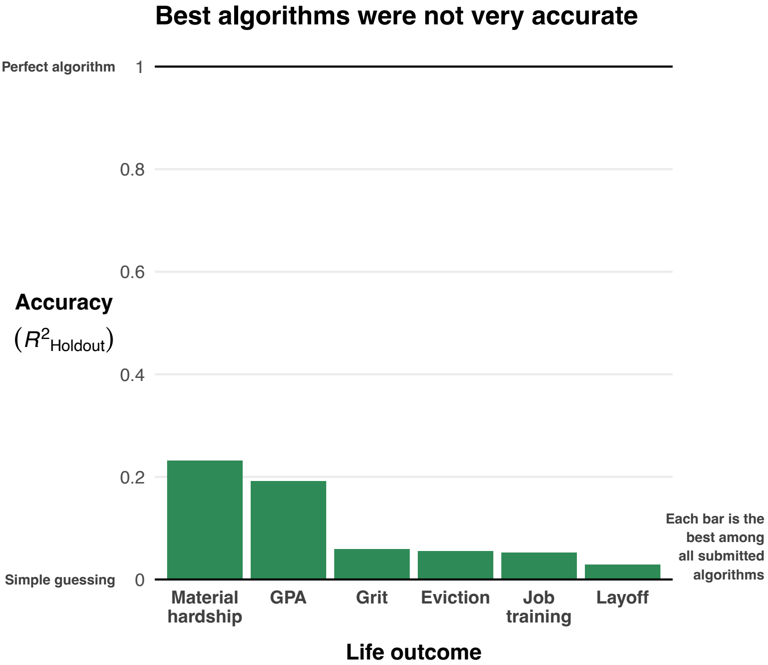
441 registered participants

- social scientists and data scientists
- undergraduates, grad students, and professionals
- many working in teams

How did they do?



Perfect algorithm
1
0.8
0.6
Accuracy
(R^2_{Holdout})
$R^2_{\text{Holdout}} = 1 - \frac{\sum_{i \in \text{Holdout}} (y_i - \hat{y}_i)^2}{\sum_{i \in \text{Holdout}} \left(y_i - \bar{y}_{\text{Training}}\right)^2}$
0.4
0.2
Each bar is the best among all submitted algorithms
Simple guessing
0
Material hardship
GPA
Grit
Eviction
Job training
Layoff
Life outcome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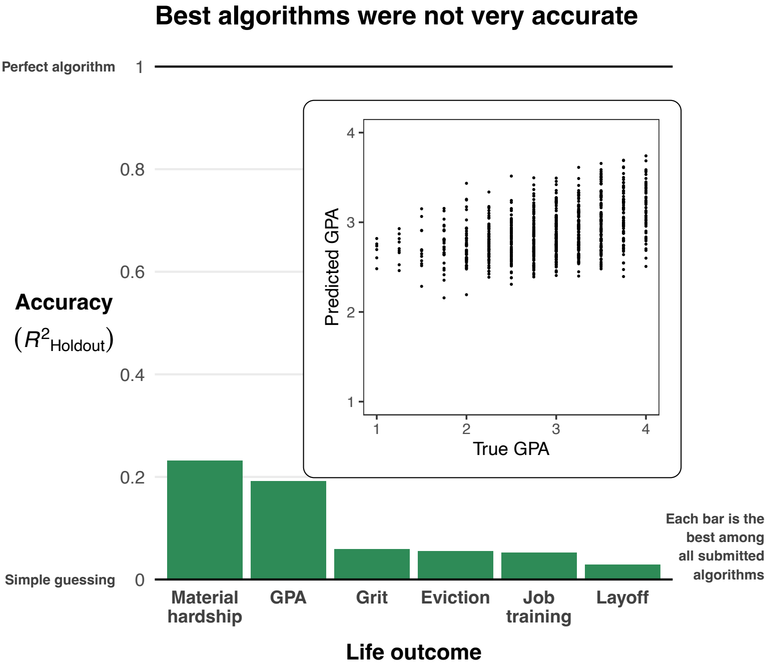
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1
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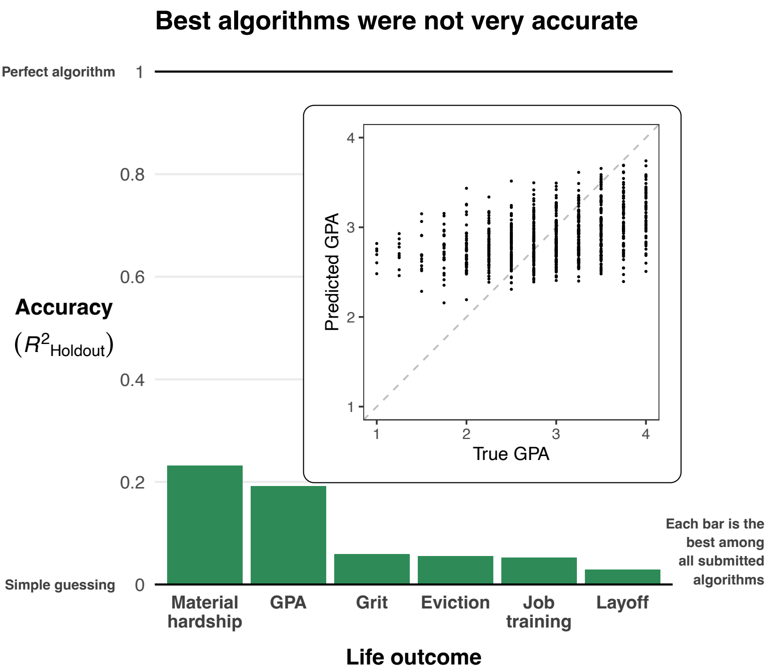
Simple guessing
Accuracy
(R^2_{Holdout})
Predicted GPA
4
3
2
1
True GPA
Material hardship
GPA
Grit
Eviction
Job training
Layoff
Each bar is the best among all submitted algorithms
Life outcome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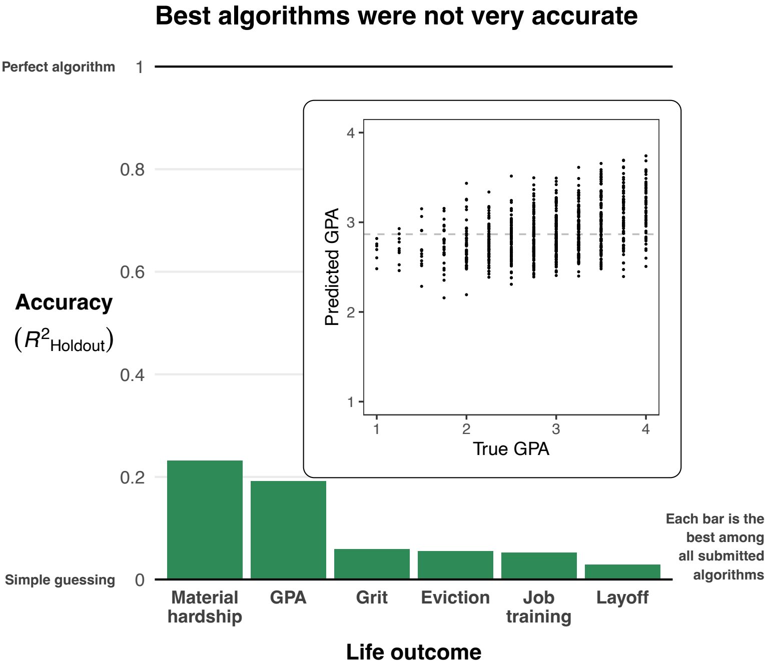
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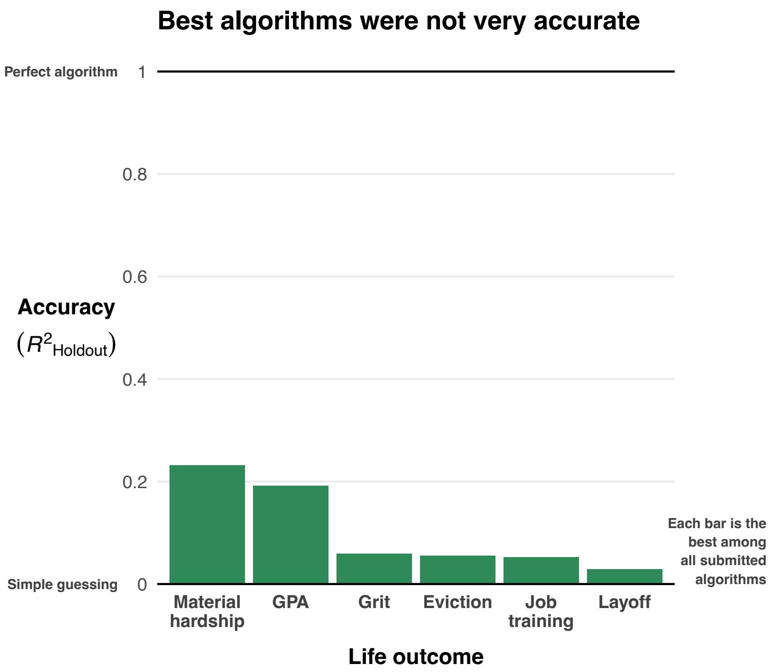
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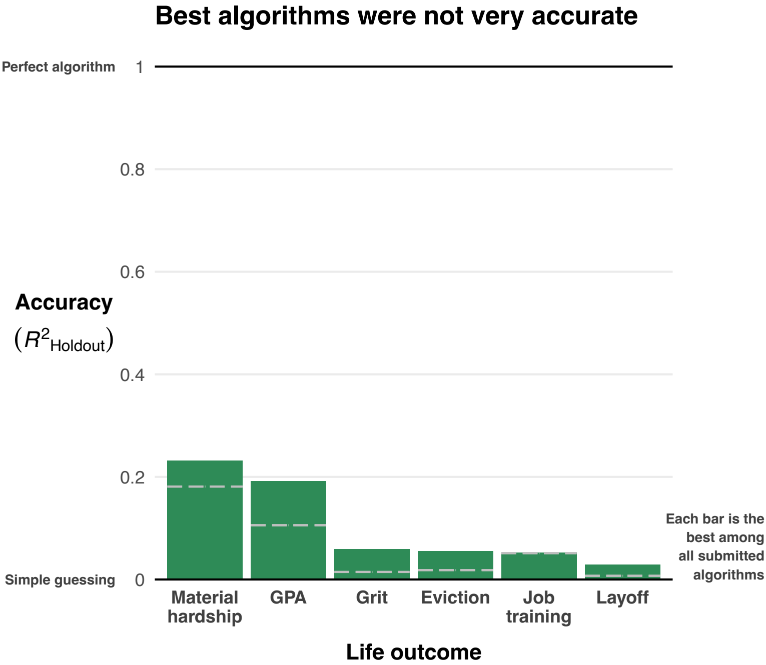
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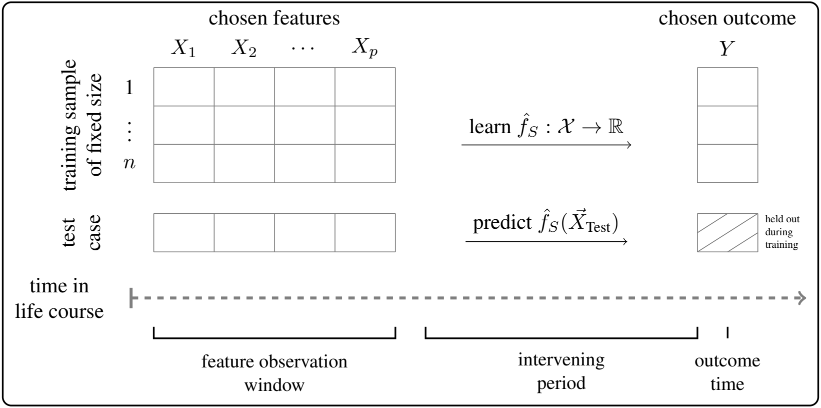
Life outcome

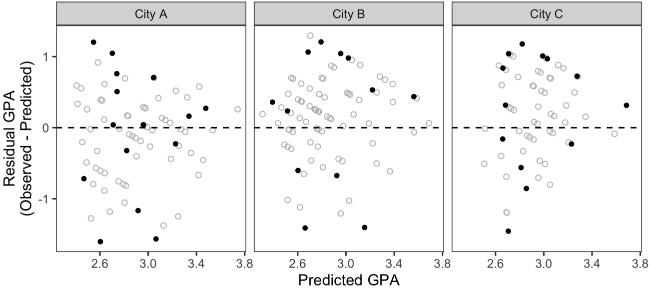
Lundberg et al. 2024.

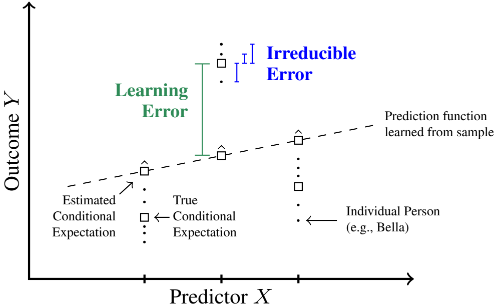
The origins of unpredictability in life outcome prediction tasks


chosen features
X_1 X_2 $\cdots$ X_p
chosen outcome
Y
training sample of fixed size
1
$\vdots$
n
learn $\hat{f}_S : \mathcal{X} \to \mathbb{R}$
test case
predict $\hat{f}_S(\vec{X}_{\text{Test}})$
held out during training
time in life course
feature observation window
intervening period
outcome time

In-depth, qualitative interviews

- 73 respondents in 40 families
- Separate interviews with the youth and primary caregiver
- Life history of the youth from birth to the interview (≈ age 18)

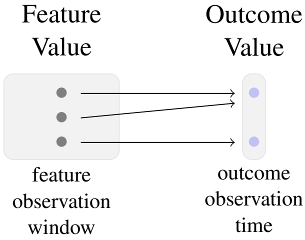


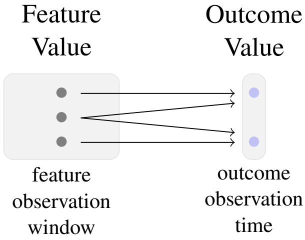


Irreducible
Error
Learning
Error
Prediction function
learned from sample
Estimated
Conditional
Expectation
True
Conditional
Expectation
Individual Person
(e.g., Bella)
Outcome Y
Predictor X

Irreducible error

Zero Irreducible Error	Non-Zero Irreducible Error
Irreducible error is zero if each feature value maps to **one** outcome value	Irreducible error is non-zero if at least one feature value maps to **multiple** outcome values





Irreducible error: Unmeasurable features

Unmeasurable features occur after the feature observation window

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- Bella: A lasting event

Irreducible error: Unmeasurable features

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- Bella: A lasting event
  - after age 9, her father died

Irreducible error: Unmeasurable features

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- Bella: A lasting event
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  - high school went off course

Irreducible error: Unmeasurable features

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- Bella: A lasting event
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  - high school went off course
- Charles: A fleeting event

Irreducible error: Unmeasurable features

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- Bella: A lasting event
  - after age 9, her father died
  - high school went off course
- Charles: A fleeting event
  - online high school

Irreducible error: Unmeasurable features

Unmeasurable features occur after the feature observation window

- Bella: A lasting event
  - after age 9, her father died
  - high school went off course
- Charles: A fleeting event
  - online high school
  - worked in the basement for one semester

Irreducible error: Unmeasurable features

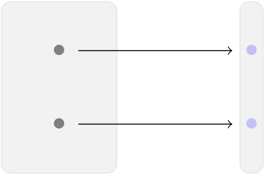
Unmeasurable features occur after the feature observation window

- Bella: A lasting event
  - after age 9, her father died
  - high school went off course
- Charles: A fleeting event
  - online high school
  - worked in the basement for one semester
  - video games = bad grades that semester

Irreducible error: Unmeasurable features

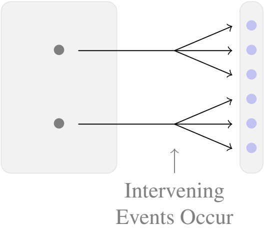
Zero Irreducible Error

Without intervening events,



Non-Zero Irreducible Error

With intervening events,



Irreducible error: Unmeasured features

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Lola's social network

Irreducible error: Unmeasured features

Lola's social network

- elderly neighbor got Lola ready for school each day

Irreducible error: Unmeasured features

Lola's social network

- elderly neighbor got Lola ready for school each day
- grandparents remodeled the basement to house Lola

Irreducible error: Unmeasured features

Lola's social network

- elderly neighbor got Lola ready for school each day
- grandparents remodeled the basement to house Lola
- aunt employed Lola's mother in a family business

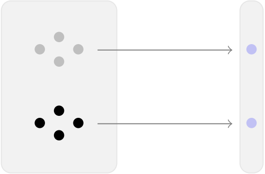
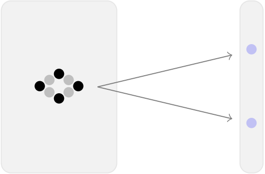
Irreducible error: Unmeasured features

Lola's social network

- elderly neighbor got Lola ready for school each day
- grandparents remodeled the basement to house Lola
- aunt employed Lola's mother in a family business

Predicted GPA: 3.04 Actual GPA: 3.75

Irreducible error: Unmeasured features

Zero Irreducible Error	Non-Zero Irreducible Error
Feature is measured,	Feature is unmeasured,
	

Irreducible error: Imperfectly measured features

Irreducible error: Imperfectly measured features

How close do you feel to your mom? Would you say…

Extremely close, ... 1
Quite close,.. 2
Fairly close, or, ... 3
Not very close?.. 4
REFUSED .... -1
DON'T KNOW .... -2

Irreducible error: Imperfectly measured features

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Extremely close,	1
Quite close,	2
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REFUSED	-1
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A daughter told us about her "not very close" mother

Irreducible error: Imperfectly measured features

How close do you feel to your mom? Would you say…

Extremely close, ... 1
Quite close,.. 2
Fairly close, or, ... 3
Not very close?.. 4
REFUSED .... -1
DON'T KNOW .... -2

A daughter told us about her “not very close” mother

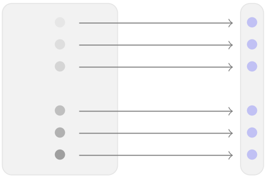
- kicked her out of the house and called police
- mother: “you better start treating me better, because I might not live that long.''
- daughter: “I couldn't even focus in class. . . I was shaking.''

Outcome: Failed 8th grade. Low GPA. Dropped out.

Irreducible error: Imperfectly measured features

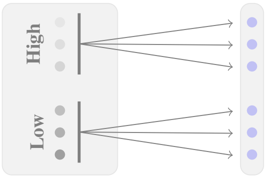
Zero Irreducible Error

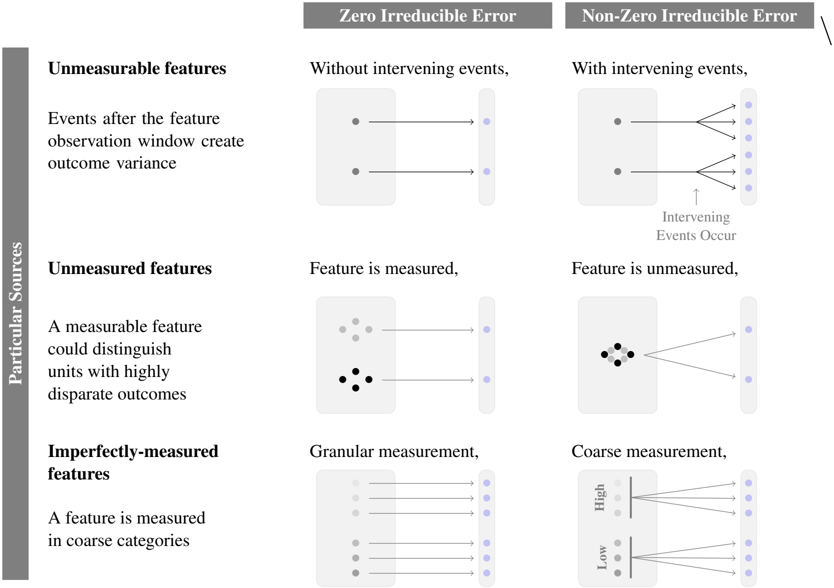
Granular measurement,

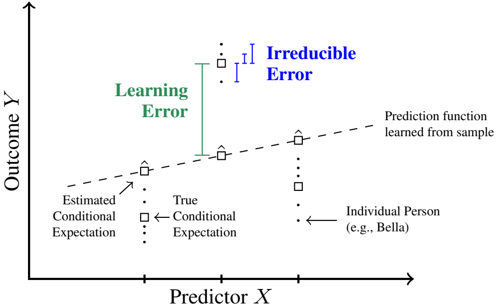


Non-Zero Irreducible Error

Coarse measurement,



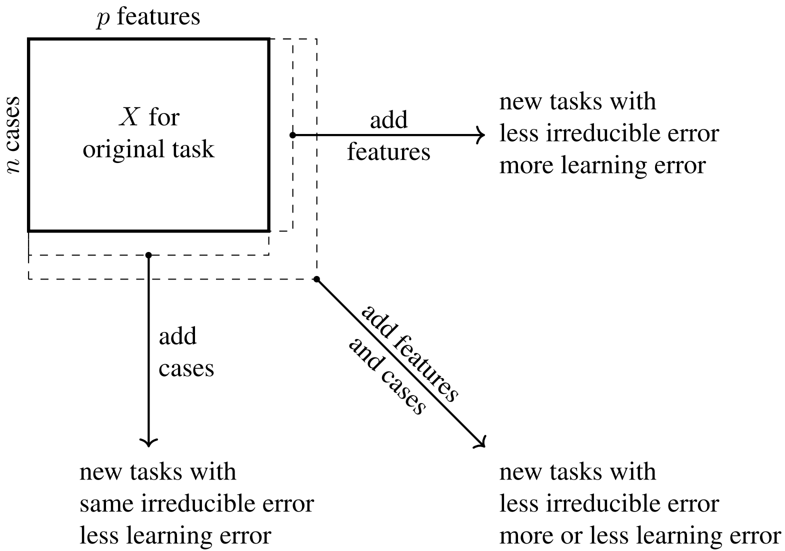

Zero Irreducible Error
Non-Zero Irreducible Error
Particular Sources
Unmeasurable features
Events after the feature observation window create outcome variance
Without intervening events,
With intervening events,
Intervening Events Occur
Unmeasured features
A measurable feature could distinguish units with highly disparate outcomes
Feature is measured,
Feature is unmeasured,
Imperfectly-measured features
A feature is measured in coarse categories
Granular measurement,
Coarse measurement,
High
Low



Irreducible
Error
Learning
Error
Outcome Y
Prediction function
learned from sample
Estimated
Conditional
Expectation
True
Conditional
Expectation
Individual Person
(e.g., Bella)
Predictor X

DISCUSSION

Generalizing to other life outcome prediction tasks



Implications for policy

Implications for policy

- life outcome predictions may be inaccurate

Implications for policy

- life outcome predictions may be inaccurate
  - if generated by algorithms
  - if generated by humans

Implications for policy

- life outcome predictions may be inaccurate
  - if generated by algorithms
  - if generated by humans
- from accuracy to impact evaluations

Implications for science

Implications for science

- old goal: between-group variability
  - how means vary across groups

Implications for science

- old goal: between-group variability
  - how means vary across groups
- new goal: within-group variability
  - how variances vary across groups

Implications for science

- old goal: between-group variability
  - how means vary across groups
- new goal: within-group variability
  - how variances vary across groups
- more work to better understand unpredictability
  - empirical estimates
  - formal models

Homework due Friday

- Submit to the PSID Income Prediction Challenge
- On Monday, we will see who won