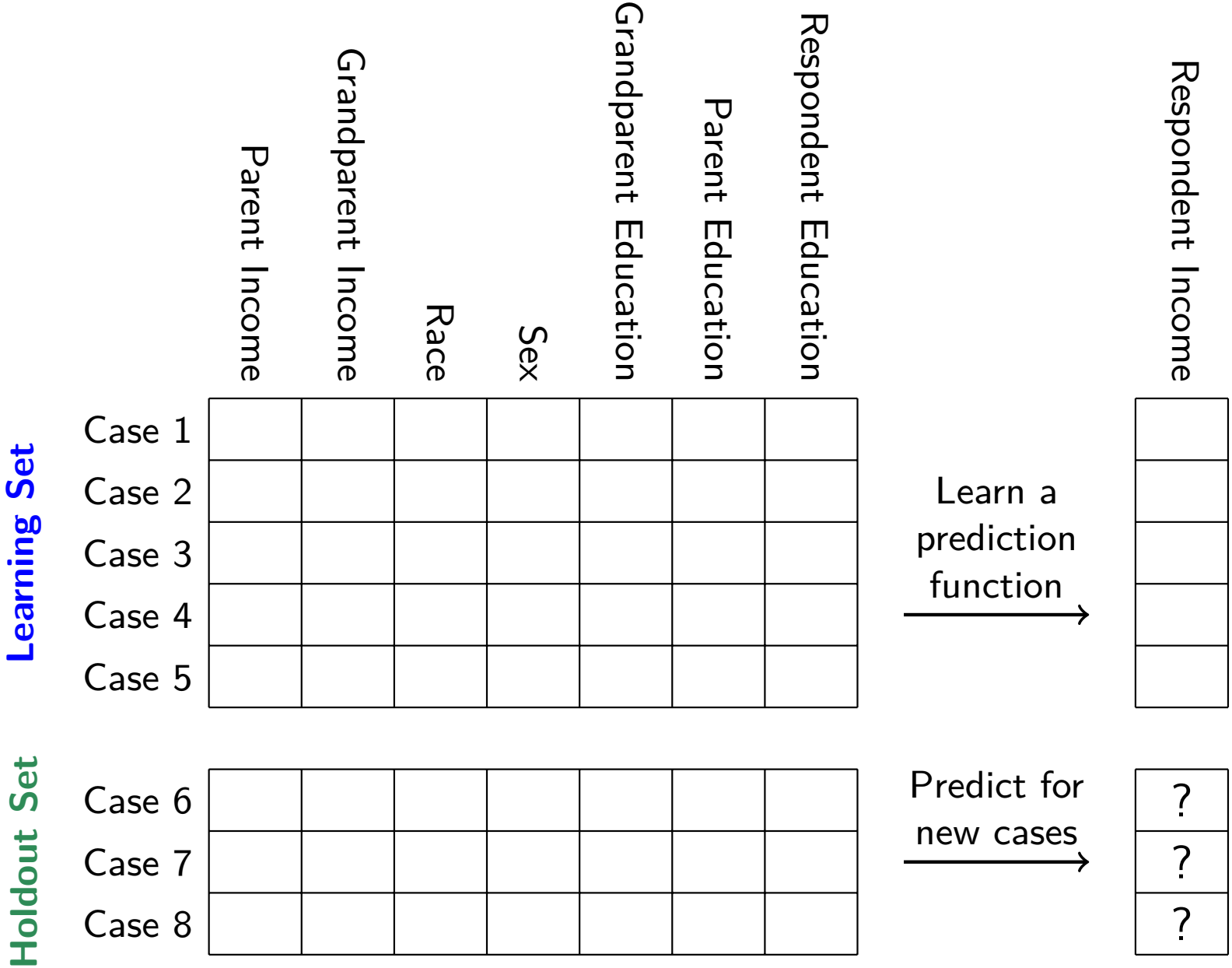
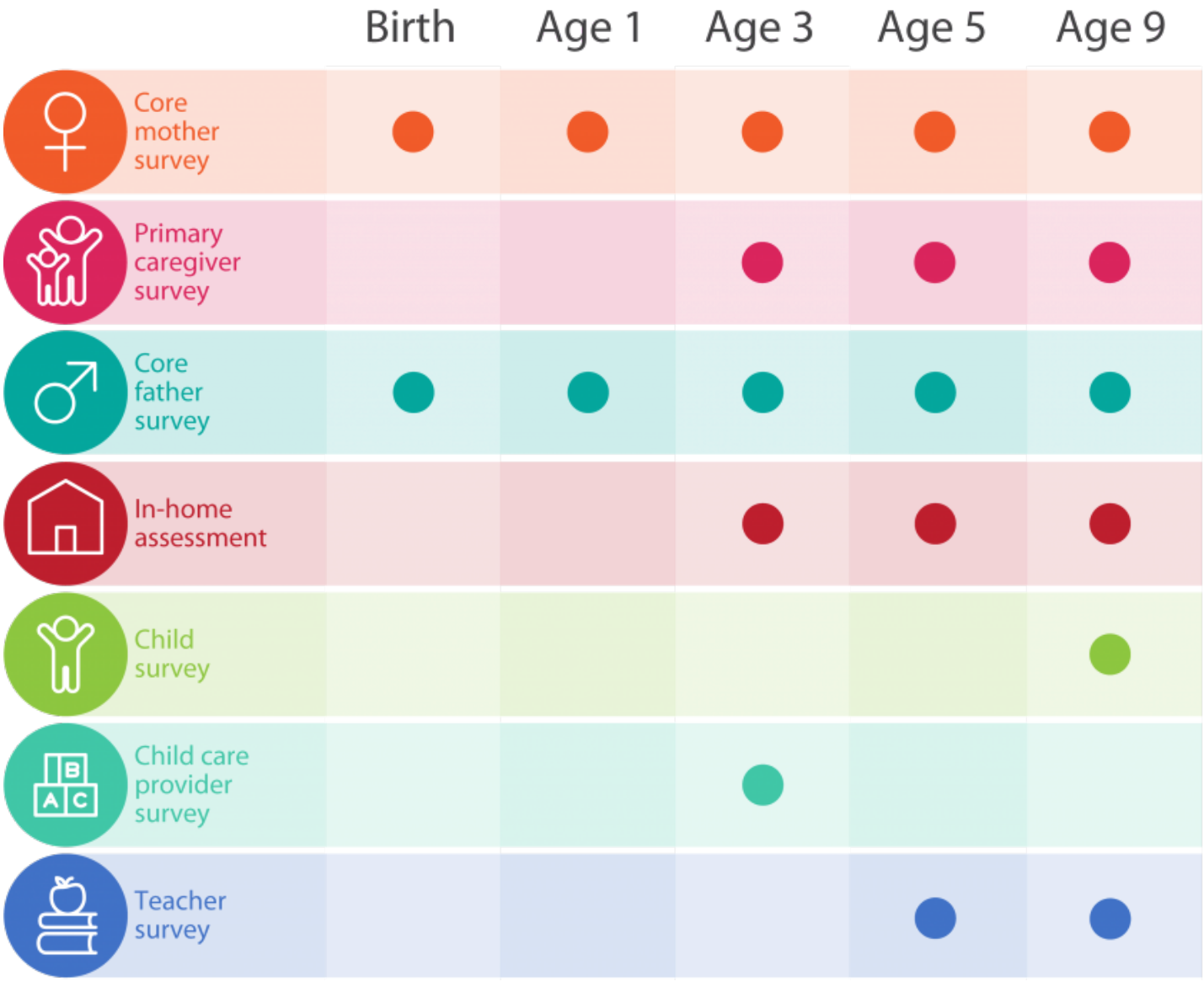
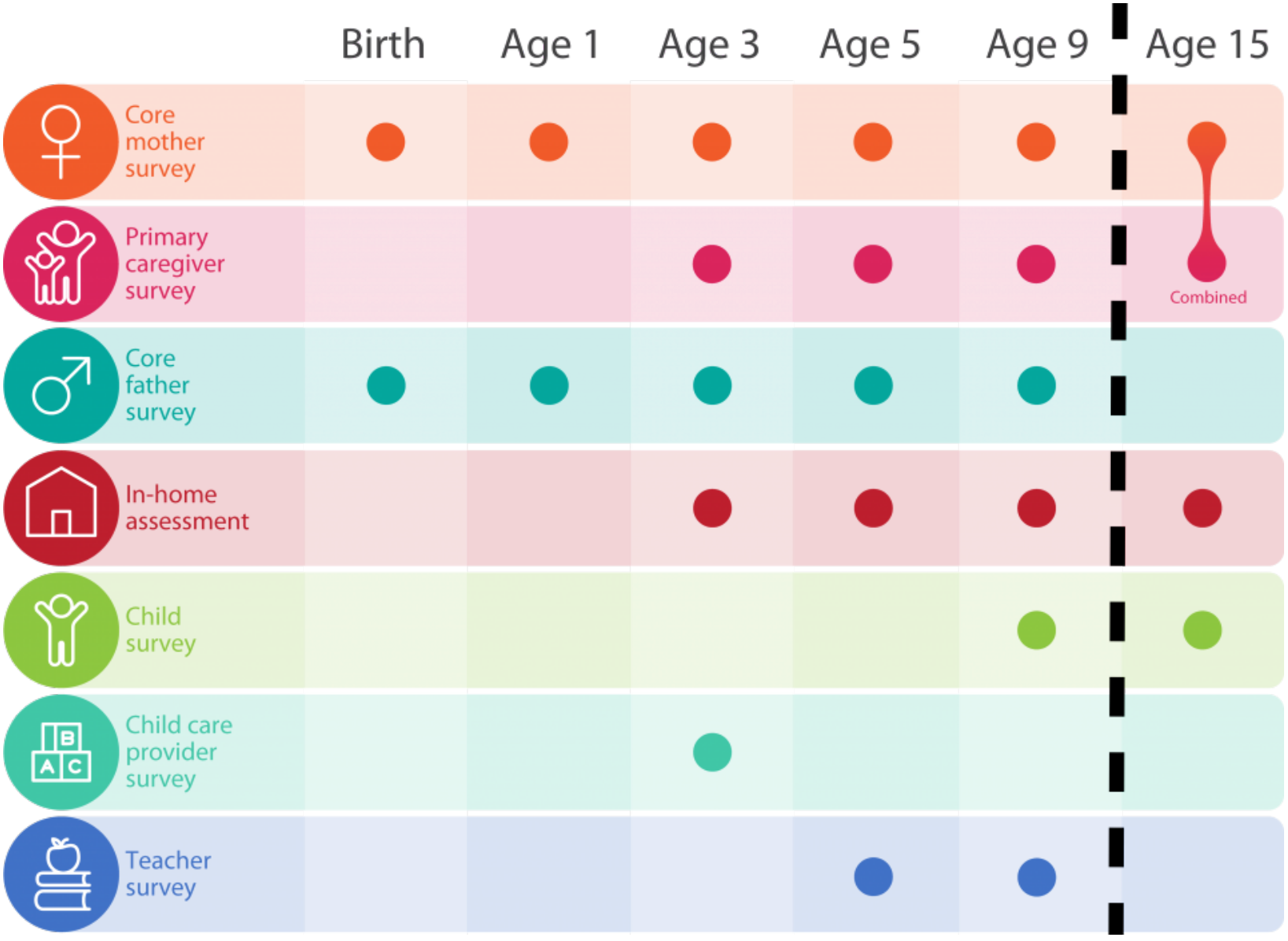
Equality Opportunity and Prediction



Measuring the predictability of life outcomes with a scientific mass collaboration

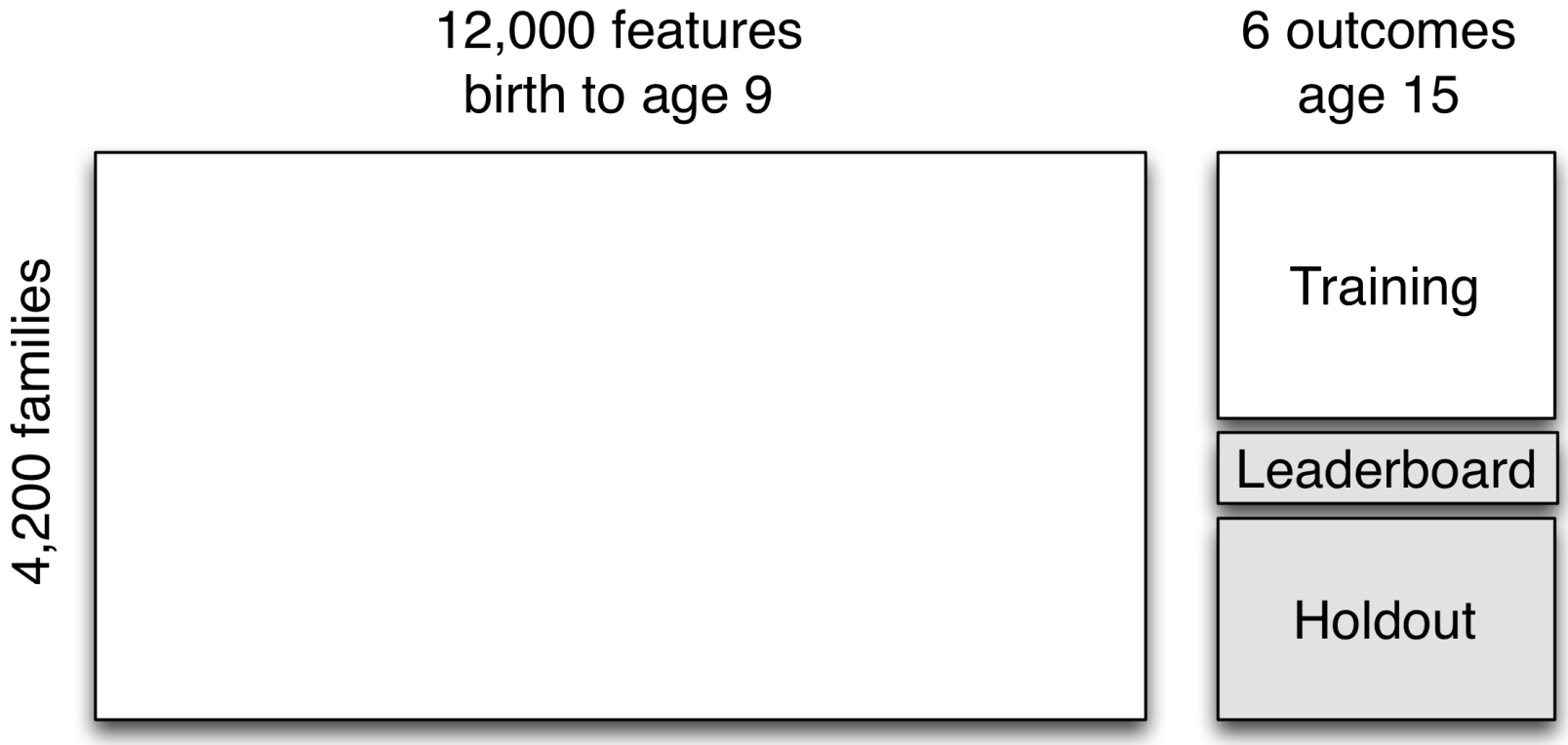
Matthew J. Salganik[a,1], Ian Lundberg[a], Alexander T. Kindel[a], Caitlin E. Ahearn[b], Khaled Al-Ghoneim[c], Abdullah Almaatouq[d,e], Drew M. Altschul[f], Jennie E. Brand[b,g], Nicole Bohme Carnegie[h], Ryan James Compton[i], Debanjan Datta[j], Thomas Davidson[k], Anna Filippova[l], Connor Gilroy[m], Brian J. Goode[n], Eaman Jahani[o], Ridhi Kashyap[p,q,r], Antje Kirchner[s], Stephen McKay[t], Allison C. Morgan[u], Alex Pentland[e], Kivan Polimis[v], Louis Raes[w], Daniel E. Rigobon[x], Claudia V. Roberts[y], Diana M. Stanescu[z], Yoshihiko Suhara[e], Adaner Usmani[aa], Erik H. Wang[z], Muna Adem[bb], Abdulla Alhajri[cc], Bedoor AlShebli[dd], Redwane Amin[ee], Ryan B. Amos[y], Lisa P. Argyle[ff], Livia Baer-Bositis[gg], Moritz Büchi[hh], Bo-Ryehn Chung[ii], William Eggert[jj], Gregory Faletto[kk], Zhilin Fan[ll], Jeremy Freese[gg], Tejomay Gadgil[mm], Josh Gagné[gg], Yue Gao[nn], Andrew Halpern-Manners[bb], Sonia P. Hashim[y], Sonia Hausen[gg], Guanhua He[oo], Kimberly Higuera[gg], Bernie Hogan[pp], Ilana M. Horwitz[qq], Lisa M. Hummel[gg], Naman Jain[x], Kun Jin[rr], David Jurgens[ss], Patrick Kaminski[bb,tt], Areg Karapetyan[uu,vv], E. H. Kim[gg], Ben Leizman[y], Naijia Liu[z], Malte Möser[y], Andrew E. Mack[z], Mayank Mahajan[y], Noah Mandell[ww], Helge Marahrens[bb], Diana Mercado-Garcia[qq], Viola Mocz[xx], Katariina Mueller-Gastell[gg], Ahmed Musse[yy], Qiankun Niu[ee], William Nowak[zz], Hamidreza Omidvar[aaa], Andrew Or[y], Karen Ouyang[y], Katy M. Pinto[bbb], Ethan Porter[ccc], Kristin E. Porter[ddd], Crystal Qian[y], Tamkinat Rauf[gg], Anahit Sargsyan[eee], Thomas Schaffner[y], Landon Schnabel[gg], Bryan Schonfeld[z], Ben Sender[fff], Jonathan D. Tang[y], Emma Tsurkov[gg], Austin van Loon[gg], Onur Varol[ggg,hhh], Xiafei Wang[iii], Zhi Wang[hhh,jjj], Julia Wang[y], Flora Wang[fff], Samantha Weissman[y], Kirstie Whitaker[kkk,lll], Maria K. Wolters[mmm], Wei Lee Woon[nnn], James Wu[ooo], Catherine Wu[y], Kengran Yang[aaa], Jingwen Yin[ll], Bingyu Zhao[ppp], Chenyun Zhu[ll], Jeanne Brooks-Gunn[qqq,rrr], Barbara E. Engelhardt[y,ii], Moritz Hardt[sss], Dean Knox[z], Karen Levy[ttt], Arvind Narayanan[y], Brandon M. Stewart[a], Duncan J. Watts[uuu,vvv,www], and Sara McLanahan[a,1]


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
Teacher survey

Six age 15 outcomes:

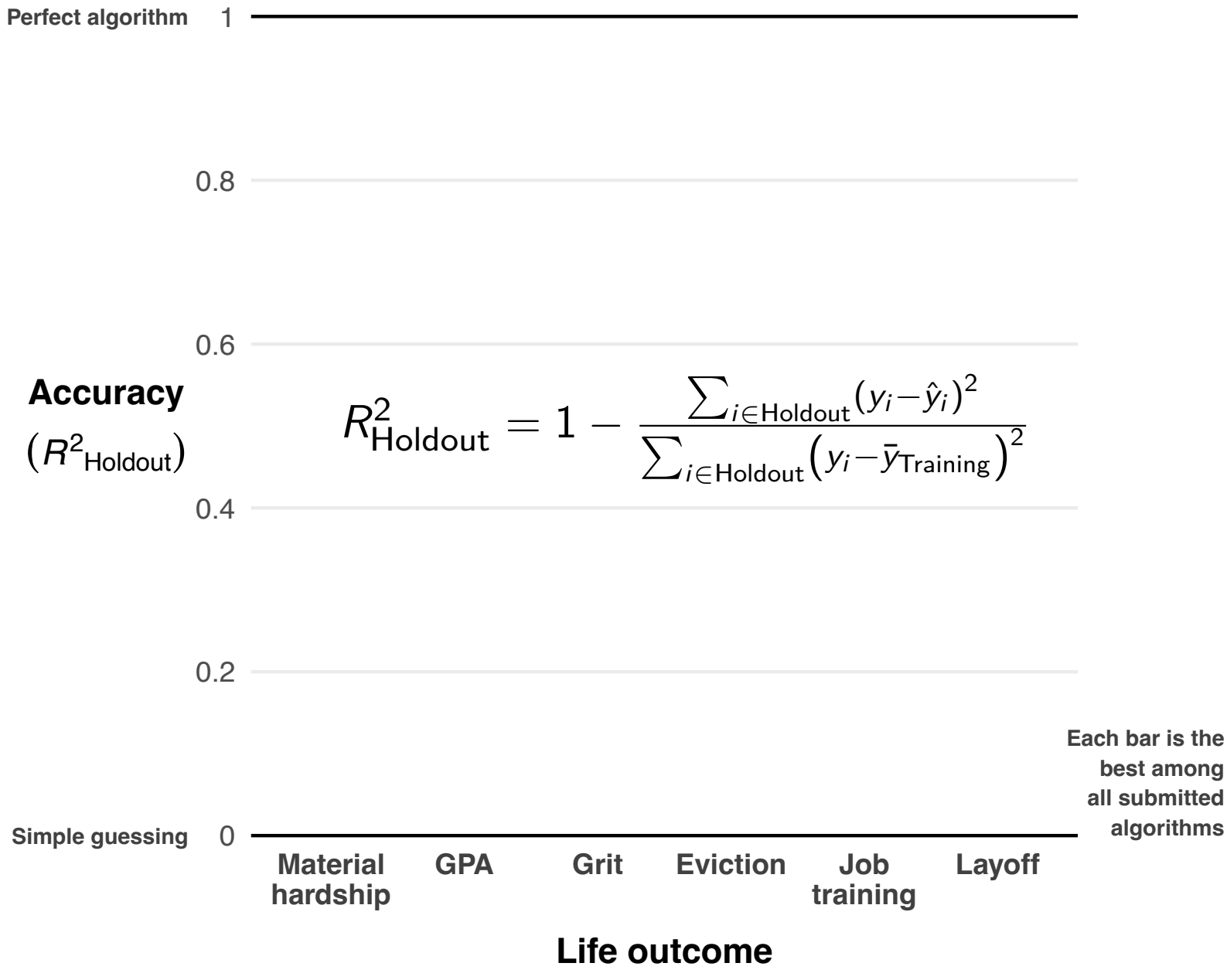
- GPA
- Material Hardship
- Grit
- Evicted
- Job training
- Job loss


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

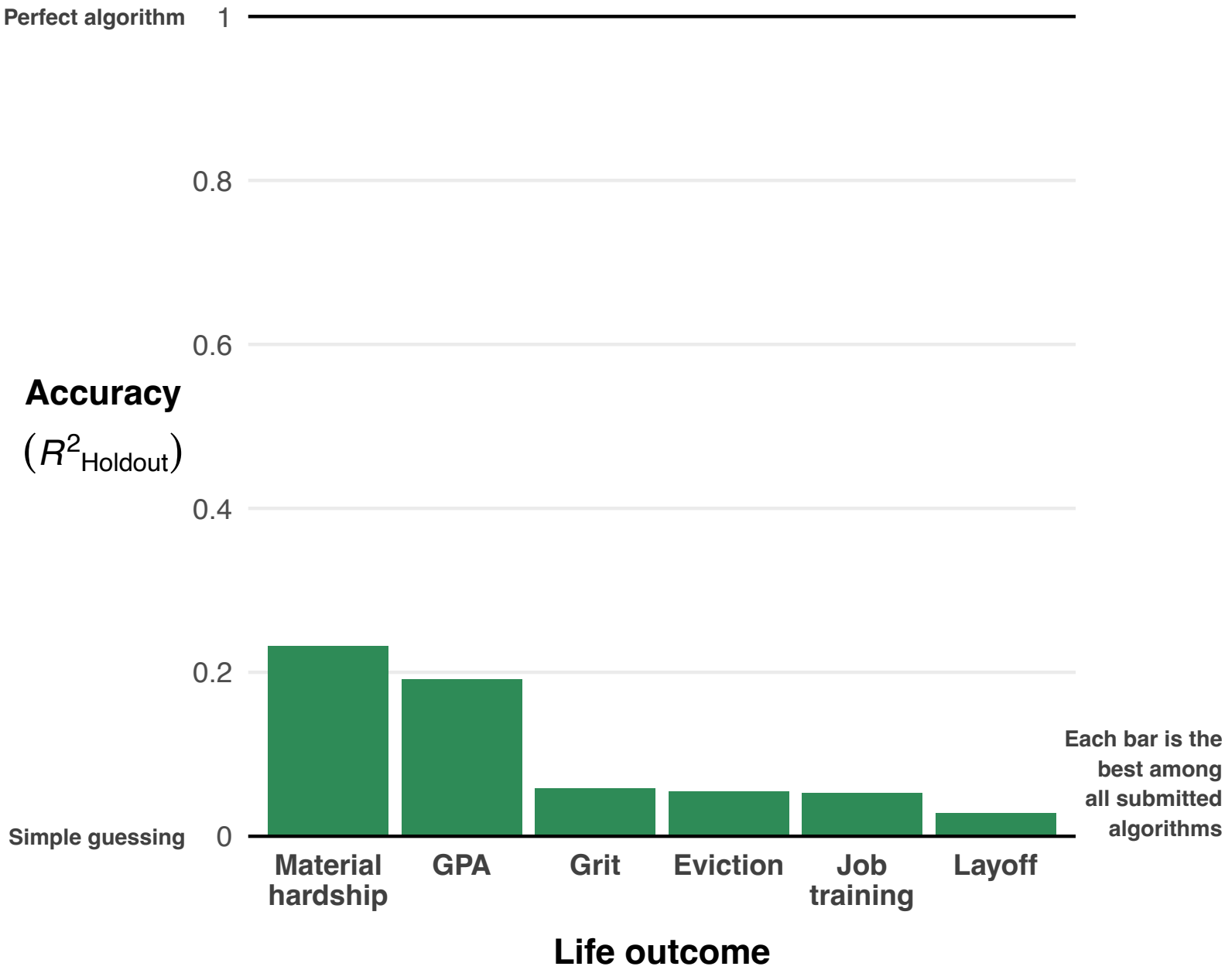
441 registered participants

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

Best algorithms were not very accurate



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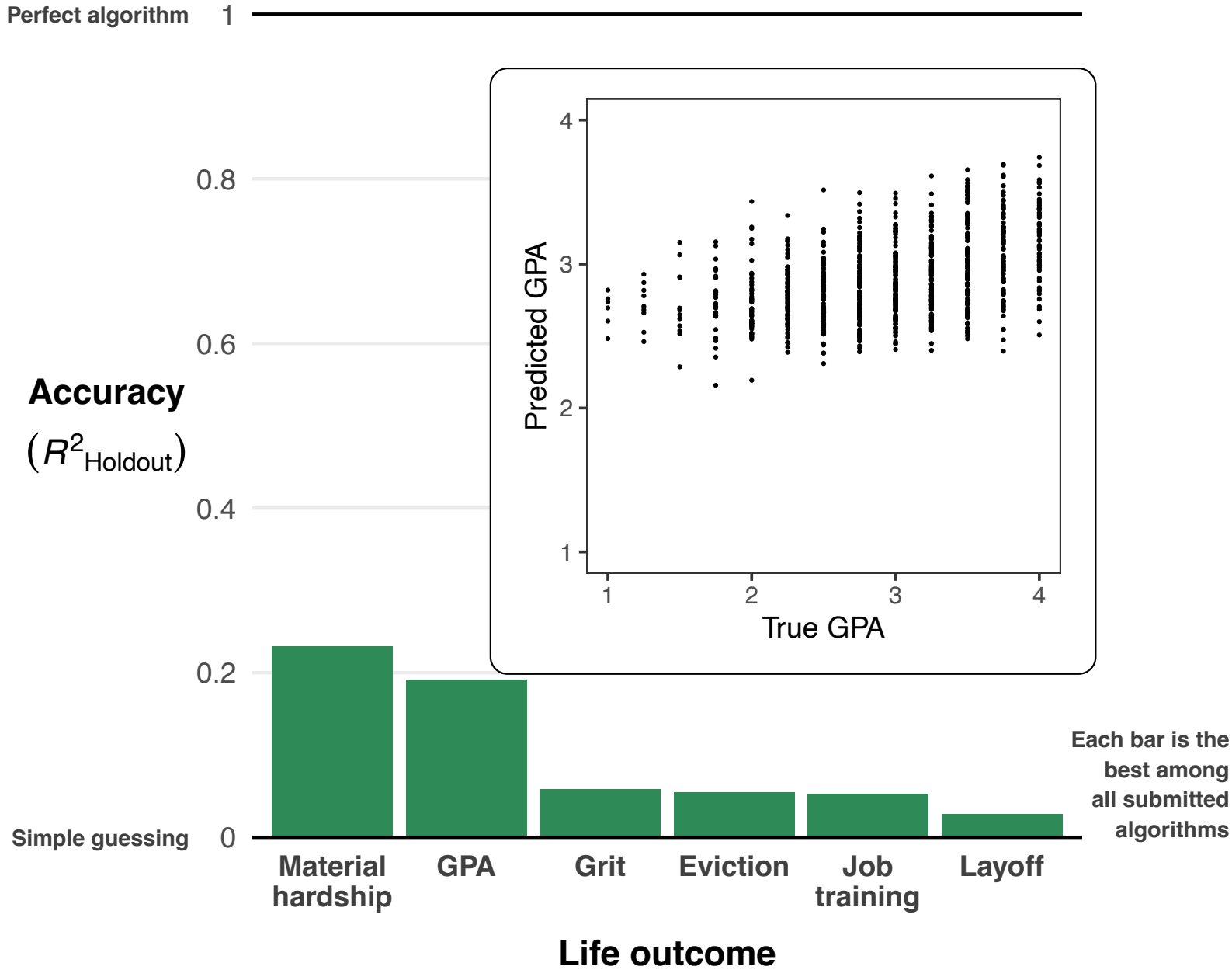

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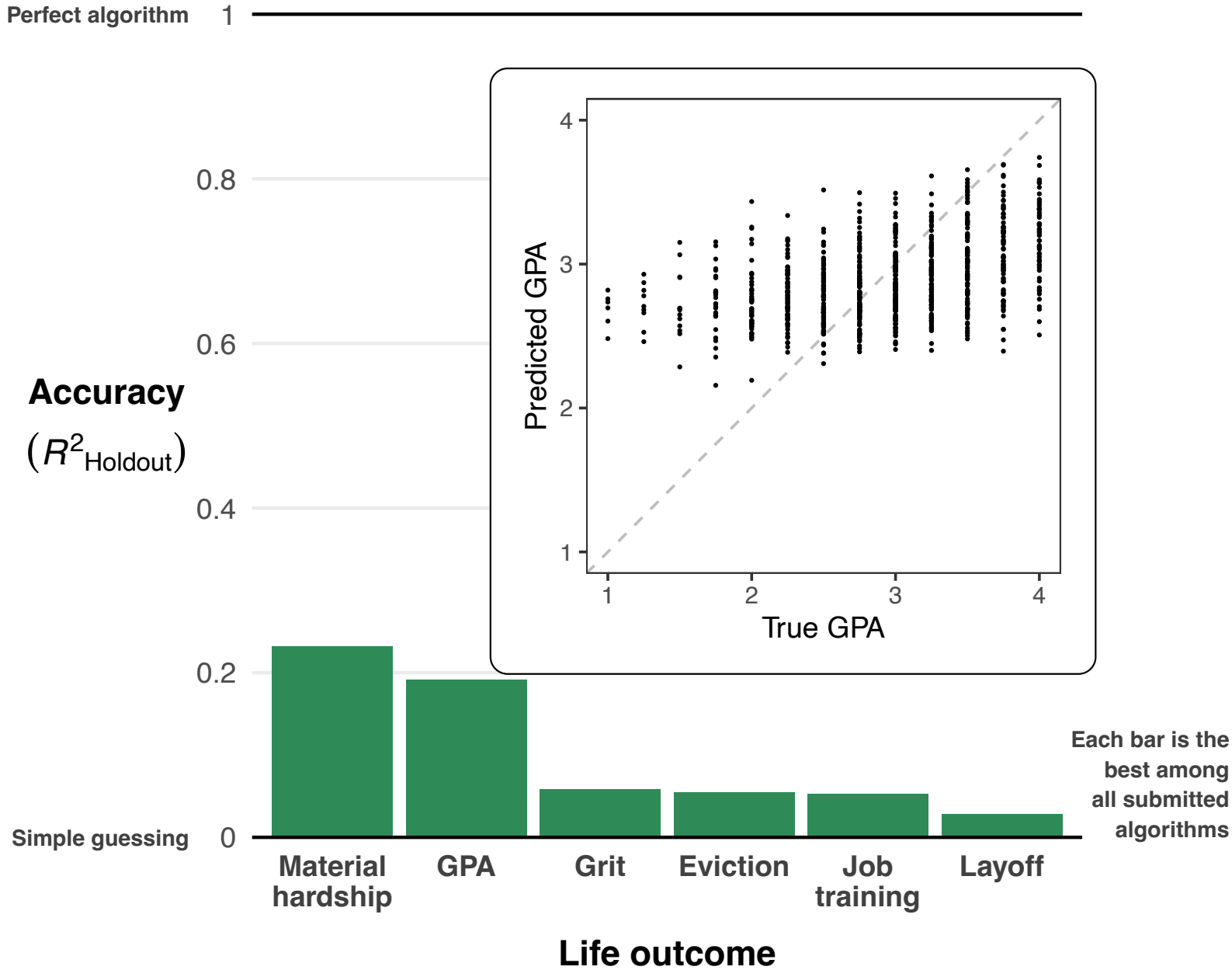

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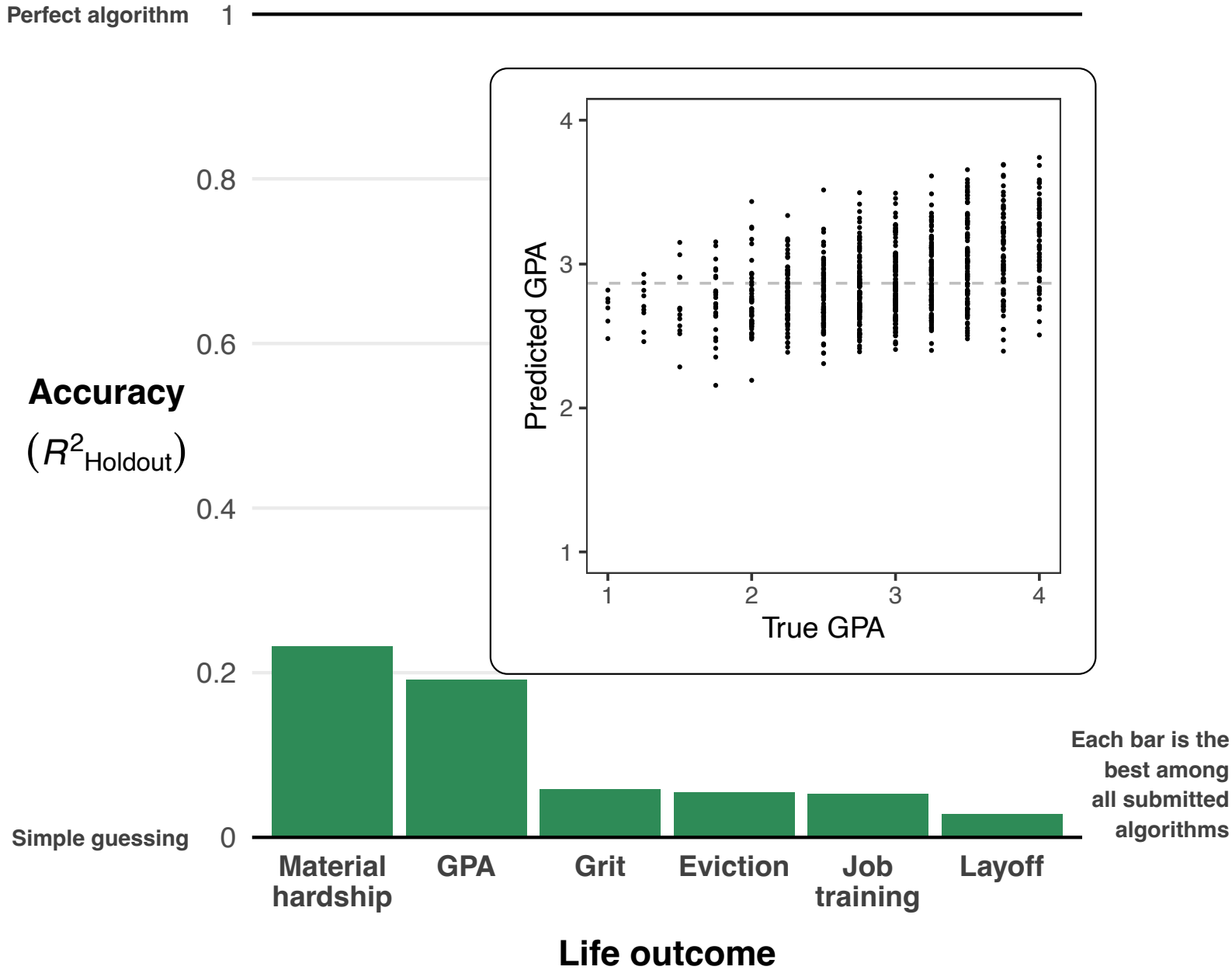

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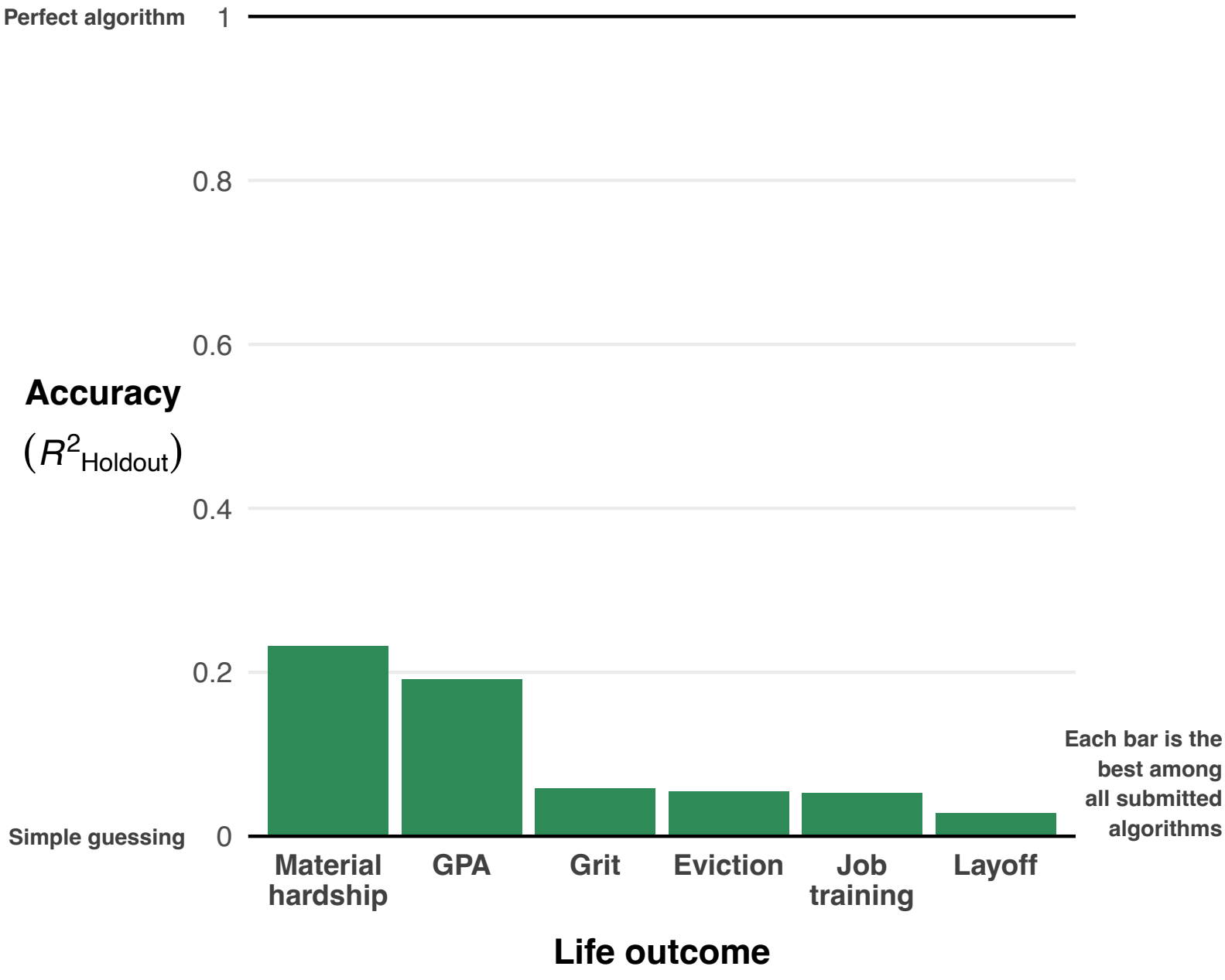

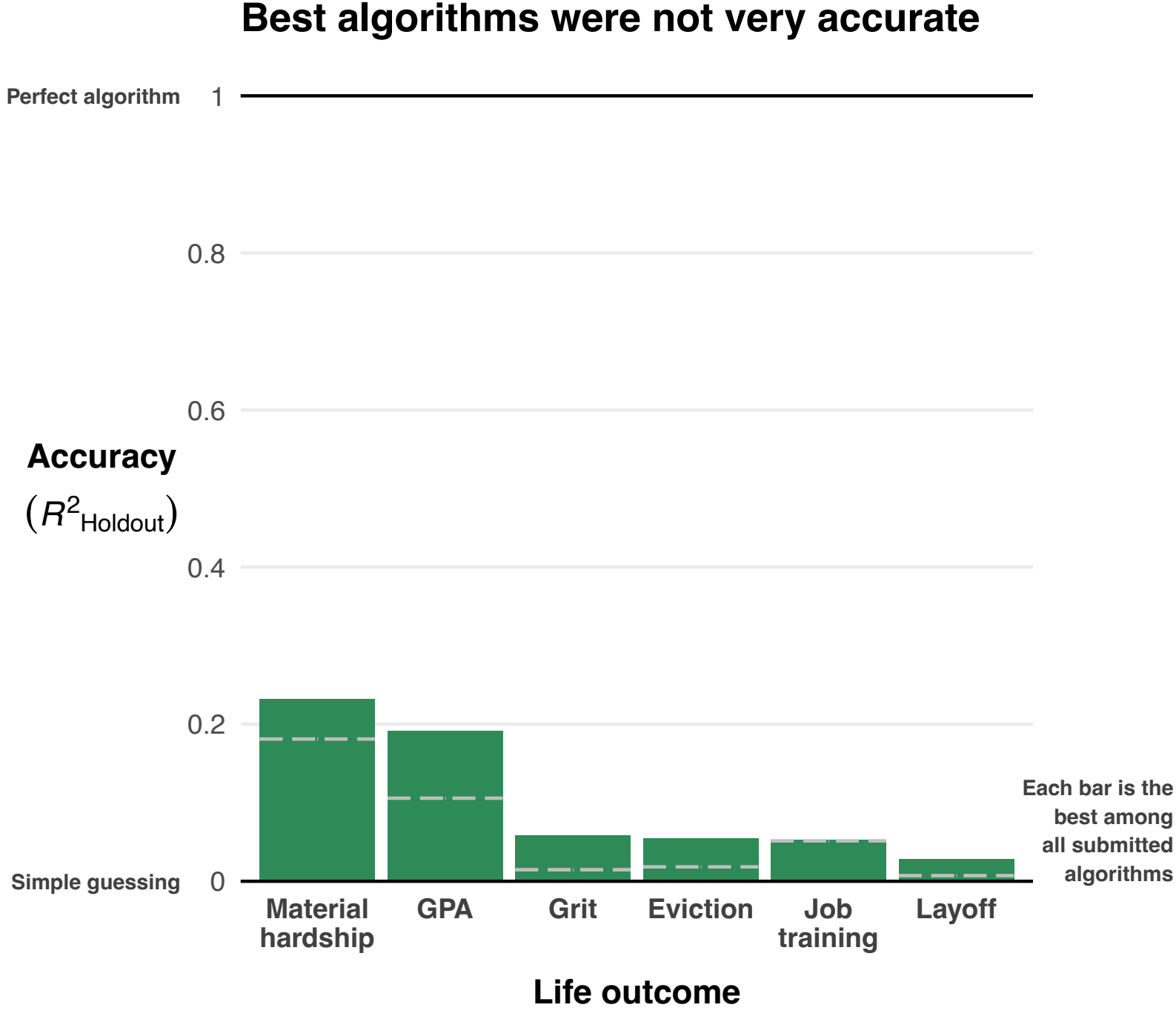
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GPA
Grit
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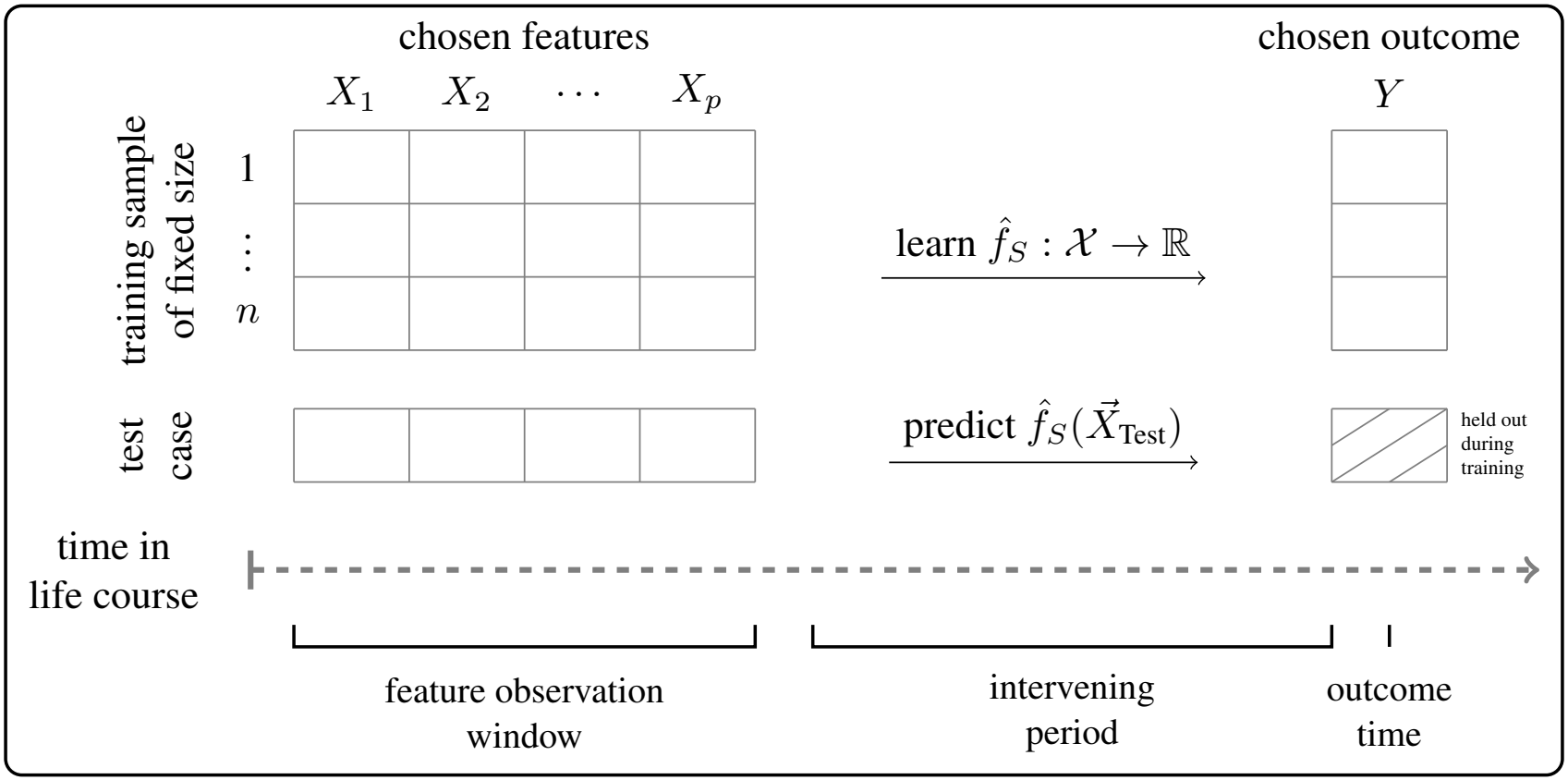
Job training
Layoff
Life outcome

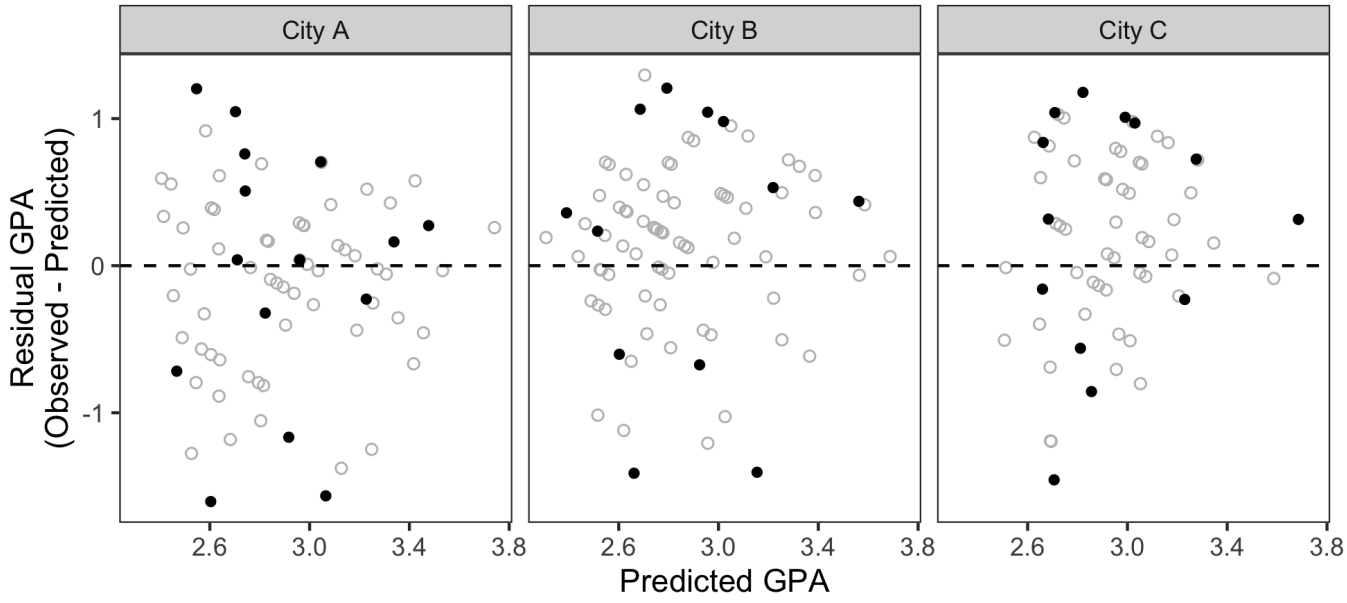
Lundberg et al. 2024.

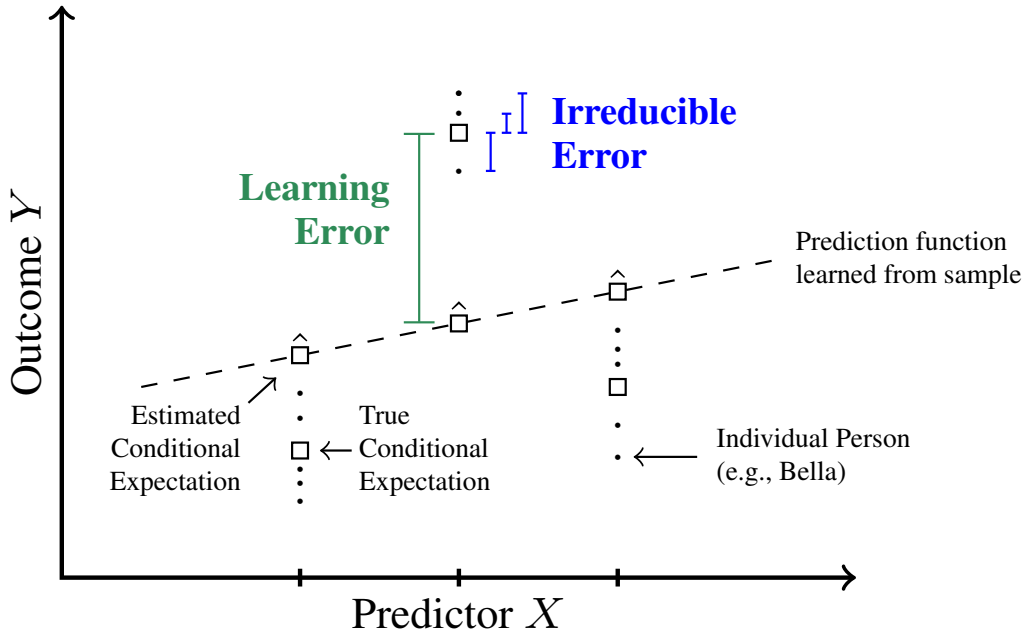
The origins of unpredictability in life outcome prediction tasks


chosen features
chosen outcome
X_1 X_2 $\cdots$ X_p
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 ($\approx$ age 18)

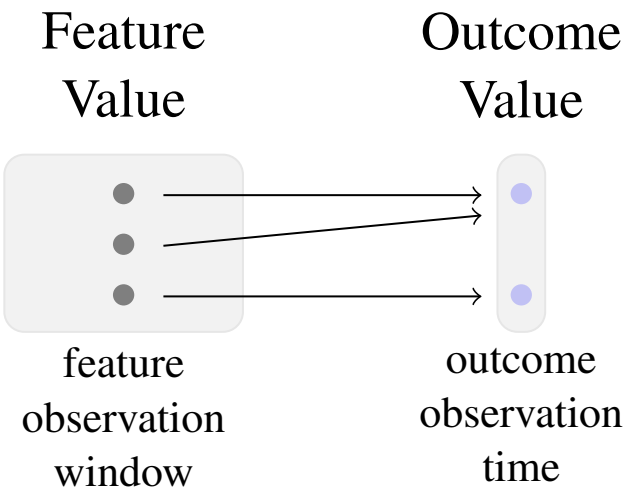



Outcome Y
Predictor X
Irreducible Error
Learning Error
Prediction function learned from sample
Estimated Conditional Expectation
True Conditional Expectation
Individual Person (e.g., Bella)

Irreducible error

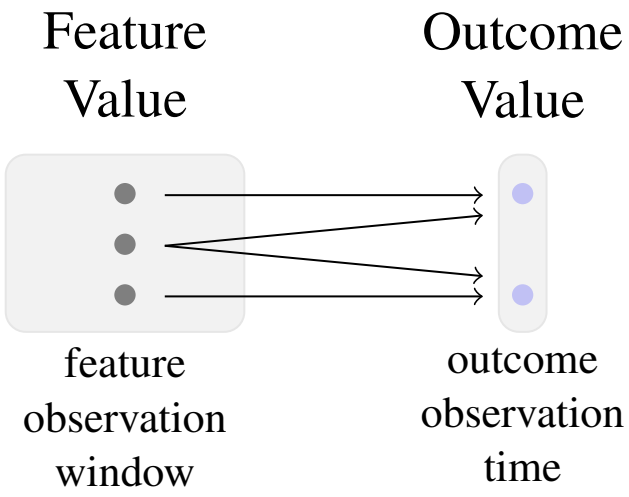
Zero Irreducible Error

Irreducible error is zero if
each feature value
maps to **one** outcome value



Non-Zero Irreducible Error

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

Irreducible error: Unmeasurable features

Unmeasurable features occur after the feature observation window

- Bella: A lasting event

Irreducible error: Unmeasurable features

Unmeasurable features occur after the feature observation window

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

Irreducible error: Unmeasurable features

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

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

Irreducible error: Unmeasurable features

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

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
  - online high school
  - worked in the basement for one semester

Irreducible error: Unmeasurable features

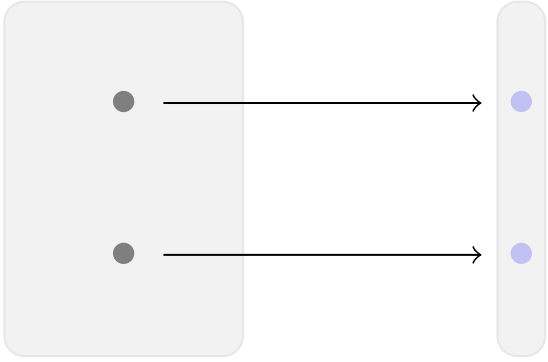
Unmeasurable features occur after the feature observation window

- 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

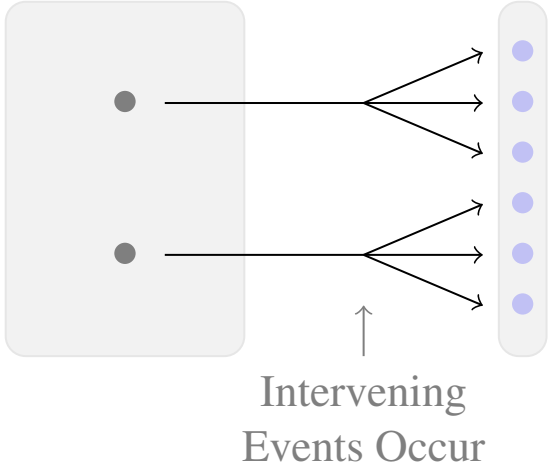
Zero Irreducible Error

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

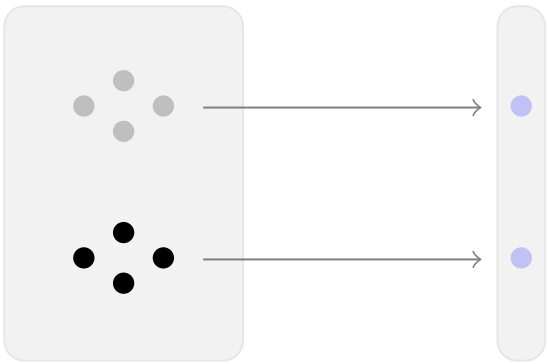
- elderly neighbor got Lola ready for school each day
- grandparents remodeled the basement to house Lola
- aunt employed Lola's mother in a family business

Predicted GPA: 3.04 Actual GPA: 3.75

Irreducible error: Unmeasured features

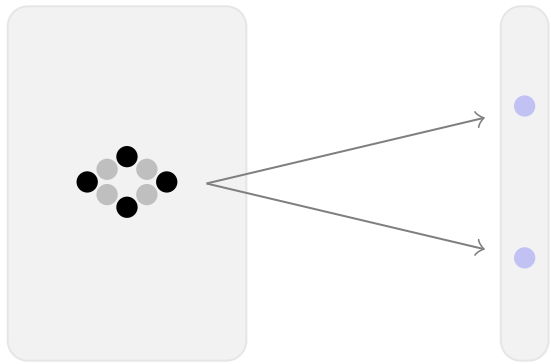
Zero Irreducible Error

Feature is measured,



Non-Zero Irreducible Error

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

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

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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

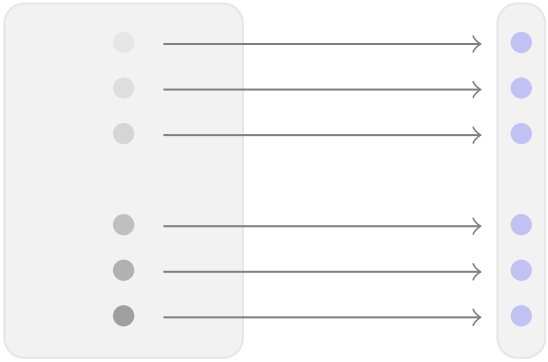
- kicked her out of the house and called police
- mother: "you better start treating me better, because I might not live that long.''
- daughter: "I couldn't even focus in class. . . I was shaking.''

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

Irreducible error: Imperfectly measured features

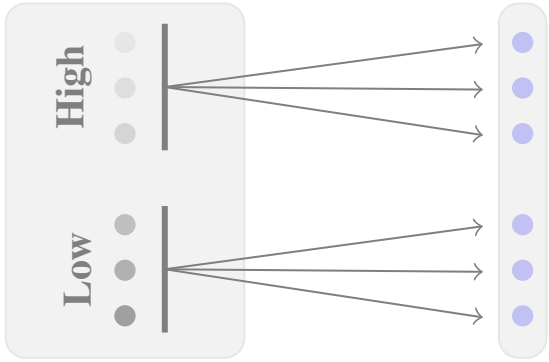
Zero Irreducible Error

Granular measurement,

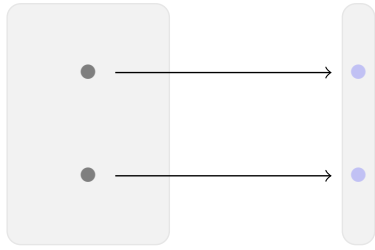
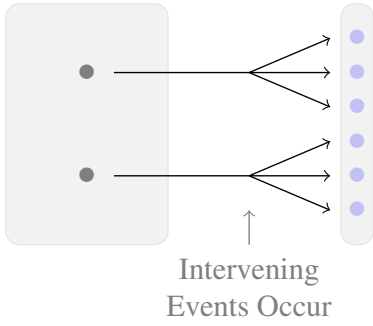
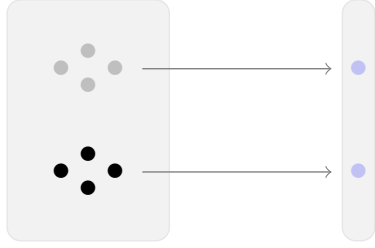
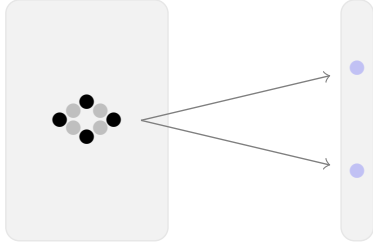
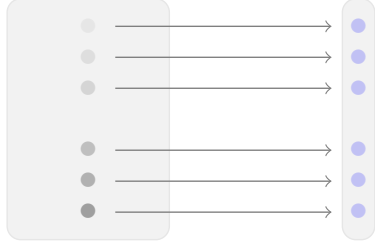
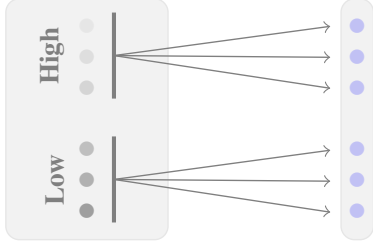


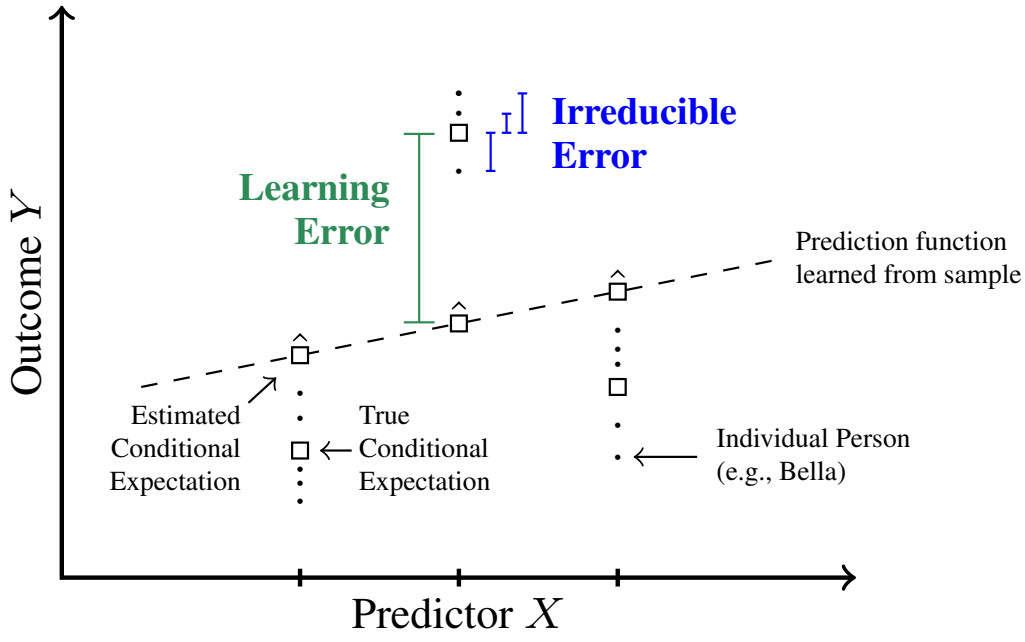
Non-Zero Irreducible Error

Coarse measurement,



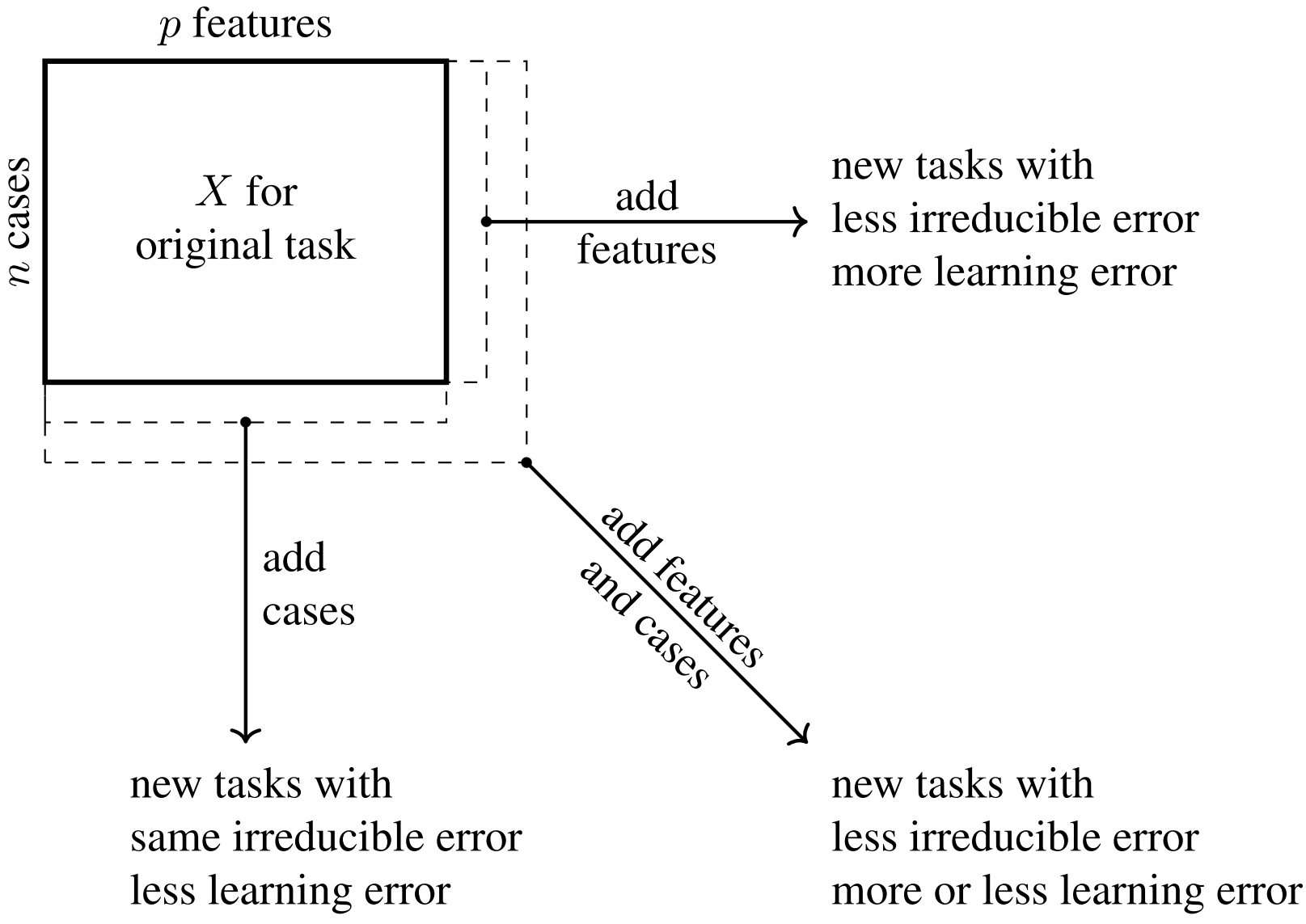
Particular Sources

	Zero Irreducible Error	Non-Zero Irreducible Error
Unmeasurable features Events after the feature observation window create outcome variance	Without intervening events, 	With intervening events, 
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, 


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

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