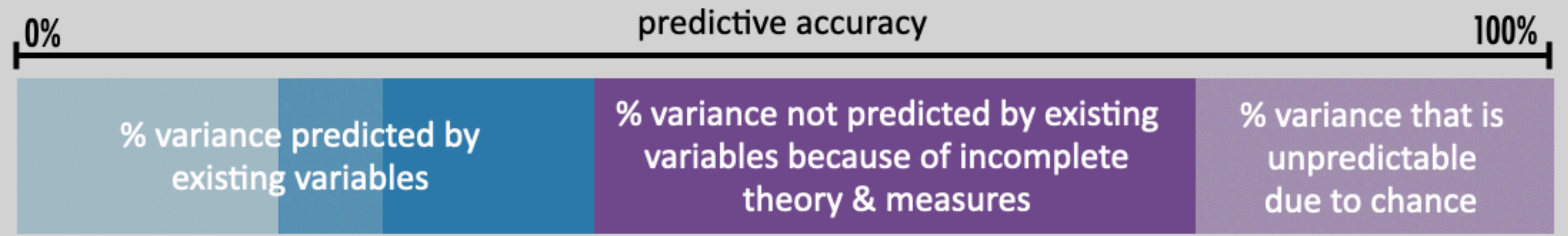


This mess we're in?

Or how simulation and prediction
will advance fertility research



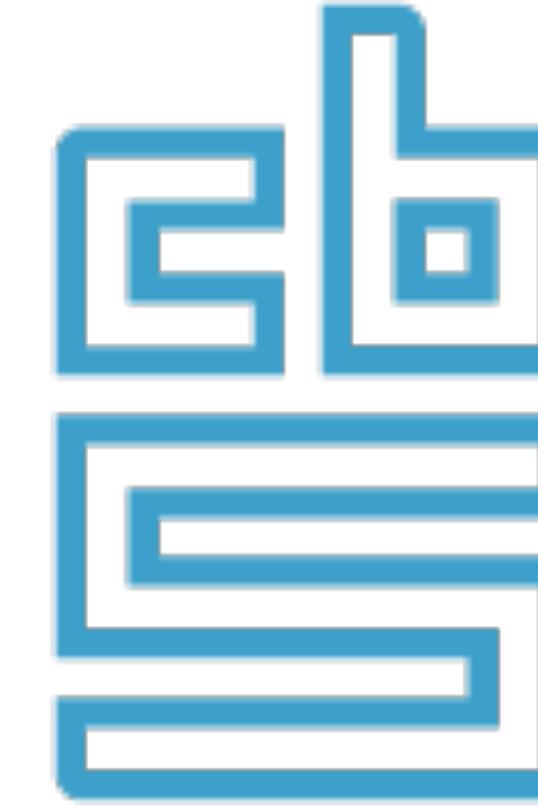


Understanding fertility outcomes
by quantifying the (un)predictable

How Well Are We Doing?

variables
explain
little

Minder geboorten door studie en flexwerk?



“total effect on fertility ...
rather small

incomparable results

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PHILOSOPHICAL
TRANSACTIONS B

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Review

Cite this article: Stulp G, Barrett S. Fertility, wealth and adaptive behaviour in industrial populations. *Philos Trans R Soc B*. 2016;371:20150355. doi:10.1098/rsta.2015.0355

Accepted: 28 December 2015

The contribution of 14 is to three issues:
Understanding variation in human fertility;
what we learn from evolutionary
demography?

Subject areas:
Intrinsic, extrinsic ecology;

Keywords:
Incomes, health, human behavioural ecology;
intrinsic, extrinsic, wealth

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e-mail: g.stulp@nuffield.ox.ac.uk

Wealth, fertility and adaptive behaviour in industrial populations

Gert Stulp¹ and Louise Barrett²

¹Department of Anatomy & Human Biology, UCLan School of Applied and Tropical Medicine, Kappel Street, Lancashire PR5 2BL, UK

²Department of Psychology, University of Lethbridge, Lethbridge, Alberta, Canada T1K 3M4

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The lack of association between wealth and fertility in contemporary industrial populations has often been used to question the value of an evolutionary perspective on human behaviour. Here, we first present the history of the debate, and the evolutionary explanations for why wealth and fertility (the number of children) are decoupled in modern industrial settings. We suggest that the nature of the relationship between wealth and fertility remains an open question because of the multi-faceted nature of wealth, and because existing cross-sectional studies are ambiguous with respect to how material wealth and fertility are linked. A literature review of longitudinal studies on wealth and fertility shows that the majority of these report positive effects of wealth, although levels of fertility seem to fall when observations would suggest otherwise. We emphasize that reproductive decision-making reflects a complex interplay between individual and societal factors that merits simple evolutionary interpretation, and highlight the role of economic inequality in fertility decisions. We conclude by discussing whether the wealth–fertility relationship can inform us about the adaptiveness of modern fertility behaviour, and argue against simplistic claims regarding maladaptive behaviour in humans.

1. Introduction

In an update to Jane Austen's famous pronouncement of 'a truth universally acknowledged, that a single man in possession of a good fortune must be in power of a wife' [1, p. 188], Waring suggested that, 'in contemporary society, it was a negative relationship between wealth and fertility (the number of children) that was close to a universal regularity' [2, p. 158]. However [2] argued similarly that wealth and fertility were decoupled in industrial societies, given that 'wealthier men did not father more offspring despite higher mating success'. These papers have been cited and discussed as the 'central theoretical problem of sociobiology' [3], as evolutionary theory asserts, individuals are attempting to maximize their fitness, then more resources should translate into a larger number of offspring, as seen in a range of non-industrial populations [3–6]. The lack of a positive relationship between income and reproductive success also fits with the large-scale pattern of fertility decline in most nations, whereby fewer children are born in more prosperous economies [6], whatever people are doing with the resources they acquire or not; however, they are not apparently investing them in having more children.

Here, we revisit briefly Vining [2] and Piraine [3], using them as a spring board for a review of the literature on wealth and fertility among industrial populations (see also [1]). We then present a new review focused exclusively on longitudinal studies that enables stronger inferences to be made about the links between wealth and reproduction. Finally, we discuss the extent to which the association between wealth and fertility speaks to the issue of maladaptive behaviour, and argue for a more balanced approach to human fertility.

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Philosophical
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Societies, Part I

atmos.com

and in modern industrial settings debate, beginning the evolutionary and social traits (e.g., fertility) offers a modern industrial example: our behavior can no longer be based on no fertility measurements in society; in particular, such much between ancestral and modern provide insight into the behaviors. Having made of fertility-related analyses of large-scale databases, even made about which may exist in such data, can represent an excellent enriching the evolutionary

Societies, Part II

ability in industrial populations have been used to argue explaining human variability, during fertility (and proxies wide availability of large as well as advantages, examining the association States, using the National-based exploratory analysis of both cross-sectional and with (income and net worth) to first, second and third be made regarding sample variables and controls of both income and net

(doi:10.1098/rsta.2015.0355)

Journal of Tropical Medicine, Kappel Street,

Topical Medicine, Kappel Street,
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Springer



surprising patterns

non-replicable results

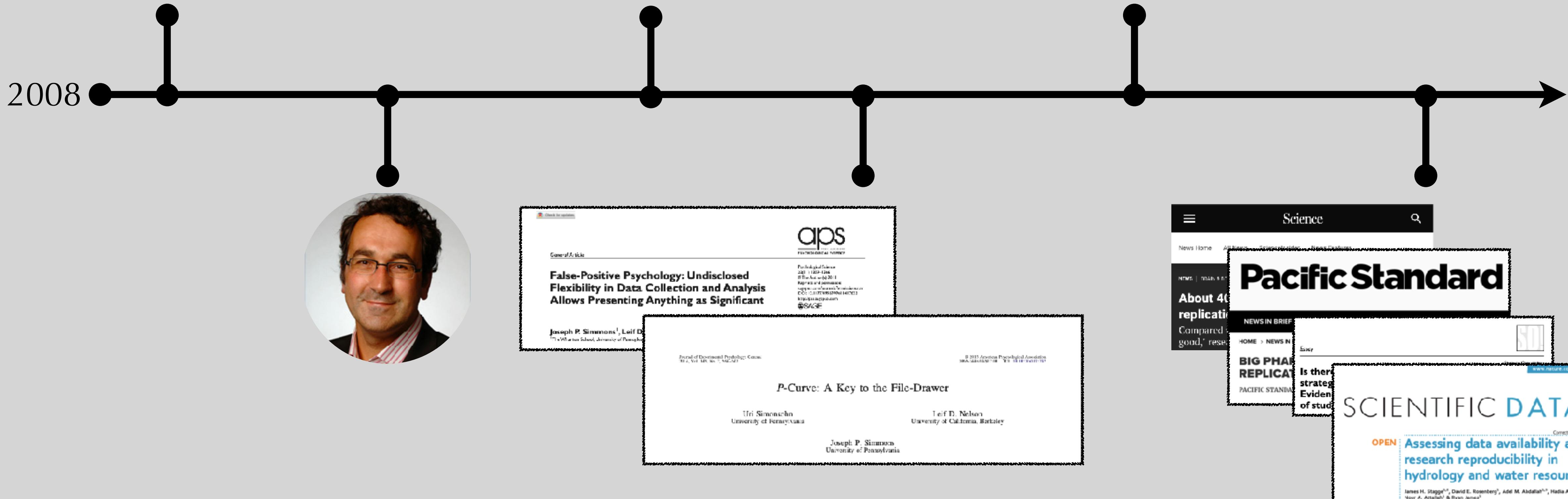
My Upbringing in Science



PSYCHOLOGY

Estimating the reproducibility of psychological science

Open Science Collaboration*



Replication (crisis) in Demography?



Reasons why not

- *Strong methods*
- *Strong focus on representative data (GGP)*
- *Less measurement error*
- *Open data*
- *Large N*
- *Often descriptive*



Reasons why

- *Non-experimental*
- *Correlational, but little causal inference*
- *Large N, yet star gazing*
- *Controlling at will*
- *“Culture” as a get-out-of-jail-for-free card*

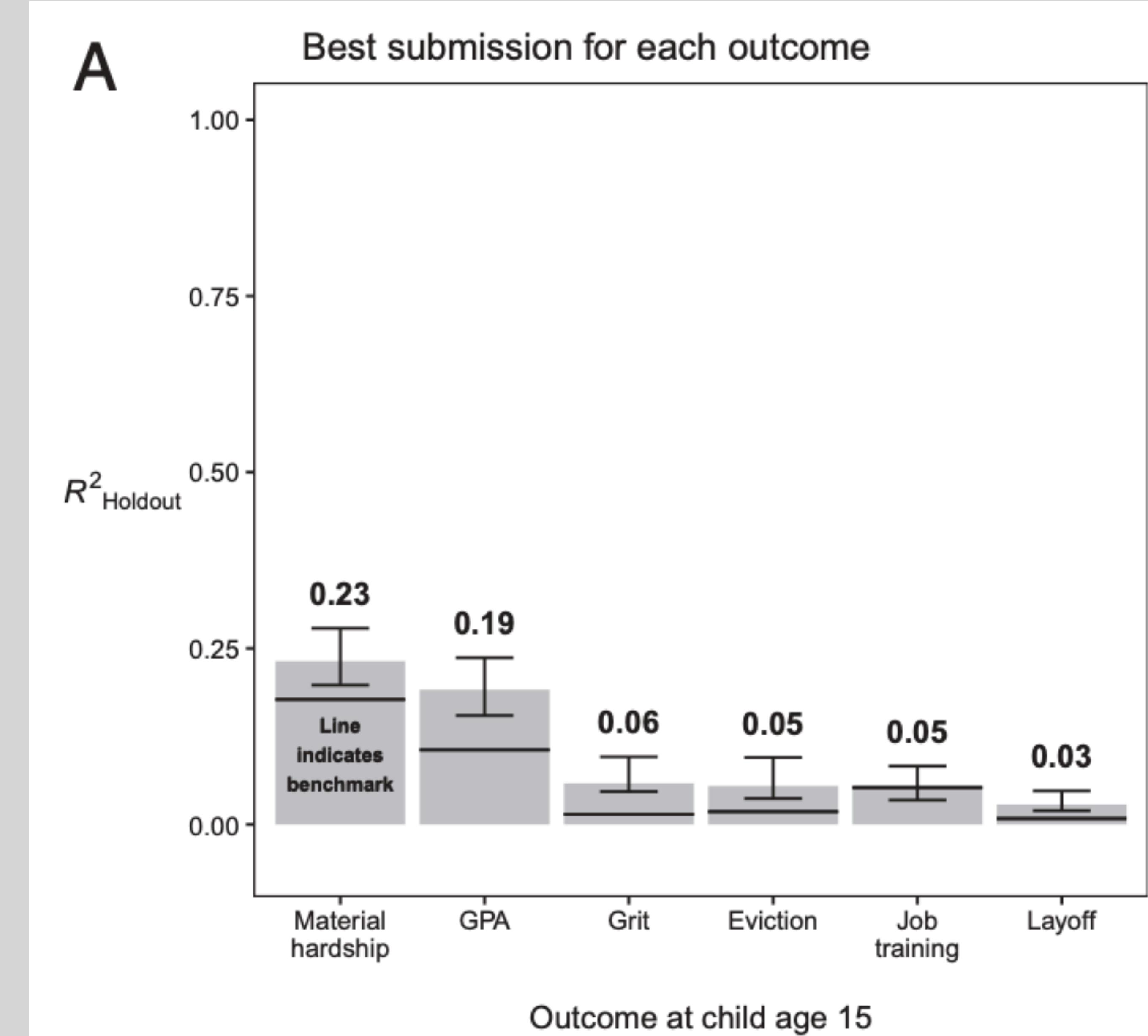
Predictability Crisis?

Check for updates

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 Comptonⁱ, Debanjan Datta^j, Thomas Davidson^k, Anna Filippova^l, Connor Gilroy^m, Brian J. Goodeⁿ, Eaman Jahani^o, Ridhi Kashyap^{p,q,r}, Antje Kirchner^s, Stephen McKay^t, Allison C. Morgan^u, Alex Pentland^v, Kivan Polimis^w, Louis Raes^x, Daniel E. Rigobon^y, Claudia V. Roberts^y, Diana M. Stanescu^z, Yoshihiko Suhara^t, Adaner Usmani^{aa}, Erik H. Wang^x, 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 Chungⁱⁱ, William Eggert^{ll}, Gregory Faletto^{kk}, Zhilin Fan^{ll}, Jeremy Freese^{gg}, Tejomay Gadgil^{mm}, Josh Gagné^{gg}, Yue Gaoⁿⁿ, 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,ww}, E. H. Kim^{gg}, Ben Leizman^y, Naijia Liu^z, Malte Möser^y, Andrew E. Mack^x, Mayank Mahajan^y, Noah Mandell^{ww}, Helge Marahrens^{bb}, Diana Mercado-Garcia^{aa}, Viola Mocz^{xx}, Katarina Mueller-Gastell^{gg}, Ahmed Musse^{yy}, Qiankun Niu^{ee}, William Nowak^{zz}, Hamidreza Omidvar^{aa}, Andrew Or^y, Karen Ouyang^y, Katy M. Pinto^{bb}, Ethan Porter^{cc}, Kristin E. Porter^{dd}, Crystal Qian^y, Tamkinat Rauf^{gg}, Anahit Sargsyan^{ee}, Thomas Schaffner^y, Landon Schnabel^{gg}, Bryan Schonfeld^z, Ben Sender^{ff}, Jonathan D. Tang^y, Emma Tsurkov^{gg}, Austin van Loon^{gg}, Onur Varol^{gg,hh,ii}, Xiafei Wangⁱⁱ, Zhi Wang^{hh,jj}, Julia Wang^y, Flora Wang^{ff}, Samantha Weissman^y, Kirstie Whitaker^{kk,ll}, Maria K. Wolters^{mm}, Wei Lee Woonⁿⁿ, James Wu^{ooo}, Catherine Wu^y, Kengran Yang^{aa}, Jingwen Yin^{ll}, Bingyu Zhao^{ppp}, Chenyun Zhu^{ll}, Jeanne Brooks-Gunn^{qqq,rrr}, Barbara E. Engelhardt^{yy,ii}, Moritz Hardt^{ss,tt}, Dean Knox^z, Karen Levy^{tt,tt}, Arvind Narayanan^y, Brandon M. Stewart^a, Duncan J. Watts^{uu,vv,ww,ww}, and Sara McLanahan^{a,1}

data challenge:
predicting life outcomes
based on ~6000 variables
by 160 teams
both theory- & data-driven



Predictability Crisis?

“

Social scientists studying the life course must find a way to reconcile a widespread belief that understanding has been generated by these data—as demonstrated by more than 750 published journal articles using the Fragile Families data with the fact that the very same data could not yield accurate predictions of these important outcomes.

How Well Are We Doing?

The Proposal

a shift towards **prediction**
leads to a more reliable
and useful social science

microsimulation can
advance traditional
statistical modelling

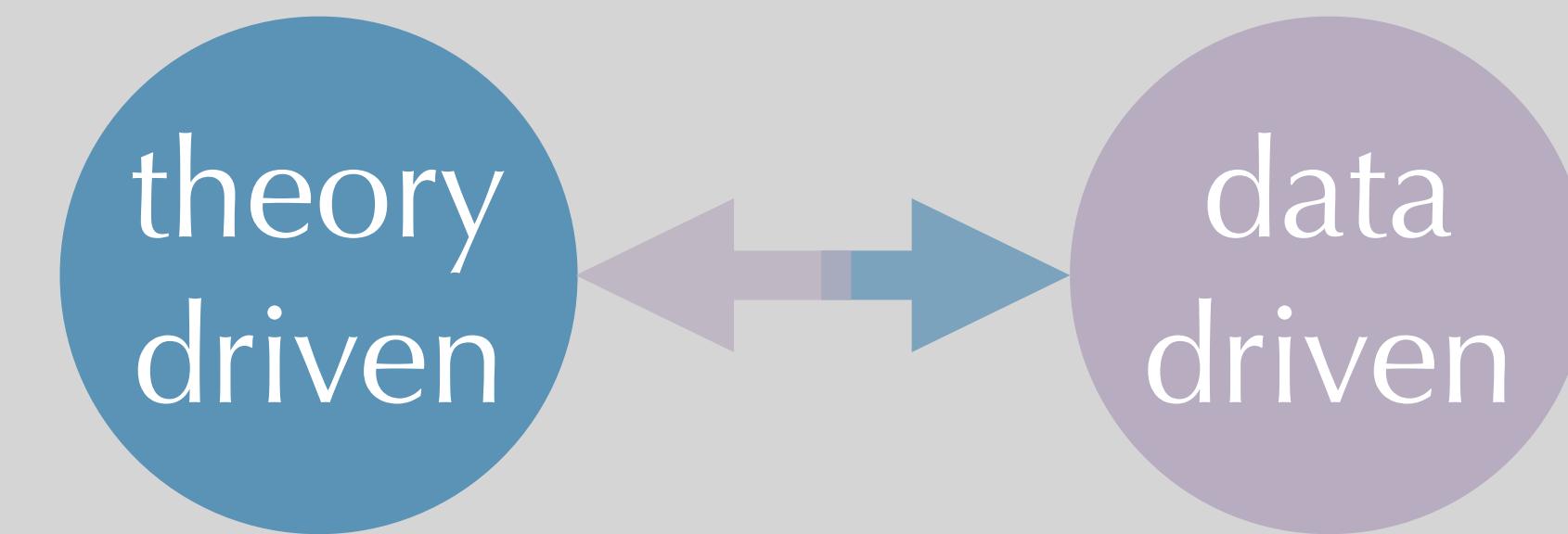
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and useful social science

out-of-sample predictive ability:



clear measure of
effect size



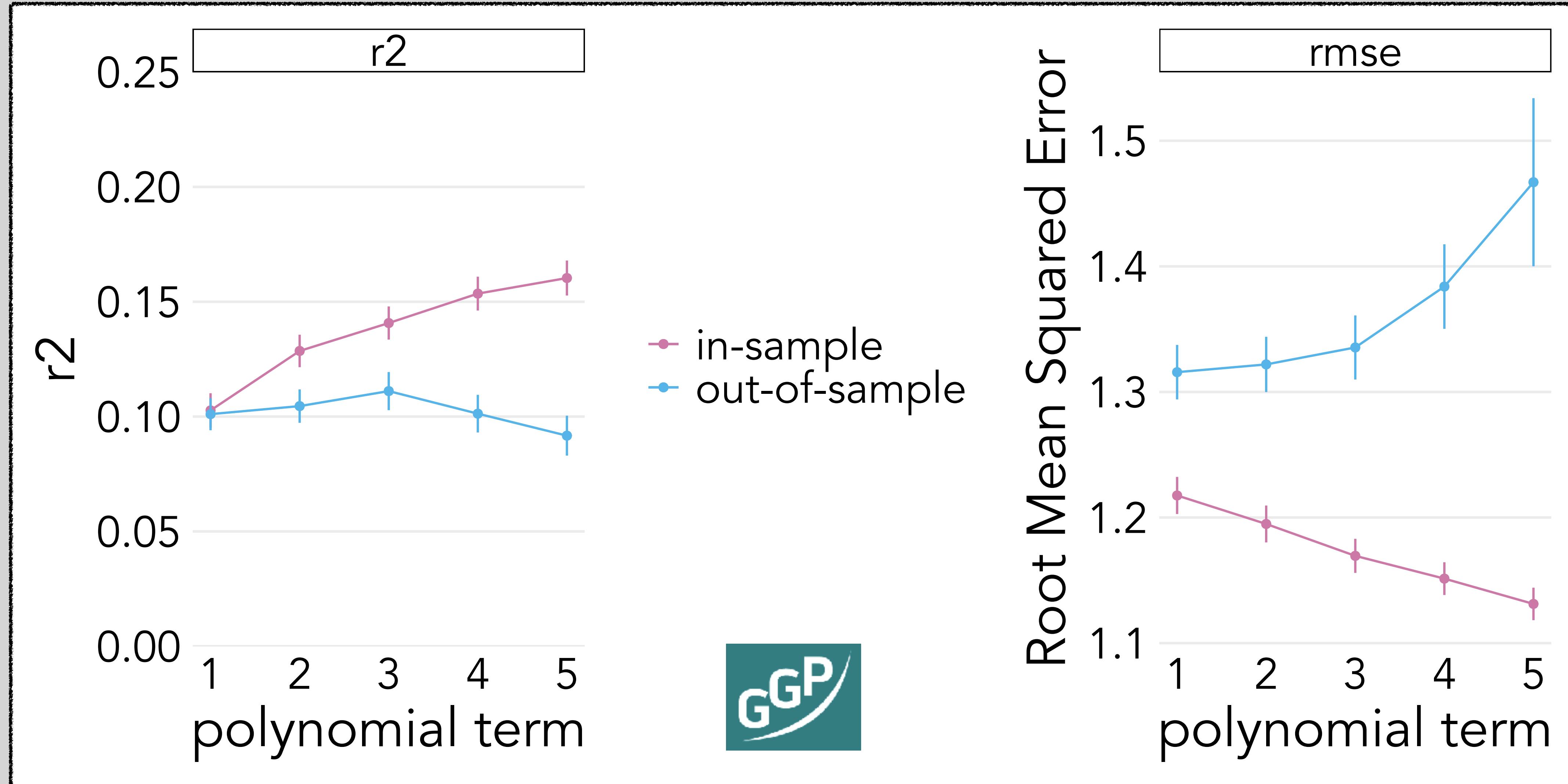
facilitates dialogue
theory- and data-
driven models



measure of distance
theory and practice

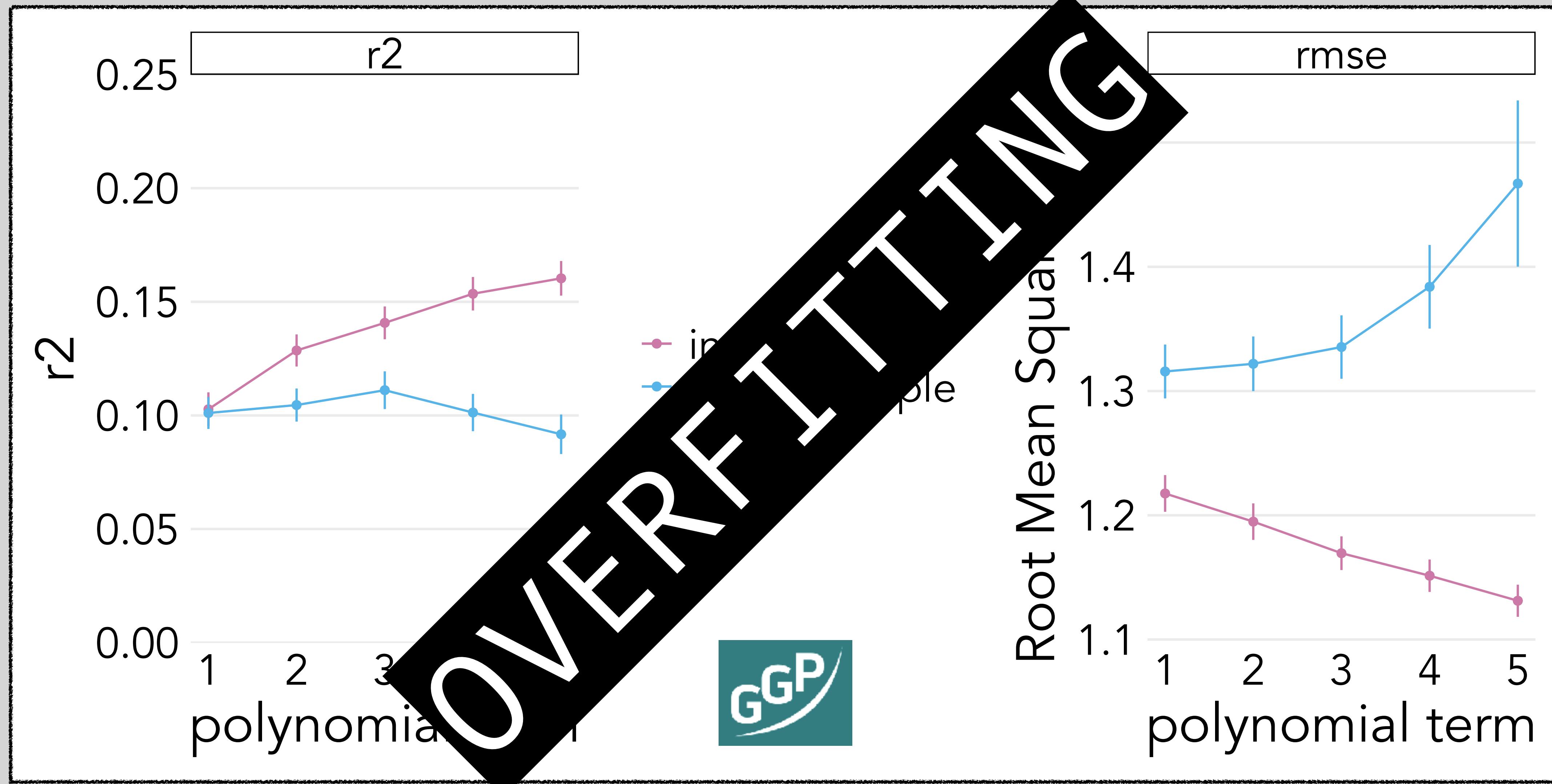
Out-of-Sample Prediction

$n = 50$ training data
 $n = 50$ test data
number of children \sim age



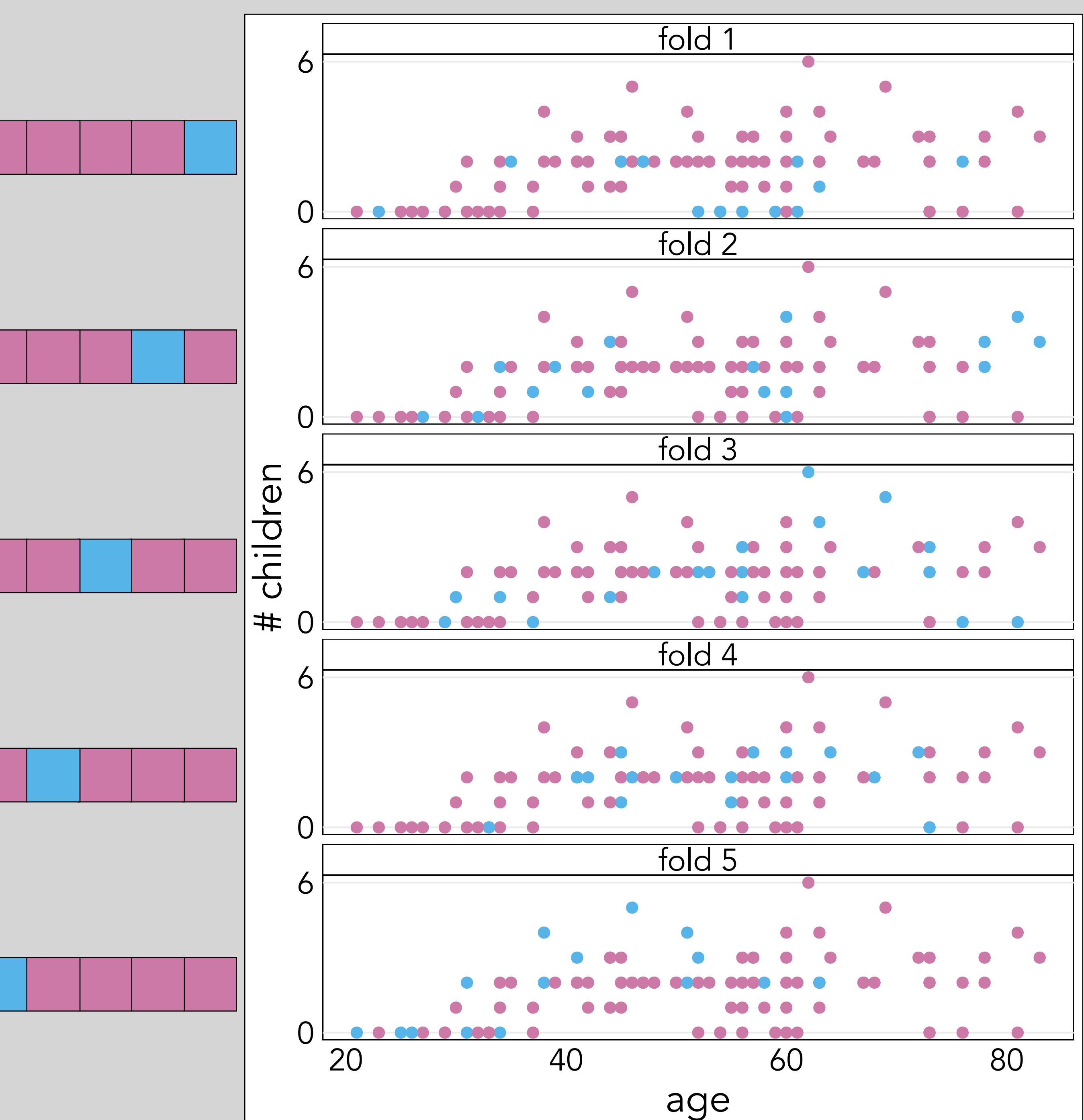
Out-of-Sample Prediction

$n = 50$ training data
 $n = 50$ test data
number of children \sim age



Cross Validation

fold	in-sample R^2	out-of-sample R^2
1	0.15	0.12
2	0.17	0.17
3	0.14	0.20
4	0.20	-0.18
5	0.27	-1.38
Average out-of-sample R^2		-0.07



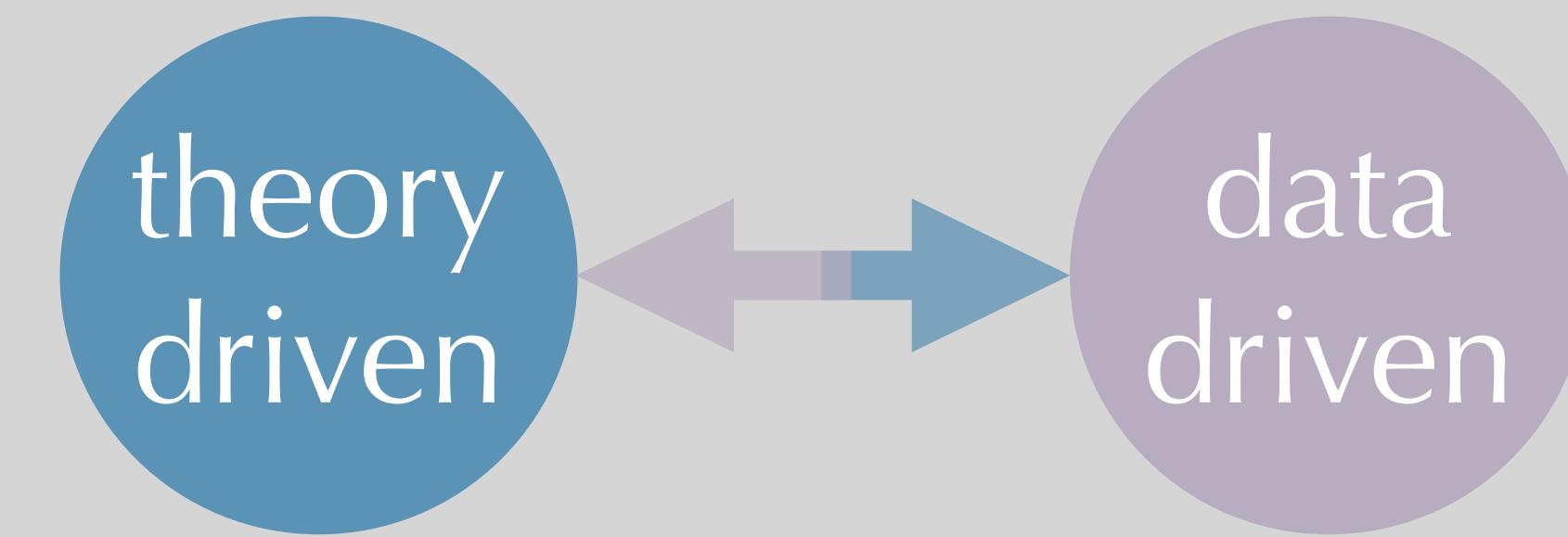
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out-of-sample predictive ability:



clear measure of
effect size



facilitates dialogue
theory- and data-
driven models



measure of distance
theory and practice



out-of-sample predictive ability

- *is easy(ier) to understand*
- *can be compared across analytical techniques*
- *can be compared across models*
- *is less gameable*

European Sociological Review, VOLUME 24 | NUMBER 1 | 2018 63–82
DOI: 10.1111/essr.12066, available online at www.esocjournals.org
Online publication 9 March 2018

Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It

Carina Mood

Logistic regression estimates do not behave like linear regression estimates in an important respect. They are affected by omitted variables unrelated to the independent variables in the model. This has been largely unnoticed by sociologists. Important: Interpret log odds ratios or odds ratios as effect measures of the degree of unobserved heterogeneity in the model. Interpret log-odds ratios or odds ratios for similar models across groups or across models with different independent variables in these problems and possible ways of overcoming them.

Introduction

The use of logistic regression is routine in the social sciences when studying outcomes that are naturally or necessarily represented by binary variables. Examples are many in stratification research (education/transitions, promotion), demographic research (divorce, childbirth, race-leaving), social medicine (diagnosis, mortality), research into social exclusion (unemployment, benefit take up), and research about political behavior (voting, participation in collective action). When fitting a dichotomous dependent variable, sociologists almost automatically turn to logistic regression, and this practice is generally recommended in textbooks in quantitative methodology. However, our common ways of interpreting results from logistic regression have some important problems.¹

The problems stem from unobservables, or the fact that we can seldom include in a model all variables that affect an outcome. Unobserved heterogeneity is

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Annual Review of Sociology

Interpreting and Understanding Logits, Probits, and Other Nonlinear Probability Models

Richard Breen,¹ Kristian Bernt Karlson,² and Anders Holm³

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<https://doi.org/10.1146/annurev-sociol-071117-044409>

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Keywords

logit, probit, KLIM method, F-standardization, marginal effects, linear probability model, mediation

Abstract

Methods textbooks in sociology and other social sciences routinely recommend the use of the logit/probit model when an outcome variable is binary, an ordered logit or ordered probit when it is ordinal, and a multinomial logit when it has more than two categories. But these methodological guidelines take little or no account of a body of work that, over the past 10 years, has pointed to problematic aspects of these nonlinear probability models and, particularly, to difficulties in interpreting their parameters. In this review, we draw on that literature to explain the problems, show how they manifest themselves in research, discuss the strengths and weaknesses of alternatives that have been suggested, and point to lines of further analysis.



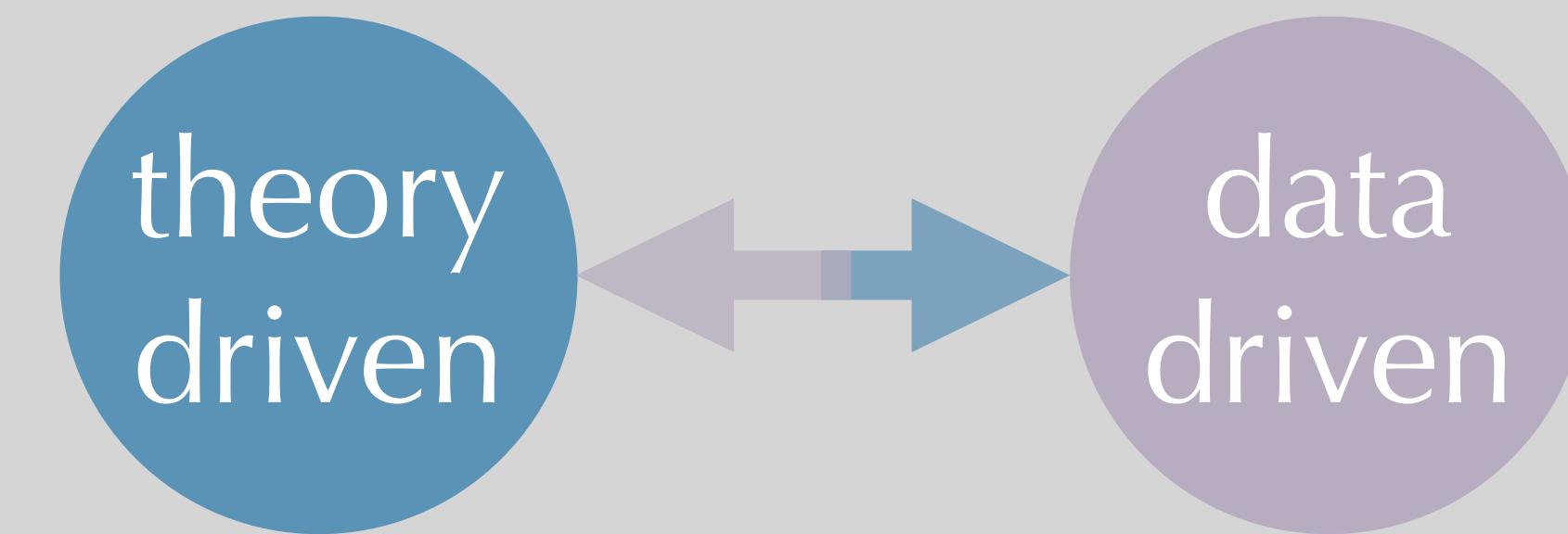
The Proposal

a shift towards **prediction**
leads to a more reliable
and useful social science

out-of-sample predictive ability:



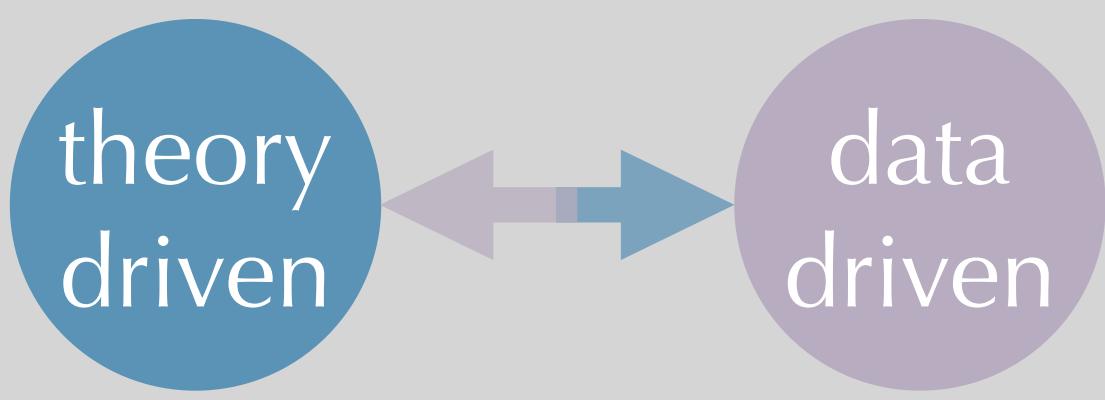
clear measure of
effect size



facilitates dialogue
theory- and data-
driven models



measure of distance
theory and practice



theory-driven vs data-driven

focus on (causal) estimates

support based on p-value

limited number of variables (k)

*NHST weird theory-testing
long reign the linear model
pet variable problem*

focus on predictive ability

support based on prediction

k may be larger than n

*estimates uninterpretable (sort of)
computing intensive*

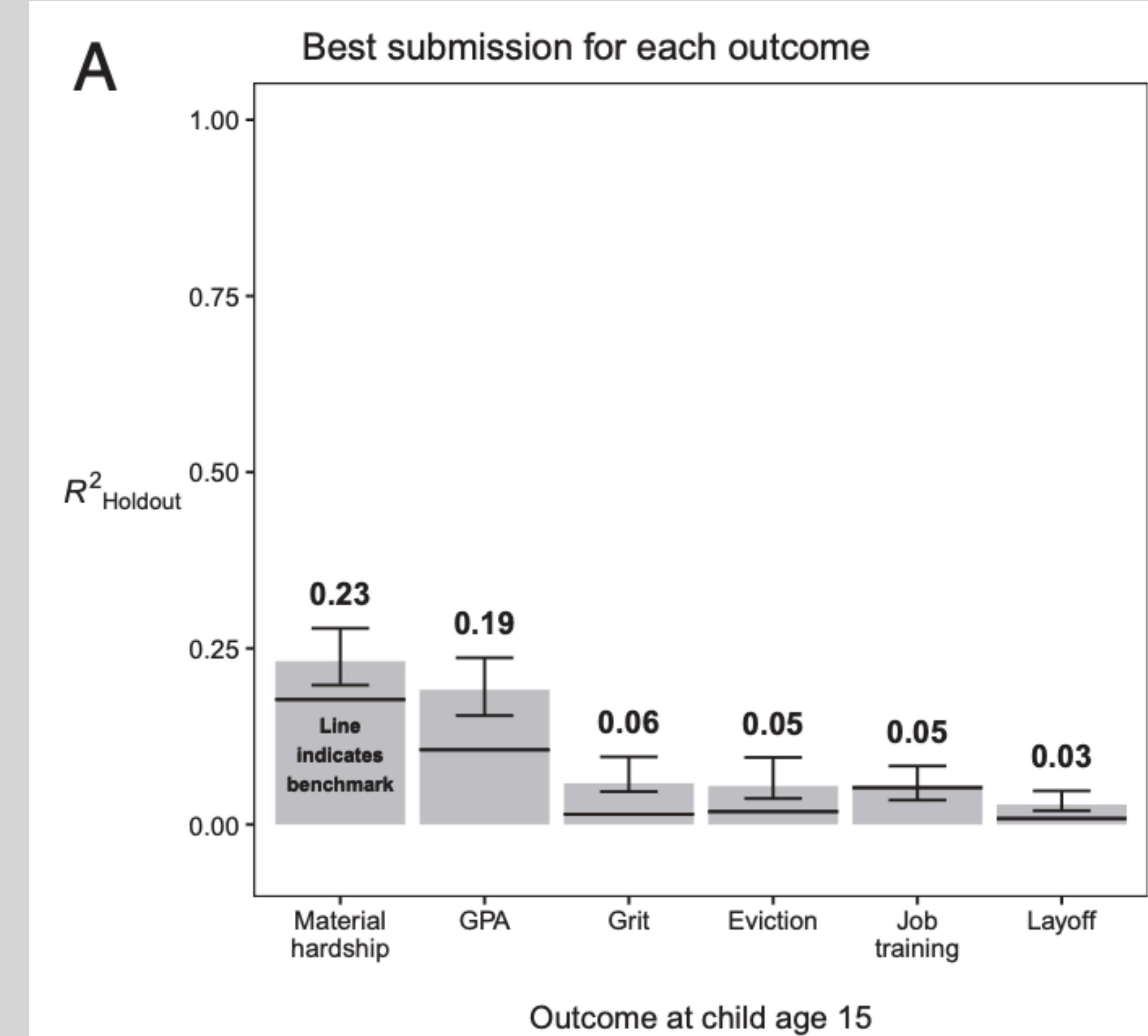
Predictability Crisis?

Check for updates

Measuring the predictability of life outcomes with a scientific mass collaboration

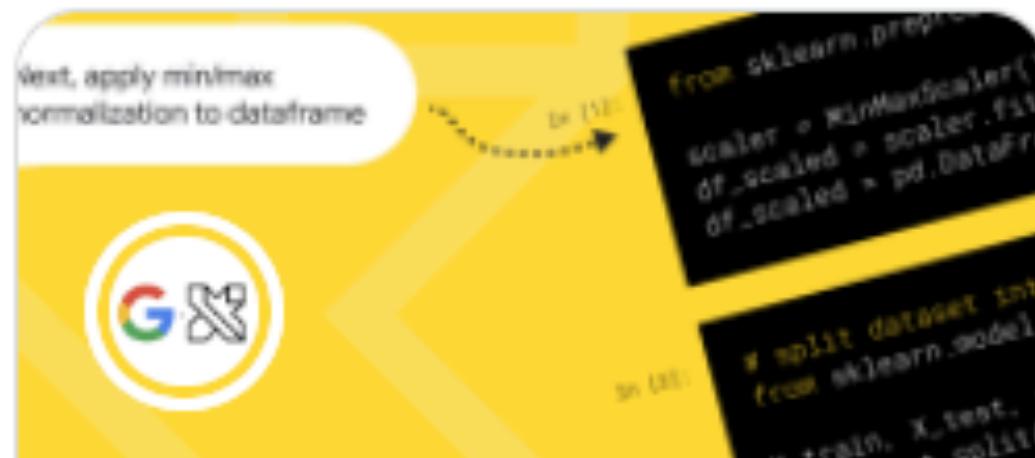
Matthew J. Salganik^{a,1}, Ian Lundberg^a, Alexander T. Kindel^a, Caitlin E. Ahearn^b, Khaled Al-Ghoneim^c, Abdullah Almaatouq^{d,e}, Drew M. Altschul^f, Jennie E. Brand^{b,g}, Nicole Bohme Carnegie^h, Ryan James Comptonⁱ, Debanjan Datta^j, Thomas Davidson^k, Anna Filippova^l, Connor Gilroy^m, Brian J. Goodeⁿ, Eaman Jahani^o, Ridhi Kashyap^{p,q,r}, Antje Kirchner^s, Stephen McKay^t, Allison C. Morgan^u, Alex Pentland^v, Kivan Polimis^w, Louis Raes^x, Daniel E. Rigobon^y, Claudia V. Roberts^y, Diana M. Stanescu^z, Yoshihiko Suhara^t, Adaner Usmani^{aa}, Erik H. Wang^x, 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 Chungⁱⁱ, William Eggert^{ll}, Gregory Faletto^{kk}, Zhilin Fan^{ll}, Jeremy Freese^{gg}, Tejomay Gadgil^{mm}, Josh Gagné^{gg}, Yue Gaoⁿⁿ, 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,ww}, E. H. Kim^{gg}, Ben Leizman^y, Naijia Liu^z, Malte Möser^y, Andrew E. Mack^x, Mayank Mahajan^y, Noah Mandell^{ww}, Helge Marahrens^{bb}, Diana Mercado-Garcia^{aa}, Viola Mocz^{xx}, Katarina Mueller-Gastell^{gg}, Ahmed Musse^{yy}, Qiankun Niu^{ee}, William Nowak^{zz}, Hamidreza Omidvar^{aa}, Andrew Or^y, Karen Ouyang^y, Katy M. Pinto^{bb}, Ethan Porter^{cc}, Kristin E. Porter^{dd}, Crystal Qian^y, Tamkinat Rauf^{gg}, Anahit Sargsyan^{ee}, Thomas Schaffner^y, Landon Schnabel^{gg}, Bryan Schonfeld^z, Ben Sender^{ff}, Jonathan D. Tang^y, Emma Tsurkov^{gg}, Austin van Loon^{gg}, Onur Varol^{gg,hh,ii}, Xiafei Wangⁱⁱ, Zhi Wang^{hh,jj}, Julia Wang^y, Flora Wang^{ff}, Samantha Weissman^y, Kirstie Whitaker^{kk,ll}, Maria K. Wolters^{mm}, Wei Lee Woonⁿⁿ, James Wu^{ooo}, Catherine Wu^y, Kengran Yang^{aa}, Jingwen Yin^{ll}, Bingyu Zhao^{ppp}, Chenyun Zhu^{ll}, Jeanne Brooks-Gunn^{qqq,rrr}, Barbara E. Engelhardt^{yy,ii}, Moritz Hardt^{ss,tt}, Dean Knox^z, Karen Levy^{tt,tt}, Arvind Narayanan^y, Brandon M. Stewart^a, Duncan J. Watts^{uu,vv,ww,ww}, and Sara McLanahan^{a,1}

data challenge:
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⌚ Active Competitions

Hotness ▾



Google AI4Code – Understand Code in...

Predict the relationship between co...

Featured

Code Competition · 166 Teams

\$150,000

3 months to go



JPX Tokyo Stock Exchange Prediction

Explore the Tokyo market with your ...

Featured

Code Competition · 983 Teams

\$63,000

2 months to go



U.S. Patent Phrase to Phrase Matching

Help Identify Similar Phrases in U.S. ...

Featured

Code Competition · 1258 Teams

\$25,000

a month to go



Foursquare - Location Matching

Match point of interest data across ...

Featured

Code Competition · 489 Teams

\$25,000

2 months to go

“

secret sauce of data science
Donoho, 2015

data challenge



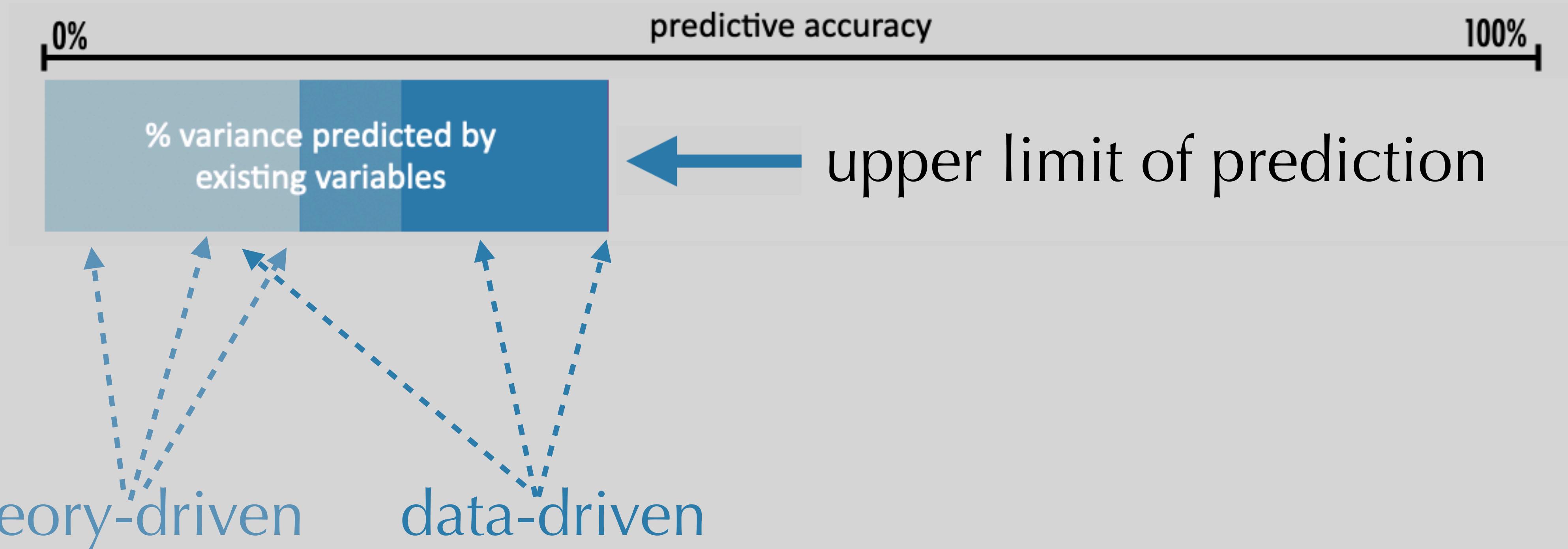
theory
driven

data
driven

theory- and data-driven teams
engage in common task
using common data
and common metric

Data Challenge

theory- and data-driven teams
engage in common task
using common data
and common metric



Prediction Benchmarks

baseline benchmarks

*established with
state-of-the-art theory*

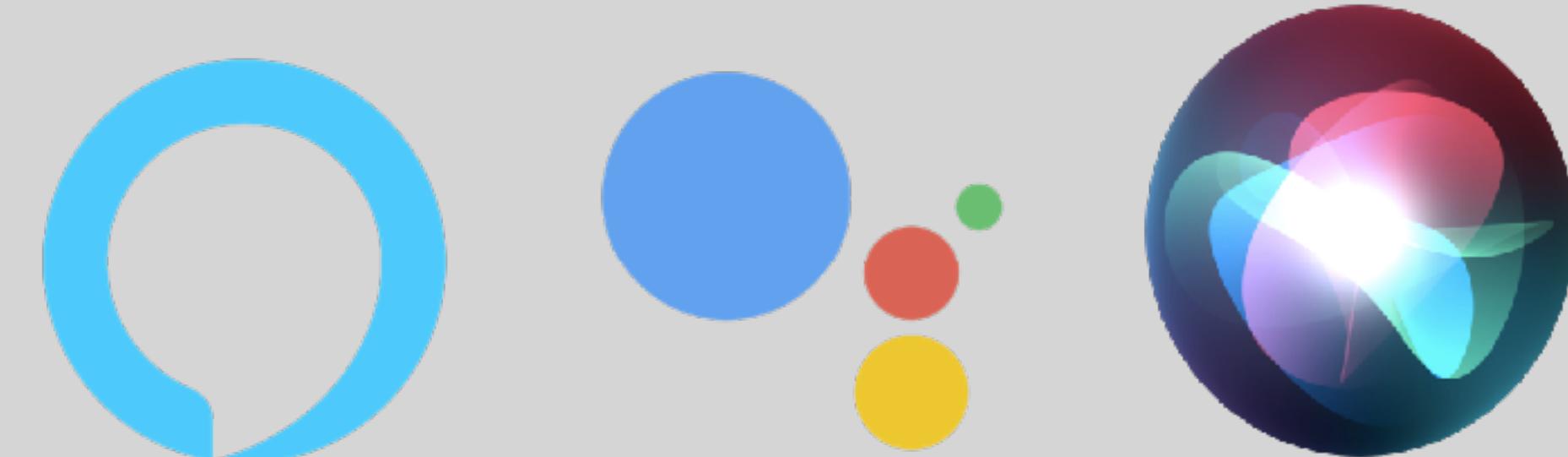
upper limit benchmarks

*established with state-of-the-
art statistical learning tools*

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Progress usually comes from many small improvements; a change of 1% can be a reason to break out the champagne

Liberman, 2012



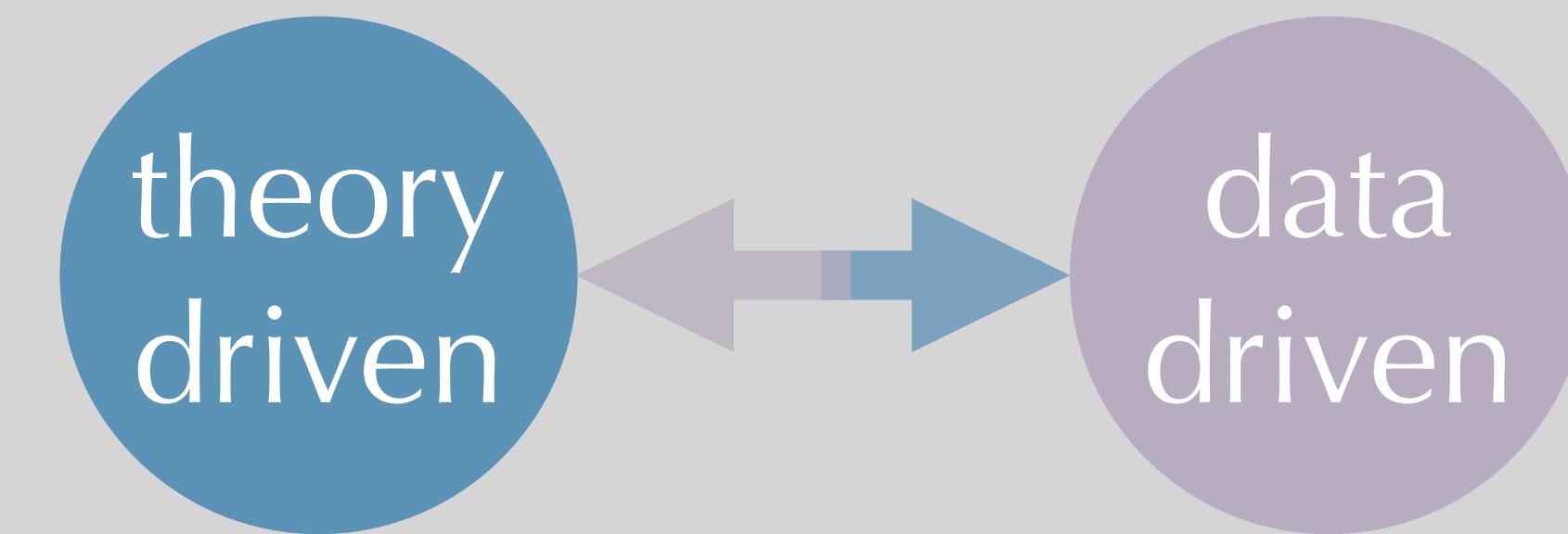
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facilitates dialogue
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driven models



measure of distance
theory and practice



out-of-sample predictive ability
is a measure of how useful
our theory is in the real world

Articles

The perils of policy by p-value: Predicting civil conflicts

Michael D Ward

Department of Political Science, Duke University

Brian D Greenhill

Department of Political Science, University of Washington

Kristin M Bakke

Department of Political Science, University College London



Journal of Peace Research
47(4) 363–375
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DOI: 10.1177/0022343309356491



So Useful as a Good Theory? The Practicality Crisis in (Social) Psychological Theory

Elliot T. Berkman^{ID} and Sylas M. Wilson

Department of Psychology and Center for Translational Neuroscience, University of Oregon



Perspectives on Psychological Science
1–11
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DOI: 10.1177/1745691620969650
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out-of-sample predictive ability
is a measure of how useful
our theory is in the real world



Why significant variables aren't automatically good predictors

Adeline Lo^a, Herman Chernoff^{b,1}, Tian Zheng^c, and Shaw-Hwa Lo^{c,1}

^aDepartment of Political Science, University of California, San Diego, La Jolla, CA 92093; ^bDepartment of Statistics, Harvard University, Cambridge, MA 02138; and ^cDepartment of Statistics, Columbia University, New York, NY 10027

Contributed by Herman Chernoff, September 17, 2015 (sent for review December 15, 2014)

Thus far, genome-wide association studies (GWAS) have been disappointing in the inability of investigators to use the results of

From the scientist's point of view there are two basic problems, complicated by the large size of the data set. These are variable



out-of-sample predictive ability
is a measure of how useful
our theory is in the real world

“

Social scientists studying the life course must find a way to reconcile a widespread belief that understanding has been generated by these data—as demonstrated by more than 750 published journal articles using the Fragile Families data with the fact that the very same data could not yield accurate predictions of these important outcomes.

A Pragmatist's Guide to Using Prediction in the Social Sciences

Mark D. Verhagen^{1,2}

Abstract

Prediction is an underused tool in the social sciences, often for the wrong reasons. Many social scientists confuse prediction with unnecessarily complicated methods or with narrowly predicting the future. This is unfortunate. When we view prediction as the simple process of evaluating a model's ability to approximate an outcome of interest, it becomes a more generally applicable and disarmingly simple technique. For all its simplicity, the value of prediction should not be underestimated. Prediction can address enduring sources of criticism plaguing the social sciences, like a lack of assessing a model's ability to reflect the real world, or the use of overly simplistic models to capture social life. The author illustrates these benefits with empirical examples that merely skim the surface of the many and varied ways in which prediction can be applied, staking the claim that prediction is a truly illustrious "free lunch" that can greatly benefit social scientists in their empirical work.

Keywords

prediction, computational social sciences, explanation

Social scientists should start using prediction more often. Prediction is the process of generating predicted values of a dependent variable by applying an estimated model to a set of explanatory variables, bringing a unique analytical perspective to empirical work. Prediction can also help address enduring sources of criticism facing the social sciences. Examples are a general lack of assessing research findings in terms of their real-world relevance, and the use of overly simplistic models to study the complexities of social life. In this article, I address common misconceptions about prediction and provide a simple definition that addresses existing barriers to adoption. I then discuss and illustrate some of the many benefits that prediction can bring when used as a complement to traditional empirical methods. I argue that prediction can and should become a fundamental part of the social scientist's empirical toolkit but that this first requires us to look beyond the current dichotomy between prediction and explanation and instead view the two as complementary to each other.

The current lack of prediction in the social sciences stems from a seeming incompatibility between wanting to explain and wanting to predict, effectively forcing researchers to choose between the two approaches. A case in point is the much-cited article by Galit Shmueli (2010), aptly titled "To Predict or to Explain," which outlines how a social scientist's empirical work flow differs in terms of data processing, modeling, and postestimation diagnostics when choosing to either predict or explain. Naturally, Shmueli assumes that a researcher would not normally attempt to do both. This is an accurate reflection of social science research. The apparent

need to dogmatically choose between either approach means that, in practice, social scientists tend to stick to explanation almost exclusively. Illustratively, the terms *predict* and *prediction* are mentioned in fewer than 5 percent of abstracts over the past 10 years in various flagship journals in economics, political science, and sociology, and of the articles mentioning either term, only 13 percent proceed to generate actual predictions of the outcome variable (Table 1).^{1,2}

¹In most of the articles that mention the term *predict* or *prediction*, the authors use the commonplace, conceptual meaning term (e.g., "we predict that" or "our theory makes several predictions"). The actual process of making predictions of the outcome variable is virtually nonexistent in the literature cited. Note that the term *explain* or *explanation* features in only about 13 percent of abstracts, although this proportion likely does not reflect the proportion of work that is explanatory. Explanation is the default approach to empirical work, making it less relevant to explicitly mention the term in the abstract.

²The single sociological article making predictions in fact generated mortality forecasts (Miech et al. 2011).

¹Nuffield College, University of Oxford, Oxford, UK

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The Proposal

a shift towards **prediction**
leads to a more reliable
and useful social science

microsimulation can
advance traditional
statistical modelling

The Proposal

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advance traditional
statistical modelling

**MICROSIMULATION METHODS
FOR POPULATION PROJECTION**

Evert VAN IMHOFF* and Wendy POST**

I. – Introduction

Population projections are almost invariably produced with the so-called *cohort-component method*. In its simplest form, this method boils down to the following. The population is classified by sex (males and females) and age group (*cohorts*). For each combination of sex s and age x , the initial population is transformed into a projected final population of sex s and age $x+1$ by projecting the population changes, distinguished by type (*components*). Typical components are mortality and fertility. These calculations are repeated for successive time intervals, where the final population of one interval serves as the initial population for the next interval, until the end of the projection period has been reached.

The basic idea behind the cohort-component model is that the population changes because individuals experience certain *demographic events*, and that the mechanisms underlying these events differ between the sexes, age groups, and the type of event. The total number of events of a certain type, for each combination of age and sex, is projected as the result of two factors: the *size* of the population exposed to the risk of experiencing the event; and the *level* (or *intensity*) of the risk for individual persons, which may be interpreted as a measure of demographic behaviour.

Suppose that we want to project the number of children born during the year out of 100,000 women aged 25. The population consists of 100,000 women and each 25-year old woman has a probability of 0.10 to bear a child during the year (i.e. the age-specific fertility 'rate' is 0.10). Now according to the traditional methods of demographic projection, which might be called macrosimulation, the projected number of births is obtained by applying the fertility probability to the size of the group of women: $0.10 \times 100,000$ yields 10,000 projected births.

* Netherlands Interdisciplinary Demographic Institute (NIDI), The Hague, Netherlands.
** Department of Medical Statistics, Faculty of Medicine, Leyden University, Netherlands

Population: An English Selection, special issue New Methodological Approaches in the Social Sciences, 1998, 97-138.

Use R!

Frans Willekens

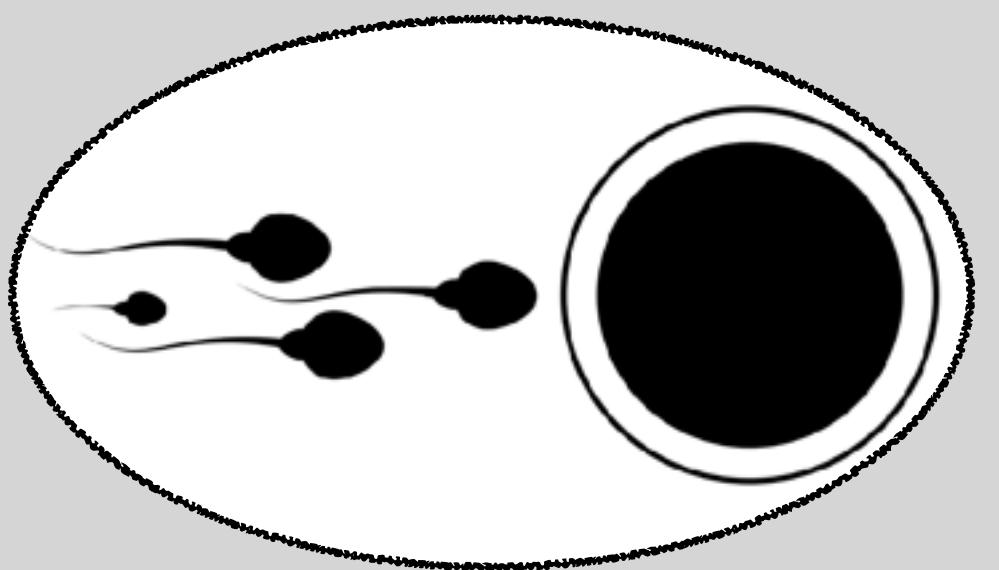
Multistate Analysis of Life Histories with R

Springer

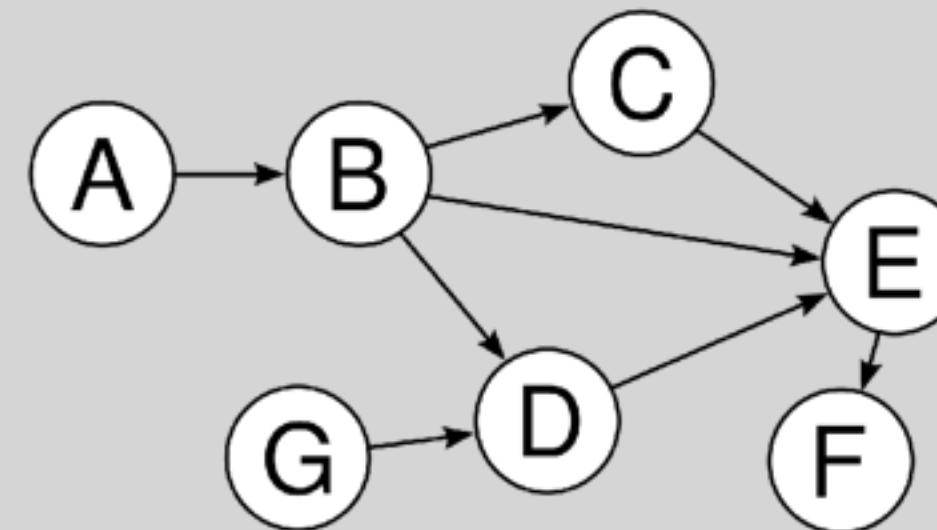
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microsimulation can:



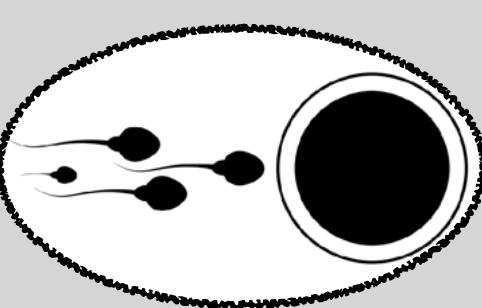
include
biological
information



test (causal)
mechanisms



quantify
unpredictability

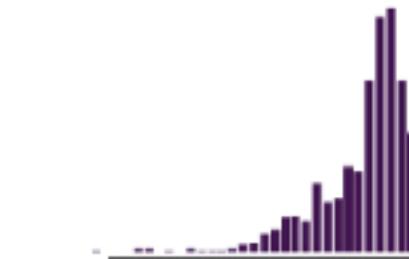


MODEL INPUT

biological parameters



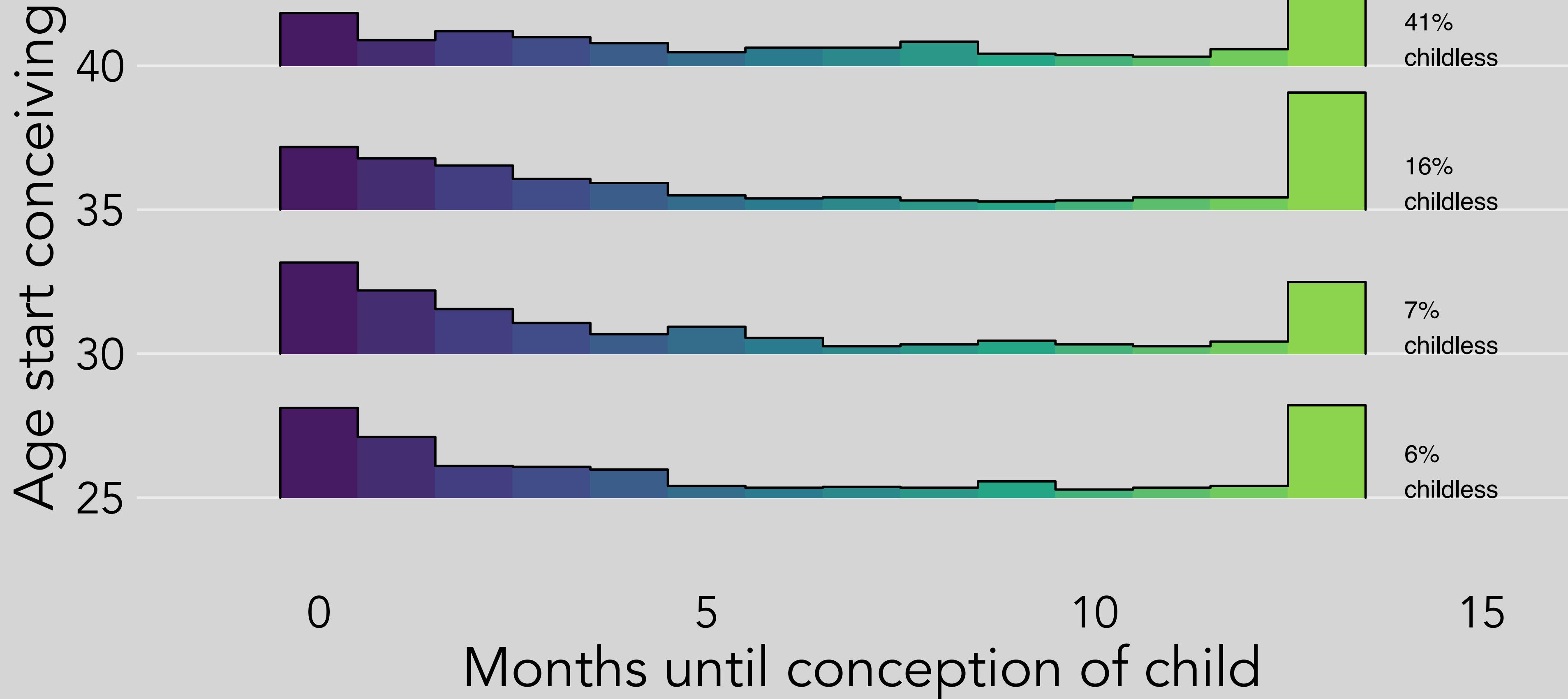
fecundability
with age

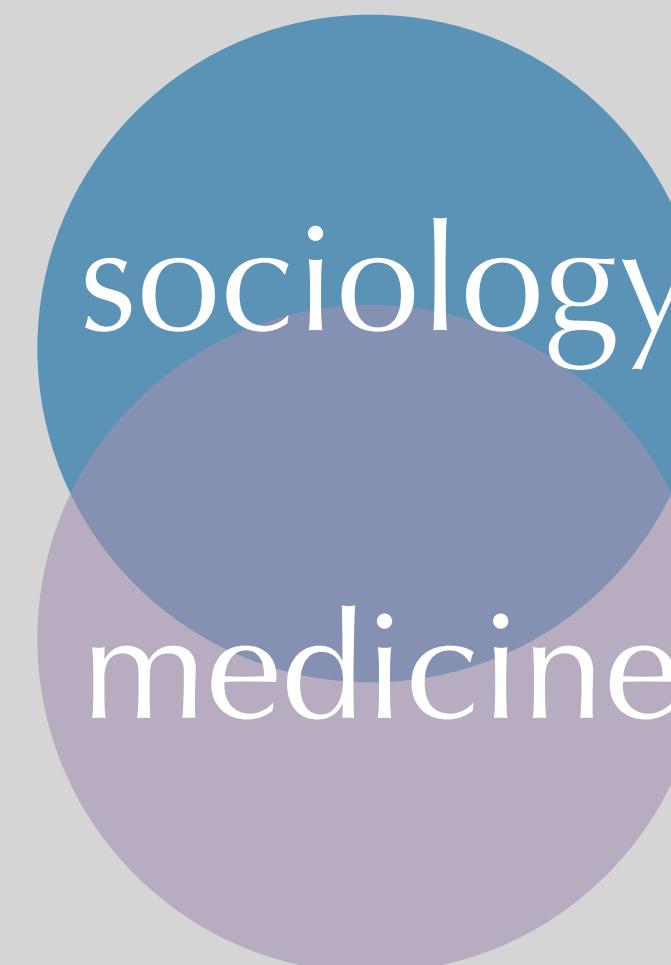
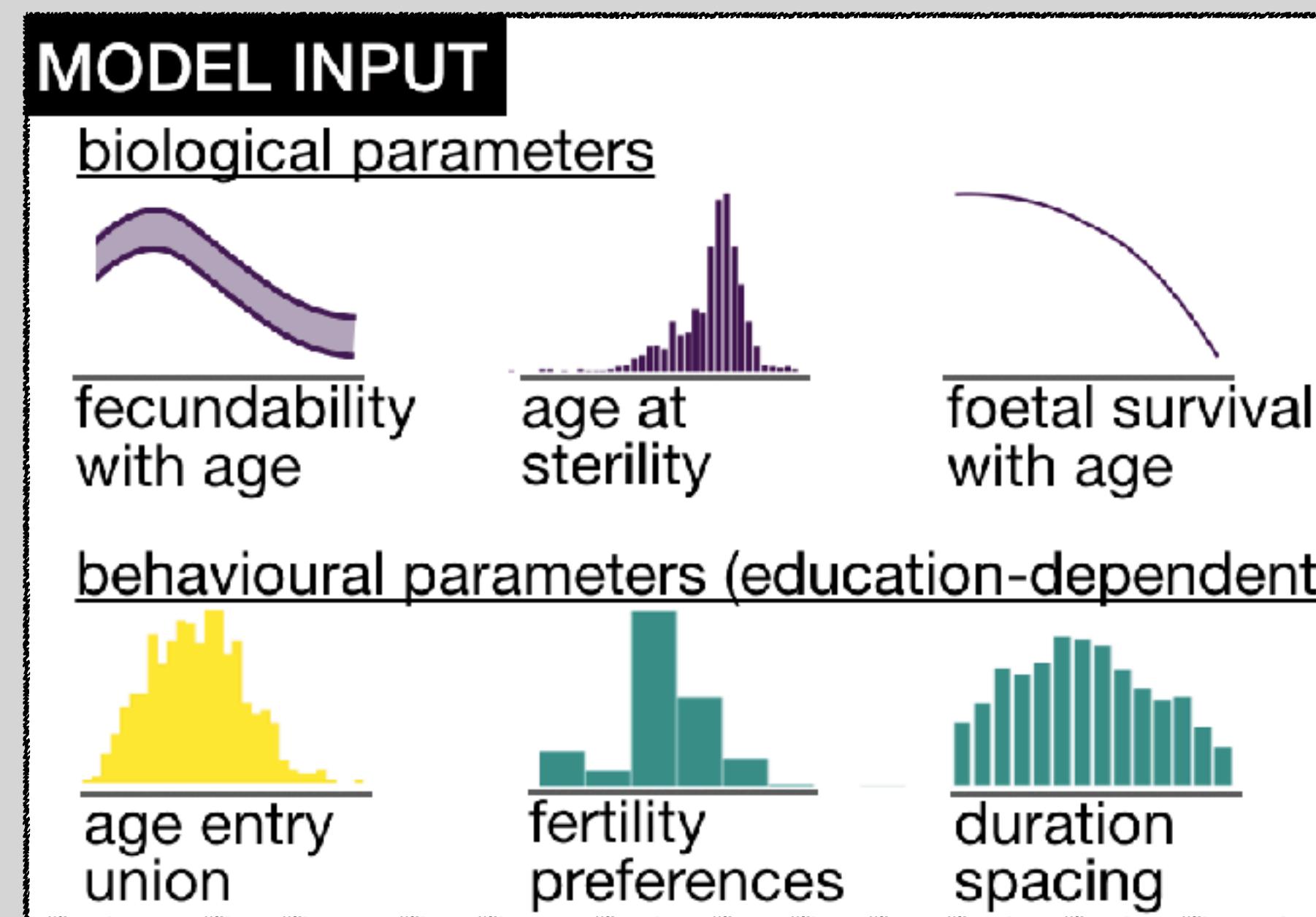
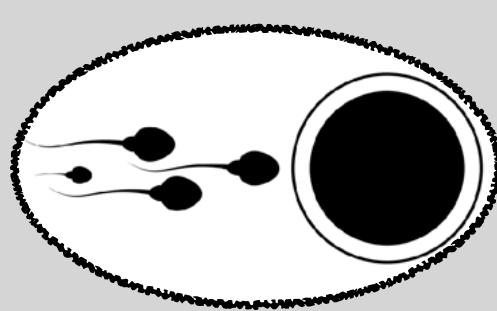


age at
sterility



foetal survival
with age



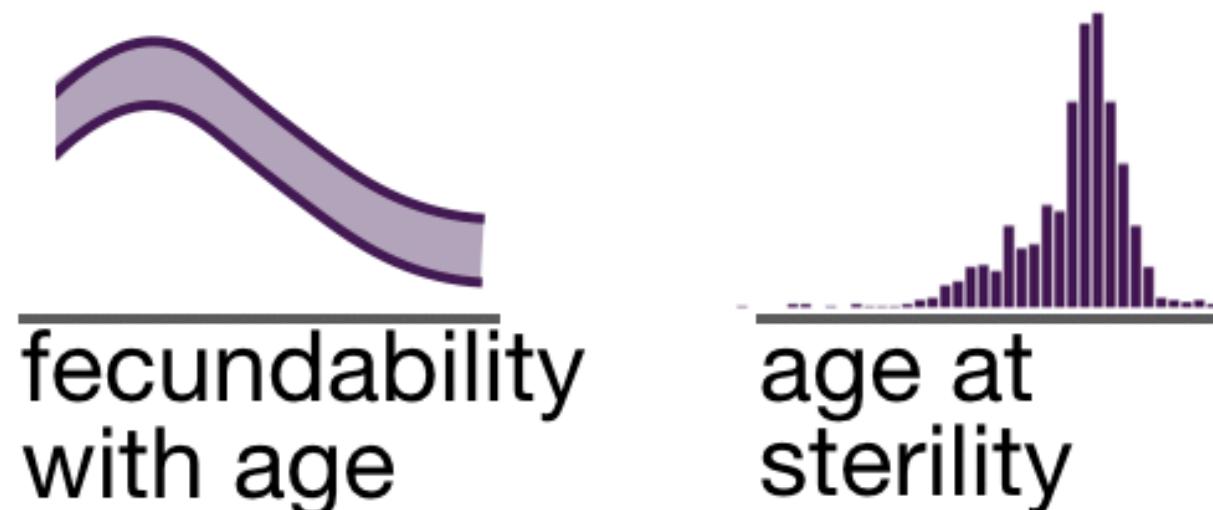


determines whether and when people would like to conceive

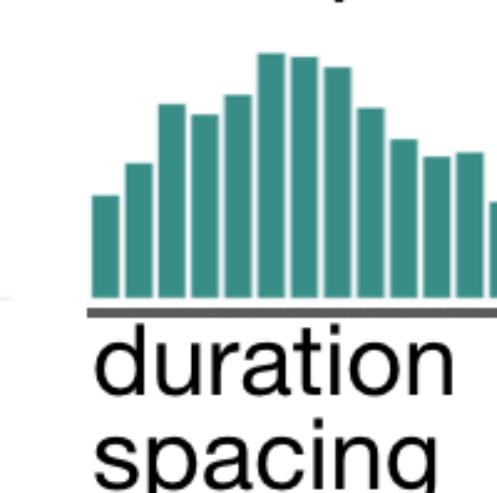
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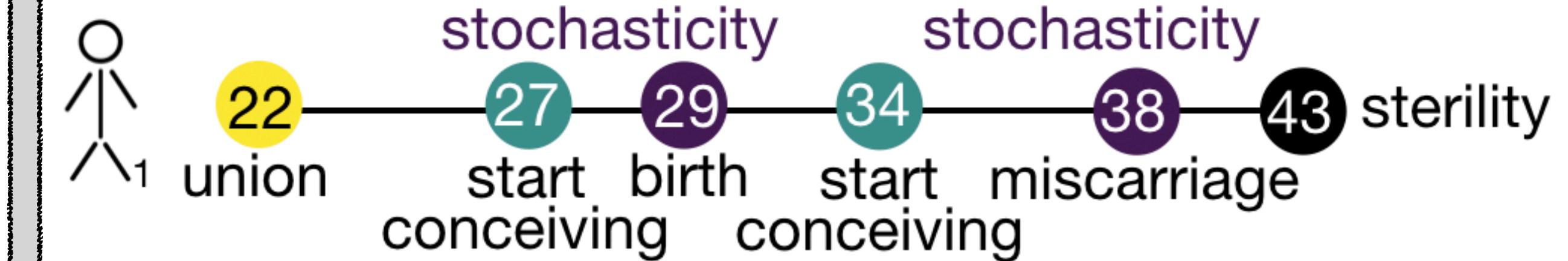
behavioural parameters (education-dependent)



MODEL RUN

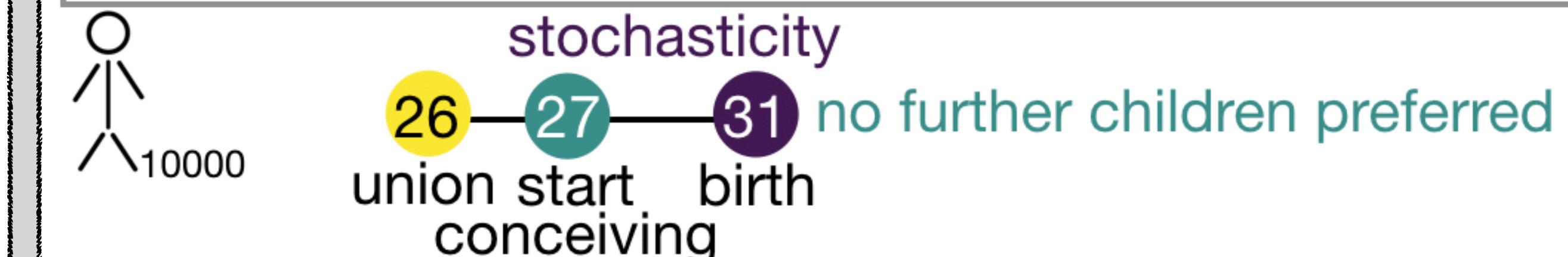
Randomly determined traits individual 1

in union =22 | spac. =5 | pref. =2 | fecund. =0.3 | steril. =43 | edu. =high



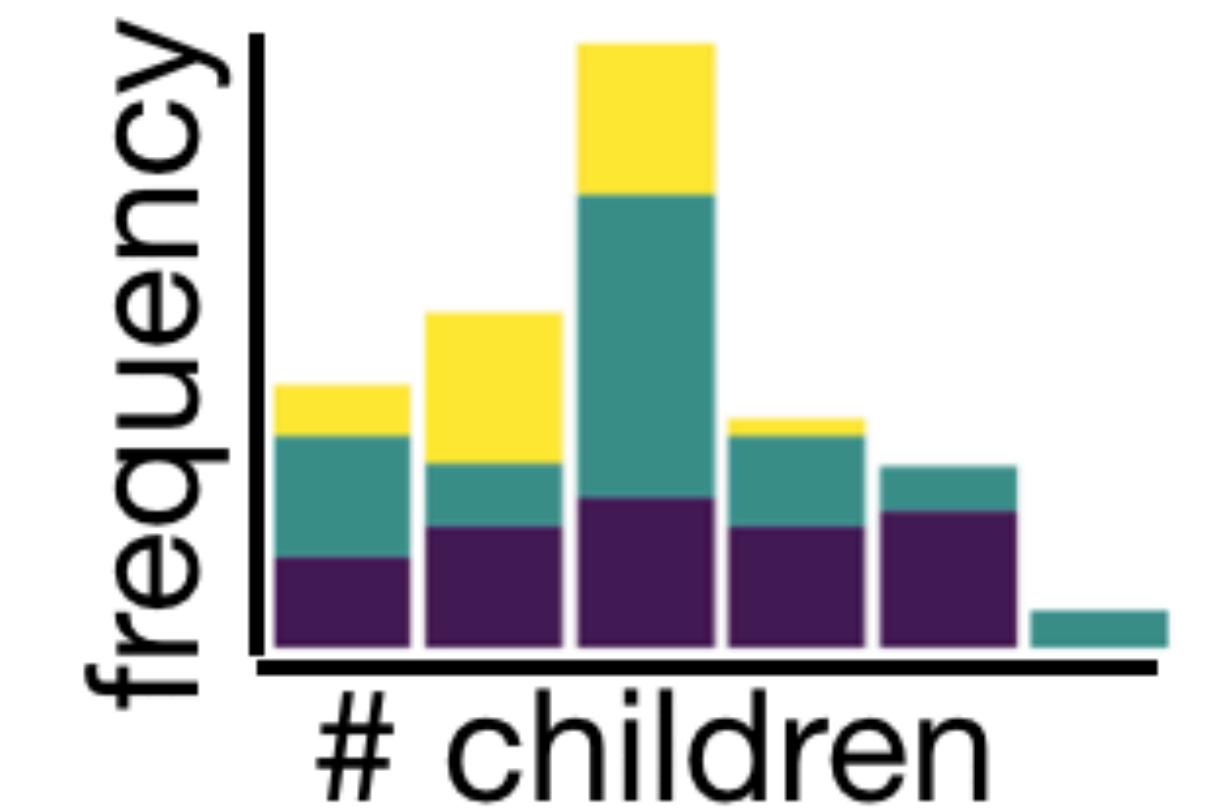
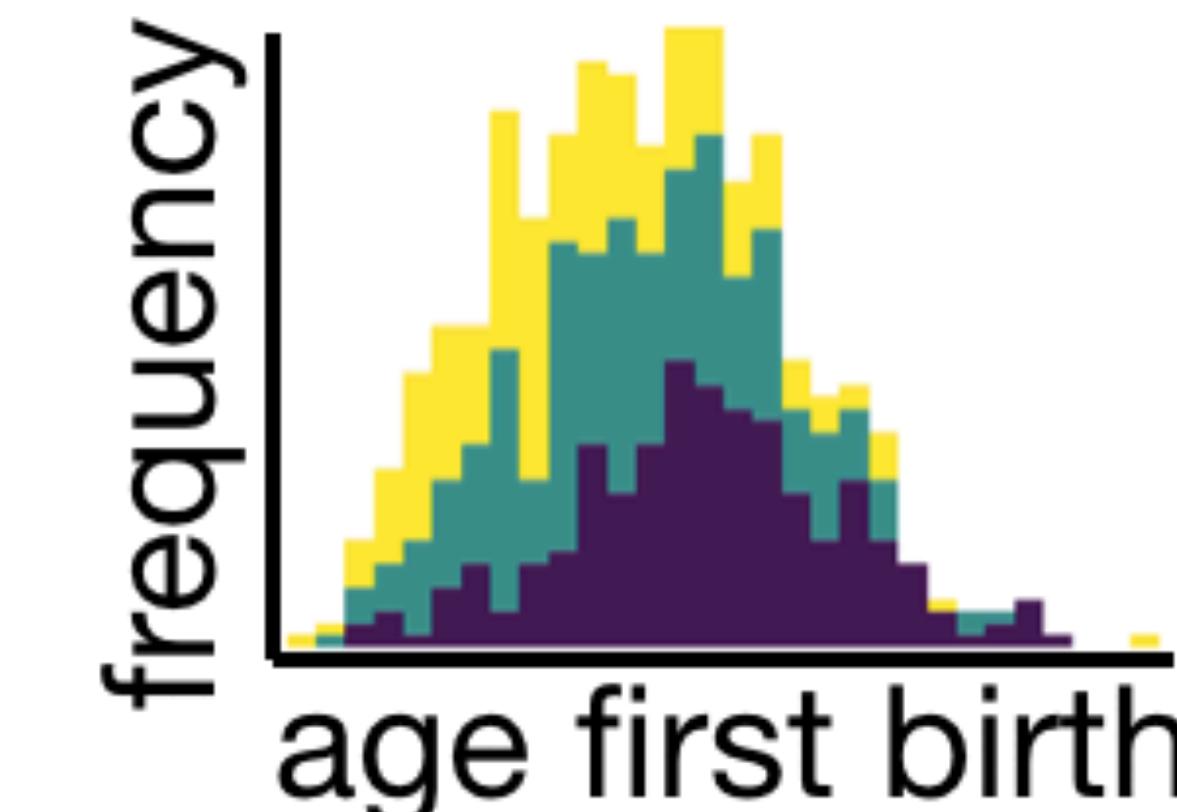
Randomly determined traits individual 10000

in union =26 | spac. =1 | pref. =1 | fecund. =0.1 | steril. =45 | edu. =low



due to:

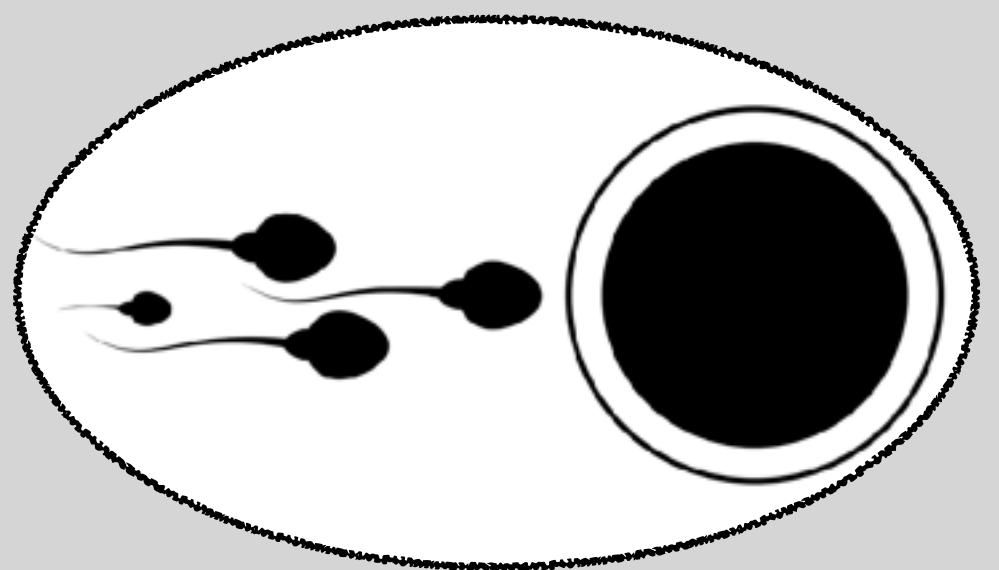
- partner status
- preferences
- stochasticity



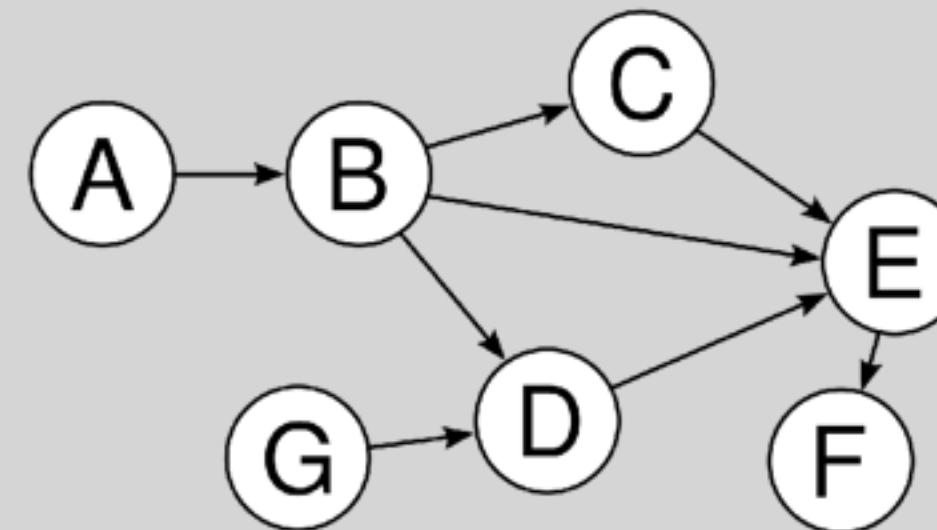
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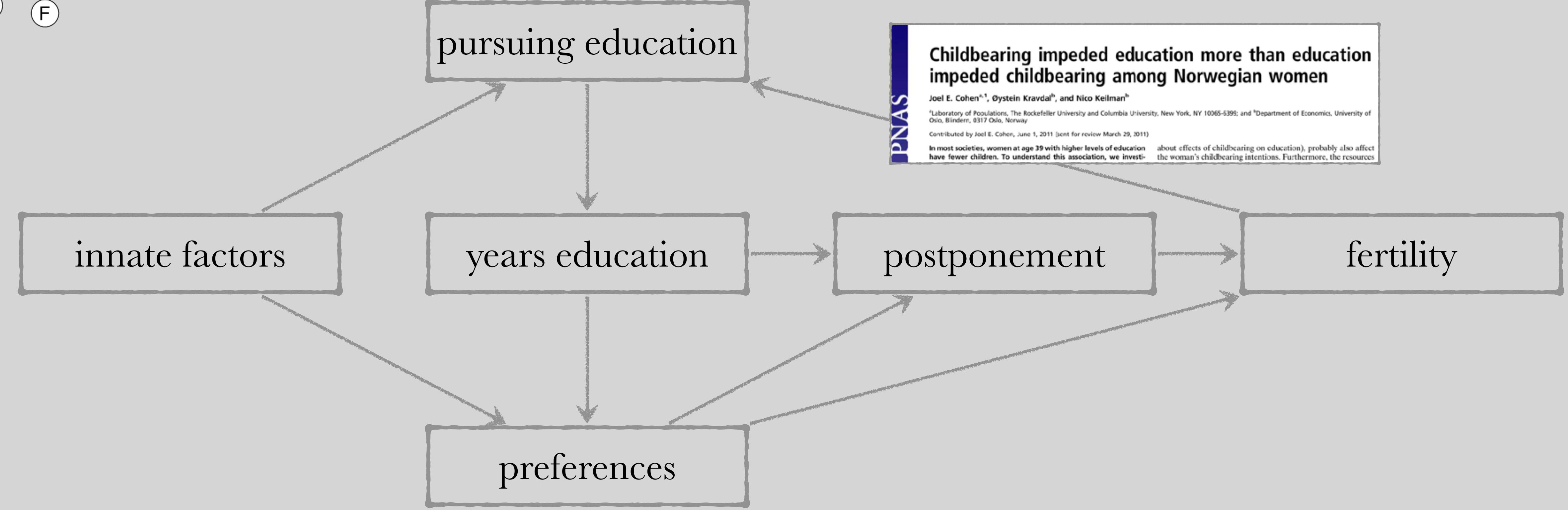
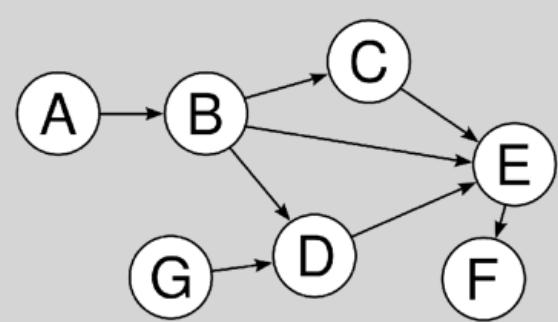
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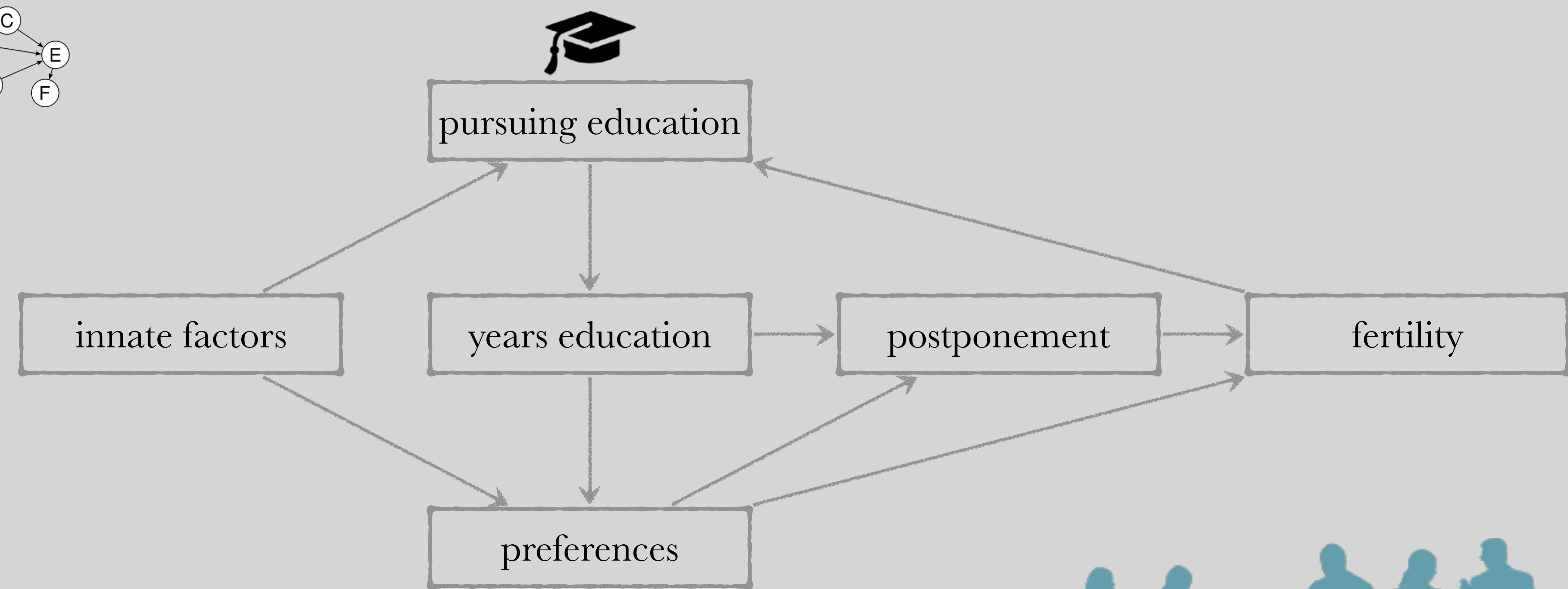
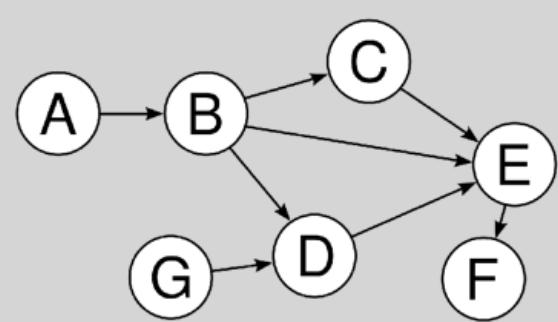


test (causal)
mechanisms

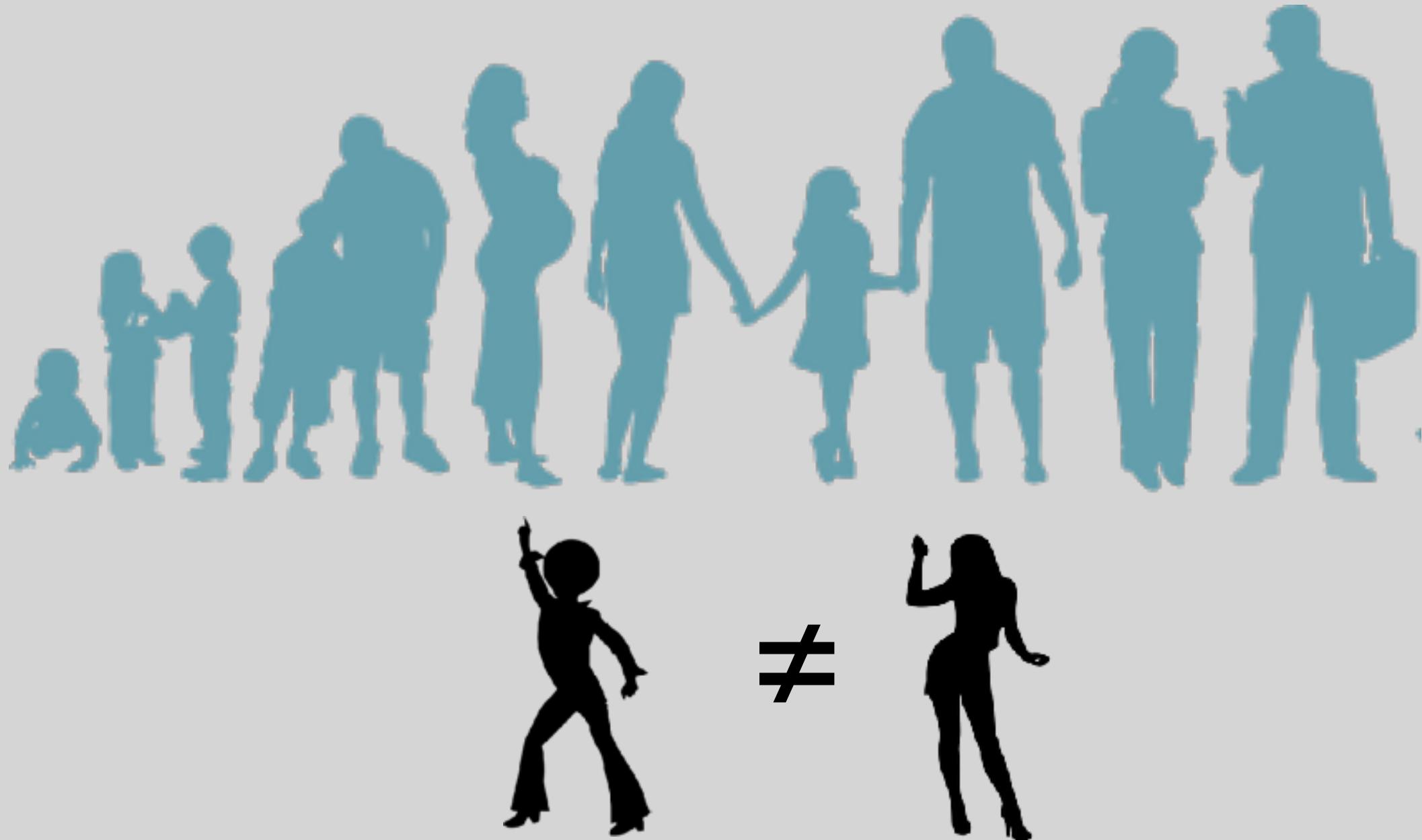


quantify
unpredictability





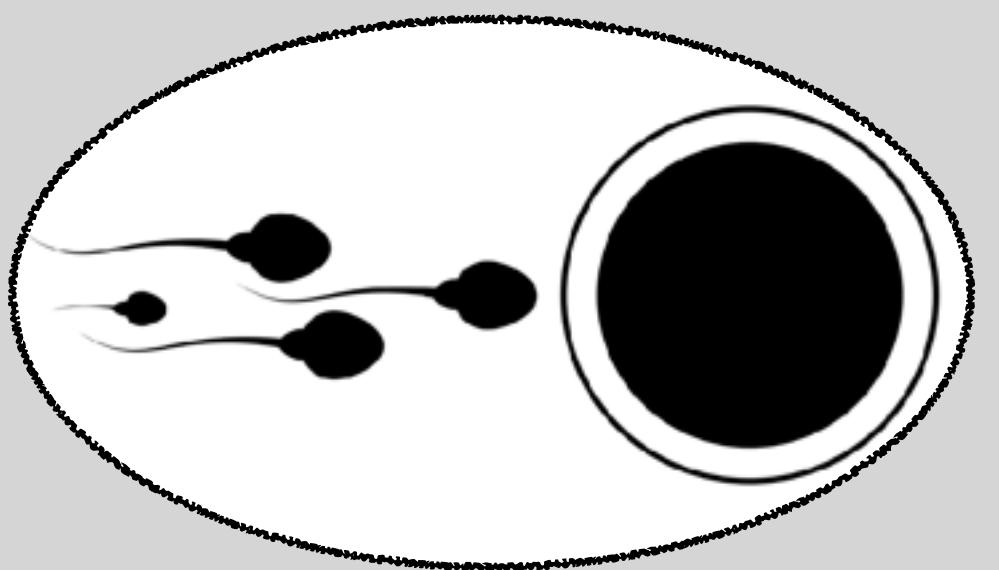
What Kind of Data
Would We need to
Address This Model?



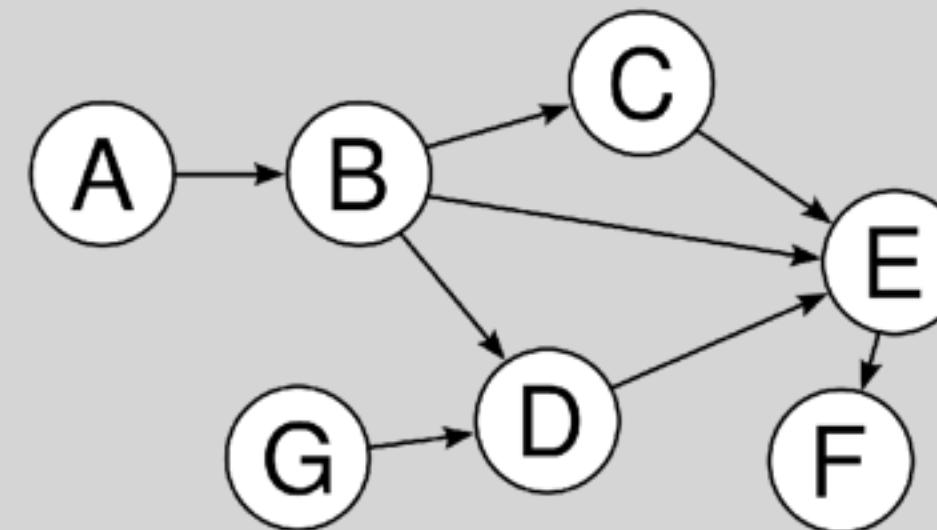
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Variation due to Stochasticity ($sd = 13$ months)

Unpredictable Variation!

%

20

15

10

5

0

0

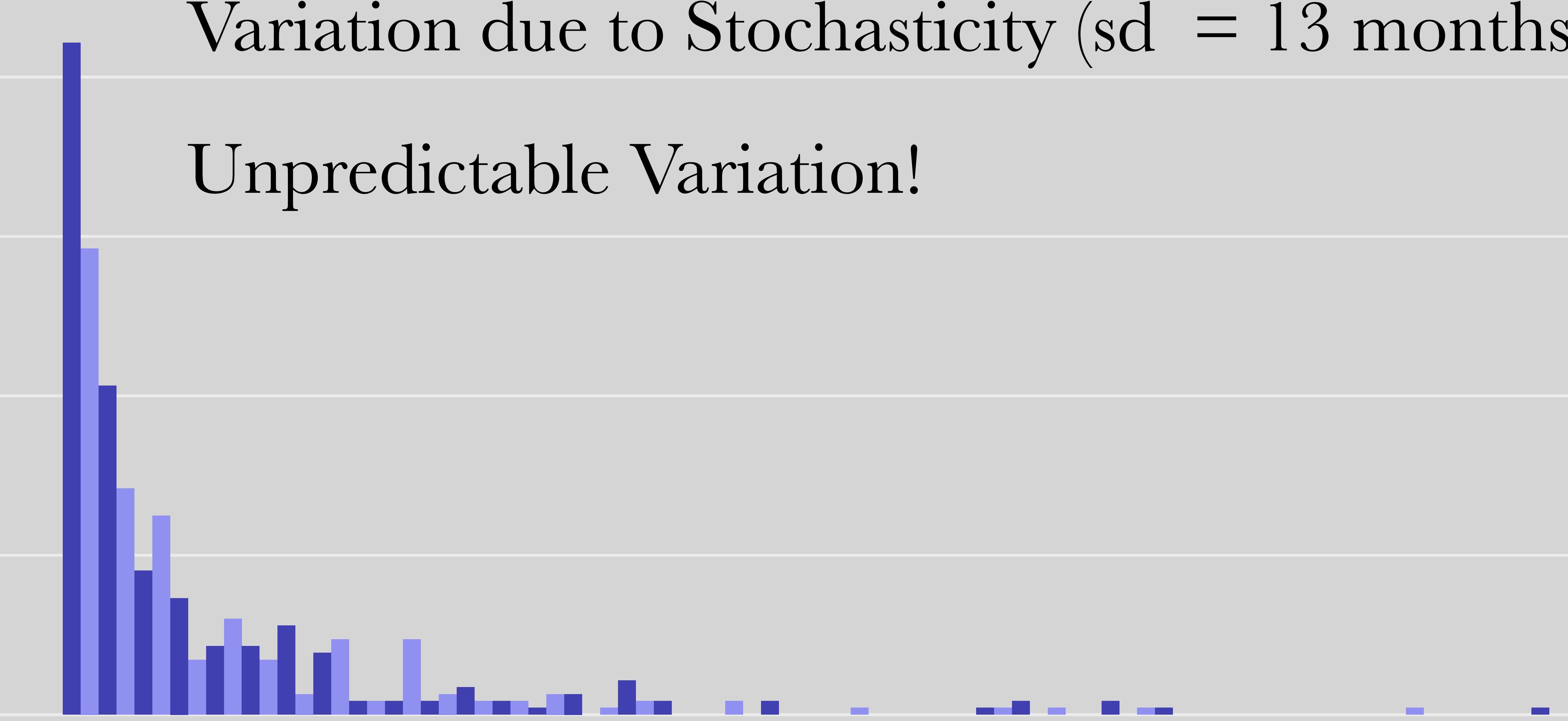
20

40

60

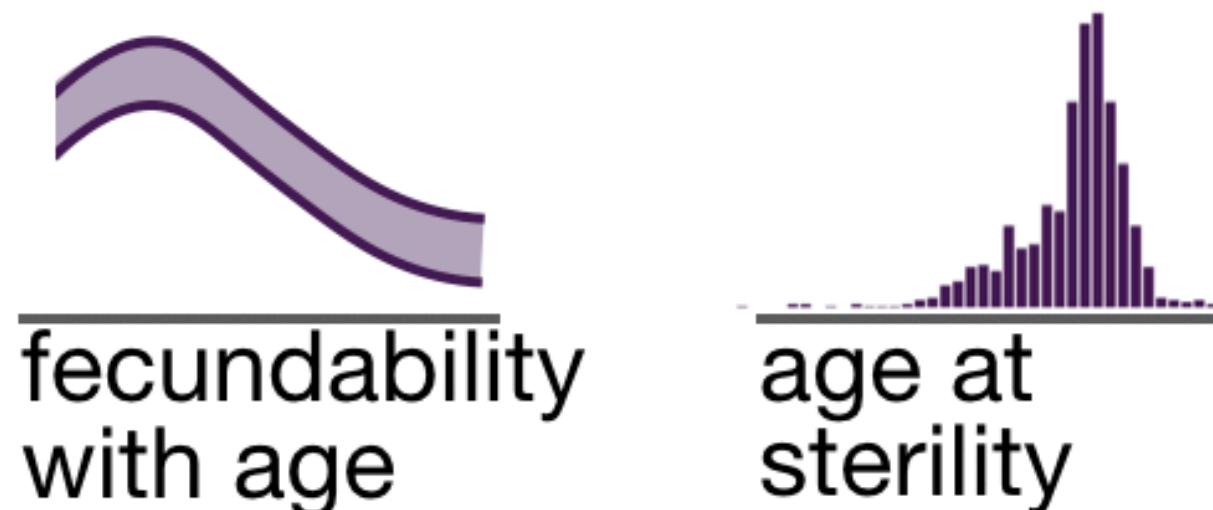
80

Months until conception for 30 year old women



MODEL INPUT

biological parameters

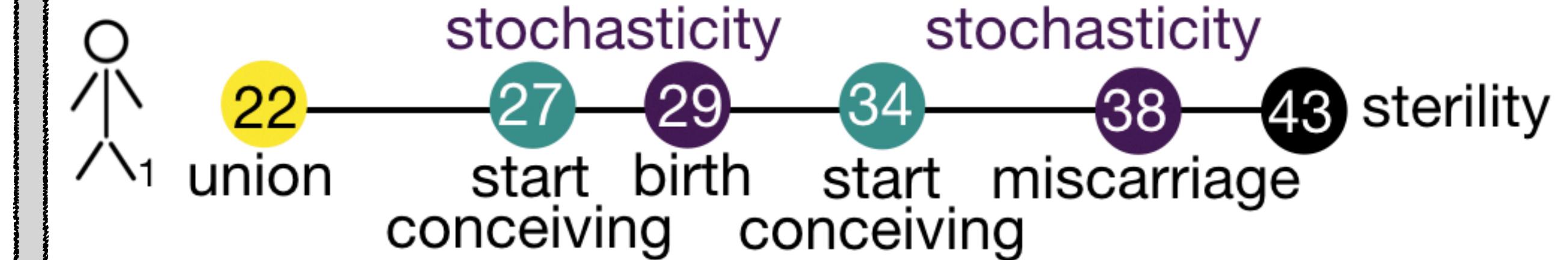


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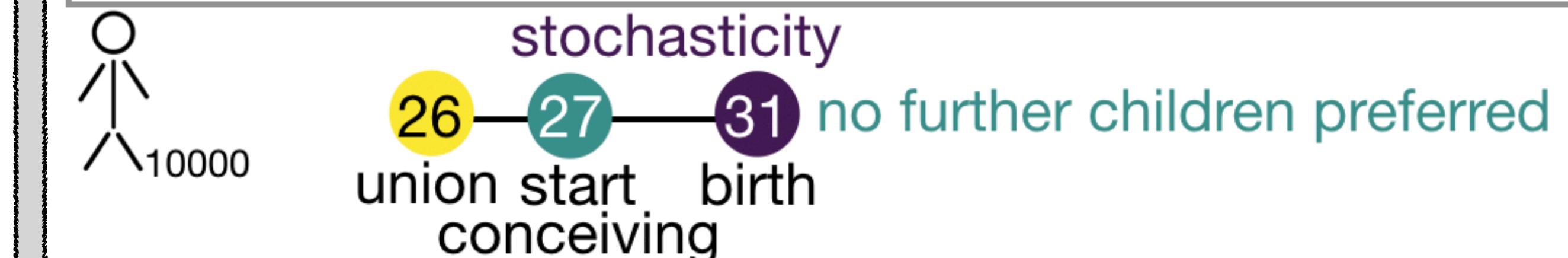


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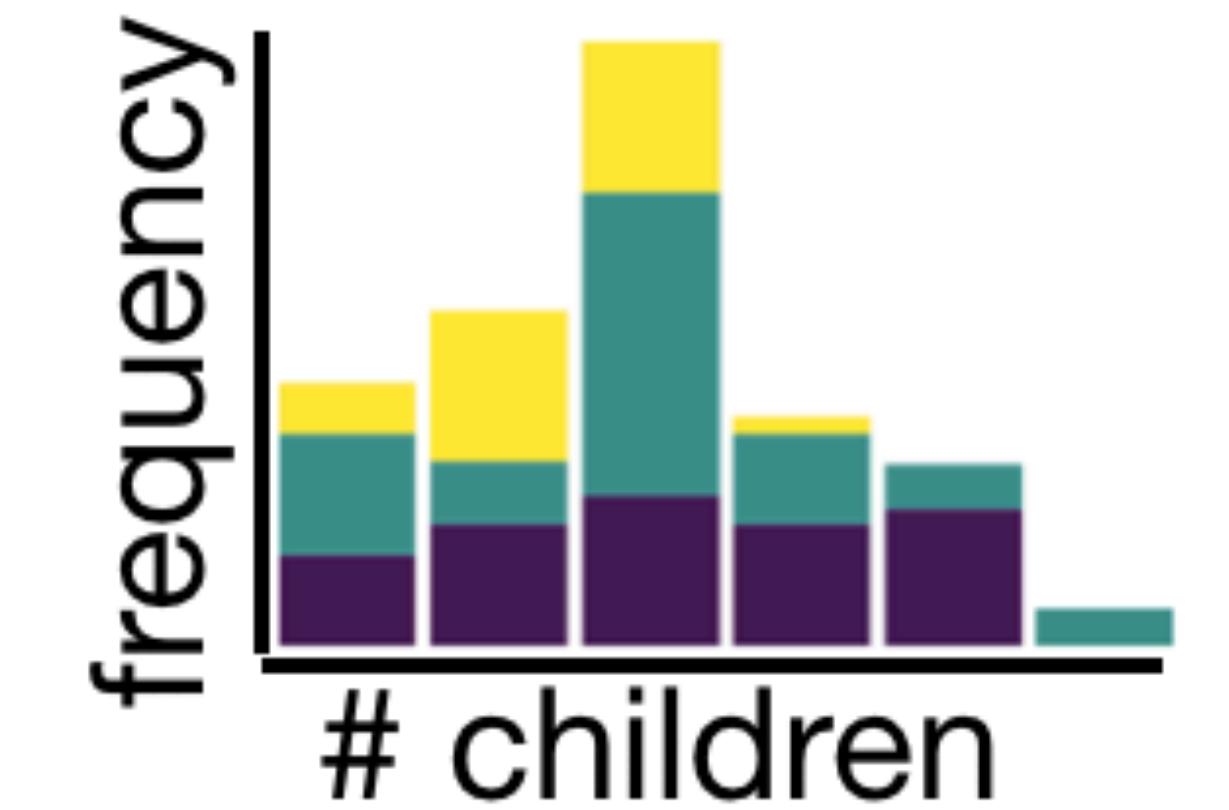
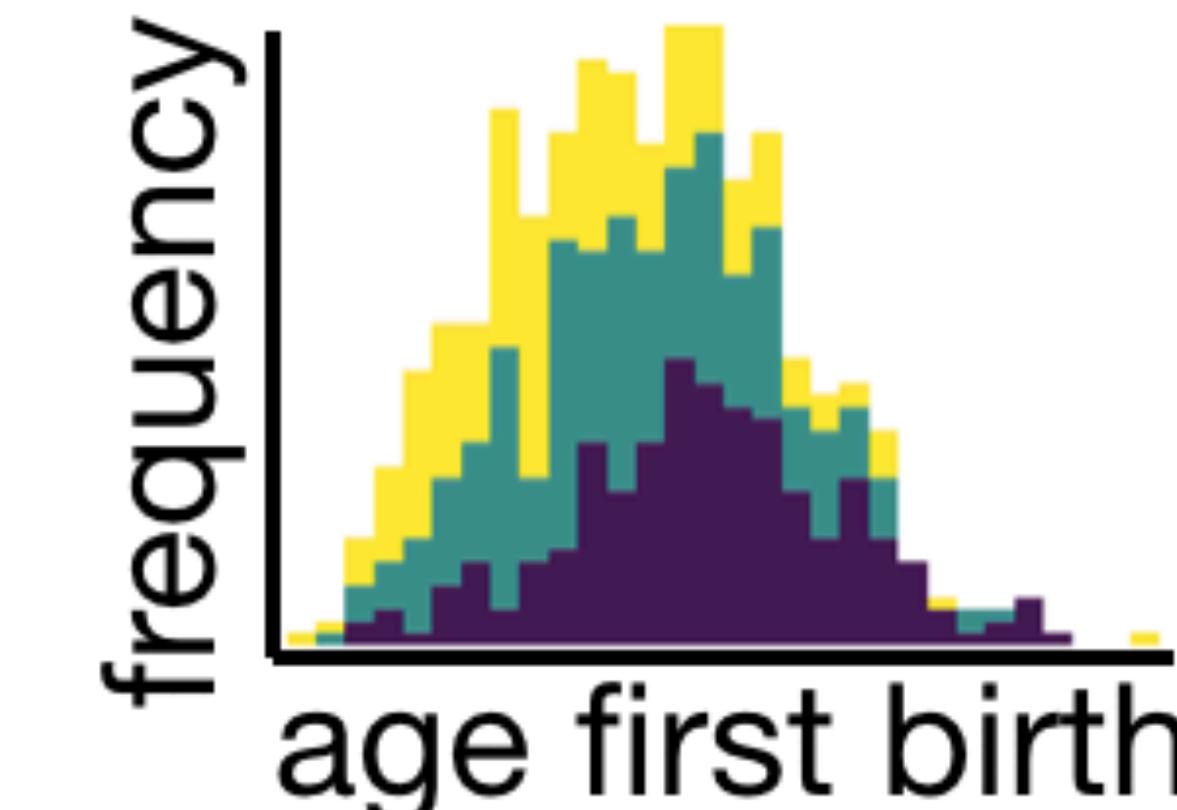


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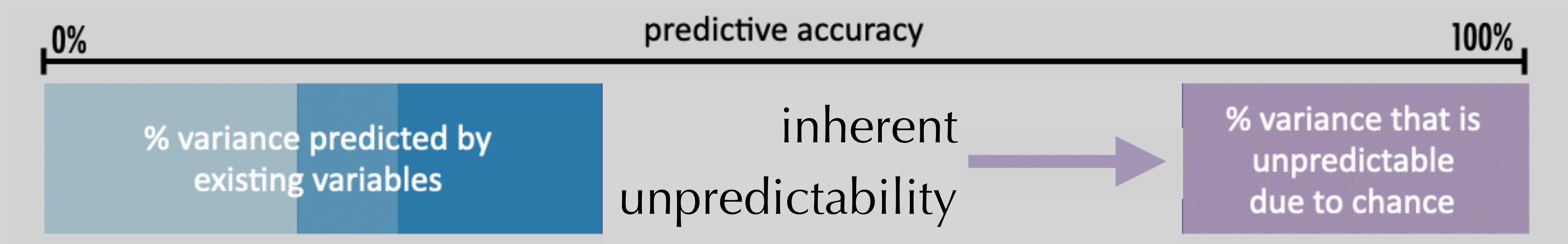


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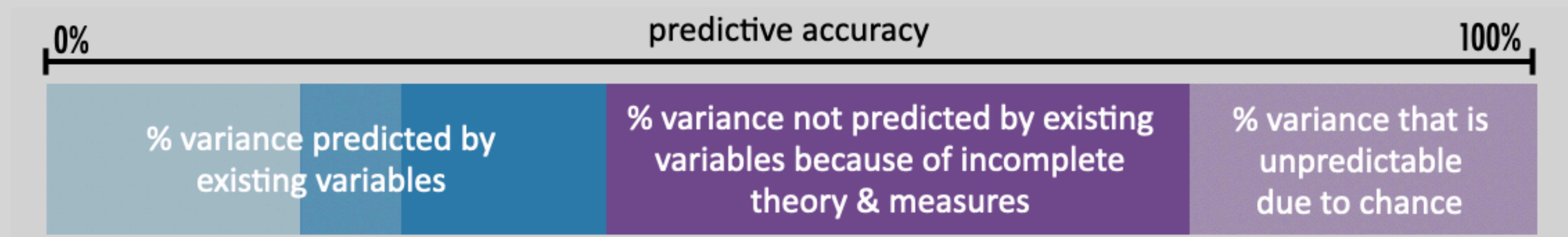
- partner status
- preferences
- stochasticity



Unpredictable Variation



Unique Insight into State of Field



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Unique Insight into State of Field

scenario 1: theories can be improved with existing variables

theory-driven

data-driven prediction

unpredictability

Unique Insight into State of Field

scenario 1: theories can be improved with existing variables

theory-driven

data-driven prediction

unpredictability

scenario 2: theories are missing something fundamental

theory-driven

data-driven

Incomplete theory / measures

Unique Insight into State of Field

scenario 1: theories can be improved with existing variables

theory-driven

data-driven prediction

unpredictability

scenario 2: theories are missing something fundamental

theory-driven

data-driven

Incomplete theory / measures

scenario 3: theories are doing well given great unpredictability

theory-driven prediction

unpredictability

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This mess we're in?

Or how simulation and prediction
will advance fertility research

