

SPARRA: Scottish Patients At Risk of Re-admission and Admission

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Durham University

& The Alan Turing Institute

Department of Health and Social Care

OR Talk

10 February 2022



Introduction

Outline

- Introduction
 - Brief biography, overview of research interests, introduce team
- SPARRA Project
 - Motivation, history, objectives, data and methodological approach
- Results
 - Highlights of performance and some insights provided by the model
- Updating Paradox
 - Important theoretical challenge raised by SPARRA

Brief Biography

- 1998–2005
 - Founder & Technical Director, 6 Internet Limited
- 2005–2008
 - BA (Mod) Mathematics, Trinity College Dublin
- 2008–2013
 - PhD Mathematical Statistics, Trinity College Dublin
- 2013–2017
 - Postdoctoral researcher, Department of Statistics, University of Oxford
 - Junior Research Fellow, Corpus Christi College, Oxford
- 2017–
 - Assistant (17–20)/Associate(20–) Professor of Statistics, Department of Mathematical Sciences, Durham University
- 2018–
 - Secondment / Health Programme Fellow, The Alan Turing Institute

Louis Aslett

Research Interests

- Privacy & cryptography in statistics
- Statistical & machine learning
 - Health applications
 - Privacy preservation
- Computational statistics
 - Markov chain Monte Carlo
 - Multilevel Monte Carlo
 - Statistical genetics
 - High performance computing
- Reliability theory



The team

Core team



James Liley
Durham



Sam Emerson
Durham



Catalina Vallejos
Edinburgh



Louis Aslett
Durham

Further Turing team

- Gergo Bohner
- Nathan Cunningham
- Ioanna Manolopoulou
- Bilal Mateen
- Sebastian Vollmer
- Katrina Payne
- Chris Holmes

Public Health Scotland team

- Rachel Porteous
- David Carr
- Simon Rogers (NSS)
- Katie Borland
- Sam Oduro
- Stephen Riddell
- Keith Moffat
- Jill Ireland
- Susan Frame
- Scott Heald

SPARRA Project

Background

*“The NHS should work with other public services and with patients and carers to provide continuous, **anticipatory** care to ensure that, as far as possible, **health care crises are prevented from happening.**”*

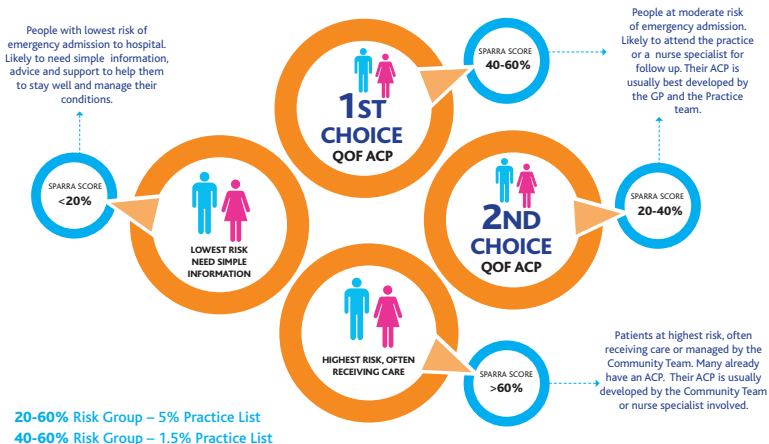
— Kerr Report, NHS Scotland, 2005

Admission to an emergency department (EA)

- breakdown of health control
- transition from primary (preventative) to secondary (curative) care
- increased morbidity and mortality risk
- more expensive and specialised healthcare services

SPARRA Motivation

Anticipatory Care Continuum of Risk



SPARRA History

A brief history of SPARRA ...

2006

Version 1

> 65 years old

EA in last 3 yr



5%

SPARRA History

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2008

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> 65 years old
EA in last 3 yr



5%

Version 2

Any age
EA in last 3 yr



13%

SPARRA History

A brief history of SPARRA ...

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2008

2009

Version 1
> 65 years old
EA in last 3 yr

Version 2
Any age
EA in last 3 yr

Version 3
Any age
Any NHS use



5%



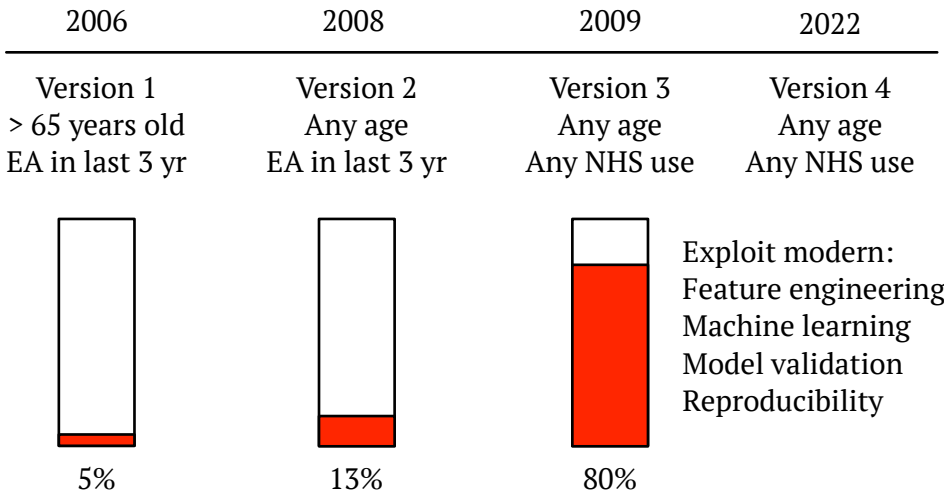
13%



80%

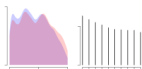
SPARRA History

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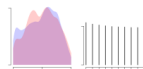
Data sources

A&E



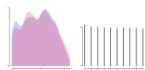
R = 7,539,454
I = 3,031,773

Outpatients

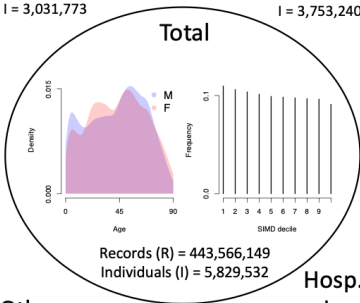


R = 27,463,987
I = 3,753,240

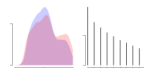
Prescriptions



R = 393,643,499
I = 5,590,857

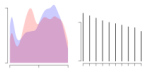


MH inp./ day case



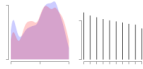
R = 111,487
I = 51,635

Other



R = 34,335^{ger}; 4,123,502^{syst}
I = 25,015^{ger}; 1,750,009^{syst}

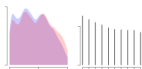
Hosp. inp./ day case



R = 8,100,908
I = 2,205,606

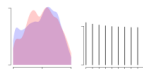
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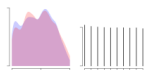
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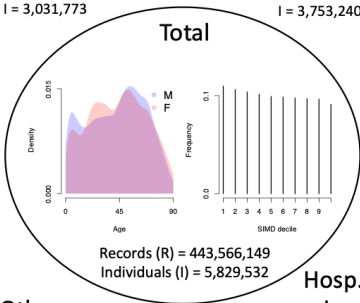


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Predictors (eg):

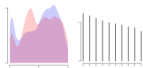
- time since last EA (if any)
- # prescriptions filled
- SIMD (deprivation)

MH inp./ day case



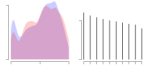
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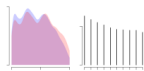
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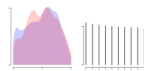
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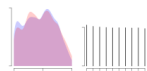
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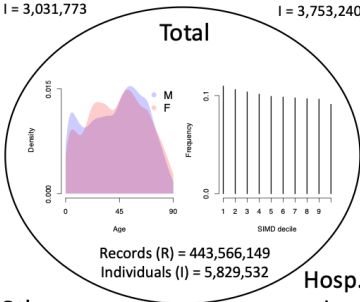


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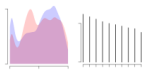
Records (R) = 443,566,149
Individuals (I) = 5,829,532

MH inp./ day case



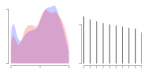
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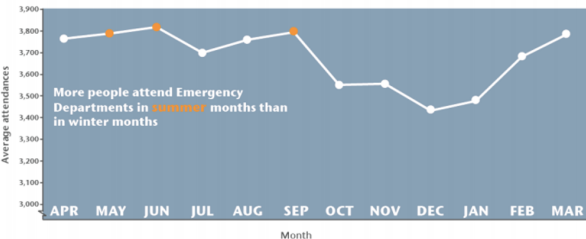
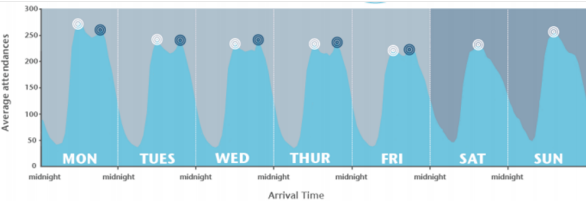
- time since last EA (if any)
- # prescriptions filled
- SIMD (deprivation)

Not available (eg):

- # engagements with primary care
- smoking, marital status, ..

Target definition

Prediction target: Emergency Admission (EA) or death within 1 year after time cutoff



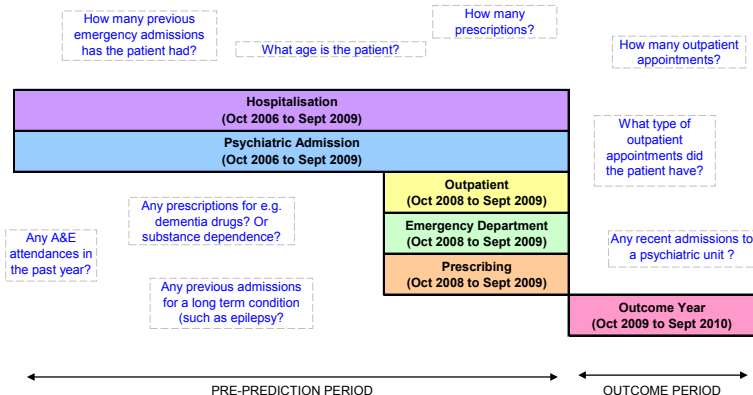
Motivation

- Do not consider seasonal, weekly or daily variation in risk
- Consider death as similar to EA in implication (may be true in younger people)
- Does not include obstetric admissions

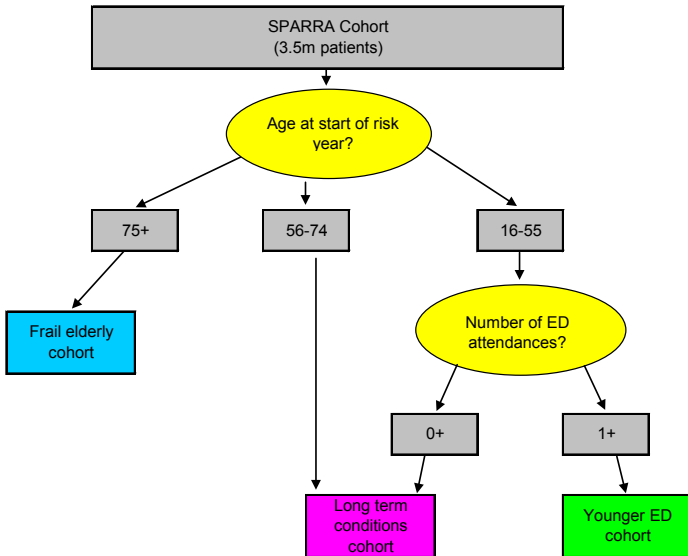
Probabilistic estimate of occurrence.

Source: NHS Scotland Emergency Care Report

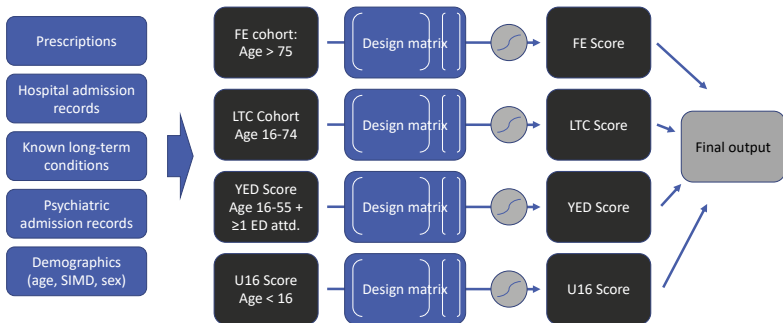
SPARRA v3 details (I)



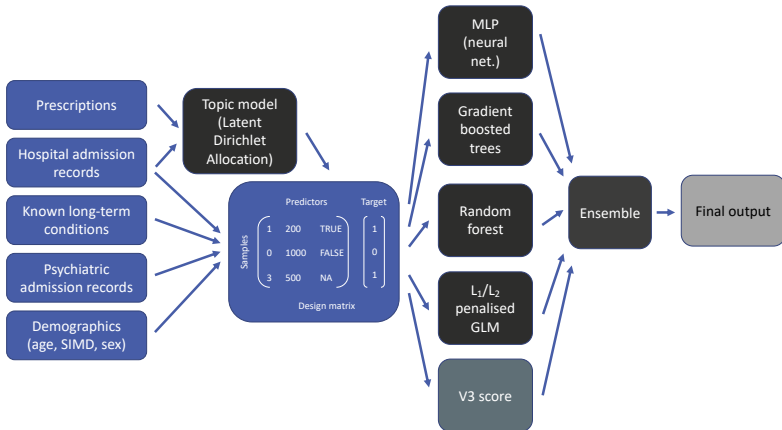
SPARRA v3 details (II)



SPARRA v3 details (III)

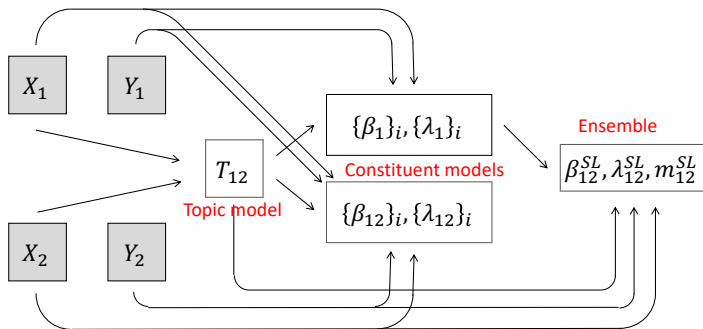


SPARRA v4 overview



SPARRA v4 cross-validation framework

Design matrices - training



$$\Pr(\widehat{Y_3|X_3}) = f(X_3, T_{12}, \{\beta_{12}\}_i, \{\lambda_{12}\}_i, \beta_{12}^{SL}, \lambda_{12}^{SL}, m_{12}^{SL})$$

$$= f_{12}(X_3)$$

Design matrices - assessment

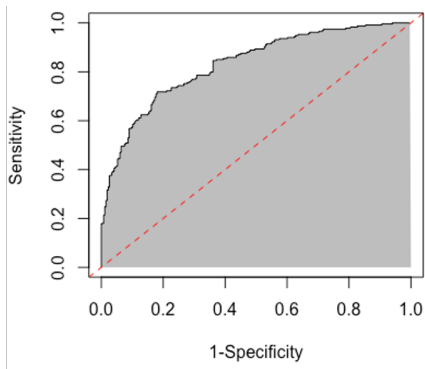
$$\Pr(\widehat{Y_3|X_3}) \perp\!\!\!\perp Y_3|X_3$$

$$f_{12}(\cdot) \perp\!\!\!\perp X_3, Y_3$$

Results

ROC and Calibration refresher

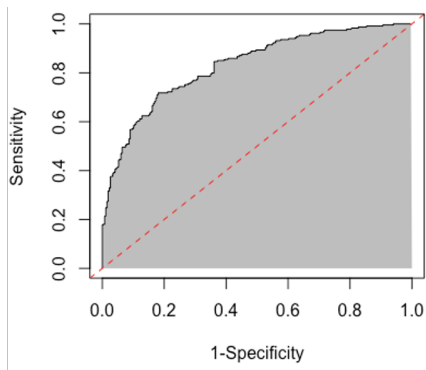
Receiver-operator characteristic (ROC)



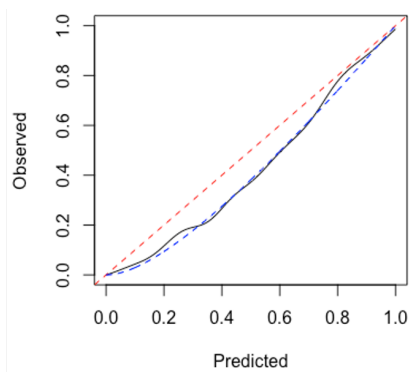
Do predictions differentiate individuals who did have an emergency admission from those who did not?

ROC and Calibration refresher

Receiver-operator characteristic (ROC)



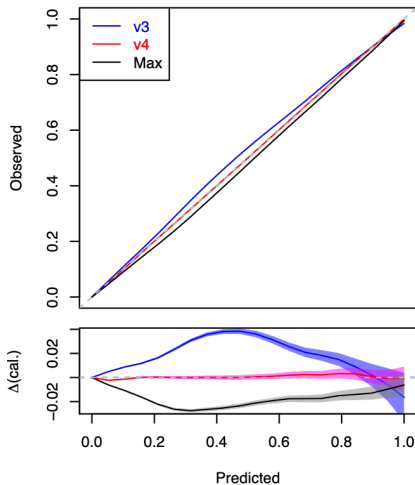
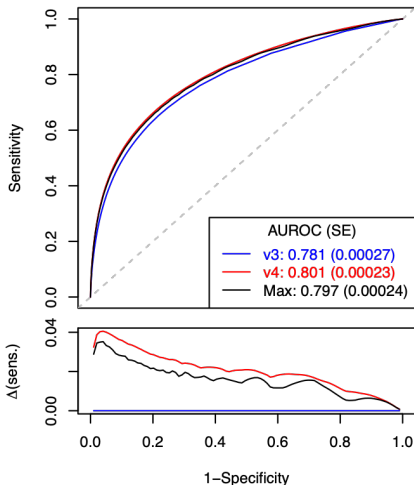
Calibration plot



Do predictions differentiate individuals who did have an emergency admission from those who did not?

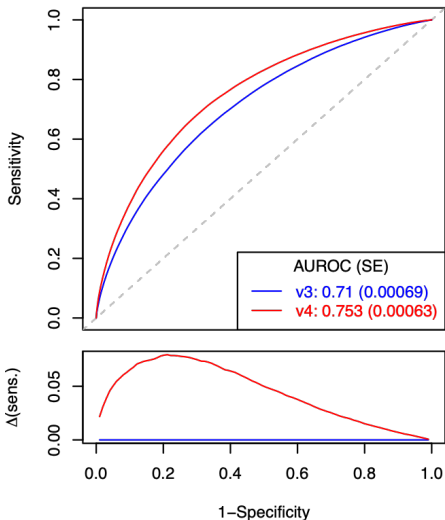
Amongst individuals with a given probability of emergency admission, was the probability correct?

SPARRA v4 overall results

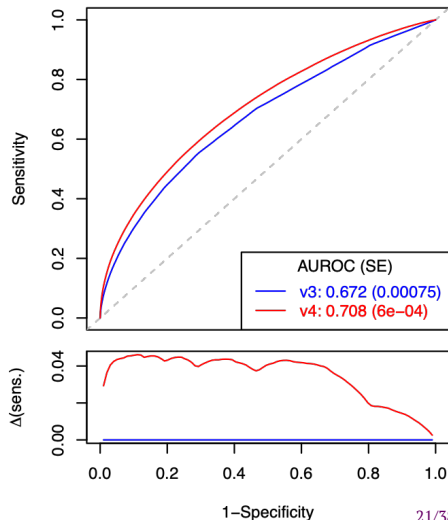


SPARRA v4 challenging cohorts

High-risk individuals (age > 80)

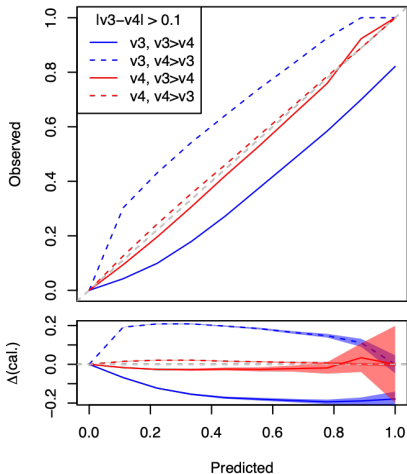


Low-risk individuals (age 20-70, no previous EA)

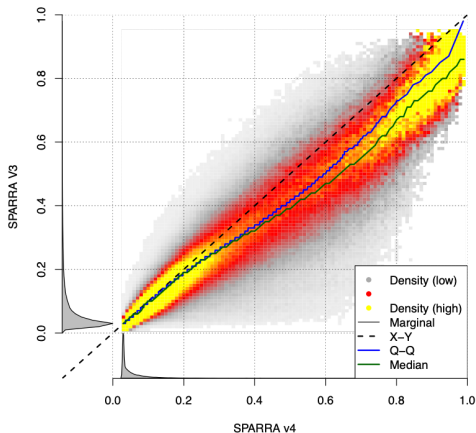


SPARRA v3/v4 direct comparison

Differential risk scores

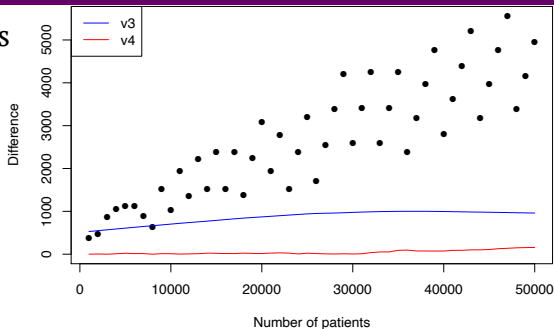


Bivariate density



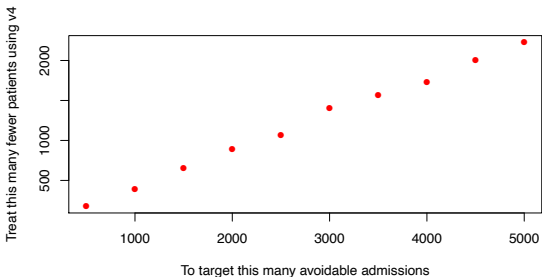
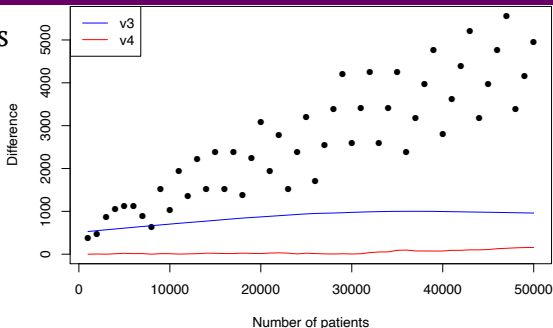
SPARRA v4 interpretable impacts (I)

Number of actual admissions
among N predicted to be
most at risk



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Number of actual admissions among N predicted to be most at risk



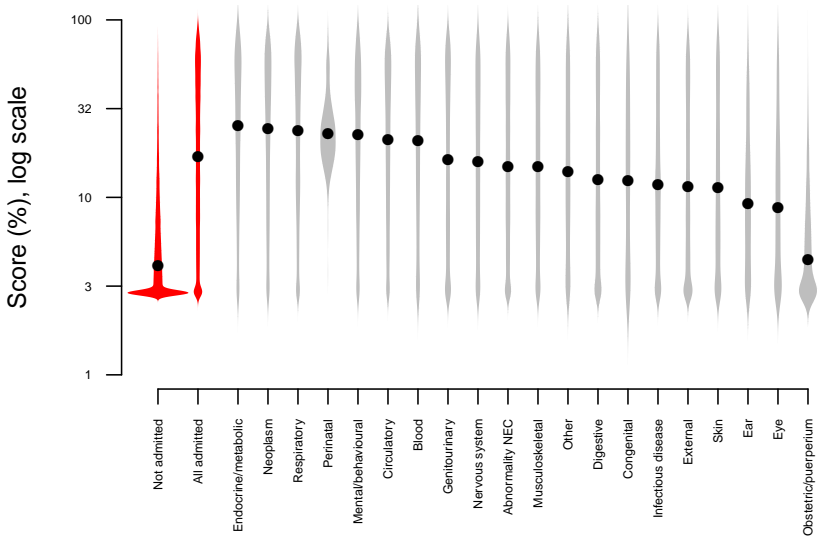
Reductions in targeted intervention required

SPARRA v4 recap so far ...

In other words:

- improvements to calibration in high risk score region
- higher accuracy in challenging cohorts
- upon matching at-risk cohort size to SPARRA v3's top 50,000:
 - recommended follow-up for an extra $\approx 4,000$ patients who did later undergo emergency admission
 - $\approx 4,000$ fewer incorrect follow-up recommendations to GPs
 - significant opportunity for improved patient outcomes and NHS cost savings

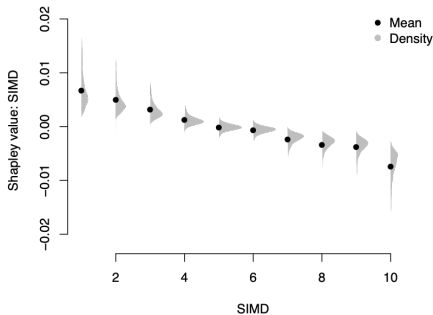
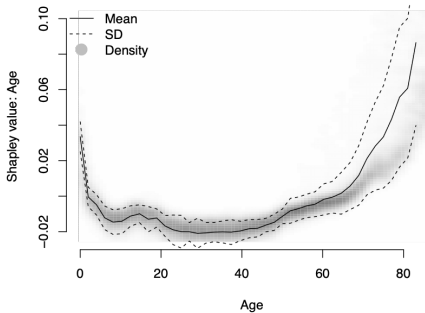
SPARRA v4 effectiveness by admission type



SPARRA v4 Shapley values

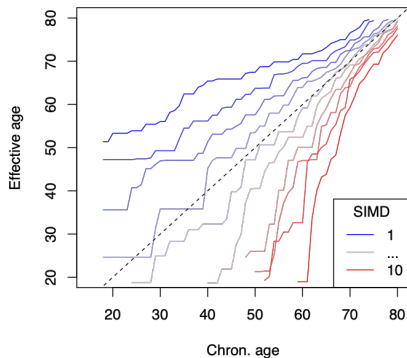
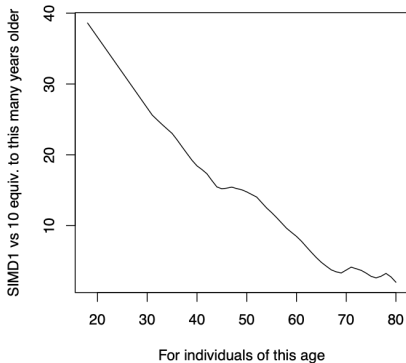
Importance of age

Importance of deprivation



SPARRA v4 age/deprivation equivalence

Using Shapley value to explore age equivalent effect of deprivation levels:



Some thoughts about these results ...

- Emergency admissions can be predicted to a potentially useful degree from routinely collected healthcare data on a population scale in Scotland.

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- Contemporary machine learning methods enable meaningfully more accurate prediction on this scale.

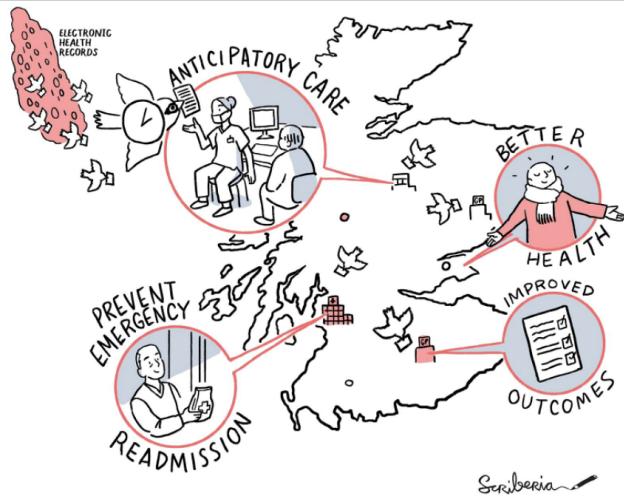
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- Apparent opportunities for improved patient outcomes and NHS cost savings.
- Contemporary machine learning methods enable meaningfully more accurate prediction on this scale.
- Certain types of admissions can be predicted differentially well: cancer and endocrine-related admissions are predicted well, eye/ear and traumatic admissions poorly.

Some thoughts about these results ...

- Emergency admissions can be predicted to a potentially useful degree from routinely collected healthcare data on a population scale in Scotland.
- Apparent opportunities for improved patient outcomes and NHS cost savings.
- Contemporary machine learning methods enable meaningfully more accurate prediction on this scale.
- Certain types of admissions can be predicted differentially well: cancer and endocrine-related admissions are predicted well, eye/ear and traumatic admissions poorly.
- SIMD has a substantial effect on EA probability, with the difference between SIMD1 and SIMD10 equivalent to 20-40 additional years of age.

SPARRA v4 deployment



SPARRA v4 deployment
~ Q2, 2022

Scores to be deployed nationwide to GPs and may be used to guide intervention or public health actions.

Reproducibility has been taken seriously throughout and final deployed code/models will be open sourced.

Updating Paradox

The setting

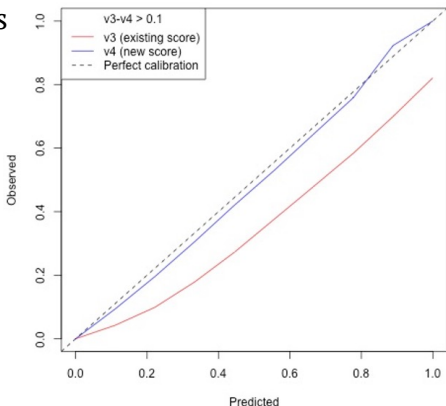
SPARRA v4

- 80% of Scottish population
- Modern machine learning methods
- Up-to-date

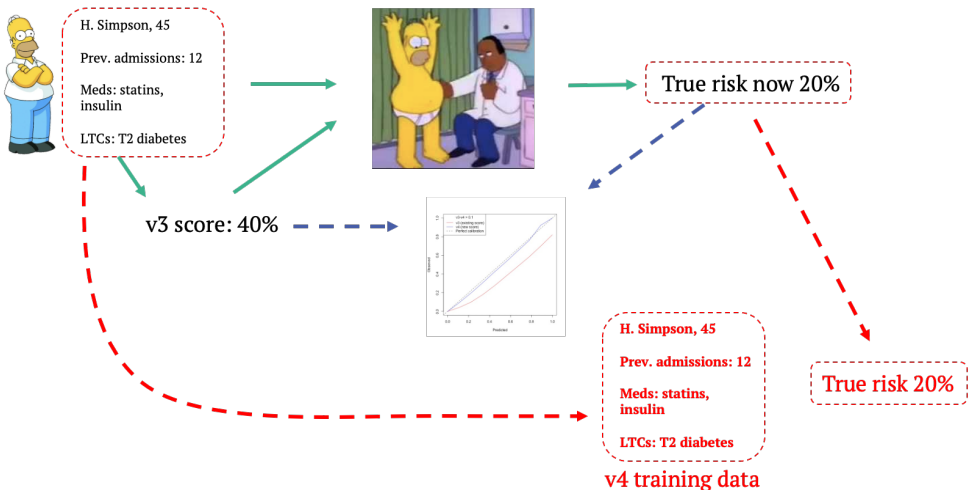
SPARRA v3

- 80% of Scottish population
- Logistic regression
- Fitted 2012 and *in use ever since*
- Can overestimate risk – *why?*

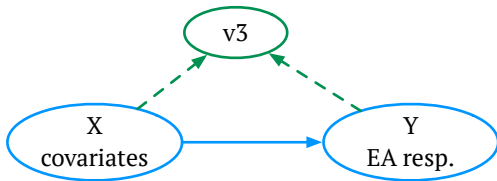
Healthcare system might have just improved (*concept drift*)



Model updating paradox: what's happening?

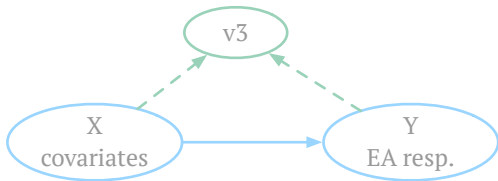


Model updating paradox: why?

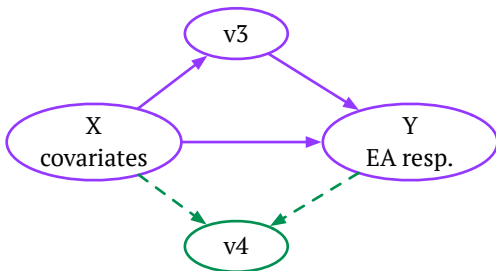


SPARRA v3 trained to **blue** system

Model updating paradox: why?

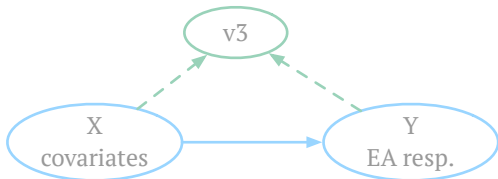


SPARRA v3 trained to blue system

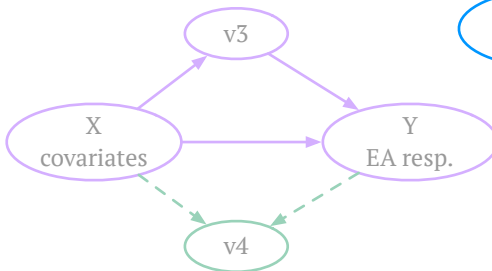


SPARRA v4 trained to purple system

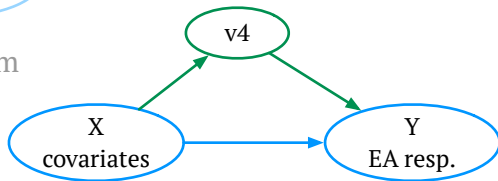
Model updating paradox: why?



SPARRA v3 trained to **blue** system

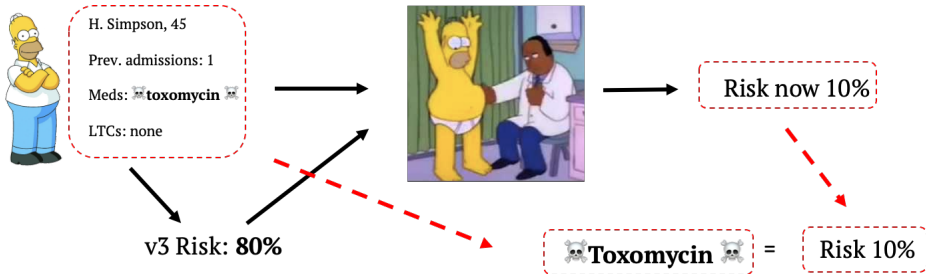


SPARRA v4 trained to **purple** system

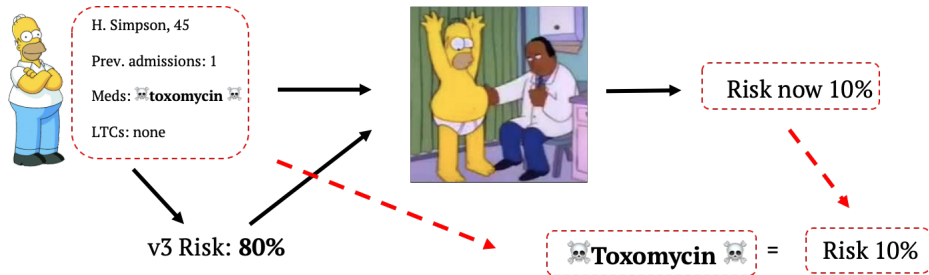


SPARRA v4 used for predictions in **blue** system, which is ***not*** the system it was trained on!

Model updating paradox: is it bad, really?



Model updating paradox: is it bad, really?



- This effect has been observed in real life (Caruana, 2015)
- This is a problem right now! USFDA 2019 working paper notes RCTs expensive: posits avoiding repeating each time a model is updated.
- The more the score is used, the more it exacerbates the problem
- Can prove the better the model is, the worse subsequent updates will perform!

Naïve model updating + updating framework

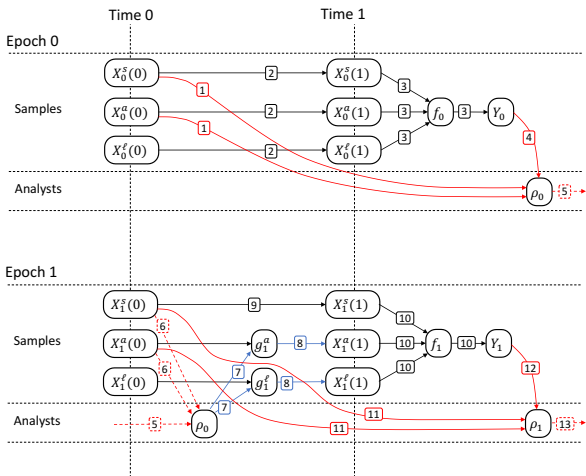
Timeline



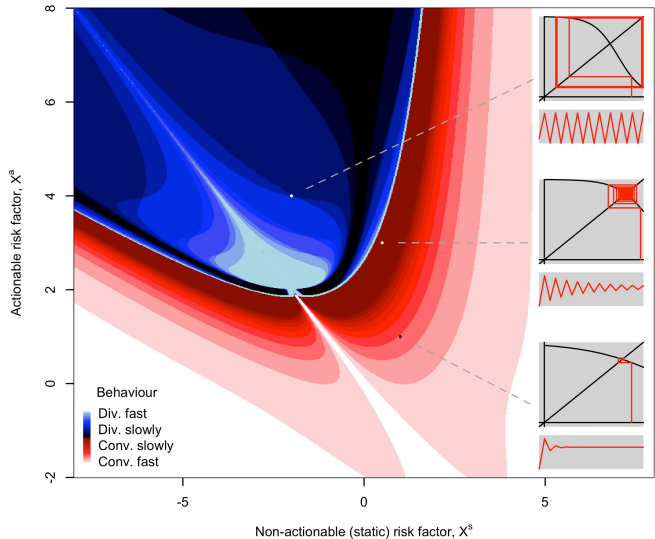
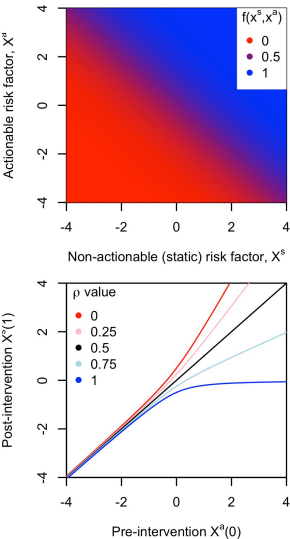
Notation

Class
Object $X_0^s(0)$ Time
Epoch

Dependencies



Results



Is equilibrium a bad thing?



H. Simpson, 45
Prev. admissions: 1
Meds: ~~toxomycin~~
LTCs: none

Score: 80%



Risk now 10%



H. Simpson, 45
Prev. admissions: 1
Meds: ~~toxomycin~~
LTCs: none

Score: 45%



Risk still 45%

Possible resolutions?

- Model full causal structure and interventions (practicality?)
- Holdout set (work forthcoming)
- Stacked interventions (J Liley)

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Thank you!