

The role of causal inference in predictive modelling

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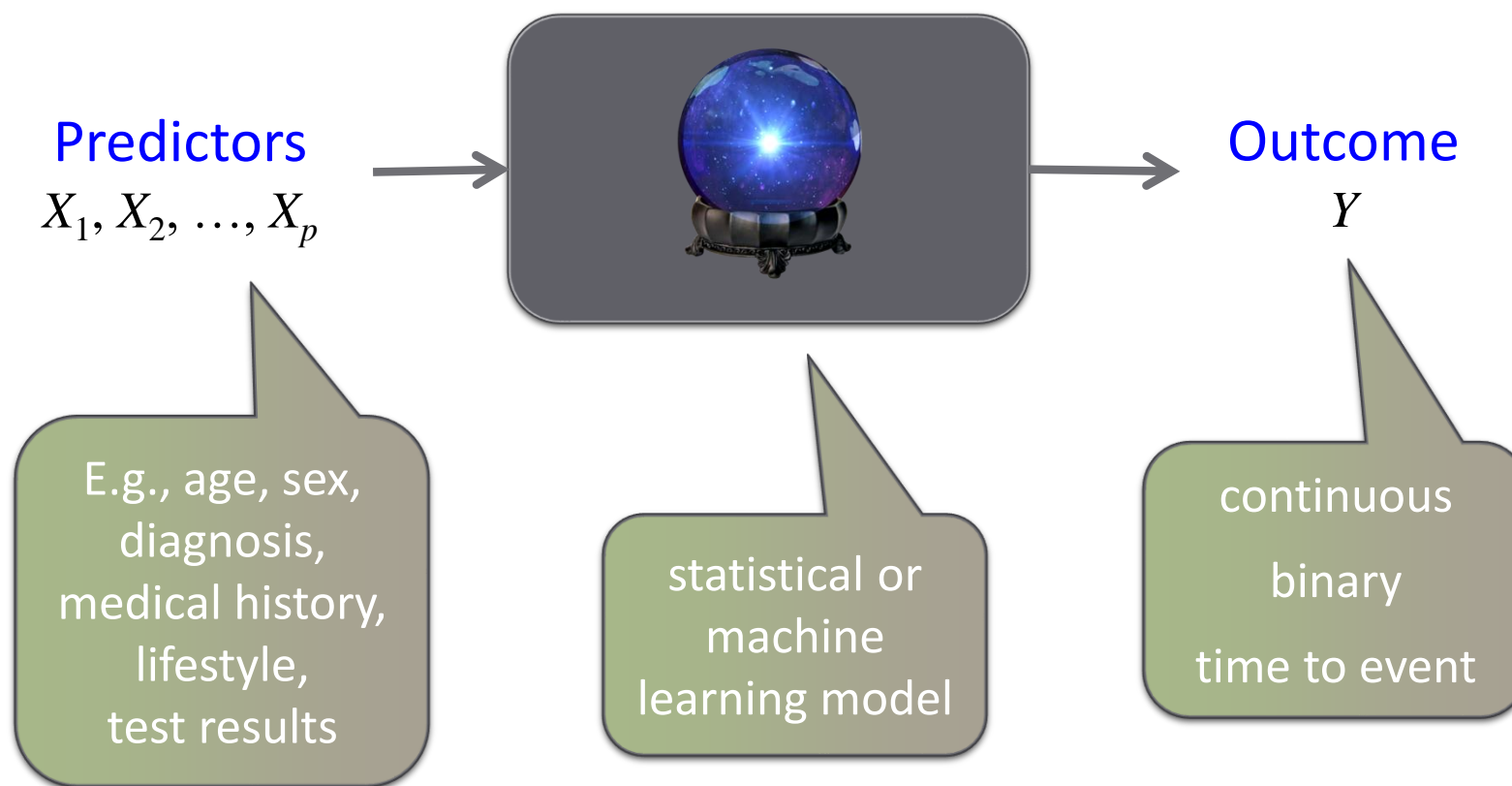


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Clinical prediction models and what they are for.



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- **Making decisions about interventions**
- Audit
- Counselling
- Patient selection for, e.g., RCTs

Risk approach to intervening

- Example: Default approach to primary prevention of CVD: risk based
 - “consider anyone with QRISK > 10% for statins”
 - Based (informally) on the idea that those at higher risk have higher benefit

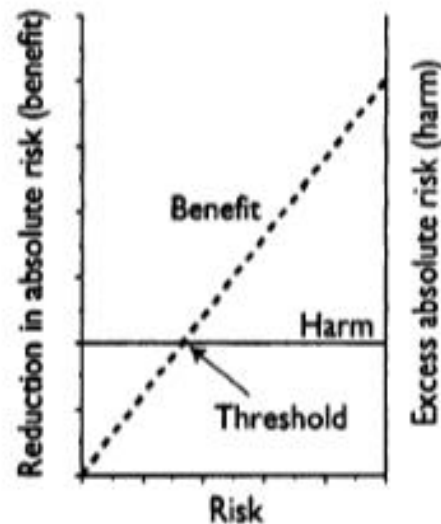


FIG 1—Benefit increases with risk, but harm is constant. Net benefit occurs only when risk is above threshold

Glasziou, Paul P., and Les M. Irwig. "An evidence based approach to individualising treatment." *Bmj* 311.7016 (1995): 1356-1359.

Instead we would like to ask “What if I...” questions – causal inference.



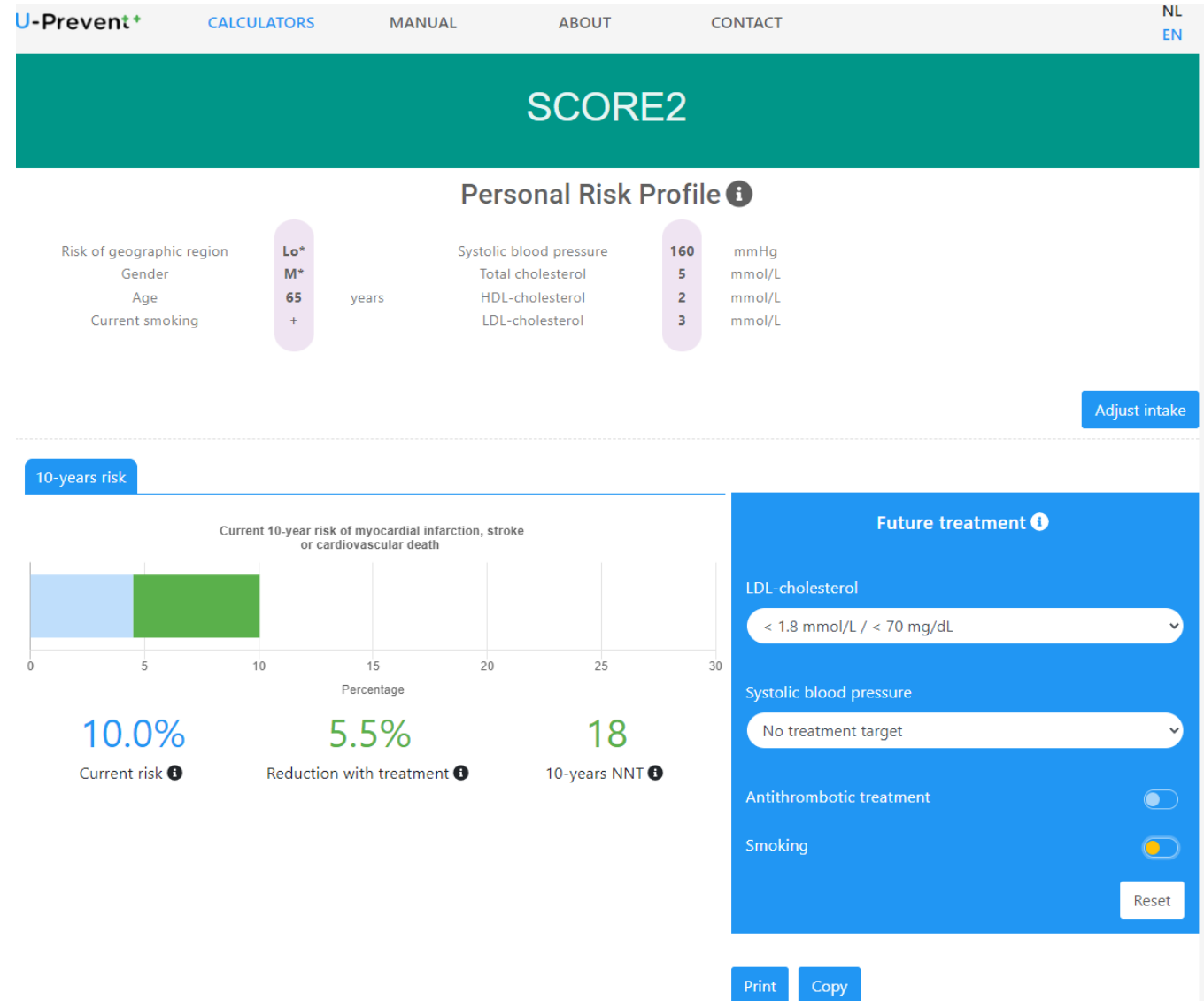
50yr old male, white, heavy smoker, overweight, type 2 diabetes, elevated blood pressure

- Suppose Joe has a CVD risk of 17%.
- Joe might ask: “What if...”
 - I stopped smoking?”
 - I lost some weight?”
 - I reduced my blood pressure?”
 - *I did nothing?*

Benefit approach to intervening

- Calculate (individualised) benefit of an intervention(s) and make decisions based on that.
- Two basic approaches:
 - Plug-in / conditional - can be very bad.
 - Absolute risk x relative risk – better.

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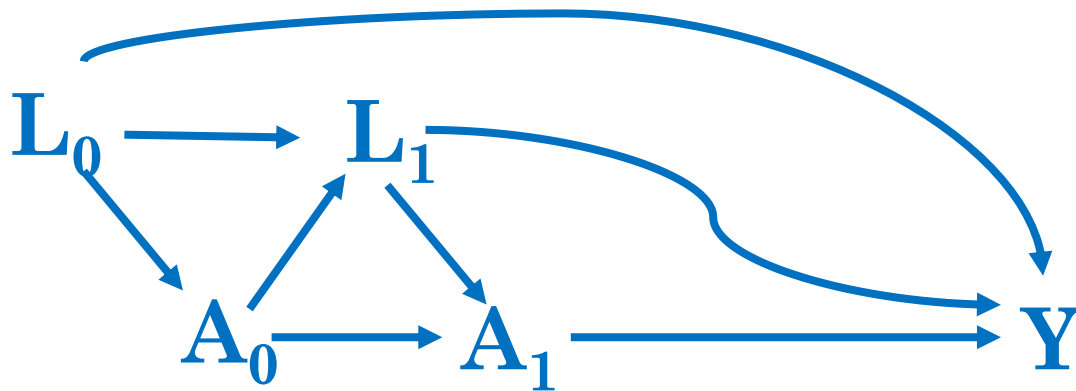


Alternative approach: target estimands and use causal inference

- Causal inference for observational data gives us a clear framework for addressing this problem.
- We are always explicit about what any absolute risk we are calculating refers to, for example:
- ‘CVD risk if we do nothing for this patient’
- ‘CVD risk if this patient takes statins’
- ‘CVD risk if this patient takes statins and loses weight’
- ‘CVD risk if this patient doesn’t take statins now, but commences them if their risk goes above 10% in future’.

‘Treatment drop-in’ – why ‘doing nothing’ risk isn’t trivial.

- Suppose we’re interested in the ‘do nothing’ risk.
- Fit a time-to-event model
- How do we handle treatment naïve at baseline, who start taking treatment during follow-up?



Sperrin, M., Martin, G. P., Pate, A., Van Staa, T., Peek, N., & Buchan, I. (2018). Using marginal structural models to adjust for treatment drop-in when developing clinical prediction models. *Statistics in medicine*, 37(28), 4142-4154.

Other potential benefits of causal modelling in prediction

- Ensuring fairness of decisions based on prediction models
 - Through criteria such as counterfactual fairness.
- Improving generalisability of prediction models
 - Causal pathways more likely to be preserved than associations
 - Or explicitly rule out ‘unstable’ edges.
 - Apply counterfactuals to match different contexts
- Handling ‘performative prediction’
 - Implementing a model changes things – feedback loops.