

*SISCER 2022 Module 4: Evaluation of
Biomarkers and Risk Models*

Part II: Evaluating Risk Models

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Kathleen Kerr, PhD

Professor of Biostatistics

SISCER Director

University of Washington

Risk Model Assessment

- Risk Model Calibration
 - required for a risk model to be *valid*
 - particularly crucial whenever a risk model will be used to convey risk to patients
- Risk Model Discrimination Performance
 - required for a risk model to be *useful*
 - performance assessment depends on what the model will be used for

CALIBRATION

Calibration

- A risk is a number of some import
 - “based on my test results, the chance (risk) I have the disease is 5%”
 - “based on my age and family history, my chance of a breast cancer diagnosis in the next 5 years is 1%”
- In order to be valid, risks must be calibrated

What does it mean for a risk model to be calibrated?

Type of Calibration	Definition	Remark
Mean	Observed event rate equals average predicted risk	“calibration-in-the-large”
Weak	No systematic overestimation or underestimation of risks	“logistic calibration”
Moderate	Predicted risks correspond to observed event rates	Often the best we can assess with limited data
Strong	For every combination of risk factors, predicted risks correspond to observed event rates	The ideal, but difficult to assess

Adapted from Van Calster et al, *J Clinical Epidemiology*, 2016 104

Mean Calibration

- Also called “calibration-in-the-large”
- Def: average predicted risk equals the prevalence
- To assess, compare event rate with average predicted risk
 - If 3% of the population are cases, then the risk model has mean calibration if the average predicted risk is 3%
- Very low bar

Weak Calibration

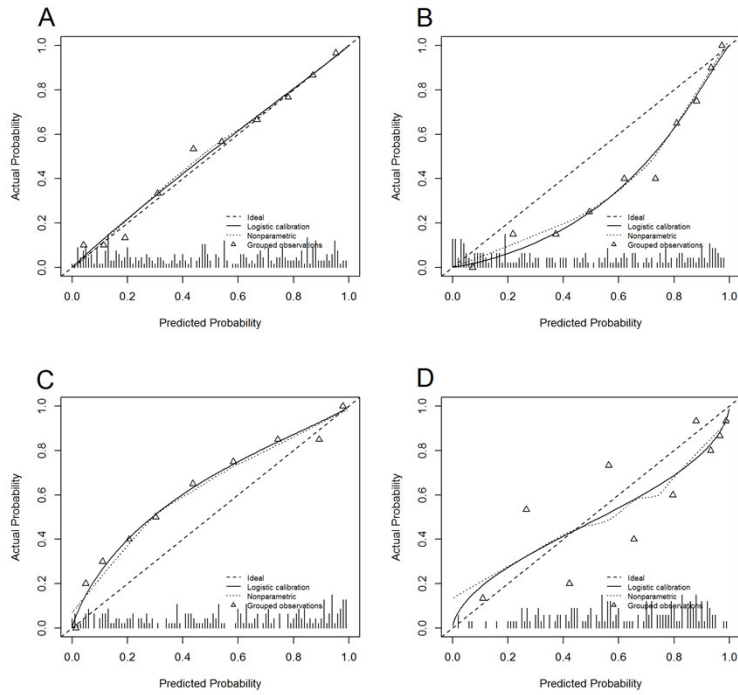
- Also called “Logistic calibration”
- Predicted risks are obtained from a previously developed model for D (e.g., based on logistic regression); the linear combination of predictors defines the “linear predictor” $L=b_0+b_1 X_1 + \dots + b_k X_k$
- Regress D on L: $\text{logit}(P(D) | L) = a + b L$
 - a is the “calibration intercept”; b is the “calibration slope”
- Def: If $a \approx 0$ and $b \approx 1$, the model is calibrated in the weak sense
- In data not used to fit the model, typically the calibration slope $b < 1$: large predicted risks are too high and low predicted risks are too low
 - (R demo)

106

Moderate Calibration

- Def: $P(D = 1 | \widehat{\text{risk}}(X_1, X_2) = r) = r$
 - here, there are two risk factors X_1 and X_2
- “collapses” data among groups of people with the same predicted risk
- Common practice to assess: divide available data into deciles based on predicted risks
- Compare event rate in a decile of individuals with similar predicted risk → calibration curve
 - Next slide: 1 risk model that has good calibration (in the moderate sense); and 3 poorly calibrated risk models

107



Forecasts of rain: are the risks well calibrated?

From *The Signal and the Noise*, Nate Silver, The Penguin Press 2012.

FIGURE 4-7: NATIONAL WEATHER SERVICE CALIBRATION

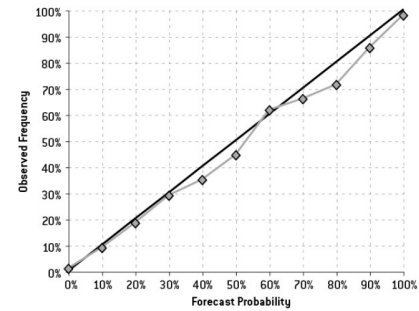


FIGURE 4-8: THE WEATHER CHANNEL CALIBRATION

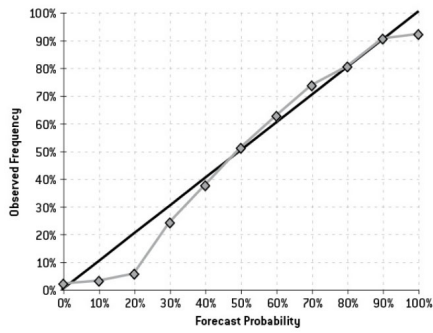
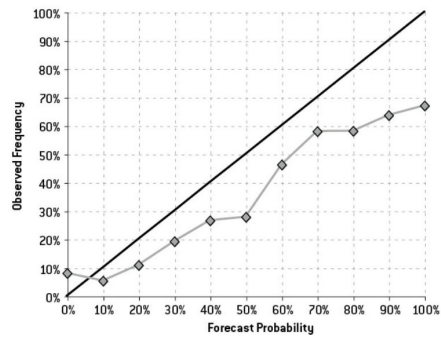


FIGURE 4-9: LOCAL TV METEOROLOGIST CALIBRATION



how NOT to assess moderate calibration

- Hosmer-Lemeshow test statistic
- p-value from Hosmer-Lemeshow test

- In small datasets, badly miscalibrated models may not give a large H-L test statistic or a significant p-value
- In large datasets, small/unimportant deviations from good calibration can produce large H-L test statistic and small p-value

110

Calibration plots

- Can be sensitive to the choice of the groups, choice of smoother, and other options (beware of smooths that eliminate “outliers”)

111

Strong Calibration

- Def: $\widehat{risk}(X_1, X_2) = P(D=1 | X_1, X_2)$
- Must consider every unique combination of predictors and ask whether observed and predicted risks agree for people with that combination
- Compared to calibration in the moderate sense, does not “collapse” groups of people with the same $\widehat{risk}(X_1, X_2)$
- Typically only feasible to assess when there are a limited number of predictors and they are all categorical

112

Example: Predicted risks for Huntington’s Disease

Level	Definition	Individuals with 1 HD Parent: risk=50%	Genotyped individuals: risk is 0% or 100%
Mean	Observed event rate equals average predicted risk		
Weak	No systematic over- or under-estimation of risks		
Moderate	Predicted risks correspond to observed event rates		
Strong	For every combination of risk factors, predicted risks correspond to observed event rates		

3rd risk model for Huntington's disease

- Genotyping not available. Instead, flip a coin. If heads, assign risk 75%. If tails, assign risk 25%.
- Is this risk model, which uses “data” from a random coin flip, calibrated?
 - Mean calibration?
 - Moderate calibration?
 - Strong calibration?

114

Calibration is not enough

- If the prevalence is ρ , a calibrated risk model assigns everyone risk ρ .
- A risk model needs to do more: stratify people into meaningful “low risk” and “high risk” groups.
 - Achieved perfectly by genotyping the *HTT* gene among those at risk for Huntington's disease, but less perfectly for most applications.

115

RISK MODEL DISCRIMINATION

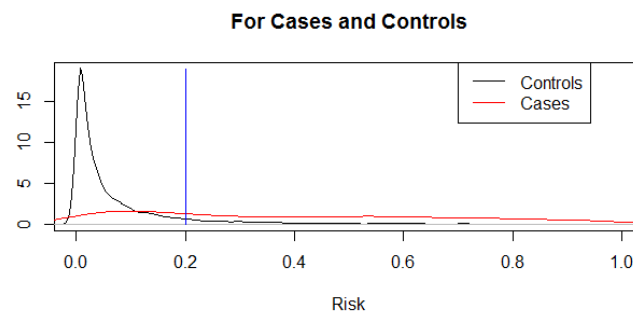
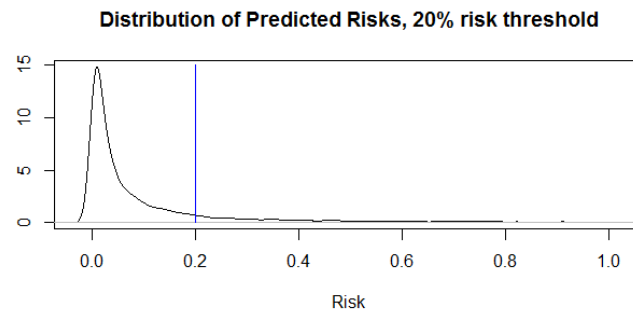
Risk Model Performance

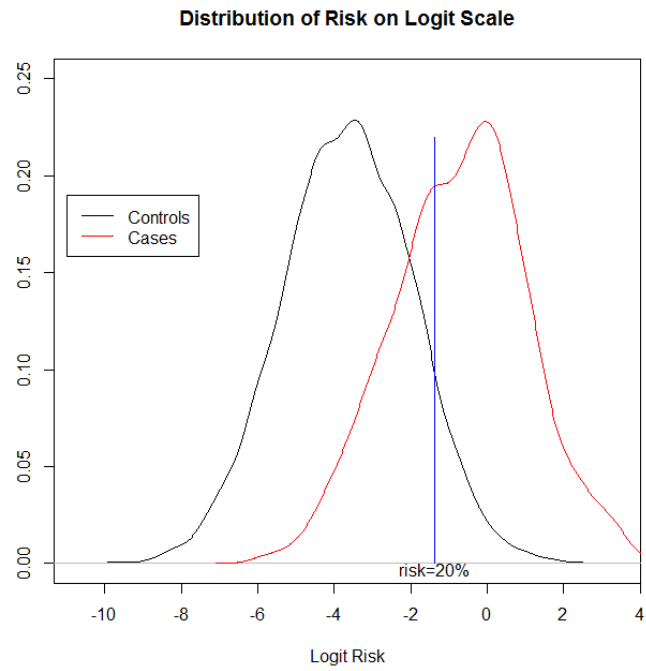
We will discuss three classes of assessment

- Generic measures
 - “purely mathematical”
 - meaning: they do not directly translate to any clinical, public health, or public policy impact of using the risk model
- Assessing performance when model will be used to recommend treatment/intervention to high risk individuals
- Assessing performance for prognostic enrichment of clinical trials

The Distribution of Risk

- Case ($D=1$) and control ($D=0$) risk distributions are fundamental components of all performance measures
- When examining risk distributions, useful to include any conventional thresholds for deciding who is “high risk”
- The logit scale may be more convenient than the 0 to 1 risk scale
- Next slide: risk model for simulated data from DABS website





GENERIC MEASURES OF RISK MODEL PERFORMANCE (MEASURES THAT DO NOT USE A RISK THRESHOLD)

MRD, AARD, AUC

- MRD = Mean Risk Difference
- AARD = Above Average Risk Difference
- AUC = Area Under the ROC Curve

These are measures of **discrimination**. They quantify:

How well does the risk model discriminate/separate cases and controls?

122

Mean Risk Difference (MRD)

$MRD \equiv \text{mean}(\text{risk}(X) | \text{case}) - \text{mean}(\text{risk}(X) | \text{control})$

- Also known as Yates' slope
- Equals PEV = Proportion of Explained Variation = $R^2 = \frac{\text{var}(\text{risk}(X))}{\text{var}(D)}$
- Change in MRD for two nested models also known as **IDI**=Integrated Discrimination Improvement Index

For the DABS data example, $\text{mean}(\text{risk} | \text{case}) = 0.391$, $\text{mean}(\text{risk} | \text{cntl}) = 0.069$; $MRD = 0.322$

123

Above Average Risk Difference (AARD)

$$\text{AARD} = P(\text{risk}(X) > \rho \mid \text{case}) - P(\text{risk}(X) > \rho \mid \text{control})$$

$$\text{AARD} = 0.797 - 0.198 = 0.599 \text{ in the DABS example}$$

- Can also write as: $HR_D(\rho) - HR_{\bar{D}}(\rho)$
 - or $\text{TPR}(\rho) - \text{FPR}(\rho)$
- Related to Net Benefit metrics (will come to these soon)
 - $\text{NB}(r) = \rho HR_D(r) - (1 - \rho) \frac{r}{1-r} HR_{\bar{D}}(r)$; set $r = \rho$ and divide by ρ

124

AUC for a Risk Model

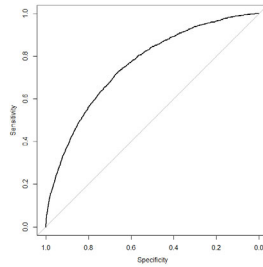
$$\text{AUC} = \text{Area Under the ROC Curve} = P(\text{risk}_{\text{case}}(X) > \text{risk}_{\text{cntl}}(X))$$

- Ignores the meaning of risk
- AUC not a clinically relevant measure of predictive performance
 - Arguably roughly similar to MRD in terms of clinical relevance
- Rather than AUC, it might be more clinically relevant to average TPR over a relevant range of FPR (rather than entire range)
 - pAUC

125

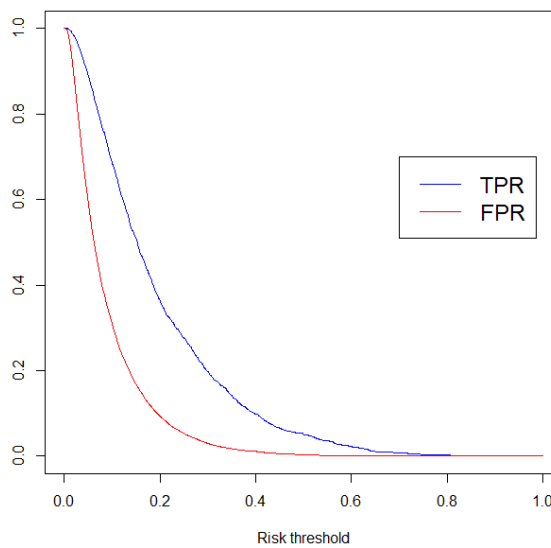
ROC Curve for a risk model

- A disadvantage of ROC curves for risk models is that the curve does not show the risk threshold corresponding to each (FPR, TPR).
- The next slide shows an alternative plot that addresses this disadvantage.



126

As an alternative to ROC, plot TPR and FPR versus risk threshold



127

Example: Models to identify patients melanoma patients with very low risk of death

- Melanoma is the most serious type of skin cancer, but most patients have a high chance of survival
- Study of early-stage melanoma. Goal: use cancer registry data to identify a subset with very low risk of death from melanoma (<0.5% 7-year risk of death)
- We developed two classification tree models and one logistic regression model, and evaluated on independent data.
 - Unpublished data (paper currently under review)

128

- The logistic model has much better AUC than the classification trees.
- Yet, for the goal of identifying patients at very low risk of death, the classification trees are more promising.

Model	AUC	Proportion of Sample with Low Risk of Death, N (%)	Number in Subset that Died	Risk of melanoma death in subset (95% CI)
Training data (N=7652)				
Model 1A: CART model with 3 leaves	0.73	2707 (35%)	12	0.44% (0.25%, 0.77%)
Model 1B: CART model 5 leaves	0.74	1950 (25%)	3	0.15% (0.05%, 0.45%)
Model 2: Logistic model, risk of death < 0.5%	0.80	1896 (25%)	9	0.47% (0.25%, 0.90%)
Testing data (N=3942)				
Model 1A: CART model with 3 leaves	0.64	1381 (35%)	8	0.58% (0.29%, 1.14%)
Model 1B: CART model with 5 leaves	0.61	993 (25%)	4	0.40% (0.16%, 1.03%)
Model 2: Logistic model, risk of death < 0.5%	0.78	969 (25%)	5	0.52% (0.22%, 1.20%)

129

EVALUATING A RISK MODEL FOR RECOMMENDING TREATMENT

Risk-based decisions

- Sometimes the purpose of a risk model is to inform who should be treated
 - e.g., screen high-risk individuals for cancer
 - e.g., treat individuals who are at high risk of a heart attack with statins
 - e.g., treat cancer patients with high risk of relapse with adjuvant chemotherapy
- What risk threshold should define “high risk”?

Benefits and Costs of Treatment

- Assume there is some expected benefit B to treating a case
 - life extended, morbidity reduced
- Assume there is some cost C to treating a control
 - cost includes side effects of treatment, stress/anxiety, toxic exposures, as well as monetary cost

132

Choice of Risk Threshold

Classical Decision Theory Result

Treatment offers benefit B to a case and cost C to a control. Then the optimal risk threshold r_H for selecting high-risk patients for treatment is

$$r_H = \frac{C}{C + B} \leftrightarrow \frac{C}{B} = \frac{r_H}{1 - r_H}$$

Pauker and Kassierer, The threshold approach to clinical decision making. *NEJM* 1980.

Vickers and Elkin, Decision Curve Analysis. *Medical Decision Making* 2006.

133

Choice of Risk Threshold

Outline of derivation:

$$r_H = \frac{C}{C+B} \leftrightarrow \frac{C}{B} = \frac{r_H}{1-r_H}$$

When should patients choose treatment?

- When expected result of treatment > 0
- $E(\text{benefit} | D=1, X)P(D=1 | X) - E(\text{cost} | D=0, X)P(D=0 | X) > 0$

$$B \cdot P(D=1 | X) - C \cdot P(D=0 | X) > 0$$

$$B \cdot P(D=1 | X) > C \cdot P(D=0 | X)$$

$$\frac{P(D=1 | X)}{1 - P(D=1 | X)} > \frac{C}{B}$$

134

Choice of Risk Threshold

Specifying a Cost-Benefit ratio C/B implies a rational choice of risk threshold.

Equivalently, a risk threshold is rational when it corresponds to the Cost/Benefit ratio.

135

Choice of Risk Threshold: Example 1

20% risk threshold for treatment is equivalent to

$$\frac{C}{C + B} = 0.2$$

$$\frac{C}{B} = \frac{0.2}{1 - 0.2} = \frac{0.2}{0.8} = 0.25$$

The cost of treating a control equals 1/4th the benefit of treating a case.

The benefit of treating a case is four times larger than the cost of treating a control.

136

Choice of Risk Threshold: Example 2

Gail (JNCI, 2009) evaluated risk models for breast cancer in terms of decisions about prophylactic tamoxifen use in 50-59 year old white women. Tamoxifen can reduce the risk of breast cancer but increases the risk of other serious diseases. Under some strong assumptions, he estimated

$$C/B = 0.0077 \rightarrow r_H = 0.0076 \text{ per year}$$

137

Net Benefit of a Risk Model

Let r_H be the appropriate risk threshold to define “high risk” and recommended for treatment.

Key elements:

$$HR_D(r_H) = P(r(X) > r_H \mid D=1)$$

– essentially, TPR of the risk model for the risk threshold

$$HR_{\bar{D}}(r_H) = P(r(X) > r_H \mid D=0)$$

– essentially, FPR of the risk model for the risk threshold

Next we calculate the net benefit of using the risk model and r_H to decide treatment in the population. We assume r_H has been *rationally selected*, i.e. r_H corresponds to the benefits and costs of treatment

138

Net Benefit of a Risk Model

Overall population impact of the risk model – combines $HR_D(r_H)$ and $HR_{\bar{D}}(r_H)$:

$$NB(r_H) = B P(D=1) HR_D(r_H) - C P(D=0) HR_{\bar{D}}(r_H)$$

$$= B \left\{ P(D=1) HR_D(r_H) - \frac{r_H}{1-r_H} P(D=0) HR_{\bar{D}}(r_H) \right\}$$

$$= P(D=1) HR_D(r_H) - \frac{r_H}{1-r_H} P(D=0) HR_{\bar{D}}(r_H)$$

In the last expression, Net Benefit is interpreted “in units of B”

B = expected benefit of treatment for a case

C = expected cost of treatment for a control

139

Net Benefit Example: DABS simulated data

- D is CVD over 10 years
 - $P(D=1)=10.17\%$
 - Marker X
- Suppose $r_H=20\%$:
 - $HR_D(r_H) = 65.2\%$
 - $HR_{\bar{D}}(r_H) = 8.9\%$
 - $NB(r_H)=0.046 \cdot$ benefit of statins to subject who would have a CVD event without them

140

Standardized Net Benefit

$$NB(r_H) = P(D=1) HR_D(r_H) - \frac{r_H}{1-r_H} P(D=0) HR_{\bar{D}}(r_H)$$

Maximum value of NB is $P(D=1) = \rho$

- The best we can do is treat all cases and no controls

Standardized Net Benefit $\equiv NB(r_H) / \rho$

$$= HR_D(r_H) - \frac{r_H}{1-r_H} \frac{1-\rho}{\rho} HR_{\bar{D}}(r_H)$$

= TPR discounted by an appropriate amount of FPR

Interpretation: sNB is z% \rightarrow risk model achieves z% of the benefit of a perfectly discriminating model

141

DABS Simulated Data Example, continued: interpreting standardized net benefit

- $sNB=0.046/0.1017=0.455=45.5\%$
- The maximum possible benefit is to detect and treat all 1017 cases and no controls per 10,000. We can achieve 45.5% of this benefit using the risk model.
- With this model, 65.2% of cases are above the high risk threshold; discounting for controls also classified as high risk, we achieve the equivalent of 45.5% of cases classified as high risk and 0% of controls
- Achieve the same net benefit to the population as 45.5% of cases and no controls called high risk.

142

Assessing Net Benefit Graphically

- Decision Curves
 - Proposed in: Vickers and Elkin, “Decision Curve Analysis: A Novel Method for Evaluation Prediction Models.” *Medical Decision Making*, 2006.
 - Additional ref: Kerr, Brown, Zhu, and Janes: “Assessing the Clinical Impact of Risk Prediction Models with Decision Curves: Guidance for Correct Interpretation and Appropriate Use.” *J Clinical Oncology*, 2016.
- Related to Relative Utility Curves
 - Papers by Baker, e.g. “Putting Risk Prediction in Perspective” *Relative Utility Curves.* *JNCI*, 2009.

143

Net Benefit

- If there is agreement on a rational risk threshold r_H for recommending treatment, we have seen that Net Benefit is:

$$HR_D(r_H) \rho - HR_{\bar{D}}(r_H) (1-\rho) \frac{r_H}{1-r_H}$$

which equals

$$P(\text{case \& high risk}) - P(\text{cntl \& high risk}) \frac{r_H}{1-r_H}$$

- Estimate with:

$$\widehat{NB} = \frac{\# \text{ positive cases}}{n} - \frac{\# \text{ positive cntls}}{n} \frac{r_H}{1-r_H}$$

144

Net Benefit → Decision Curves

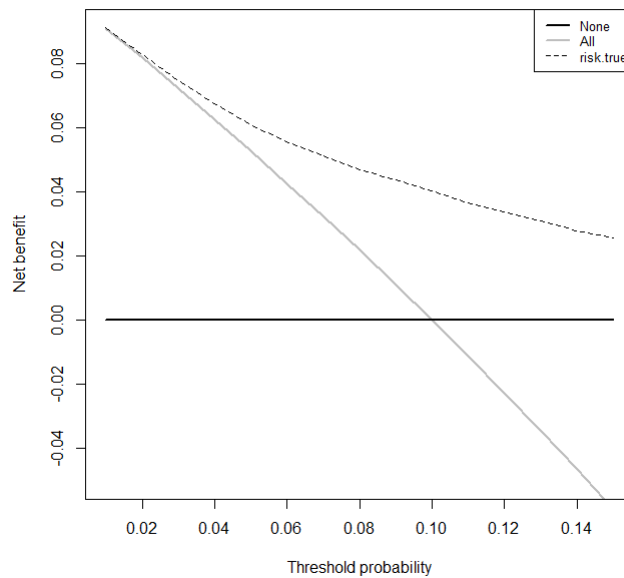
- A (rationally-chosen) risk threshold r_H encapsulates the benefits (B) of treating a case compared to the harm/cost (C) of treating a control
- A **Decision Curve** plots NB against the risk threshold r_H

145

Decision Curve Example 1

- Simulated data on 20,000 patients and a single marker X
- Marker is Normal(0,1) in controls
- Marker is Normal(1,1) in cases
- 10% of population are cases
- Using Bayes rule calculate
$$\text{risk}(X) = P(D | X)$$
 - (we don't need to model risk as a function of X)

146



147

Understanding the plot

- If the policy is “treat none,” then NB is:

$$\begin{aligned} & \# \text{ positive cases}/20000 - \# \text{ positive cntls}/20000 \frac{r_H}{1-r_H} \\ &= 0 - 0 \cdot \frac{r_H}{1-r_H} \\ &= 0 \end{aligned}$$

- Therefore the “treat none” policy has $NB \equiv 0$ for any benefits and costs.

148

Understanding the plot

- If the policy is “treat all,” then NB is:

$$\begin{aligned} & \# \text{ cases}/20000 - \# \text{ cntls}/20000 \frac{r_H}{1-r_H} \\ &= \rho - (1-\rho) \cdot \frac{r_H}{1-r_H} \end{aligned}$$

- Even though r_H is not used to decide treatment under the “treat all” policy, it is used to capture/summarize benefits and costs.
- The curve for “treat all” might look like a straight line, but it isn’t.

149

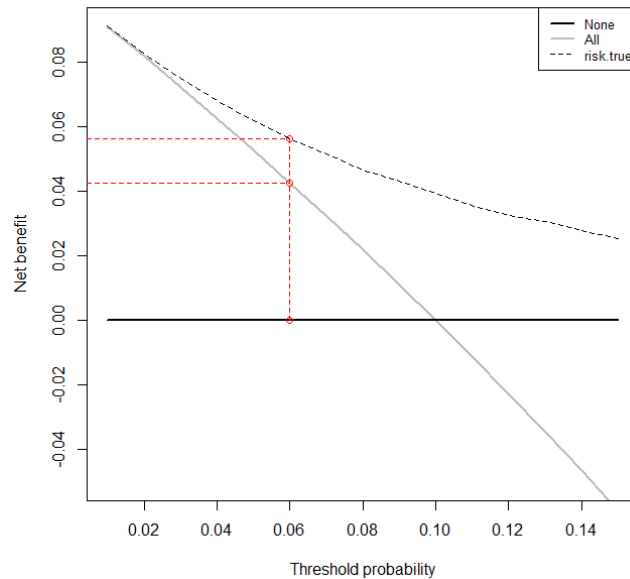
Understanding the plot

- If the policy is to use the risk model to recommend treatment, then NB is estimated by considering each risk threshold and the number of cases and controls that exceed the threshold:

$$\frac{\# \text{ positive cases}}{n} - \frac{\# \text{ positive cntls}}{n} \frac{r_H}{1-r_H}$$

150

Interpreting the plot



151

Interpreting the plot

- Suppose the risk threshold is 6%
 - The NB for using the risk model is 0.055
 - The same sNB as a rule that treated $0.055/\rho = 55\%$ of cases and no controls.
 - The NB for the “treat all” strategy is 0.043.
 - The same sNB as a rule that treated $0.043/\rho = 43\%$ of cases and no controls .

152

Interpreting the plot

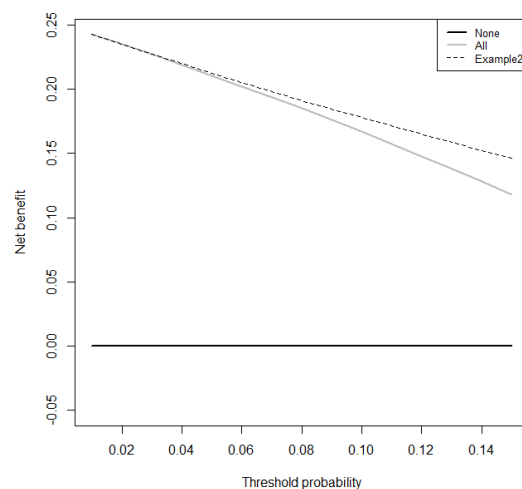
- It is challenging to interpret Net Benefit. The main use of these plots may be to examine whether a risk model has the potential to add value – examine whether NB is higher than “treat all”/“treat none” – for a range of plausible risk thresholds
- If there is consensus on the risk threshold, the plot is unnecessary (potentially distracting)
 - E.g., if clinicians agree that patients should be treated with statins if 10-year risk of CVD is at least 20%.

153

Decision Curve Example 2

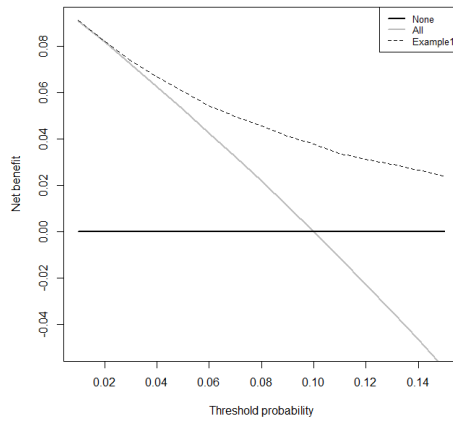
- Simulated data on 20,000 patients and a single marker X
- Marker is Normal(0,1) in controls
- Marker is Normal(1,1) in cases
- 25% of population are cases
- Use Bayes rule to calculate $\text{risk}(X)=P(D|X)$

154

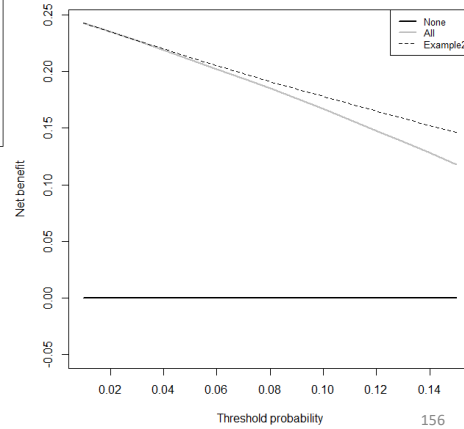


It is more difficult for risk-based treatment to “beat” Treat-All when prevalence is high.

155

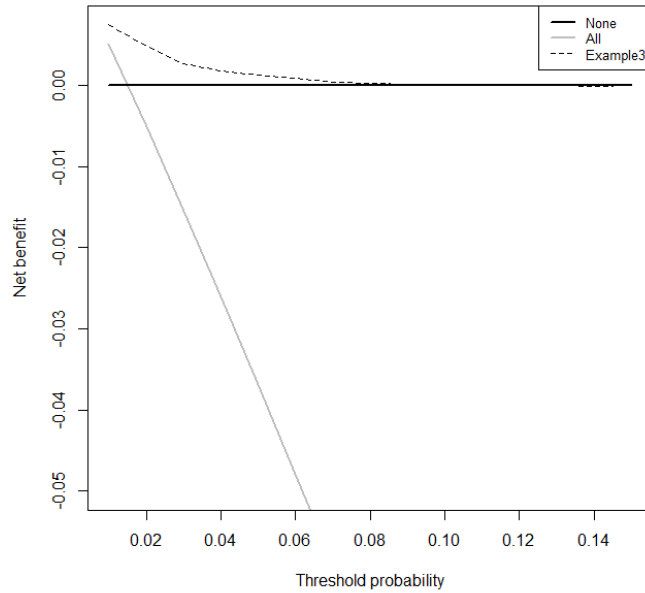


Notice the scale change between the two plots. With higher prevalence there are more Benefits and fewer Costs.



Decision Curve Example 3

- Simulated data on 20,000 patients and a single marker X
- Marker is Normal(0,1) in controls
- Marker is Normal(1,1) in cases
- 1.5% of population are cases
- Using Bayes rule calculate $\text{risk}(X)=P(D|X)$



158

Decision Curve Example 4

- Prospective study of 570 men scheduled for prostate biopsy.
- New marker: Urinary PCA3 (an RNA that is over-expressed in prostate cancer cells)
- Existing marker: Serum PSA
- Clinical risk factors: age, results of digital rectal exam
- n=541 men, prevalence 36%

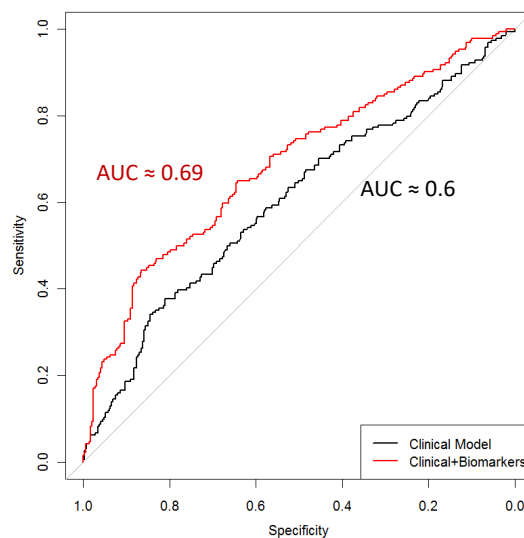
159

Decision Curve Example 4

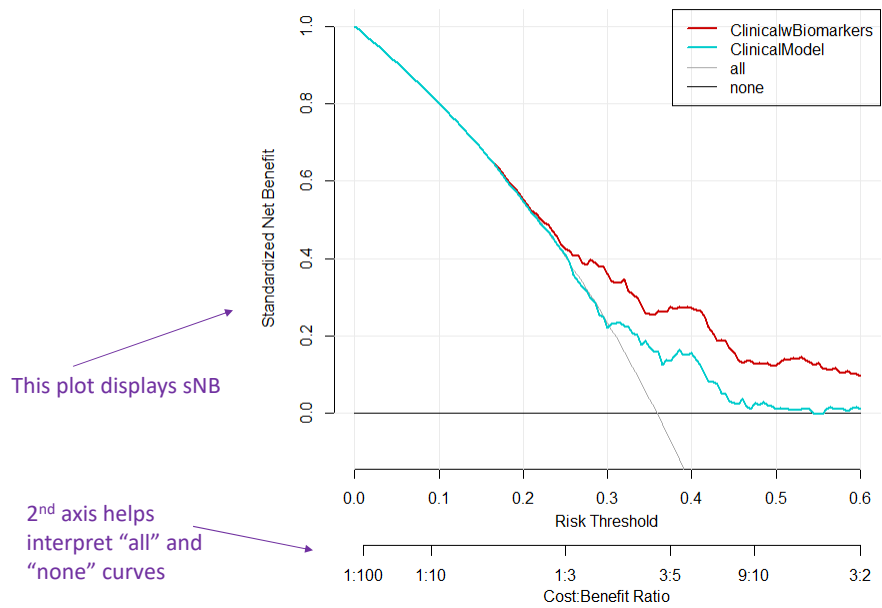
- Here, we compare
 - clinical model (using age and DRE results)
 - biomarker-aided prediction: (additionally use Serum PSA and PCA3 to predict risk of disease)
- I used logistic regression to estimate risk for each set of predictors.

160

ROC Curves



161



162

- It is tempting to use Decision Curves to choose r_H to maximize Net Benefit. This is **wrong**.
 - Net Benefit depends on benefits and harms, captured by r_H .
 - The data used to make the plot contain no information of the benefit of treatment to cases or the harms of treatment to controls.
 - r_H *must* be selected from other considerations (data), then used to evaluate the relative merits of treatment policies.

163

- Decision curves are potentially useful when there is no consensus on an appropriate risk threshold. Compare different risk models across a range of plausible thresholds.
- In the prostate cancer example, the risk model that used biomarkers only offers higher Net Benefit than the clinical model if r_H exceeds about 25%
 - It is likely that patients and clinicians would say r_H is much smaller than 25%.

164

Notes on Decision Curves and Net Benefit

- The curve for treat-all and treat-none always cross at the prevalence:

$$NB_{\text{treat-all}} = 1 \cdot \rho - 1 \cdot (1 - \rho) \cdot \frac{r_H}{1 - r_H} = \rho - (1 - \rho) \frac{r_H}{1 - r_H} = 0$$

if and only if $r_H = \rho$

- treat-all beats treat-none for $r_H < \rho$
- treat-none beats treat-all for $r_H > \rho$.

165

Alternative Formulation

- Most published Decision Curves use treat-none as the reference
- These are “opt-in Decision Curves”
 - implicitly assume the default is treat-none
 - high risk patient *opt into* treatment
- But what if standard is treat-all and we envision opting *low-risk* patients *out* of treatment?
 - benefits accrue from controls who avoid cost C at the expense of cases who miss out on B

166

Alternative Formulation

Opt-out Decision Curves use treat-all as the reference and display the “opt-out Net Benefit”

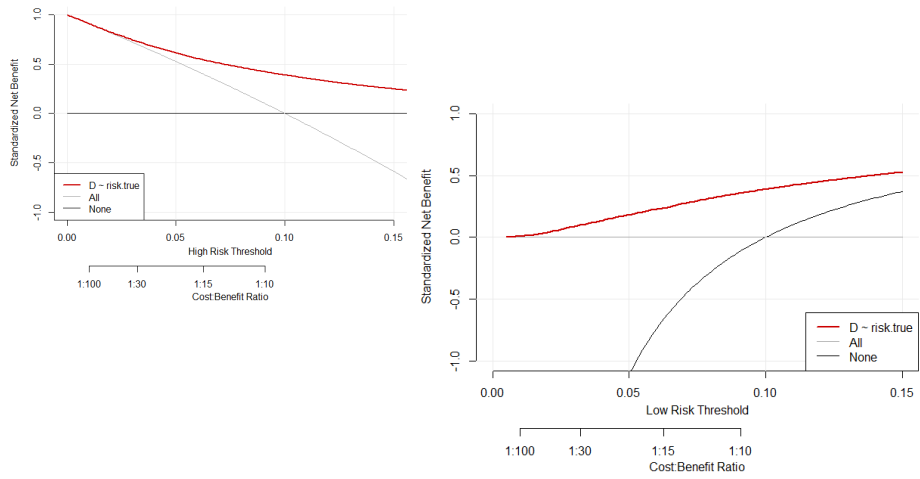
$$NB^{opt-out} = (1 - \rho)LR_{\bar{D}}(r_H) - \rho \frac{1 - r_H}{r_H} LR_D(r_H)$$

$$sNB^{opt-out} = LR_{\bar{D}}(r_H) - \frac{\rho}{1-\rho} \frac{1-r_H}{r_H} LR_D(r_H)$$

true negative rate

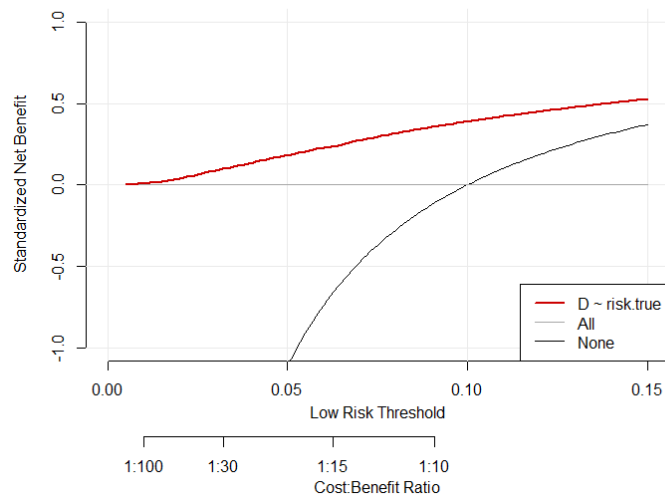
false negative rate

Example 1 revisited: Opt-in and Opt-out Decision Curves



168

Example 1 revisited: Opt-out Decision Curve



169

Opt-out Decision Curves


- More useful than opt-in decision curves when current default is treat-all.
- Better suited to evaluate the evidence for switching from treat-all to risk-based treatment

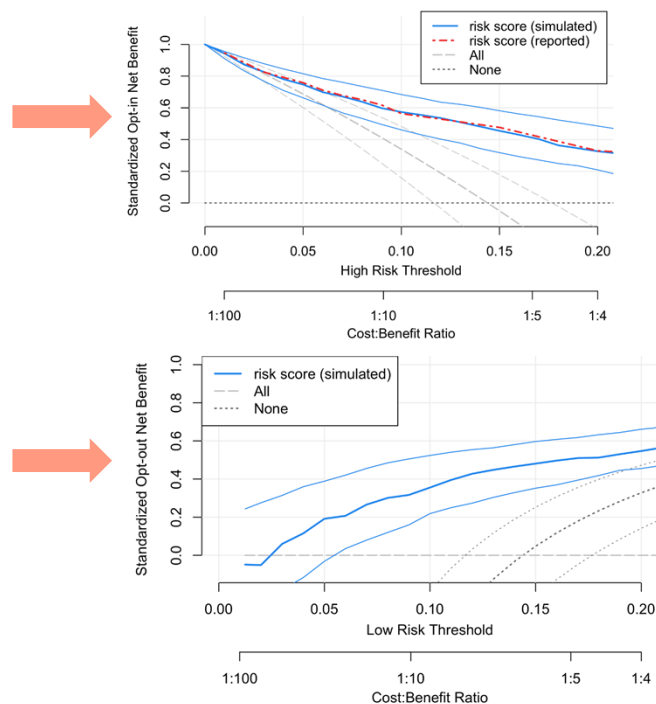
Brief Report

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Assessing the Clinical Impact of Risk Models for Opting Out of Treatment

Kathleen F. Kerr , Marshall D. Brown, Tracey L. Marsh, and Holly Janes



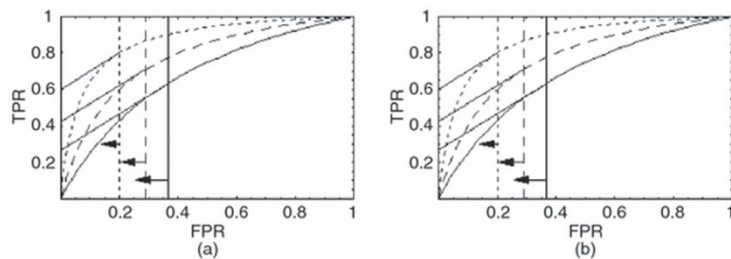
Relative Utility Curves

- Baker’s Relative Utility Curves use treat-none as the reference above ρ and treat-all as the reference below ρ .
 - Thus the reference policy changes at ρ
 - Creates “hill shaped” curves that crest at ρ
 - Relative Utility is related to standardized Net Benefit

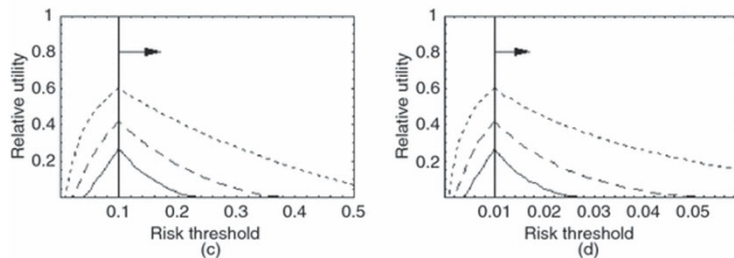
172

Baker, Cook, Vickers, & Kramer (2009)

ROC Curves:



Relative Utility Curves:



$\rho=10\%$

$\rho=1\%$

Key Assumptions of all Decision Curves/Relative Utility Curves

- Expected benefit of treatment B is the same for all cases; expected cost of treatment C is the same for all controls
 - Biomarker does not predict treatment effect
- Risk threshold r_H is rational – reflects the Cost:Benefit Ratio
- Reminder: under these assumptions, curves show the Net Benefit of the risk model *to the population*

174

Don't forget uncertainty

- To focus on interpretation, I showed Decision Curves without confidence intervals
- Unfortunately, Decision Curves often appear in the literature without any acknowledgement of uncertainty
- As in any other inference from biomedical data, we should acknowledge the uncertainty in our inferences
 - Confidence intervals in plots and/or tables of Net Benefit (R demo)

175

EVALUATING A RISK MODEL FOR PROGNOSTIC ENRICHMENT OF CLINICAL TRIALS

Prognostic Enrichment

- Sometimes the intended use of a risk model is to identify patients at high risk for inclusion in a clinical trial
 - Temple (2010) called this “Prognostic Enrichment”

Temple, Enrichment of Clinical Study Populations, *Clinical Pharmacology and Therapeutics*, 2010

**Enrichment Strategies for
Clinical Trials to Support
Determination of
Effectiveness of Human Drugs
and Biological Products
Guidance for Industry**

U.S. Department of Health and Human Services
Food and Drug Administration
Center for Drug Evaluation and Research (CDER)
Center for Biologics Evaluation and Research (CBER)

March 2019
Clinical/Medical

178

Three broad categories of enrichment strategies as listed below are addressed in this guidance:

- (1) Strategies to decrease variability — These include choosing patients with baseline measurements of a disease or a biomarker characterizing the disease in a narrow range (decreased interpatient variability) and excluding patients whose disease or symptoms improve spontaneously or whose measurements are highly variable (decreased inpatient variability). The decreased variability provided by these strategies would increase study power (see section III., Decreasing Variability).
- (2) Prognostic enrichment strategies — These include choosing patients with a greater likelihood of having a disease-related endpoint event (for event-driven studies) or a substantial worsening in condition (for continuous measurement endpoints) (see section IV., Prognostic Enrichment Strategies — Identifying High-Risk Patients). These strategies would increase the absolute effect difference between groups but would not be expected to alter relative effect.
- (3) Predictive enrichment strategies — These include choosing patients who are more likely to respond to the drug treatment than other patients with the condition being treated. Such selection can lead to a larger effect size (both absolute and relative) and can permit use of a smaller study population. Selection of patients could be based on a specific aspect of a patient's physiology, a biomarker, or a disease characteristic that is related in some manner to the study drug's mechanism. Patient selection could also be empiric (e.g., the patient has previously appeared to respond to a drug in the same class) (see section V., Predictive Enrichment — Identifying More-Responsive Patients).



179

Prognostic Enrichment: Example

- ADPKD patients: 20% will experience substantial decline in renal function in one year (D)
- new therapy believed to reduce the risk of D
- Designing a trial to have 90% power to detect a 30% reduction in the risk of D would require 1643 patients
 - possibly prohibitively expensive

180

Prognostic Enrichment Biomarker

- Suppose a biomarker has some ability to identify ADPKD patients at higher risk of D
- For example, suppose that 40% of biomarker-positive patients will experience D (compared to 20% of all ADPKD patients)
- Conducting the trial in biomarker-positive patients requires 651 patients to have 90% power to detect a 30% reduction in the risk of D
 - may be much more practical

181

Prognostic Enrichment Biomarker

Examine the impact of using the biomarker on:

- trial sample size
- total number of patients to screen to enroll trial
 - proxy for calendar time to enroll trial
- total cost of patient screening & patients in trial

182

Prognostic Enrichment Biomarker

Trial sample size: calculated based on statistical testing and clinical parameters

- Based on the desired power $0 < 1 - \beta < 1$, Type I error rate $0 < \alpha < 1$, event rate without intervention $0 < \pi < 1$, and event rate with intervention $0 < \tau < 1$, the sample size SS across the two arms of the trial for a two-sided test is $SS =$

$$2 \times \frac{\left(\phi^{-1}\left(1 - \frac{\alpha}{2}\right) \sqrt{2 \left(\frac{\pi + \tau}{2}\right) \left(1 - \frac{\pi + \tau}{2}\right)} + \phi^{-1}(1 - \beta) \sqrt{\pi(1 - \pi) + \tau(1 - \tau)} \right)^2}{(\pi - \tau)^2},$$

where $\pi \neq \tau$ and $\phi^{-1}(x)$ is the quantile function of the standard Normal distribution such that $\phi^{-1}(x) = z$ where $P[Z < z] = x$. For a one-sided test the formula is the same except replacing $\phi^{-1}\left(1 - \frac{\alpha}{2}\right)$ with $\phi^{-1}(1 - \alpha)$

183

Prognostic Enrichment Biomarker

Total number of patients to screen to enroll trial

- Suppose we use threshold t to decide eligibility for the trial. That is, the fraction t of patients at lowest risk for D are screened from the trial.
- That implies that $1/(1-t)$ patients must be screened to identify one patient eligible for the trial.
- Therefore total patients screened =
(Trial Sample Size) / (1-t)

184

Prognostic Enrichment Biomarker

total cost of patient screening & patients in trial

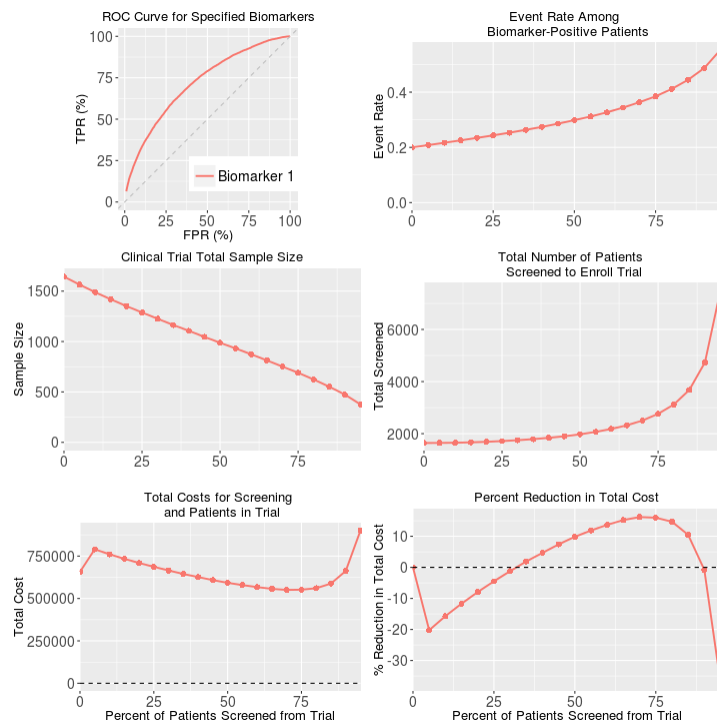
- Let $C1$ be the cost of running a patient through the trial and let $C2$ be the cost of screening a patient for the trial using the biomarker
- Total Cost with screening threshold t is
$$TC = C1 \times SS + C2 \times \frac{SS}{1-t} = SS(C1 + \frac{C2}{1-t})$$
- However, when $t=0$ no screening is needed so in this special case $TC = C1 \times SS$

185

Prognostic Biomarker 1

- Event rate without prognostic enrichment: 20%
- AUC of biomarker: **0.72**
- Cost to measure biomarker: \$100
- Cost to run one patient through trial: \$400
- Specifying trial design to have 90% power to detect a 30% reduction in event rate using $\alpha=0.025$ with one-sided testing

186

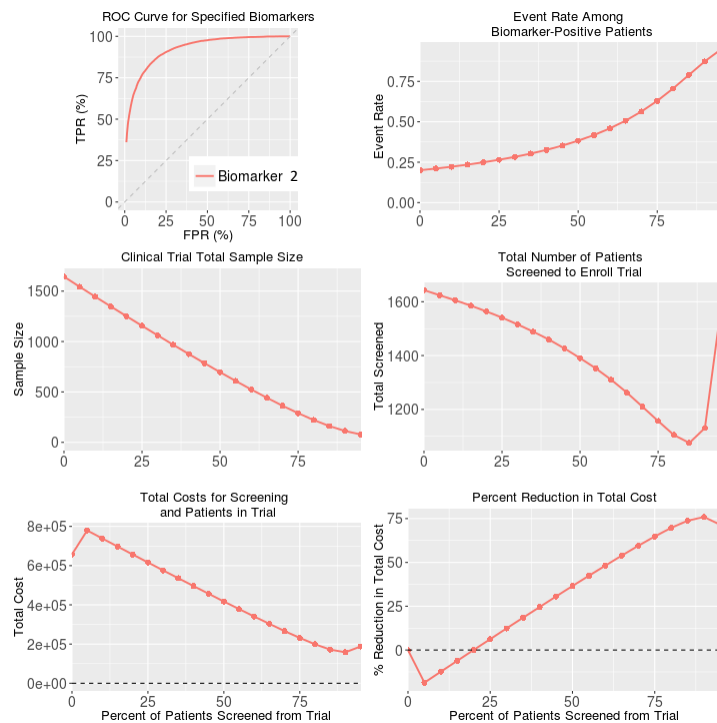


187

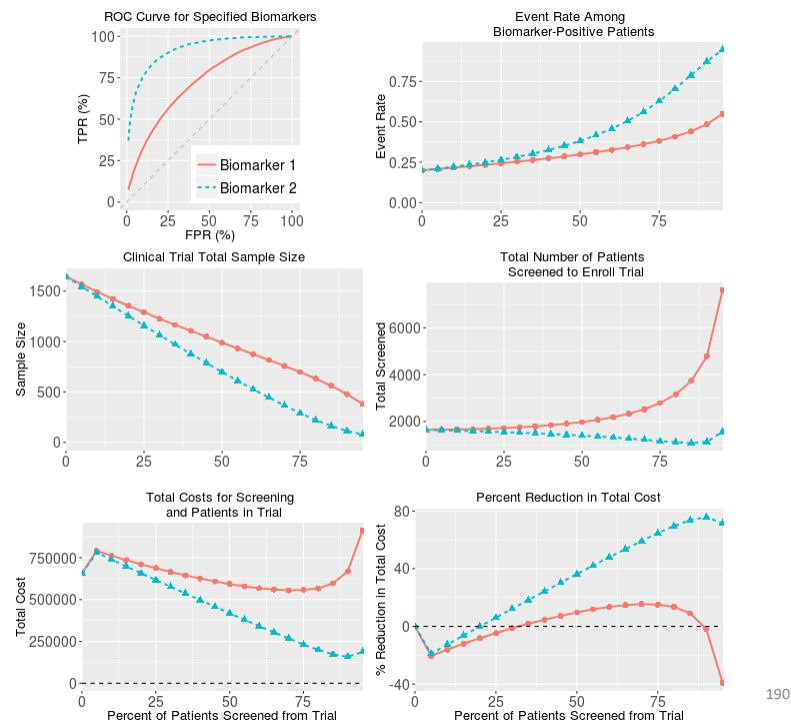
Prognostic Biomarker 2

- Event rate without prognostic enrichment: 20%
- AUC of biomarker: **0.92**
- Cost to measure biomarker: \$100
- Cost to run one patient through trial: \$400
- Specifying trial design to have 90% power to detect a 30% reduction in event rate using $\alpha=0.025$ with one-sided testing

188



189



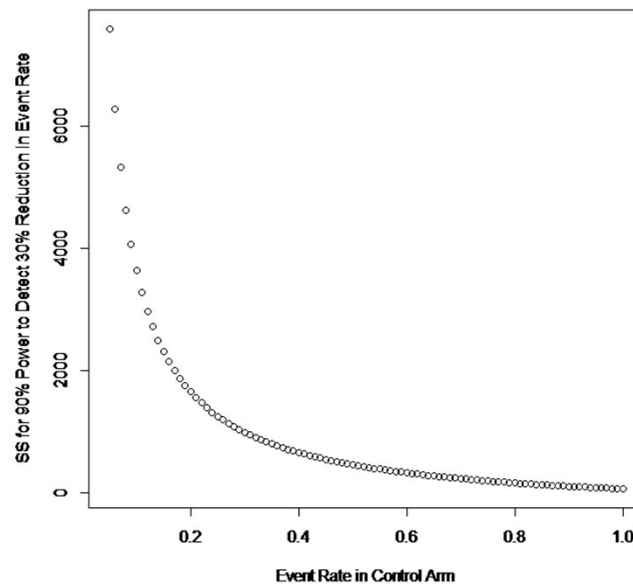
Prognostic Enrichment – Other Important Considerations

- Generalizability
 - by definition, the intervention will not be tested on patients screened out of the trial
 - this may lead to investigators to err on the side of less stringent screening
- Ethics
 - In oncology, the primary motivation for prognostic enrichment is traditionally not cost. Rather, therapies are often toxic and only ethical to test on patients with poor prognosis (very likely to have the bad clinical outcome)
 - The “event-rate in biomarker positive patients” becomes a quantity of primary interest
 - Such ethical considerations may lead investigators to err on the side of more stringent screening.

Insight into the utility of markers for prognostic enrichment

- Sometimes (nominally) unimpressive markers are helpful for prognostic enrichment
 - e.g. prognostic biomarker 1 had modest AUC, 0.72
- This is because the biggest “gains” in reducing sample size are at the low end of the event rate (next slide)
 - Detecting a 30% reduction in the event rate requires much larger sample sizes if the event rate is 10% (vs 7%) compared to 20% (vs 14%)
 - “a little bit of enrichment can go a long way”

192

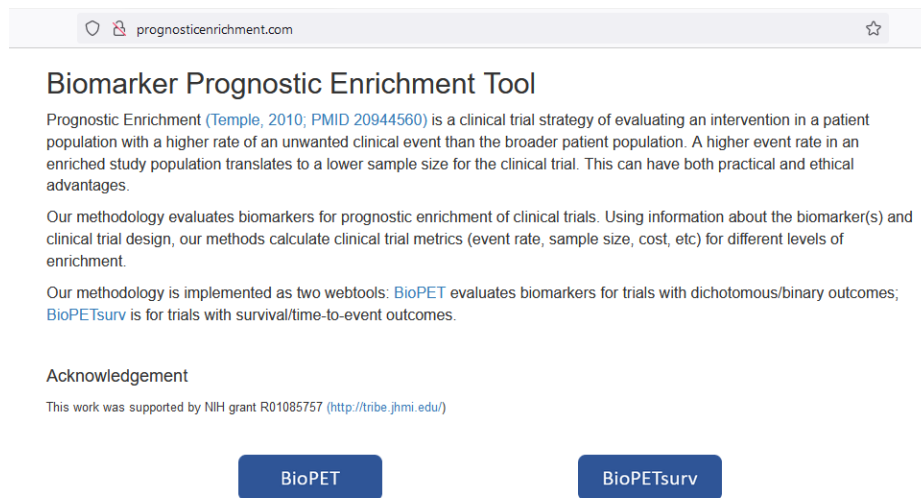


193

Prognostic Enrichment - Resources

- Biomarker Prognostic Enrichment Tool
 - BioPET for trials with binary outcomes
 - BioPETsurv for survival outcomes
- *R* packages
 - BioPET for binary trial endpoints
 - BioPETsurv for time-to-event trial endpoints
- prognosticenrichment.com
- Kerr et al, BioPET methodology, *Clinical Trials* 2017
- Cheng et al, BioPETsurv methodology, *PLoS One* 2020

194



The screenshot shows a web browser window with the URL prognosticenrichment.com. The page title is "Biomarker Prognostic Enrichment Tool". The main text describes prognostic enrichment as a clinical trial strategy for evaluating an intervention in a patient population with a higher rate of an unwanted clinical event than the broader patient population. It mentions that a higher event rate in an enriched study population translates to a lower sample size for the clinical trial. The methodology evaluates biomarkers for prognostic enrichment of clinical trials, calculating metrics like event rate, sample size, and cost. Two webtools are mentioned: BioPET for dichotomous/binary outcomes and BioPETsurv for survival/time-to-event outcomes. An acknowledgement section states that the work was supported by NIH grant R01085757.

[BioPET](#) [BioPETsurv](#)

195

Summary of Part II

- In order for a risk model to be valid it must be well-calibrated
 - Otherwise, cannot interpret predicted risks as risks
 - Recommend graphical assessment (moderate calibration)
 - Should assess strong calibration when possible
- Risk model discrimination
 - Can use ROC curve; more informative to use an alternative that shows the risk threshold
 - Presented AUC and other numeric measures

196

Summary of Part II

- Decision Curves
 - Potentially useful to evaluate risk-based treatment policies over a range of plausible risk thresholds
 - Challenging to interpret values of NB
 - Aids the assessment of the population impact of treatment policies
 - If standard is treat-all and motivation is to opt low-risk patients out of treatment, use opt-out Decision Curves
- I prefer standardized Net Benefit over Net Benefit
 - Maximum sNB always 1.0 (or 100%)
 - Easier to interpret

197

Summary of Part II

- Evaluating a risk model (or biomarker) for prognostic enrichment of a clinical trial. Key considerations:
 - trial sample size
 - total patients screened to enroll trial/calendar time to enroll
 - cost savings of smaller trial vs. cost of screening
 - generalizability
 - ethics of eligibility criteria

198



Misconceptions about Biomarkers and Risk Models



- A large odds ratio implies that a biomarker is useful for prediction. ❌
- A data analyst can identify the optimal threshold from an ROC curve. ❌
- A data analyst can identify the optimal risk threshold from a Decision Curve. ❌
- The best biomarker to improve a risk model is the one with strongest association with the outcome.
- To improve prediction, a new biomarker should be independent of existing predictors
- To assess whether to add new biomarker to a risk model, multiple stages of hypothesis testing are needed.
- We can often use biomarkers to identify which patients will benefit from treatment.