# Receiver Operating Characteristic Curves 

Elizabeth Hill, PhD<br>Associate Professor of Biostatistics Hollings Cancer Center<br>Medical University of South Carolina hille@musc.edu

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## Outline

- Adapted primarily from The Statistical Evaluation of Medical Tests for Classification and Prediction (2003). MS Pepe, Oxford University Press, NY.
- Prediction and classification tests
- Assessing performance of a binary test
- Assessing performance of a continuous test
- Discussion of AJE article


## Prediction and classification

- Diagnosis: disease versus non-disease
- Screening: for early diagnosis
- Prognosis: predicting outcome
- Treatment selection: predict treatment response
- Tests can be based on
- clinical signs or symptoms
- laboratory tests
- imaging technology
- genomic/proteomic/metabolomic signature
- antibody arrays


## Measuring classifier performance of a binary test

## Definitions

Binary Test: $Y=1$ (positive) 0 (negative)
Disease: $\quad D=1$ (present) 0 (absent)
Classification of test results by disease status

|  | $D=0$ | $D=1$ |
| :---: | :---: | :---: |
| $Y=0$ | True negative | False negative |
| $Y=1$ | False positive | True positive |

## Classification probabilities

True positive fraction $=$ TPF $=P[Y=1 \mid D=1]=$ Sensitivity
False positive fraction $=\mathrm{FPF}=P[Y=1 \mid D=0]=1$ - Specificity

## Measuring classifier performance of a continuous test

- Assume larger values of $Y \Rightarrow D=1$
- Thresholding positivity rule - " $Y \geq c$ "
- $\operatorname{TPF}(c)=P[Y \geq c \mid D=1]=$ Sensitivity $(c)$ $\operatorname{FPF}(c)=P[Y \geq c \mid D=0]=1-\operatorname{Specificity}(c)$
- Receiver Operating Characteristic (ROC) Curve


## ROC definition

$$
\operatorname{ROC}(c)=\{(\operatorname{FPF}(c), \operatorname{TPF}(c)), c \in \mathcal{R}\}
$$

## Historical context

> "ROC analysis is part of a field called 'Signal Detection Theory' developed during World War II for the analysis of radar images. Radar operators had to decide whether a blip on the screen represented an enemy target, a friendly ship, or just noise. Signal detection theory measures the ability of radar receiver operators to make these important distinctions. Their ability to do so was called the Receiver Operating Characteristics. It was not until the 1970s that signal detection theory was recognized as useful for interpreting medical test results." (Practical Graph Mining with R, p.391. CRC Press, 2014)

## Simple logistic regression example

- $\pi=P[D=1]$
- $\operatorname{logit}(\pi)=\beta_{0}+\beta_{1} Y, Y$ continuous
- $\pi=\frac{1}{1+e^{-\left(\beta_{0}+\beta_{1} \gamma\right)}}$ (inverse logit)
- Large $\pi \Rightarrow D=1$ so we can use $\pi$ instead of $Y$ for classification

| Subject | $D$ | $\hat{\pi}$ |
| :---: | :---: | :---: |
| 1 | 1 | 0.95 |
| 2 | 1 | 0.95 |
| 3 | 0 | 0.72 |
| 4 | 1 | 0.72 |
| 5 | 1 | 0.72 |
| 6 | 0 | 0.24 |
| 7 | 1 | 0.12 |
| 8 | 0 | 0.08 |
| 9 | 0 | 0.08 |
| 10 | 0 | 0.04 |

## $c=1.0$ (or any $c$ larger than 0.95)

| Subject | $D$ | $\hat{\pi}$ | $\hat{\pi} \geq 1.0 ?$ |
| :---: | :---: | :---: | :---: |
| 1 | 1 | 0.95 | No |
| 2 | 1 | 0.95 | No |
| 3 | 0 | 0.72 | No |
| 4 | 1 | 0.72 | No |
| 5 | 1 | 0.72 | No |
| 6 | 0 | 0.24 | No |
| 7 | 1 | 0.12 | No |
| 8 | 0 | 0.08 | No |
| 9 | 0 | 0.08 | No |
| 10 | 0 | 0.04 | No |

- $\operatorname{TPF}(1.0)=P[\hat{\pi} \geq 1.0 \mid D=1]=0 / 5=0.0$
- $\operatorname{FPF}(1.0)=P[\hat{\pi} \geq 1.0 \mid D=0]=0 / 5=0.0$


## $c=0.95$

| Subject | $D$ | $\hat{\pi}$ | $\hat{\pi} \geq 0.95 ?$ |
| :---: | :---: | :---: | :---: |
| 1 | 1 | 0.95 | Yes |
| 2 | 1 | 0.95 | Yes |
| 3 | 0 | 0.72 | No |
| 4 | 1 | 0.72 | No |
| 5 | 1 | 0.72 | No |
| 6 | 0 | 0.24 | No |
| 7 | 1 | 0.12 | No |
| 8 | 0 | 0.08 | No |
| 9 | 0 | 0.08 | No |
| 10 | 0 | 0.04 | No |

- $\operatorname{TPF}(0.95)=P[\hat{\pi} \geq 0.95 \mid D=1]=2 / 5=0.4$
- $\operatorname{FPF}(0.95)=P[\hat{\pi} \geq 0.95 \mid D=0]=0 / 5=0.0$


## $c=0.72$

| Subject | $D$ | $\hat{\pi}$ | $\hat{\pi} \geq 0.72 ?$ |
| :---: | :---: | :---: | :---: |
| 1 | 1 | 0.95 | Yes |
| 2 | 1 | 0.95 | Yes |
| 3 | 0 | 0.72 | Yes |
| 4 | 1 | 0.72 | Yes |
| 5 | 1 | 0.72 | Yes |
| 6 | 0 | 0.24 | No |
| 7 | 1 | 0.12 | No |
| 8 | 0 | 0.08 | No |
| 9 | 0 | 0.08 | No |
| 10 | 0 | 0.04 | No |

- $\operatorname{TPF}(0.72)=P[\hat{\pi} \geq 0.72 \mid D=1]=4 / 5=0.8$
- $\operatorname{FPF}(0.72)=P[\hat{\pi} \geq 0.72 \mid D=0]=1 / 5=0.2$


## $c=0.24$

| Subject | $D$ | $\hat{\pi}$ | $\hat{\pi} \geq \mathbf{0 . 2 4 ?}$ |
| :---: | :---: | :---: | :---: |
| 1 | 1 | 0.95 | Yes |
| 2 | 1 | 0.95 | Yes |
| 3 | 0 | 0.72 | Yes |
| 4 | 1 | 0.72 | Yes |
| 5 | 1 | 0.72 | Yes |
| 6 | 0 | 0.24 | Yes |
| 7 | 1 | 0.12 | No |
| 8 | 0 | 0.08 | No |
| 9 | 0 | 0.08 | No |
| 10 | 0 | 0.04 | No |

- $\operatorname{TPF}(0.24)=P[\hat{\pi} \geq 0.24 \mid D=1]=4 / 5=0.8$
- $\operatorname{FPF}(0.24)=P[\hat{\pi} \geq 0.24 \mid D=0]=2 / 5=0.4$


## $c=0.12$

| Subject | $D$ | $\hat{\pi}$ | $\hat{\pi} \geq 0.12 ?$ |
| :---: | :---: | :---: | :---: |
| 1 | 1 | 0.95 | Yes |
| 2 | 1 | 0.95 | Yes |
| 3 | 0 | 0.72 | Yes |
| 4 | 1 | 0.72 | Yes |
| 5 | 1 | 0.72 | Yes |
| 6 | 0 | 0.24 | Yes |
| 7 | 1 | 0.12 | Yes |
| 8 | 0 | 0.08 | No |
| 9 | 0 | 0.08 | No |
| 10 | 0 | 0.04 | No |

- $\operatorname{TPF}(0.12)=P[\hat{\pi} \geq 0.12 \mid D=1]=5 / 5=1.0$
- $\operatorname{FPF}(0.12)=P[\hat{\pi} \geq 0.12 \mid D=0]=2 / 5=0.4$


## $c=0.08$

| Subject | $D$ | $\hat{\pi}$ | $\hat{\pi} \geq 0.08 ?$ |
| :---: | :---: | :---: | :---: |
| 1 | 1 | 0.95 | Yes |
| 2 | 1 | 0.95 | Yes |
| 3 | 0 | 0.72 | Yes |
| 4 | 1 | 0.72 | Yes |
| 5 | 1 | 0.72 | Yes |
| 6 | 0 | 0.24 | Yes |
| 7 | 1 | 0.12 | Yes |
| 8 | 0 | 0.08 | Yes |
| 9 | 0 | 0.08 | Yes |
| 10 | 0 | 0.04 | No |

- $\operatorname{TPF}(0.08)=P[\hat{\pi} \geq 0.08 \mid D=1]=5 / 5=1.0$
- $\operatorname{FPF}(0.08)=P[\hat{\pi} \geq 0.08 \mid D=0]=4 / 5=0.8$


## $c=0.04$

| Subject | $D$ | $\hat{\pi}$ | $\hat{\pi} \geq 0.04 ?$ |
| :---: | :---: | :---: | :---: |
| 1 | 1 | 0.95 | Yes |
| 2 | 1 | 0.95 | Yes |
| 3 | 0 | 0.72 | Yes |
| 4 | 1 | 0.72 | Yes |
| 5 | 1 | 0.72 | Yes |
| 6 | 0 | 0.24 | Yes |
| 7 | 1 | 0.12 | Yes |
| 8 | 0 | 0.08 | Yes |
| 9 | 0 | 0.08 | Yes |
| 10 | 0 | 0.04 | Yes |

- $\operatorname{TPF}(0.04)=P[\hat{\pi} \geq 0.04 \mid D=1]=5 / 5=1.0$
- $\operatorname{FPF}(0.04)=P[\hat{\pi} \geq 0.04 \mid D=0]=4 / 5=1.0$


## Estimated ROC curve

## ROC definition

$$
\operatorname{ROC}(c)=\{(\operatorname{FPF}(c), \operatorname{TPF}(c)), c \in \mathcal{R}\}
$$

| $c$ | $\mathrm{FPF}(c)$ | $\mathrm{TPF}(c)$ |
| :---: | :---: | :---: |
| 1.0 | 0.0 | 0.0 |
| 0.95 | 0.0 | 0.4 |
| 0.72 | 0.2 | 0.8 |
| 0.24 | 0.4 | 0.8 |
| 0.12 | 0.4 | 1.0 |
| 0.08 | 0.8 | 1.0 |
| 0.04 | 1.0 | 1.0 |

## Estimated ROC curve (cont.)



## Theoretical ROC curves



## Estimated ROC curve with reference line



## Attributes of ROC curve

- Provides complete description of potential performance
- Facilitates comparing and combining information across studies of the same test
- Facilitates comparing different tests on a common relevant scale
- Guides the choice of threshold in applications


## Area Under the Curve



## AUC summary

- $\operatorname{AUC}=\int_{0}^{1} \operatorname{ROC}(t) d t$
- $\mathrm{AUC}=0.5 \Rightarrow$ useless test
- AUC $=1 \Rightarrow$ perfect test
- AUC = Probability that test correctly 'orders' randomly selected diseased and non-disease subjects
- $\mathrm{AUC}=P[(Y \mid D=1)>(Y \mid D=0)]=P\left[Y_{D+}>Y_{D_{-}}\right]$


## AUC interpretation - informal proof



- Area of rectangle $=P\left[Y_{D+} \geq c\right] \cdot P\left[Y_{D-} \in[c-d, c)\right]$ by independence of $Y_{D+}$ and $Y_{D_{-}}$
- Summation across all rectangles yields $P\left[Y_{D+}>Y_{D-}\right]$


## Example using R library ROCR



## References and resources

- R library ROCR - nice graphics
- R library pROC - compares ROC curves and partial ROC curves
- Bioconductor library ROC
- The Statistical Evaluation of Medical Test for Classification and Prediction by MS Pepe (2003). Oxford University Press.
- Statistical Methods in Diagnostic Medicine, 2nd Edition by X Zhou, NA Obuchowski and DK McClish (2011). Wiley.
- Clinical Prediction Models by EW Steyerberg (2010). Springer.

