

# Notes

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## 1 Sensitivity

$$\frac{\text{Number of true positives}}{\text{Number of true positives} + \text{Number of false positives}}$$

## 2 Specificity

$$\frac{\# \text{ of true -ve}}{\# \text{ of true -ve} + \# \text{ of false +ve}}$$

## 3 1 - Specificity

$$\frac{\# \text{ of false +ve}}{\# \text{ of true -ve} + \# \text{ of false +ve}}$$

## 4 ROC Curve

Plot Sensitivity vs. 1-Specificity

Higher Area Under the Curve (AUC) greater is better

Curve should be above x=y. Otherwise, better to flip a coin.

AUC = Probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one.

low cutoff  $\Rightarrow$  lots of false +ve and few false -ve

high cutoff  $\Rightarrow$  lots of false -ve and few false +ve

## 5 Time-dependent ROC Curves

Classify subjects

Classify based on the risk score

Vary threshold C

Base Sensitivity/Specificity on whether subject has actually experienced event by time T

$D(t) = 1$  if subject has experienced event

$D(t) = 0$  otherwise.

Sensitivity =  $P[X > c | D(t) = 1]$

Specificity =  $P[X \leq c | D(t) = 0]$

X = risk score =  $e^{x'\beta}$

Time-varying component: calculate AUC at all t

Look for:  
One AUC curve higher than another to select models.

## 6 12 March 2014

Sensitivity =  $P[e^{x\beta} > c | D(t) = 1]$   
Specificity =  $P[e^{x\beta} \leq c | D(t) = 0]$

## 7 Multiple Testing

CI: one CI will likely retain parameter of interest  
100 CI's, each with coverage .95: highly likely that at least one will not contain the parameter.  
Expected that 5 will not .  
 $P(\text{at least 1 doesn't}) = 99.4\%$

## 8 Hypothesis Testing

One test: 5% chance of incorrectly rejecting  $H_0$   
100 test: Expected number of false rejections = 5

## 9 Familywise Error Rate

$1 - (1 - \alpha)^p = P[\text{At least 1 rejected } H_0 | H_0 \text{ true}]$

## 10 18 March: Confusion Matrix

Draw this table when I have time.

- V = false positive
- T = false negative
- U = true negative
- S = true positive
- $M_0$  = true null hypothesis
- $M - M_0$  = false null hypothesis
- R = declared significant
- M-R = declared not significant
- M = total counts
- FWER:  $P[V \geq 1]$
- FDR:  $E[\frac{V}{V+S}] = E[\frac{V}{R}]$  = Expected % of false positives.

- False Positive Rate:  $\frac{V}{M_0}$ . % of truly null features declared significant.
- False Discovery Rate:  $\frac{V}{R}$ . % of those declared significant that are non-significant.

## 11 Code

p.adjust