# Advanced Network Analysis

Model Comparison Using ROC Curves

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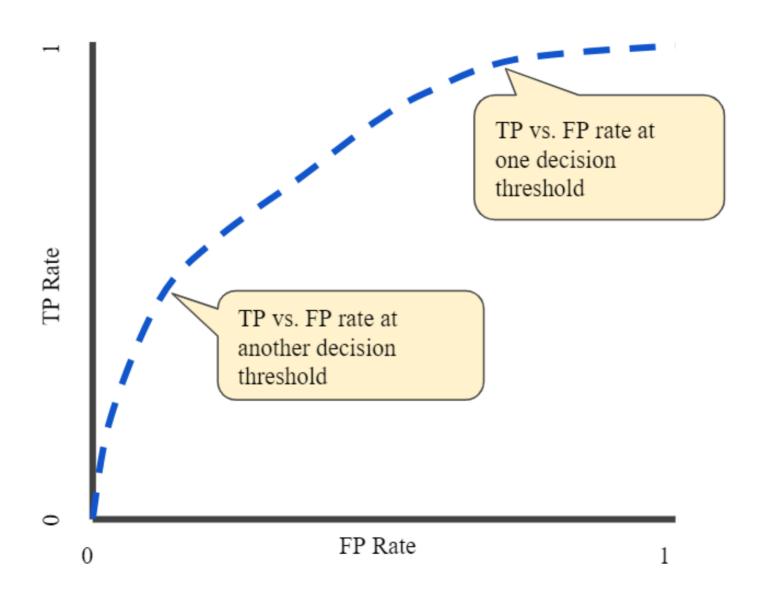
#### **ROC Curves**

- An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:
  - True Positive Rate (recall or sensitivity):

$$TPR = rac{TP}{TP + FN} = rac{correct \ ones}{total \ ones}$$

False Positive Rate (specificity):

$$FPR = rac{FP}{FP + TN} = rac{incorrect\ ones}{total\ zeroes}$$



## What We Need (Binary DV)

- Our DV (in vector form)
- The predicted probability for each observation based on our model

### Example: ERGM

##

```
library(tidyverse)
library(magrittr)
library(sna)
library(ergm)
data(sampson)
m1 = ergm(samplike ~ edges + nodematch('group'))
summary(m1)
## Call:
## ergm(formula = samplike ~ edges + nodematch("group"))
##
## Maximum Likelihood Results:
##
                  Estimate Std. Error MCMC % z value Pr(>|z|)
##
                   -2.0015
## edges
                              0.2131
                                          0 -9.393 <1e-04 ***
                                          0 8.751 <1e-04 ***
## nodematch.group
                  2.6481
                              0.3026
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
       Null Deviance: 424.2 on 306 degrees of freedom
##
##
   Residual Deviance: 276.9 on 304 degrees of freedom
```

#### Get Y and Predicted Probabilities

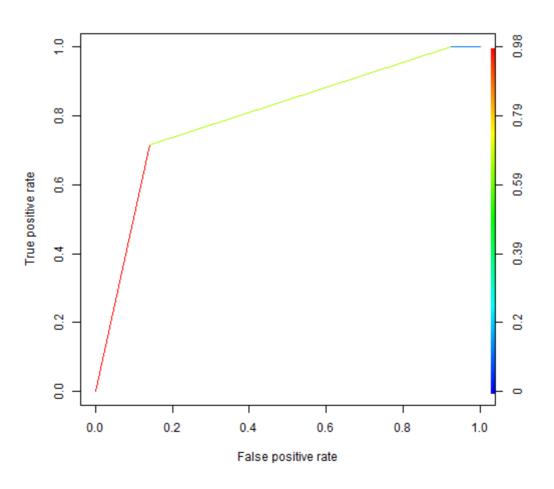
```
myDV<-as.matrix(samplike) %>% data.frame() %>% mutate(name1=row.names
    pivot_longer(cols=-name1, names_to="name2", values_to="Y")

pred_ergm %>% data.frame() %>% mutate(name1=row.names(.)) %>%
    pivot_longer(cols=-name1, names_to="name2", values_to="p") %>% left
```

#### Make a Plot

```
#install.packages("ROCR")
library(ROCR)
pred <- prediction(mydat$p, mydat$Y)
perf <- performance(pred,"tpr","fpr")
ergmplot<-plot(perf,colorize=TRUE)</pre>
```

## Make a Plot



#### Your Turn

Change the model specification (add an endogenous variable), estimate the new model, and re-make the plot.

#### Your Turn

- 1. Transform the data as necessary to estimate an AME model that matches m1 in specification.
- 2. Estimate the AME model equivalent to m1.

#### Let's Make an ROC Plot

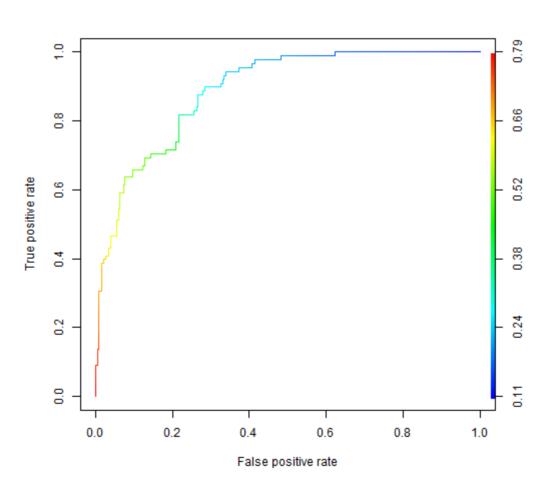
```
lfmFit<-readRDS("data/lfmFit_sampson.rds")

#Get predicted probabilities from AME:
theta<-lfmFit$'EZ' #logged odds ratios for each obs
plogis(as.matrix(theta)) %>% as.data.frame() %>% #convert to probability
mutate(name1=row.names(.)) %>%
    pivot_longer(cols=c(1:18),names_to="name2", values_to="p")->p

as.matrix(samplike) %>% as.data.frame() %>% mutate(name1=row.names(.))
    pivot_longer(cols=-name1, names_to="name2", values_to="Y") %>% left

pred1 <- prediction(mydat1$p, mydat1$Y)
perf1 <- performance(pred1,"tpr","fpr")
plot(perf1,colorize=TRUE, smooth=FALSE)</pre>
```

## Let's Make an ROC Plot

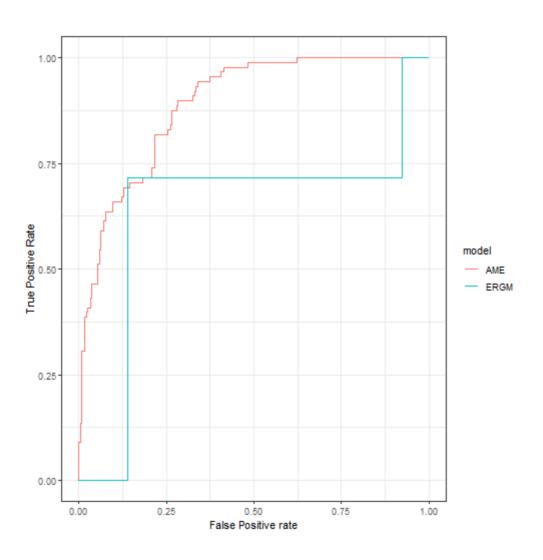


## Put These Together

```
library(ggplot2)

ggdata<-rbind.data.frame(cbind.data.frame(x=unlist(perf@x.values),y=cbind.data.frame(x=unlist(perf1@x.values),y=ggplot(data=ggdata)+geom_step(aes(x=x, y=y, color=model)) +
   ylab("True Positive Rate")+
   xlab("False Positive rate")+
   theme_bw()</pre>
```

## Put These Together



#### Your Turn

1. Re-specify the ERGM to increase the classification power. Plot the ROCs for the two models again.