STOR 320 Modeling VI

Lecture 19

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Introduction

- Now We Consider
  - Categorical Response (Outcome) Variable
  - Numerical/Categorical Explanatory Variables
- Focus is on Classification
- Read Chapter 4 in ISLR

Introduction

- Basic Case: Binary Response
  - Variable Has Two Possible Outcomes
  - Typically, Yes or No Responses to a Question
  - Example
    - Y = Will You Pass Your STOR 320 Class?
    - Y = What Factors Influence the Admission into Graduate School?

Scenario

- Question: Are Students Who Get Good Grades Likely to be Admitted to Graduate School?
    - Y = Would the Student be Admitted to a Graduate School?
    - X = College GPA
- Why is Linear Regression Inappropriate?

$$P(Admission|X) = \beta_0 + \beta_1 X$$

Problem Setting

- Bernouilli Random Variable

$$Y = \begin{cases} 1 & if\ Yes \\ 0 & if\ No \end{cases}$$

$$p = E(Y) = P(Y = 1)$$

- Sample n Students

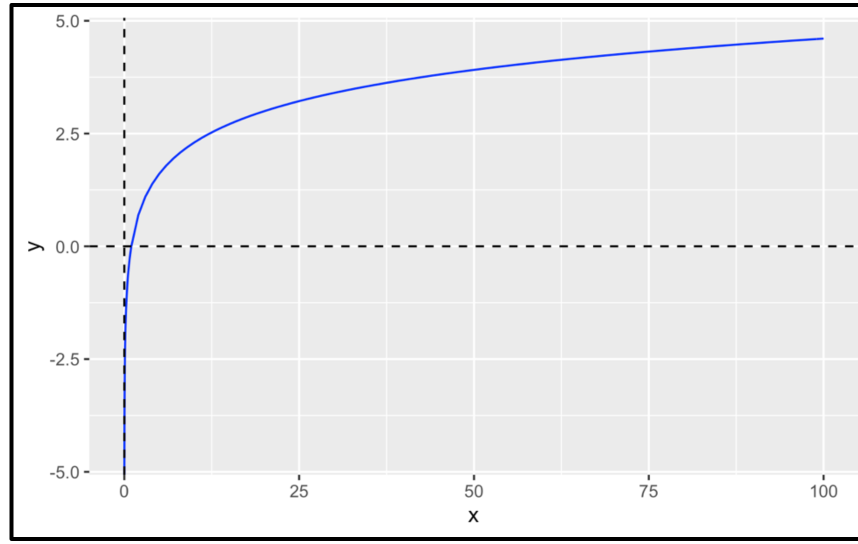
$$\text{Y}' = \sum Y_i \sim Binomial(n, p)$$

$$\hat{p} = \frac{\sum y_i}{n}$$

Estimated Probability that a Student Would be Admitted to a Graduate School

- Analyze the Effect of X on p: $p = E(Y|X) \neq \beta_0 + \beta_1 X$

Logit Link



- Modeling the Mean
  - Logit Link Function

$$\underbrace{\log\left(\frac{p}{1-p}\right)}_{\text{Odds of Admission}} = \beta_0 + \beta_1 X$$

  - Understanding Odds
    - Odds of Admission = 1
    - Odds of Admission < 1
    - Odds of Admission > 1

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Model Construction

- Solving for $\frac{p}{1-p}$

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X$$

$$\frac{p}{1-p} = e^{\beta_0+\beta_1 X}$$

Odds of Admission Given the Student's GPA

- Solving for p

$$p = e^{\beta_0+\beta_1 X} - pe^{\beta_0+\beta_1 X}$$

$$p(1 + e^{\beta_0+\beta_1 X}) = e^{\beta_0+\beta_1 X}$$

$$p = \frac{e^{\beta_0+\beta_1 X}}{1 + e^{\beta_0+\beta_1 X}}$$

Probability of Admission Given the Student's GPA

Logistic Regression for Classification

- Recall: $Y = \begin{cases} 1 & if\ Yes \\ 0 & if\ No \end{cases}$

- After Getting Data, We Estimate
  - $\hat{\beta}_0$
  - $\hat{\beta}_1$
  - $\hat{p} = \frac{e^{\hat{\beta}_0+\hat{\beta}_1 X}}{1+e^{\hat{\beta}_0+\hat{\beta}_1 X}}$ ➡ Estimated Probability of Admission Given the Student's GPA

- Two Scenarios
  - $\hat{p} < 0.5$ ➡ $\hat{Y} = 0$
  - $\hat{p} > 0.5$ ➡ $\hat{Y} = 1$

Evaluating the LR Model

- Two Methods
  - Leave Out Data Intentionally
  - Use Cross-Validation

- Positives and Negatives
  - True Positive = Predicted an Admission and the Student Got Admitted
  - False Positive=Predicted an Admission and the Student Didn’t Get Admitted
  - False Negative = Predicted a Student Wouldn’t be Admitted and They Did Get Admitted
  - True Negative = Predicted a Student Wouldn’t be Admitted and They Didn’t Get Admitted

Confusion Matrix

- Confusion Matrix

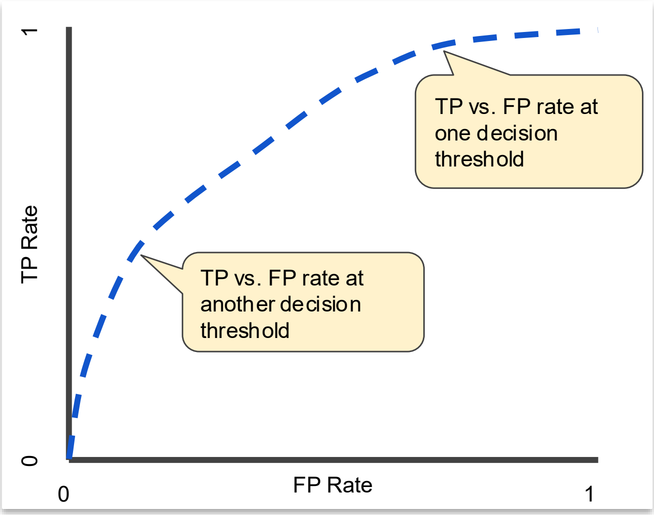
	Predicted	
Actual	*Will be Admitted*	*Won't be Admitted*
Admission	n_{11}	n_{12}
Isn't Admitted	n_{21}	n_{22}

- Sensitivity:
  $$n_{11}/(n_{11}+n_{12})$$
- Specificity:
  $$n_{22}/(n_{21}+n_{22})$$
- False Positive Rate:
  $$n_{21}/(n_{21}+n_{22})$$
- False Negative Rate:
  $$n_{12}/(n_{11}+n_{12})$$

Area Under ROC Curve

	Predicted	
Actual	*Will be Admitted*	*Won't be Admitted*
Admission	n_{11}	n_{12}
Isn't Admitted	n_{21}	n_{22}

- True Positive Rate (Sensitivity): $n_{11}/(n_{11}+n_{12})$
- False Positive Rate: $n_{21}/(n_{21}+n_{22})$



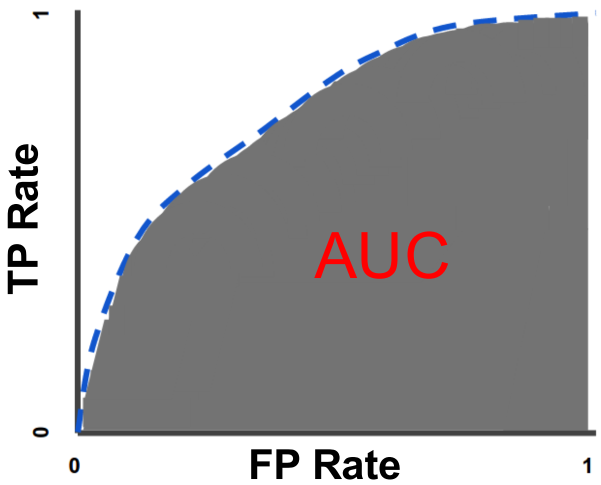


Image from machine learning crash course

Titanic: Data

- Titanic Survival Data

```
> library(titanic)
```

  - Response Variable

$$Y = \begin{cases} 1 & if\ \ Survived \\ 0 & if\ \ Did\ Not\ Survive \end{cases}$$

  - Explanatory Variables
    - Passenger Class
    - Sex
    - Age
    - Siblings/Spouses Aboard
    - Parents/Children Aboard
    - Passenger Fare
    - Port of Embarkation

Titanic: Data

- Titanic Survival Data (Continued)
  - Selecting Variables of Interest

```
> TRAIN=titanic_train[,c(2,3,5,6,7,8,10,12)]
> TEST=titanic_test[,c(2,4,5,6,7,9,11)])
```

  - Glimpse of Data

```
glimpse(TRAIN)

## Observations: 891
## Variables: 8
## $ Survived <int> 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1,...
## $ Pclass   <int> 3, 1, 3, 1, 3, 3, 1, 3, 3
## $ Sex      <chr> "male", "female", "female
## $ Age      <dbl> 22, 38, 26, 35, 35, NA, 5
## $ SibSp    <int> 1, 1, 0, 1, 0, 0, 0, 3, 0
## $ Parch    <int> 0, 0, 0, 0, 0, 0, 0, 1, 2
## $ Fare     <dbl> 7.2500, 71.2833, 7.9250,
## $ Embarked <chr> "S", "C", "S", "S", "S",
```

```
glimpse(TEST)
```

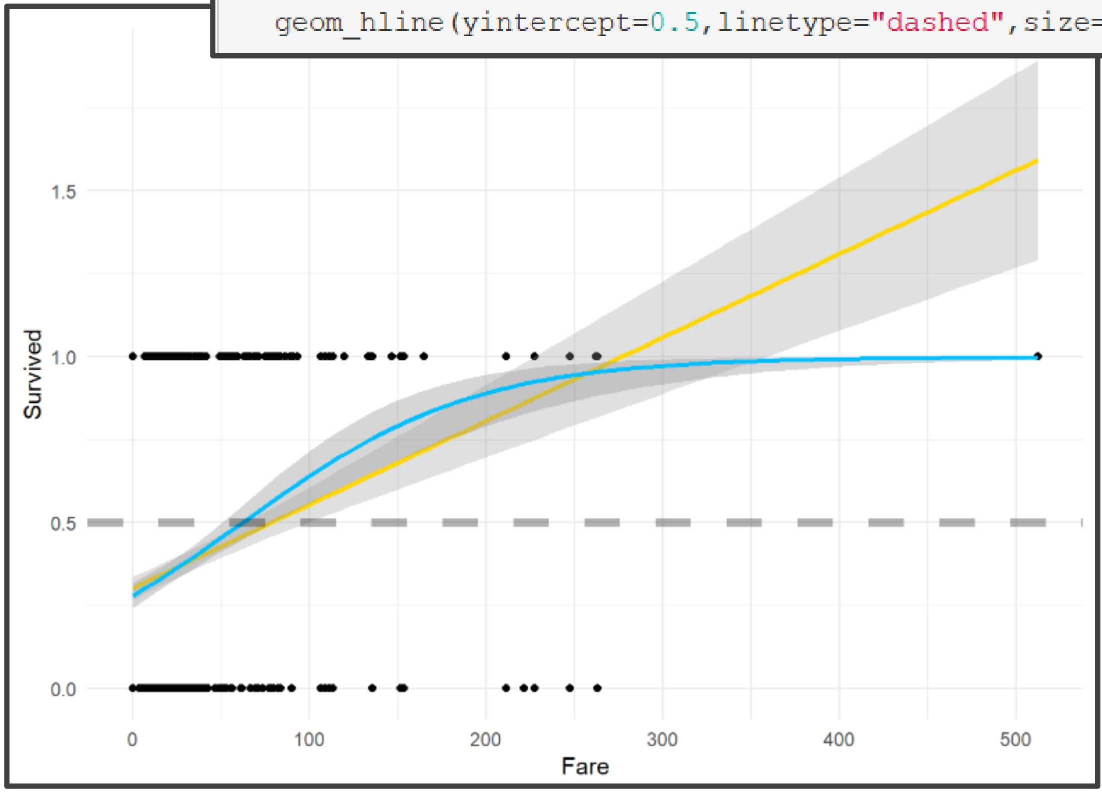
Problem?

```
## Observations: 418
## Variables: 7
## $ Pclass   <int> 3, 3, 2, 3, 3, 3, 3, 2, 3, 3, 3, 1, 1, 2, 1, 2, 2, 3,...
## $ Sex      <chr> "male", "female", "male", "male", "female", "male", "...
## $ Age      <dbl> 34.5, 47.0, 62.0, 27.0, 22.0, 14.0, 30.0, 26.0, 18.0,...
## $ SibSp    <int> 0, 1, 0, 0, 1, 0, 0, 1, 0, 2, 0, 0, 1, 1, 1, 1, 0, 0,...
## $ Parch    <int> 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
## $ Fare     <dbl> 7.8292, 7.0000, 9.6875, 8.6625, 12.2875, 9.2250, 7.62...
## $ Embarked <chr> "Q", "S", "Q", "S", "S", "S", "Q", "S", "C", "S", "S"...
```

Visualization: Survival vs. Fare

- Visualizing the Data

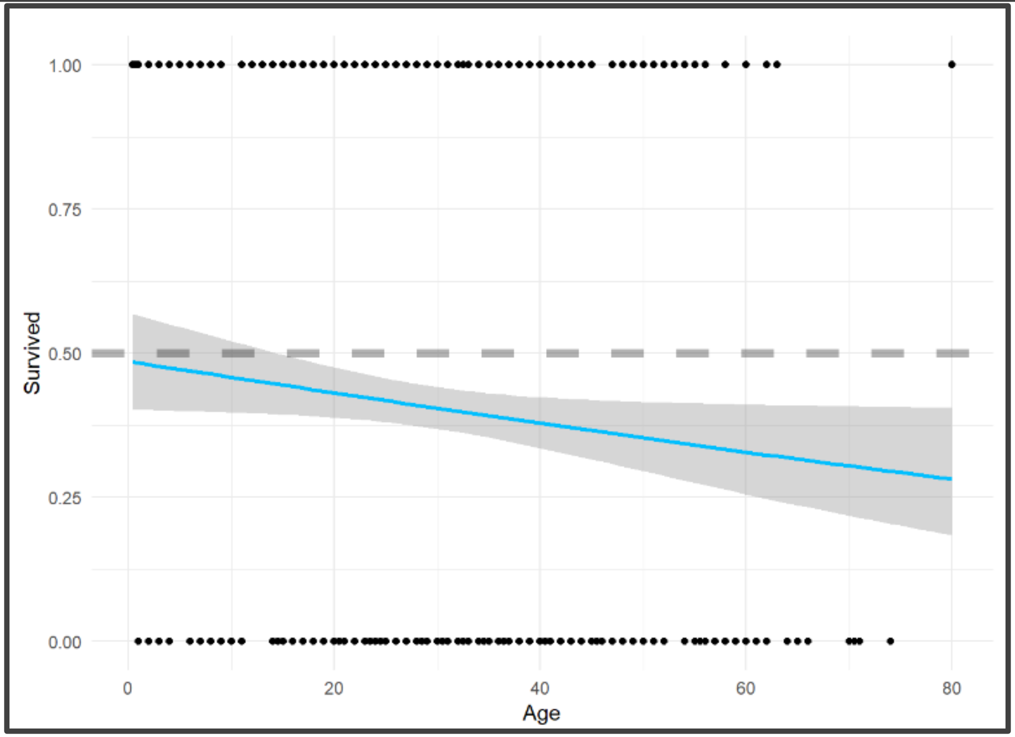
```
ggplot(TRAIN) + geom_point(aes(x=Fare,y=Survived)) + theme_minimal() +
  geom_smooth(aes(x=Fare,y=Survived),method="lm",alpha=0.3,color="gold") +
  geom_smooth(aes(x=Fare,y=Survived),method="glm",
              method.args=list(family="binomial"),color="deepskyblue1") +
  geom_hline(yintercept=0.5,linetype="dashed",size=2,alpha=0.3)
```



Visualization: Survival vs. Age

- Visualizing the Data (Continued)

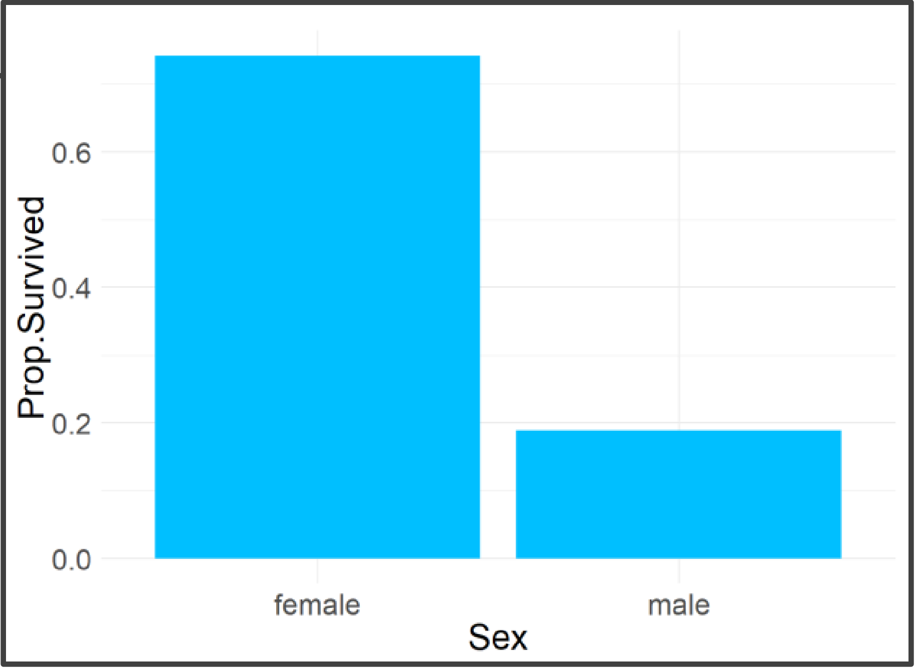
```
ggplot(TRAIN) + geom_point(aes(x=Age,y=Survived)) + theme_minimal() +
  geom_smooth(aes(x=Age,y=Survived),method="glm",
              method.args=list(family="binomial"),color="deepskyblue1") +
  geom_hline(yintercept=0.5,linetype="dashed",size=2,alpha=0.3)
```



Visualization: Survival vs. Sex

- Visualizing the Data (Continued)

```
TRAIN %>%
  mutate(Sex=factor(Sex)) %>%
  group_by(Sex) %>%
  summarize(Prop.Survived=mean(Survived)) %>%
  ggplot() +
  geom_bar(aes(x=Sex,y=Prop.Survived),
           stat="Identity",fill="deepskyblue1") +
  theme_minimal() +
  theme(text=element_text(size=20))
```



Data Splitting

- Logistic Regression Models
  - Split Training Set Up

```
> set.seed(216)
> sample.in=sample(1:dim(TRAIN)[1],
                size=floor(0.8*dim(TRAIN)[1]))
> TRAIN.IN=TRAIN[sample.in,
                c("Survived","Fare","Sex","Age")]
> TRAIN.OUT=TRAIN[-sample.in,
                c("Survived","Fare","Sex","Age")]
```

  - Modeling the Probability of Survival Given the Ticket Fare, the Sex of the Passenger, and the Age of the Passenger

Model 1

- Logistic Regression Models (Cont.)
  - Including 3-Way Interaction

```
logmod1=glm(Survived~.^3,family="binomial",data=TRAIN.IN)
tidy(logmod1)[,c("term","estimate","p.value")]
```

```
## # A tibble: 8 x 3
##   term               estimate p.value
##   <chr>                 <dbl>   <dbl>
## 1 (Intercept)         1.16    0.0254
## 2 Fare               -0.0156  0.265
## 3 Sexmale            -1.91    0.00314
## 4 Age                -0.0380  0.0636
## 5 Fare:Sexmale        0.0226  0.148
## 6 Fare:Age            0.00175 0.00840
## 7 Sexmale:Age         0.0118  0.623
## 8 Fare:Sexmale:Age -0.00169 0.0147
```

Model 2

- Logistic Regression Models (Cont.)
  - Only 2-Way Interactions

```
logmod2=glm(Survived~.*.,family="binomial",data=TRAIN.IN)
tidy(logmod2)[,c("term","estimate","p.value")]
```

```
## # A tibble: 7 x 3
##   term            estimate p.value
##   <chr>              <dbl>   <dbl>
## 1 (Intercept)    0.311      0.453
## 2 Fare           0.0161     0.0926
## 3 Sexmale       -0.849      0.0924
## 4 Age            0.000682   0.961
## 5 Fare:Sexmale  -0.0151     0.0681
## 6 Fare:Age       0.000253   0.229
## 7 Sexmale:Age   -0.0343     0.0333
```

Model 3

- Logistic Regression Models (Cont.)
  - No Way Interactions

```
logmod3=glm(Survived~.,family="binomial",data=TRAIN.IN)
tidy(logmod3)[,c("term","estimate","p.value")]
```

```
## # A tibble: 4 x 3
##   term        estimate  p.value
##   <chr>          <dbl>    <dbl>
## 1 (Intercept)   0.901  6.84e- 4
## 2 Fare          0.0125 1.68e- 5
## 3 Sexmale      -2.22   1.34e-26
## 4 Age          -0.0106 1.51e- 1
```

Predictions

- Getting Predictions

```
TRAIN.OUT2 = TRAIN.OUT %>%
             mutate(p1=predict(logmod1,newdata=TRAIN.OUT,type="response"),
                    p2=predict(logmod2,newdata=TRAIN.OUT,type="response"),
                    p3=predict(logmod3,newdata=TRAIN.OUT,type="response")) %>%
             select(Survived,p1,p2,p3) %>%
             mutate(S1=ifelse(p1<0.5,0,1),
                    S2=ifelse(p2<0.5,0,1),
                    S3=ifelse(p3<0.5,0,1))
head(TRAIN.OUT2,15)
```

```
##    Survived        p1        p2        p3 S1 S2 S3
## 1         0 0.1679674 0.1631565 0.1695469  0  0  0
## 2         0        NA        NA        NA NA NA NA
## 3         1 0.7028675 0.6456134 0.7441205  1  1  1
## 4         1 0.7739275 0.7629271 0.6503765  1  1  1
## 5         0 0.3543259 0.3635900 0.2734311  0  0  0
## 6         1 0.1780810 0.1743017 0.1799857  0  0  0
## 7         1        NA        NA        NA NA NA NA
## 8         0 0.5379343 0.6426473 0.6450425  1  1  1
## 9         0        NA        NA        NA NA NA NA
## 10        0 0.2241130 0.2324596 0.1908923  0  0  0
```

Why?

Predictions

- Getting Predictions

```
TRAIN.OUT3=na.omit(TRAIN.OUT2)
head(TRAIN.OUT3,20)
```

```
##     Survived          p1         p2        p3 S1  S2  S3
## 1          0 0.16796737 0.16315653 0.1695469  0   0   0
## 3          1 0.70286747 0.64561340 0.7441205  1   1   1
## 4          1 0.77392753 0.76292710 0.6503765  1   1   1
## 5          0 0.35432593 0.36359002 0.2734311  0   0   0
## 6          1 0.17808100 0.17430173 0.1799857  0   0   0
## 8          0 0.53793429 0.64264728 0.6450425  1   1   1
## 10         0 0.22411295 0.23245962 0.1908923  0   0   0
```

```
mean(TRAIN.OUT3$S1==TRAIN.OUT3$S2)
```

```
## [1] 0.993007
```

```
mean(TRAIN.OUT3$S2==TRAIN.OUT3$S3)
```

```
## [1] 1
```

What Do You Notice About the Predictions?

Predictions

- Getting Predictions

```
TRAIN.OUT4=TRAIN.OUT3 %>% select(-p2,-S2)
head(TRAIN.OUT4,8)
```

```
##    Survived        p1        p3 S1 S3
## 1         0 0.1679674 0.1695469  0  0
## 3         1 0.7028675 0.7441205  1  1
## 4         1 0.7739275 0.6503765  1  1
## 5         0 0.3543259 0.2734311  0  0
## 6         1 0.1780810 0.1799857  0  0
## 8         0 0.5379343 0.6450425  1  1
## 10        0 0.2241130 0.1908923  0  0
## 11        1 0.9907016 0.7929174  1  1
```

Where Do You See Error?

Evaluation

- Evaluating Results
  - Helpful Modifications

```
TRAIN.OUT5 = TRAIN.OUT4 %>%
              select(-p1,-p3) %>%
              mutate(Survived=factor(Survived),S1=factor(S1),S3=factor(S3)) %>%
              mutate(Survived=fct_recode(Survived,"Survived"="1","Died"="0"),
                     S1=fct_recode(S1,"Will Survive"="1","Will Die"="0"),
                     S3=fct_recode(S3,"Will Survive"="1","Will Die"="0")) %>%
              mutate(Survived=factor(Survived,levels=c("Survived","Died")),
                     S1=factor(S1,levels=c("Will Survive","Will Die")),
                     S3=factor(S3,levels=c("Will Survive","Will Die")))
head(TRAIN.OUT5)
```

```
##   Survived           S1           S3
## 1     Died     Will Die     Will Die
## 2 Survived Will Survive Will Survive
## 3 Survived Will Survive Will Survive
## 4     Died     Will Die     Will Die
## 5 Survived     Will Die     Will Die
## 6     Died Will Survive Will Survive
```

Evaluation: Confusion Matrix

- Evaluating Results (Continued)
  - Confusion Matrix
    - Including 3-Way Interactions

```
RESULTS1=table(TRAIN.OUT5$Survived,TRAIN.OUT5$S1) %>%
            prop.table()
print(RESULTS1)
```

```
##
##              Will Survive   Will Die
##   Survived     0.25174825 0.11188811
##   Died         0.06293706 0.57342657
```

    - No Way Interactions

```
RESULTS3=table(TRAIN.OUT5$Survived,TRAIN.OUT5$S3) %>%
            prop.table()
print(RESULTS3)
```

```
##
##              Will Survive   Will Die
##   Survived     0.25874126 0.10489510
##   Died         0.06293706 0.57342657
```

Evaluation: Rates

- Evaluating Results (Continued)
  - Error Statistics
    - Code

```
ERROR.RESULTS = tibble(
    Model=c("3 Way","No Way"),
    Sensitivity=c(RESULTS1[1,1]/sum(RESULTS1[1,]),RESULTS3[1,1]/sum(RESULTS3[1,])),
    Specificity=c(RESULTS1[2,2]/sum(RESULTS1[2,]),RESULTS3[2,2]/sum(RESULTS3[2,])),
    FPR=c(RESULTS1[2,1]/sum(RESULTS1[2,]),RESULTS3[2,1]/sum(RESULTS3[2,])),
    FNR=c(RESULTS1[1,2]/sum(RESULTS1[1,]),RESULTS3[1,2]/sum(RESULTS3[1,]))
)
print(ERROR.RESULTS)
```

    - Results

Model	Sensitivity	Specificity	FPR	FNR
<chr>	<dbl>	<dbl>	<dbl>	<dbl>
3 Way	0.692	0.901	0.0989	0.308
No Way	0.712	0.901	0.0989	0.288

Evaluation: Package

- Evaluating with ROCit and caret Package

```
> library(ROCit)
```

```
> library(caret)
```

  - Generate Confusion Matrix with caret
    - Data: Prediction
    - Reference: Response
    - Input: factor

```
```{r}
confusionMatrix(as.factor(TRAIN.OUT4$S1),as.factor(TRAIN.OUT4$Survived),positive='1')
confusionMatrix(as.factor(TRAIN.OUT4$S3),as.factor(TRAIN.OUT4$Survived),positive='1')
```
```

Caret Output

- Model 1:

```
Confusion Matrix and Statistics

          Reference
Prediction  0  1
         0 82 16
         1  9 36

               Accuracy : 0.8252
                 95% CI : (0.7528, 0.8836)
    No Information Rate : 0.6364
    P-Value [Acc > NIR] : 0.0000005904

                  Kappa : 0.611

 Mcnemar's Test P-Value : 0.2301

            Sensitivity : 0.6923
            Specificity : 0.9011
         Pos Pred Value : 0.8000
         Neg Pred Value : 0.8367
             Prevalence : 0.3636
         Detection Rate : 0.2517
   Detection Prevalence : 0.3147
      Balanced Accuracy : 0.7967

       'Positive' Class : 1
```

- Model 3:

```
Confusion Matrix and Statistics

          Reference
Prediction  0  1
         0 82 15
         1  9 37

               Accuracy : 0.8322
                 95% CI : (0.7606, 0.8894)
    No Information Rate : 0.6364
    P-Value [Acc > NIR] : 0.0000002115

                  Kappa : 0.6282

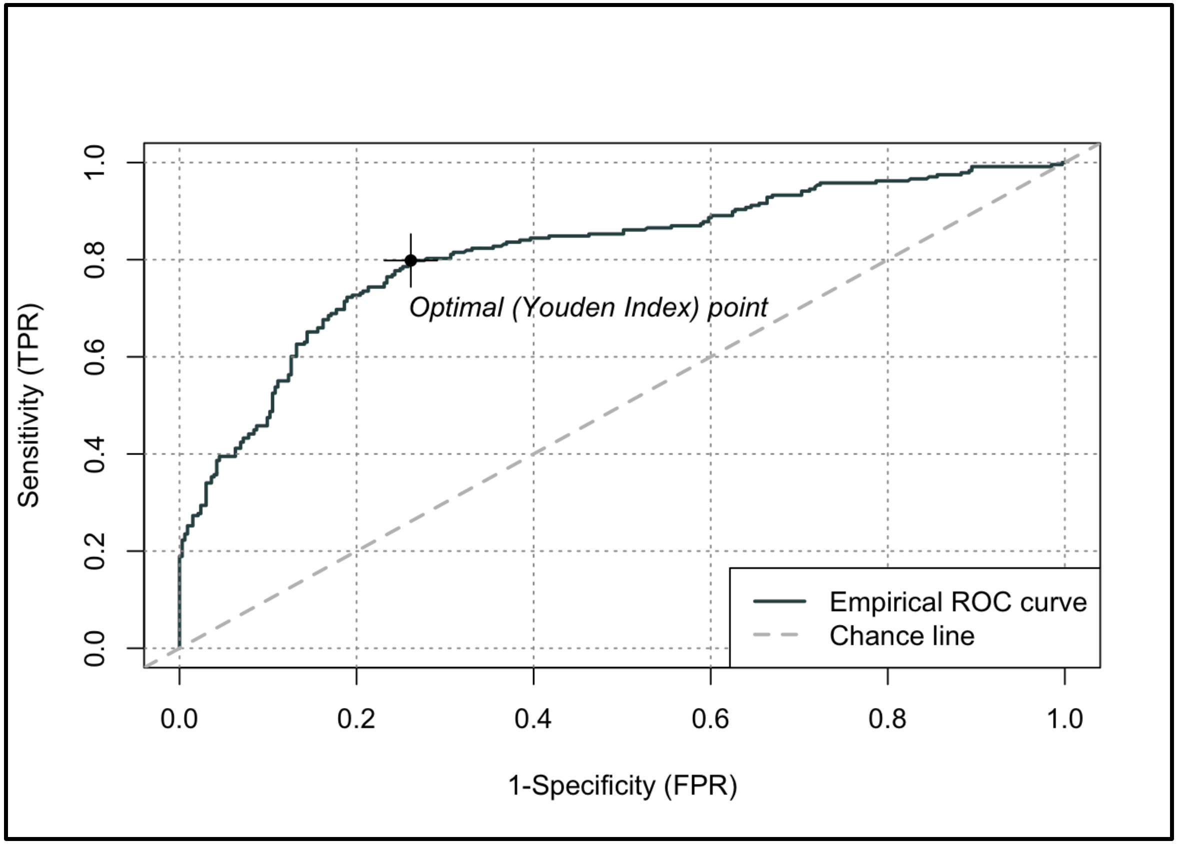
 Mcnemar's Test P-Value : 0.3074

            Sensitivity : 0.7115
            Specificity : 0.9011
         Pos Pred Value : 0.8043
         Neg Pred Value : 0.8454
             Prevalence : 0.3636
         Detection Rate : 0.2587
   Detection Prevalence : 0.3217
      Balanced Accuracy : 0.8063

       'Positive' Class : 1
```

ROC Curve: Model 1

```
logmod1_roc = rocit(score = logmod1$fitted.values, class = logmod1$y,negref=0)
plot(logmod1_roc)
```

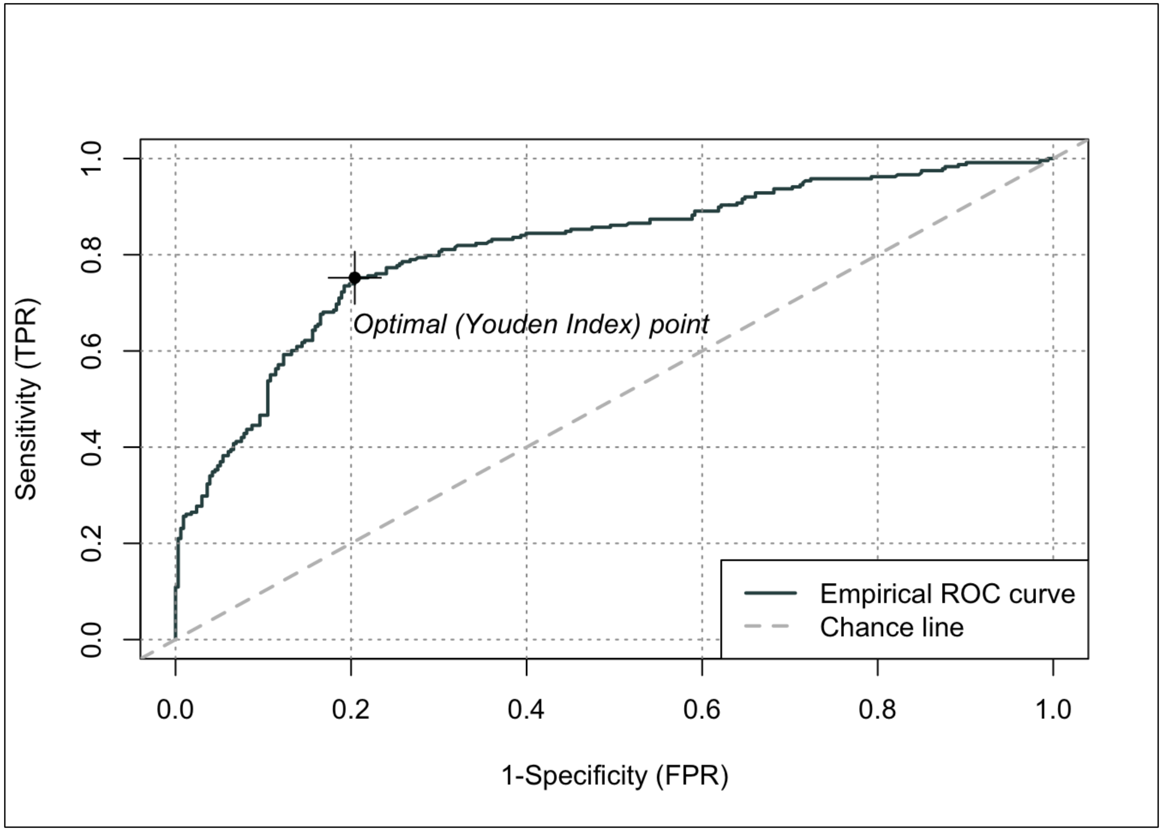



```
summary(logmod1_roc)
```

```
##
##   Method used: empirical
##   Number of positive(s): 238
##   Number of negative(s): 333
##   Area under curve: 0.8146
```

ROC Curve: Model 2

```
logmod2_roc = rocit(score = logmod2$fitted.values, class = logmod2$y,negref=0)
plot(logmod2_roc)
```




```
summary(logmod2_roc)
```

```
##
##  Method used: empirical
##  Number of positive(s): 238
##  Number of negative(s): 333
##  Area under curve: 0.813
```