

Modeling VI

Introduction



- Now We Consider
 - Categorical Response Variables
 - Numerical/Categorical Explanatory Variables
- Focus is on Classification
- Bless Your Soul with Ch 4 in ISLR

Introduction



- Basic Case: Binary Response
 - Variable Has Two Possible Outcomes
 - Typically, Yes or No Responses to a Question
 - Example
 - Y = Do You Enjoy Your Experience in the Presence of the Doctor?
 - Y = Did You Pass Your STOR 320 Class?
 - Y = Are You Comfortable Having Your Mind Blown?

Scenario



- Question: Are Students Who Get Good Grades in STOR 320 Less Likely to Recommend This Class To an Enemy?
 - Y = Would You Recommend STOR 320 to an Enemy?
 - X = Grade in STOR 320
- Why is Linear Regression Inappropriate?

Model Construction



Bernouilli Random Variable

$$Y = \begin{cases} 1 & if Yes \\ 0 & if No \end{cases}$$
$$p = E(Y) = P(Y = 1)$$

Sample n Students

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

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

Estimated Probability that a Student Would This Recommend Class to an Enemy Based on a Sample

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

Model Construction



Modeling the Mean

Logit Link Function

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X$$
Odds of
Recommending
STOR 320

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

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 Recommending STOR 320 Given the Student's Grade

Solving for p

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

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

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

Probability a Student Will Recommend STOR 320 Given the Student's Grade

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 a Student Recommends
Course Given the Student's Grade

Two Scenarios

•
$$\hat{p} < 0.5 \implies \hat{Y} = 0$$

•
$$\hat{p} > 0.5 \implies \hat{Y} = 1$$

Evaluating the Logistic Regression Model



- Two Methods
 - Leave Out Data Intentionally
 - Use Cross-Validation
- Positives and Negatives
 - True Positive = Predicted a Recommendation and the Student Recommended
 - False Positive=Predicted a Recommendation and the Student Didn't Recommend
 - False Negative = Predicted a Student Wouldn't Recommend and They Did Recommend
 - True Negative = Predicted a Student Wouldn't Recommend and They Didn't Recommend

Evaluating the Logistic Regression Model



Confusion Matrix

	Predicted		
Actual	Will Recommend	Won't Recommend	
Recommends	n_{11}	n_{12}	
Doesn't Recommend	n_{21}	n_{22}	

Sensitivity:

$$n_{11}/(n_{11}+n_{12})$$

Specificity:

$$n_{22}/(n_{21}+n_{22})$$

False Positive Rate:

$$n_{12}/(n_{11}+n_{12})$$

False Negative Rate:

$$n_{21}/(n_{21}+n_{22})$$



Titanic Survival Data

> library(titanic)

Response Variable

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

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



- 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, 1, 3, 3, 2, 3, 1, 3, 3, 3, 2, 3, 2,...
## $ Sex
             <chr> "male", "female", "female", "female", "male", "male", ...
             <dbl> 22, 38, 26, 35, 35, NA, 54, 2, 27, 14, 4, 58, 20, 39,...
## $ SibSp
             <int> 1, 1, 0, 1, 0, 0, 0, 3, 0, 1, 1, 0, 0, 1, 0, 0, 4, 0,...
## $ Parch
             <int> 0, 0, 0, 0, 0, 0, 0, 1, 2, 0, 1, 0, 0, 5, 0, 0, 1, 0,...
## $ Fare
             <dbl> 7.2500, 71.2833, 7.9250, 53.1000, 8.0500, 8.4583, 51....
Problem?
## Observations: 418
## Variables: 7
## $ Pclass <int> 3, 3, 2, 3, 3, 3, 2, 3, 3, 3, 1, 1, 2, 1, 2, 2, 3,...
             <chr> "male", "female", "male", "male", "female", "male", "...
             <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,...
             <int> 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
## $ Parch
             <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"...
```

Pause For Lyrics

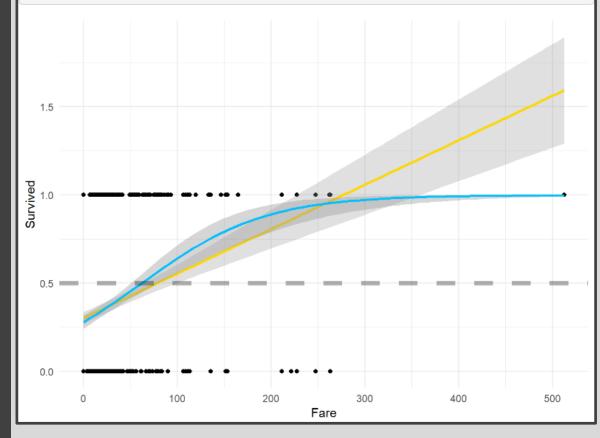




Every night in my dreams
I see you, I feel you
That is how I know you go on



Visualizing the Data





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)
 0.75
 0.25
 0.00
```



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))
  0.6
Prop.Survived
  0.0
                  female
                                              male
                                 Sex
```

Pause For Lyrics





Far across the distance
And spaces between us
You have come to show you go on



- Logistic Regression Models
 - Split Training Set Up
- - Modeling the Probability of Survival Given the Ticket Fare, the Sex of the Passenger, and the Age of the Passenger



- 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
                  estimate p.value
  term
  <chr>
                     <dbl> <dbl>
## 1 (Intercept) 0.959 0.0719
## 2 Fare
                 -0.0132 0.357
## 3 Sexmale
              -1.54 0.0182
         -0.0362 0.0745
## 4 Age
## 5 Fare:Sexmale 0.0180 0.255
## 6 Fare: Age 0.00177 0.00684
## 7 Sexmale:Age -0.000359 0.988
## 8 Fare:Sexmale:Age -0.00168 0.0140
```



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

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



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

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

Pause For Lyrics





Near, far, wherever you are
I believe that the heart does go on



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
                                           p3 S1 S2 S3
             1 0.9690919 0.9092749 0.7802745 1 1 1
             1 0.7754082 0.7600334 0.6058744
             1 0.2080353 0.2054202 0.2124202
             0 0.6660041 0.6390900 0.7598035 1 1 1
                                           NA NA NA NA
                                           NA NA NA NA
                                NA
## 8
                      NA
                                NA
                                           NA NA NA NA
## 9
             0 0.3504463 0.3477779 0.2826244
             0 0.2084528 0.2141609 0.1755685
## 10
## 11
             0 0.3588175 0.3684181 0.2646063
## 12
             0 0.2278485 0.2365545 0.1841222
## 13
             0 0.1588185 0.1560858 0.1590190
## 14
             1 0.2135621 0.2103355 0.2445736
## 15
                      NA
                                NA
                                           NA NA NA NA
```



Getting Predictions

```
## Survived p1 p2 p3 s1 s2 s3
## 1 1 0.9690919 0.9092749 0.7802745 1 1 1
## 2 1 0.7754082 0.7600334 0.6058744 1 1 1
## 3 1 0.2080353 0.2054202 0.2124202 0 0 0
## 4 0 0.6660041 0.6390900 0.7598035 1 1 1
## 7 0 0.5144529 0.6150895 0.6255526 1 1 1
## 9 0 0.3504463 0.3477779 0.2826244 0 0 0
## 10 0 0.2084528 0.2141609 0.1755685 0 0
```

```
mean(TRAIN.OUT3$$1==TRAIN.OUT3$$2)

## [1] 0.993007

mean(TRAIN.OUT3$$2==TRAIN.OUT3$$3)

## [1] 1
```

What Do You Notice About the Predictions?



Getting Predictions

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



Where Do You See Error?

Pause For Lyrics





Once more you open the door And you're here in my heart And my heart will go on and on



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
## 1 Survived Will Survive Will Survive
## 2 Survived Will Survive Will Survive
## 3 Survived
                  Will Die
                               Will Die
         Died Will Survive Will Survive
## 5
        Died Will Survive Will Survive
         Died
                  Will Die
                               Will Die
```



Evaluating Results (Continued)

- Confusion Matrix
 - Including 3-Way Interactions

```
## Will Survive Will Die ## Survived 0.32867133 0.13986014 ## Died 0.07692308 0.45454545
```

No Way Interactions

```
## Will Survive Will Die ## Survived 0.33566434 0.13286713 ## Died 0.07692308 0.45454545
```



Evaluating Results (Continued)

Error Statistics

Code

Results

Model	Sensitivity	Specificity	FPR	FNR
<chr></chr>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>
3 Way	0.701	0.855	0.299	0.145
No Way	0.716	0.855	0.284	0.145

Closing



Disperse and Make Reasonable Decisions