PSY 308d DA3 Binary Logistic Regression

Daniel Pinedo

April 16, 2019

```
## Warning: package 'knitr' was built under R version 3.5.3
```

You have been hired as an Organizational Psychologist for a local restaurant. The Head of HR is concerned about high turnover amongst their servers. Specifically, she is interested in figuring out what predicts whether a server will stay at the restaurant for another year or not. Although a survey of her staff included responses of uncertainty of staying or not, HR *only* cares about those who are planning to stay or leave.

Analyses: After speaking with the managers, you think that the two best predictors will be number of overtime hours worked per week and amount earned in tips each week. You decide to survey the wait staff to see whether (a) tips, (b) overtime hours, or (c) both tips AND overtime hours should be used by the HR manager in predicting someone's retention status.

Additional Discussion Question: Additionally, the HR manager is particularly worried that she is going to lose her star waitress Trudy. Given that, on average, Trudy works 7 hours of overtime a week and makes $100 in tips, what would you tell the HR manager about the probability of Trudy staying for another year? *Please address this concern in your discussion section.*

Variables: 1. Hours - continuous, average overtime hours worked per week (in hours) 2. Tips - continuous, average amount of tips earned each week (in dollars) 3. Re (Retention) a. "Yes" (plans on staying at the restaurant for another year) b. "No" (does not plan on staying at the restaurant for another year) c. "border" (is unsure whether or not they will stay for another year)

TIP: Please center your predictor variables for your main analyses and when using it to calculate the likelihood of Trudy staying!

```r
library(pacman)
```

```
## Warning: package 'pacman' was built under R version 3.5.3
```

```r
p_load(psych, jmv, aod, QuantPsyc, popbio, summarytools)

# Add summarytools css
#st_css(bootstrap=FALSE)

dat <- read.csv("https://www.dropbox.com/s/jej8t73qnelvijp/PSY.308d.DA3-4.csv?dl=1")
head(dat)
```

```
##   Hours Tips     Re
## 1  2.10  467 border
## 2  2.22  591 border
## 3  2.35  541 border
## 4  2.41  444 border
## 5  2.57  572 border
## 6  2.63  483 border
```

```r
dim(dat)
```

```
## [1] 100   3
```

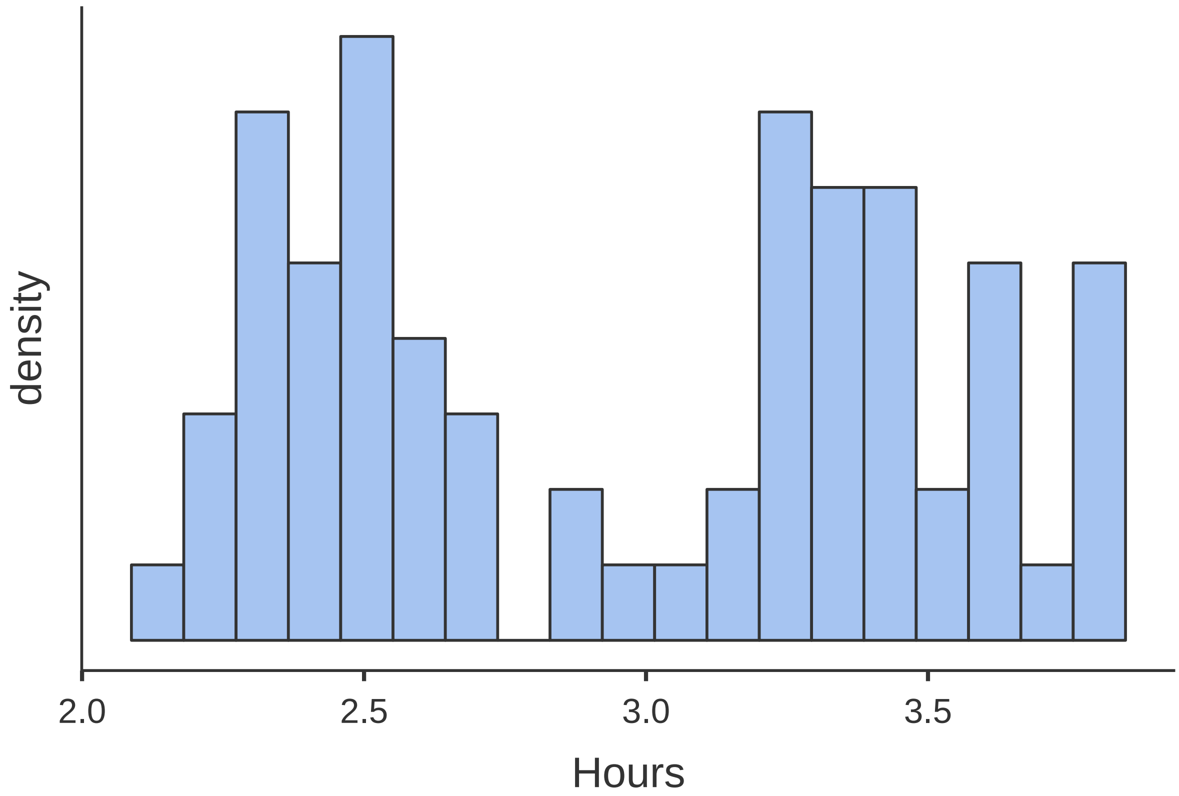
Subset dataset and check for missing parameters

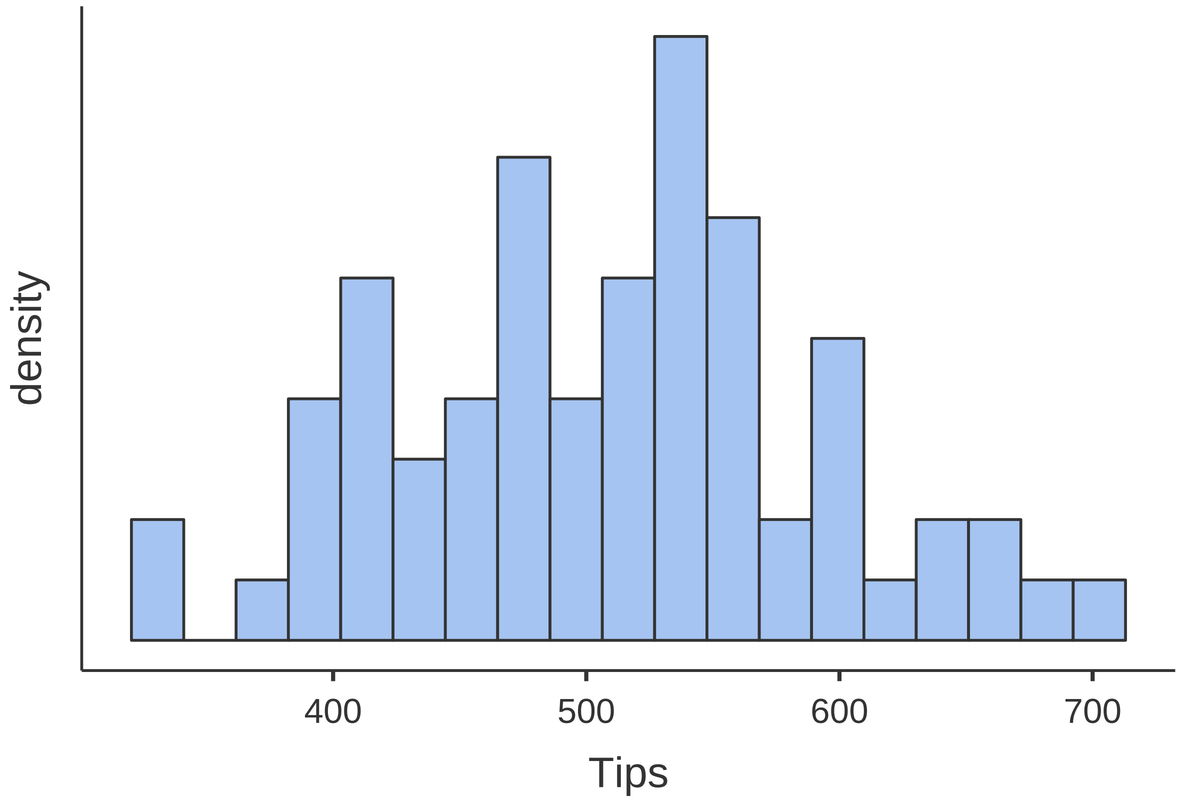
```r
#remove observations that are not "yes" or "no" for Retention variable
dat.subset <- dat[which(dat$Re!='border'), ] # N=100 changes to N=69
```

```r
dat.subset <- droplevels(dat.subset) # change levels for Retention variable by dropping "border"

#see what is missing
#run descriptives
desc <- descriptives(data = dat.subset,
                        vars = c('Re', 'Hours', 'Tips'),
                        mode = TRUE,
                        sd = TRUE,
                        skew = TRUE,
                        kurt = TRUE,
                        freq = TRUE,
                        hist = TRUE)
desc
```

```
##
##  DESCRIPTIVES
##
##  Descriptives
##  -------------------------------------------------
##                           Re    Hours     Tips
##  -------------------------------------------------
##    N                      69       69       69
##    Missing                 0        0        0
##    Mean                          2.97      509
##    Median                        3.03      521
##    Mode                          2.36      399
##    Standard deviation           0.518     84.2
##    Minimum                       2.13      321
##    Maximum                       3.80      693
##    Skewness                    0.0184   0.0913
##    Std. error skewness          0.289    0.289
##    Kurtosis                     -1.51   -0.374
##    Std. error kurtosis          0.570    0.570
##  -------------------------------------------------
##
##
##  FREQUENCIES
##
##  Frequencies of Re
##  --------------------------------------------------
##    Levels    Counts    % of Total    Cumulative %
##  --------------------------------------------------
##    No            33          47.8            47.8
##    Yes           36          52.2           100.0
##  --------------------------------------------------
```


density
2.0
2.5
3.0
3.5
Hours




```
# baseline classification success is equal to the reference frequency for Retention (No = 48%)
# it also looks like Hours is bimodal - likely non-normal distribution
```

Summarytools goodies

```
opts_chunk$set(results = 'asis',      # knitr chunk settings
               comment = NA,
               prompt = FALSE,
               cache = FALSE)

st_options(plain.ascii = FALSE,        # This is very handy in all Rmd documents
             style = "rmarkdown",        # This too
             footnote = NA,             # Avoids footnotes which would clutter the results
             subtitle.emphasis = FALSE) # This is a setting to experiment with - according to the theme

print(dfSummary(dat.subset, plain.ascii = FALSE, style = "grid",
                graph.magnif = 0.75, valid.col = FALSE), method = "render")
```

```
## text graphs are displayed; set 'tmp.img.dir' parameter to activate png graphs
```

Data Frame Summary

dat.subset Dimensions: 69 x 3 Duplicates: 0

No

Variable

Stats / Values

Freqs (% of Valid)

Graph

Missing

1

Hours [numeric]

Mean (sd) : 3 (0.5) min < med < max: 2.1 < 3 < 3.8 IQR (CV) : 0.9 (0.2)

52 distinct values

0 (0%)

2

Tips [integer]

Mean (sd) : 509.2 (84.2) min < med < max: 321 < 521 < 693 IQR (CV) : 113 (0.2)

55 distinct values

0 (0%)

3

Re [factor]

1. No
2. Yes
   33
   (
   47.8%
)
   36
   (
   52.2%
)
   0 (0%)

Assumptions 1. Independence of Observations 2. Predictor Variables Normally Distributed *(Hours is bi-modal)* 3. Multicollinearity

Correlations

```
# Correlations of continuous variables
cortable <- corrMatrix(data = dat.subset,
                       vars = c('Hours', 'Tips'),
                       flag = TRUE)
cortable
```

CORRELATION MATRIX

Correlation Matrix
Hours Tips

Hours Pearson's r — 0.436
p-value — < .001

Tips Pearson's r —
p-value —

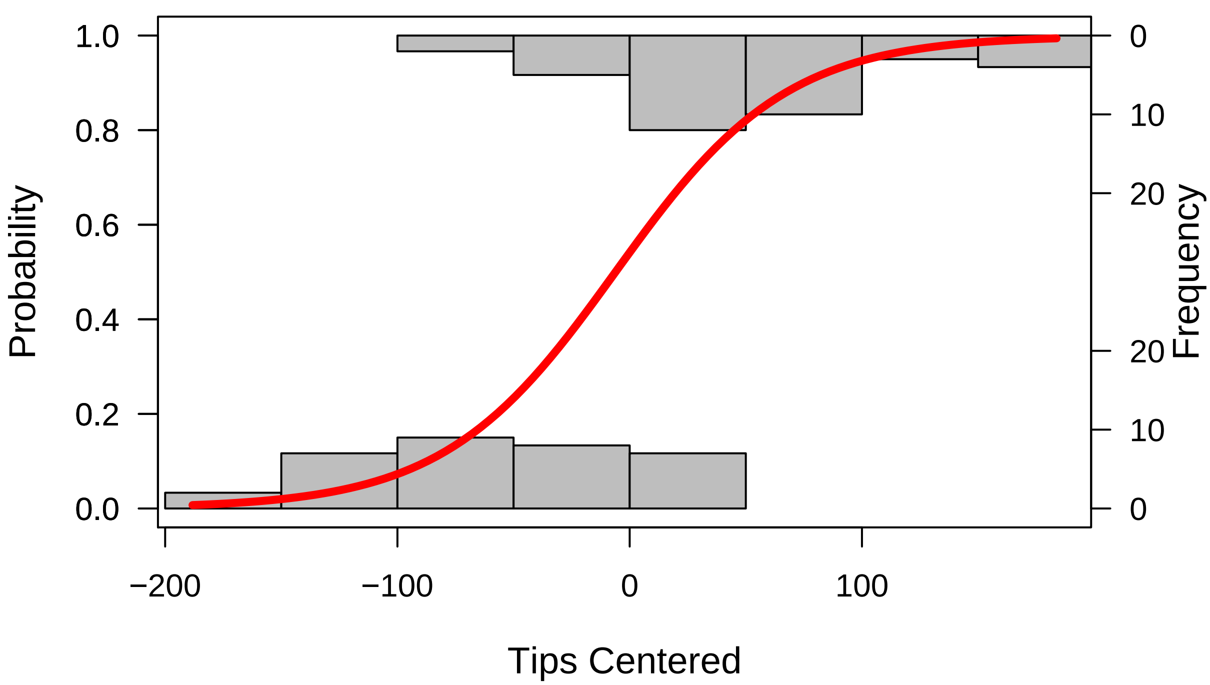
—————————————————- Note. * p < .05, ** p < .01, *** p < .001

Logistic Plots

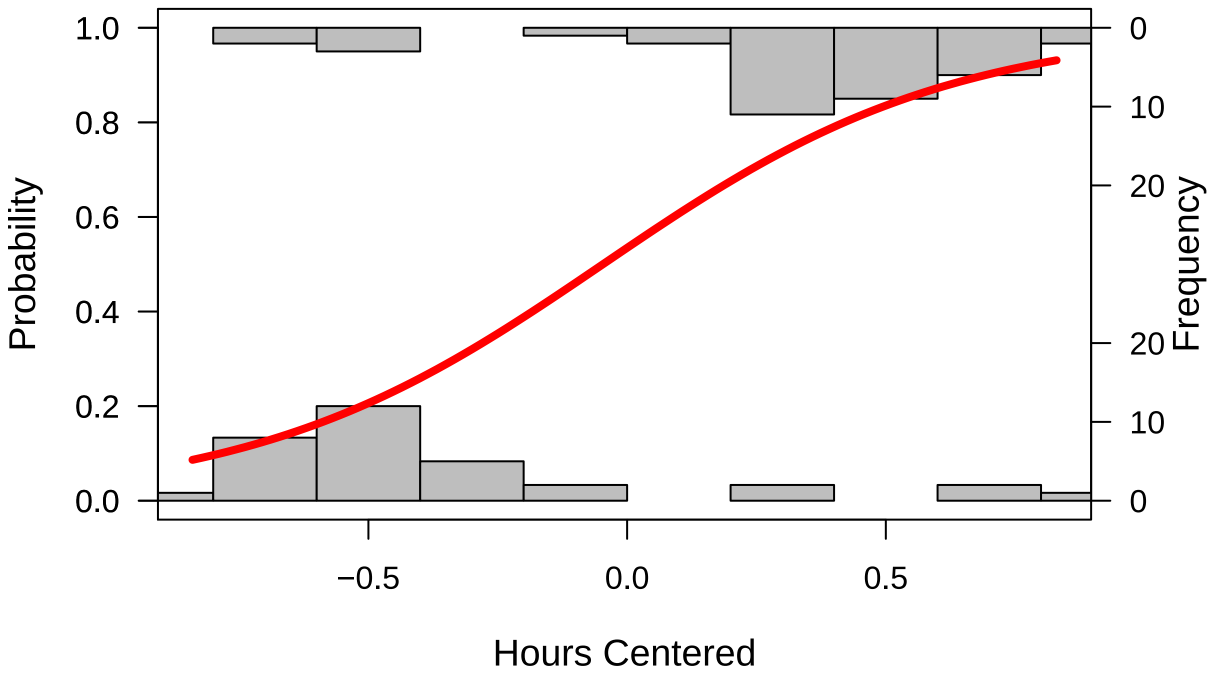
```
#Transform binary outcome to integer for the plot to work
dat.subset$Re.int[dat.subset$Re == "No"] <- 0
dat.subset$Re.int[dat.subset$Re == "Yes"] <- 1

#Center Predictors
dat.subset$HoursC <- dat.subset$Hours - round(mean(dat.subset$Hours), digits = 2)
dat.subset$TipsC <- dat.subset$Tips - round(mean(dat.subset$Tips), digits = 2)

#Show Plots for centered predictors
logi.hist.plot(dat.subset$TipsC, dat.subset$Re.int, boxp=FALSE, type="hist", col="gray", xlabel = "Tips
```




```
  # when tips are above average, people tend to stay vs. below average they go
logi.hist.plot(dat.subset$HoursC, dat.subset$Re.int, boxp=FALSE, type="hist", col="gray", xlabel = "Hou
```




```
# when OT hours are above average, people tend to stay vs. below they go (caveat: bimodal dsitributio
```

BiLoRe Models Null model

```
# Null deviance = Chi squared for the model
# df = N - (# of parameters) - 1 [68]
model0 <- glm(dat.subset$Re ~ 1, family = binomial)
summary(model0)
```

Call: glm(formula = dat.subset$Re ~ 1, family = binomial)

Deviance Residuals: Min 1Q Median 3Q Max
-1.215 -1.215 1.141 1.141 1.141

Coefficients: Estimate Std. Error z value Pr(>|z|) (Intercept) 0.08701 0.24100 0.361 0.718

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 95.524  on 68  degrees of freedom
```

Residual deviance: 95.524 on 68 degrees of freedom AIC: 97.524

Number of Fisher Scoring iterations: 3

```
print("Logit")
```

[1] “Logit”

```
coef(model0)
```

(Intercept) 0.08701138

```r
model0.odds <- exp(coef(model0)) #converts coefficient to odds [P(outcome)/(1-P(outcome))]
print("Odds")
```

[1] "Odds"

```r
model0.odds
```

(Intercept) 1.090909

```r
model0.probs <- model0.odds / (1 + model0.odds) #
print("Probabilities")
```

[1] "Probabilities"

```r
model0.probs
```

(Intercept) 0.5217391

```r
print("Columns = Observed, Rows = Predicted")
```

[1] "Columns = Observed, Rows = Predicted"

```r
print("Null model")
```

[1] "Null model"

```r
ClassLog(model0, dat.subset$Re) # classification success under the null model (baseline)
```

$rawtab resp No Yes TRUE 33 36

$classtab resp No Yes TRUE 1 1

$overall [1] 0.4782609

$mcFadden [1] 0

Model 1 - Hours predicting Retention

```r
#Multicollinearity
  #Tolerance = 1 - R squared --> for our purpose < .4 is bad
  #VIF = 1/Tolerance
  #Small VIF values indicates low correlation among variables under ideal conditions
  #Multicollinearity occurs when two or more predictors in the model are correlated and provide redunda

# when odds ratio < 1 just flip (invert) the result(in relation to "no" instead of in relation to "yes"

# Deviance score is the chi-squared for this model
# AIC is used to compare non-nested models for fit (lower means better fit)
# top chi-squared indicates the change of chi-squared vs the null model (Deviance + chi squared)
# top df score indicates the change of df vs the null model
# df = N - (# of predictors) - 1 [67]

model1.jmv <- jmv::logRegBin( # Multicollinearity is not relevant for this answer
  data = dat.subset,
  dep = Re,
  covs = vars(HoursC),
  blocks = list(
    list(
      'HoursC')),
  refLevels = list(
    list(
```

```
      var = 'Re',
      ref = 'No')),
  modelTest = TRUE,
  OR = TRUE,
  class = TRUE,
  acc = TRUE,
  collin = TRUE)

model1.jmv
```

BINOMIAL LOGISTIC REGRESSION

Model Fit Measures

Model	Deviance	AIC	R^2-McF	<U+03C7>^{2}	df	p
1	67.4	71.4	0.295	28.1	1	< .001

MODEL SPECIFIC RESULTS

MODEL 1

Model Coefficients

Predictor	Estimate	SE	Z	p	Odds ratio
Intercept	0.139	0.304	0.457	0.648	1.15
HoursC	2.973	0.667	4.458	< .001	19.54

Note. Estimates represent the log odds of "Re = Yes" vs. "Re = No"

ASSUMPTION CHECKS

Collinearity Statistics

	VIF	Tolerance
HoursC	1.00	1.00

PREDICTION

Classification Table – Re

Observed	No	Yes	% Correct
No	28	5	84.8
Yes	5	31	86.1

Note. The cut-off value is set to 0.5

Predictive Measures

Accuracy
0.855

Note. The cut-off value is set to 0.5

Model 2 - Tips predicting Retention

```
#Multicollinearity
  #Tolerance = 1 - R squared --> for our purpose < .4 is bad
  #VIF = 1/Tolerance
  #Small VIF values indicates low correlation among variables under ideal conditions
  #Multicollinearity occurs when two or more predictors in the model are correlated and provide redunda

# when odds ratio < 1 just flip (invert) the result(in relation to "no" instead of in relation to "yes"

# Deviance score is the chi-squared for this model
# AIC is used to compare non-nested models for fit (lower means better fit)
# top chi-squared indicates the change of chi-squared vs the null model (Deviance + chi squared)
# top df score indicates the change of df vs the null model
# df = N - (# of predictors) - 1 [67]

model2.jmv <- jmv::logRegBin( # Multicollinearity is not relevant for this answer
  data = dat.subset,
  dep = Re,
  covs = vars(TipsC),
  blocks = list(
    list(
      'TipsC')),
  refLevels = list(
    list(
      var = 'Re',
      ref = 'No')),
  modelTest = TRUE,
  OR = TRUE,
  class = TRUE,
  acc = TRUE,
  collin = TRUE)

model2.jmv
```

BINOMIAL LOGISTIC REGRESSION

Model Fit Measures

Model	Deviance	AIC	R^2-McF	<U+03C7>²	df	p
1	58.3	62.3	0.389	37.2	1	< .001

MODEL SPECIFIC RESULTS

MODEL 1

Model Coefficients					
Predictor	Estimate	SE	Z	p	Odds ratio
Intercept	0.1660	0.32620	0.509	0.611	1.18
TipsC	0.0271	0.00646	4.199	< .001	1.03

Note. Estimates represent the log odds of "Re = Yes" vs. "Re = No"

ASSUMPTION CHECKS

Collinearity Statistics		
	VIF	Tolerance
TipsC	1.00	1.00

PREDICTION

Classification Table – Re			
Observed	No	Yes	% Correct
No	23	10	69.7
Yes	6	30	83.3

Note. The cut-off value is set to 0.5

Predictive Measures
Accuracy
0.768

Note. The cut-off value is set to 0.5

Model 3 - Comparing Hours Model to Full Model

```r
#Multicollinearity
  #Tolerance = 1 - R squared --> for our purpose < .4 is bad
  #VIF = 1/Tolerance
  #Small VIF values indicates low correlation among variables under ideal conditions
  #Multicollinearity occurs when two or more predictors in the model are correlated and provide redunda

# when odds ratio < 1 just flip (invert) the result(in relation to "no" instead of in relation to "yes")

# Deviance score is the chi-squared for this model
# AIC is used to compare non-nested models for fit (lower means better fit)
# top chi-squared indicates the change of chi-squared vs the null model (Deviance + chi squared)
# top df score indicates the change of df vs the null model
# df = N - (# of predictors) - 1 [66 for full model]

model2.jmv <- jmv::logRegBin( # Multicollinearity is relevant for this answer
```

```
  data = dat.subset,
  dep = Re,
  covs = vars(HoursC, TipsC),
  blocks = list(
    list(
      'HoursC'),
    list(
      'TipsC')),
  refLevels = list(
    list(
      var = 'Re',
      ref = 'No')),
  modelTest = TRUE,
  OR = TRUE,
  class = TRUE,
  acc = TRUE,
  collin = TRUE)

model2.jmv
```

BINOMIAL LOGISTIC REGRESSION

Model Fit Measures

Model	Deviance	AIC	R^2-McF	<U+03C7>^{2}	df	p
1	67.4	71.4	0.295	28.1	1	< .001
2	45.3	51.3	0.526	50.3	2	< .001

Model Comparisons

Model		Model	<U+03C7>^{2}	df	p
1	-	2	22.1	1	< .001

MODEL SPECIFIC RESULTS

MODEL 1

Model Coefficients

Predictor	Estimate	SE	Z	p	Odds ratio
Intercept	0.139	0.304	0.457	0.648	1.15
HoursC	2.973	0.667	4.458	< .001	19.54

Note. Estimates represent the log odds of "Re = Yes" vs. "Re = No"

ASSUMPTION CHECKS

Collinearity Statistics

VIF	Tolerance

HoursC 1.00 1.00

PREDICTION

Classification Table – Re			
Observed	No	Yes	% Correct
No	28	5	84.8
Yes	5	31	86.1

Note. The cut-off value is set to 0.5

Predictive Measures

Accuracy
0.855

Note. The cut-off value is set to 0.5

MODEL 2

Model Coefficients					
Predictor	Estimate	SE	Z	p	Odds ratio
Intercept	0.1737	0.37858	0.459	0.646	1.19
HoursC	2.5360	0.78704	3.222	0.001	12.63
TipsC	0.0256	0.00735	3.490	< .001	1.03

Note. Estimates represent the log odds of "Re = Yes" vs. "Re = No"

ASSUMPTION CHECKS

Collinearity Statistics		
	VIF	Tolerance
HoursC	1.03	0.968
TipsC	1.03	0.968

PREDICTION

Classification Table – Re			
Observed	No	Yes	% Correct
No	29	4	87.9
Yes	5	31	86.1

Note. The cut-off value is set to 0.5

Predictive Measures

Accuracy
0.870

Note. The cut-off value is set to 0.5

Use regression equation to calculate predicted logit, odds, and probability

```
#Discussion: star performer Trudy
print("Given that Trudy works 7 hours of ovetime and makes $100 in tips, the odds she will remain for an
```

[1] "Given that Trudy works 7 hours of ovetime and makes $100 in tips, the odds she will remain for another year:"

```
# Let OT = Overtime Hours, T = tips
OT = 7
T = 100

print("Model - Full model")
```

[1] "Model - Full model"

```
predlogit <- .17 + (2.54*OT) + (.03*T)
predodds <- exp(predlogit)
predprob <- predodds / (1 + predodds)

print("Predicted Logit")
```

[1] "Predicted Logit"

```
predlogit
```

[1] 20.95

```
print("Predicted Odds")
```

[1] "Predicted Odds"

```
predodds
```

[1] 1254496332

```
print("Predicted Probability")
```

[1] "Predicted Probability"

```
predprob
```

[1] 1