

Homework4

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```
pacman::p_load(data.table, MASS, ggplot2, dplyr, ISLR, RColorBrewer,
               rpart, rpart.plot, gbm, caret, tree, leaps, moments, randomForest, gains)
knitr::opts_chunk$set(echo = TRUE, fig.height=8, fig.width=12, fig.path = 'Figs/')
theme_set(theme_classic())
options(digits = 3)
```

```
data(Hitters)
head(Hitters)
```

```
##           AtBat Hits HmRun Runs RBI Walks Years CAtBat CHits CHmRun
## -Andy Allanson   293   66    1   30  29   14    1    293   66    1
## -Alan Ashby      315   81    7   24  38   39   14   3449   835   69
## -Alvin Davis      479  130   18   66  72   76    3   1624   457   63
## -Andre Dawson     496  141   20   65  78   37   11   5628  1575  225
## -Andres Galarra   321   87   10   39  42   30    2    396   101   12
## -Alfredo Griffin  594  169    4   74  51   35   11   4408  1133   19
##           CRuns CRBI CWalks League Division PutOuts Assists Errors
## -Andy Allanson    30   29   14      A      E      446    33    20
## -Alan Ashby       321  414   375    N      W      632    43    10
## -Alvin Davis       224  266   263    A      W      880    82    14
## -Andre Dawson      828  838   354    N      E      200    11    3
## -Andres Galarra    48   46   33     N      E     805    40    4
## -Alfredo Griffin  501  336   194    A      W     282   421   25
##           Salary NewLeague
## -Andy Allanson     NA      A
## -Alan Ashby        475.0    N
## -Alvin Davis        480.0    A
## -Andre Dawson       500.0    N
## -Andres Galarra     91.5     N
## -Alfredo Griffin   750.0     A
```

```
tail(Hitters)
```

```
##           AtBat Hits HmRun Runs RBI Walks Years CAtBat CHits CHmRun
## -Wayne Krenchicki  221   53    2   21  23   22    8   1063   283   15
## -Willie McGee      497  127    7   65  48   37    5   2703   806   32
## -Willie Randolph   492  136    5   76  50   94   12   5511  1511   39
## -Wayne Tolleson    475  126    3   61  43   52    6   1700   433    7
## -Willie Upshaw     573  144    9   85  60   78    8   3198   857   97
## -Willie Wilson     631  170    9   77  44   31   11   4908  1457   30
```

```
##           CRuns CRBI CWalks League Division PutOuts Assists Errors
## -Wayne Krenchicki  107  124   106     N       E    325    58     6
## -Willie McGee      379  311   138     N       E    325     9     3
## -Willie Randolph   897  451   875     A       E    313   381    20
## -Wayne Tolleson    217   93   146     A       W     37   113     7
## -Willie Upshaw     470  420   332     A       E   1314   131    12
## -Willie Wilson     775  357   249     A       W    408    4     3
##           Salary NewLeague
## -Wayne Krenchicki    NA      N
## -Willie McGee        700      N
## -Willie Randolph     875      A
## -Wayne Tolleson      385      A
## -Willie Upshaw       960      A
## -Willie Wilson      1000      A
```

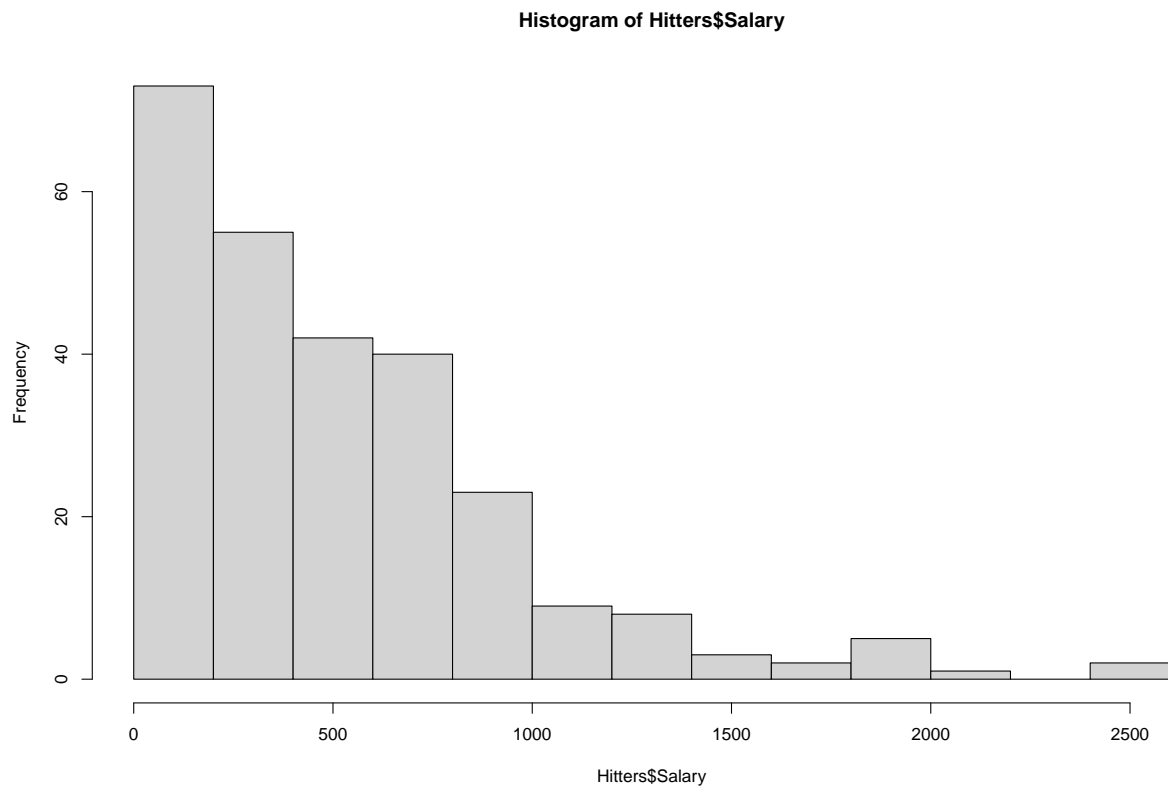
```
colSums(is.na(Hitters))
```

```
##      AtBat      Hits      HmRun      Runs      RBI      Walks      Years      CAtBat
##         0         0         0         0         0         0         0         0
##      CHits     CHmRun     CRuns     CRBI     CWalks     League     Division     PutOuts
##         0         0         0         0         0         0         0         0
##      Assists     Errors     Salary NewLeague
##         0         0         59         0
```

```
Hitters <- Hitters[!is.na(Hitters$Salary), ]
```

1 Ans: The dataset had 322 observations initially. When I checked for missing values in the dataset which had observations with unknown salary information, I found out that there were 59 observations having missing values. So those 59 observations were removed, leaving 263 observations in this dataset.

```
hist(Hitters$Salary)
```

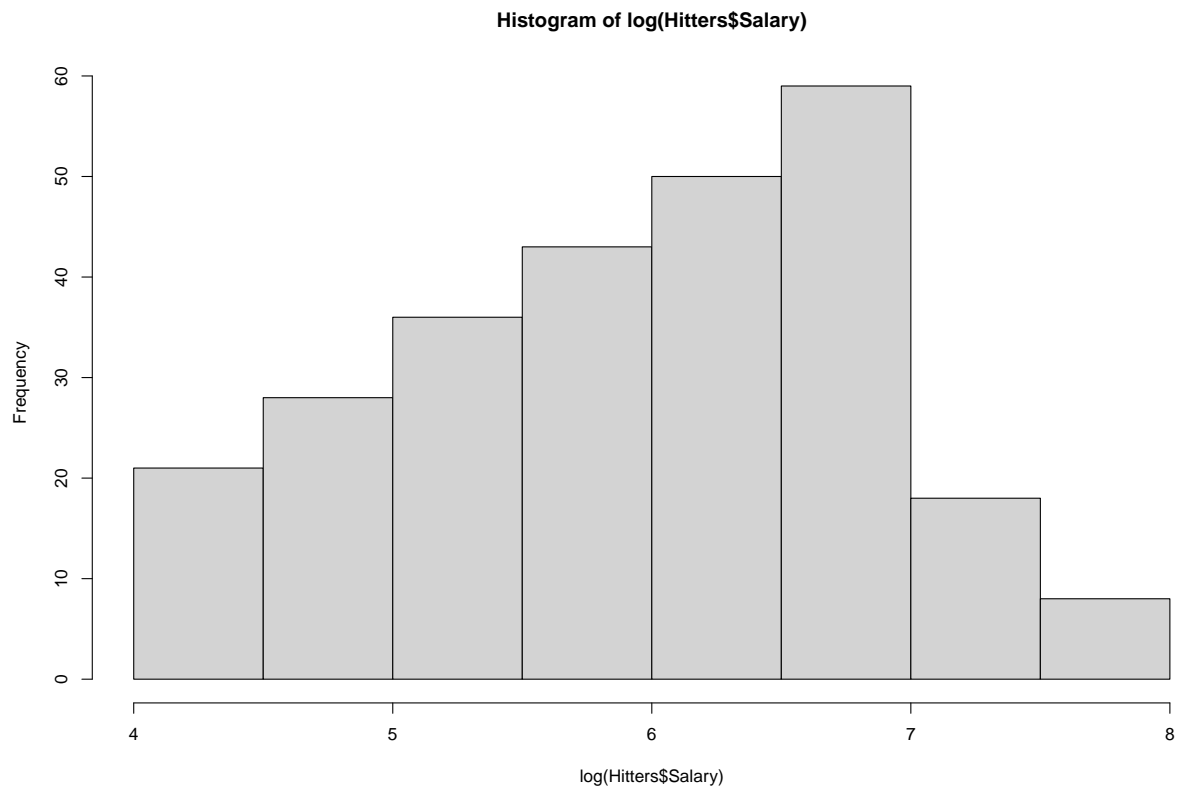


```
skewness(Hitters$Salary)
```

```
## [1] 1.58
```

2 Ans: To transform the salaries using a natural log transformation, let's first visualize how our data looks like. By looking at the above histogram we can see that it is right skewed with a skewness of 1.58. Logarithmic transformation is transforming a highly skewed variable into a more normalized distribution. Hence, let us see what impact does log transformation of the salary have on skewness.

```
hist(log(Hitters$Salary))
```



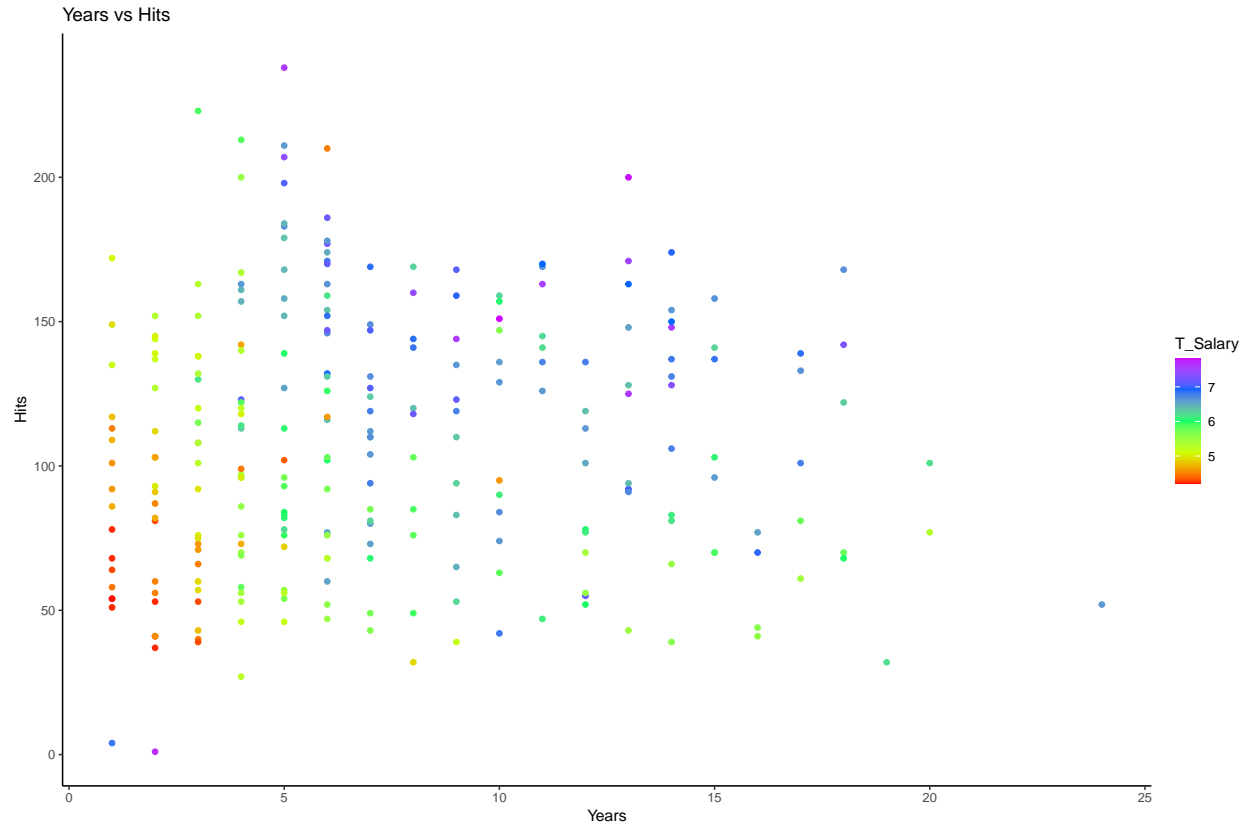
```
skewness(log(Hitters$Salary))
```

```
## [1] -0.181
```

From above we can see that the skewness has been significantly decreased to -0.181. So now we make changes in the dataset by transforming the salaries.

```
T_Salary<- Hitters[,19]
T_Salary<- log(T_Salary)
Hitters<-Hitters[,1:19]
Hitters<-cbind(Hitters,T_Salary)
```

```
ggplot(Hitters, aes (x=Years, y=Hits))+ geom_point(aes(color = T_Salary)) +
  scale_color_gradientn(colours = rainbow(5)) +
  ggtitle("Years vs Hits")
```



3 Ans: From the above scatter plot we can see that by considering players having 0-5 years of experience, the salary is on the lower end of the spectrum regardless of having higher number of hits. And as number of years are increasing, the salary is also increasing. There are more number of players who have 7 or less years of experience. There is an outlier where players have higher salary as compared to the other players with the same number of experience and higher hits.

```
options(digits=6)
search <- regsubsets(T_Salary ~ ., data = Hitters, nbest = 1,
                     nvmax = dim(Hitters),
                     method = "exhaustive")
sum <- summary(search)
sum$which
```

##	(Intercept)	AtBat	Hits	HmRun	Runs	RBI	Walks	Years	CAtBat	CHits	CHmRun
## 1	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
## 2	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
## 3	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
## 4	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE
## 5	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	TRUE	FALSE
## 6	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	TRUE	FALSE
## 7	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
## 8	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
## 9	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
## 10	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
## 11	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
## 12	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
## 13	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE
## 14	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	TRUE	TRUE	TRUE	FALSE	FALSE

```
## 15      TRUE TRUE TRUE TRUE FALSE FALSE TRUE TRUE TRUE TRUE TRUE FALSE
## 16      TRUE TRUE TRUE TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE FALSE
## 17      TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE FALSE
## 18      TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE FALSE
## 19      TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
##      CRuns  CRBI CWalks LeagueN DivisionW PutOuts Assists Errors NewLeagueN
## 1  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## 2  FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## 3  FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## 4  FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## 5  FALSE FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE
## 6  FALSE FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE
## 7  TRUE FALSE TRUE FALSE FALSE FALSE TRUE FALSE FALSE FALSE
## 8  TRUE FALSE TRUE FALSE TRUE TRUE FALSE FALSE FALSE FALSE
## 9  TRUE FALSE TRUE TRUE TRUE TRUE FALSE FALSE FALSE FALSE
## 10 TRUE FALSE TRUE TRUE TRUE TRUE FALSE FALSE FALSE TRUE
## 11 TRUE FALSE TRUE TRUE TRUE TRUE FALSE FALSE FALSE TRUE
## 12 TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE FALSE
## 13 TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## 14 TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## 15 TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## 16 TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## 17 TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## 18 TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## 19 TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
```

```
sum$bic
```

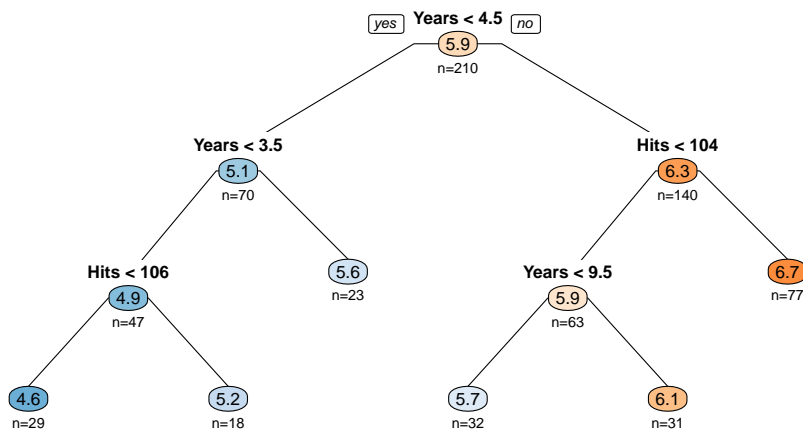
```
## [1] -117.030 -156.429 -159.278 -159.218 -159.089 -157.921 -157.123 -156.195
## [9] -152.765 -148.806 -144.596 -140.654 -136.548 -131.094 -125.711 -120.199
## [17] -114.713 -109.186 -103.614
```

4 Ans: We know that lower the BIC value better is the model, and in order to calculate the BIC value, I have used `regsubsets()` to perform best subset selection from the regression model in the above code with the exhaustive method. So if we consider above BIC values, “-159.278” is the lowest among all others which gives us the sub-model 3 in exhaustive search as the best model having the following predictors: 1.Hits 2.Walks 3.Years

5 Ans: Creating a training dataset consisting of 80% of the observations and test/validation dataset consisting of the remaining observations.

```
set.seed(42)
train.index<-sample(1:nrow(Hitters), nrow(Hitters)*0.8)
train.df <- Hitters[train.index, ]
valid.df<- Hitters[-train.index, ]

dpr.ct <- rpart(T_Salary ~ Years + Hits, data = train.df,
               method = "anova")
prp(dpr.ct, type = 1, extra = 1, under = TRUE,roundint=FALSE,
    split.font = 2, varlen = -10,
    box.palette = "BuOr")
```



```

for(i in 1:nrow(Hitters))
{
if(((Hitters$Hits[i]>= 104) && Hitters$Years[i] >= 4.5))
{
print(row.names(Hitters)[i])
}
}

```

```

## [1] "-Andre Dawson"
## [1] "-Alfredo Griffin"
## [1] "-Alan Trammell"
## [1] "-Buddy Bell"
## [1] "-Bob Brenly"
## [1] "-Bill Buckner"
## [1] "-Brett Butler"
## [1] "-Bo Diaz"
## [1] "-Bill Doran"
## [1] "-Brian Downing"
## [1] "-Brook Jacoby"
## [1] "-Bill Madlock"
## [1] "-Chili Davis"
## [1] "-Carney Lansford"
## [1] "-Cal Ripken"
## [1] "-Don Baylor"
## [1] "-Doug DeCinces"
## [1] "-Darrell Evans"
## [1] "-Dwight Evans"

```

[1] "-Damaso Garcia"
[1] "-Don Mattingly"
[1] "-Dale Murphy"
[1] "-Dave Parker"
[1] "-Denny Walling"
[1] "-Dave Winfield"
[1] "-Eddie Milner"
[1] "-Eddie Murray"
[1] "-Frank White"
[1] "-George Bell"
[1] "-George Brett"
[1] "-Gary Carter"
[1] "-Gary Gaetti"
[1] "-Gary Pettis"
[1] "-Garry Templeton"
[1] "-Gary Ward"
[1] "-Glenn Wilson"
[1] "-Harold Baines"
[1] "-Hubie Brooks"
[1] "-Jesse Barfield"
[1] "-Jose Cruz"
[1] "-Jody Davis"
[1] "-Julio Franco"
[1] "-Jim Gantner"
[1] "-Jim Morrison"
[1] "-Johnny Ray"
[1] "-Jim Rice"
[1] "-Kevin Bass"
[1] "-Kirk Gibson"
[1] "-Ken Griffey"
[1] "-Keith Hernandez"
[1] "-Kent Hrbek"
[1] "-Keith Moreland"
[1] "-Ken Oberkfell"
[1] "-Leon Durham"
[1] "-Lee Lacy"
[1] "-Lloyd Moseby"
[1] "-Larry Parrish"
[1] "-Lou Whitaker"
[1] "-Marty Barrett"
[1] "-Mike Davis"
[1] "-Mike Easler"
[1] "-Mel Hall"
[1] "-Mookie Wilson"
[1] "-Ozzie Smith"
[1] "-Paul Molitor"
[1] "-Pat Tabler"
[1] "-Ron Hassey"
[1] "-Rickey Henderson"
[1] "-Ray Knight"
[1] "-Ron Oester"
[1] "-Rafael Ramirez"
[1] "-Ryne Sandberg"
[1] "-Roy Smalley"


```

## [1] "-Robin Yount"
## [1] "-Steve Balboni"
## [1] "-Scott Fletcher"
## [1] "-Steve Garvey"
## [1] "-Steve Sax"
## [1] "-Tony Bernazard"
## [1] "-Tom Brunansky"
## [1] "-Tony Gwynn"
## [1] "-Tommy Herr"
## [1] "-Tony Pena"
## [1] "-Tony Phillips"
## [1] "-Tim Wallach"
## [1] "-Von Hayes"
## [1] "-Wally Backman"
## [1] "-Wade Boggs"
## [1] "-Willie McGee"
## [1] "-Willie Randolph"
## [1] "-Wayne Tolleson"
## [1] "-Willie Upshaw"
## [1] "-Willie Wilson"

```

6 Ans: From the above tree we can see that highest salary is transformed salary of 6.7, so the rule for players receiving the highest salary is Years should be 4.5 or more and Number of hits should be greater than or equals 104. The players likely to receive highest salaries according to this model are as stated above in the results.