DATA621_HW1 Spring'18

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Purpose

This assignment explores, analyzes , and models data from baseball team seasons from 1871-2006 inclusive (stats adjusted to match 162-game season). Each record represents the performance of a given baseball team per year.

The goal is to create a model that can predict baseball team wins based on the performance metrics captured in the training dataset `moneyball-training-data.csv` and then review the predictive quality by running the model with `moneyball-evaluation-data.csv` the testing dataset.

Data Exploration

High-level Findings

- There are ~2300 observations with 16 variables included
- Five of the variables have a number of missing values
- Two of the variables have outliers
- Multicollinearity present in seven variables
- Untransformed (raw) data is not highly correlated with response

Findings Detail

The below investigation was completed prior to model-fitting in order to get a sense for the density and quality of the training data set and to preview what types of actions may need to be taken in the model-fitting steps.

Summary Statistics:

Table 1: Selected Stats

	vars	n	mean	sd	median	min	max	range	kurtosis	IQR
TARGET_WINS	1	2276	80.79	15.75	82.0	0	146	146	1.03	21.00
TEAM_BATTING_H	2	2276	1469.27	144.59	1454.0	891	2554	1663	7.28	154.25
TEAM_BATTING_2B	3	2276	241.25	46.80	238.0	69	458	389	0.01	65.00
TEAM_BATTING_3B	4	2276	55.25	27.94	47.0	0	223	223	1.50	38.00
TEAM_BATTING_HR	5	2276	99.61	60.55	102.0	0	264	264	-0.96	105.00
TEAM_BATTING_BB	6	2276	501.56	122.67	512.0	0	878	878	2.18	129.00
TEAM_BATTING_SO	7	2174	735.61	248.53	750.0	0	1399	1399	-0.32	382.00
TEAM_BASERUN_SB	8	2145	124.76	87.79	101.0	0	697	697	5.49	90.00
TEAM_BASERUN_CS	9	1504	52.80	22.96	49.0	0	201	201	7.62	24.00
TEAM_BATTING_HBP	10	191	59.36	12.97	58.0	29	95	66	-0.11	16.50
TEAM_PITCHING_H	11	2276	1779.21	1406.84	1518.0	1137	30132	28995	141.84	263.50

	vars	n	mean	sd	median	min	max	range	kurtosis	IQR
TEAM_PITCHING_HR	12	2276	105.70	61.30	107.0	0	343	343	-0.60	100.00
TEAM_PITCHING_BB	13	2276	553.01	166.36	536.5	0	3645	3645	96.97	135.00
TEAM_PITCHING_SO	14	2174	817.73	553.09	813.5	0	19278	19278	671.19	353.00
TEAM_FIELDING_E	15	2276	246.48	227.77	159.0	65	1898	1833	10.97	122.25
TEAM_FIELDING_DP	16	1990	146.39	26.23	149.0	52	228	176	0.18	33.00

Missing Values:

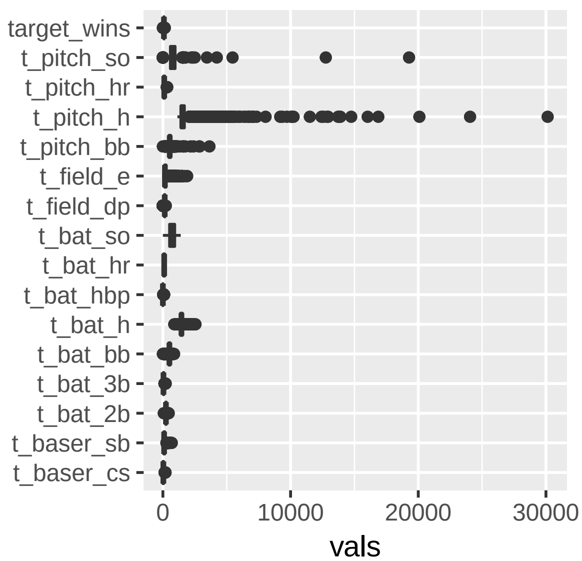
Review of the NA's (see column `n`, Table1) revealed the following sparse variables. The value after the variable name represents the number of missing values followed % density on 2,276 records available in most (11 of 16) variables:

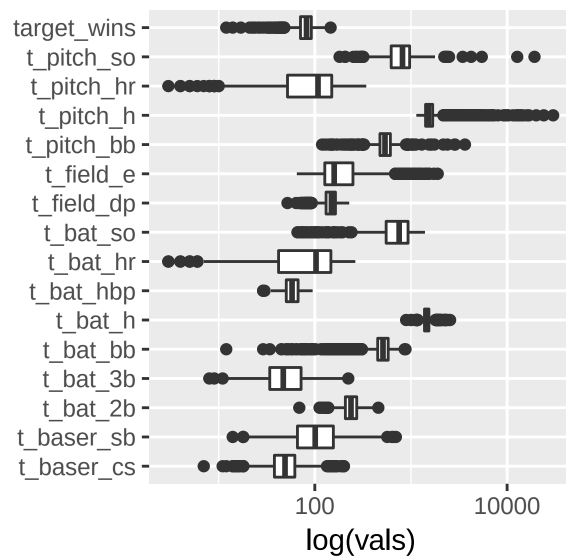
- `TEAM_BATTING_HBP`: 2085: 8%
- `TEAM_BASERUN_CS`: 772: 66%
- `TEAM_FIELDING_DP`: 286: 87%
- `TEAM_PITCHING_SO`: 102: 96%
- `TEAM_BATTING_SO`: 102: 96%

Outliers:

Below, a preview of each variable in the data using box plots reveals at least 2 variables containing points with significant outliers:

- `TEAM_PITCHING_H` (hits allowed by pitchers)
- `TEAM_PITCHING_SO` (strikeouts by pitchers)

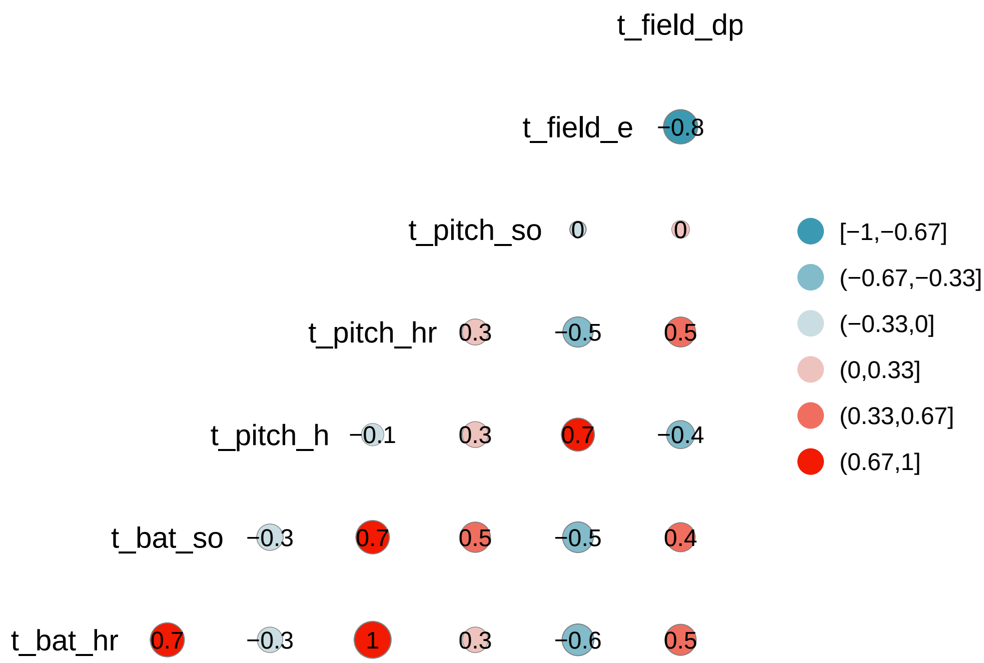




Note that the right-hand side plot is a duplicate of the left-hand plot but uses a log scale for the value-axis.

Multicollinearity

The below heat-map style plot highlights the correlation that exists between some of the predictor variables in the training set:



From the above plot above, selected variables and their respective correlation to other selected variables include:

- `TEAM_BATTING_HR` and `TEAM_BATTING_SO` (HRs by batters and Strikeouts by batters)
- `TEAM_BATTING_SO` and `TEAM_PITCHING_HR` (Strikeouts by batters and HR's allowed by pitchers)
- `TEAM_BATTING_HR` and `TEAM_PITCHING_HR` (HRs by batters and HRs allowed by pitch)
- `TEAM_FIELDING_E` and `TEAM_PITCHING_H` (Fielding errors and Hits allowed by pitchers)
- `TEAM_FIELDING_DP` and `TEAM_FIELDING_E` (Double-plays and fielding errors)

The presence of these values could indicate that some of these variables are doing 'double-duty' and may be removed in the fitting process with little loss of information.

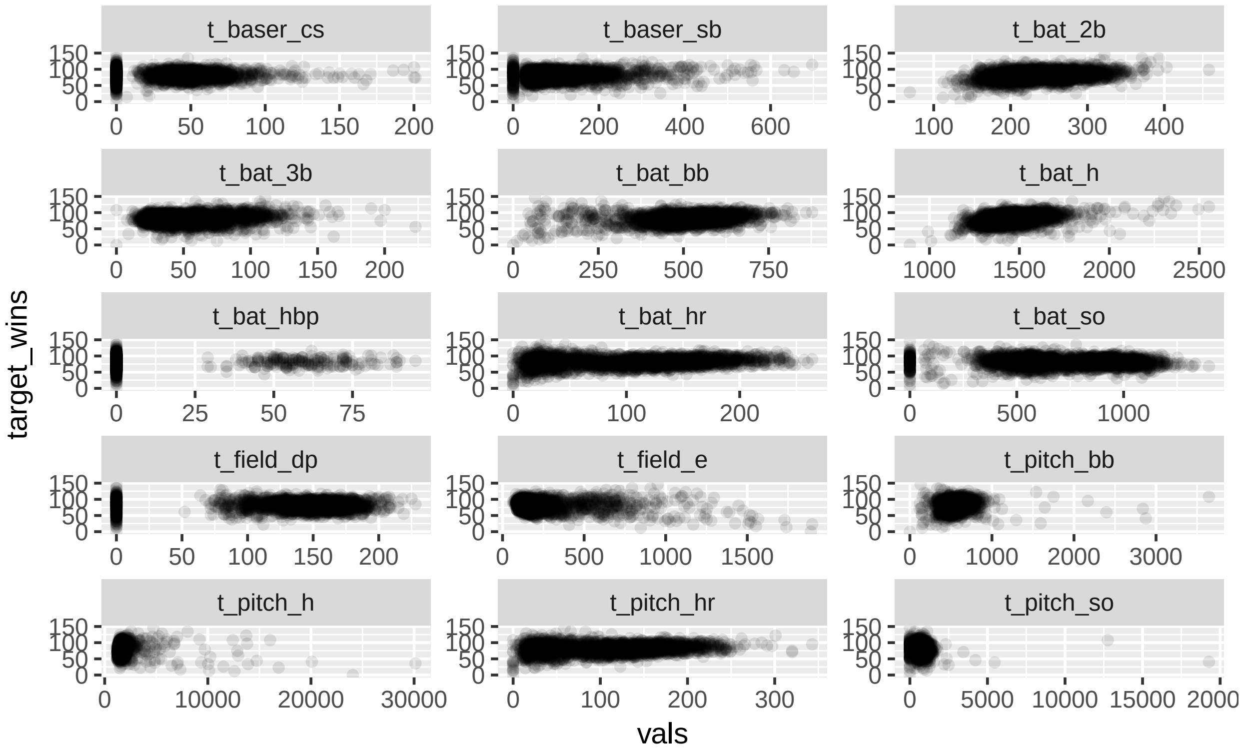
Low Correlation To Response Variable

Pre-transformation `TARGET_WINS` vs. all other variables within the dataset in isoloation results in low correlation values and hints that transformations may be necessary in the modelling stage.

Table 2: Abs. Correlation Betwen Target Wins and other variables

var_name	abs_cor_val	cor_val
target_wins	1.0000	1.0000
t_bat_h	0.3888	0.3888
t_bat_2b	0.2891	0.2891
t_bat_bb	0.2326	0.2326
t_pitch_hr	0.1890	0.1890
t_field_e	0.1765	-0.1765

Plotting all the variables against `TARGET_WINS` further highlights these low values:



For convenience, the above plot was built by substituting 0's for `NA`'s for all data but model fits do not. The primary takeaway is that in isolation, none of the variables appears to be a great predictor of `TARGET_WINS`.

Data Preperation

Several different methods were investigated. The below provides a summary of methods used to prepare each of the data-sets for 3 different model fits for the purpose of prediction.

Below, I have outlined the steps taken to prepare individual data-sets for each model.

Model 1 Data:

Motivation: Based on the most complete set of records with minimal imputation:

- For `TEAM_BATTING_SO` and `TEAM_PITCHING_SO`, `NA`-values replaced with the `mean` and `median` respectively to address normal and skewed distributions respectively - these variables were only missing 4% of their records.
- Removed `TEAM_BATTING_HBP` because of its numerous missing values (92% of records missing values for this variable.)

Model 2 Data:

Motivation: a refinement of the first model data-set that excludes variables that may be doing 'double-duty':

- Replace `NA` with `mean` for: `TEAM_FIELD_DP` to cover 13% of missing values
- Replace `NA` with `median` for `TEAM_PITCH_SO` to cover 4% missing values

- Remove `TEAM_BATTING_SO` because it's highly correlated with `TEAM_PITCHING_SO`
- Remove `TEAM_BASERUN_CS` and `TEAM_BATTING_HBP` because 44% and 92% of records are missing respectively.

Model3 Data:

Motivation: Address all/most multicollinearity encountered and reduce the number of predictors overall to simplify the model. Variable selection between correlated predictors was based on 'hitting-variables' because those intuitively may result in more runs, and therefore, more wins.

- Remove `TEAM_BASERUN_CS` and `TEAM_BATTING_HBP` because 44% and 92% of records are missing respectively.
- Remove `TEAM_BATTING_2B/3B/HR` as `TEAM_BATTING_H` covers all hit types - this is an attempt to simplify the model fit
- Remove one side of the correlated pairs focusing on batting-related variables such that:
  - `TEAM_BATTING_SO` kept in, removed `TEAM_PITCHING_SO`
  - `TEAM_BATTING_H` kept in, removed `TEAM_PITCHING_H`
  - `TEAM_PITCHING_HR` kept in, removed `TEAM_BATTING_HR` as `TEAM_BATTING_H` covers all hits
  - `TEAM_FIELDING_E` kept in, removed `TEAM_FIELDING_DP`

Build Models

Model Fitting

Models were fit with the respective data-sets created in the previous section. Each section will display the resulting fit's coefficients but the discussion of the coefficients will be saved for the *Model Selection* section.

Fit1:

Fit1 utilized the `stepAIC` function from the `MASS` package to perform step-wise model selection by AIC. I used this auto-selection method to investigate an off-the-shelf model's performance with no additional transformations or imputation beyond what was originally discussed.

Table 3: Model 1 coefficients

Vars	Coefs.
(Intercept)	58.4461
t__bat__h	0.0255
t__bat__2b	-0.0698
t__bat__3b	0.1616
t__bat__hr	0.0977
t__bat__bb	0.0395
t__baser__sb	0.0360
t__baser__cs	0.0518
t__pitch__h	0.0091
t__pitch__so	-0.0208
t__field__e	-0.1560
t__field__dp	-0.1131

Model 2 Fit:

An attempt at employing the `powerTransform` function from the `car` package to see if box-cox would yeild any transformation but my result was $\lambda \approx 1$ so I did not transform the model.

Table 4: Model 2 coefficients

Vars	Coefs.
(Intercept)	29.7307
t__bat__h	0.0422
t__bat__2b	-0.0490
t__bat__3b	0.0741
t__bat__hr	0.0147
t__bat__bb	0.0303
t__baser__sb	0.0565
t__pitch__h	0.0027
t__pitch__hr	0.0557
t__pitch__bb	-0.0030
t__pitch__so	-0.0102
t__field__e	-0.0517
t__field__dp	-0.1168

Model 3 Fit:

The result of the box-cox transform here was a value of $\lambda \approx 1$ which again called for no transformation.

Table 5: Model 3 coefficients

Vars	Coefs.
(Intercept)	24.3922
t__bat__h	0.0343
t__bat__bb	0.0239
t__bat__so	-0.0160
t__baser__sb	0.0558
t__pitch__hr	0.0681
t__pitch__bb	-0.0034
t__field__e	-0.0346

Select Models

Criteria:

My selection criteria is based on comparing R^2 and F-Statistics. If the performance is similar across these measures, I will select the model that is the easiest to describe of the two.

Model Selection:

I utilized the `stargazer` package to create the table below that compares Models 1, 2, and 3. Note that at the bottom of the table the models are compared by R^2, adjusted R^2, and the F-statistic.

```
##
## ===============================================================================================
##                                             Dependent variable:
##              ---------------------------------------------------------------------------------
##                                                 target_wins
##                          (1)                           (2)                           (3)
## -----------------------------------------------------------------------------------------------
## t_bat_h          0.026*** (0.006)          0.042*** (0.004)          0.034*** (0.003)
## t_bat_2b        -0.070*** (0.009)         -0.049*** (0.009)
## t_bat_3b         0.162*** (0.022)          0.074*** (0.017)
## t_bat_hr         0.098*** (0.009)           0.015 (0.027)
## t_bat_bb         0.039*** (0.003)          0.030*** (0.006)          0.024*** (0.004)
## t_bat_so                                                            -0.016*** (0.002)
## t_baser_sb       0.036*** (0.009)          0.057*** (0.004)          0.056*** (0.004)
## t_baser_cs       0.052*** (0.018)
## t_pitch_h        0.009*** (0.002)         0.003*** (0.0004)
## t_pitch_hr                                 0.056** (0.025)           0.068*** (0.008)
## t_pitch_bb                                  -0.003 (0.004)            -0.003 (0.003)
## t_pitch_so      -0.021*** (0.002)         -0.010*** (0.002)
## t_field_e       -0.156*** (0.010)         -0.052*** (0.003)         -0.035*** (0.003)
## t_field_dp      -0.113*** (0.013)         -0.117*** (0.012)
## Constant        58.446*** (6.589)         29.731*** (5.187)         24.392*** (4.803)
## -----------------------------------------------------------------------------------------------
## Observations           1,486                     2,145                     2,043
## R2                     0.438                     0.374                     0.337
## Adjusted R2            0.434                     0.370                     0.335
## F Statistic  104.596*** (df = 11; 1474) 106.144*** (df = 12; 2132) 147.644*** (df = 7; 2035)
## ===============================================================================================
## Note:                                                          *p<0.1; **p<0.05; ***p<0.01
```

Observations from these 3 models:

- None of the 3 models have very high R^2 values.
- Each model's F-statistic indicates that there is a relationship between predictor and the response variables included in the fits

Coefficients:

Model1: The intercept ('Constant') is too low for the mean value of `TARGET_WINS` but it's not likely that every baseball team will get ~58 wins a season. The signs of the coefficients are problematic for several cases e.g. `TEAM_BASERUN_CS` (caught stealing) is positive but that would be detrimental to the wins and `TEAM_FIELDING_E` (fielding errors) are negative but fielding errors would lead to more on-bases and therefore, more runs.

Model2: More-intuitive intercept value but similarly un-intuitive coefficient signs that mirror the issues pointed out in Model1.

Model3: This model contains the fewest variables but 2 of them still have problematic signs including `TEAM_FIELDING_E` and `TEAM_PITCHING_BB` which I would expect to be positively correlated with wins.

Based on my criteria, since the performance of Model 1 is superior compared to the three models, I have selected **Model 1**.

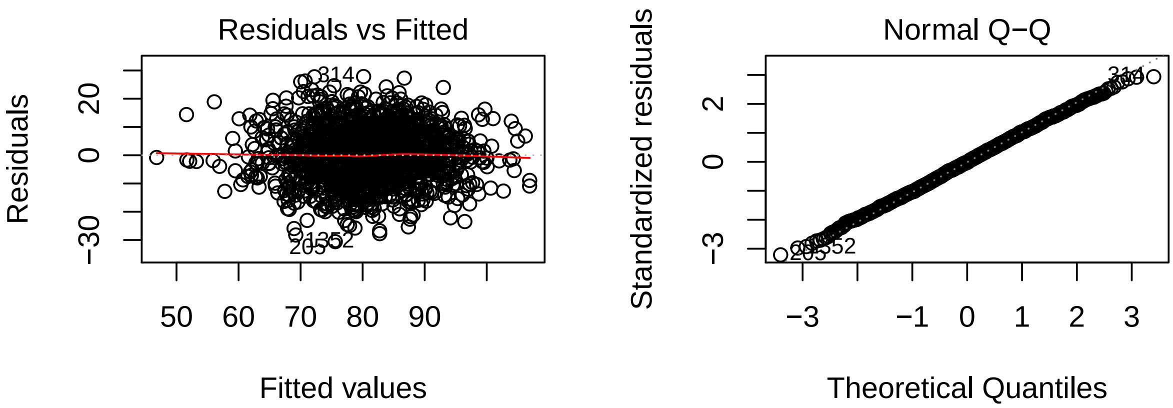
Model Evaluation:

```
##
## Call:
## lm(formula = target_wins ~ t_bat_h + t_bat_2b + t_bat_3b + t_bat_hr +
##     t_bat_bb + t_baser_sb + t_baser_cs + t_pitch_h + t_pitch_so +
##     t_field_e + t_field_dp, data = f1_bsb_raw[, -1])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -30.5830  -6.7313  -0.1643   6.5323  27.8502
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 58.446058   6.588864   8.870  < 2e-16 ***
## t_bat_h      0.025502   0.005837   4.369 1.34e-05 ***
## t_bat_2b    -0.069828   0.009292  -7.515 9.86e-14 ***
## t_bat_3b     0.161620   0.022159   7.294 4.91e-13 ***
## t_bat_hr     0.097746   0.009435  10.360  < 2e-16 ***
## t_bat_bb     0.039484   0.003356  11.765  < 2e-16 ***
## t_baser_sb   0.036034   0.008668   4.157 3.41e-05 ***
## t_baser_cs   0.051768   0.018200   2.844 0.004511 **
## t_pitch_h    0.009070   0.002353   3.855 0.000121 ***
## t_pitch_so  -0.020827   0.002312  -9.006  < 2e-16 ***
## t_field_e   -0.155970   0.009917 -15.728  < 2e-16 ***
## t_field_dp  -0.113149   0.013121  -8.623  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.548 on 1474 degrees of freedom
##   (790 observations deleted due to missingness)
## Multiple R-squared:  0.4384, Adjusted R-squared:  0.4342
## F-statistic: 104.6 on 11 and 1474 DF,  p-value: < 2.2e-16
```

The summary output from Model 1, above, reveals a number of challenges:

- The `Intercept` value of ~ 60 could be too high given that `TARGET_WINS` can take values as low as 0 (team loses all games) but it could also be too low given that the `mean` and `median` is *approx* 80.
- The coefficients have very low p-values so the observed data is extremely unlikely to to have arisen if the the null hypothesis were true (i.e. that $H_0 : \beta_i = 0$ so we can reject the null hypothesis)
- 790 observations related to the missing values in columns `TEAM_BATTING_HBP`
- The R^2 and multiple R^2 values are low ($R^2 < .70$) at $\approx .43$ - this indicates to me that the data isn't very close to the fitted regression and may provide poor predictions
- The negative coefficients under `TEAM_BATTING_2B` and other base-gaining activities is counter-intuitive as getting on-base intuitively would result in more wins.

Below, the residual and QQ plots of *Model1* appear to support a normal classification with some reservations. The residuals vs. the fitted plot appear to have a slight 'kink' when I expected an even, straight line. The normal QQ plot doesn't deviate from the diagnol except in a few outlying cases.

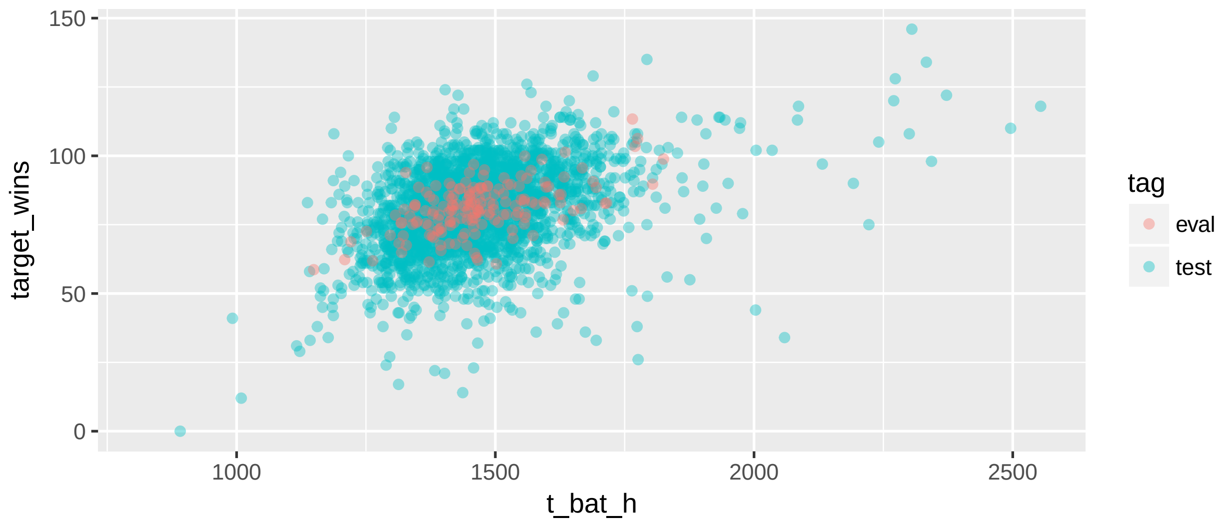


Model CI:

```
##                     2.5 %      97.5 %
## (Intercept) 45.521508029 71.37060756
## t_bat_h      0.014051637  0.03695139
## t_bat_2b    -0.088055314 -0.05160018
## t_bat_3b     0.118153213  0.20508673
## t_bat_hr     0.079239109  0.11625374
## t_bat_bb     0.032900919  0.04606681
## t_baser_sb   0.019031119  0.05303599
## t_baser_cs   0.016067233  0.08746819
## t_pitch_h    0.004455242  0.01368480
## t_pitch_so  -0.025362847 -0.01629076
## t_field_e   -0.175422721 -0.13651774
## t_field_dp  -0.138887843 -0.08741043
```

Prediction:

Below, I've used the evaluation data set, predicted the wins based on its ~200 records, and plotted the `TARGET_WINS` vs `TEAM_BATTING_H`. You can see the values wins predicted based on model 1 red in color.



R Code for Assignment 1:

```
#confint(fitA)
```

```
knitr::opts_chunk$set(echo = TRUE)
#library(memisc)
library(stargazer)
library(tidyverse)
#library(GGally)
# read in data.
bsb_train_raw <- read.csv("moneyball-training-data.csv")
mini_tbl<-psych::describe(bsb_train_raw[,-1], IQR=T)[,c(1:5,8:10,12,14)]

bsb_train <- data.table::setnames(bsb_train_raw,
                                  tolower(names(bsb_train_raw[1:17])))
bsb_train[is.na(bsb_train)] <- 0  # used for simple plots - not used for model fitting
                                  # see data preperation section for more details.
col_name_updater <- function(x, text_to_updt, replc_text){
  colnames(x) = gsub(text_to_updt, replc_text, colnames(x))
  return(x)
}
# shorten and clean colnames
c1 <- col_name_updater(bsb_train, "batting", "bat")
c2 <- col_name_updater(c1, "pitching", "pitch")
c3 <- col_name_updater(c2, "fielding", "field")
c4 <- col_name_updater(c3, "baserun", "baser")
bsb_data <- col_name_updater(c4, "team", "t")
rm(c1,c2,c3, c4)

c1 <- col_name_updater(bsb_train_raw, "batting", "bat")
c2 <- col_name_updater(c1, "pitching", "pitch")
c3 <- col_name_updater(c2, "fielding", "field")
c4 <- col_name_updater(c3, "baserun", "baser")
bsb_train_raw <- col_name_updater(c4, "team", "t")
```

```r
rm(c1,c2,c3, c4)
knitr::kable(round(mini_tbl,2), caption = "Selected Stats")
rm(mini_tbl)

p1 <- bsb_data %>%
  gather(-index, key = "vars", value = "vals") %>%
  select_("vars", "vals") %>%
  ggplot() +
  geom_boxplot(aes(x = vars, y=vals)) +
  coord_flip() + xlab("")

p2 <- bsb_data %>%
  gather(-index, key = "vars", value = "vals") %>%
  select_("vars", "vals") %>%
  ggplot() +
  geom_boxplot(aes(x = vars, y=vals)) +
  scale_y_log10() +
  coord_flip() + ylab("log(vals)") + xlab("")

suppressMessages(gridExtra::grid.arrange(p1, p2, nrow=1))

# check correlations between prediction vars:
GGally::ggcorr(bsb_data[,c(6,8,12,13,15:17)],
               geom = "circle", nbreaks = 6,
               label=T, label_size = 3)
# see if there's cor btween target wins and others...
sm_tab <- cor(bsb_data[,-1]) %>% as.data.frame() %>%
  tibble::rownames_to_column(var = "var_name") %>%
  mutate(cor_val = round(target_wins , 4),
         abs_cor_val = abs(cor_val)) %>%
  select_("var_name", "abs_cor_val", "cor_val") %>%
  arrange(desc(abs_cor_val)) %>%
  na.omit()
knitr::kable(head(sm_tab), caption = "Abs. Correlation Betwen Target Wins and other variables")
bsb_data[,-1] %>%
  gather(-target_wins, key = "vars", value = "vals") %>%
  ggplot(aes(x = vals, y = target_wins)) +
    geom_point(alpha=.1) +
    facet_wrap(~ vars, scales = "free", ncol = 3)
na_ifelse <- function(x, metric){
  #function to replace NAs
  if(metric=="mean"){
    result = ifelse(is.na(x), mean(x, na.rm=T), x)
  }else if (metric == "med"){
    result = ifelse(is.na(x), median(x, na.rm=T), x)
  }else if (metric == "min"){
    result = ifelse(is.na(x), min(x, na.rm=T), x)
  }else
    result = ifelse(is.na(x), 0, x)
  return(result)
}
f1_bsb_raw <- bsb_train_raw %>%
  mutate(t_bat_so = na_ifelse(t_bat_so, "mean"),
```

```r
         t_pitch_so = na_ifelse(t_pitch_so, "med")) %>%
  select(-t_bat_hbp)
# sapply(new_bsb_raw, function(x) sum(is.na(x)))   # count na's per column!
# View(new_bsb_raw)
f2_bsb_raw <- bsb_train_raw %>%
  mutate(t_field_dp = na_ifelse(t_field_dp, "mean"),
         t_pitch_so = na_ifelse(t_pitch_so, "med")) %>%
  select(-t_bat_so, -t_baser_cs, -t_bat_hbp)
f3_bsb_raw <- bsb_train_raw %>%
  select(-t_baser_cs, -t_bat_hbp,
         -t_bat_2b, -t_bat_3b, -t_bat_hr,
         -t_pitch_so, -t_pitch_h, -t_field_dp)


## A function to pull the coefficients from a linear model and present them nicely.
get_coefs <- function(an_lm){
  temp = an_lm$coefficients %>% as.data.frame()
  temp$Vars = rownames(temp)
  colnames(temp)[1] = "Coefs."
  rownames(temp) = NULL
  return(temp[,2:1])
}
######## MODEL 1 FIT ########################
fitA <- lm(target_wins ~., f1_bsb_raw[,-1])
fitA_stepped <- MASS::stepAIC(fitA, trace=F)

knitr::kable(get_coefs(fitA_stepped),
             caption = "Model 1 coefficients",
             digits = 4)
#summary(fitA_stepped)
par(mfrow=c(1,2))
plot(fitA_stepped,which=c(2,1))
par(mfrow=c(1,1))
######## MODEL 2 FIT ########################
fitB <- lm(target_wins ~., f2_bsb_raw[,-1])
#fitB1 <- lm(target_wins+.01 ~., f2_bsb_raw[,-1])
#fitB_bc <- car::powerTransform(fitB1, family="bcPower") # 1.193639
#fitB_bc$roundlam # provides maximum estimator
#df <- cbind(lambda = fitB_bc$lambda, log_likli = fitB_bc$llik) %>% as.data.frame()
#df <- df %>% ungroup() %>% arrange(desc(log_likli))

#summary(fitB)
knitr::kable(get_coefs(fitB),
             caption = "Model 2 coefficients",
             digits = 4)
par(mfrow=c(1,2))
plot(fitB,which=c(2,1))
par(mfrow=c(1,1))
######## MODEL 3 FIT ########################
fitC <- lm(target_wins ~., f3_bsb_raw[,-1])
#summary(fitC)
#fitC_bc <- lm(target_wins +1~., f3_bsb_raw[,-1])
#summary(fitC_bc)
```

```r
#fitC1 <- lm(target_wins+1 ~., f3_bsb_raw[,-1])
#c1_bc <- car::powerTransform(fitC_bc, family="bcPower")
#c1_bc$roundlam # provides maximum estimator 1.275905
knitr::kable(get_coefs(fitC),
             caption = "Model 3 coefficients",
             digits = 4)
stargazer(fitA_stepped,fitB, fitC,
          type='text',
          column.sep.width = "1pt",
          single.row = T,
          omit.stat=c('ser'),
          no.space=TRUE)
summary(fitA_stepped)
par(mfrow=c(1,2))
plot(fitA_stepped,which=c(2,1))
par(mfrow=c(1,1))
confint(fitA_stepped)
#READ IN EVALUATION DATA
bsb_eval_raw <- read.csv("moneyball-evaluation-data.csv")
bsb_eval_raw <- data.table::setnames(bsb_eval_raw,
                                     tolower(names(bsb_eval_raw[1:16])))

c1 <- col_name_updater(bsb_eval_raw, "batting", "bat")
c2 <- col_name_updater(c1, "pitching", "pitch")
c3 <- col_name_updater(c2, "fielding", "field")
c4 <- col_name_updater(c3, "baserun", "baser")
bsb_eval_raw <- col_name_updater(c4, "team", "t")

bsb_eval_raw <- bsb_eval_raw %>%
  mutate(t_bat_so = na_ifelse(t_bat_so, "mean"),
         t_pitch_so = na_ifelse(t_pitch_so, "med")) %>%
  select(-t_bat_hbp)
# load test data into prediction
target_wins <- predict.lm(fitA_stepped, newdata=bsb_eval_raw[,-1])

# complete the test set
eval_set <- cbind(as.data.frame(target_wins),bsb_eval_raw[,-1]) %>%
  mutate(tag='eval')

tot_set <- f1_bsb_raw[,-1] %>%
  mutate(tag='test')

tot_set <- rbind(tot_set, eval_set)

x<-ggplot(tot_set, aes(x=t_bat_h, y=target_wins, color=tag)) +
  geom_point(alpha=.4)
x

# par(mfrow=c(1,2))
# plot(fitC)
# par(mfrow=c(1,1))
#confint(fitA)
```