

# Modeling Shot Efficiency in the NBA

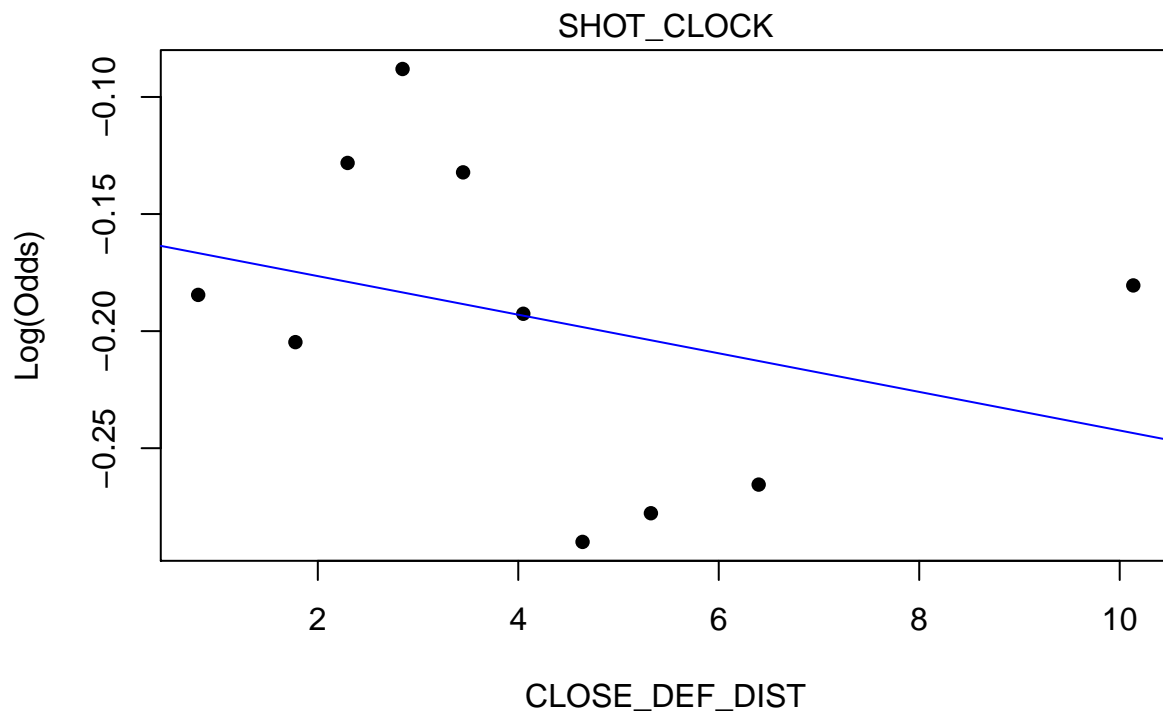
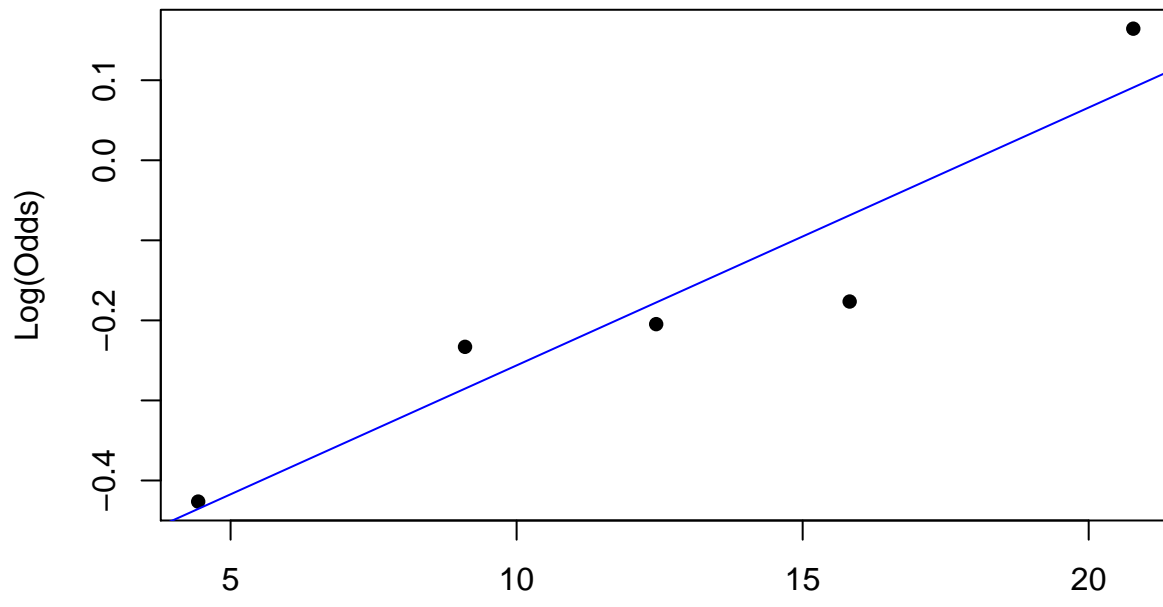
Stat guys: Lewis Eatherton, Chris Yang, Charlie Bonetti

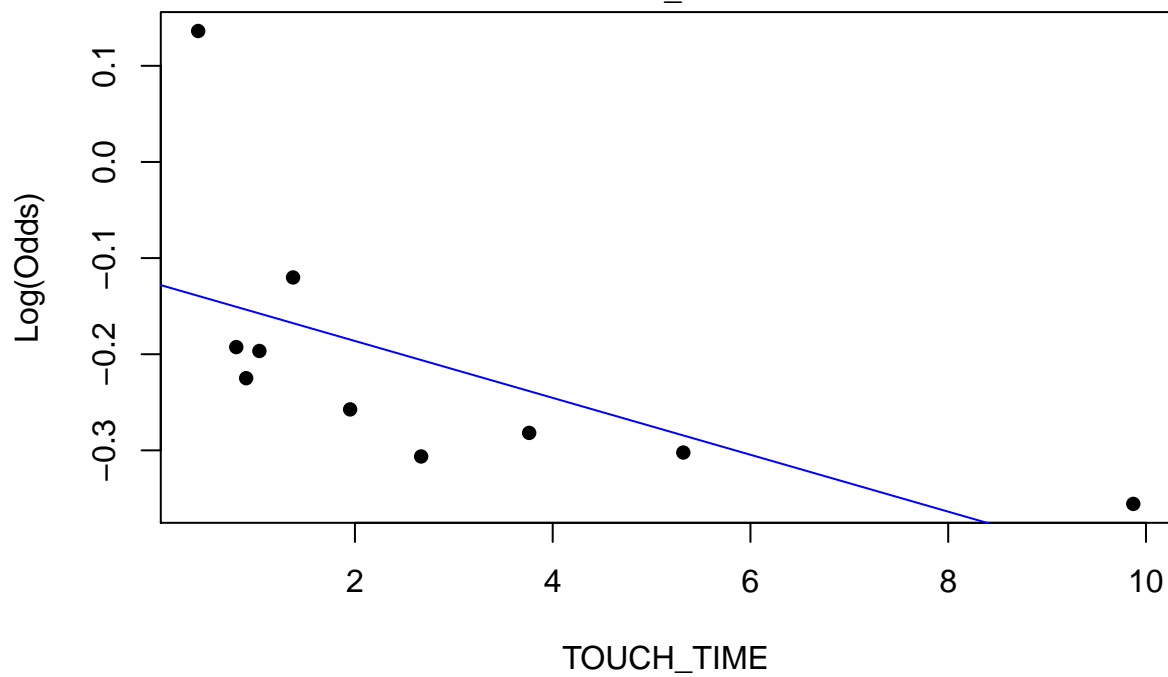
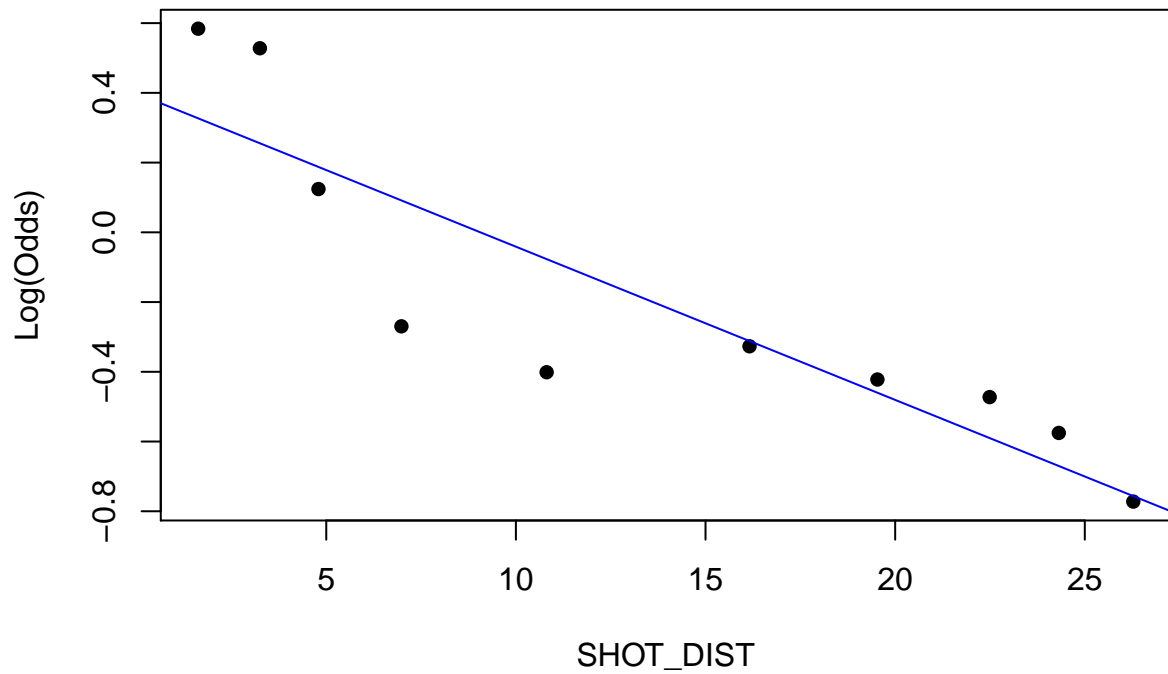
10/28/20

Your written report goes here! Before you submit, make sure your code chunks are turned off with `echo = FALSE` and there are no warnings or messages with `warning = FALSE` and `message = FALSE`

## Introduction and EDA

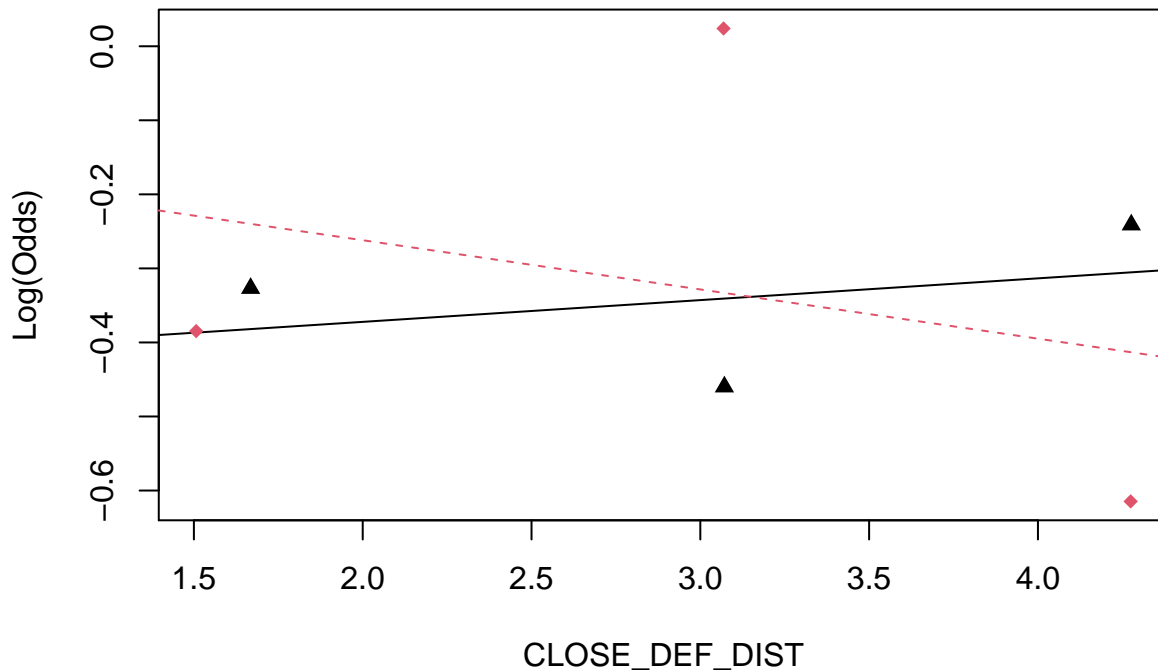
For our STA 210 Final Project, our group is interested in investigating how certain variables may have an influence on a basketball players' shot efficiency in the National Basketball Association (NBA). We are all avid NBA fans and express great curiosity in what makes a good shot versus a bad shot. Thus, we are excited by the opportunity to explore whether or not certain factors exist which surprisingly have an effect on shot success versus other factors that surprisingly don't have an effect. An 2015 article titled "Basketball Shot Types and Shot Success in Different Levels of Competitive Basketball" published by Frane Erčulj and Erik Štrumbel piqued our interest in this subject matter. We became intrigued by how different shot types affected shot success across different levels of competition. Additionally, it was insightful to learn that there were no discernable differences between different situational variables on shot type and shot success between levels. Since the effect of situation variables on shot success seemed to be constant throughout all levels of competition, we wanted to see what exactly the situation variables might be, and to what degree of influence they had on an individual's shot. As a result, we formulated our research question: "Do certain situational variables during a game have an effect on an NBA player's shot success?" Based on our prior knowledge of the game of basketball, we recognize that both players and coaches deem certain shots as "good shots" and some as "bad". Furthermore, through our own intuition after watching countless games and playing the sport ourselves, we hypothesize that some situational variables (e.g. shot distance or the distance of the closest defender) will have a greater effect on an NBA player's shot success than other situational variables.





```
## # A tibble: 470 x 5
## # Groups:   CLOSEST_DEFENDER [470]
##   CLOSEST_DEFENDER Make      n prop emp_logit
##   <chr>           <fct> <int> <dbl>    <dbl>
## 1 Acy, Quincy      1      118 0.428   -0.292
## 2 Adams, Jordan    1       16 0.533    0.134
## 3 Adams, Steven    1     215 0.444   -0.224
## 4 Adrien, Jeff     1      40 0.548    0.192
## 5 Afflalo, Arron   1     191 0.417   -0.335
## 6 Ajinca, Alexis   1     114 0.465   -0.139
## 7 Aldemir, Furkan  1      33 0.465   -0.141
```

```
## 8 Aldrich, Cole      1      142 0.532    0.128
## 9 Aldridge, LaMarcus 1      302 0.461   -0.156
## 10 Allen, Lavoy      1      141 0.449   -0.205
## # ... with 460 more rows
```



Linearity is not totally satisfied... graphs aren't linear

independence and randomness seems fine according to how data was collected

we should also look into collinearity

### Creating Model

```
## Single term deletions
##
## Model:
## Make ~ SHOT_CLOCK + DRIBBLES + TOUCH_TIME + SHOT_DIST + CLOSE_DEF_DIST
##
```

	Df	Deviance	AIC
<none>		162325	162337
SHOT_CLOCK	1	162532	162542
DRIBBLES	1	162354	162364
TOUCH_TIME	1	162434	162444
SHOT_DIST	1	167561	167571
CLOSE_DEF_DIST	1	163764	163774

```
## Single term deletions
##
## Model:
## Make ~ SHOT_CLOCK + DRIBBLES + TOUCH_TIME + SHOT_DIST + CLOSE_DEF_DIST +
##       CLOSEST_DEFENDER
##
```

	Df	Deviance	AIC
<none>		855.93	869.93
SHOT_CLOCK	1	858.72	870.72
DRIBBLES	1	855.93	867.93
TOUCH_TIME	1	855.94	867.94

```

## SHOT_DIST      1    872.34 884.34
## CLOSE_DEF_DIST  1    865.25 877.25
## CLOSEST_DEFENDER 1    855.98 867.98

## Single term deletions
##
## Model:
## Make ~ SHOT_CLOCK + TOUCH_TIME + SHOT_DIST + CLOSE_DEF_DIST +
##         CLOSEST_DEFENDER
##           Df Deviance    AIC
## <none>                855.93 867.93
## SHOT_CLOCK           1    858.81 868.81
## TOUCH_TIME           1    855.99 865.99
## SHOT_DIST            1    872.34 882.34
## CLOSE_DEF_DIST       1    865.25 875.25
## CLOSEST_DEFENDER     1    855.98 865.98

## Single term deletions
##
## Model:
## Make ~ SHOT_CLOCK + TOUCH_TIME + SHOT_DIST + CLOSE_DEF_DIST
##           Df Deviance    AIC
## <none>                855.98 865.98
## SHOT_CLOCK           1    858.90 866.90
## TOUCH_TIME           1    856.02 864.02
## SHOT_DIST            1    872.45 880.45
## CLOSE_DEF_DIST       1    865.36 873.36

## Single term deletions
##
## Model:
## Make ~ SHOT_CLOCK + SHOT_DIST + CLOSE_DEF_DIST
##           Df Deviance    AIC
## <none>                856.02 864.02
## SHOT_CLOCK           1    859.04 865.04
## SHOT_DIST            1    872.60 878.60
## CLOSE_DEF_DIST       1    865.68 871.68

## # A tibble: 2 x 5
##   Resid..Df Resid..Dev    df Deviance p.value
##   <dbl>      <dbl> <dbl>    <dbl>   <dbl>
## 1      645      856.    NA     NA      NA
## 2      643      855.     2    0.813  0.666

```

term	estimate	std.error	statistic	p.value
(Intercept)	-0.737	0.294	-2.508	0.012
SHOT_CLOCK	0.026	0.015	1.733	0.083
SHOT_DIST	-0.048	0.012	-4.013	0.000
CLOSE_DEF_DIST	0.243	0.079	3.067	0.002

talk about final model outcome and how we came to it

###Discussion

Talk about our results, the limitations of these results, and what'd we do differently...