Analyze Results

Basketball Salaries Team

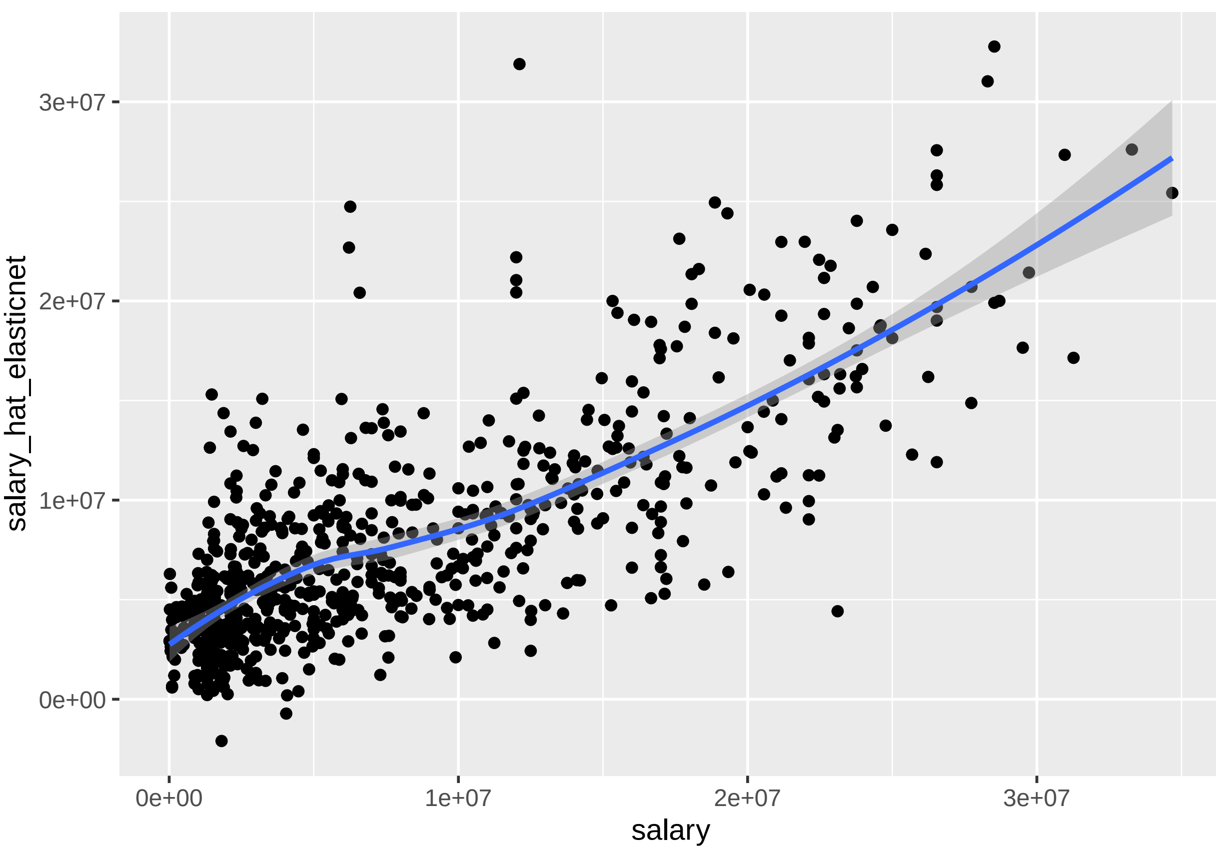
Load Results from Optimal ElasticNet Model

```
df_enet <- read.csv('../data/predictions/elasticnet.csv')
head(df_enet)
```

```
##              name year  salary salary_hat_elasticnet
## 1  aaron brooks 2016 2700000             4429343.4
## 2  aaron brooks 2017 2116955             2773620.2
## 3  aaron gordon 2016 4351320             8584724.1
## 4  aaron gordon 2017 5504420             8932442.4
## 5 adreian payne 2016 2022240              252768.3
## 6    aj hammons 2017 1312611             2868394.9
```

Plot Salary vs Predicted Salary

```
library(ggplot2)
ggplot(df_enet,aes(x=salary,y=salary_hat_elasticnet)) +
  geom_point() +
  geom_smooth()
```

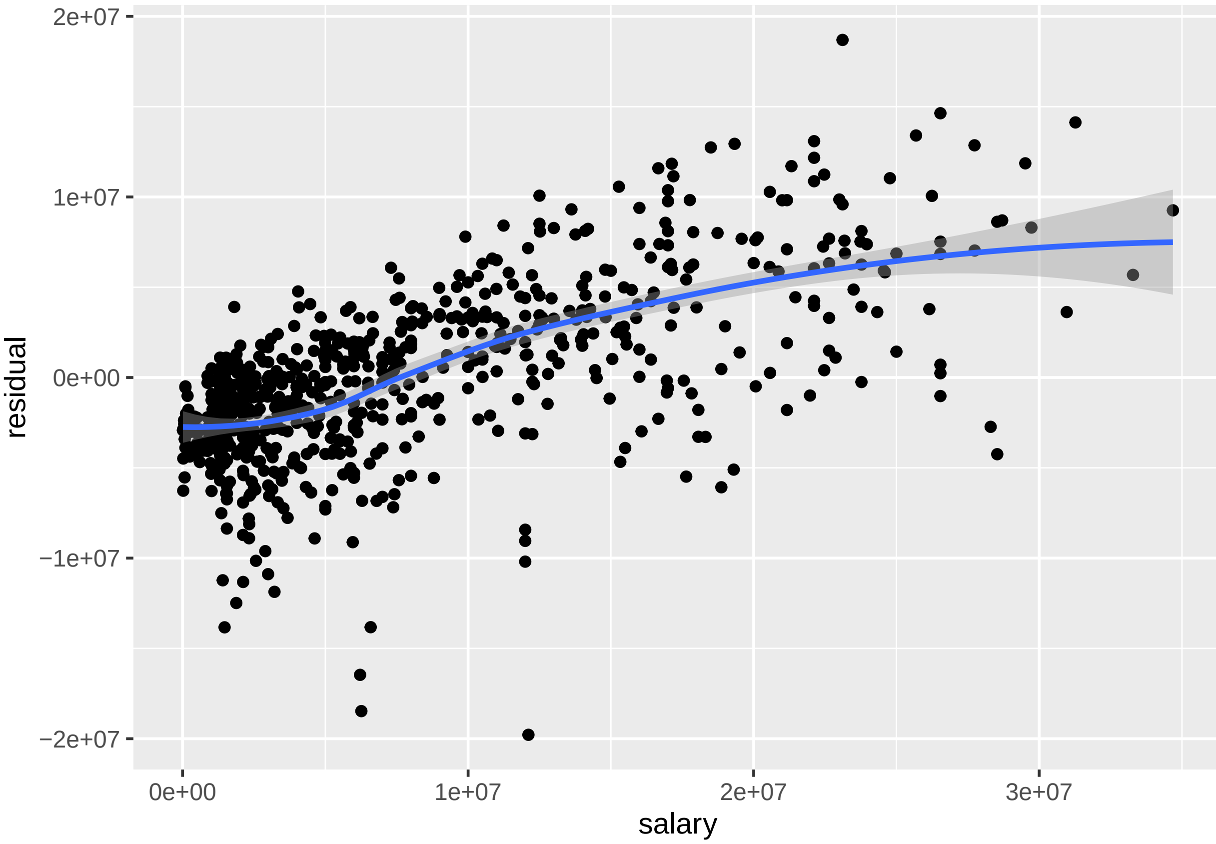



```
ggsave("../figures/elasticnet_salary_vs_prediction_scatter.png", width=10, height=7)
```

Plot Salary vs Redisual Prediction

Appears to be a positive linear trend between the salary and residuals.
Thus, the optimal elasticnet model tends to underestimate players with higher salaries.

```r
library(ggplot2)
residual <- df_enet$salary - df_enet$salary_hat_elasticnet
ggplot(df_enet, aes(x=salary,y=residual)) +
  geom_point() +
  geom_smooth()
```




```r
ggsave("../figures/elasticnet_salary_vs_residual_scatter.png", width=10, height=7)
```

Underrated Players in 2016

An underrated player is any player who should be making 50% more
$\hat{salary} - salary > \frac{1}{2} salary$
Players who our model classifies as underrated tend to get higher salaries the next year

```r
# get underrated players in 2016
df_underrated_2016 <- df_enet[
  ((df_enet$salary_hat_elasticnet-df_enet$salary) > (df_enet$salary/2)) &
  df_enet$year==2016,]
# link with 2017 stats
df_underrated_2017 <- df_enet[(df_enet$name%in%df_underrated_2016$name)&(df_enet$year==2017),]
df_underrated <- merge(df_underrated_2016,df_underrated_2017,all.x=F,all.y=F,by='name')
names(df_underrated) <- c('name','2016','salary_2016','salary_hat_2016','2017','salary_2017','salary_hat_2017')
df_underrated <- df_underrated[,c('name','salary_2016','salary_hat_2016','salary_2017','salary_hat_2017')]
df_underrated
```

```
##                         name salary_2016 salary_hat_2016 salary_2017
## 1               aaron brooks     2700000         4429343     2116955
## 2               aaron gordon     4351320         8584724     5504420
## 3          anderson varejao     1984005         4588133     1913345
## 4            andre roberson     2183072         4900199     9259259
## 5            andrew wiggins     6006600        11292995     7574322
## 6              bobby portis     1453680         3637803     1516320
```

```
## 7          bojan bogdanovic    3730653          5772384   10500000
## 8               cj mccollum    3219579         15086086   23962573
## 9                  cj miles    4583450          8554341    7936509
## 10             clint capela    1296240          6385962    2334520
## 11              cody zeller    5318313          9310330   12584270
## 12          darren collison    5229454          9445185   10000000
## 13               david west    1551659          9914146    2328652
## 14             delon wright    1577280          3730829    1645200
## 15          dennis schroder    2708582          7343010   15500000
## 16             devin booker    2223600          5697483    2319360
## 17             dion waiters    2898000          5819329   11000000
## 18           doug mcdermott    2483040          5376382    3294994
## 19            elfrid payton    2613600          7272016    3332340
## 20          emmanuel mudiay    3241800          4885337    3381480
## 21           frank kaminsky    2730000          6206151    2847600
## 22              gary harris    1655880          7424455    2550055
## 23              george hill    8000000         13442935   20000000
## 24    giannis antetokounmpo    2995421         13883216   22471910
## 25             gorgui dieng    2348783          8889477   14112360
## 26            isaiah canaan    1015696          5870521     200000
## 27            isaiah thomas    6587132         20411826    6261395
## 28              jae crowder    6286408         13115037    6796117
## 29             jarell eddie     175000          1190385      17224
## 30             jarrett jack    1551659          7566231    2328652
## 31              jason terry    1551659          4499960    2328652
## 32             javale mcgee    1403611          4547203    2116955
## 33              jeff teague    8800000         14363040   19000000
## 34              jeff withey    1015696          3967919    1577320
## 35             jerami grant     980431          5721625    1524305
## 36                 jj barea    4096950          9059696    3903900
## 37                jj redick    7377500         14563392   23000000
## 38        joffrey lauvergne    1709720          4513898    1524305
## 39          jonathon simmons     874636          4487135    6300000
## 40             josh huestis    1191480          3604672    1471382
## 41          josh richardson     874636          3818816    1471382
## 42            julius randle    3267120          7170577    4149242
## 43           justin holiday    1015696          2268835    4615385
## 44          justise winslow    2593440          4548986    2705040
## 45             jusuf nurkic    1921320          3648187    2947305
## 46       karl anthony towns    5960160         15077544    6216840
## 47             kelly olynyk    3094014          7307825   10607169
## 48             kemba walker   12000000         21046311   12000000
## 49 kentavious caldwell pope    3678319         11450976   17745894
## 50             kevon looney    1182840          2699270    1471382
## 51       kristaps porzingis    4317720         10380436    4503600
## 52            kyle anderson    1192080          4822624    2151704
## 53              kyle korver    5239437         11476562    7000000
## 54               kyle lowry   12000000         22195346   28703704
## 55             lou williams    7000000         10919977    7000000
## 56             luke babbitt    1227000          3948212    1974159
## 57            marcus morris    4625000         13533857    5000000
## 58             marcus smart    3578880          5597367    4538020
## 59        marreese speights    1403611          4732343    2116955
## 60             mason plumlee    2328530         11228349   14041096
## 61           michael beasley    1403611          5252882    2116955
## 62  michael carter williams    3183526          6022334    2700000
## 63             mike muscala    1015696          1932945    5000000
## 64               mike scott    3333334          5359219    1709538
## 65             myles turner    2463840          6035784    2569920
## 66             nerlens noel    4384490          6937211    4187599
## 67             nikola jokic    1358500          8870674    1471382
## 68           nikola mirotic    5782450          9328800   12500000
## 69            norman powell     874636          3077193    1471382
## 70              omri casspi    3000000          8973374    2106470
```

```
## 71              otto porter    5893981         9989088    24773250
## 72              paul pierce    3500000         6392577     1096080
## 73                pj tucker    5300000         8081325     7590035
## 74               quincy acy    1914544         3301908     1709538
## 75         rakeem christmas    1052342         4419877      172552
## 76                raul neto     937800         3586839     1471382
## 77           raymond felton    1551659         8298032     2328652
## 78        richard jefferson    2500000         5920924     2500000
## 79         robert covington    1015696         7302511    16698103
## 80              rodney hood    1406520        12633269     2386864
## 81  rondae hollis jefferson    1395600         2846022     1471382
## 82             rudy gobert     2121288        13442305    21974719
## 83              salah mejri     874636         4939818     1471382
## 84          sean kilpatrick     980431         4455404     1524305
## 85         shabazz muhammad    3046299         5520301     1577230
## 86             shelvin mack    2433334         6203218     6000000
## 87        spencer dinwiddie     726672         4776254     1524305
## 88            stephen curry   12112359        31895262    34682550
## 89             steven adams    3140517         9330964    22471910
## 90           thabo sefolosha   3850000         8602689     5250000
## 91              tim frazier    2090000         3538490     2000000
## 92                tj warren    2128920         4190908     3152931
## 93               trey lyles    2340600         4334203     2441400
## 94           victor oladipo    6552960        11319949    21000000
## 95              will barton    3533333        10772432     3533333
## 96              zach lavine    2240880         6666870     3202217
## 97             zaza pachulia   2898000        12512036     3477600
##    salary_hat_2017
## 1        2773620.2
## 2        8932442.4
## 3        6166630.1
## 4        8020581.3
## 5       13257930.7
## 6        4506013.1
## 7        9341911.9
## 8       16582615.8
## 9        8326992.9
## 10      10454670.1
## 11       9256680.0
## 12       9415694.0
## 13       5787281.3
## 14       3483362.1
## 15      13223819.7
## 16      10131818.2
## 17       9306744.2
## 18       5971264.6
## 19      10242168.9
## 20       4457911.4
## 21       8008941.2
## 22       8755451.9
## 23      13662004.8
## 24      22067084.5
## 25       9562430.0
## 26       1987624.2
## 27      24734118.5
## 28      13627870.2
## 29       2896612.6
## 30       2999446.3
## 31       4317814.2
## 32       5997526.8
## 33      16161460.2
## 34       3008823.2
## 35       3629591.6
## 36       8486217.3
```

```
## 37      13142885.9
## 38       3863763.1
## 39       4673306.9
## 40       5305991.2
## 41       6144874.5
## 42       9165260.8
## 43       4534866.9
## 44       3794882.2
## 45       6857325.2
## 46      22680261.7
## 47       6955683.0
## 48      20428050.5
## 49      11655371.7
## 50       1694135.4
## 51      10870779.5
## 52       3412920.5
## 53       9330801.3
## 54      20004242.9
## 55      13609609.3
## 56       3767037.1
## 57      12305372.5
## 58       7323006.6
## 59       7282657.2
## 60      11647275.4
## 61       5425964.8
## 62       3762336.0
## 63       5249495.1
## 64       3194586.6
## 65      12718990.4
## 66       5733416.0
## 67      15303527.9
## 68       9049707.1
## 69       4838078.3
## 70       3365207.3
## 71      13737033.8
## 72       5014373.4
## 73       6213030.8
## 74       3354049.4
## 75       3252078.4
## 76        517326.8
## 77       5618663.9
## 78       5478247.2
## 79       9302578.5
## 80       8834002.9
## 81       6041925.5
## 82      22972010.3
## 83       3591467.0
## 84       7947907.8
## 85       5096995.2
## 86       5370645.9
## 87       4896699.7
## 88      25424887.1
## 89      11234156.3
## 90       7874896.9
## 91       6048829.5
## 92       7567767.2
## 93       3536228.0
## 94      11185030.3
## 95       8764403.0
## 96       8421316.0
## 97       9189165.8
```

```
# calculate percent increase factor
sal_factor_2016 = .25
```

```r
p_increase <- 100*mean(
  (df_underrated$salary_2017-df_underrated$salary_2016) > sal_factor_2016*df_underrated$salary_2016)
sprintf(
  'Percent of underrated players in 2016 whose salary increased by more than 25%% for 2017: %.1f%%',p_increase)
```

```
## [1] "Percent of underrated players in 2016 whose salary increased by more than 25% for 2017: 61.9%"
```

Overrated Players in 2016

An overrated player is any player who should be making 50% more
$salary - \hat{salary} > \frac{1}{2}salary$
Hard for players who have high salaries to get a salary cut despite lacking stats

```r
df_overrated_216 <- df_enet[
  ((df_enet$salary-df_enet$salary_hat_elasticnet) > (df_enet$salary/2)) &
  df_enet$year==2016,]
# link with 2017 stats
df_overrated_2017 <- df_enet[(df_enet$name%in%df_overrated_216$name)&(df_enet$year==2017),]
df_overrated <- merge(df_overrated_216,df_overrated_2017,all.x=F,all.y=F,by='name')
names(df_overrated) <- c('name','2016','salary_2016','salary_hat_2016','2017','salary_2017','salary_hat_2017')
df_overrated <- df_overrated[,c('name','salary_2016','salary_hat_2016','salary_2017','salary_hat_2017')]
df_overrated
```

```
##                     name salary_2016 salary_hat_2016 salary_2017
## 1           allen crabbe    18500000       5758846.3    19332500
## 2          austin rivers    11000000       4503059.3    11825000
## 3           bradley beal    22116750       9030000.4    23775506
## 4           corey brewer     7600000       3185765.4     7579366
## 5        demarre carroll    14200000       5968589.8    14800000
## 6           derrick rose    21323250       9619627.6     2116955
## 7        harrison barnes    22116750       9949025.6    23112004
## 8          iman shumpert     9700000       4035035.6    10337079
## 9            joakim noah    17000000       7238431.9    17765000
## 10           john henson    12517606       4433189.7    11422536
## 11           kj mcdaniels     3333333        921703.4      100000
## 12           kyle singler     4837500       1500922.2     4666500
## 13          mario hezonja     3909840       1054856.5     4078320
## 14      maurice harkless     8988764       4022118.2    10162922
## 15 michael kidd gilchrist    13000000       4722079.4    13000000
## 16           mike conley    26540100      11905453.4    28530608
## 17          miles plumlee    12500000       3984371.1    12500000
## 18           noah vonleh     2751360        941379.1     3505233
## 19         rashad vaughn     1811040      -2096791.6     1889040
## 20            sam dekker     1720560        736471.8     1794600
## 21          solomon hill    11241218       2827291.2    12236535
## 22           tarik black     6191000       2906521.4     3290000
## 23        timofey mozgov    16000000       6607935.3    15280000
##    salary_hat_2017
## 1        6392591.5
## 2        7341045.8
## 3       17520192.8
## 4        2091652.8
## 5        8829094.6
## 6       10835915.7
## 7       13521202.0
## 8        4715575.5
## 9        7938896.6
## 10       5617584.5
## 11        654362.2
## 12       2338158.0
## 13        194609.0
## 14       7043488.2
## 15       9743681.9
```

```
## 16      19908167.7
## 17       2430453.7
## 18       2484779.8
## 19        596597.5
## 20       4719205.3
## 21       6572530.5
## 22       2937630.2
## 23       4714734.3
```

```r
# calculate percent decrease factor
p_decrease <- 100*mean((df_overrated$salary_2016-df_overrated$salary_2017) > 0)
sprintf('Percent of overrated players in 2016 whose salary decreased for 2017: %.1f%%',p_decrease)
```

```
## [1] "Percent of overrated players in 2016 whose salary decreased for 2017: 30.4%"
```