A Predictive Model for ODI World Cup Matches

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Introduction

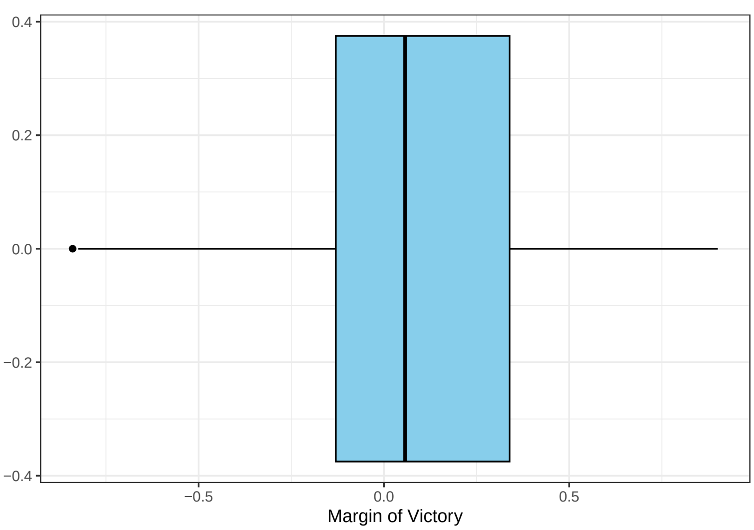
Given that this is a One Day International (ODI) World Cup year, our analysis of batting and bowling performance metrics on the margin of victory, `mov`, is focused on prior World Cup matches. With knowledge of how the ODI format has changed since the introduction of the shorter, Twenty20 (T20) format, particularly the 2007 T20 World Cup, we have limited our data to the last five ODI World Cups (2003, 2007, 2011, 2015, and 2019). After wrangling six batting metrics and four bowling metrics from 4774 individual player performances, we are looking to build a predictive model and gain insight as to which metrics, if any, have an effect on `mov`. In doing so, while this may be beyond the scope of this project, we hope to ultimately use our model to predict the outcome of the 2023 ODI World Cup.

Exploratory Analysis

Response Variable

`mov` is the difference between the target set by the team batting first and the total that the chasing team achieved. For example, in a 2003 match between England and Pakistan, England scored 246 runs, setting 247 as the target for Pakistan to chase. They, however, were bowled out for 134, resulting in England winning by 112 runs. Therefore, the `mov` for this match is calculated as $winner\_margin/target = 112/247 = 0.453$.

The figure below is a boxplot of `mov` values.




```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.8400 -0.1300  0.0570  0.0709  0.3390  0.9010
```

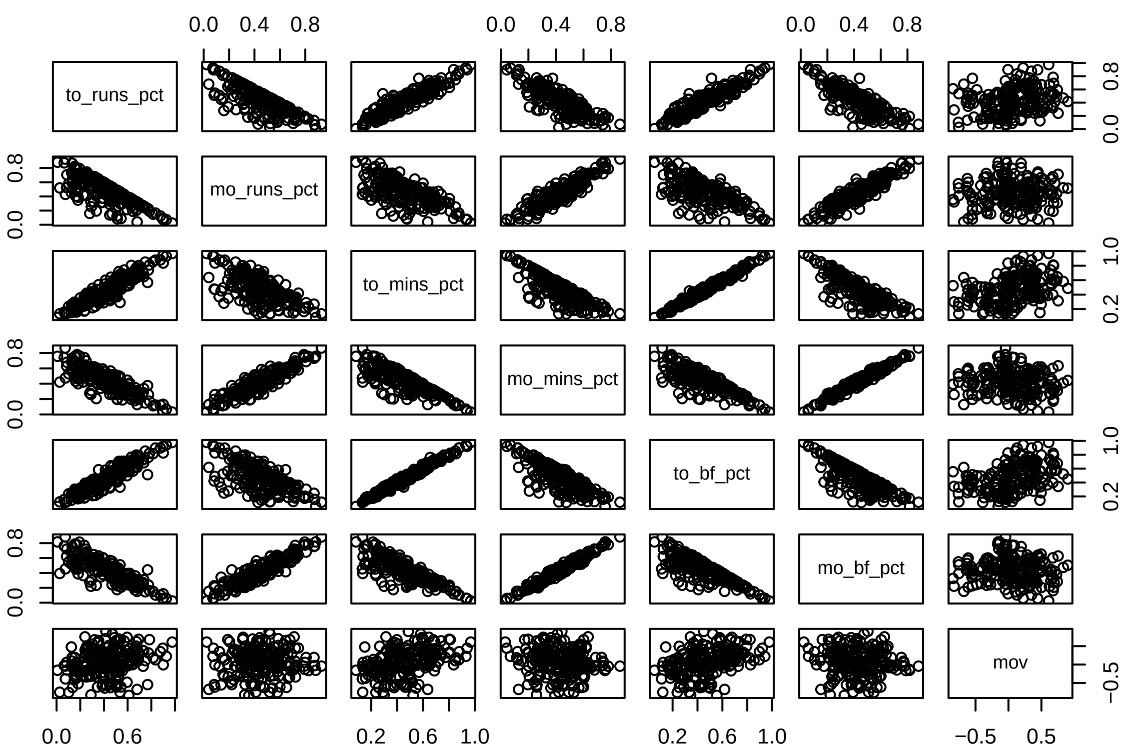
From the figure and summary, we can see that `mov` is approximately normally distributed on 7.1%. The single outlier is a 2011 match between Kenya and New Zealand in which Kenya lost by 84.0%. While large `mov` values can be attributed to a blowout, the extreme values probably occurred due to a wide skill gap between two teams. New Zealand, for example, is an established cricketing nation with a strong, experienced team compared to Kenya.

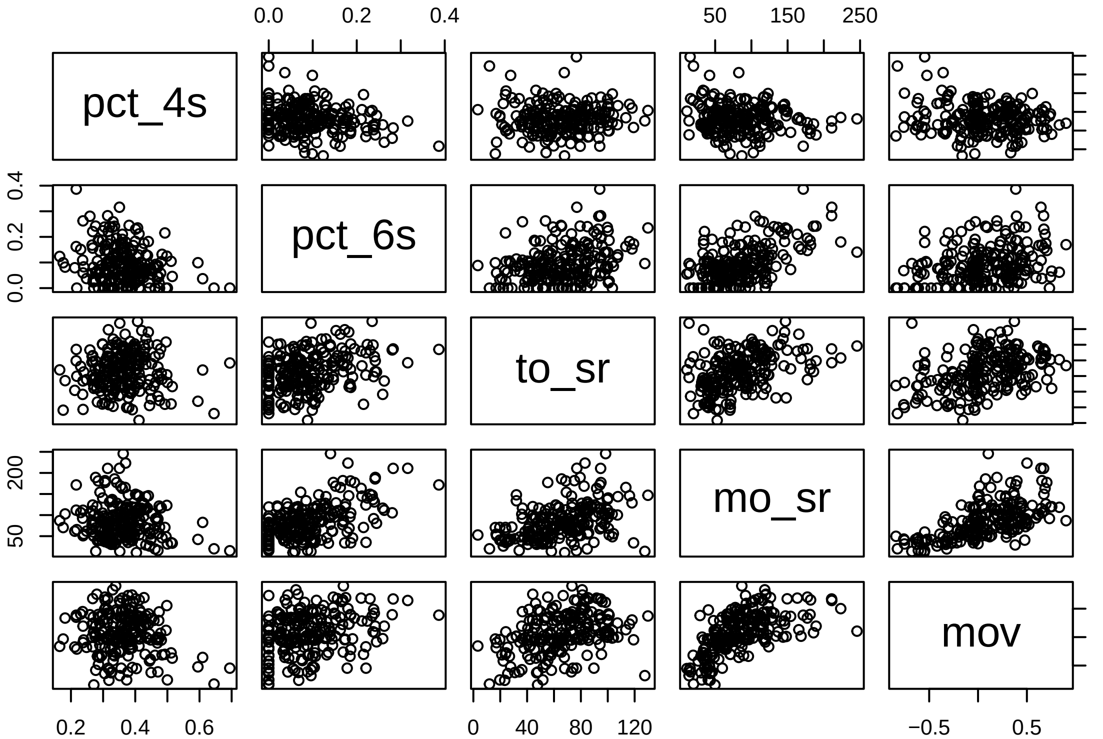
Predictor Variables

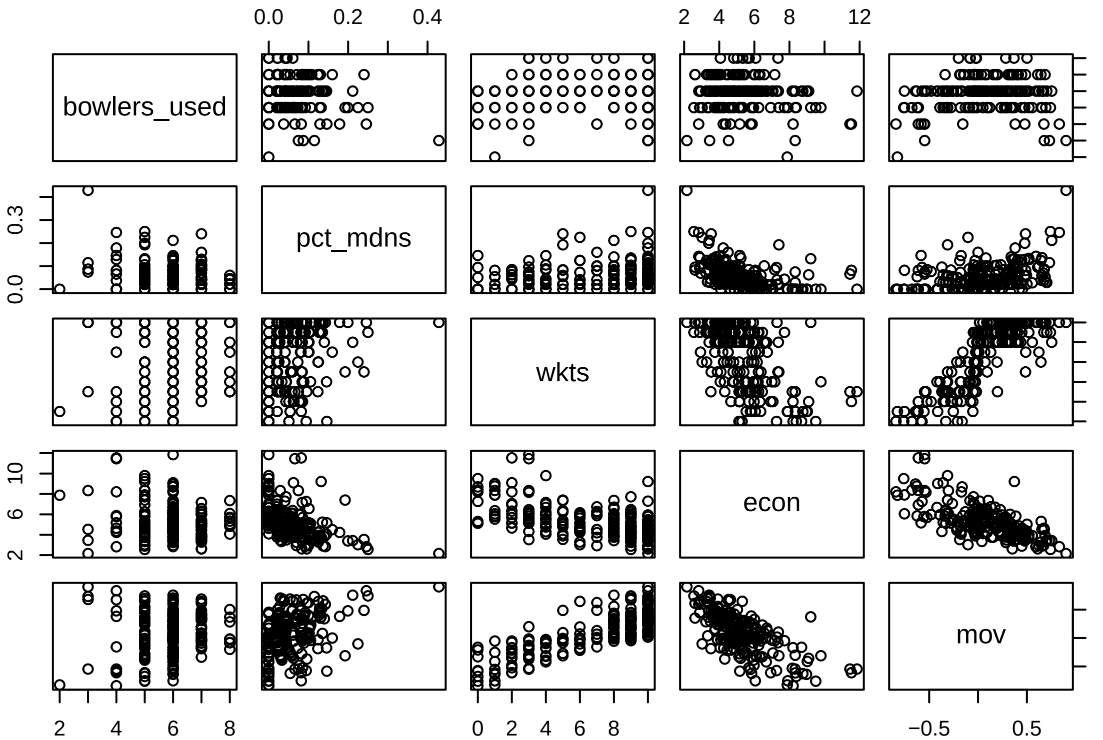
Batting metrics:
Given that top-order batsmen (players 1, 2, and 3) generally play a different role to that of middle-order batsmen (players 4, 5, 6, and 7), these metrics have been separated by batting position.
1. `to_runs_pct` - percentage of total runs scored by the top-order
2. `mo_runs_pct` - percentage of total runs scored by the middle-order
3. `to_mins_pct` - percentage of total time spent in crease by the top-order
4. `mo_mins_pct` - percentage of total time spent in crease by the middle-order
5. `to_bf_pct` - percentage of total balls faced by the top-order
6. `mo_bf_pct` - percentage of total balls faced by the middle-order
7. `pct_4s` - percentage of total runs that are 4s
8. `pct_6s` - percentage of total runs that are 6s
9. `to_sr` - average strike rate of the top-order
10. `mo_sr` - average strike rate of the middle-order

Bowling metrics:
1. `bowlers_used` - total number of bowlers used
2. `pct_mdns` - percentage of total overs that are maidens (an over in which no runs are scored)
3. `wkts` - total number of wickets taken
4. `econ` - average number of runs conceded per over bowled

The figures below are scatterplots of the pairwise relationship between predictor variables.




pct_4s
pct_6s
to_sr
mo_sr
mov


bowlers_used
pct_mdns
wkts
econ
mov

	to_runs_pct	mo_runs_pct	to_mins_pct	mo_mins_pct	to_bf_pct	mo_bf_pct	pct_4s	pct_6s	to_sr	mo_sr	bowlers_used	pct_mdns	wkts	econ	mov
to_runs_pct	1.00	-0.77	0.93	-0.83	0.93	-0.82	-0.08	0.17	0.65	0.36	0.07	-0.07	0.28	0.04	0.26
mo_runs_pct	-0.77	1.00	-0.65	0.91	-0.64	0.91	-0.13	-0.01	-0.42	0.04	0.05	0.07	-0.02	-0.16	0.04
to_mins_pct	0.93	-0.65	1.00	-0.83	0.99	-0.81	-0.14	0.26	0.58	0.54	0.13	-0.05	0.37	-0.07	0.41
mo_mins_pct	-0.83	0.91	-0.83	1.00	-0.80	0.98	-0.04	-0.12	-0.43	-0.22	0.00	0.07	-0.12	-0.06	-0.11
to_bf_pct	0.93	-0.64	0.99	-0.80	1.00	-0.82	-0.13	0.28	0.59	0.57	0.13	-0.06	0.38	-0.07	0.41
mo_bf_pct	-0.82	0.91	-0.81	0.98	-0.82	1.00	-0.06	-0.12	-0.43	-0.24	0.01	0.09	-0.13	-0.07	-0.11
pct_4s	-0.08	-0.13	-0.14	-0.04	-0.13	-0.06	1.00	-0.21	0.02	-0.13	-0.14	-0.07	-0.07	0.14	-0.14
pct_6s	0.17	-0.01	0.26	-0.12	0.28	-0.12	-0.21	1.00	0.32	0.54	0.11	-0.02	0.18	0.05	0.29
to_sr	0.65	-0.42	0.58	-0.43	0.59	-0.43	0.02	0.32	1.00	0.43	0.08	-0.05	0.36	0.04	0.38
mo_sr	0.36	0.04	0.54	-0.22	0.57	-0.24	-0.13	0.54	0.43	1.00	0.22	0.02	0.50	-0.21	0.61
bowlers_used	0.07	0.05	0.13	0.00	0.13	0.01	-0.14	0.11	0.08	0.22	1.00	-0.18	0.05	-0.14	0.12
pct_mdns	-0.07	0.07	-0.05	0.07	-0.06	0.09	-0.07	-0.02	-0.05	0.02	-0.18	1.00	0.25	-0.46	0.39
wkts	0.28	-0.02	0.37	-0.12	0.38	-0.13	-0.07	0.18	0.36	0.50	0.05	0.25	1.00	-0.56	0.83
econ	0.04	-0.16	-0.07	-0.06	-0.07	-0.07	0.14	0.05	0.04	-0.21	-0.14	-0.46	-0.56	1.00	-0.69
mov	0.26	0.04	0.41	-0.11	0.41	-0.11	-0.14	0.29	0.38	0.61	0.12	0.39	0.83	-0.69	1.00

From the figures and correlation matrix, we can see that `runs_pct`, `mins_pct`, and `bf_pct` have high collinearity. This exists because the impact of a top-order batsman is not entirely independent of a middle-order batsman. Although the correlation of certain variables exceeds ± 0.80, we decided to let the backward step-wise process filter out and select the metrics with the greatest effect on `mov`.

Model Development

Our objective at each step of the backward step-wise selection process is to minimize *RMSE* and maximize *adjusted R-squared.* First, we split our data into training and test sets. The training set consists of World Cup matches from 2003 to 2015, whereas the test set is composed solely of 2019 data.

```
##
## Call:
## lm(formula = mov ~ ., data = train_set)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.31506 -0.08535  0.00520  0.08190  0.33314
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.4882452  0.1587330  -3.076 0.002467 **
## to_runs_pct  -0.8628535  0.2637747  -3.271 0.001310 **
## mo_runs_pct  -0.8042278  0.2725020  -2.951 0.003638 **
## to_mins_pct   0.6292071  0.6287787   1.001 0.318482
## mo_mins_pct   0.0862708  0.6099045   0.141 0.887692
## to_bf_pct     0.6309025  0.6772988   0.931 0.352991
## mo_bf_pct     1.1391437  0.6397287   1.781 0.076853 .
## pct_4s        0.0158615  0.1478799   0.107 0.914717
## pct_6s        0.2999686  0.1898668   1.580 0.116095
## to_sr         0.0023055  0.0006801   3.390 0.000880 ***
## mo_sr         0.0020120  0.0005138   3.916 0.000133 ***
## bowlers_used -0.0208609  0.0112526  -1.854 0.065587 .
## pct_mdns      0.6888521  0.1977250   3.484 0.000637 ***
## wkts          0.0451133  0.0046679   9.665  < 2e-16 ***
## econ         -0.0713556  0.0086423  -8.257 5.15e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.132 on 161 degrees of freedom
## Multiple R-squared:  0.8906, Adjusted R-squared:  0.881
## F-statistic: 93.57 on 14 and 161 DF,  p-value: < 2.2e-16
```

After training our model using all 14 predictor variables, we observe an *adjusted R-squared* value of 0.881, meaning we are able to explain 88.1% of the variation in `mov` with all 14 variables.

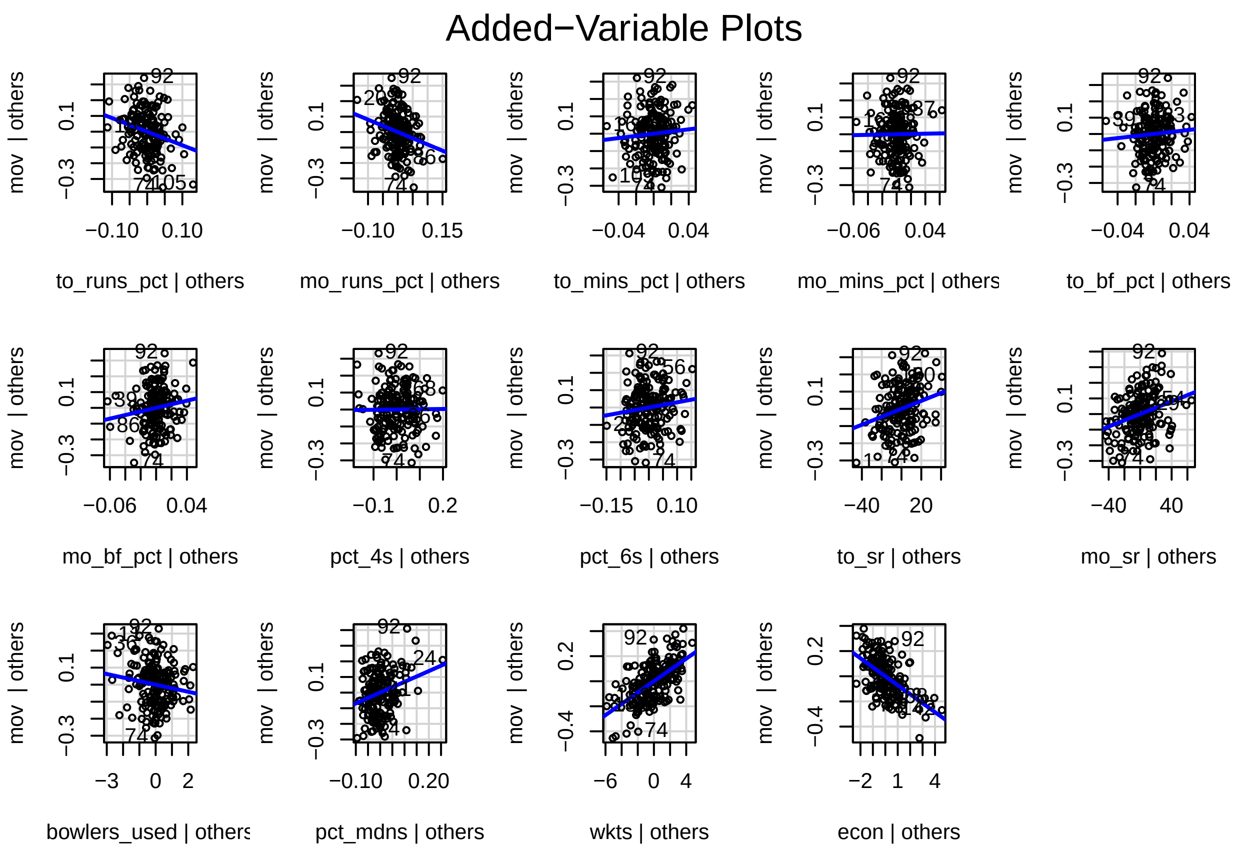
Using this model, we predict `mov` based on the test set and calculate the *RMSE* value displayed below.

```
## [1] 0.1531916
```

Normalizing this by dividing *RMSE* by the range of `mov` from the test set results in the following value.

```
## [1] 0.1327484
```

We further verify these relationships with the use of added-variable plots.



Backward step-wise selection removes each of these 14 variables from the model, one at a time, and checks for improvement in the performance metric *RMSE*. Using a loop, we remove one variable at a time from the training set. We remove the *i*-th column using `train_set[,-i]`. This allows us to iterate through columns 1 to 14.

We want to find the lowest *RMSE* value from the table below and remove the predictor variable associated with it. The lowest value appears to be 0.142 which is the 10th row and corresponds to the `mo_sr` variable. We will then remove this variable from the training set and repeat this process.

```
##         vals
## 1  0.1541412
## 2  0.1452954
## 3  0.1559078
## 4  0.1532753
## 5  0.1513644
## 6  0.1504844
## 7  0.1534606
```

```
## 8  0.1549225
## 9  0.1627135
## 10 0.1423925
## 11 0.1457553
## 12 0.1601905
## 13 0.1797444
## 14 0.1889362
```

The table below shows all of the *RMSE* values after removing `mo_sr`. The lowest value appears to be 0.138 which is the 10th row and corresponds to the `bowlers_used` variable. We will then remove this variable from the training set and repeat this process.

```
##         vals
## 1  0.1401743
## 2  0.1407669
## 3  0.1453592
## 4  0.1425708
## 5  0.1396741
## 6  0.1411606
## 7  0.1442560
## 8  0.1410817
## 9  0.1454950
## 10 0.1382726
## 11 0.1493844
## 12 0.1793459
## 13 0.1749365
```

The table below shows all of the *RMSE* values after removing `bowlers_used`. The lowest value appears to be 0.136 which is the 5th row and corresponds to the `to_bf_pct` variable. We will then remove this variable from the training set and repeat this process.

```
##         vals
## 1  0.1373298
## 2  0.1373746
## 3  0.1410767
## 4  0.1384229
## 5  0.1362954
## 6  0.1376920
## 7  0.1401080
## 8  0.1379419
## 9  0.1431505
## 10 0.1426865
## 11 0.1698732
## 12 0.1778158
```

The table below shows all of the *RMSE* values after removing `to_bf_pct`. The lowest value appears to be 0.1339 which is the 7th row and corresponds to the `pct_6s` variable. We will then remove this variable from the training set and repeat this process.

```
##         vals
## 1  0.1389401
## 2  0.1362618
## 3  0.1409512
## 4  0.1340669
## 5  0.1368344
## 6  0.1380571
## 7  0.1338812
```

```
## 8  0.1422163
## 9  0.1401365
## 10 0.1693369
## 11 0.1755852
```

The table below shows all of the *RMSE* values after removing `pct_6s`. The lowest value appears to be 0.12886 which is the 4th row and corresponds to the `mo_mins_pct` variable. We will then remove this variable from the training set and repeat this process.

```
##         vals
## 1  0.1383374
## 2  0.1329154
## 3  0.1391656
## 4  0.1288591
## 5  0.1336530
## 6  0.1343008
## 7  0.1402499
## 8  0.1408747
## 9  0.1623683
## 10 0.1697544
```

The table below shows all of the *RMSE* values after removing `mo_mins_pct`. The lowest value appears to be 0.1289 which is the 2nd row and corresponds to the `mo_runs_pct` variable. However, since this value is slightly higher than the previous lowest *RMSE* value, we can stop the process and create our final model.

```
##        vals
## 1 0.1355545
## 2 0.1288692
## 3 0.1416369
## 4 0.1300969
## 5 0.1294081
## 6 0.1321559
## 7 0.1363999
## 8 0.1687512
## 9 0.1639578
```

Our final model, after taking out `mo_sr`, `bowlers_used`, `to_bf_pct`, `pct_6s`, and `mo_mins_pct`, has an *adjusted R-Squared* of 0.857 and a *RMSE* value of 0.129. Therefore, we are able to account for 85.7% of the variation in `mov`.

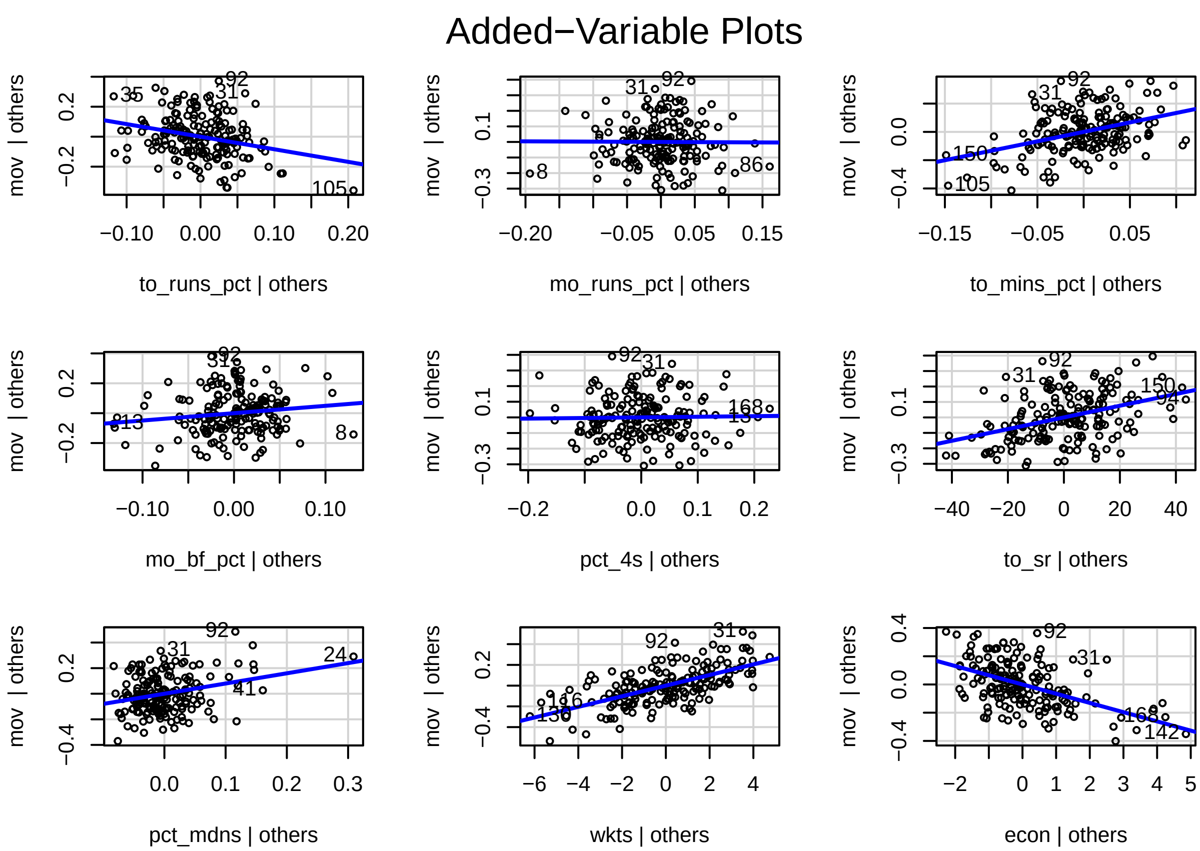
```
##
## Call:
## lm(formula = mov ~ ., data = train_min5)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.30963 -0.10122 -0.00361  0.08405  0.39258
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.6843105  0.1395203  -4.905 2.22e-06 ***
## to_runs_pct -0.8401548  0.2325325  -3.613 0.000401 ***
## mo_runs_pct -0.0201497  0.2208547  -0.091 0.927416
## to_mins_pct  1.3362872  0.2441730   5.473 1.61e-07 ***
## mo_bf_pct    0.4915536  0.2690876   1.827 0.069535 .
## pct_4s       0.0394186  0.1546612   0.255 0.799138
## to_sr        0.0037793  0.0006734   5.612 8.23e-08 ***
```

```
## pct_mdns     0.7987057  0.2083292   3.834 0.000179 ***
## wkts         0.0512169  0.0049609  10.324  < 2e-16 ***
## econ        -0.0654071  0.0090644  -7.216 1.82e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1448 on 166 degrees of freedom
## Multiple R-squared:  0.8642, Adjusted R-squared:  0.8569
## F-statistic: 117.4 on 9 and 166 DF,  p-value: < 2.2e-16
```

Normalizing the *RMSE* results in the below value.

```
## [1] 0.0740144
```

Verifying the relationships with the updated added-variable plots.



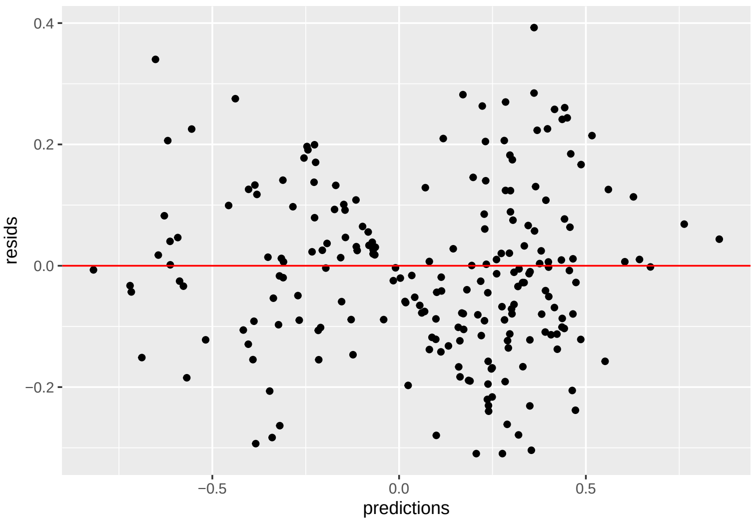
Final Model

mov = -0.68 - 0.84 * to_runs_pct - 0.02 * mo_runs_pct + 1.34 * to_mins_pct + 0.49 * mo_bf_pct + 0.04 * pct_4s + 0.004 * to_sr + 0.80 * pct_mdns + 0.05 * wkts - 0.07 * econ

Model Analysis

To analyze our final model, we test it on the entire dataset of all five World Cups. The model's final *adjusted R-squared* is 0.857, which means we are able to account for 85.7% of the variation in `mov`. With a final *RMSE* of 0.138, our predicted values generally differ from the observed values of `mov` by 13.8%. However, normalizing this value results in 0.08 or 8%. Before applying the backwards step-wise process, our first model had an *adjusted R-squared* of 0.881 and a *RMSE* of 0.153. Comparing the two models, our *adjusted R-squared* decreased by around 3%, however we were also able to decrease *RMSE* by around 2%. We believe that this trade-off is ultimately worth it as this model best minimizes the difference between predicted and observed values. Thereby, prioritizing the accuracy of the model's predictions rather than the overall quality of the model's fit to the data.

The figure below is a scatterplot of the predicted values and their residuals.



We can analyze our model's accuracy by testing it using one random ODI World Cup match throughout the years. The match we used is a match from the 2007 ODI World Cup of Bangladesh versus New Zealand. The `mov` for the match was -0.413 and the predicted `mov` was -0.619. Our predicted `mov` value is -0.206 off of the observed `mov` value which indicates our model is fairly accurate and not too far off of the observed value.

```
## [1] -0.413
```

```
##         68
## -0.6192819
```

```
##         68
## -0.2062819
```

Conclusion

We can conclude that `to_runs_pct`, `mo_runs_pct`, `to_mins_pct`, `mo_bf_pct`, `pct_4s`, `to_sr`, `pct_mdns`, `wkts`, and `econ` are the variables that best predict `mov`. Due to either multicollinearity or low correlation, `mo_mins_pct`, `to_bf_pct`, `pct_6s`, `mo_sr`, and `bowlers_used` were excluded from our model. This is somewhat surprising as we believed that `mo_mins_pct` and `mo_sr` would have a greater impact on `mov`, particularly since the role of middle-order batsmen has been heightened since the introduction of the T20 format. The lack of `pct_6s` inclusion in the model is not as surprising as we expect batsmen to score more of their boundaries through 4s in a longer format where each wicket is more "valuable." We initially included `bowlers_used` on a suspicion that the more bowlers a team employed, the less faith they had in their front-line bowlers, implying that they had a weaker bowling lineup overall. This, however, was proven not to be the case as whether a team used 4 bowlers or 8, there was no effect on `mov`. Given more time, we would incorporate non-World Cup data in order to assess whether the chosen predictor variables would differ depending on more varied playing conditions.