

# STA531 Final Project-Preliminary Report

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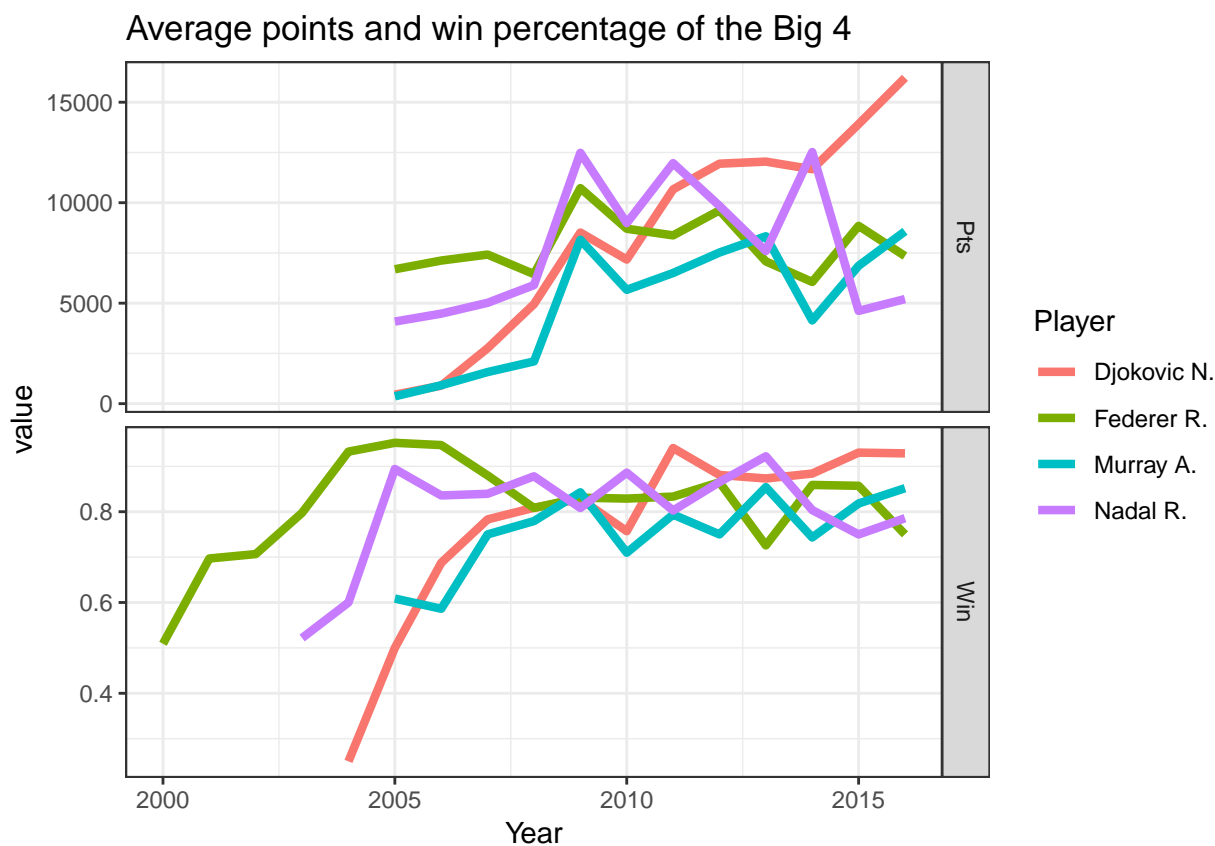
2019-04-08

## R Markdown

```
## # A tibble: 5 x 3
##   Series      Pts Rank
##   <chr>    <dbl> <dbl>
## 1 ATP250     960.  93.4
## 2 ATP500    1419.  75.9
## 3 Grand Slam 1773.  68.9
## 4 Masters 1000 2060.  46.5
## 5 Masters Cup  5201.   4.95

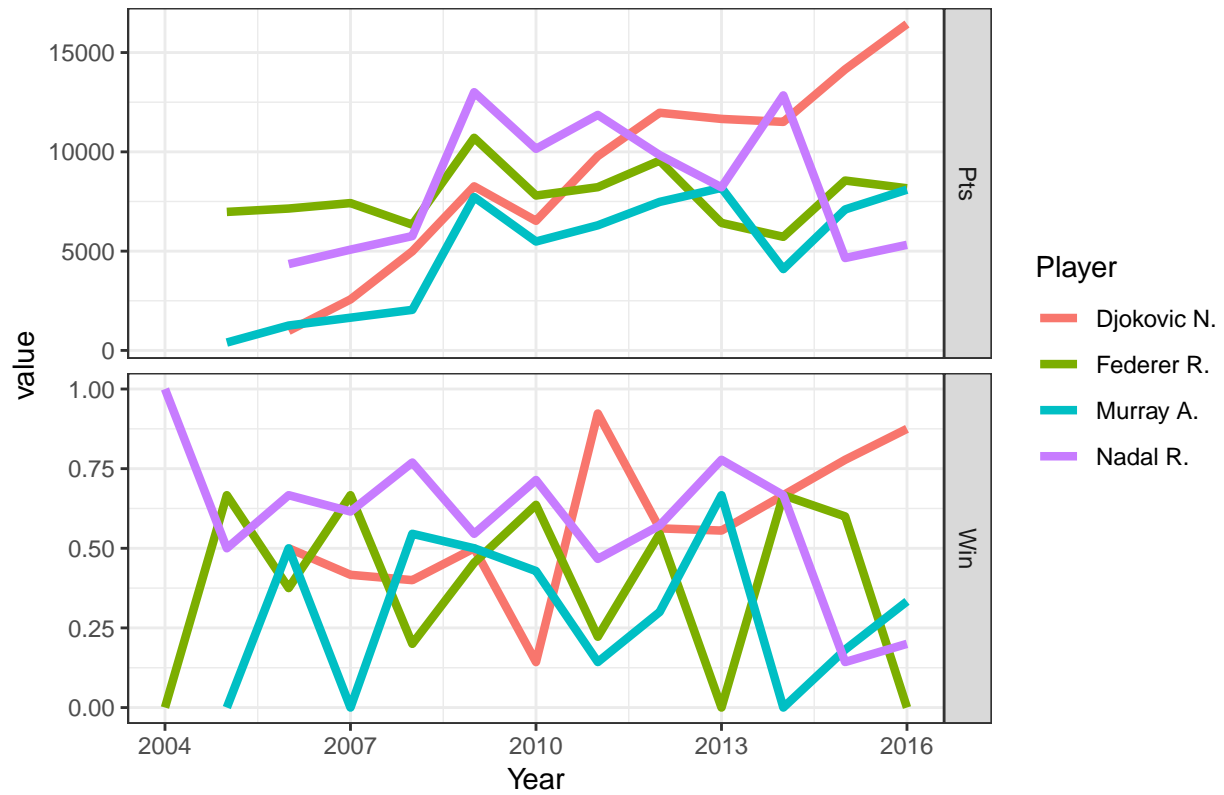
##           Pts    logPts      Rank      WL
## Pts      1.0000000  0.7740350 -0.3450371  0.2156367
## logPts   0.7740350  1.0000000 -0.8023401  0.2519962
## Rank     -0.3450371 -0.8023401  1.0000000 -0.1754293
## WL        0.2156367  0.2519962 -0.1754293  1.0000000

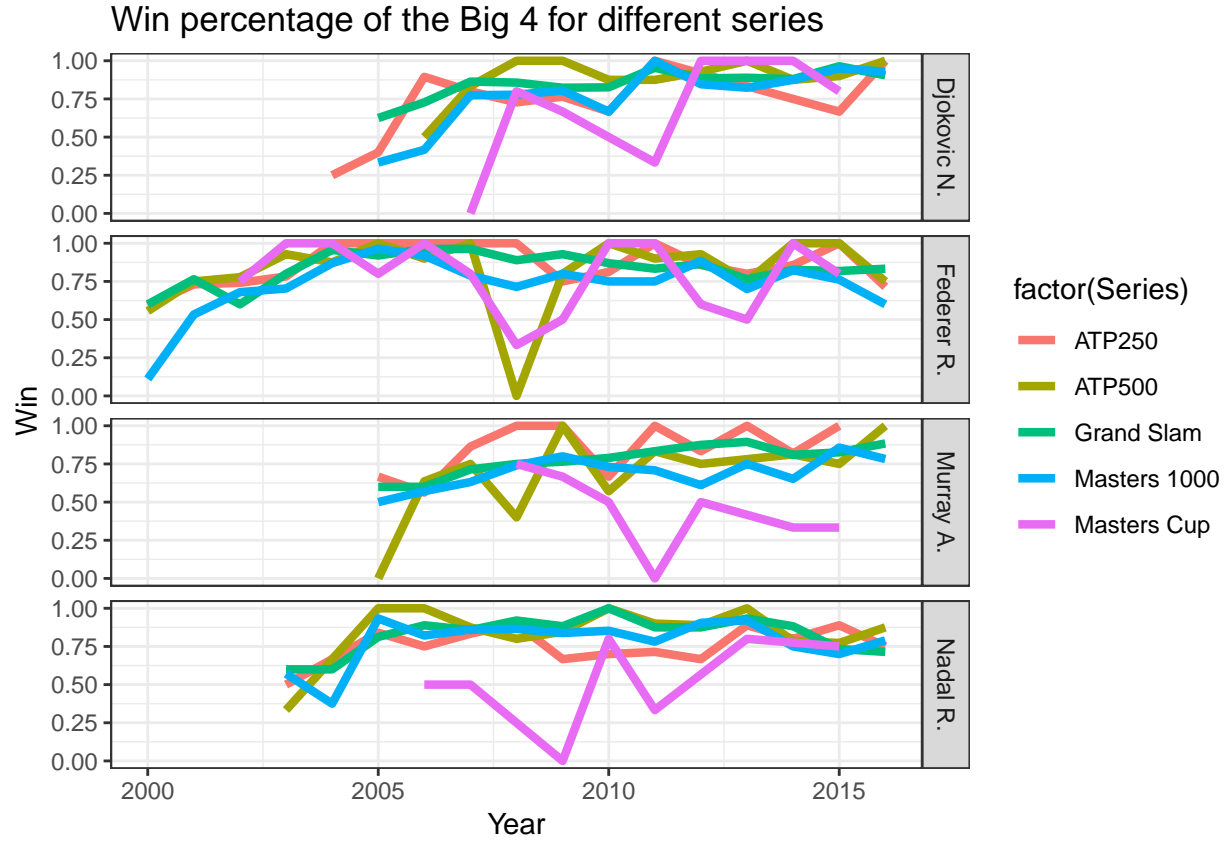
##           Win      Pts
## Win 1.0000000 0.6515231
## Pts 0.6515231 1.0000000
```



```
##           Win      Pts
## Win 1.0000000 0.4765591
## Pts 0.4765591 1.0000000
```

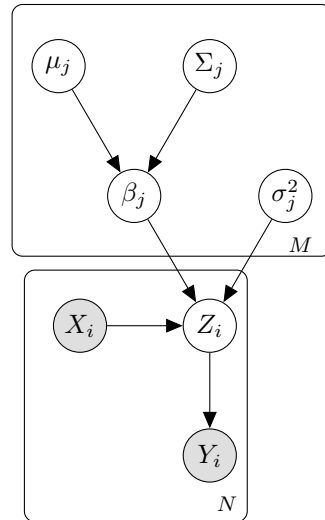
Average points and win percentage(against each other) of the Big 4





## Model

For each match, the model can be expressed using the graph below.



where matches are represented using the index  $i = 1, \dots, N$  and players are represented using the index

$j = 1, \dots, M$  with variables

$X_i$  : Vector of external conditions (Series, Court, Surface, Round, Best of 3/4, Opponent rank)

$Y_i$  : Match outcome

$Z_{i,1:2}$  : Performance level of the two players

$\beta_j$  : Vector of regression coefficients

$\sigma_j^2$  : Variance parameter for performance

$\mu_j$  : Mean hyperparameter for  $\beta_j$

$\Sigma_j$  : Variance hyperparameter for  $\beta_j$

The outcome of each match will be modelled using the distribution:

$$Y_i = \begin{cases} 1 & \text{if } Z_{i,1} \geq Z_{i,2} \\ 0 & \text{if } Z_{i,1} < Z_{i,2} \end{cases}$$

For player  $j$ , his performance level in match  $i$  will be a linear combination of  $X_i$  (external factors) as shown below.

$$Z_{i,1 \text{ or } 2}^{(j)} = X_i^T \beta_j + \epsilon_{i,j} \quad \epsilon_{i,j} \sim N(0, \sigma_j^2)$$

with

$$\beta_j \sim N(\mu_j, \Sigma_j)$$

The prior distributions for this model will be

$$\mu_j \sim$$

The parameters of our model would be estimated using a Gibbs sampler with full conditionals as follows.

$$\begin{aligned} p(Z_{i,1}^{(j)} | X_i, Y_i, Z_{i,2}, \beta_j, \sigma_j^2) &= \begin{cases} \text{Truncated Normal}(X_i^T \beta_j, \sigma_j^2, Z_{i,2}, \infty) & \text{if } Y_i = 1 \\ \text{Truncated Normal}(X_i^T \beta_j, \sigma_j^2, -\infty, Z_{i,2}) & \text{if } Y_i = 0 \end{cases} \\ p(Z_{i,2}^{(j)} | X_i, Y_i, Z_{i,1}, \beta_j, \sigma_j^2) &= \begin{cases} \text{Truncated Normal}(X_i^T \beta_j, \sigma_j^2, -\infty, Z_{i,1}) & \text{if } Y_i = 1 \\ \text{Truncated Normal}(X_i^T \beta_j, \sigma_j^2, Z_{i,1}, \infty) & \text{if } Y_i = 0 \end{cases} \\ p(\beta_j |) & \\ p(\mu_j |) & \end{aligned}$$