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# Sports Strategy Analytics using **Player Clustering** & **Probabilistic Model Checking**

Capstone Presentation

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December 2022

# OUTLINE

INTRODUCTION

- BACKGROUND & RELATED WORKS
- OBJECTIVE

METHODOLOGY

- DATA SOURCE
- FEATURE SELECTION
- CLUSTERING
- EVALUATION

EXPERIMENT RESULTS

FUTURE WORKS

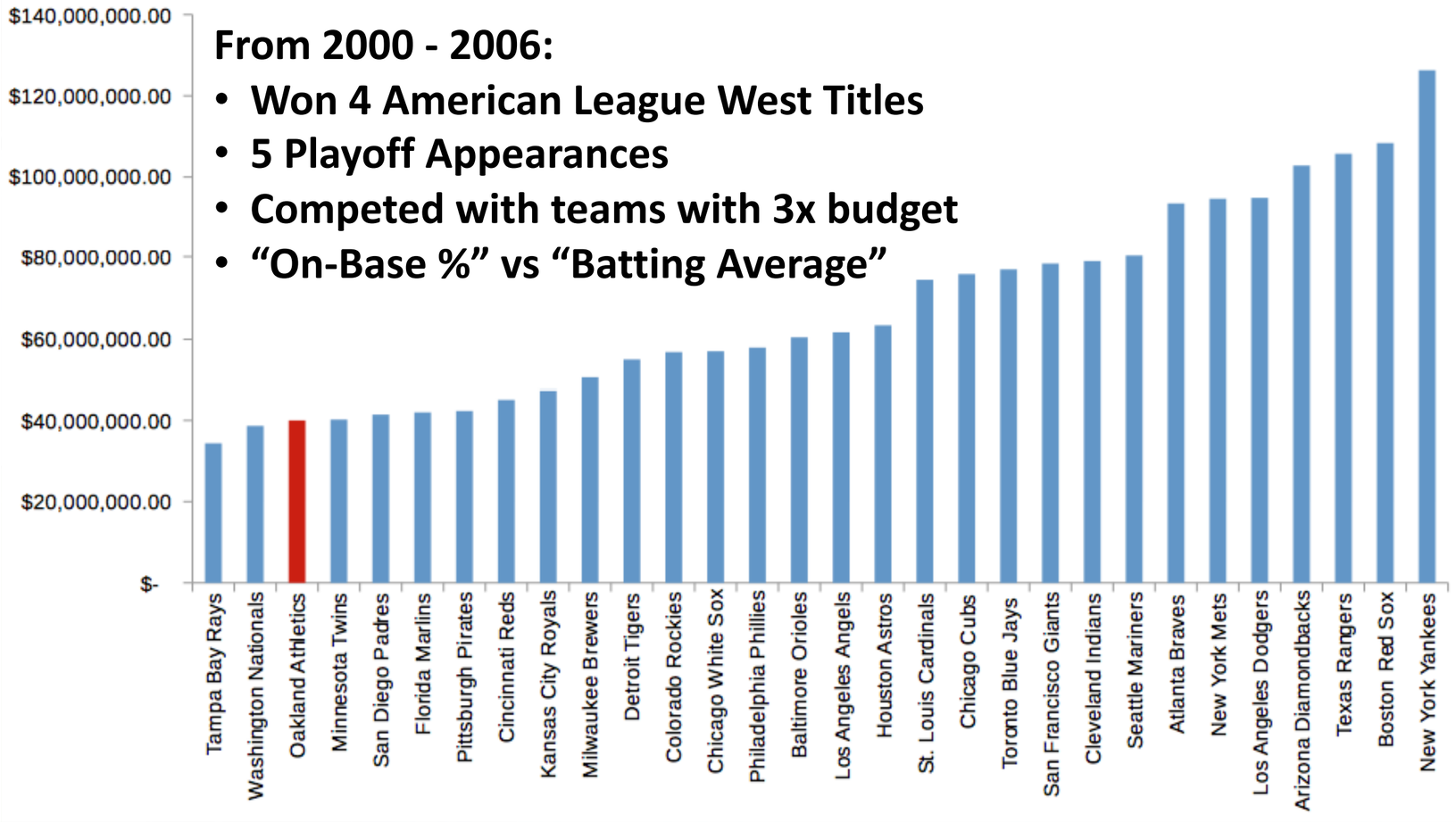
TECHNICAL RESEARCH CONTRIBUTIONS

# Background

# DATA

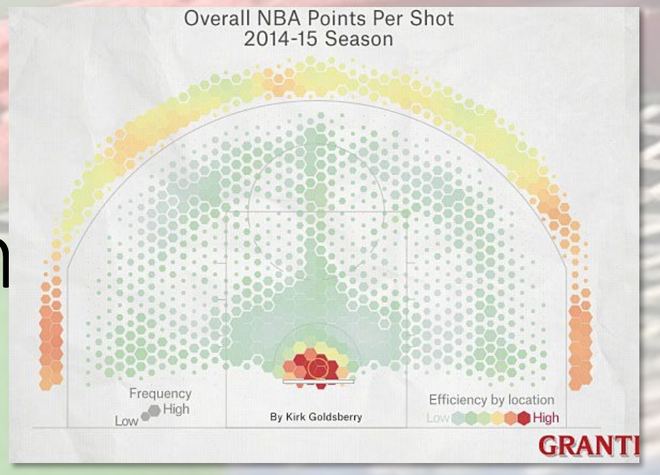

?

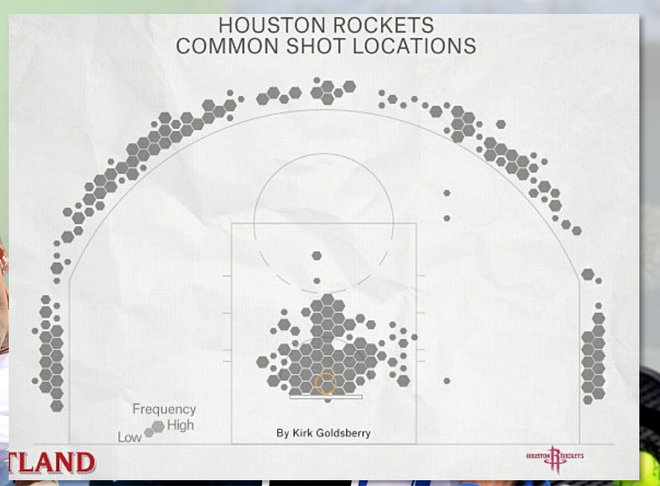
## Moneyball Year (2002)
## MLB Team Salaries




From 2000 - 2006:

- Won 4 American League West Titles
- 5 Playoff Appearances
- Competed with teams with 3x budget
- “On-Base %” vs “Batting Average”



# RELATED WORKS

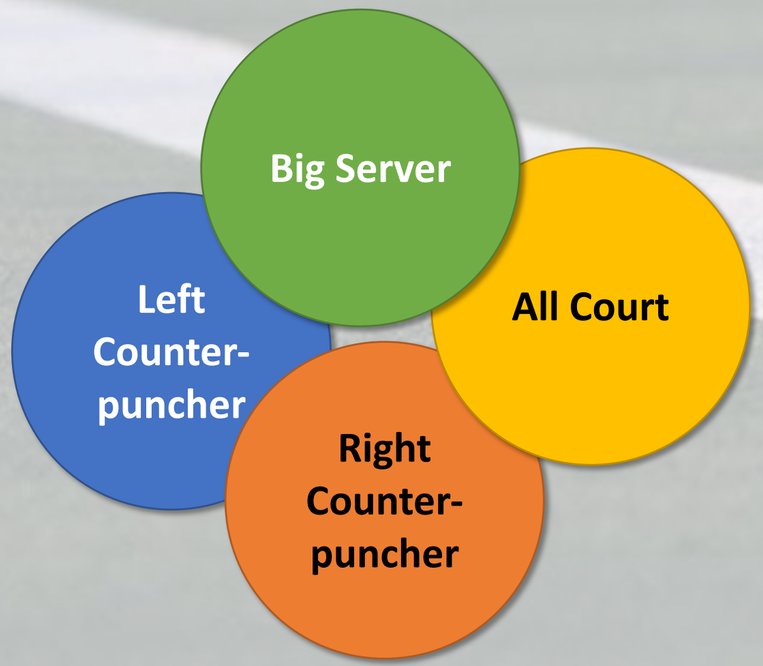
# Study #1: Sorting Strokes - Classifying Tennis Players Based on Style (by Harvard Sports Analysis Collective)

HSAC

- Cluster into play styles, and impact on win probability.

Differences:

- High-level data only
- Lack of quantitative evaluation – take results as is
- Uses historical match-level data to determine winning likelihood

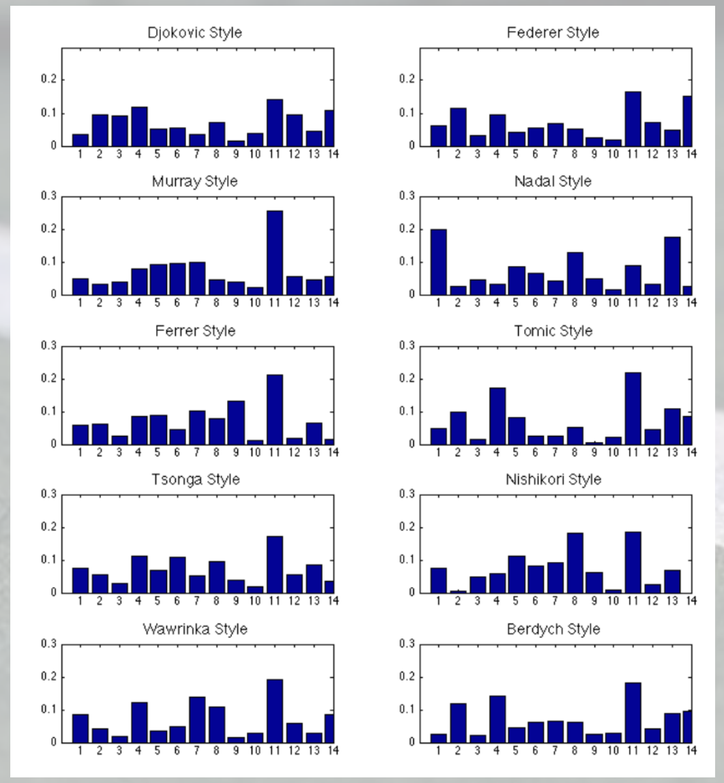


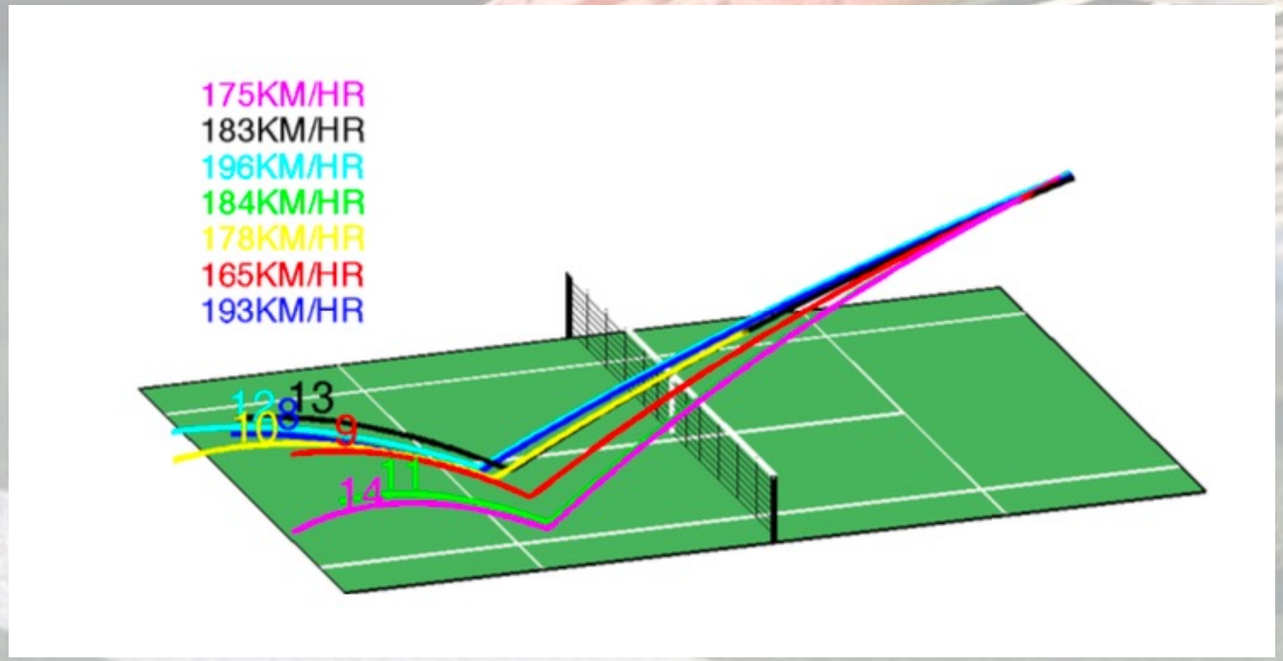

| Elo Adv. (P1) | Elo Disadv. (P2) | Multiplied Effect on Win Odds Elo Adv. |
|---|---|---|
| Left Counter-puncher | Big Server | 1.95 |
| Right Counter-puncher | Left Counter-puncher | 1.21 |
| Right Counter-puncher | All-court | 0.84 |
| All-court | Big Server | 0.4 |
| Big Server | Right Counter-puncher | 1.4 |

# Study #2: Predicting Serves in Tennis using Style Priors

(by Wei et al.)

- Used Hawk-eye data and “style priors” to predict **serve location**.




## Differences:

- Hawk-eye data
- Focuses on 1 part of the game

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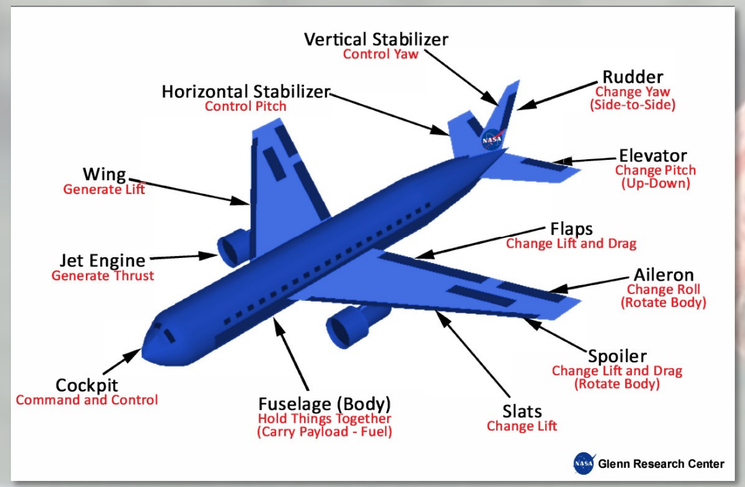
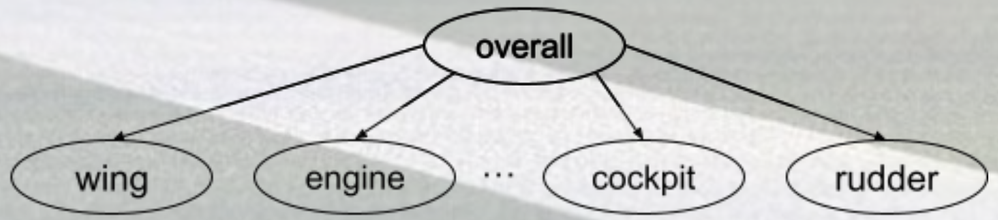
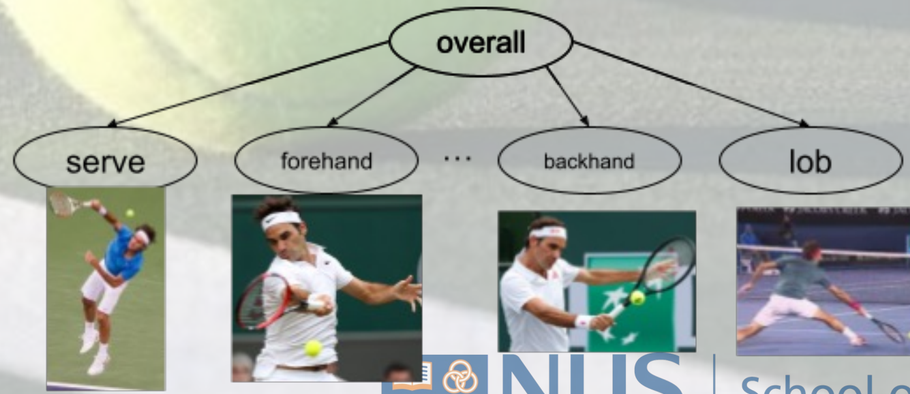
# PCSP Model &
# PAT Model Checker

# What is PCSP & PAT Model Checker?





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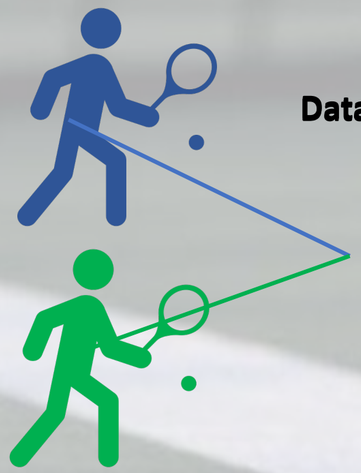
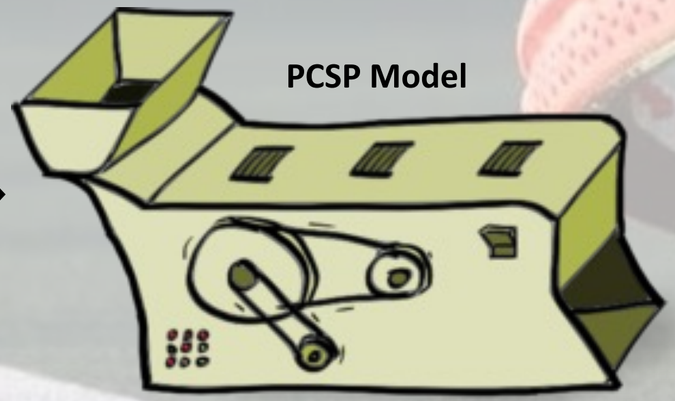
# PCSP & PAT Model Checker



Data of Player A vs Player B



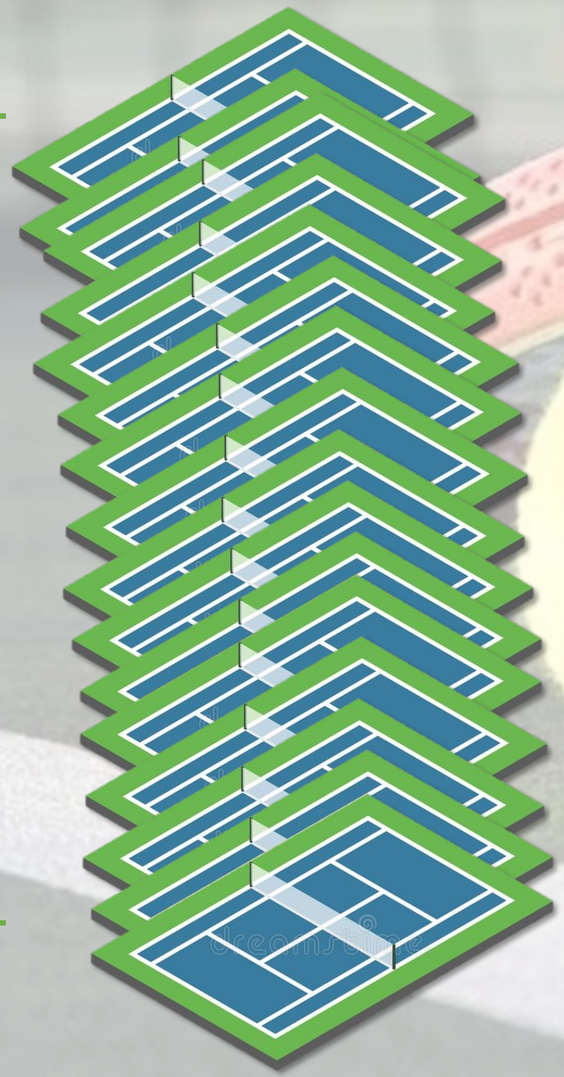
PCSP Model

**RESULT:**
**Player A has a 48-53% of winning against Player B!**

```
*********Verification Result*********
The Assertion (TieBreakGame() reaches player2Win with prob) is Valid with Probability [0.4886, 0.53511];
```

**35 matches recorded**
(~35-45 between each of the **BIG 3**)

Federer



Nadal

# CHALLENGES

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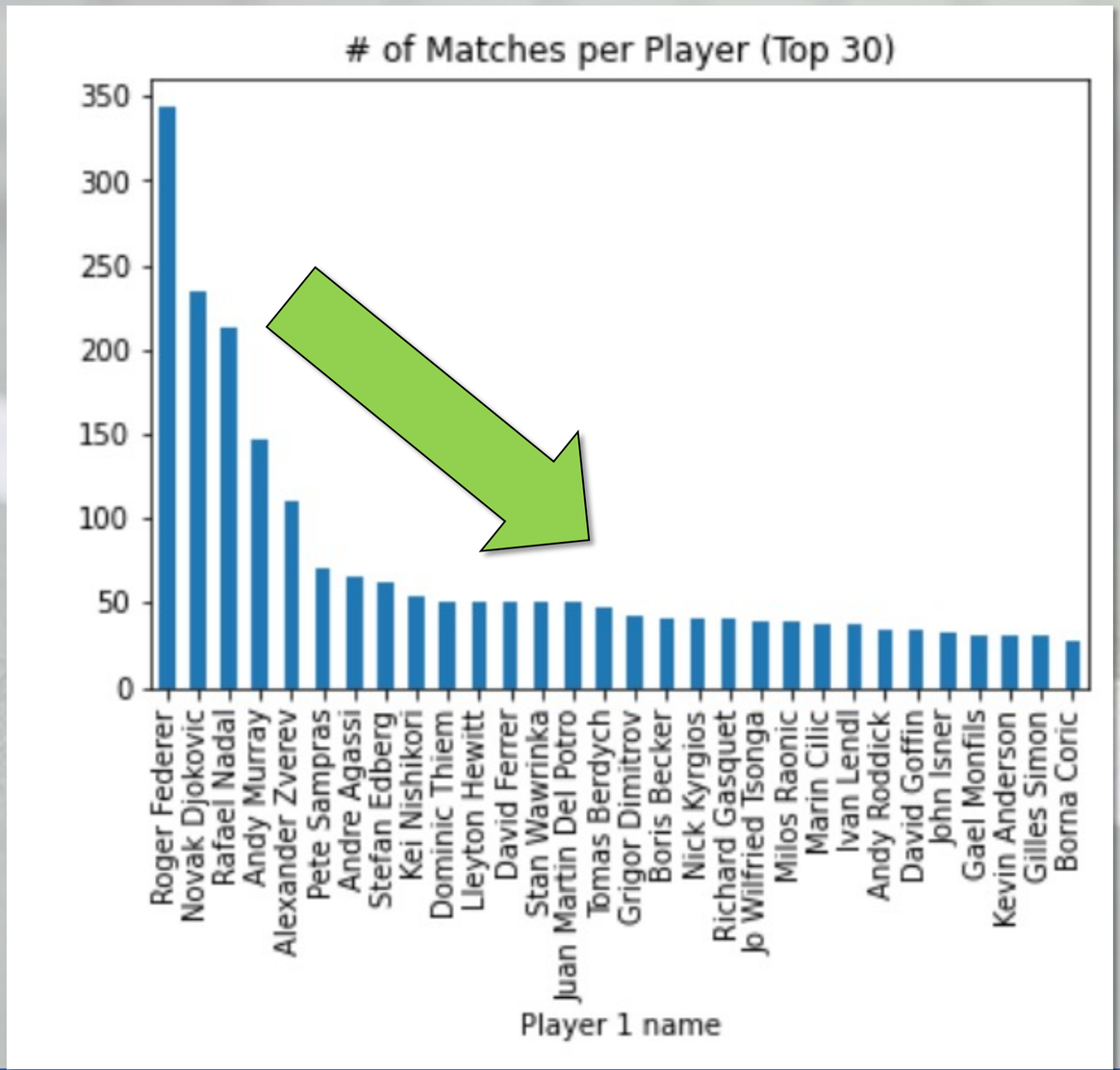



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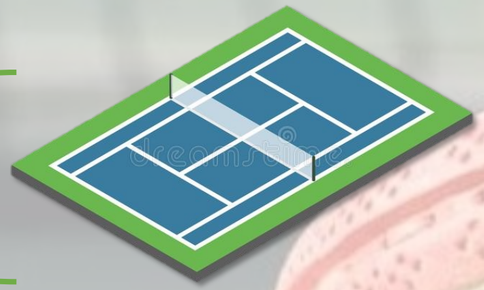
**1 total match recorded**



**Milos Raonic**
**Ranked #18**
**(2018)**

I'VE NEVER EVEN PLAYED AGAINST THESE GUYS!

**Nick Kyrgios**
**Ranked #35**
**(2018)**

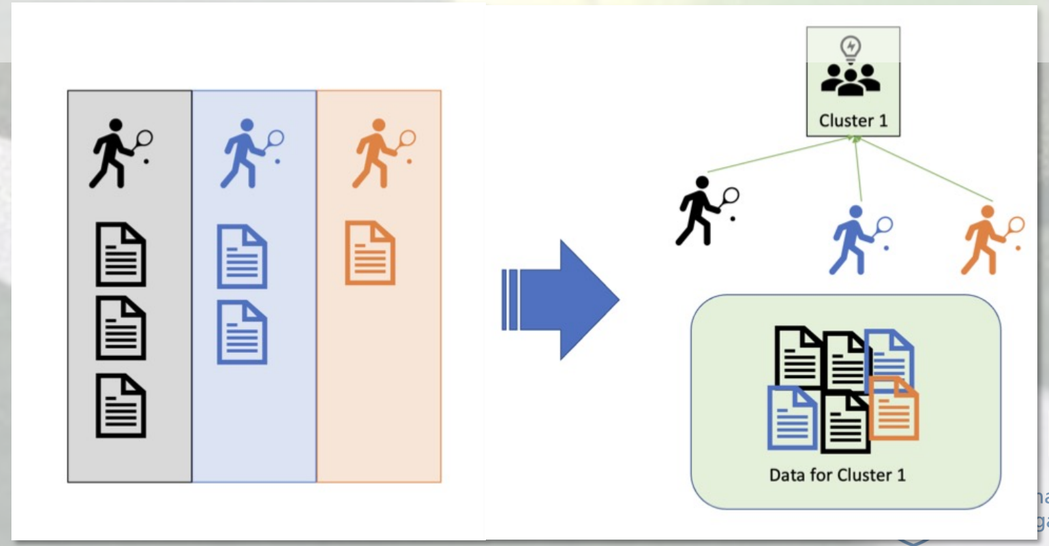
# OBJECTIVE

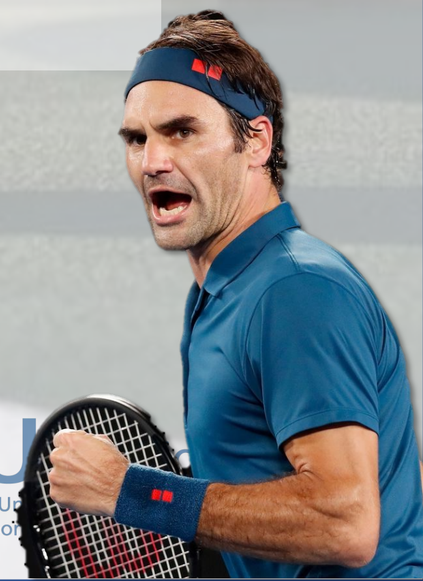
# OBJECTIVE

Group together similar tennis players into **clusters**, which will enable us to model their interactions **even if they never played with one another**, so long as similar players in their clusters have.

**Benefits:**

- Increase data availability and access of PCSP functionality for players outside of top players
- Allow players to use “clustered” data in PCSP model
- Many more implications!



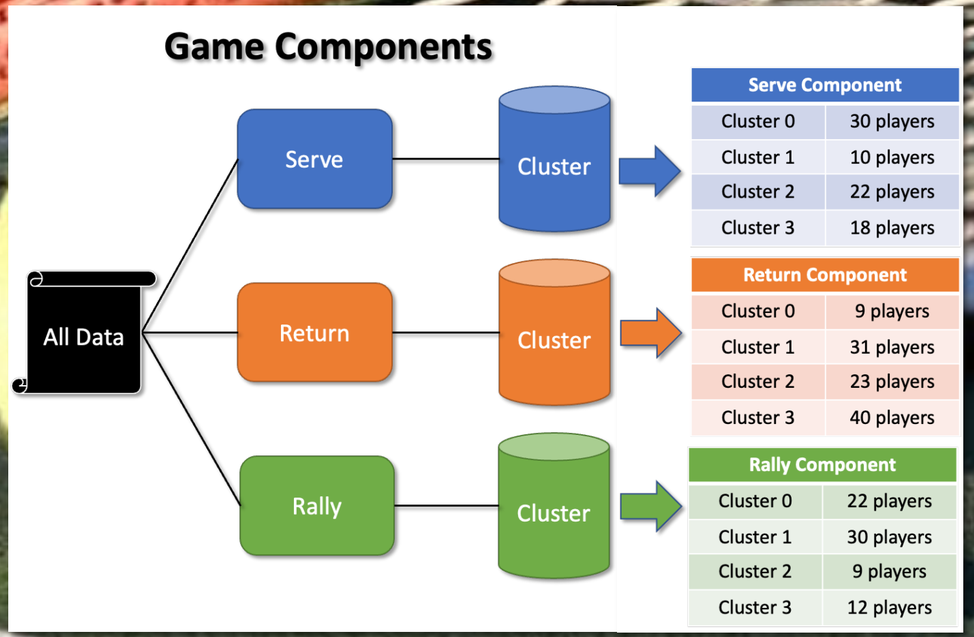
# APPROACH

## Game Components

Serve

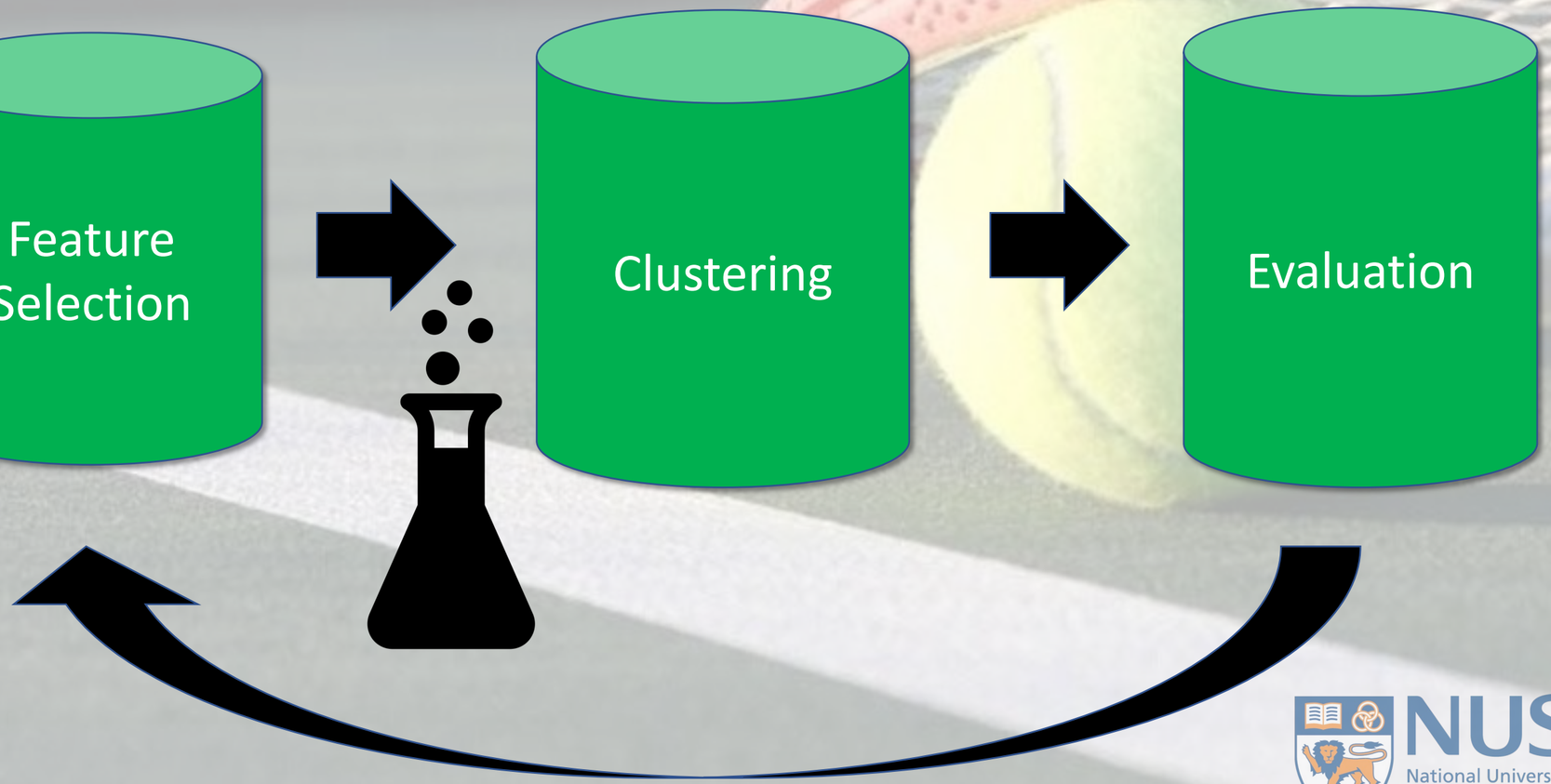

Return


Rally

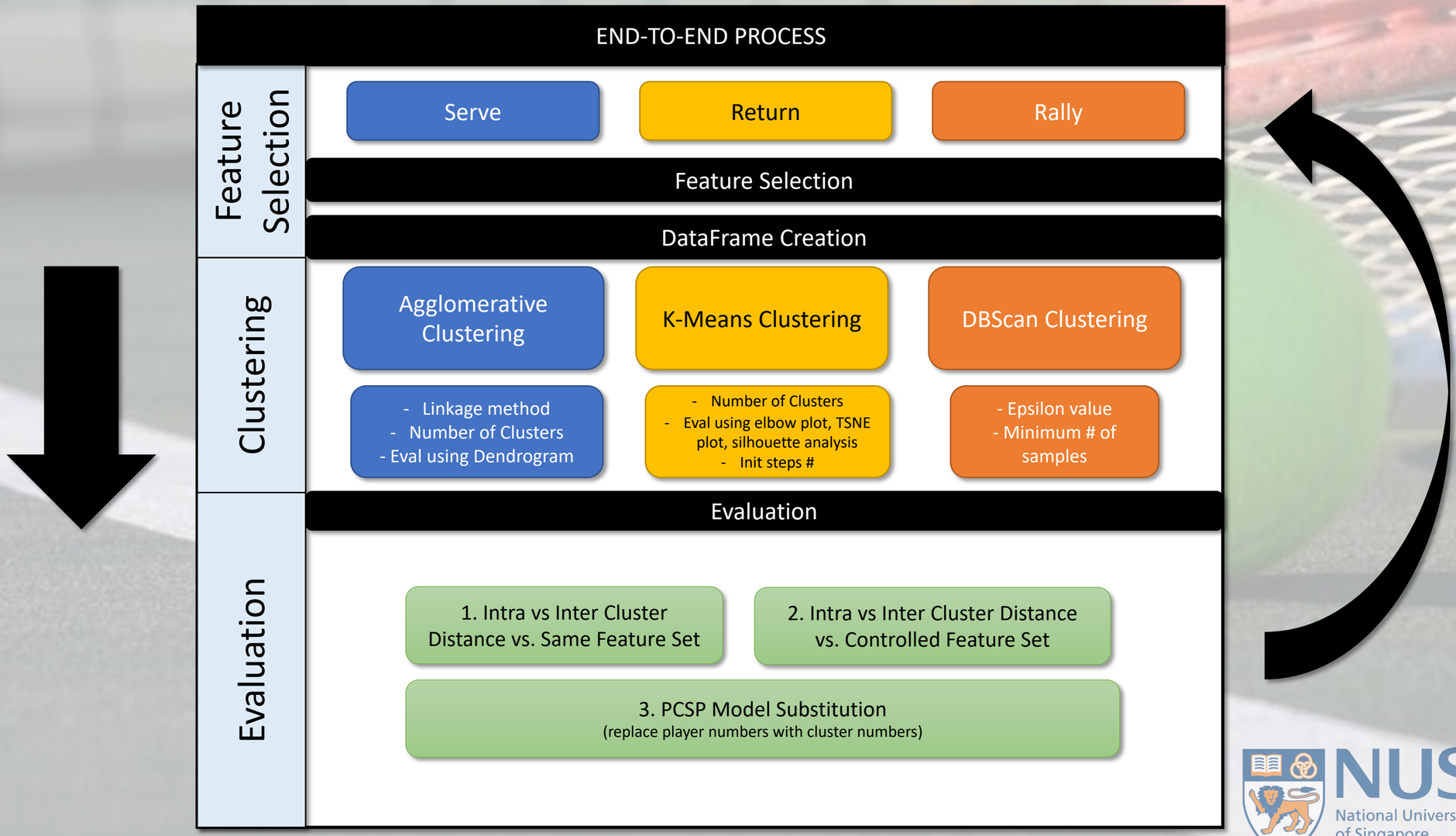


# The Process…

# METHODOLOGY



# METHODOLOGY

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# DATA SOURCE

## 1. High-level data: Career Summary Statistics

Tennis Abstract

**Men's Reports**

[ATP Stats Leaderboard](#)
The ATP top 50, sortable by almost 60 stats.

Match Charting Project Leaderboards:
*Last 52:* [Serve](#) | [Return](#) | [Rally](#) | [Tactics](#)
*Career:* [Serve](#) | [Return](#) | [Rally](#) | [Tactics](#)

[ATP H2H Matrix](#)
Head-to-head records of the current top 15.
[The Best ATP Players Who Haven't...](#)
...won titles, reached main draws, etc.
[ATP Lottery Matches](#)
...and equally befuddling results from the [Challenger tour](#)

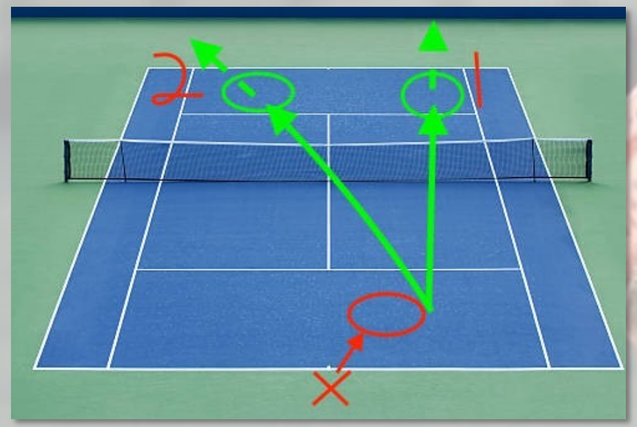

| Service Game | Feature Definition |
|---|---|
| Matches | Matches logged by the Match Charting Project |
| Unret% | Percent of serves that were unreturned |
| <=3 W% | Percent of service points won on either the serve or second shot |
| RiP W% | Percent of points won when return was put in play |
| SvImpact | Serve Impact: Advanced stat estimating how many service points were won due to the serve |
| 1st: Unret% | Percent of first serves that were unreturned |
| 1st: <=3 W% | Percent of first serve points won on either the serve or second shot |
| 1st: RiP W% | Percentage of first serve points won when return was put in play |
| 1st: SvImpact | Serve Impact: Advanced stat estimating how many first serve points were won due to the serve |
| D Wide% | Percent of deuce-court first serves that were hit wide |
| A Wide% | Percent of ad-court first serves that were hit wide |
| BP Wide% | Percent of (ad-court) break point first serves that were hit wide |
| 2nd: Unret% | Percent of second serves that were unreturned |
| 2nd: <=3 W% | Percent of second serve points won on either the serve or second shot |
| 2nd: RiP W% | Percentage of second serve points won when return was put in play |
| 1st: D Wide% | Percent of deuce-court second serves that were hit wide |
| 1st: A Wide% | Percent of ad-court second serves that were hit wide |
| 1st: BP Wide% | Percent of (ad-court) break point second serves that were hit wide |
| 2ndAgg | 2nd Serve Aggression Score (0 is average, higher = more aggressive) |

| Player | Matches | Unret% | <=3 W% | RiP W% | SvImpact | 1st: Unret% | <=3 W% | RiP W% | SvImpact | D Wide% | A Wide% | BP Wide% | 2nd: Unret% | <=3 W% | RiP W% | D Wide% | A Wide% | BP Wide% | 2ndAgg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ivo Karlovic | 35 | 48.0% | 63.2% | 50.9% | 55.3% | 59.0% | 74.8% | 57.0% | 70.1% | 42.9% | 56.9% | 57.5% | 31.6% | 48.0% | 42.7% | 26.4% | 30.2% | 14.3% | 126 |
| Maxime Cressy | 26 | 43.8% | 59.2% | 55.8% | 52.1% | 51.0% | 68.5% | 58.1% | 64.3% | 55.4% | 59.9% | 74.2% | 43.6% | 59.5% | 51.4% | 47.0% | 55.3% | 56.0% | 245 |
| John Isner | 84 | 45.5% | 59.2% | 48.5% | 52.1% | 54.1% | 67.4% | 51.2% | 63.5% | 50.1% | 45.9% | 57.2% | 26.7% | 42.7% | 44.1% | 22.4% | 52.1% | 68.5% | 34 |
| Reilly Opelka | 53 | 46.3% | 58.8% | 48.6% | 51.7% | 57.5% | 69.2% | 50.6% | 65.6% | 50.0% | 44.1% | 44.8% | 26.9% | 42.2% | 46.2% | 33.3% | 53.9% | 82.7% | 33 |
| Goran Ivanisevic | 44 | 42.1% | 53.9% | 49.8% | 47.4% | 58.9% | 72.1% | 55.4% | 68.6% | 38.1% | 55.0% | 56.8% | 26.3% | 38.3% | 45.4% | 16.9% | 51.7% | 65.6% | 119 |
| Milos Raonic | 78 | 39.7% | 54.0% | 51.6% | 47.1% | 52.0% | 68.1% | 57.3% | 63.8% | 53.6% | 50.2% | 45.5% | 21.4% | 34.1% | 45.0% | 28.1% | 54.4% | 71.8% | 76 |
| Richard Krajicek | 20 | 40.2% | 53.6% | 47.8% | 46.8% | 54.9% | 69.8% | 56.7% | 66.5% | 45.7% | 39.9% | 27.8% | 23.9% | 37.0% | 39.9% | 12.4% | 49.8% | 70.0% | 60 |
| Nick Kyrgios | 111 | 40.5% | 51.8% | 51.0% | 46.4% | 51.0% | 63.2% | 54.2% | 59.8% | 43.3% | 40.9% | 57.0% | 23.0% | 33.7% | 46.4% | 31.1% | 50.5% | 43.3% | 103 |
| Gilles Muller | 20 | 37.3% | 54.3% | 53.1% | 45.9% | 49.3% | 69.5% | 60.4% | 63.2% | 45.5% | 46.6% | 40.0% | 19.8% | 33.2% | 44.5% | 24.2% | 30.4% | 23.5% | 75 |
| Sam Querrey | 34 | 39.7% | 51.2% | 48.5% | 45.6% | 54.0% | 67.4% | 52.8% | 63.7% | 47.3% | 47.0% | 51.7% | 20.0% | 30.0% | 44.1% | 36.4% | 47.4% | 41.8% | 77 |

# DATA SOURCE

## 2. Low-level data: Shot-by-Shot data

**Summary:**
- 3 million+ rows (shots)
- 800+ players
- 8000+ matches
- Around 400 shots/match
- 59 columns
  - 11 features = “shot attributes”



### Tennis Abstract (GitHub)

| | Short | Player 1 name | Player 2 name | Player 1 handness | Player 2 handness | Player 1 points | Player 2 points | Player 1 games | Player 2 games | Player 1 sets | Player 2 sets | ... | Prev prev shot From which court | Prev prev Shot | Prev prev shot Direction | Prev prev shot To which court | Prev prev shot Depth | Prev prev shot Touched Net? | Prev prev Hit at de |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | Novak Djokovic | Alexander Zverev | RH | RH | 0 | 0 | 0 | 0 | 0 | 0 | ... | 99 | 99 | 99 | 99 | 99 | 99 | |
| | 1 | Alexander Zverev | Novak Djokovic | RH | RH | 0 | 0 | 0 | 0 | 0 | 0 | ... | 99 | 99 | 99 | 99 | 99 | 99 | |
| | 2 | Novak Djokovic | Alexander Zverev | RH | RH | 0 | 0 | 0 | 0 | 0 | 0 | ... | 1 | 99 | 6 | 2 | 99 | 2 | |
| | 3 | Alexander Zverev | Novak Djokovic | RH | RH | 0 | 0 | 0 | 0 | 0 | 0 | ... | 2 | 22 | 2 | 2 | 2 | 2 | |
| | 4 | Novak Djokovic | Alexander Zverev | RH | RH | 0 | 0 | 0 | 0 | 0 | 0 | ... | 2 | 1 | 7 | 1 | 99 | 2 | |
| | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| | 3306473 | Ken Rosewall | Rod Laver | RH | LH | 3 | 4 | 3 | 5 | 2 | 2 | ... | 99 | 99 | 99 | 99 | 99 | 99 | |
| | 3306474 | Rod Laver | Ken Rosewall | LH | RH | 4 | 3 | 5 | 3 | 2 | 2 | ... | 99 | 99 | 99 | 99 | 99 | 99 | |
| | 3306475 | Ken Rosewall | Rod Laver | RH | LH | 3 | 4 | 3 | 5 | 2 | 2 | ... | 3 | 99 | 5 | 3 | 99 | 2 | |
| | 3306476 | Rod Laver | Ken Rosewall | LH | RH | 4 | 3 | 5 | 3 | 2 | 2 | ... | 3 | 22 | 2 | 2 | 2 | 2 | |
| | 3306477 | Ken Rosewall | Rod Laver | RH | LH | 3 | 4 | 3 | 5 | 2 | 2 | ... | 2 | 13 | 2 | 2 | 99 | 2 | |

= 1 shot

3306478 rows × 45 columns

| Field Name | Feature Definition |
|---|---|
| **Player 1 name** | Player's name |
| **Player 2 name** | Opponent's name |
| **Player 1 handness** | Dominant hand of player (RH for Right-hand, LH for Left-hand) |
| **Player 2 handness** | Dominant hand of opponent |
| **Date** | Date of match |
| **Tournament Name** | Name of tournament |
| **Shot Type** | Type of shot<br>(1=1st serve, 2=2nd serve, 3=return, 4=rally) |
| **From which court** | Court location of when ball is hit by Player 1<br>(1=deuce court, 2=middle court, 3=ad court, 99=unknown) |
| **Shot** | Shot description<br>(1~20 are forehand shots, 21~40 are backhand shots, 41 is trick shot, 99=unknown), detailed codes for all shots are: |
| **Direction (serve)** | Serve direction<br>(1=deuce court, 2=middle court, 3=ad court, 4=serve to wide, 5=serve to body, 6=server to T, 99=unknown) |
| **To which court** | Shot direction<br>(1=deuce court, 2=middle court, 3=ad court, 99=unknown) |
| **Depth** | (1=shallow, 2=deep, 3=very deep, 99=unknown) |
| **Touched Net?** | (1=yes touched net, 2=not) |
| **Hit at what depth?** | (1=at net, 2=at baseline, 99=unknown) |
| **Approach shot?** | (1=yes, 2=no) |
| **Shot outcome** | Outcome of shot<br>(1=ace, 2=fault, 3=forced error, 4=unforced error, 5=-winner, 6=service winner, 7=no outcome) |
| **Fault type** | Fault type, if Shot Type = serve<br>(1=(net), 2=(wide), 3=(long), 4=(wide and long), 5=(foot fault), 6=(shank), 7=no fault, 99=other) |

# EXPLORATORY DATA ANALYSIS

Djokovic

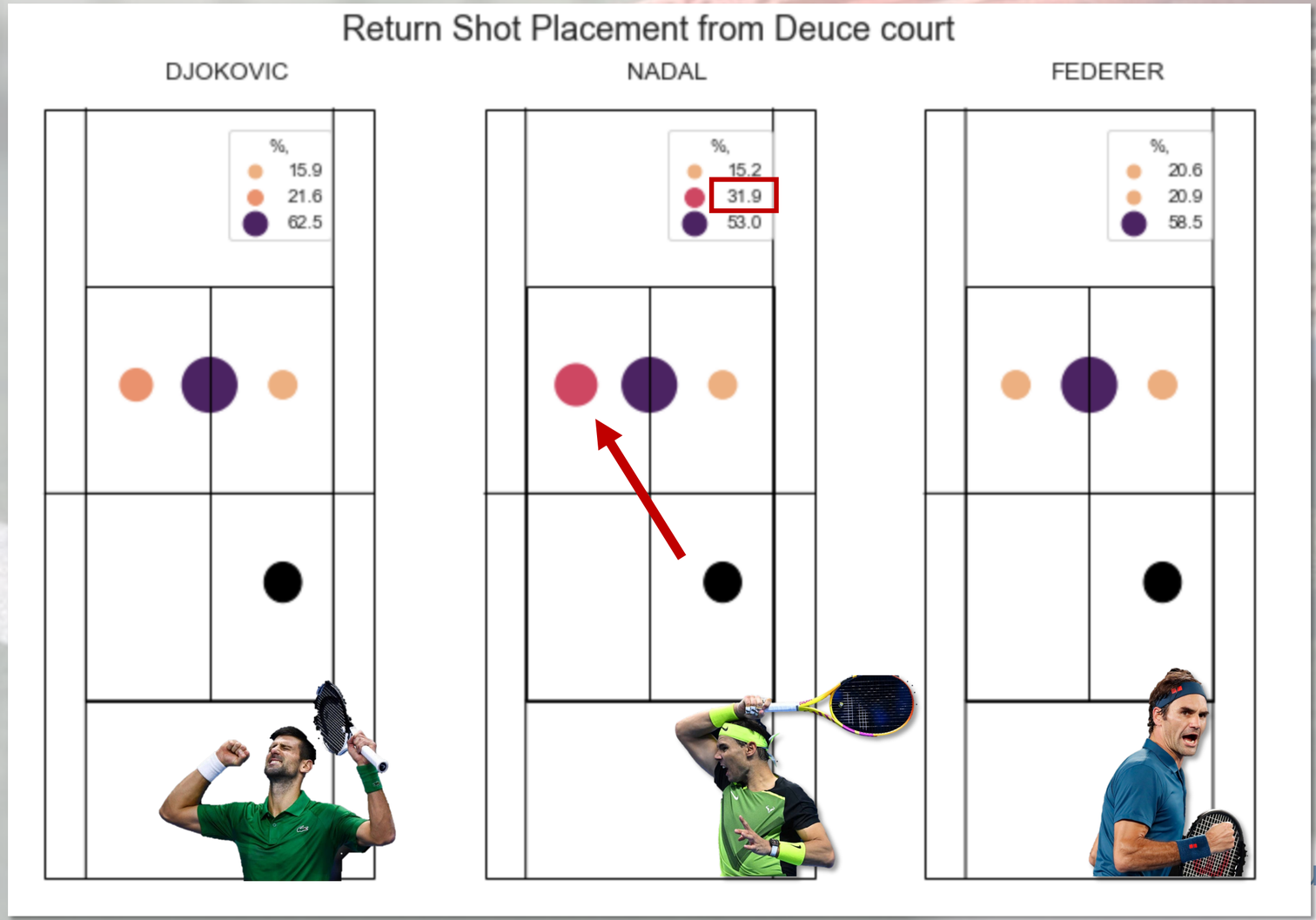
| | court | count | percent |
|---|---|---|---|
| 0 | mid | 3594 | 62.5 |
| 1 | deuce | 1242 | 21.6 |
| 2 | ad | 912 | 15.9 |

Nadal

| | court | count | percent |
|---|---|---|---|
| 0 | mid | 3363 | 53.0 |
| 1 | deuce | 2023 | 31.9 |
| 2 | ad | 963 | 15.2 |

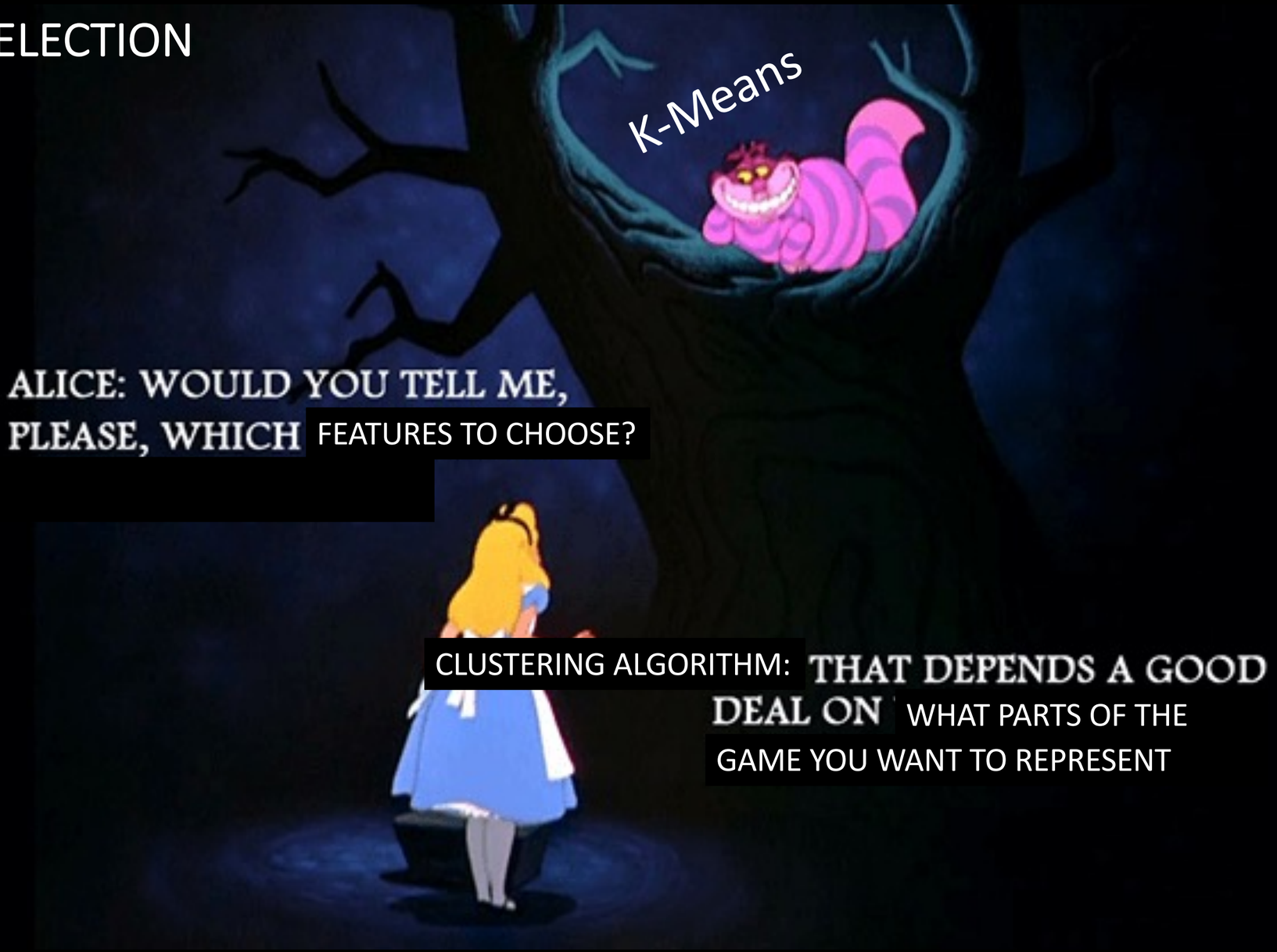
Federer

| | court | count | percent |
|---|---|---|---|
| 0 | mid | 4678 | 58.5 |
| 1 | ad | 1668 | 20.9 |
| 2 | deuce | 1647 | 20.6 |

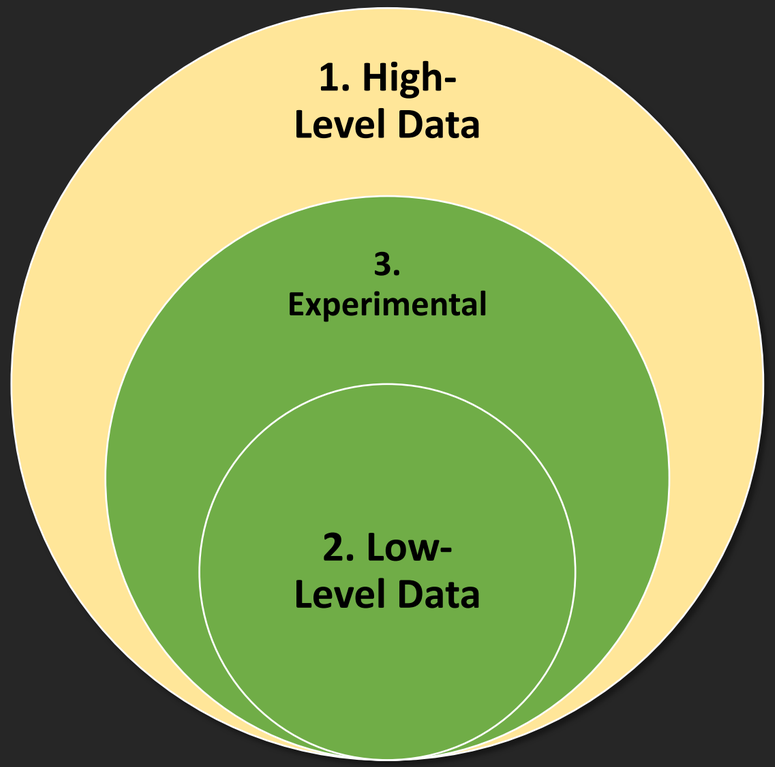


# PHASE 1: FEATURE SELECTION

# FEATURE SELECTION



# FEATURE SELECTION




## 1. High-Level Summary Data

| Service Game | Feature Definition |
|---|---|
| **Matches** | Matches logged by the Match Charting Project |
| **Unret%** | Percent of serves that were unreturned |
| **<=3 W%** | Percent of service points won on either the serve or second shot |
| **RiP W%** | Percent of points won when return was put in play |
| **SvImpact** | Serve Impact: Advanced stat estimating how many service points were won due to the serve |
| **1st: Unret%** | Percent of first serves that were unreturned |
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| **A Wide%** | Percent of ad-court first serves that were hit wide |
| **BP Wide%** | Percent of (ad-court) break point first serves that were hit wide |
| **2nd: Unret%** | Percent of second serves that were unreturned |
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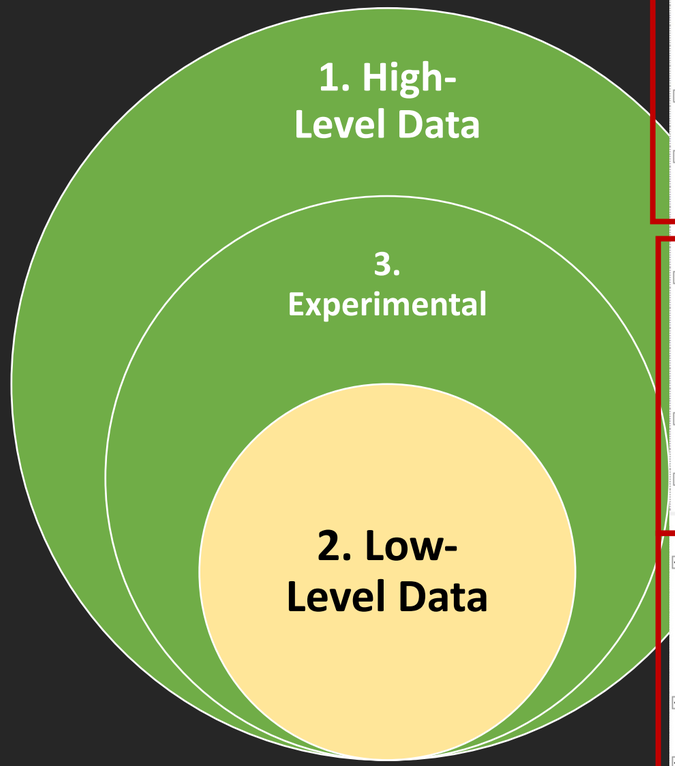
| **1st: BP Wide%** | Percent of (ad-court) break point second serves that were hit wide |
| **2ndAgg** | 2nd Serve Aggression Score (0 is average, higher = more aggressive) |

# FEATURE SELECTION




**PCSP Functions**

```
// deuce stroke is when player1 hit position is 1
Ply1_de_stroke = pcase{
    13: FH_Crosscourt { ball = 6} -> Ply2_de_stroke
    13: FH_Downline { ball = 4} -> Ply2_ad_stroke
    13: FH_DownMid { ball = 5} -> Ply2_mid_stroke
    13: BH_InsideIn {ball = 4} -> Ply2_ad_stroke
    12: BH_InsideOut { ball = 6} -> Ply2_de_stroke
    12: BH_DownMid { ball = 5} -> Ply2_mid_stroke
    12: FH_Error { ball = 9} -> {nscore++; if (nscore == 7) {won = player2}
                                                    else { turn = (turn+1)%4 }
                                                    } -> NextPt
    12: BH_Error { ball = 9} -> {nscore++; if (nscore == 7) {won = player2}
                                                    else { turn = (turn+1)%4 }
                                                    } -> NextPt
    };
```

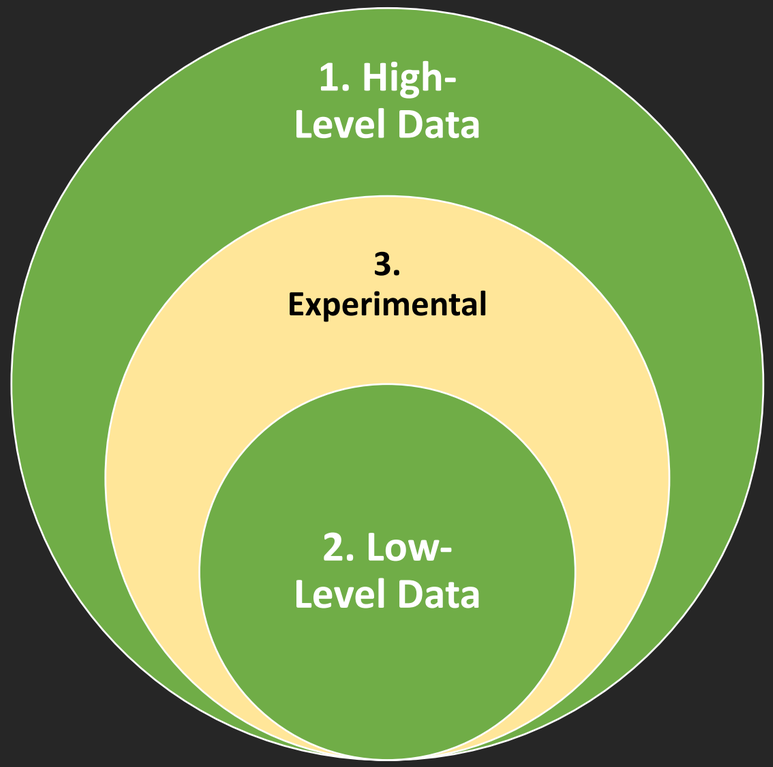
```
// mid stroke is when player1 hit position is 2
Ply1_mid_stroke = pcase{
    13: FH_InsideOut{ball = 4} -> Ply2_ad_stroke
    13: FH_Crosscourt { ball = 6} -> Ply2_de_stroke
    13: FH_DownMid { ball = 5 } -> Ply2_mid_stroke
    13: BH_InsideOut { ball = 6} -> Ply2_de_stroke
    12: BH_DownMid { ball = 5} -> Ply2_mid_stroke
    12: BH_Crosscourt { ball = 4} -> Ply2_ad_stroke
    12: FH_Error { ball = 9} -> {nscore++; if (nscore == 7) {won = player2}
                                                    else { turn = (turn+1)%4 }
                                                    } -> NextPt
    12: BH_Error { ball = 9} -> {nscore++; if (nscore == 7) {won = player2}
                                                    else { turn = (turn+1)%4 }
```

```
// ad stroke is when player1 hit position is 3
Ply1_ad_stroke = pcase{
    13: BH_Crosscourt { ball = 4} -> Ply2_ad_stroke
    13: BH_Downline { ball = 6} -> Ply2_de_stroke
    13: BH_DownMid { ball = 5 } -> Ply2_mid_stroke
    13: FH_InsideOut { ball = 4} -> Ply2_ad_stroke
    12: FH_InsideIn { ball = 6} -> Ply2_de_stroke
    12: FH_DownMid { ball = 5} -> Ply2_mid_stroke
    12: FH_Error { ball = 9} -> {nscore++; if (nscore == 7) {won = player2}
                                                    else { turn = (turn+1)%4 }
                                                    } -> NextPt
    12: BH_Error { ball = 9} -> {nscore++; if (nscore == 7) {won = player2}
                                                    else { turn = (turn+1)%4 }
                                                    } -> NextPt
    };
```

## 2. Low-Level Shot % Data

| {0: From_Court | rally_outcome | |
|---|---|---|
| middle court | BH_Error | 0.080589 |
| | BH_cross_court | 0.170786 |
| | BH_down_mid | 0.097845 |
| | BH_inside_out | 0.094301 |
| | FH_Error | 0.093835 |
| | FH_cross_court | 0.195411 |
| | FH_down_mid | 0.079657 |
| | FH_inside_out | 0.187576 |
| deuce court | BH_Error | 0.002019 |
| | BH_down_mid | 0.001863 |
| | BH_inside_in | 0.003416 |
| | BH_inside_out | 0.001708 |
| | FH_Error | 0.261180 |
| | FH_cross_court | 0.318944 |
| | FH_down_line | 0.260404 |
| | FH_down_mid | 0.150466 |
| ad court | BH_Error | 0.193075 |
| | BH_cross_court | 0.354506 |
| | BH_down_line | 0.185508 |
| | BH_down_mid | 0.168769 |
| | FH_Error | 0.015746 |
| | FH_down_mid | 0.010166 |
| | FH_inside_in | 0.027669 |
| | FH_inside_out | 0.044562 |

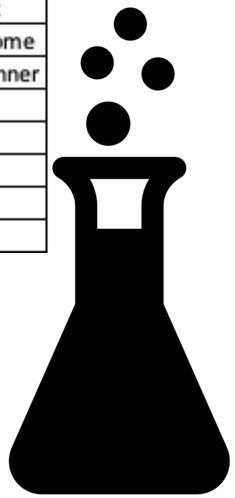
# FEATURE SELECTION

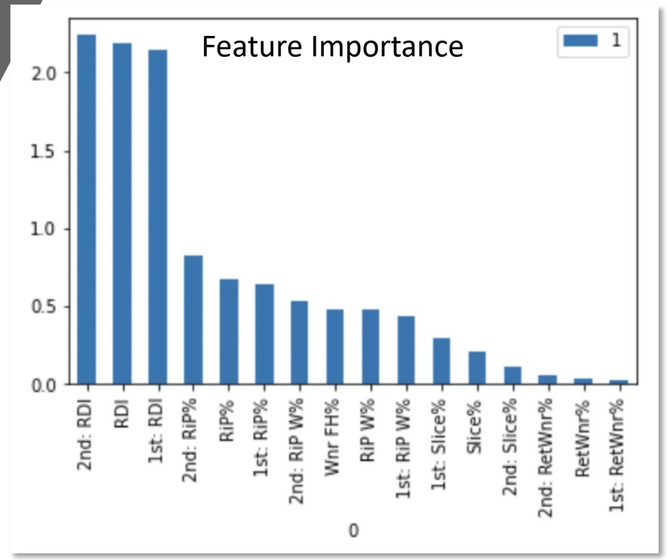



## 3. Experimental

Feature Combinations

| Shot Type | Shot Description | From Court | Direction | Outcome |
|---|---|---|---|---|
| 1st serve | Forehand | Deuce court | Deuce court | Fault |
| 2nd serve | Backhand | Ad court | Middle court | No outcome |
| Return | Forehand Volley | Middle court | Ad court | Serve winner |
| Rally | Slice | | | |
| | Smash | | | |
| | Backhand lob | | | |
| | Forehand drop shot | | | |
| | ... | | | |



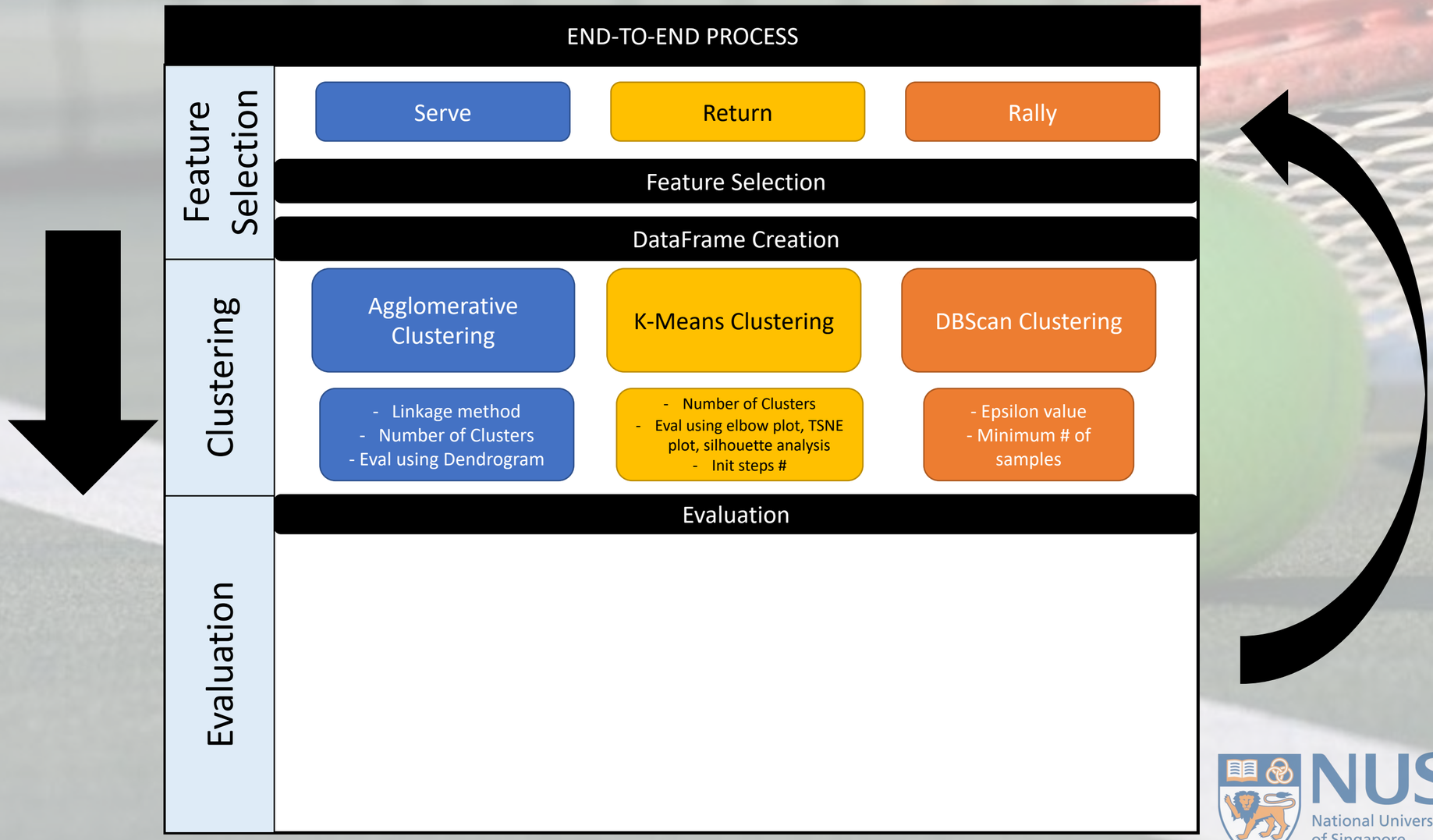



Feature Variance

```
feature: 0 Mean difference: 1.69 Total Variance: 459.464
feature: 1 Mean difference: 0.879 Total Variance: 449.829
feature: 2 Mean difference: 66.213 Total Variance: 154932.184
feature: 3 Mean difference: 2.076 Total Variance: 2731.953
```

| | feature | percentage |
|---|---|---|
| 0 | middle court-BH_Error | 0.044010 |
| 1 | middle court-BH_cross_court | 0.120941 |
| 2 | middle court-BH_down_mid | 0.109487 |
| 3 | middle court-BH_inside_out | 0.063157 |
| 4 | middle court-FH_Error | 0.080256 |
| ... | ... | ... |
| 19 | ad court-BH_down_mid | 0.189106 |
| 20 | ad court-FH_Error | 0.032507 |
| 21 | ad court-FH_down_mid | 0.031118 |
| 22 | ad court-FH_inside_in | 0.054525 |
| 23 | ad court-FH_inside_out | 0.102736 |

# PHASE 2: CLUSTERING

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# K-Means Clustering

1. Decide on # of clusters (k)

2. Randomly assign centroid to each cluster

3. Calculate distance of each observation (player's feature) to each of the k centroids

4. Assign each observation to closest centroid

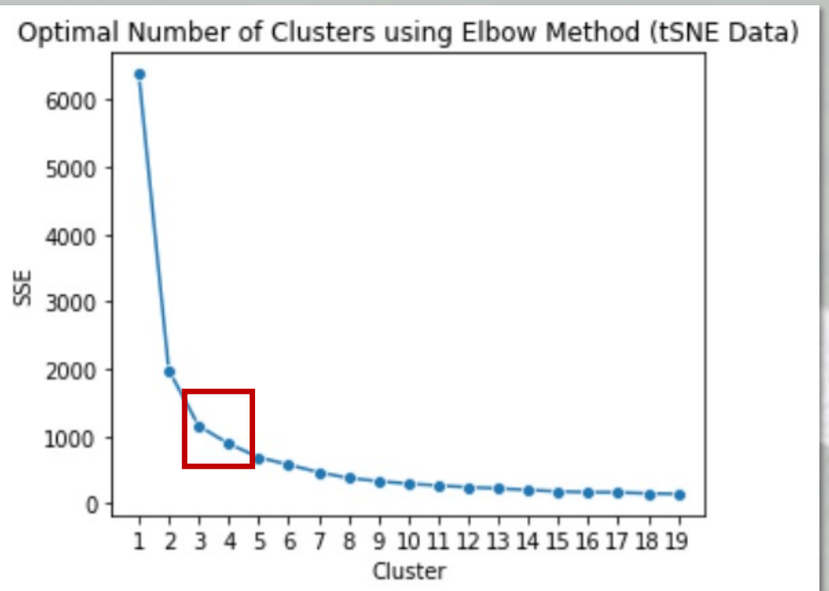
5. Find new location of centroid (mean of all observations in cluster)

6. Repeat steps 3-5 until centroids do not change position

*K-Means minimizes **Intra-cluster Distance**

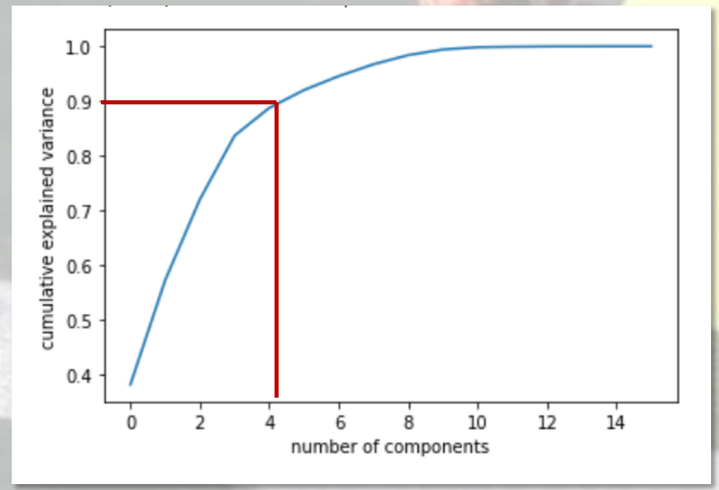
# K-Means Clustering: Considerations

## Elbow Method:



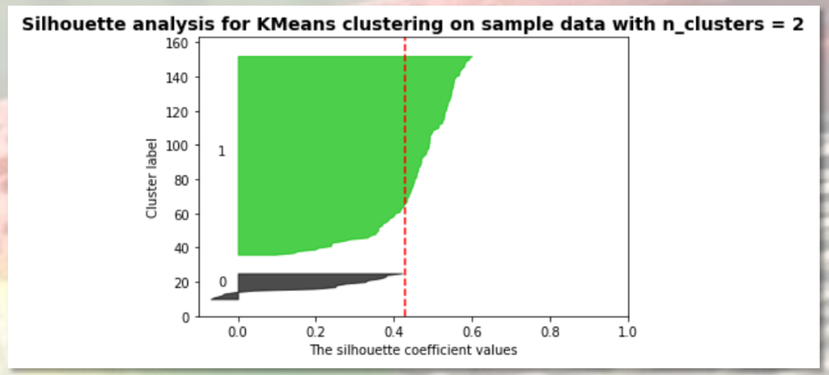

n = 3 or 4 seem to be good 'elbow' values

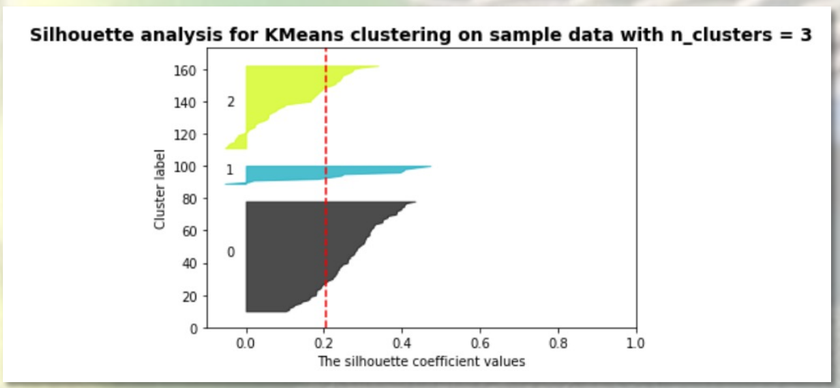
## PCA Analysis:

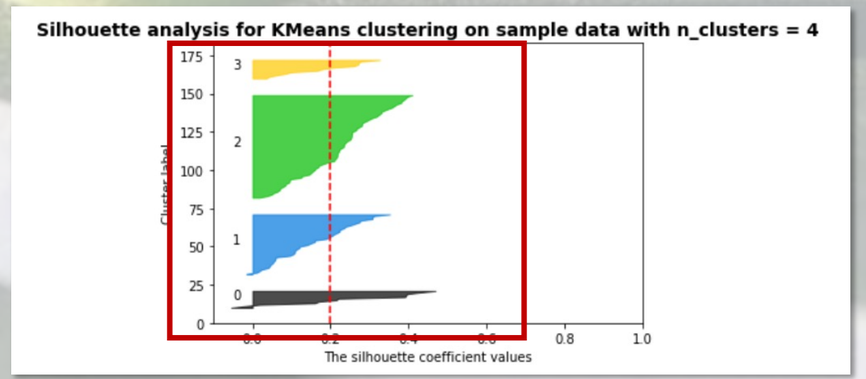



| | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 |
|---|---|---|---|---|---|---|
| **Standard Deviation** | 2.468874 | 1.746458 | 1.538812 | 1.367278 | 0.901955 | 0.723117 |
| **Proportion of Variance** | 0.380959 | 0.190632 | 0.147996 | 0.116841 | 0.050845 | 0.032681 |
| **Cumulative Proportion** | 0.380959 | 0.571591 | 0.719587 | 0.836428 | 0.887273 | 0.919954 |

## Silhouette Analysis:

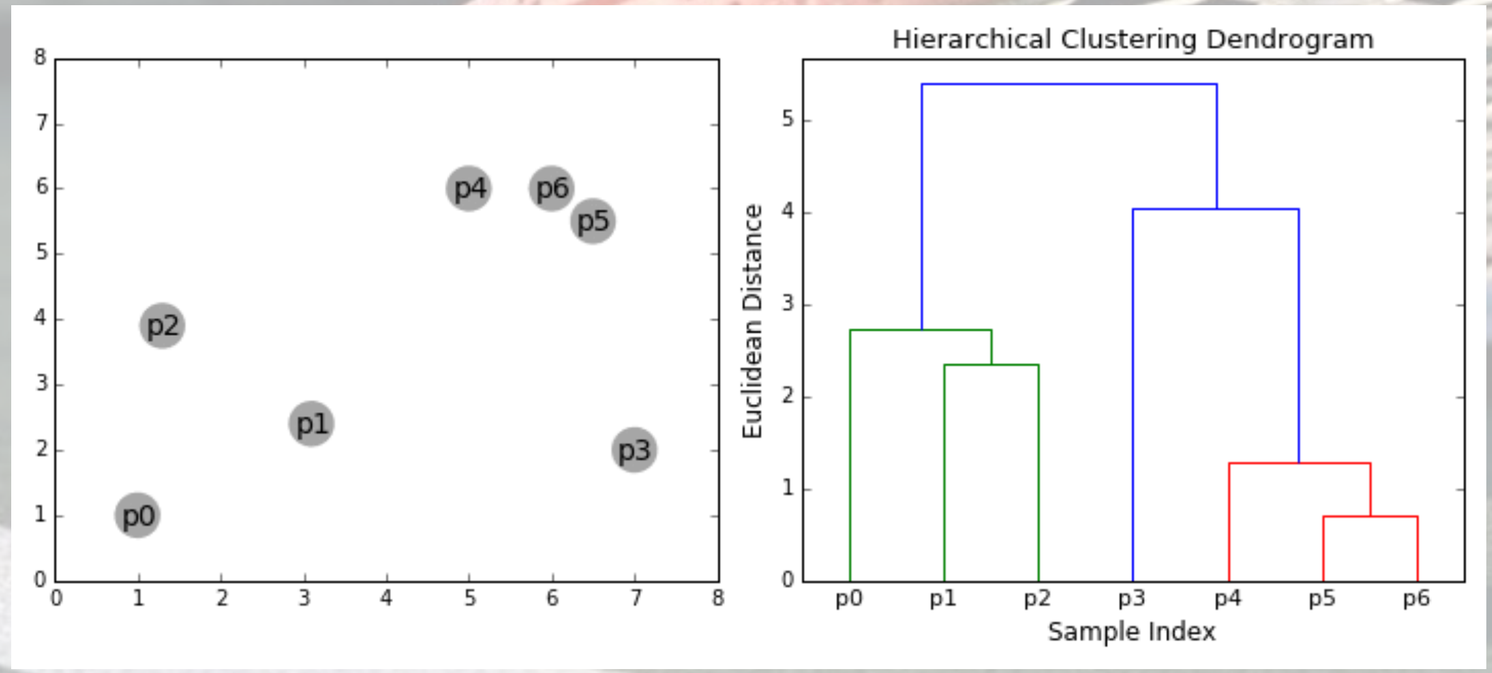


# Agglomerative Clustering

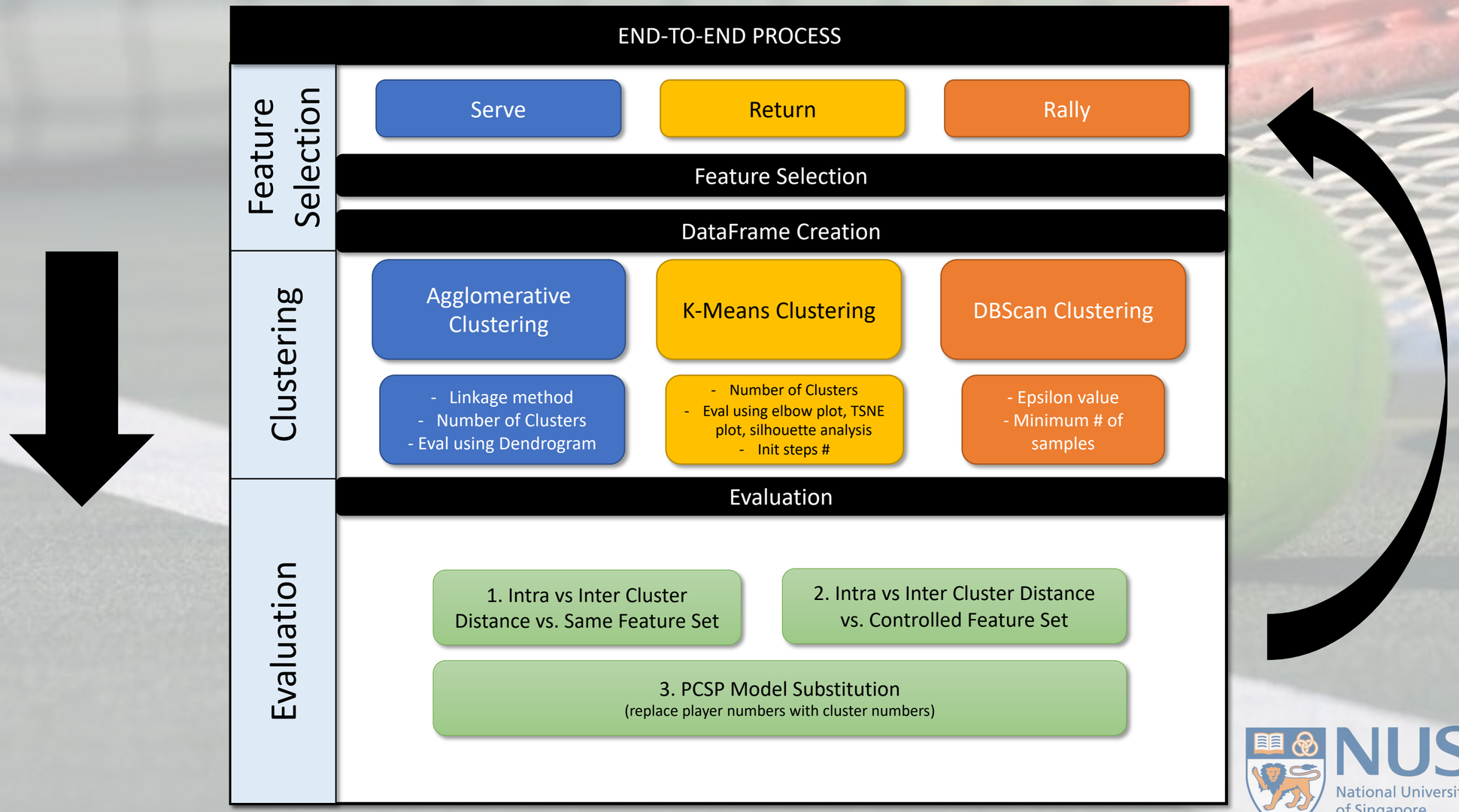
1. Determine distance measurement (eg. Euclidean distance)
2. Determine the linkage criteria to merge clusters (eg. Ward, Complete, Single)
3. Every data point starts as its own cluster
4. Continually merge the nearest clusters
5. Repeat the process until every data point become one cluster




**Considerations:**

- Where to “cut” the dendrogram
- Linkage method: Ward

# PHASE 3: EVALUATION

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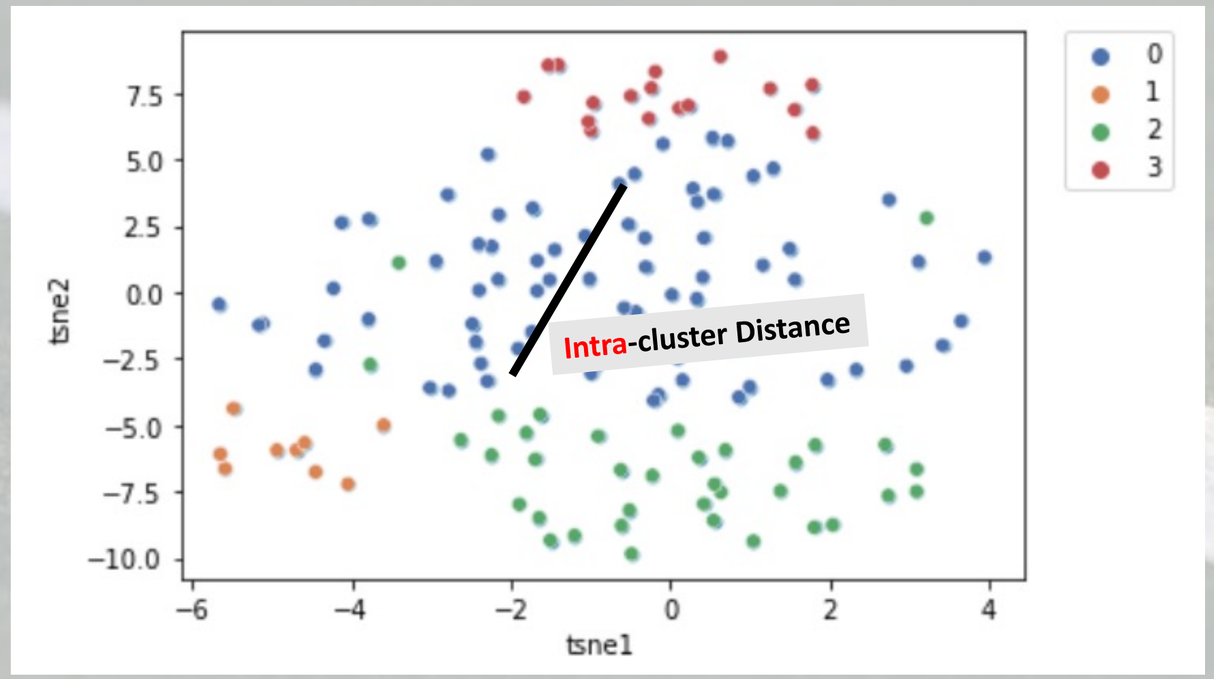
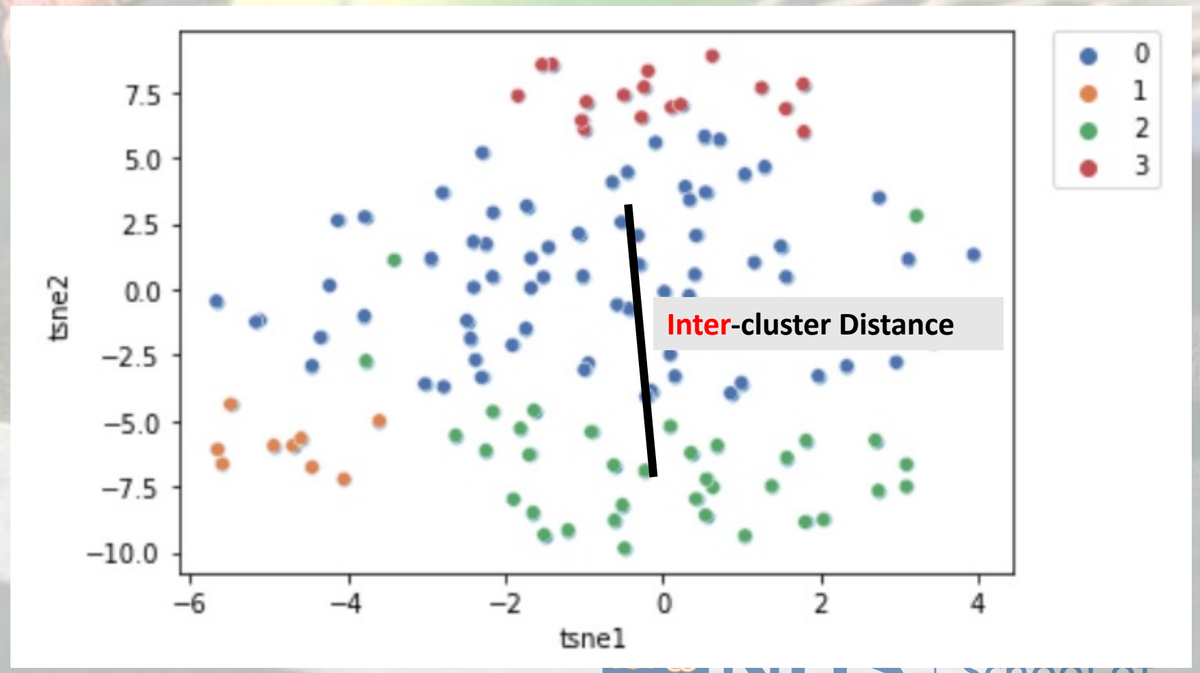
# EVALUATION #1 & #2

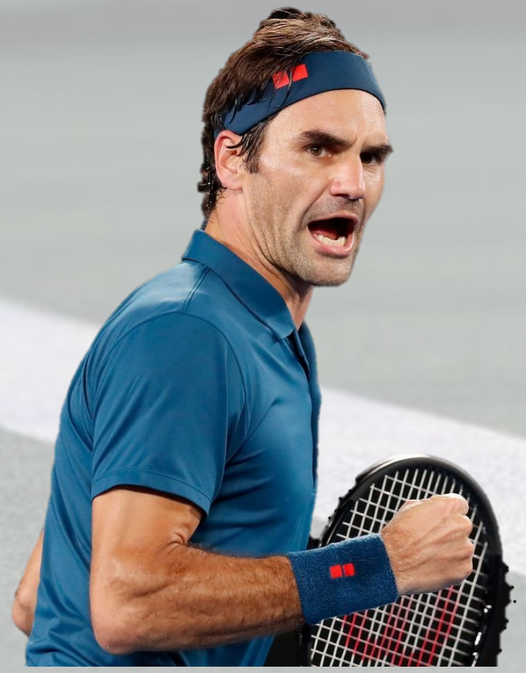
## Metric: Intra-Cluster Distance & Inter-Cluster Distance

- #1: Using Same Feature Set
- #2: Using Different Feature Set for Evaluation



# Evaluation #1: Intra-Inter Cluster Distance using Same Feature Set

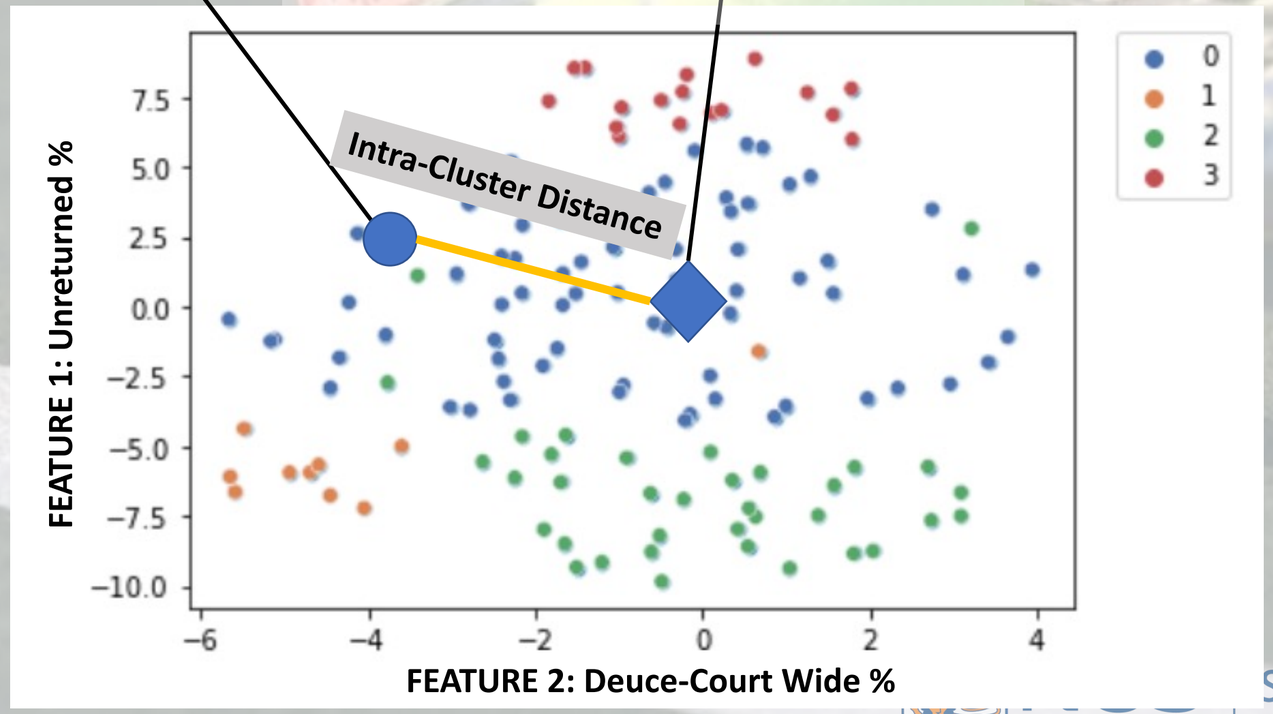


**Roger Federer (Serve Cluster 0)**

**Federer**

**Cluster 0 Centroid (average)**

## Intra-Cluster Distance

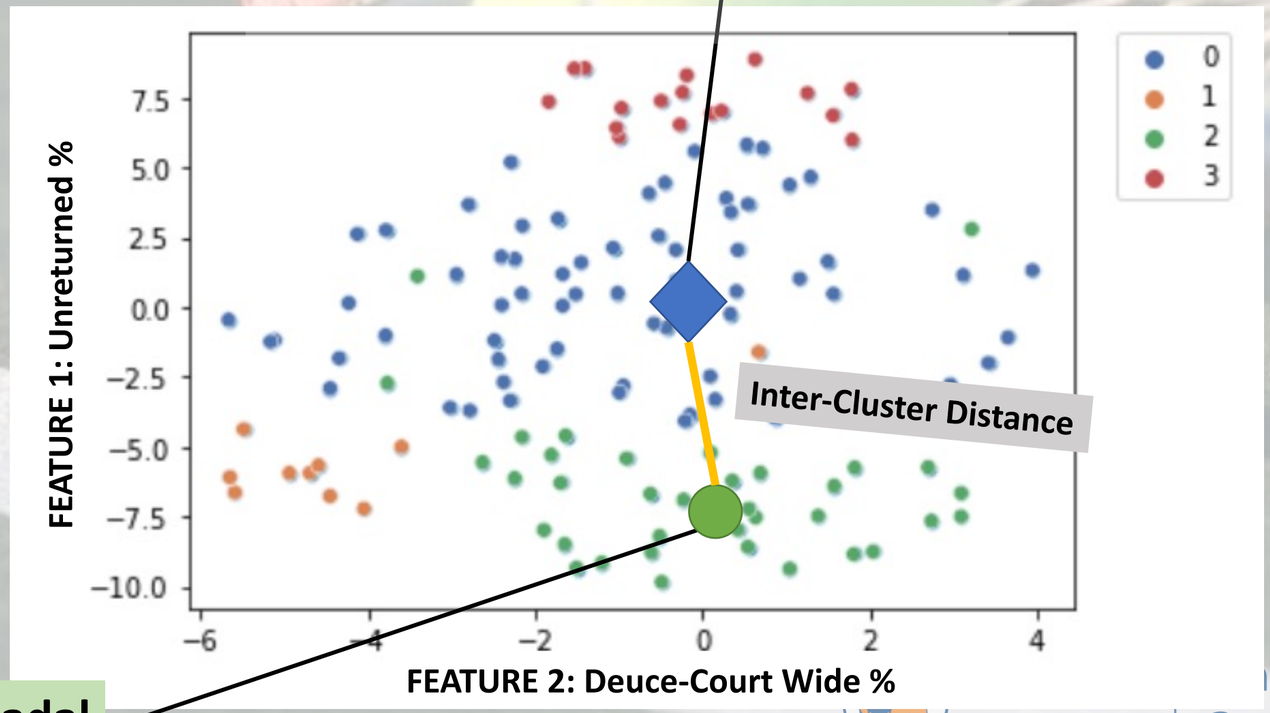


# Evaluation #1: Intra-Inter Cluster Distance using Same Feature Set

**Rafael Nadal (Serve Cluster 2)**

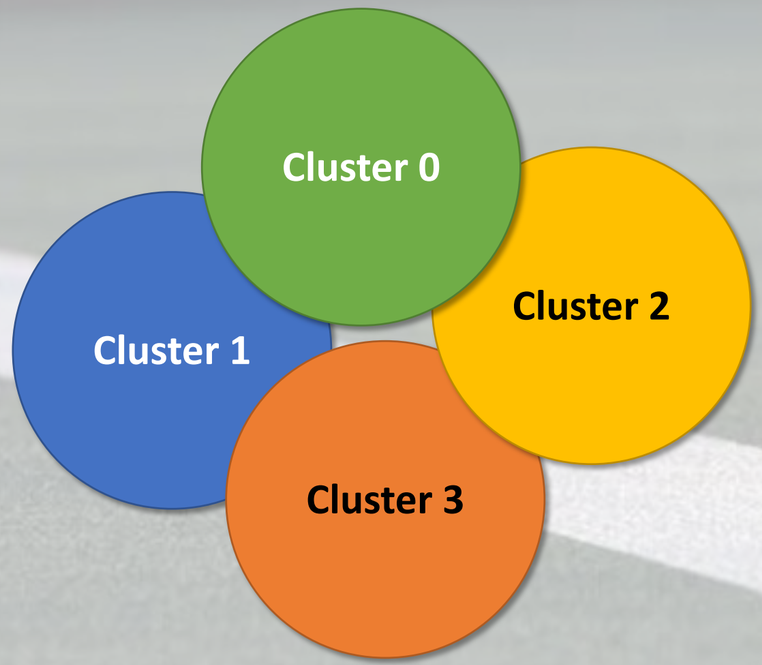
**Cluster 0 Centroid (average)**

## Inter-Cluster Distance




**Nadal**

# Evaluation #1: Intra-Inter Cluster Distance using Same Feature Set




```
---Evaluating Cluster 0---
Size of Cluster: 70
Intra-cluster Distance Avg: 10.06
Inter-cluster Distance Avg: 27.78
% Difference (Inter - Intra) for Cluster 0: 176.10%
-------------------------------------------------
---Evaluating Cluster 1---
Size of Cluster: 10
Intra-cluster Distance Avg: 10.14
Inter-cluster Distance Avg: 41.94
% Difference (Inter - Intra) for Cluster 1: 313.73%
-------------------------------------------------
---Evaluating Cluster 2---
Size of Cluster: 36
Intra-cluster Distance Avg: 9.80
Inter-cluster Distance Avg: 32.95
% Difference (Inter - Intra) for Cluster 2: 236.37%
-------------------------------------------------
---Evaluating Cluster 3---
Size of Cluster: 17
Intra-cluster Distance Avg: 10.68
Inter-cluster Distance Avg: 52.43
% Difference (Inter - Intra) for Cluster 3: 391.07%
-------------------------------------------------
Overall Average of % Difference (Inter-Intra): 279.32%
```

# Evaluation #2: Intra-Inter Cluster Distance using Controlled (Evaluation) Feature Set

## CLUSTER FEATURE SET

| Rally Game | Rally Definition |
|---|---|
| **Matches** | Matches logged by the Match Charting Project |
| **RallyLen** | Average rally length |
| **RLen-Serve** | Average rally length on serve points |
| **RLen-Return** | Average rally length on return points |
| **1-3 W%** | Win percentage on points between 1 and 3 shots |
| **4-6 W%** | Win percentage on points between 4 and 6 shots |
| **7-9 W%** | Win percentage on points between 7 and 9 shots |
| **10+W%** | Win percentage on points of at least 10 shots |
| **FH/GS** | Forehands per groundstroke |
| **BH Slice%** | Slices per backhand groundstroke |
| **FHP/Match** | Forehand Potency per match (higher is better) |
| **FHP/100** | Forehand Potency per 100 forehands |
| **BHP/Match** | Backhand Potency per match (higher is better) |
| **BHP/100** | Backhand Potency per 100 backhands |

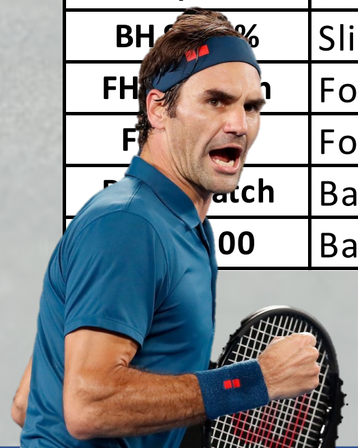
## EVALUATION FEATURE SET

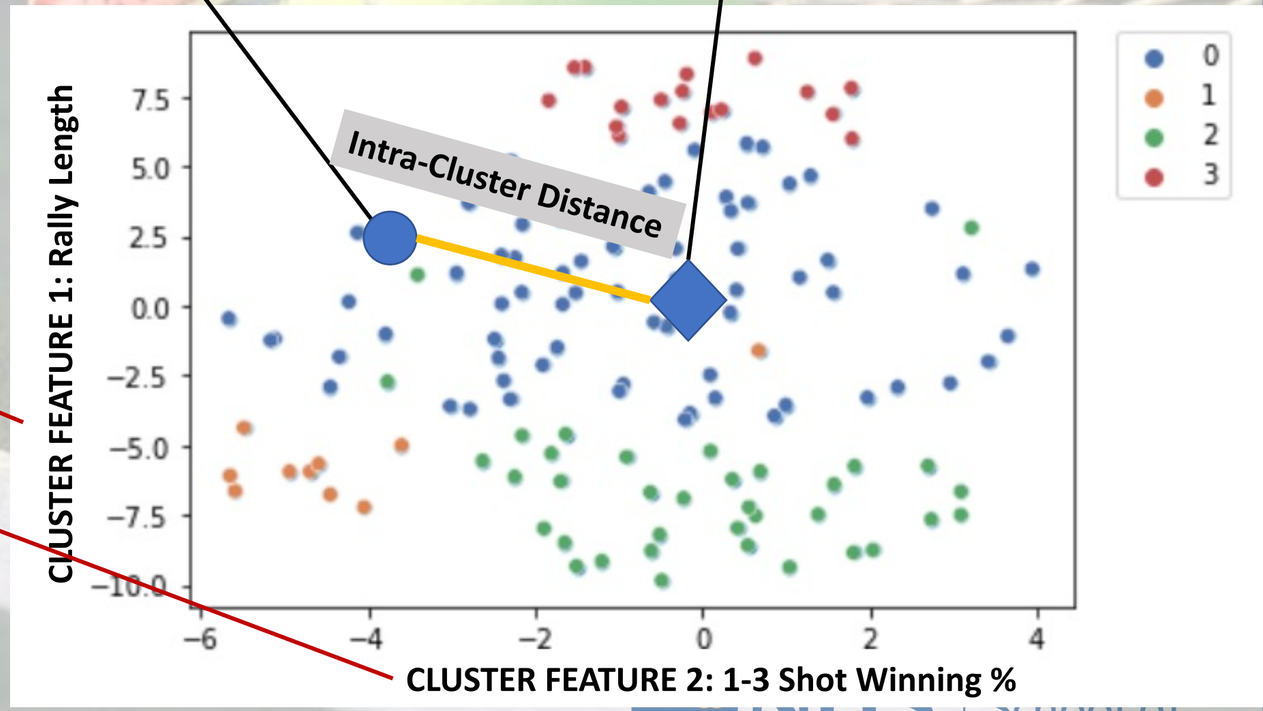
| | feature | percentage |
|---|---|---|
| **0** | middle court-BH_Error | 0.044010 |
| **1** | middle court-BH_cross_court | 0.120941 |
| **2** | middle court-BH_down_mid | 0.109487 |
| **3** | middle court-BH_inside_out | 0.063157 |
| **4** | middle court-FH_Error | 0.080256 |
| **...** | ... | ... |
| **19** | ad court-BH_down_mid | 0.189106 |
| **20** | ad court-FH_Error | 0.032507 |
| **21** | ad court-FH_down_mid | 0.031118 |
| **22** | ad court-FH_inside_in | 0.054525 |
| **23** | ad court-FH_inside_out | 0.102736 |

# Evaluation #2: Intra-Inter Cluster Distance using Controlled (Evaluation) Feature Set

## During Clustering:

| Rally Game | Rally Definition |
|---|---|
| Matches | Matches logged by the Match Charting Project |
| RallyLen | Average rally length |
| RLen-Serve | Average rally length on serve points |
| RLen-Return | Average rally length on return points |
| 1-3 W% | Win percentage on points between 1 and 3 shots |
| 4-6 W% | Win percentage on points between 4 and 6 shots |
| 7-9 W% | Win percentage on points between 7 and 9 shots |
| 10+ W% | Win percentage on points of at least 10 shots |
| FH/GS | Forehands per groundstroke |
| BH [illegible]% | Slices per backhand groundstroke |
| FH [illegible]n | Forehand Potency per match (higher is better) |
| F [illegible] | Forehand Potency per 100 forehands |
| [illegible]atch | Backhand Potency per match (higher is better) |
| [illegible]00 | Backhand Potency per 100 backhands |



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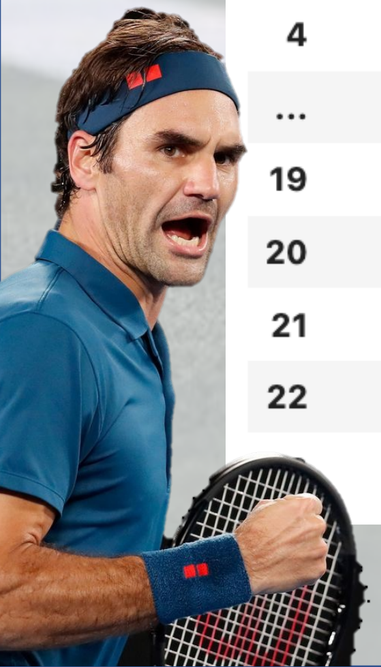
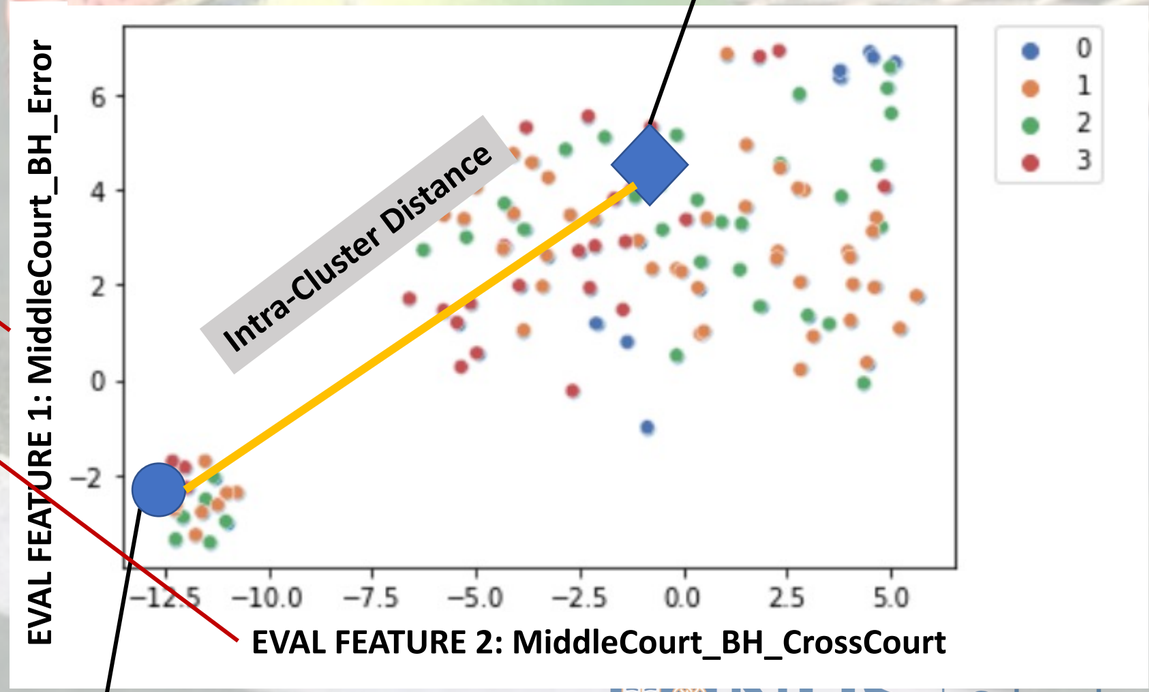
# Evaluation #2: Intra-Inter Cluster Distance using Controlled (Evaluation) Feature Set

**During Evaluating:**

| | feature | percentage |
|---|---|---|
| 0 | middle court-BH_Error | 0.044010 |
| 1 | middle court-BH_cross_court | 0.120941 |
| 2 | middle court-BH_down_mid | 0.109487 |
| 3 | middle court-BH_inside_out | 0.063157 |
| 4 | middle court-FH_Error | 0.080256 |
| ... | ... | ... |
| 19 | ad court-BH_down_mid | 0.189106 |
| 20 | ad court-FH_Error | 0.032507 |
| 21 | ad court-FH_down_mid | 0.031118 |
| 22 | ad court-FH_inside_in | 0.054525 |
| | ad court-FH_inside_out | 0.102736 |

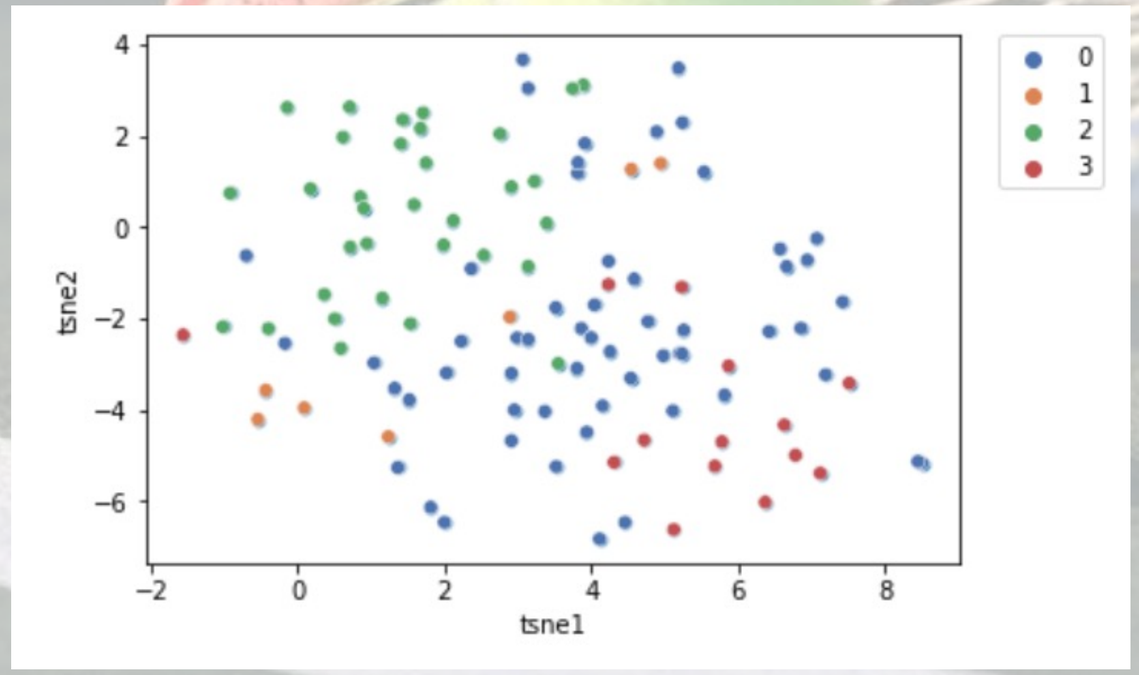




# 2. Intra-inter Cluster Distance using Controlled Feature Set

```
Cluster Results:
---Evaluating Cluster 0---
Size of Cluster: 57
Intra-cluster Distance Avg: 28.14
Inter-cluster Distance Avg: 46.32
% Difference (Inter - Intra) for Cluster 0: 64.59%
-------------------------------------------------
---Evaluating Cluster 1---
Size of Cluster: 7
Intra-cluster Distance Avg: 24.95
Inter-cluster Distance Avg: 55.82
% Difference (Inter - Intra) for Cluster 1: 123.70%
-------------------------------------------------
---Evaluating Cluster 2---
Size of Cluster: 33
Intra-cluster Distance Avg: 27.58
Inter-cluster Distance Avg: 49.83
% Difference (Inter - Intra) for Cluster 2: 80.68%
-------------------------------------------------
---Evaluating Cluster 3---
Size of Cluster: 14
Intra-cluster Distance Avg: 45.72
Inter-cluster Distance Avg: 54.84
% Difference (Inter - Intra) for Cluster 3: 19.93%

Overall Average of % Difference (Inter-Intra): 72.22%
```

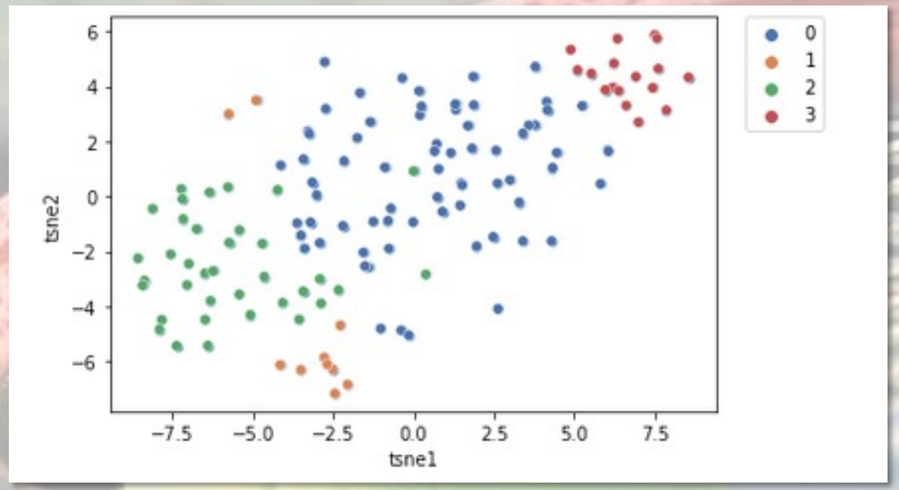


# EXPERIMENT RESULTS

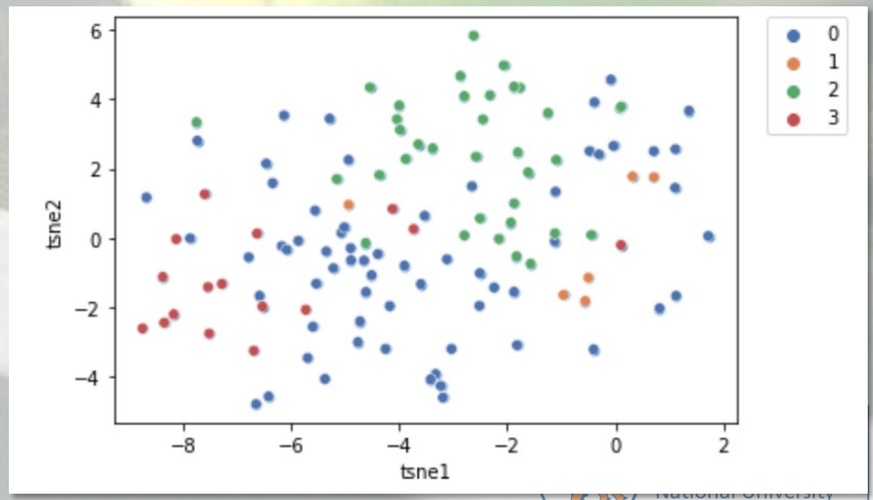
# RESULTS: SERVE GAME

| Serve Cluster | | | | |
|---|---|---|---|---|
| Evaluation #1 | **Cluster Method** | **Cluster Feature Set** | **Evaluation Feature Set** | **Overall Average of % Difference (Inter-Intra)** |
| | Agglomerative, Ward linkage, 4 clusters | 19 summary-level features | 19 summary-level features | 279.32% |
| | Kmeans, init=100, 4 clusters | 19 summary-level features | 19 summary-level features | 242.79% |
| Evaluation #2 | **Cluster Method** | **Cluster Feature Set** | **Evaluation Feature Set** | **Overall Average of % Difference (Inter-Intra)** |
| | Agglomerative, Ward linkage, 4 clusters | 19 summary-level features | 36 PCSP serve function features | 72.22% |
| | Kmeans, init=100, 4 clusters | 19 summary-level features | 36 PCSP serve function features | 54.72% |

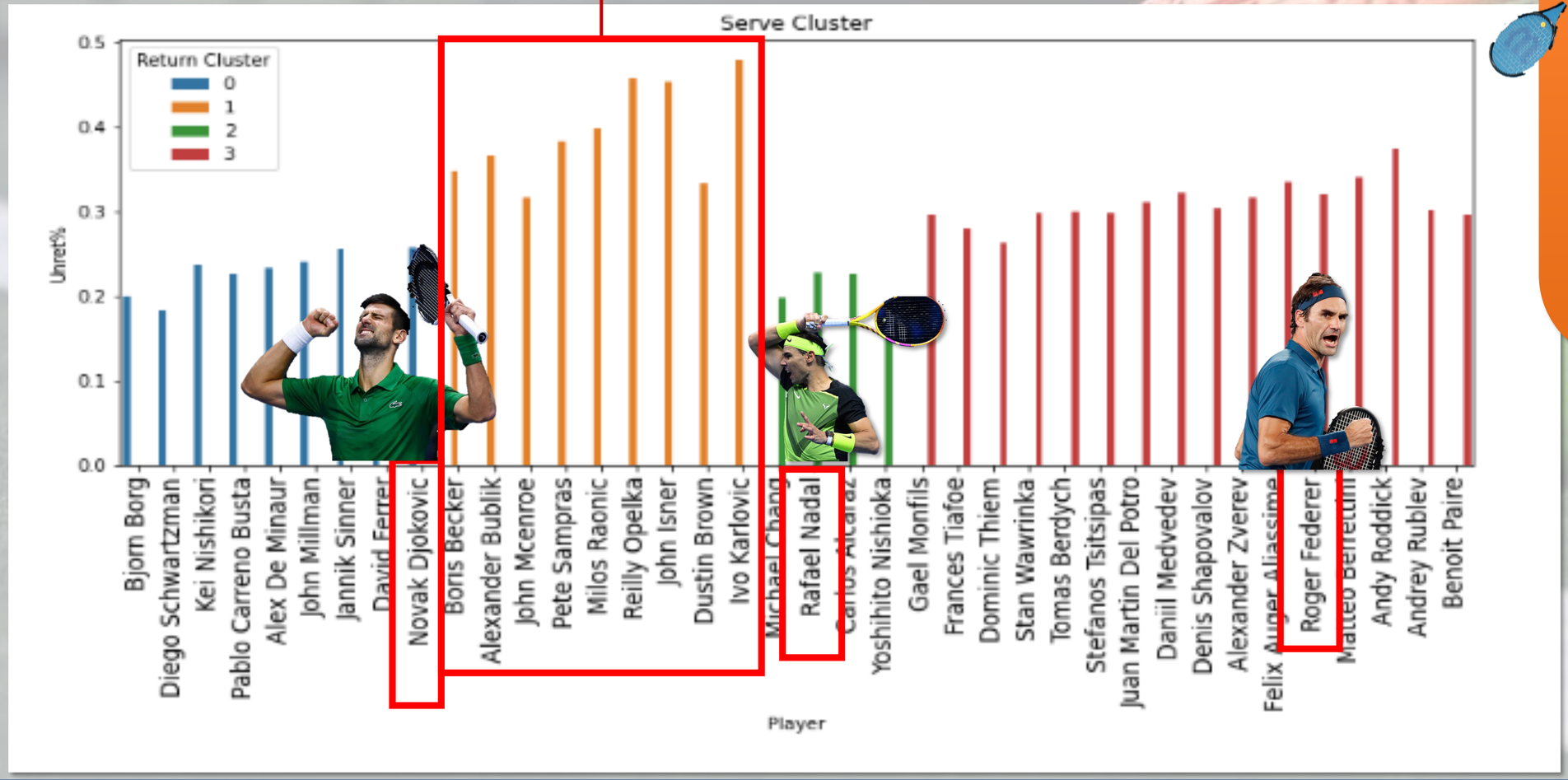
**Eval #1 using Agglom**




**Eval #2 using Agglom**



# RESULTS: SERVE GAME




**Cluster 3: BIG SERVERS**

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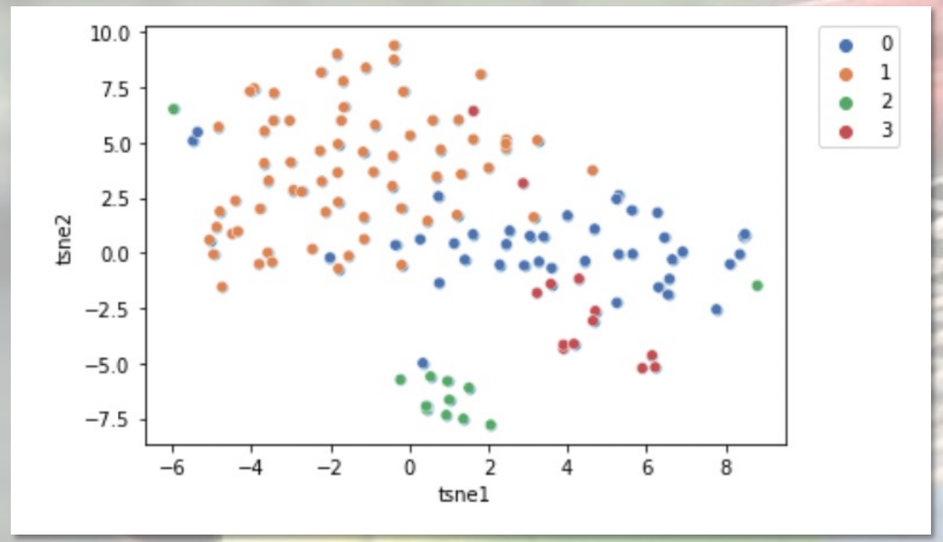
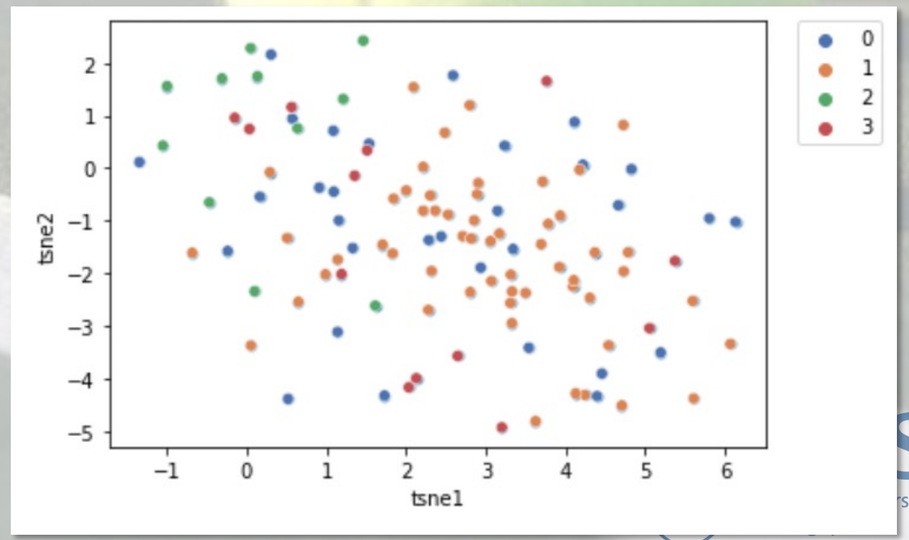
# RESULTS: RETURN GAME

| Return Cluster | | | | |
|---|---|---|---|---|
| **Evaluation #1** | **Cluster Method** | **Cluster Feature Set** | **Evaluation Feature Set** | **Overall Average of % Difference (Inter-Intra)** |
| | Agglomerative, Ward linkage, 4 clusters | 16 summary-level features | 16 summary-level features | 222.54% |
| | Kmeans, init=100, 4 clusters | 16 summary-level features | 16 summary-level features | 254.57% |
| **Evaluation #2** | **Cluster Method** | **Cluster Feature Set** | **Evaluation Feature Set** | **Overall Average of % Difference (Inter-Intra)** |
| | Agglomerative, Ward linkage, 4 clusters | 16 summary-level features | 72 PCSP return function features | 14.85% |
| | Kmeans, init=100, 4 clusters | 16 summary-level features | 72 PCSP return function features | 24.39% |

**Eval #1 using K-Means**




**Eval #2 using K-Means**

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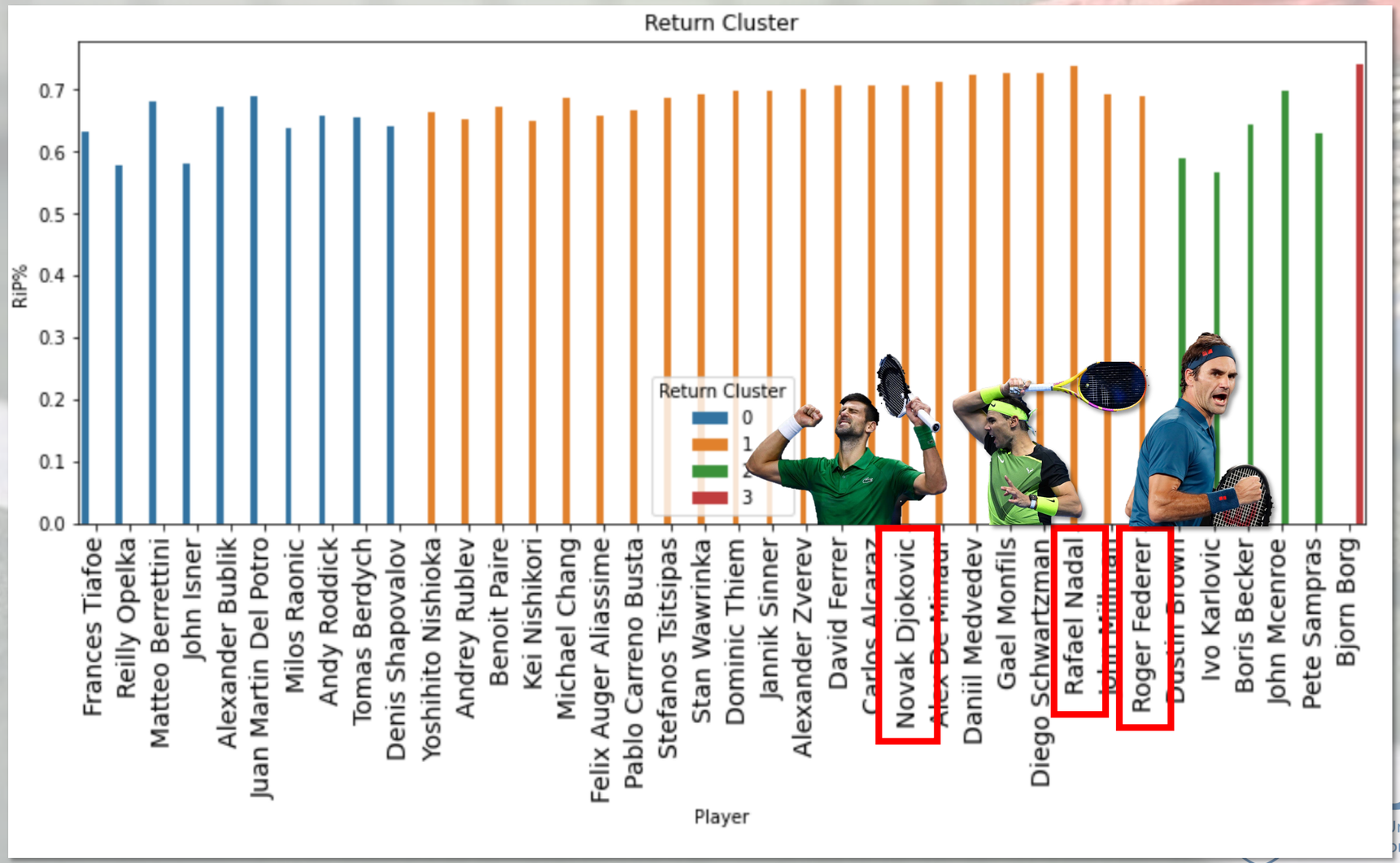
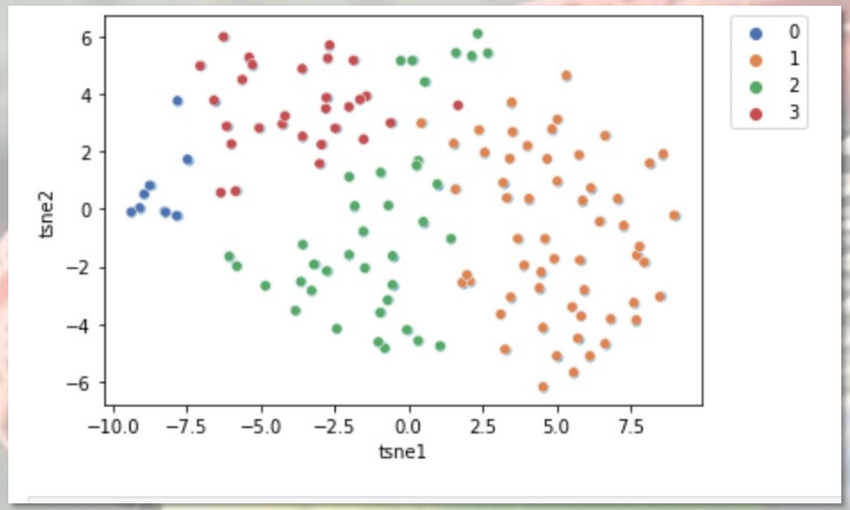
# RESULTS: RETURN GAME



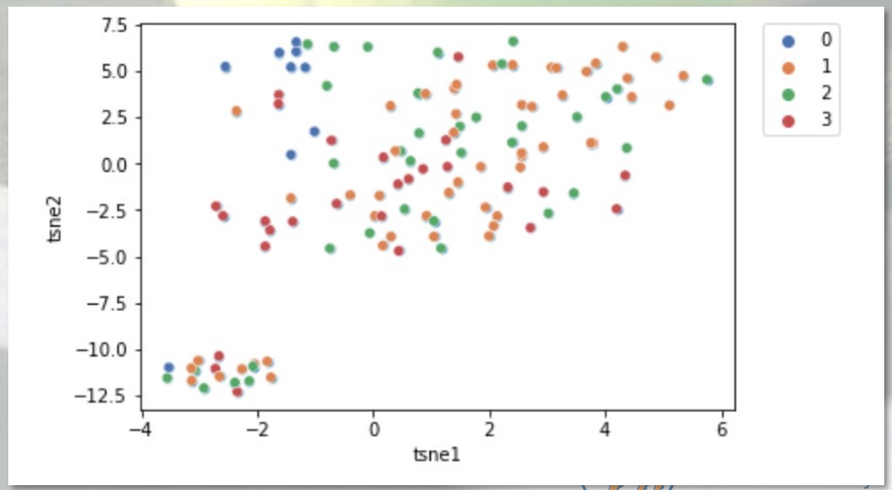
# RESULTS: RALLY GAME

| Rally Cluster | | | | |
|---|---|---|---|---|
| Evaluation #1 | **Cluster Method** | **Cluster Feature Set** | **Evaluation Feature Set** | **Overall Average of % Difference (Inter-Intra)** |
| | Agglomerative, Ward linkage, 4 clusters | 13 summary-level features | 13 summary-level features | 173.18% |
| | Kmeans, init=100, 4 clusters | 13 summary-level features | 13 summary-level features | 186.19% |
| Evaluation #2 | **Cluster Method** | **Cluster Feature Set** | **Evaluation Feature Set** | **Overall Average of % Difference (Inter-Intra)** |
| | Agglomerative, Ward linkage, 4 clusters | 13 summary-level features | 24 PCSP rally function features | 34.66% |
| | Kmeans, init=100, 4 clusters | 13 summary-level features | 24 PCSP rally function features | 31.90% |

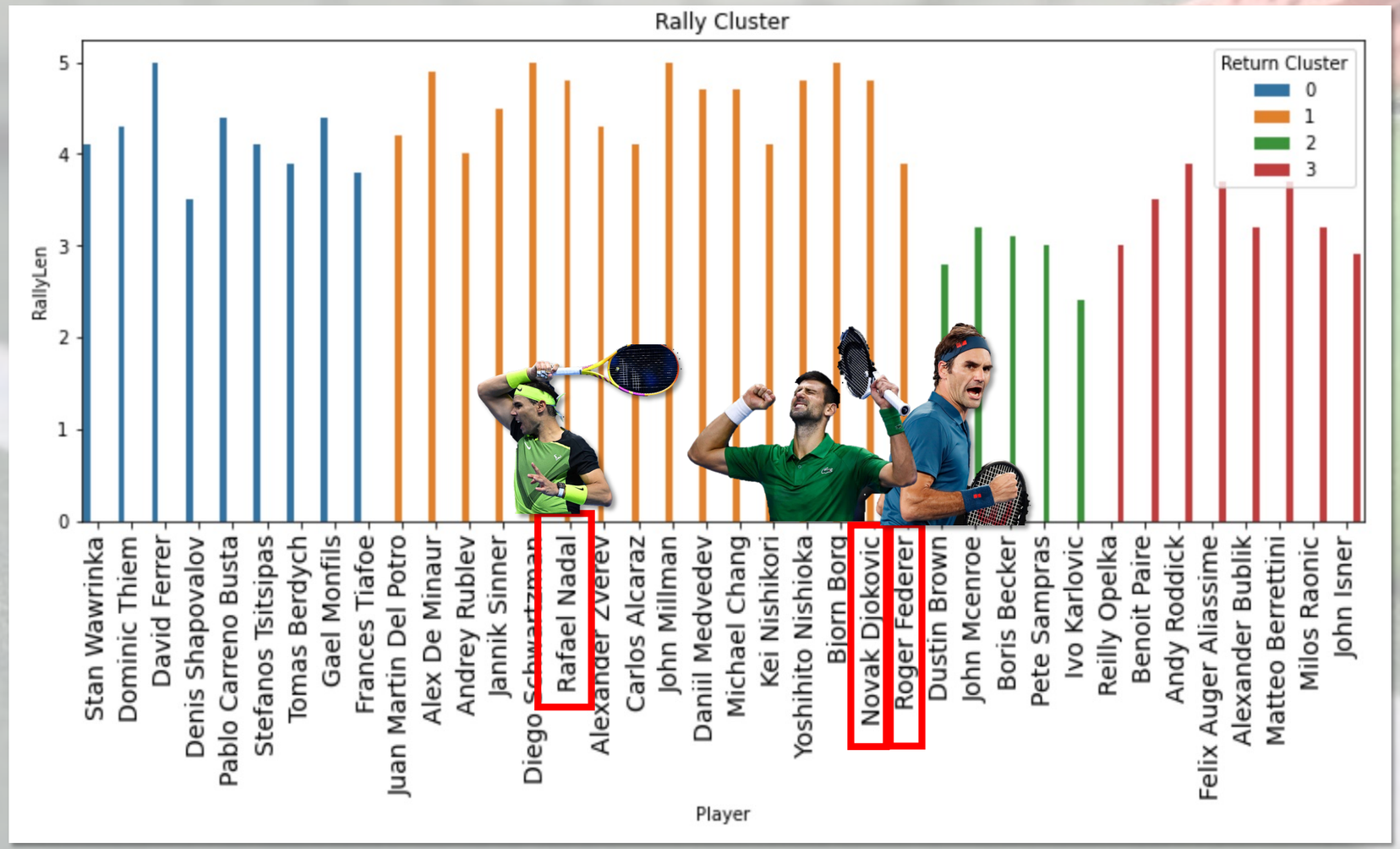
**Eval #1 using K-Means**




**Eval #2 using K-Means**



# RESULTS: RALLY GAME

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# Evaluation #3: PCSP Data Replacement




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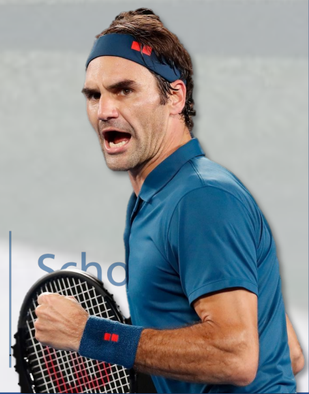
# Evaluation #3: PCSP Data Replacement

```
De_Ply1Serve = pcase {                                  // all probability is bas
            231: ServeT_in{ball= 6} -> Ply2_BackHandR  // T will have oppone
            119: ServeT_err{ball=9} -> De_Ply1Serve_2nd   // Federer tries t
            337: ServeWide_in{ball =6} -> Ply2_ForeHandR
            173: ServeWide_err{ball=9} -> De_Ply1Serve_2nd
            92: ServeBody_in{ball=6} -> (Ply2_BackHandR [] Ply2_ForeHandR)
            48: ServeBody_err{ball=9} -> De_Ply1Serve_2nd};
```

```
De_Ply1Serve = pcase {
            30: ServeT_in{ball= 6} -> Ply2_BackHandR
            17: ServeT_err{ball=9} -> De_Ply1Serve_2nd
            29: ServeWide_in{ball =6} -> Ply2_ForeHandR
            14: ServeWide_err{ball=9} -> De_Ply1Serve_2nd
            7: ServeBody_in{ball=6} -> (Ply2_BackHandR [] Ply2_ForeHandR)
            2: ServeBody_err{ball=9} -> De_Ply1Serve_2nd};
```

# RESULTS: Evaluation #3 - PCSP Data Replacement

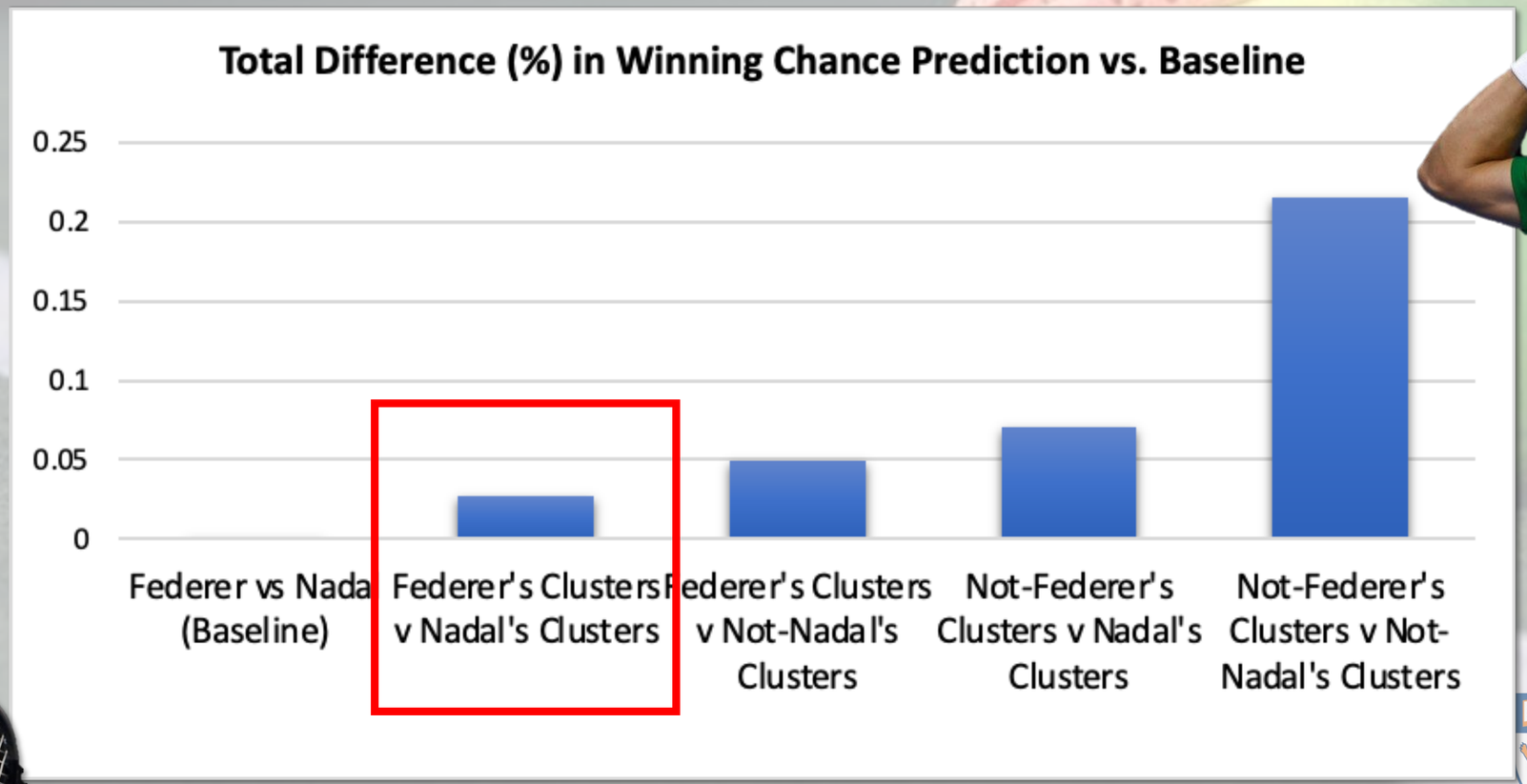
| | | | | Game components | | | Results | | | | Difference from Baseline | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| # | Test Case | Ply1 | Ply2 | Serve | Return | Rally | Ply1 prob | Ply1 2 prob | Ply1 Avg | Ply2 Avg | Ply1 Difference | Ply2 Difference | Total Difference |
| 0 | **Baseline** | Federer | Nadal | Fed vs Nadal | Fed vs Nadal | Fed vs Nadal | [48.084, 50.94] | [49.059,51.915] | 0.49512 | 0.50487 | - | - | - |
| 1 | **Cluster v Cluster** | Federer Cluster | Nadal Cluster | Fed's cluster (3) vs Nadal's cluster (2) | Fed's cluster (1) vs Nadal's cluster (1) | Fed's cluster (0) vs Nadal's cluster (1) | [0.46736, 0.5087]; | [0.4913, 0.53263]; | 0.4880 | 0.5120 | 1.43% | -1.41% | **2.67%** |
| 2 | Cluster v Non-Cluster | Federer Cluster | Non-Nadal Cluster | Fed cluster (3) vs Isner cluster (1) | Fed cluster (1) vs Isner cluster (0) | Fed cluster (0) vs Medvedev cluster (2) | [0.48341, 0.53201]; | [0.46798, 0.51658]; | 0.5077 | 0.4923 | -2.54% | 2.49% | **4.91%** |
| 3 | Non-Cluster v Cluster | Non-Federer Cluster | Nadal Cluster | John Isner cluster (1) vs Nadal cluster (2) | John Isner cluster (0) vs Nadal cluster (1) | Medvedev cluster (2) vs Nadal cluster (1) | [0.45157, 0.50242]; | [0.49757, 0.54842]; | 0.4770 | 0.5230 | 3.66% | -3.59% | **7.07%** |
| 4 | Non-Cluster v Non-Cluster | Non-Federer Cluster | Non-Nadal Cluster | John Isner cluster (1) vs Mats Wilander cluster (0) | John Isner cluster (0) vs Karlovic cluster (2) | Medvedev cluster (2) vs Sampras cluster (3) | [0.51802, 0.58273]; | [0.41726, 0.48197]; | 0.55038 | 0.44962 | -11.16% | 10.94% | **21.55%** |



of Singapore

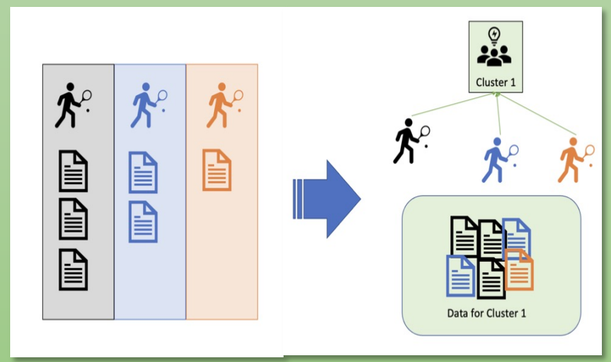
# CONCLUSION

**Based on these results, clusters are a good representation of players themselves!**

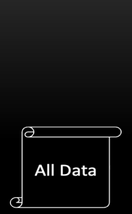



# TECHNICAL RESEARCH CONTRIBUTIONS

## 1. Data Generalization via Clustering




## 2. Player Clustering via Game Components




Serve → Cluster

| Serve Component | |
|---|---|
| Cluster 0 | 30 players |
| Cluster 1 | 10 players |
| Cluster 2 | 22 players |
| Cluster 3 | 18 players |

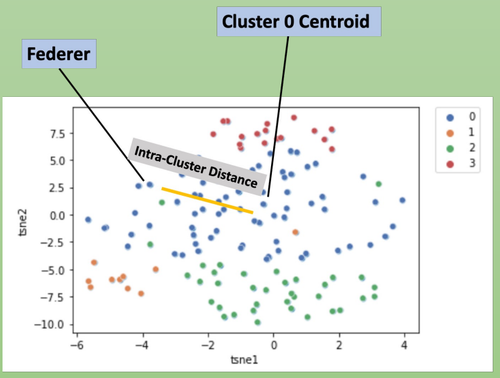
Return → Cluster

| Return Component | |
|---|---|
| Cluster 0 | 9 players |
| Cluster 1 | 31 players |
| Cluster 2 | 23 players |
| Cluster 3 | 40 players |

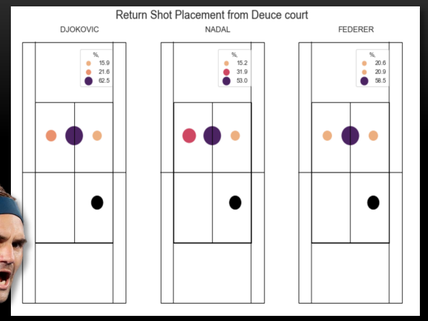
Rally → Cluster

| Rally Component | |
|---|---|
| Cluster 0 | 22 players |
| Cluster 1 | 30 players |
| Cluster 2 | 9 players |
| Cluster 3 | 12 players |

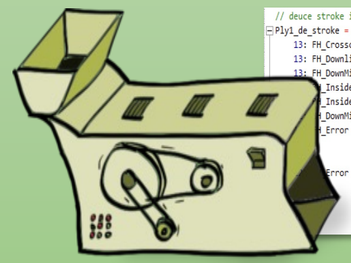
## 3. 3-Part Evaluation Process




## 4. Interactive Shot Location Preference Chart

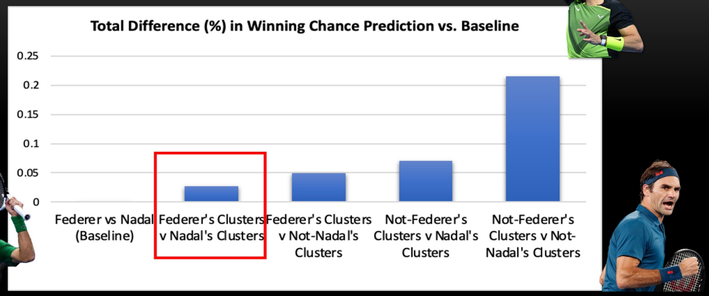


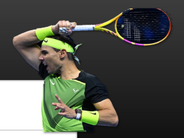

## 5. Automated PCSP Cluster Data Populator Script



```
// deuce stroke is when player1 hit position is 1
Ply1_de_stroke = pcase{
    13: FH_Crosscourt { ball = 6} -> Ply2_de_stroke
    13: FH_Downline { ball = 4} -> Ply2_ad_stroke
    13: FH_DownMid { ball = 5} -> Ply2_mid_stroke
    _InsideIn {ball = 4} -> Ply2_ad_stroke
    _InsideOut { ball = 6} -> Ply2_de_stroke
    _DownMid { ball = 5} -> Ply2_mid_stroke
    _Error { ball = 9} -> {nscore++; if (nscore == 7) {won = player2}
                                                    else { turn = (turn+1)%4 }
                                                    } -> NextPt
    Error { ball = 9} -> {nscore++; if (nscore == 7) {won = player2}
                                                    else { turn = (turn+1)%4 }
                                                    } -> NextPt
```

## 6. Experiment Results



# FUTURE WORKS

1. Systematically Test Combo's:
   - Feature set combinations
   - # of clusters, cluster-size
   - # of game components
   - More players for PCSP-replacement
   - Etc..

2. Data Variety:
   - Spatial-temporal data, speed, position etc.
   - Skill-level scaling (eg. factor in Elo ratings)
   - Scaling by time / recency of matches

3. Play Styles:
   - Sequence patterns - eg. Serve-and-volley likelihood
   - Isolating left-handed players

# Lessons Learned


- Data modeling is a very empirical process
- No “one size fits all” solution

# QUESTIONS