Bayesian Networks for the Prediction of Ranking in Male Tennis Players

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tennis Australia's Favourite
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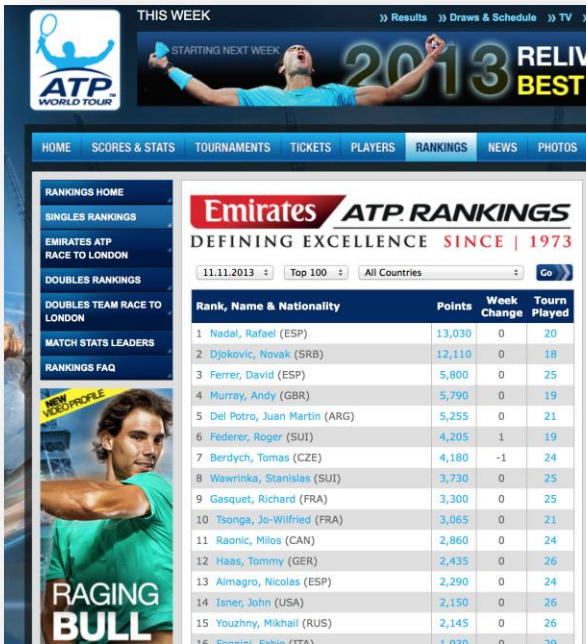
Overview

- *Athletes only break even if ranked within the top 100.*
- *Investment in athletes is big business, LTA and TA high-performance expenditure of £12M and $24M respectively*
- *Can we improve our return on investment?*

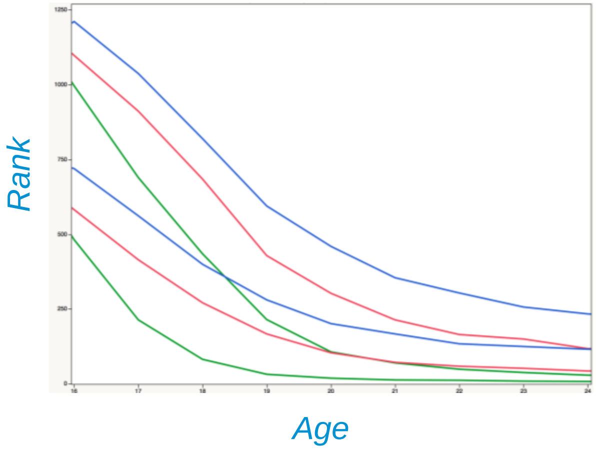
Data



Rank, Name & Nationality	Points	Week Change	Tourn Played
1 Nadal, Rafael (ESP)	13,030	0	20
2 Djokovic, Novak (SRB)	12,110	0	18
3 Ferrer, David (ESP)	5,800	0	25
4 Murray, Andy (GBR)	5,790	0	19
5 Del Potro, Juan Martin (ARG)	5,255	0	21
6 Federer, Roger (SUI)	4,205	1	19
7 Berdych, Tomas (CZE)	4,180	-1	24
8 Wawrinka, Stanislas (SUI)	3,730	0	25
9 Gasquet, Richard (FRA)	3,300	0	25
10 Tsonga, Jo-Wilfried (FRA)	3,065	0	21
11 Raonic, Milos (CAN)	2,860	0	24
12 Haas, Tommy (GER)	2,435	0	26
13 Almagro, Nicolas (ESP)	2,290	0	24
14 Isner, John (USA)	2,150	0	26
15 Youzhny, Mikhail (RUS)	2,145	0	26
16 Fognini, Fabio (ITA)	1,930	0	29

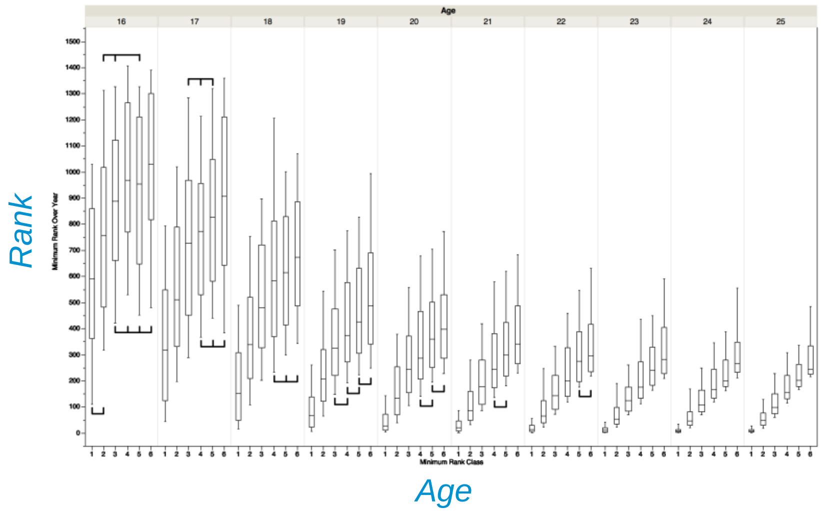
- *Data is sourced from weekly ranking lists provided by the ATP.*
- *Data relates to the accumulated ranking points and net ranking.*
- *Date of birth of athletes also sourced.*
- *Rankings obtained as far back as 1973 (data is complete from 1984)*
- *2338 athletes whom achieved at least Top 500 (80/20 train-test split)*

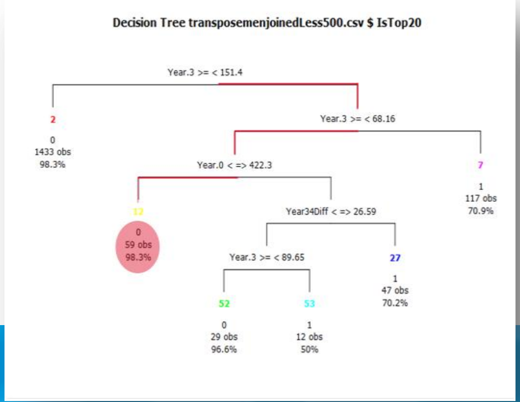
Putting a toe in the water



🡐 *The 25th/75th quartiles of ranking, conditioned on best career ranking (Top 10/50/100). Prosecutors fallacy at play!*

🡒 *Trends have been modelled by ANOVA*





🡐 *Decision trees were fitted with limited success*

Why BNs

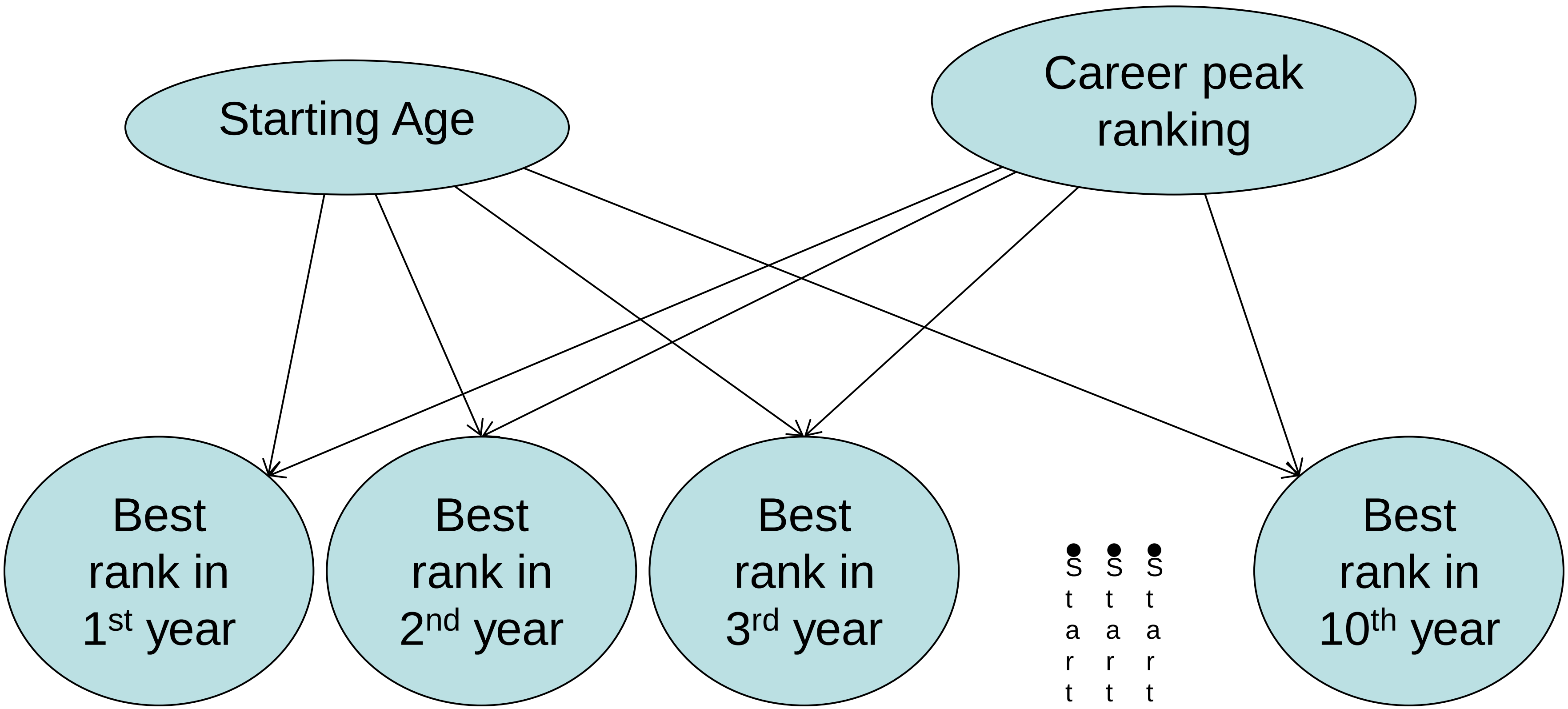
- *Intuitive, relative to other machine learning techniques.*

- *Versatile applications.*

- *Works well with variable amounts of data.*

- *Simple to implement to a wide audience.*

Naive Network



- Starting Age
- Starting Age
- Starting Age

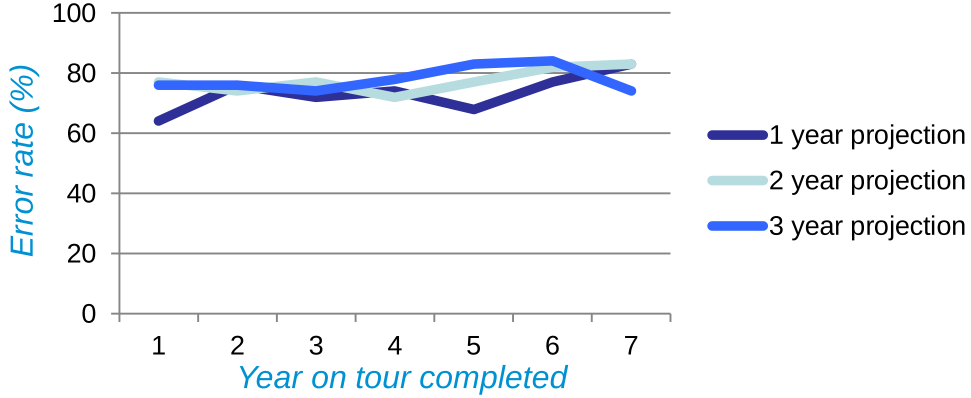
Can't use current athletes

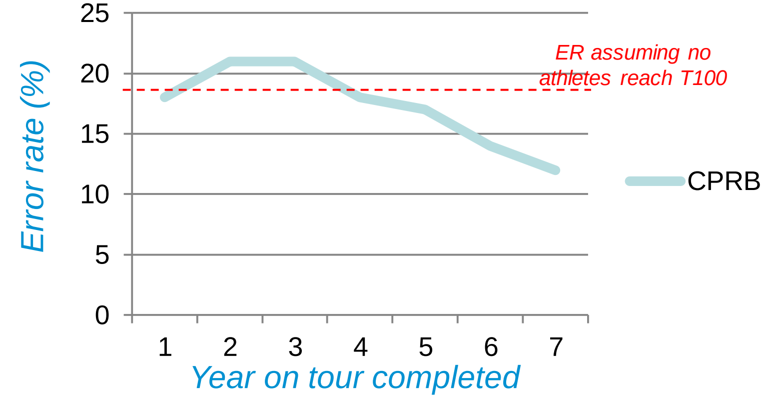
Naive Network

Demonstration

Naive Network (results)

The Bad





The Good

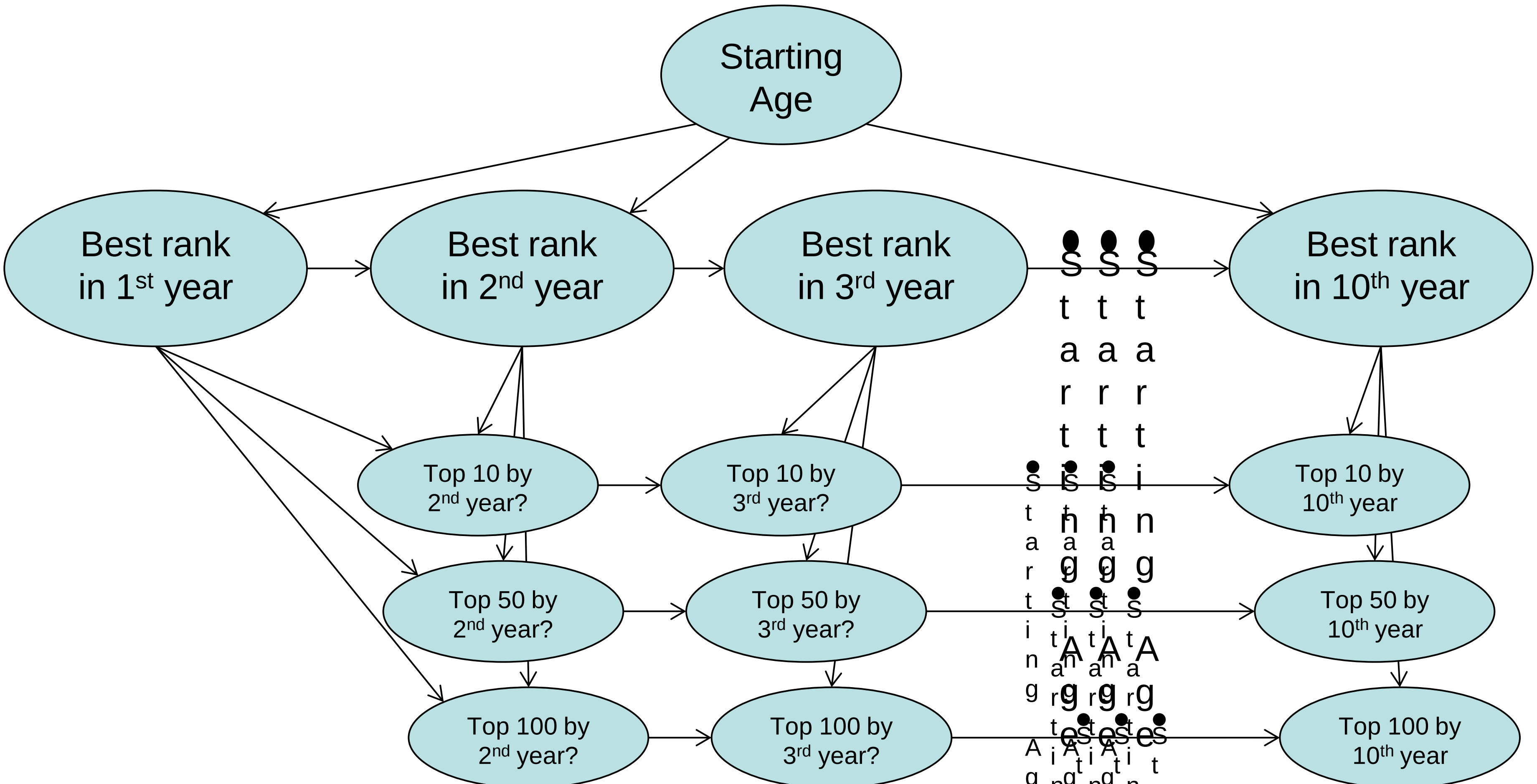
Calibration

Y1-2,+1 0-0.5: 0 | 0.5-1: 0 | 1-2: 0.279| 2-5: 2.46 | 5-10: 6.76 | 10-15: 14.4 | 15-20: 13.2 | 20-30: 26.5 | 30-40: 34.7 |
Y1-3,+1 0-0.5: 0 | 0.5-1: 0.844| 1-2: 1.18 | 2-5: 3.33 | 5-10: 6.8 | 10-15: 12.9 | 15-20: 20.6 | 20-30: 24.4 |
Y1-2,+2 0-0.5: 0 | 0.5-1: 0.379| 1-2: 1.3 | 2-5: 2.73 | 5-10: 6.89 | 10-15: 11.9 | 15-20: 18.4 | 20-30: 26.7 | 30-100: 50 |
Y1-7,+2 0-0.5: 0 | 0.5-1: 0.413| 1-2: 0.498| 2-5: 2.29 | 5-10: 5.69 | 10-15: 14.2 | 15-20: 19.4 | 20-30: 23.7 | 30-100: 66.7 |
Y1-3,+3 0.2-0.5: 6.52 | 0.5-1: 0 | 1-2: 4.65 | 2-5: 3 | 5-10: 8.61 | 10-15: 11.4 | 15-20: 15.9 | 20-30: 22.6 | 30-40: 25 | 40-100: 50 |

Times surprised

Ex.	<1%	<10%	>90%	>99%
Y1-2, +1	0 (0/437)	2.94 (58/1974)	0 (0/0)	0 (0/0)
Y1-3, +1	0.53 (2/378)	3.66 (70/1911)	0 (0/0)	0 (0/0)
Y1-2, +2	0.19 (1/526)	3.21 (62/1930)	0 (0/0)	0 (0/0)
Y1-7, +3	0.21 (1/473)	2.56 (43/1681)	0 (0/0)	0 (0/0)
Y1-3, +3	1.57 (8/511)	3.30 (28/848)	0 (0/0)	0 (0/0)

Temporal Network



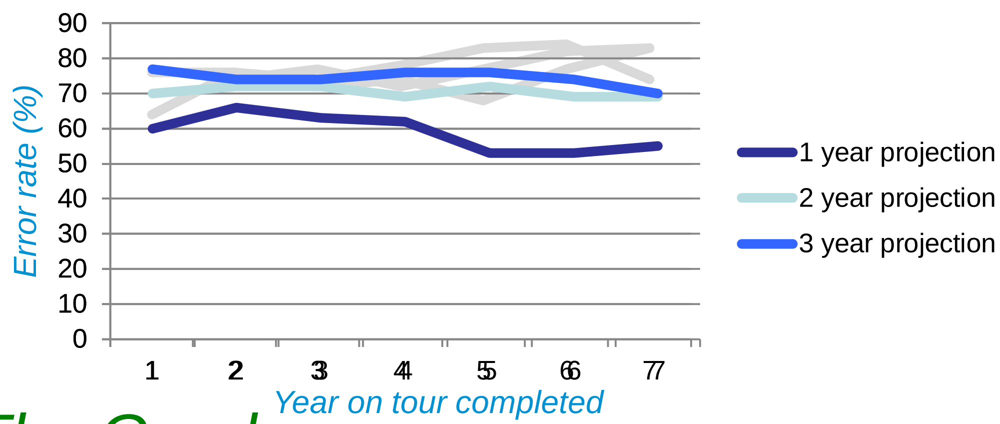
Can us current athletes

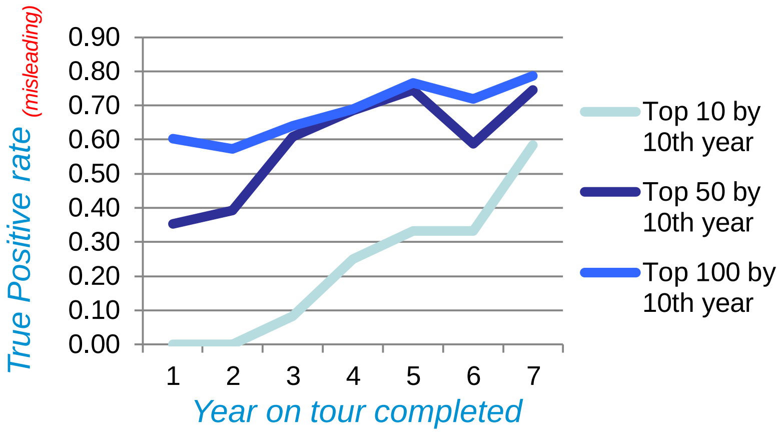
Temporal Network

Demonstration

Temporal Network (results)

The Bad





The Good

Calibration

Y1-2,+1 0-0.5: 0 | 0.5-1: 0.14 | 1-2: 0.607| 2-5: 2.69 | 5-10: 9.64 | 10-15: 9.52 | 15-20: 18 | 20-30: 28.2 | 30-40: 34.9 | 40-50: 34 |
Y1-3,+1 0-0.5: 0 | 0.5-1: 0 | 1-2: 0.836| 2-5: 2.05 | 5-10: 9.92 | 10-15: 6.11 | 15-20: 24.8 | 20-30: 28.2 | 30-40: 35.6 | 40-50: 44.3 | 50-100: 48 |
Y1-2,+2 0-1: 0 | 1-2: 0.563| 2-5: 2.26 | 5-10: 8.63 | 10-15: 13.4 | 15-20: 20.4 | 20-30: 23.7 | 30-40: 32.9 |
Y1-7,+2 0-2: 0 | 2-5: 0.901| 5-10: 5.38 | 10-15: 13.3 | 15-20: 21 | 20-30: 29.2 | 30-50: 43.2 |
Y1-3,+3 0-2: 0 | 2-5: 1.19 | 5-10: 5.54 | 10-15: 13.4 | 15-20: 20.5 | 20-30: 26.3 |

Times surprised

Ex.	<1%	<10%	>90%	>99%
Y1-2, +1	0.12 (1/845)	2.29 (73/3181)	0 (0/0)	0 (0/0)
Y1-3, +1	0 (0/691)	2.46 (78/3175)	0 (0/0)	0 (0/0)
Y1-2, +2	0 (0/120)	3.73 (107/2870)	0 (0/0)	0 (0/0)
Y1-7, +3	0 (0/0)	3.14 (55/1750)	0 (0/0)	0 (0/0)
Y1-3, +3	0 (0/0)	3.13 (73/2329)	0 (0/0)	0 (0/0)

Problems

- *Athletes follow junior/senior/mixed pathways throughout their early career*
- *Lack of variety in data. Relying on historical accumulation.*
- *Nature of benchmarking implies only rank can be used.*
- *Very long term predictions.*
- *Variability in ranking pathways is huge.*

Successes

- *We can learn from history, and objectively calculate accurate probabilities of events*
- *An improvement from previous prediction attempts (there are none!)*
- *Identify how poor ranking is as a predictor success at peak*

Acknowledgements

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Dr. Machar Reid tennis Australia's Favourite

Thanks for listening