Player evaluation based on match performance

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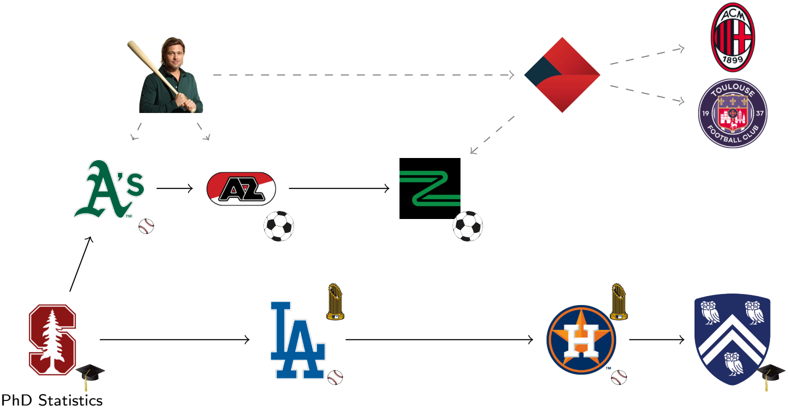
der 5. April 2024

RICE UNIVERSITY
Sport Analytics

Outline

1. My Background
2. Player evaluation based on match performance
   - Descriptive metrics
   - Predictive metrics
3. My Research
   - Basic descriptive metrics in volleyball
   - Advanced predictive metrics in baseball
   - Advanced descriptive metrics in football

My Background



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What is player evaluation?

"How good is this player?"

Player recruitment and team selection

Transfer signings

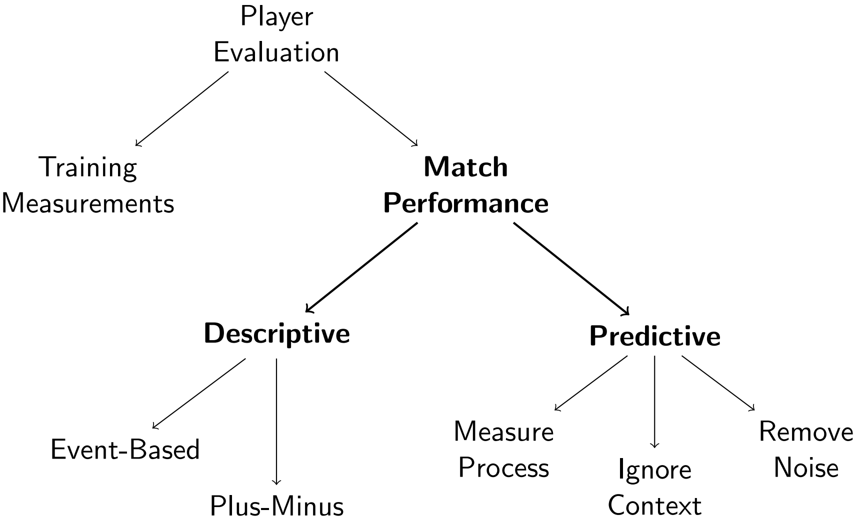
Trades and free agency (American sports)

- If we add this player, how many more matches will we win?

Big Picture

- Player Evaluation
  - Training Measurements
    - ?
  - Match Performance
    - Descriptive
      - Event-Based
      - Plus-Minus
    - Predictive
      - Measure Process
      - Ignore Context
      - Remove Noise

Big Picture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Player evaluation based on match performance

Two guiding principles:

1. (Descriptive) Measure impact on team wins
   - How do player actions cause us to win (or lose) matches?

2. (Predictive) Separate signal from noise
   - How will the player perform in the **future?**

Example (from *Moneyball*):

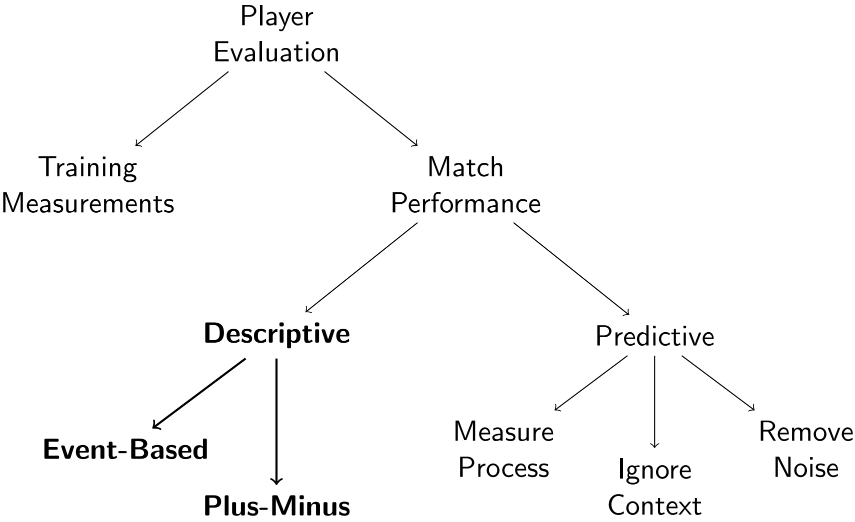
Batting Average $= \frac{H}{AB}$

- Less descriptive
- Less predictive

On-Base Percentage $= \frac{H+BB+HBP}{AB+BB+HBP+SF}$

- More descriptive
- More predictive

Big Picture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Descriptive Approach #1: Event-Based

Approach: Estimate win probability (or score expectancy) using event data. As score expectancy changes, assign credit to players responsible for those actions.

Methods: Markov chain (for low-dimensional game state) or machine learning (for high-dimensional game state)

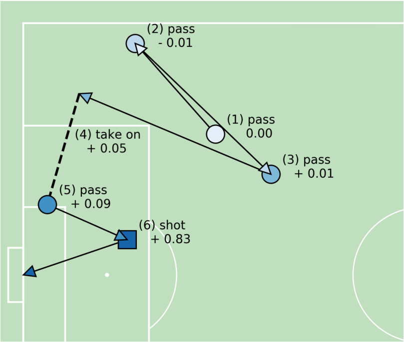
Baseball Example: Base-out run expectancy

Runners	0 Outs	1 Out	2 Outs
Empty	0.461	0.243	0.095
1 _ _	0.831	0.489	0.214
_ 2 _	1.068	0.644	0.305
1 2 _	1.373	0.908	0.343
_ _ 3	1.426	0.865	0.413
1 _ 3	1.798	1.140	0.471
_ 2 3	1.920	1.352	0.570
1 2 3	2.282	1.520	0.736

https://thebaseballscholar.com/2017/08/14/sabermetrics-101-re24/

- Goal expectancy estimated via Markov chain model
- Bases empty, 0 out, single $= 0.831 - 0.461 = +0.370$ runs
- Bases loaded, 2 out, strikeout $= 0 - 0.736 = -0.736$ runs

Football Example: VAEP (Decroos et al. 2019)



Decroos et al. 2019

- Goal expectancy estimated via machine learning

See also: Expected Threat (Singh 2018)

Descriptive Approach #2: Plus-Minus

Approach: Infer player contributions based on outcomes when they are playing vs. when they are off. Use regression to control for quality of teammates and quality of opposition.

Methods: Ridge regression, hierarchical Bayesian modeling, or linear mixed-effects regression

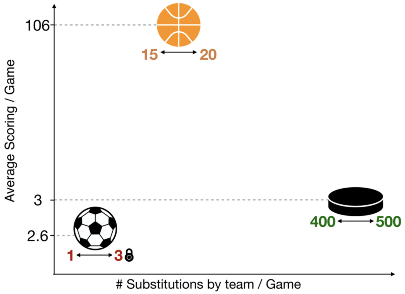
Basketball Example: Regularized Adjusted Plus-Minus

$$\begin{bmatrix} 40 \\ -25 \\ 60 \\ 0 \\ -30 \\ -12.5 \\ -12.5 \\ -30 \\ 50 \\ 30 \\ -50 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & -1 & -1 & -1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & -1 & -1 & 0 & -1 & 0 \\ 1 & 0 & 0 & 1 & 1 & -1 & 0 & 0 & -1 & -1 \\ 1 & 0 & 0 & 1 & 1 & 0 & 0 & -1 & -1 & -1 \\ 0 & 1 & 1 & 1 & 0 & 0 & -1 & -1 & -1 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 & -1 & -1 & 0 & -1 \\ 1 & 1 & 1 & 0 & 0 & 0 & -1 & 0 & -1 & -1 \\ 1 & 1 & 1 & 0 & 0 & -1 & 0 & 0 & -1 & -1 \\ 0 & 0 & 1 & 1 & 1 & -1 & 0 & 0 & -1 & -1 \\ 1 & 0 & 1 & 1 & 0 & -1 & -1 & -1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 & -1 & -1 & -1 & 0 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \\ \beta_7 \\ \beta_8 \\ \beta_9 \\ \beta_{10} \end{bmatrix}$$

(Jacobs 2017)

- Works well (many substitutions and scoring events)

Football Example: **Augmented** Adjusted Plus-Minus

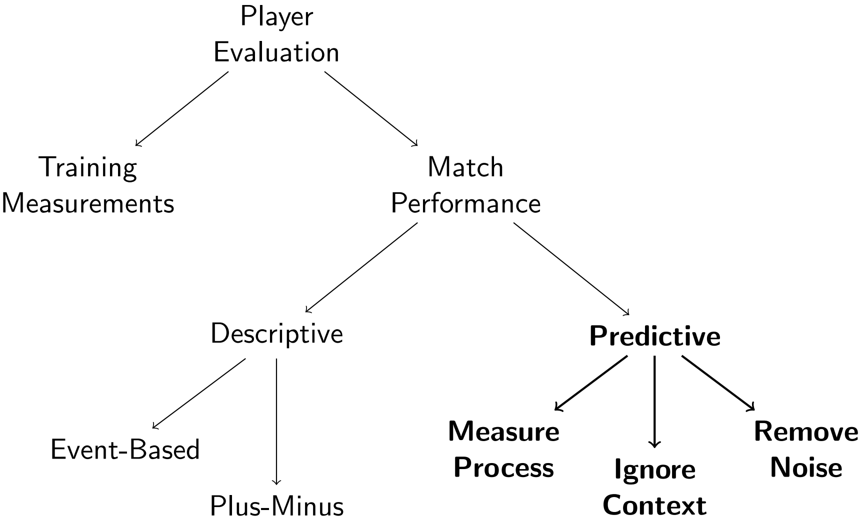


(Matano et al. 2023)

- Problem: Football has few scoring events AND few subs
- Solution: Set your prior belief using additional information (e.g. video game player ratings, Matano et al. 2023)

See also: Box Plus-Minus (Myers 2020)

Big Picture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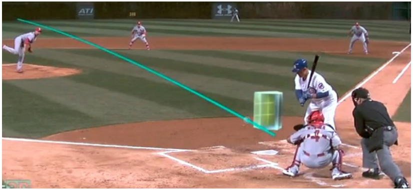
Predictive Strategy #1: Measure process, not results

Strategy: Measure more granular data. Create predictions of outcomes using the more granular data. These predicted outcomes (usually) have higher signal-to-noise ratio than actual outcomes.

Baseball Example: Pitch outcome modeling



Football Example: xG vs. goals

Predictive Strategy #2: Use context-neutral metrics

Strategy: (Sometimes) It helps to ignore the context in which an event occurred. This happens when the value of the event is sensitive to context, but the performance of the event is not.

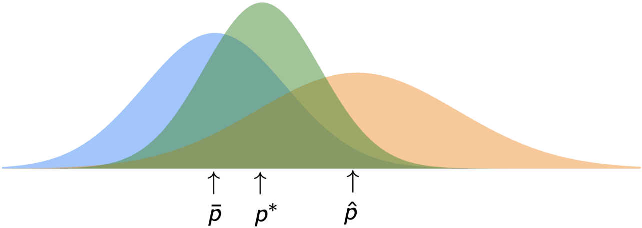
Baseball Example: Linear weights

2015 Linear Weights (Relative To Outs)	
Event	Run Value
BB	0.55
HBP	0.57
1B	0.70
2B	1.00
3B	1.27
HR	1.65

https://library.fangraphs.com/principles/linear-weights/

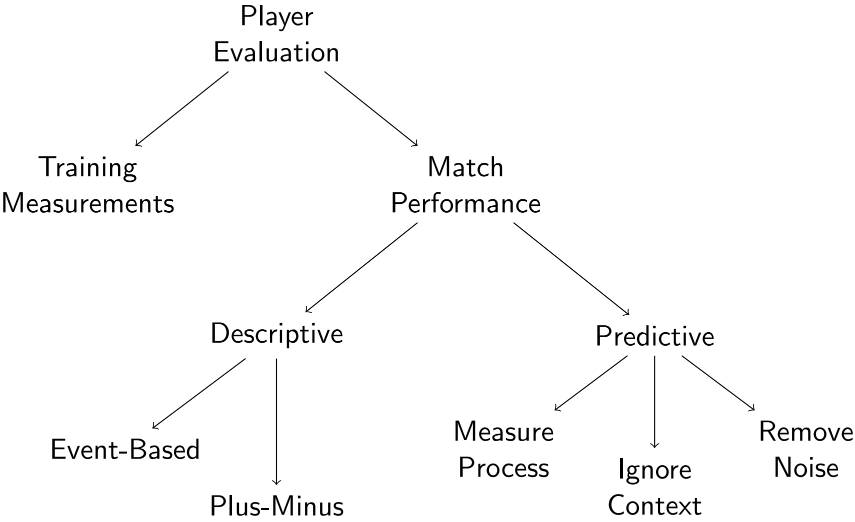
Predictive Strategy #3: Extract signal from noise

Strategy: Performance = Skill + Luck. Regression to the mean estimates a player's skill based on their performance. The amount of mean regression depends on the signal-to-noise ratio of the stat.



Football Example: The average take-on success rate is $\bar{p} = 45\%$. If a player is successful in 30 of 46 attempts ($\hat{p} = 65\%$), we expect his future success rate to be $p^* = 52\%$.

Big Picture



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Project #1: Basic descriptive metrics in volleyball

Joint work with Luke Stancil and Naomi Consiglio

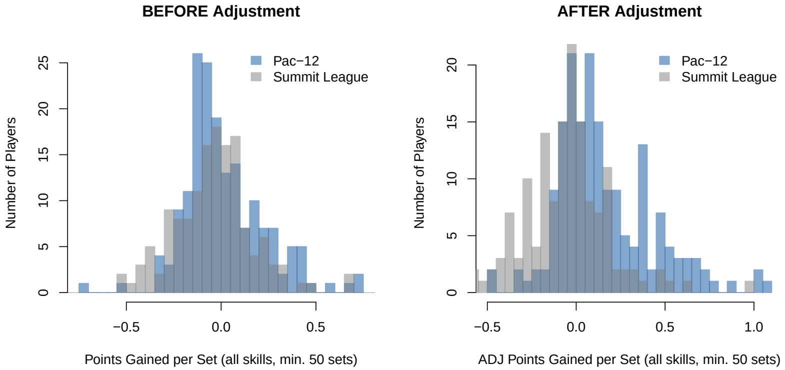
- 4,147 matches, 600K+ points, 5M+ contacts, ∼6,000 players
- We used a Markov chain to estimate point win probability

Player	Skill	Eval	State	P(Sideout)
Anna Deeber	Serve		(S, SV)	57%
Emma Halter	Reception	#	(R, R#)	63%
Saige K.-Torres	Set	#	(R, R#S#)	64%
Molly Phillips	Attack		(R, R#S#A)	64%
Raquel Lazaro	Dig	+	(S, D+)	49%
Elena Scott	Set	#	(S, D+S#)	47%
Claire Chaussee	Attack		(S, D+S#A)	47%
Kayla Caffey	Block	+	(R, B+)	56%
Phekran Kong	Dig	!	(S, D!)	51%
Raquel Lazaro	Set	#	(S, D!S#)	51%
Claire Chaussee	Attack		(S, D!S#A)	51%
Point Louisville				**0%**

Project #1: Basic descriptive metrics in volleyball

Joint work with Luke Stancil and Naomi Consiglio

- We used a hierarchical linear mixed-effects regression to adjust each player's performance based on her quality of competition



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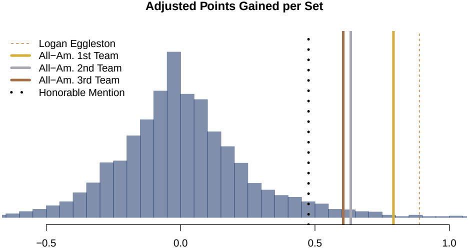
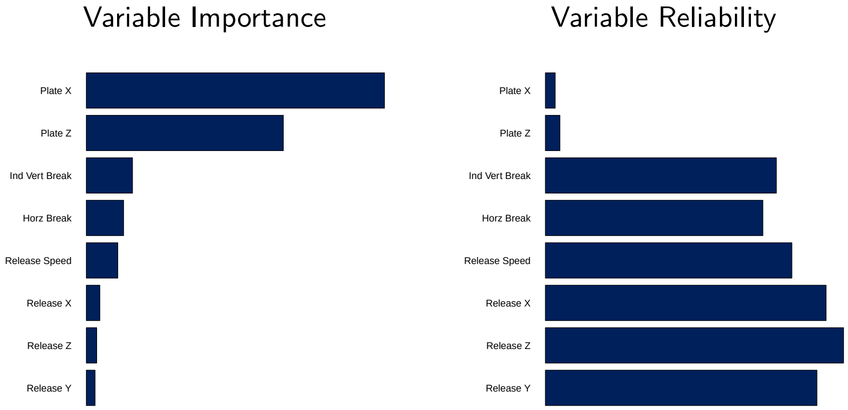


PLAYER	TEAM	CONF	POS	SETS PLAYED	POINTS GAINED PER SET (ADJ)	SERVE PG*/S	PASS PG*/S	SET PG*/S	ATTACK PG*/S	BLOCK PG*/S
Brooke Nuneviller	Oregon	Pac-12	OH	122	**+1.09**	+0.07	+0.41	+0.00	+0.56	+0.04
Mckenna Melville	Central Florida	AAC	OH	104	**+1.09**	-0.14	+0.23	-0.00	+0.79	+0.22
Claire Hoffman	Washington	Pac-12	OH	112	**+1.04**	+0.13	+0.23	-0.00	+0.65	+0.02
Julia Bergmann	Georgia Tech	ACC	OH	86	**+1.03**	+0.09	+0.25	-0.01	+0.64	+0.06
Kendall Kipp	Stanford	Pac-12	OPP	117	**+1.02**	+0.03	-0.02	-0.00	+0.72	+0.29
Amber Igiede	Hawaii	Big West	MB	102	**+0.98**	+0.07	+0.04	+0.01	+0.47	+0.38
Elizabeth Juhnke	South Dakota	Summit	OH	113	**+0.96**	+0.01	-0.01	-0.00	+0.69	+0.26
Madi Kubik	Nebraska	Big Ten	OH	109	**+0.94**	+0.05	+0.42	-0.01	+0.44	+0.05
Asjia Oneal	Texas	Big 12	MB	87	**+0.93**	+0.05	+0.04	+0.00	+0.35	+0.50
Logan Eggleston	Texas	Big 12	OH	91	**+0.89**	+0.09	+0.05	+0.01	+0.70	+0.05

Project #2: Advanced predictive metrics in baseball

Joint work with Vicente Iglesias

- Pitch outcome modeling is very useful, but the problem is that the most important variables are the least reliable!



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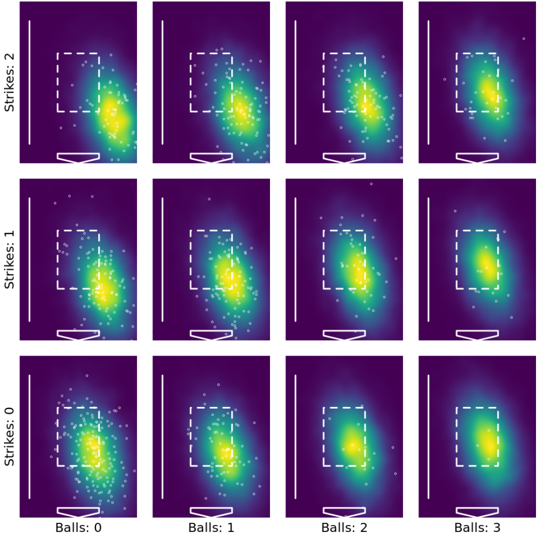
Joint work with Vicente Iglesias

We used a Bayesian hierarchical model to estimate the probability distribution over the 9-dimensional pitch trajectory for each pitcher in each count.

We predicted future pitcher outcomes using this model.



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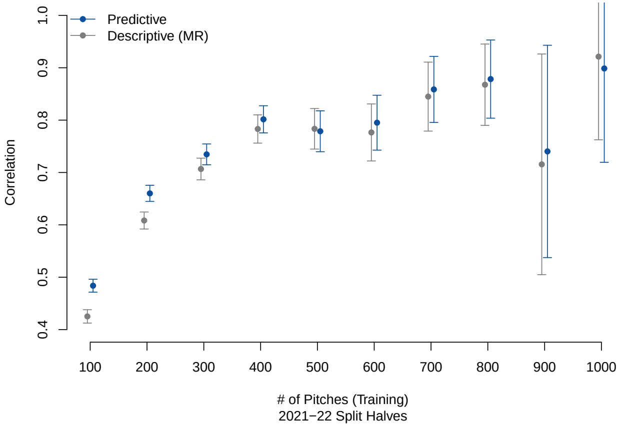


- Our **predictive** model outperforms mean-regressed pitch outcome model for pitchers with < 300 pitches.

Project #3: Advanced predictive metrics in football

Joint work with Andrew Kang

Motivation: Parma-led proposal for 2024 Opta Forum

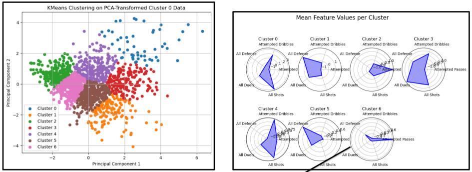
Using a combination of Opta Vision events, and spatial tracking data captured for all on-field players, propose a method for categorising players, based on role-specific performance traits, to group similar stylistic players to help enhance a recruitment profiling pipeline.

- BUT we had only 100 games of (anonymized) data
- We clustered players and fit cluster-specific box plus-minus
  - This identifies players well-suited for specific game models
- Andrew presented this work at Opta Forum!

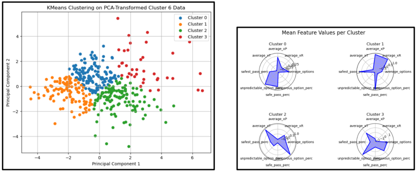
Project #3: Advanced predictive metrics in football

Joint work with Andrew Kang

- Step 1: Cluster players based on *style*, not performance



Step 1: PCA and Initial Clusters

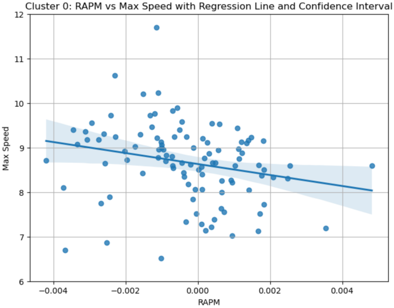


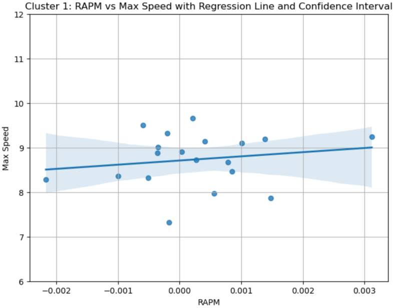
Step 2: PCA and Passers' Passing Sub-clusters

Project #3: Advanced predictive metrics in football

Joint work with Andrew Kang

- Step 2: Evaluate player performance relative to their style





A more refined equation that uses the cluster as an indicator variable is shown below.

$$\text{RAPM} = \beta_0 + \sum_{k=1}^{p} \beta_k b_k + \sum_{i=0}^{n-1} \sum_{k=1}^{p} \gamma_{ik} I(\text{Cluster} = i) b_k$$

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Vielen Dank!

References

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