

# Massey's ranking

DSTA

## 1 Rating and Ranking

### 1.1 Motivations

the ability to

- *rate* something (is this a cold day for February in London?), or to
- *rank* a set of elements (which is the coldest day of the month?)

is part of Science and Engineering since before Data Science.

...

Rating & ranking is a good framework to introduce Data Science techniques of general value and wide applicability.

Sports R&R is both fun and a huge Data Science market!

### 1.2 Definition

A measure of value of the subject, as objective and replicable as possible.

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E.g., temperature.

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Normally, abilities are

- **latent**
- hard to measure
- time-dependent
- place-dependent

Exercise: take the [Prof or Hobo?](#) quiz!

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yet, abilities are also

- hard to *transcend* (revert-to-the-mean effect, RTTM)
- relatively easy to perceive and project

### 1.3 Example: Football

- hard to guess the single score  $\implies$  entertainment value

...

- easy for experts to guess the long-term effect  $\implies$  different levels of enjoyment; RTTM: Revert To The Mean effect

...

Low scoring creates **randomness**

## 2 Formalisation

### 2.1 1-dimensional ranking

$P$  : players,  $|P| = n$

$T$  : time instants

$r : P \times T \rightarrow \mathbb{R}$

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A given rating function  $r$  creates a ranking ( $\rho$ ) on a set:

$$\rho : P \times T \rightarrow [1..n]$$

$$\rho(p, t) = k \leftrightarrow |\{p_j : r(p_j, t) \leq r(p_i, t)\}| = k$$

...

$$\delta(p_i, p_j, t) = |r(p_i, t) - r(p_j, t)|$$

$\delta$  captures both similarity and distance

## 2.2 multi-dimensional ranking

Multi-dim. rating:

$$r_{multi} : P \times T \rightarrow \mathbb{R}^d$$

...

Often:

$$r_{multi}(p_i, t) : f(r_1(p_i, t), \dots, r_d(p_i, t))$$

...

*Pareto dominance:*

$p_i$  dominates  $p_j$  (at time  $t$ ) if on every dimension  $x$

$$r_x(p_i, t) \geq r_x(p_j, t)$$

## 3 Rating in games

### 3.1 Ratings in games

- score-based games are better-suited to create ratings

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- yet effect of time and hardness of the proposed test match could be hard to assess.

### 3.2 Should games keep user ratings?

#### 3.2.1 Yes:

- feeling of improvement

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- a gauge for new features

...

- leads to rankings:
  - better matchmaking  $\implies$  entertainment value
  - fraud/anomaly detection?

### 3.3 No: game prowess as social ranking?

The spectacle is a social relation mediated by images, not a collection of images.

«Le spectacle n'est pas un ensemble d'images, mais un rapport social entre des personnes, médiatisé par des images»

[Guy Debord, La Société du spectacle (1967), Thèse 4]

...

- a reflection of US culture?

...

- a turn-off for people who don't feel competitive?
- turns-off casual users?

## 4 Sport ranking/estimation

### 4.1 Domain

- n teams play each other in a tournament
- final scores are recorded, e.g., Real Madrid–Borussia Dortmund: 2-0.
- predict the score for a match in the future.

...

-focus on predicting the score difference (eg, 2-0=2)

### 4.2 Running example

	Duke	Miami	UNC	UVA	VT	Record	Point Differential
Duke		7-52	21-24	7-38	0-45	0-4	-124
Miami	52-7		34-16	25-17	27-7	4-0	91
UNC	24-21	16-34		7-5	3-30	2-2	-40
UVA	38-7	17-25	5-7		14-52	1-3	-17
VT	45-0	7-27	30-3	52-14		3-1	90

the win-loss balance and the points balance are second-level performance measures  
they are not considered sufficient to create valuable ratings/rankings/predictions.

### 4.3 [In]credible Assumptions

1. to each team a **latent** variable for *strength* is assigned

...

numerical **ratings** determine a **ranking** among teams (at t=end, so we can drop it)

and a prediction  $Pr[a \rightarrow b] = \frac{\rho(a)}{\rho(a)+\rho(b)}$

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2. strength/rating is immutable during the tournament

3. teams play each other exactly once during the tournament

...

Now, consider the score difference in each match, say  $i$  vs.  $j$ , defined as  $s_i - s_j$

Define  $\mathbf{y}_{m \times 1}$  as the vector of all score differences in matches

Assume (assumption 4) that strength/rating imbalance determines score difference:

$$r_i - r_j = s_i - s_j$$

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$$X_{m \times n} \cdot \mathbf{r}_{n \times 1} = \mathbf{y}_{m \times 1}$$

...

$$\begin{bmatrix} 0 & 0 & +1 & 0 & -1 & 0 \\ 0 & \ddots & \ddots & & & \\ \ddots & \ddots & \ddots & \ddots & & \\ \ddots & \ddots & \ddots & \ddots & & \\ & & \ddots & \ddots & \ddots & \\ 0 & -1 & 0 & +1 & 0 & 0 \end{bmatrix}$$

$X_{m \times n}$  with  $m \gg n$  is overconstrained, no hope of finding a solution.

## 5 Massey's ratings

### 5.1 Data preparation

Massey considered the equivalent formulation of

$$X_{m \times n} \cdot \mathbf{r}_{n \times 1} = \mathbf{y}_{m \times 1}$$

as

$$X^T \cdot X \cdot \mathbf{r} = X^T \cdot \mathbf{y}$$

Both sides are easier to work with.

On the right-hand side,  $X^T \cdot \mathbf{y}$  is the all-season points difference vector, called  $\mathbf{p}$ .

Notice that  $\sum p_i = 0$ .

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On the left-hand side,

$$M_{n \times n} = X^T X$$

is squared, semidefinite and positive.

However, the rows sum to 0 and cols. are not independent:  $0/\infty$  solutions ensue...

M. also noticed that  $M$  has a fixed structure and does not need to be re-computed all the times.

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$$\begin{bmatrix} n-1 & 0 & -x & 0 & -y & 0 \\ & n-1 & \ddots & \ddots & & \\ & & \ddots & \ddots & \ddots & \\ & & & \ddots & \ddots & \\ & & & & \ddots & \\ 0 & -z & 0 & -w & 0 & n-1 \end{bmatrix}$$

$m_{i,i} = n - 1$  is the numbers of games  $i$  played,

$m_{i,j}$  is the negation of the no. of matches between  $i$  and  $j$  : here all values are set to -1.

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$$\begin{pmatrix} 4 & -1 & -1 & -1 & -1 \\ -1 & 4 & -1 & -1 & -1 \\ -1 & -1 & 4 & -1 & -1 \\ -1 & -1 & -1 & 4 & -1 \\ 1 & 1 & 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} r_1 \\ r_2 \\ r_3 \\ r_4 \\ r_5 \end{pmatrix} = \begin{pmatrix} -124 \\ 91 \\ -40 \\ -17 \\ 0 \end{pmatrix}$$

## 5.2 Massey

1. drops the last row/match
2. replaces it with a row of 1s, and sets  $p_n = 0$

(all ratings, positive and negative, will sum to 0)

$\bar{M} = M$  everywhere but for the last row which is full of 1s

$\bar{\mathbf{p}}$  is  $\mathbf{p}$  everywhere but for the last el.  $p_n = 0$ .

- 
1. now  $\bar{M}$  is non-singular and invertible
  2. solves

$$\bar{M}\mathbf{r} = \bar{\mathbf{p}}$$

to obtain an approximated rating for the teams.

The MSE solution to Massey's formula is a form of **regression**.

It can also be seen as  $\mathbf{r} = (\bar{X}^T \bar{X})^{-1} \bar{X}^T \bar{\mathbf{y}}$ .

## 5.3 Output

Team	Rating $r$	Rank
Duke	-24.8	5th
Miami	18.2	1st
UNC	-8.0	4th
UVA	-3.4	3rd
VT	18.0	2nd

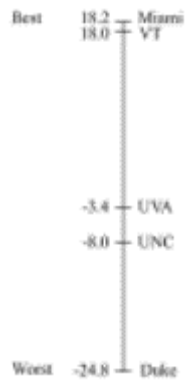
ratings sum to zero

values have no direct interpretation.

however, they effectively generate a **hierarchy**.

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## 6 Conclusions

### 6.1 Points to focus on

- rating and rating is the fun side of Data Science!

...

- *latent* variables that represent *non-measurable* skills
- those leave in a *feature space* possibly separated from the *data space*
- yet they may get a numeric estimate, and inform our predictions
- Massey regresses on the latent variables



## 6.2 Further readings

