



Workshop on Probabilistic
and Statistical Methods

MÉTODOS ESTATÍSTICOS PARA ANÁLISE DE DADOS DO ESPORTE

Daniel Takata Gomes

ENCE/IBGE



Aula 1: Apanhado acerca das aplicações da estatística no esporte



Aula 1: Apanhado acerca das aplicações da estatística no esporte

Aula 2: Métodos para análise de dados de futebol



Aula 1: Apanhado acerca das aplicações da estatística no esporte

Aula 2: Métodos para análise de dados de futebol

Aula 3: Métodos para análise de dados de esportes individuais

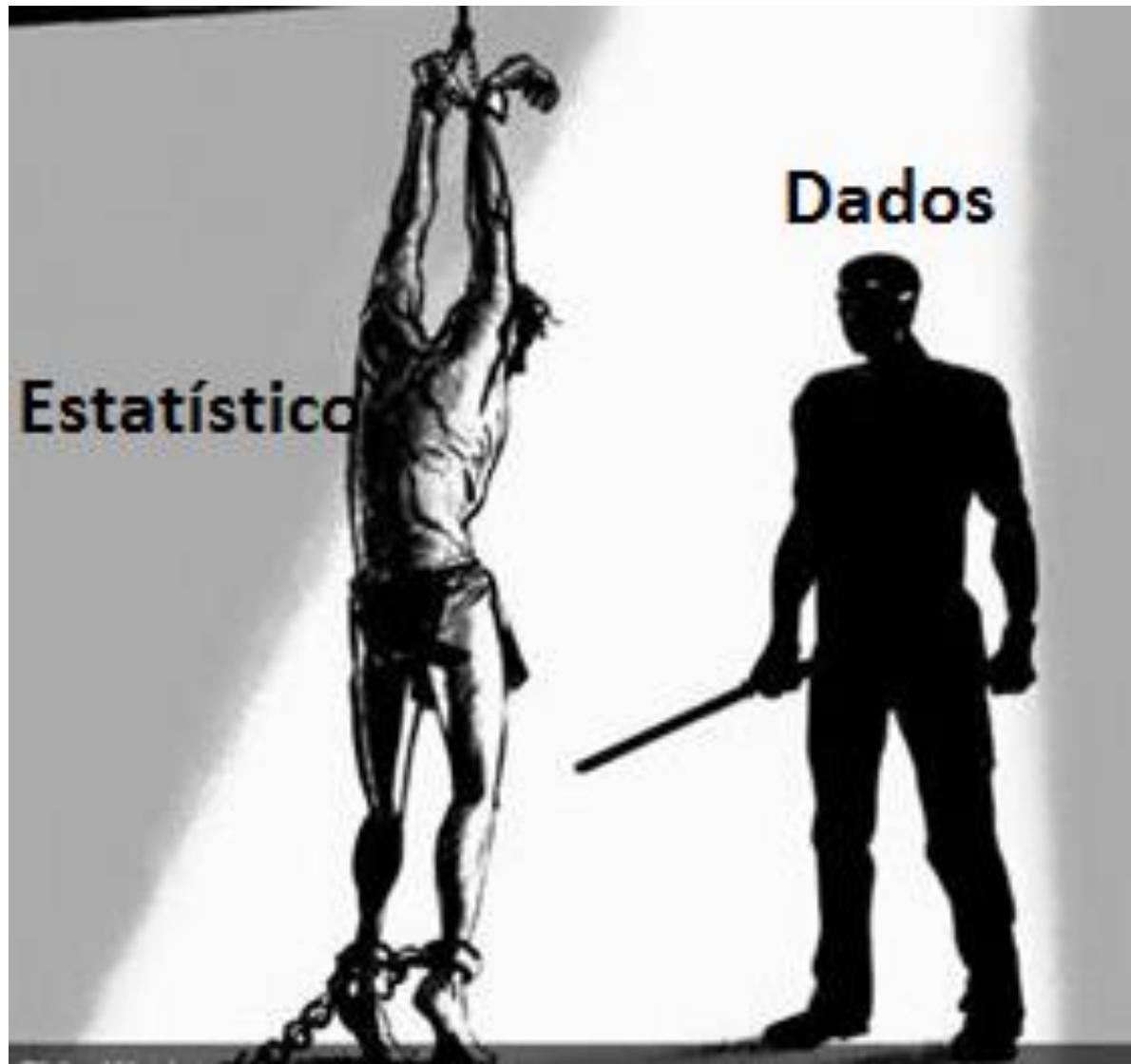


“Assim como no esporte, todos podem brincar de modelar. Se você é o tipo de pessoa que enxerga coisas mais claramente através de analogias com esporte, com o clima, com filmes e músicas, com a natureza ou com qualquer outra coisa, então você está a um passo de se tornar especialista em modelagem.”

David Sumpter, livro Soccermatics









#tenyearchallenge



neymarjr • Seguindo

neymarjr A cara de menino se foi, mas o olhar e o foco de quem quer vencer sempre estará comigo. #10yearschallenge

zelove9 🙌

gabipozzi 🙌

xanndys2 🙌

joanasanz Y los granos también hahahaha

lucaslima Caralho 🥑





#tenyearchallenge





#tenyearchallenge

2009



2019



boredpanda.com



#tenyearchallenge

2009

$$Y = \beta X + \epsilon$$

STATISTICS



#tenyearchallenge

2009	2019
$y = \beta x + \epsilon$	$y = \beta x + \epsilon$
STATISTICS	MACHINE LEARNING
※ 10 YEARS CHALLENGE	



Exclusivo: os tempos que podem rolar em Atlanta!

O estudo foi feito pelo sr. Ing. Viktor Svoboda, da Associação Internacional de Estatísticas da Natação (ISSA), que mora na República Tcheca. A análise foi feita em novembro/95. Confira o resultado da pesquisa e faça sua aposta...

Homens

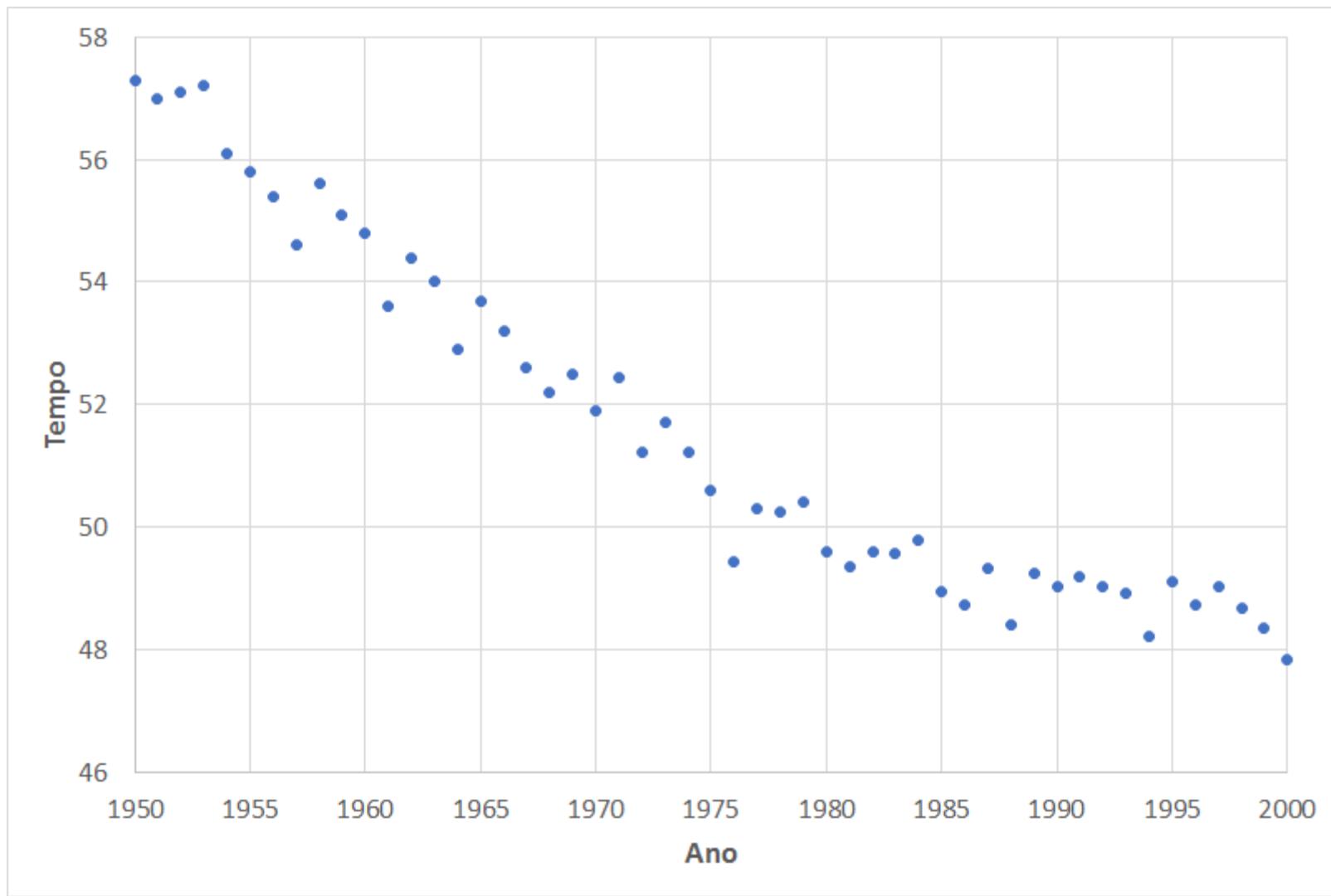
Prova	1o. lugar			Final A	Final B
	Previsão	Máximo	Mínimo		
50 L	21.78	21.64	22.08	22.38	22.80
100 L	48.39	48.08	48.70	49.36	50.22
200 L	1.46.63	1.45.94	1.47.44	1.48.05	1.50.01
400 L	3.43.20	3.41.77	3.46.32	3.49.33	3.52.65
1500 L	14.41.76	14.36.11	14.54.10	15.12.75	15.26.17
100 C	53.78	53.38	54.18	55.20	56.26
200 C	1.56.83	1.55.91	1.57.77	1.58.76	2.00.60
100 P	1.00.59	1.00.20	1.01.43	1.02.09	1.03.00
200 P	2.10.64	2.09.80	2.12.46	2.14.20	2.15.29
100 B	52.63	52.27	52.99	53.45	54.10
200 B	1.54.89	1.54.09	1.55.79	1.58.58	1.59.98
200 M	1.59.35	1.57.59	2.00.00	2.01.74	2.03.40
400 M	4.10.84	4.08.84	4.12.15	4.18.74	4.21.87

Mulheres

50 L	24.66	24.39	24.73	25.67	26.16
100 L	54.30	53.90	54.70	55.91	56.61
200 L	1.57.11	1.56.32	1.57.91	1.59.63	2.01.28
400 L	4.05.19	4.03.62	4.07.45	4.11.11	4.15.81
800 L	8.24.17	8.20.94	8.28.24	8.34.24	8.44.35
100 C	1.00.19	59.80	1.01.30	1.02.20	1.03.26
200 C	2.06.55	2.05.53	2.07.59	2.11.76	2.15.19
100 P	1.07.52	1.07.08	1.08.46	1.10.02	1.10.83
200 P	2.24.88	2.24.08	2.27.40	2.30.08	2.32.15

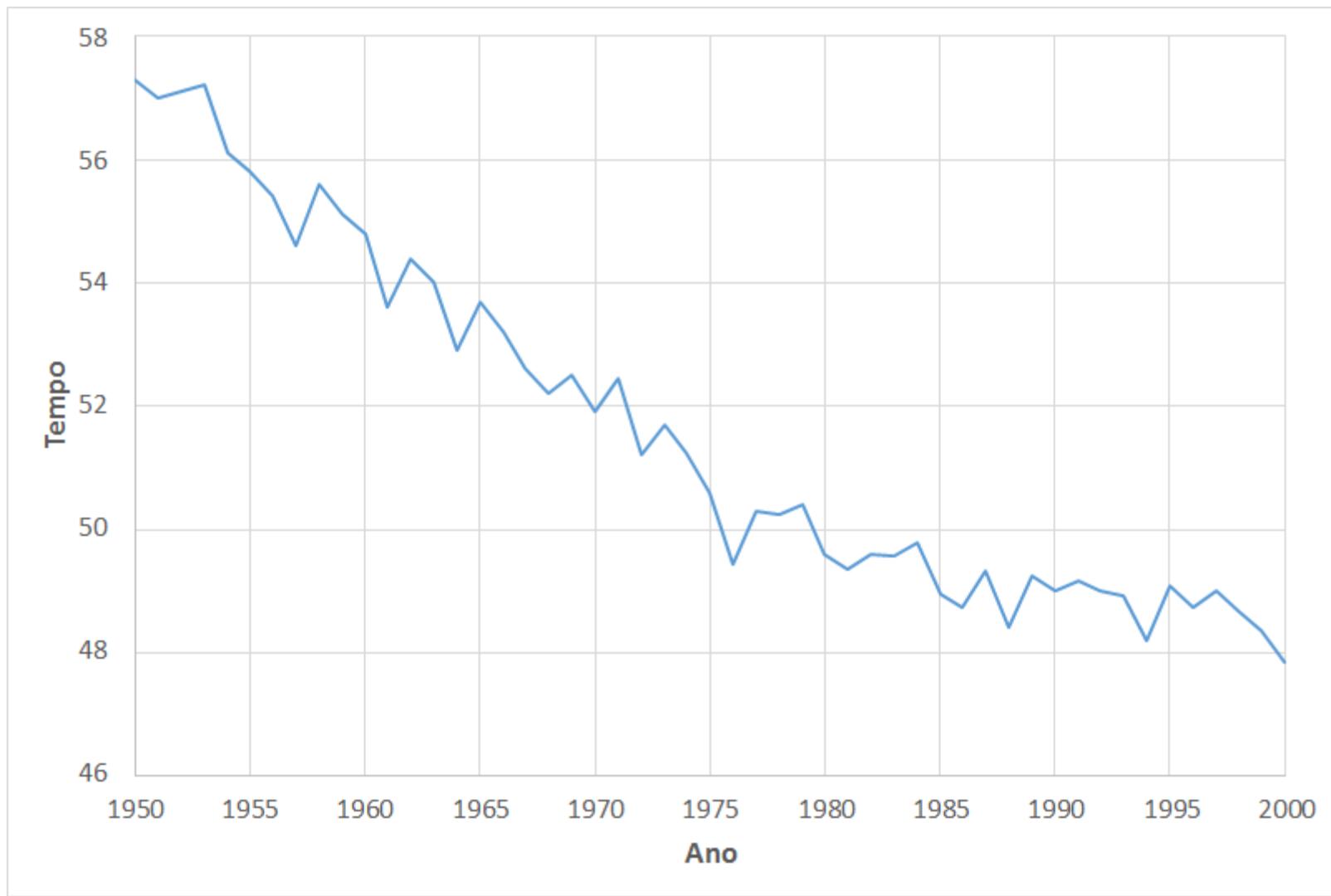


Evolução dos tempos dos líderes do ranking mundial dos 100m livre masculino





Evolução dos tempos dos líderes do ranking mundial dos 100m livre masculino







Graduação: Estatística (Unicamp)



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Doutorado: Estatística (USP)

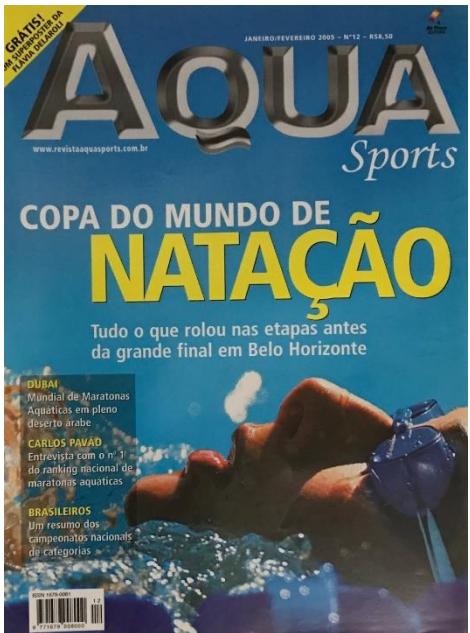
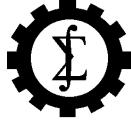


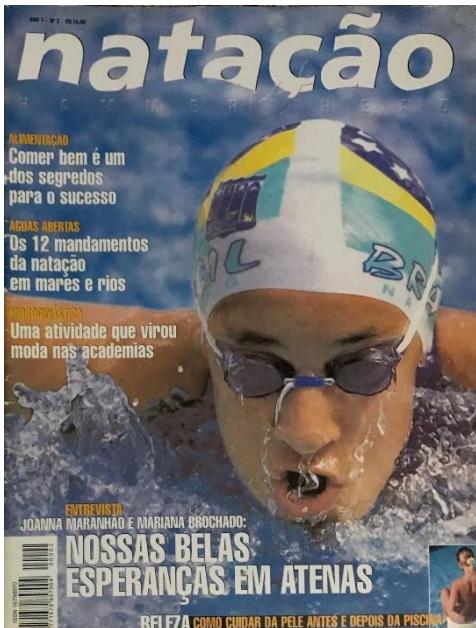
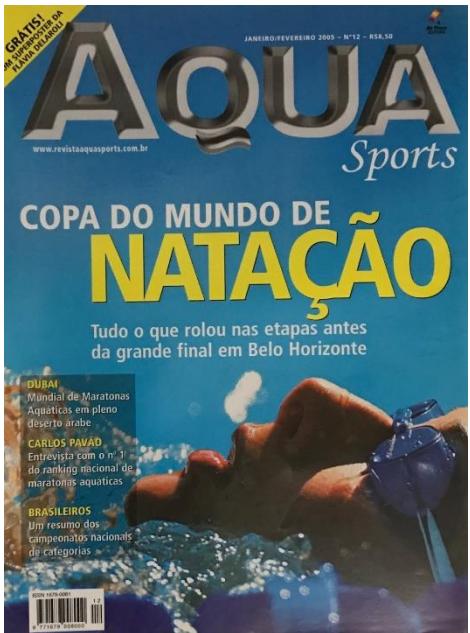
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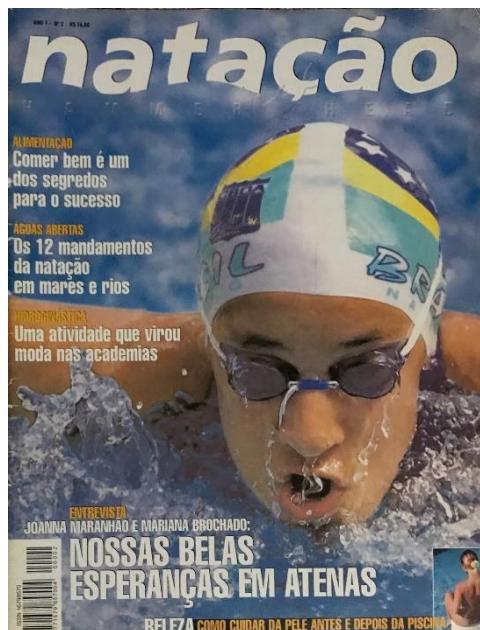
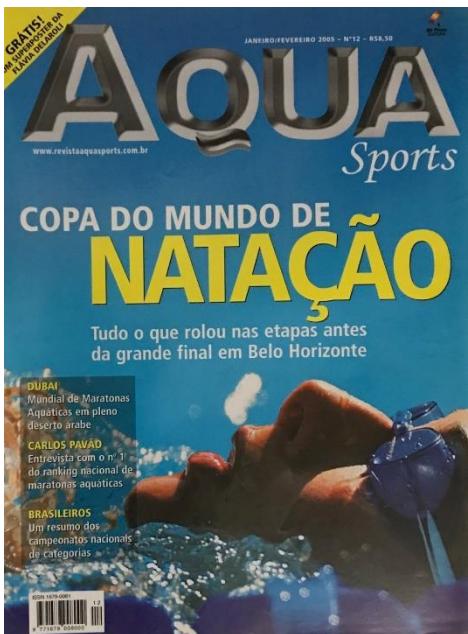
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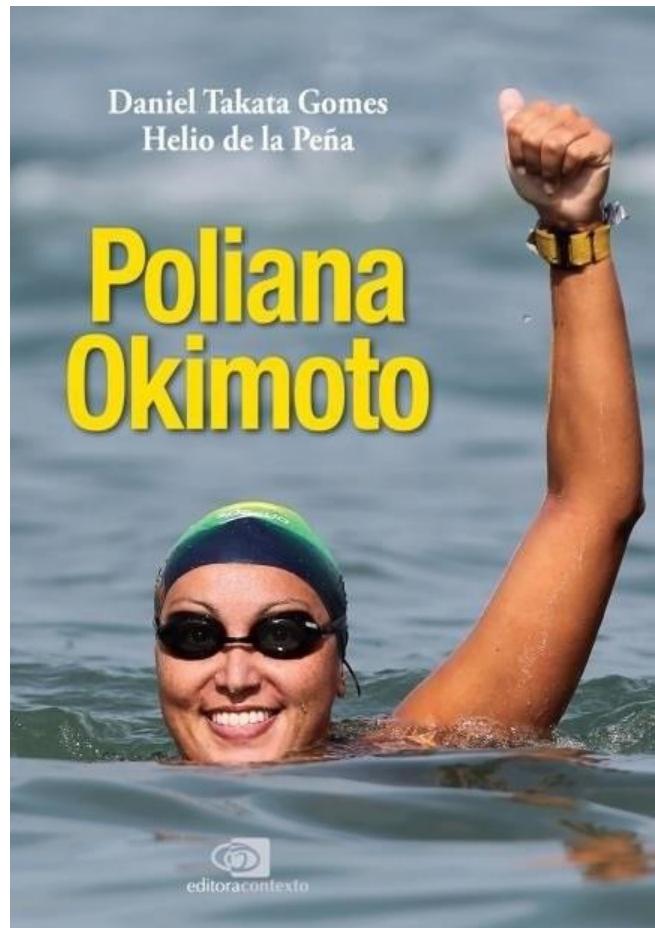
Ocupação atual: Professor e pesquisador na
Escola Nacional de Ciências Estatísticas (ENCE/IBGE)

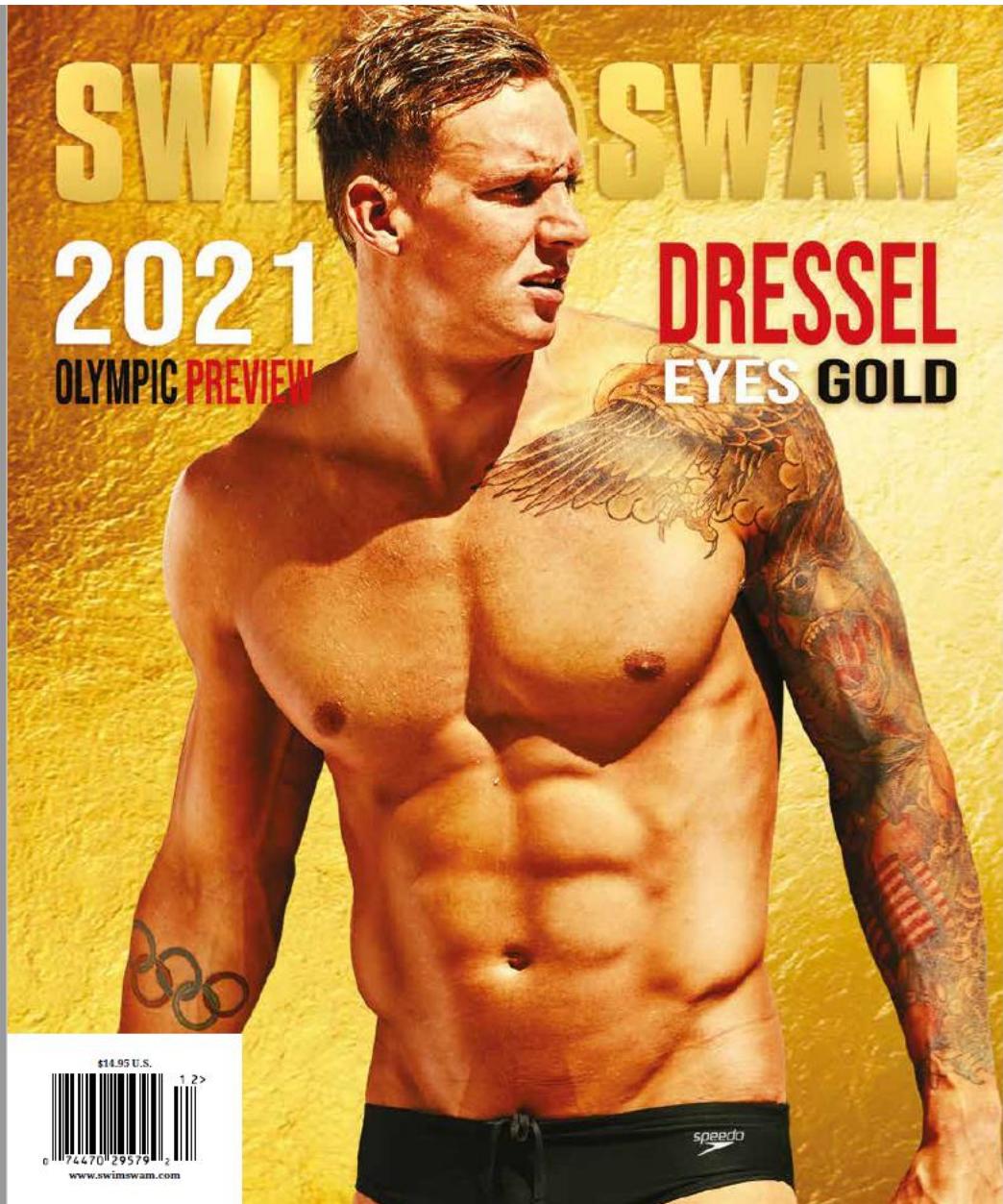




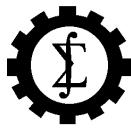




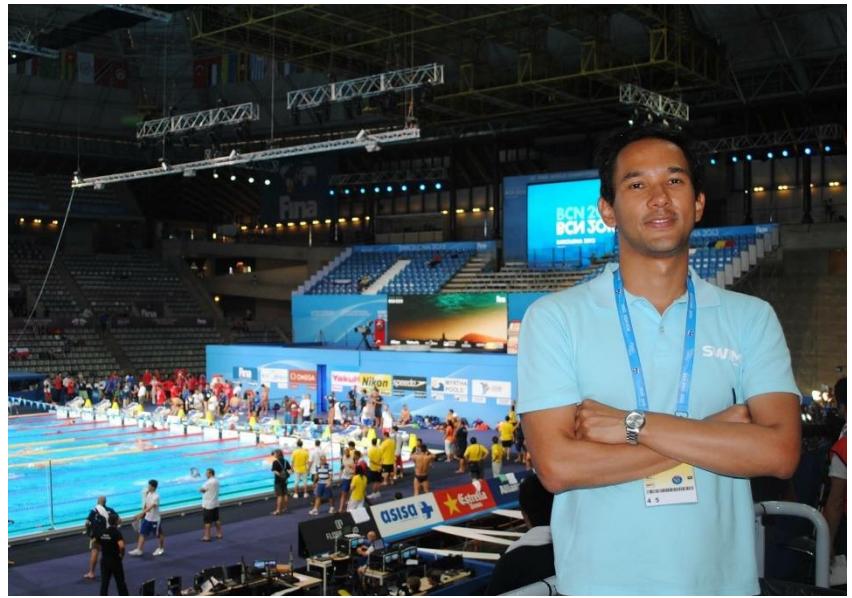




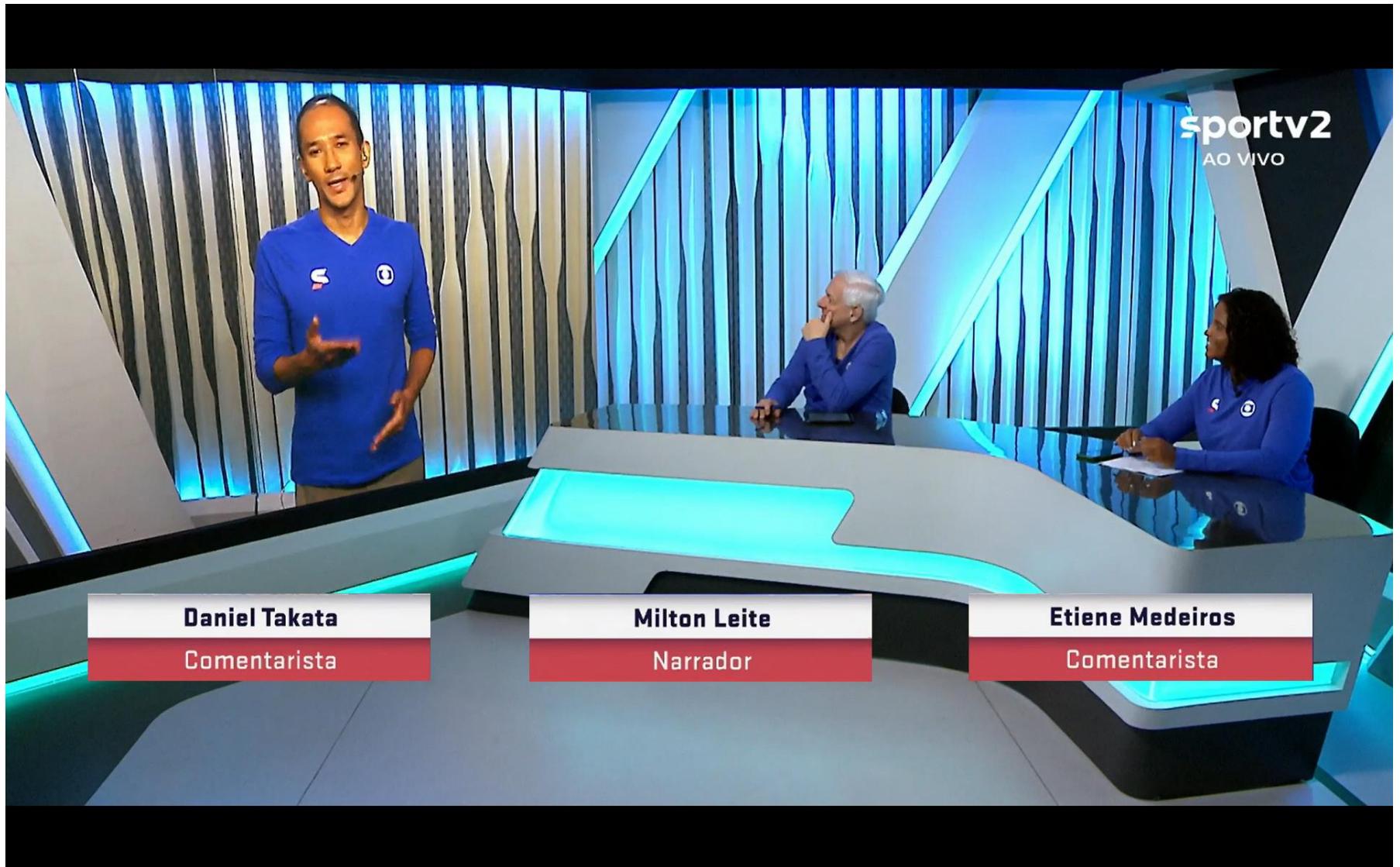














E o que isso tem a ver com estatística?



E o que isso tem a ver com estatística?

Resposta: tudo!



Home > BEST MEMÓRIA

BEST MEMÓRIA ESPECIAIS

Best Memória: Hoje é Dia do Estatístico

Por **Alex Pussieldi** - maio 29, 2019

94 0



Nada melhor do que homenagear Daniel Takata, o maior estatístico que a natação brasileira já produziu. Takata está com site novo e um canal no YouTube. Veja a postagem de hoje que faz



USUÁRIO

SENHA

ENTRAR

Ainda não tem um email UOL? Assine

Dólar ↑ 3,978
Euro ↑ 4,454Rio de Janeiro ↓
20°C 15°C

BUSCAR NO UOL



OPERAÇÃO CRAVADA

PCC cria 'tributação do crime' e cobra até R\$ 250 por mês de membro, diz PF



EM BRASÍLIA E SÃO PAULO

Em meia hora, ministro e Bolsonaro se contradizem sobre privatizar Correios



ANÁLISE

Depoimento de ex de Najila ajudou Neymar; presença na mídia intriga polícia



NO RIO DE JANEIRO

Homem que tentou fugir de presídio vestido de mulher é achado morto



CONTRA BOLSONARO

Corinthians repudia ação da PM por protesto de torcedor



VOTAÇÃO EM 2º TURNO

Reforma da Previdência tem teste final na Câmara

Onyx diz esperar aprovação na Câmara até amanhã



FEITO INÉDITO

O Brasil vai enfim correr os 100m abaixo de 10 segundos? A chance aumentou



MARCADO PARA 15/8

Jóias de Adriana Ancelmo têm 78% de desconto em leilão



ARTIGO EM REVISTA

Professor de Harvard avalia



DINAMITANDO A TORRE DE BABEL

Tradução automática pode derrubar o inglês como língua global?



TIRE SUAS DÚVIDAS



Sonza fala de fama de 'sonsa' e masturbação ao explicar novo álbum



UMA QUESTÃO CULTURAL

Por que homem não gême no sexo? Tabu compromete a transa



O que pode ser: o que causa tosse seca, com catarro ou crônica?



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Robson Caetano acena na Vila Olímpica durante a realização dos Jogos de Seul-1988

Imagen: Wilson Meio/Folhapress

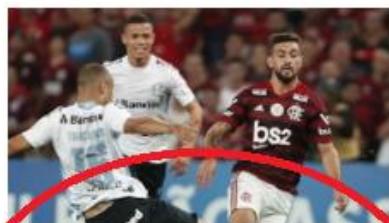


Daniel Takata*

Colaboração para o UOL, em São Paulo

06/08/2019 12h00

Lá se vão 31 anos. Na disputa do Ibero-Americano de 1988, na Cidade do México, o legendário Robson Caetano completou os 100m rasos em 10 segundos cravados. Cravados, mesmo. À época, essa era uma marca muito expressiva. Até aquela data, apenas seis corredores, na história, haviam corrido a distância abaixo dos 10 segundos. Um deles, o canadense Ben Johnson, teria suas marcas anuladas posteriormente por doping.



MATA-MATA NA LIBERTADORES

Afinal, é melhor jogar a 1^a ou a 2^a partida em casa? UOL analisa números

- | Blogueiros opinam se Fla ou Grêmio chega melhor à semi
- | Partida terá transmissão Fox, com UOL Esporte Clube
- | Obsessão do Fla e sossego do Grêmio marcam reencontro em semi após 35 anos



RANKING ATUALIZADO

Palmeiras lidera e Corinthians é o 2º que mais gasta em salários no Brasil

SITUAÇÃO-LIMITE

Análise: Com somente um diretor, Ancine está à beira do colapso

iPhone 11 dos EUA



SAQUE-ANIVERSÁRIO

App simula quanto você poderá sacar do FGTS no ano que vem



SIGA O UOL [f](#) [t](#) [i](#)



INTERNET NA

Como pequeno empreendedor usa fibra para a...



IMPACTO POS

Lamborghini Ferrari: 8 r... se rendera



EM BOM POR

Veja dicas um texto si... masculino



PRIMEIRA EDIÇÃO

Brasileira vence concurso de bumbum mais bonito do mundo



FAMOSOS SE DIVERTEM

De biquíni, Paula Lavigne ironiza fala de Luana Piovani



SÉRIE DOS ANOS 2000

Atriz de O Mundo É dos Jovens estreia como atriz pornô



AGORA YOUTUBER

'Eu só transo com fã, não sou burra', garante Geisy Arruda



TATUADO

Henrique Fogaça posta foto sem camisa, e fãs piram



Mata-mata: afinal, é melhor jogar a primeira ou a segunda partida em casa?



Filipe Luís e Galhardo disputam uma jogada em Flamengo x Grêmio

Imagen: Alexandre Vidal/Flamengo



Daniel Takata

Colaboração para o UOL, em São Paulo

02/10/2019 04h00

Essa é uma questão recorrente em mesas redondas e até em conversas de bar sobre futebol. Um time que joga a primeira partida em casa pode fazer um resultado e controlar o adversário na partida seguinte. Por outro lado,



WHAT IF THE SUPER SUITS HAD NEVER EXISTED?

BY DANIEL TAKATA

It has been 11 years since the high-technology suits were banned from swimming.

Such suits were used by almost every elite swimmer in 2008 and 2009 and helped them to break several world records. Some of these records still stand as of today, such as Cesar Cielo's 50 and 100 freestyle, Michael Phelps' 400 IM, and Federica Pellegrini's 200 freestyle.

There was much discussion at the time about the effect of the suits on the swimmers' performances. In this article, we try to estimate this effect through data and statistical analysis.

THE SUITS' IMPACT

In 2008, Speedo launched the LZR Racer suit, adding polyurethane panels to its existing design, replacing the Teflon coating used in previous models. The more polyurethane the suits had, the less drag they created. The result was that 55 world records were broken in that year in long course meters, 25 during the Beijing Olympics.

In 2009, other manufacturers like Jaked and Arena went further and made their suits entirely with polyurethane, allowing the swimmers to glide through water even faster.

Sixty-seven world records were broken that year in long course meters, 43 at the World Championships in Rome, the most ever.

In the beginning of 2010, FINA banned those suits for good. Now, swimmers have to be made only with textile material, no polyurethane.

But the effects of those suits remain strong. As of today, several of the fastest performances of all time were registered in that period. Some world records still remain untouched.

The list below shows the current world records in individual events in long course meters from 2008 and 2009.

Men			
Gesar Cielo (BRA)	50 freestyle	20.91	
Gesar Cielo (BRA)	100 freestyle	46.91	
Paul Biedermann (GER)	200 freestyle	1:42.00	
Paul Biedermann (GER)	400 freestyle	3:40.06	
Zhang Lin (CHN)	800 freestyle	7:32.12	
Aaron Peirsol (USA)	200 backstroke	1:51.92	
Michael Phelps (USA)	400 medley	4:03.84	

The question is inevitable: If the swimmers were not using high-tech suits in 2008-2009, what would be their times? How many world records from that period would still stand?

MODELING THE DATA

Let's take a look of the evolution of the men's 100 freestyle over the years. The following graph shows the average time of the fastest 100

swimmers in each year since 1990.

AVERAGE TIME OF THE FASTEST 100 SWIMMERS IN EACH YEAR IN THE MEN'S 100 FREESTYLE, SINCE 1990



The decreasing pattern is evident, as we would expect. But we can observe another interesting aspect.

Every four years, it is possible to notice a dramatic drop in the average time.

Which is not coincidence, since it corresponds to the Olympic years. The only exception is the period 2008-2009: The times decrease from 2007 to 2008, and decrease even more from 2008 to 2009, which is unusual, since 2009 was not an Olympic year. Of course, the suits were the cause.

The same pattern is observed in all other events included in the Olympic program. That is why, in this analysis, only these events are considered. We do not take into account the 50 strokes events, nor the men's 800 freestyle and the women's 1500 freestyle, which will make their first appearance this year at the Tokyo Olympics.

In a statistical perspective, we can estimate

the decreasing trend over the years and the seasonal effect each four years, using data from 1990-2007 and 2010 on, to estimate the times from 2008-2009 period in "normal" conditions, in other words, without super suits.

The statistical model is called ARIMA (Autoregressive Integrated Moving Average), one of the most used models to adjust time series data.

Since the 2009 suits were faster than the 2008 suits, different effects were considered for each of those years.

In the men's events, there were swimmers who preferred to use only the leg suit, and others used the full body suit. A very careful data analysis was conducted to estimate the percentage of swimmers who used each type of suit in each event, using data from the major competitions.

It is important to notice that we are able only to calculate the average effect of the suits. The suits' effects could vary from swimmer to swimmer, and the individual effect is impossible to measure without a designed experiment.

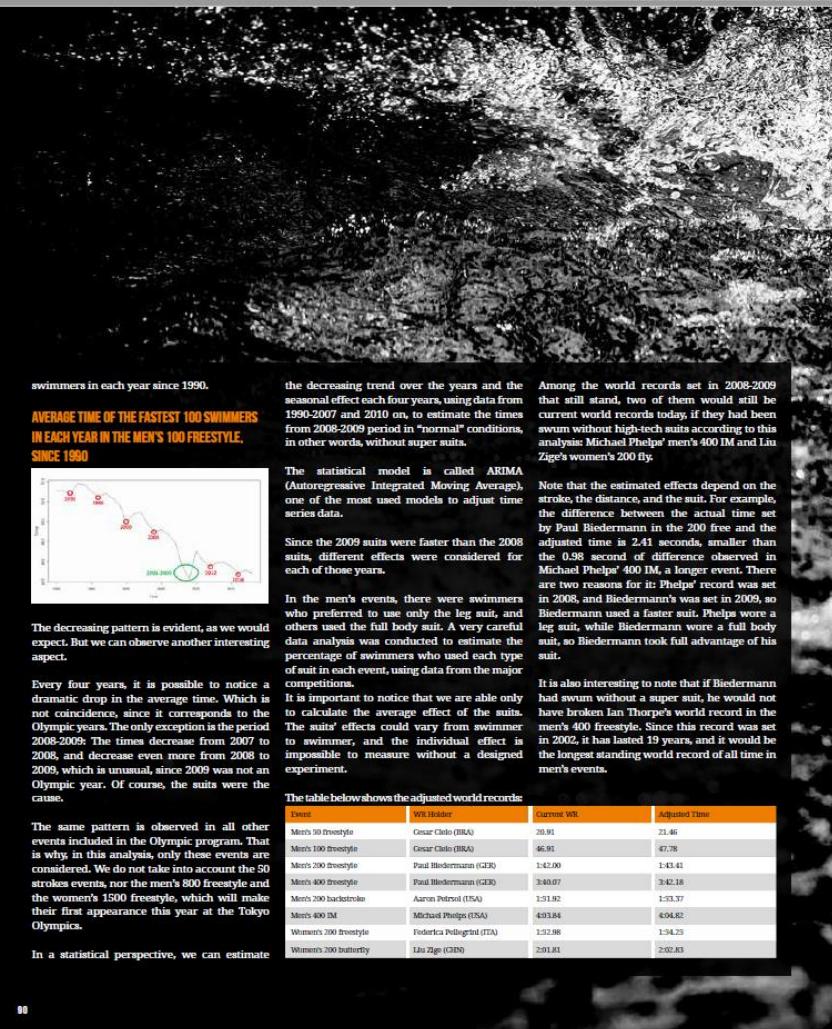
The table below shows the adjusted world records:

Event	WR Holder	Current WR	Adjusted Time
Men's 50 freestyle	Gesar Cielo (BRA)	20.91	21.46
Men's 100 freestyle	Gesar Cielo (BRA)	46.91	47.78
Men's 200 freestyle	Paul Biedermann (GER)	1:42.00	1:43.41
Men's 400 freestyle	Paul Biedermann (GER)	3:40.07	3:42.18
Men's 200 backstroke	Aaron Peirsol (USA)	1:51.92	1:53.37
Men's 400 IM	Michael Phelps (USA)	4:03.84	4:04.82
Women's 200 freestyle	Federica Pellegrini (ITA)	1:52.88	1:54.25
Women's 200 butterfly	Liu Zige (CHN)	2:01.81	2:02.83

Among the world records set in 2008-2009 that still stand, two of them would still be current world records today, if they had been swum without high-tech suits according to this analysis: Michael Phelps' men's 400 IM and Liu Zige's women's 200 fly.

Note that the estimated effects depend on the stroke, the distance, and the suit. For example, the difference between the actual time set by Paul Biedermann in the 200 free and the adjusted time is 2.41 seconds, smaller than the 0.98 second of difference observed in Michael Phelps' 400 IM, a longer event. There are two reasons for it: Phelps' record was set in 2008, and Biedermann's was set in 2009, so Biedermann used a faster suit. Phelps wore a leg suit, while Biedermann wore a full body suit, so Biedermann took full advantage of his suit.

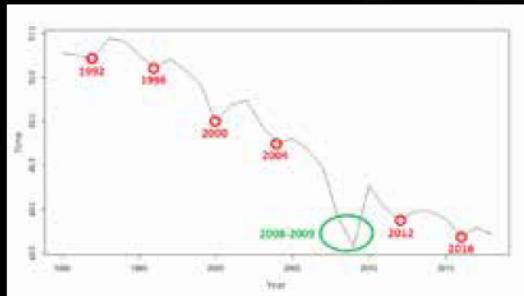
It is also interesting to note that if Biedermann had swum without a super suit, he would not have broken Ian Thorpe's world record in the men's 400 freestyle. Since this record was set in 2002, it has lasted 19 years, and it would be the longest standing world record of all time in men's events.





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veja

ASSINAR [BUSCAR](#)

RADAR COLUNISTAS ECONOMIA POLÍTICA MUNDO CIÊNCIA E TECNOLOGIA PLACAR ENTRETENIMENTO

Espor e

Uma a cada 69 anos: campanha do Fla no Brasileiro   exce o estat stica

Daniel Takata, professor da Escola Nacional de Ci ncias Estat sticas do Rio de Janeiro, estudou os n meros quase inalcan  veis do rubro-negro

Por [Alexandre Senechal](#), [Luiz Felipe Castro](#) - Atualizado em 13 nov 2019, 09h54 - Publicado em 13 nov 2019, 09h17



Flamengo, lider com 77 pontos em 32 rodadas Kaio Lakaio/VEJA

An nuncio fechado por Google



S o 77 pontos em 32 rodadas. Dez de vantagem para o segundo colocado. A marca que coloca o [Flamengo](#) com uma m o na ta a a seis jogos do fim do [Campeonato Brasileiro](#)   um recorde. Utilizando um modelo matem tico para analisar todas as edi es do torneio desde 2003 – quando a competi o passou a ser disputada por pontos corridos





swimmingstats 3

1.016 Posts 60,9 k Followers 1.112 Following

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Sport & recreation
Swimming Stats by SwimSwam
swimswam.com/swimmingstats

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Ad Tools Insights Add Shop

Story Highlights
Keep your favourite stories on your profile

New

+

TOP 50 ALL-TIME MEN'S 100 FLY PERFORMERS

AS OF FEBRUARY 1, 2022

RANK	SWIMMER	NAME	YEAR	COMPETITION
1	CALEB DRESEL	49.45	2021	Olympics
2	KRISTÓF MILÁK	49.68	2021	Olympics
3	MICHAEL PHILIPS	49.82	2009	World Champs
4	MILORAD ČAVIĆ	49.95	2010	World Champs
5	JOSEPH SCHOLING	50.39	2010	Olympics
6	IAN CRICKER	50.40	2005	World Champs
7	RAFAEL MUÑOZ	50.41	2009	World Champs
8	MATTHEW TEMPLE	50.45	2021	US Olympic Trials
9	CHAD LE CLOS	50.56	2015	World Champs
10	PIERO CODA	50.64	2018	Euro Champs

LONG COURSE METERS

SWIMMINGSTATS BY SWIMSWAM

TOP SWIMMERS WHO SET THE MOST WORLD RECORDS IN A CALENDAR YEAR

AS OF JANUARY 31, 2022

RANK	SWIMMER	NAME	YEAR	TYPE
1	MARK SPITZ	12	1972	100, 200 FREE, 100, 200, 400 IM, RELAY
2	IGOR DE BRUYN	11	2005	50, 100 FREE, 50, 100, 200 FREE
3	CHEY ASTERHEDM	9	1991	100, 200, 400, 400 IM, RELAY
4	KORNELIA ERDÉI	9	1973	50, 100 FREE, 100, 200, 400 IM, RELAY
5	KORNELIA ERDÉI	9	1976	50, 100 FREE, 50, 100 BACK, 100, 200, 400 IM, RELAY
6	MICHAEL PHILIPS	8	2000	200, 400 IM, 200, 300, 400 FREE, 400, 400 IM, RELAY
7	CLAUDIO DI KARMA	8	1984	200, 400 IM, RELAY
8	CLAUDIO DI KARMA	8	1987	200, 400 IM, 200, 300, 400 FREE, 400, 400 IM, RELAY
9	MARK SPITZ	8	1987	200, 400 IM, 200, 300, 400 FREE, 400, 400 IM, RELAY
10	BRIGIT MEYER	8	1988	100, 200, 400, 400 IM, RELAY
11	BRUNO RICHTER	8	1994	100, 200, 400, 400 IM, RELAY
12	PENNY HEINS	8	1994	50, 100, 200, 400 IM
13	MICHAEL PHILIPS	8	2000	100, 200 FREE, 100, 200, 400 IM

SWIMMINGSTATS BY SWIMSWAM

SWIMMERS WITH THE MOST SUB-16 MINUTE SWIMS IN WOMEN'S 1500 FREE (LCM)

AS OF JANUARY 31, 2022

RANK	SWIMMER	NAME	YEAR	TIME	TIME	PERSONAL	BEST
1	KATIE LEDECKY	54	2013	20:21	20:21	15:28.48	
2	SIMONA GUARACELLA	55	2016	20:21	20:21	15:48.88	
3	WANIE JUAJAHANE	55	2018	20:21	20:21	15:43.48	
4	LOTTIE FRIS	56	2009	20:15	20:15	15:38.88	
5	SABINA KÖHLER	58	2017	20:21	20:21	15:42.81	
6	LI BINGJIE	6	2017	20:18	20:21	15:52.87	
7	RIAN MELLERTON	6	2018	20:21	20:21	15:58.48	
8	MADDY RUSH	6	2019	20:18	20:21	15:48.19	
9	MIREIA BELMONTE	5	2013	20:17	20:17	15:58.48	
10	ERICA SULLIVAN	5	2019	20:21	20:21	15:43.43	



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TOP 50 ALL-TIME MEN'S 100 FLY PERFORMERS

RANK	SWIMMER	NAME	YEAR	TIME
1	CALEB DRESEL	49.45	2021	Olympics
2	KRISTÓF MILÁK	49.68	2021	Olympics
3	MICHAEL PHELPS	49.82	2009	World Champs
4	MILORAD ČAVIĆ	49.95	2009	World Champs
5	JOSEPH SCHOLING	50.39	2016	Olympics
6	IAN CRICKER	50.40	2005	World Champs
7	RAFAEL MUÑOZ	50.41	2009	World Champs
8	MATTHEW TEMPLE	50.45	2021	US Olympic Trials
9	CHAD LE CLOS	50.56	2015	World Champs
10	PIERO CODA	50.64	2018	Euro Champs

TOP 50 ALL-TIME WOMEN'S 100 FLY PERFORMERS

RANK	SWIMMER	NAME	YEAR	TIME
1	MARK SPITZ	52.12	1972	100, 200 FREE, 100, 200 FLY, RELAYS
2	INGE DE BRUIJN	52.20	2000	50, 100 FREE, 50, 100 FLY
3	CHEY JASTREMSKI	52.68	1961	100, 200 BREAST, 4X100 MEDLEY
4	KORNELIA ENDER	52.73	1973	100 FREE, 100 FLY, 200 IM, RELAYS
5	KORNELIA ENDER	52.82	1976	100, 200 FR, 100 BACK, 100 FLY, 200 IM, 4X100 M
6	MICHAEL PHELPS	52.90	2008	200 FREE, 100, 200 FLY, 200, 400 IM, RELAYS
7	DONNA DE VARONA	53.04	1964	200, 400 IM, RELAYS
8	CLAUDIA KOLB	53.07	1967	200, 400 IM, 4X200 FREE
9	MARK SPITZ	53.07	1967	400 FREE, 100, 200 FLY, 4X200 FREE
10	DEBBIE MEYER	53.08	1968	200, 400, 800 FREE, 4X200 FREE
11	ULRIKE RICHTER	53.14	1974	100, 200 BACK, 4X100 MEDLEY
12	PENNY HEYNS	53.19	1999	50, 100, 200 BREAST
13	MICHAEL PHELPS	53.20	2003	100, 200 FLY, 200, 400 IM

SWIMMERS WHO SET THE MOST WORLD RECORDS IN A CALENDAR YEAR

AS OF JANUARY 31, 2022

RANK	SWIMMER	NAME	YEAR	RECORDS
1	MARK SPITZ	MARK SPITZ	1972	100, 200 FREE, 100, 200 FLY, RELAYS
2	INGE DE BRUIJN	INGE DE BRUIJN	2000	50, 100 FREE, 50, 100 FLY
3	CHEY JASTREMSKI	CHEY JASTREMSKI	1961	100, 200 BREAST, 4X100 MEDLEY
4	KORNELIA ENDER	KORNELIA ENDER	1973	100 FREE, 100 FLY, 200 IM, RELAYS
5	KORNELIA ENDER	KORNELIA ENDER	1976	100, 200 FR, 100 BACK, 100 FLY, 200 IM, 4X100 M
6	MICHAEL PHELPS	MICHAEL PHELPS	2008	200 FREE, 100, 200 FLY, 200, 400 IM, RELAYS
7	DONNA DE VARONA	DONNA DE VARONA	1964	200, 400 IM, RELAYS
8	CLAUDIA KOLB	CLAUDIA KOLB	1967	200, 400 IM, 4X200 FREE
9	MARK SPITZ	MARK SPITZ	1967	400 FREE, 100, 200 FLY, 4X200 FREE
10	DEBBIE MEYER	DEBBIE MEYER	1968	200, 400, 800 FREE, 4X200 FREE
11	ULRIKE RICHTER	ULRIKE RICHTER	1974	100, 200 BACK, 4X100 MEDLEY
12	PENNY HEYNS	PENNY HEYNS	1999	50, 100, 200 BREAST
13	MICHAEL PHELPS	MICHAEL PHELPS	2003	100, 200 FLY, 200, 400 IM

SWIMMERS WITH THE MOST SUB-16 MINUTE SWIMS IN WOMEN'S 1500 FREE (LCM)

AS OF JANUARY 31, 2022

RANK	SWIMMER	NAME	YEAR	TIME
1	KATIE LEDECKY	KATIE LEDECKY	2013	2021 15:28.48
2	BIRUNA GUARAGELLA	BIRUNA GUARAGELLA	2016	2021 15:48.88
3	WANIE JAAKAJÄRVE	WANIE JAAKAJÄRVE	2018	2021 15:48.88
4	LOTTIE FRIS	LOTTIE FRIS	2009	2015 15:38.88
5	SARAH KÖHLER	SARAH KÖHLER	2017	2021 15:42.81
6	LI BINGJIE	LI BINGJIE	2017	2021 15:42.81
7	RIAN MELVERTON	RIAN MELVERTON	2018	2021 15:58.48
8	MADDY RUSH	MADDY RUSH	2018	2021 15:58.48
9	MIREIA BELMONTE	MIREIA BELMONTE	2013	2017 15:58.48
10	ERICA SULLIVAN	ERICA SULLIVAN	2019	2021 15:43.43

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SWIMMERS WHO SET THE MOST WORLD RECORDS IN A CALENDAR YEAR

LONG COURSE METERS, SINCE 1957

AS OF JANUARY 31, 2022

RANK	SWIMMER	NAME	YEAR	RECORDS
1	MARK SPITZ	MARK SPITZ	1972	100, 200 FREE, 100, 200 FLY, RELAYS
2	INGE DE BRUIJN	INGE DE BRUIJN	2000	50, 100 FREE, 50, 100 FLY
3	CHEY JASTREMSKI	CHEY JASTREMSKI	1961	100, 200 BREAST, 4X100 MEDLEY
4	KORNELIA ENDER	KORNELIA ENDER	1973	100 FREE, 100 FLY, 200 IM, RELAYS
5	KORNELIA ENDER	KORNELIA ENDER	1976	100, 200 FR, 100 BACK, 100 FLY, 200 IM, 4X100 M
6	MICHAEL PHELPS	MICHAEL PHELPS	2008	200 FREE, 100, 200 FLY, 200, 400 IM, RELAYS
7	DONNA DE VARONA	DONNA DE VARONA	1964	200, 400 IM, RELAYS
8	CLAUDIA KOLB	CLAUDIA KOLB	1967	200, 400 IM, 4X200 FREE
9	MARK SPITZ	MARK SPITZ	1967	400 FREE, 100, 200 FLY, 4X200 FREE
10	DEBBIE MEYER	DEBBIE MEYER	1968	200, 400, 800 FREE, 4X200 FREE
11	ULRIKE RICHTER	ULRIKE RICHTER	1974	100, 200 BACK, 4X100 MEDLEY
12	PENNY HEYNS	PENNY HEYNS	1999	50, 100, 200 BREAST
13	MICHAEL PHELPS	MICHAEL PHELPS	2003	100, 200 FLY, 200, 400 IM

@swimmingstats

Cool stat.



A importância do conhecimento do contexto no esporte



Ranking football players

Ian McHale, Phil Scarf

First published: 10 June 2005 | <https://doi.org/10.1111/j.1740-9713.2005.00091.x> | Citations: 5

SECTIONS

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Abstract

The Actim index is the official player rating system of the Barclays Premiership, which was introduced for the 2004–2005 football season. It was devised by Ian McHale and Phil Scarf for the Press Association in partnership with the Premier League and Football Data Co. Here they describe the development of the index and take a look at player performance this season.





The greatest F1 driver of all time?

Juan Manuel Fangio is the greatest Formula One driver of all time, according to research from the Sheffield Methods Institute's Dr Andrew Bell.



Dr Andy Bell used statistical analysis to work out who the sport's most accomplished



Formula for success: Multilevel modelling of Formula One Driver and Constructor performance, 1950–2014

Andrew Bell , James Smith, Clive E. Sabel and Kelvyn Jones 

From the journal *Journal of Quantitative Analysis in Sports*

<https://doi.org/10.1515/jqas-2015-0050>

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Abstract

This paper uses random-coefficient models and (a) finds rankings of who are the best formula 1 (F1) drivers of all time, conditional on team performance; (b) quantifies how much teams and drivers matter; and (c) quantifies how team and driver effects vary over time and under different racing conditions. The points scored by drivers in a race (standardised across seasons and Normalised) is used as the response variable in a cross-classified multilevel model that partitions variance into team, team-year and driver levels. These effects are then allowed to vary by year, track type and weather conditions using complex variance functions. Juan Manuel Fangio is found to be the greatest F1 driver of all time. The effect of team varies over time and is affected by the number of drivers in the team.

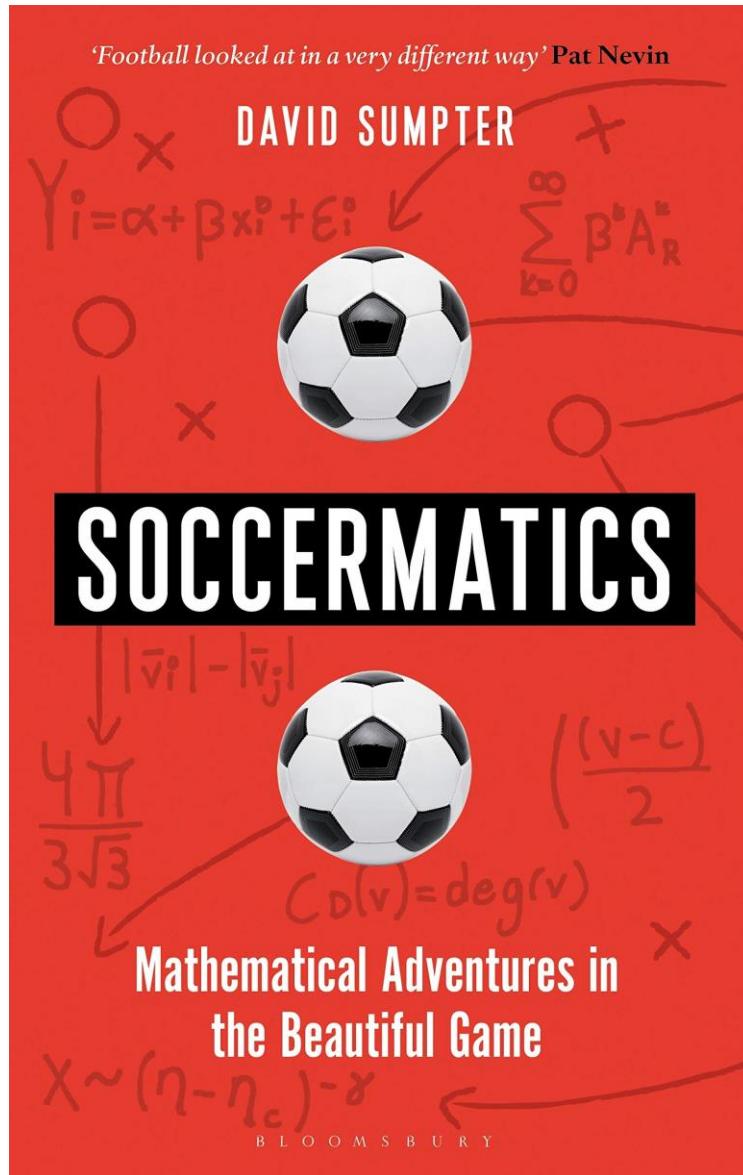


Table A9: Top 50 drivers based on the driver level residuals from model A1d (Michael Schumacher treated as two drivers, pre 2006 and post 2010)

Rank	Driver	Residual	Rank	Driver	Residual
1	Juan Manuel Fangio	0.333	26	Robert Kubica	0.129
2	Alain Prost	0.300	27	Carlos Reutemann	0.128
3	Michael Schumacher (pre-2006)	0.286	28	Tom Pryce	0.128
4	Jim Clark	0.276	29	Stirling Moss	0.123
5	Ayrton Senna	0.265	30	Martin Brundle	0.121
6	Fernando Alonso	0.263	31	Rubens Barrichello	0.119
7	Nelson Piquet	0.238	32	Daniel Ricciardo	0.119
8	Jackie Stewart	0.232	33	Alan Jones	0.119
9	Emerson Fittipaldi	0.217	34	Kimi Raikkonen	0.118
10	Sebastian Vettel	0.213	35	Patrick Depailler	0.118
11	Christian Fittipaldi	0.198	36	Carlos Pace	0.117
12	Lewis Hamilton	0.175	37	Richie Ginther	0.116
13	Graham Hill	0.169	38	Denny Hulme	0.115
14	Dan Gurney	0.166	39	Thierry Boutsen	0.113
15	Jody Scheckter	0.165	40	Mike Hawthorn	0.111
16	Jenson Button	0.160	41	Jean-Pierre Beltoise	0.106
17	Marc Surer	0.158	42	Heinz-Harald Frentzen	0.105
18	Damon Hill	0.157	43	Prince Bira	0.102
19	Louis Rosier	0.143	44	Keke Rosberg	0.100
20	Elio de Angelis	0.141	45	Clay Regazzoni	0.098
21	Ronnie Peterson	0.140	46	Luigi Fagioli	0.097
22	Nino Farina	0.130	47	Jack Brabham	0.093
23	Nick Heidfeld	0.130	48	Jacques Villeneuve	0.093
24	Pedro Rodríguez	0.129	49	Nico Rosberg	0.092
25	John Watson	0.129	50	Phil Hill	0.090



Algumas referências interessantes





OS NÚMEROS DO JOGO

Por que tudo
que você sabe
sobre futebol
está errado.

CHRIS ANDERSON & DAVID SALLY



*o sinal e o ruído e o
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previsões falham e
e outras não e o ruí
ruído e o ruído e o r
e o ruído e o ruído e
nate silver e o ruído
e o ruído e o ruído e
o ruído e intrínseca*



Anthology of Statistics in Sports

Edited by

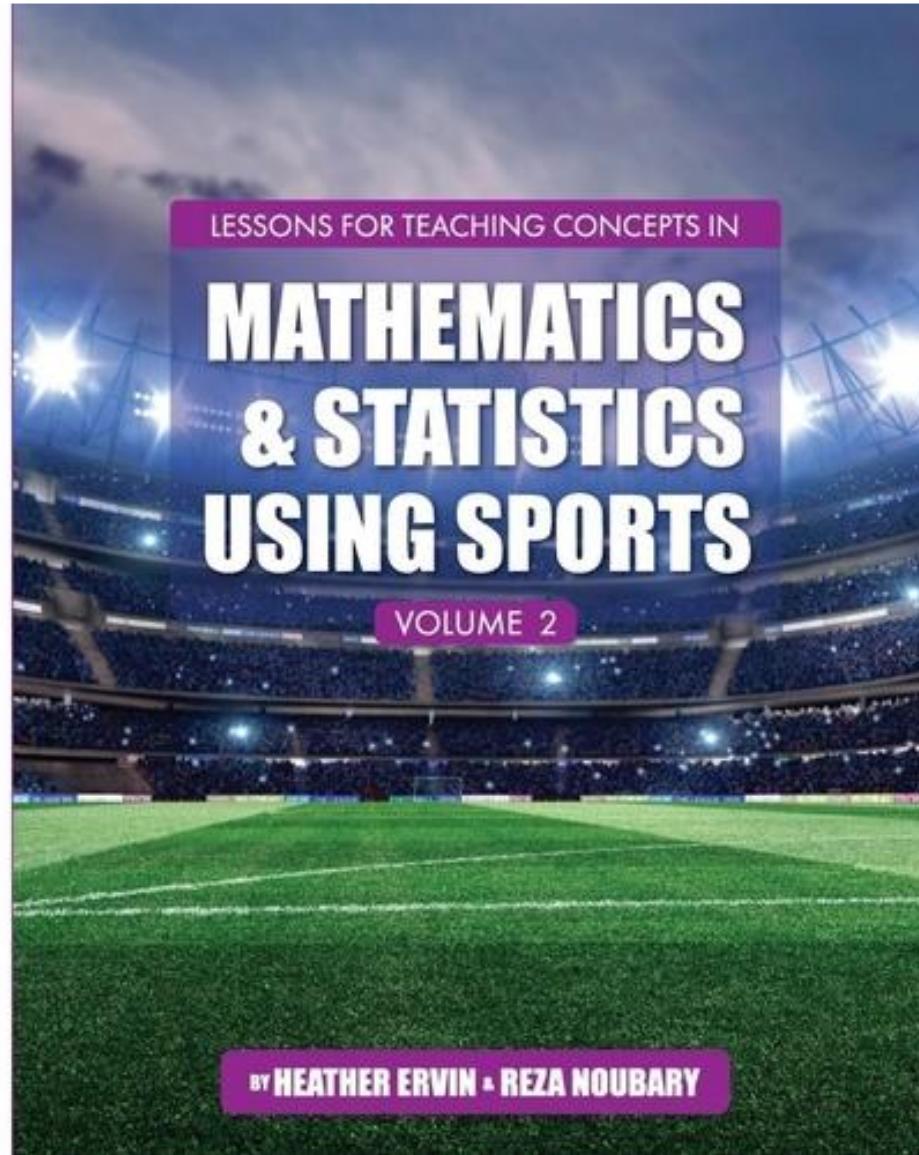
Jim Albert, Jay Bennett, and James J. Cochran



The ASA Section on
Statistics in Sports

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Q

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Welcome To The Statistics in Sports Section

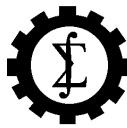
The Section on Statistics in Sports (SIS) was founded during the 1992 Joint Statistical Meetings, filling a need to foster the development of statistics and its applications in sports. The mission of SIS has been to stimulate statistical research with an application to sports, promoting publications devoted to statistical theory and methodology and their application to statistics in sports, and to increase the availability of information concerning the science of statistics and its contribution to sports. Over the years, SIS has been active in cooperating with other organizations, both within and outside the American Statistical Association, fostering statistical education in sports, and, in general, making statistics accessible to individuals interested in sports.

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Journals & Publications

- This is a listing of journals and publications that publish articles related to our field of study.

Journals

- [Journal of Quantitative Analysis in Sports](#)

From the Aims & Scope section:

The Journal of Quantitative Analysis in Sports (JQAS), an official journal of the American Statistical Association, publishes timely, high-quality peer-reviewed research on the quantitative aspects of professional and amateur sports, including collegiate and Olympic competition. The scope of application reflects the increasing demand for novel methods to analyze and understand data in the growing field of sports analytics. Articles come from a wide variety of sports and diverse perspectives, and address topics such as game outcome models, measurement and evaluation of player performance, tournament structure, analysis of rules and adjudication, within-game strategy, analysis of sporting technologies, and player and team ranking methods. JQAS seeks to publish manuscripts that demonstrate original ways of approaching problems, develop cutting edge methods, and apply innovative thinking to solve difficult challenges in sports contexts. JQAS brings together researchers from various disciplines, including statistics, operations research, machine learning, scientific computing, econometrics, and sports management.

If you are an SIS member, you can access JQAS journal articles through the following process: (1) Go through the login process on [amstat.org](#), (2) click on "Go to my publications" on the subsequent screen, (3) click on the Journal of Quantitative Analysis in Sports link, and (4) click on the "Access JQAS" button.

- [Journal of Sports Analytics](#)

From the Aims & Scope section:

The Journal of Sports Analytics (JSA) aims to be the central forum for the discussion of practical applications of sports analytics research, serving team owners, general managers, coaches, fans, and academics. We invite analytical research on any single sport or across sports that seeks to improve our understanding of the game or strategies for improving a team or a league.

- [International Journal of Computer Science in Sport](#)

From the Aims & Scope section:

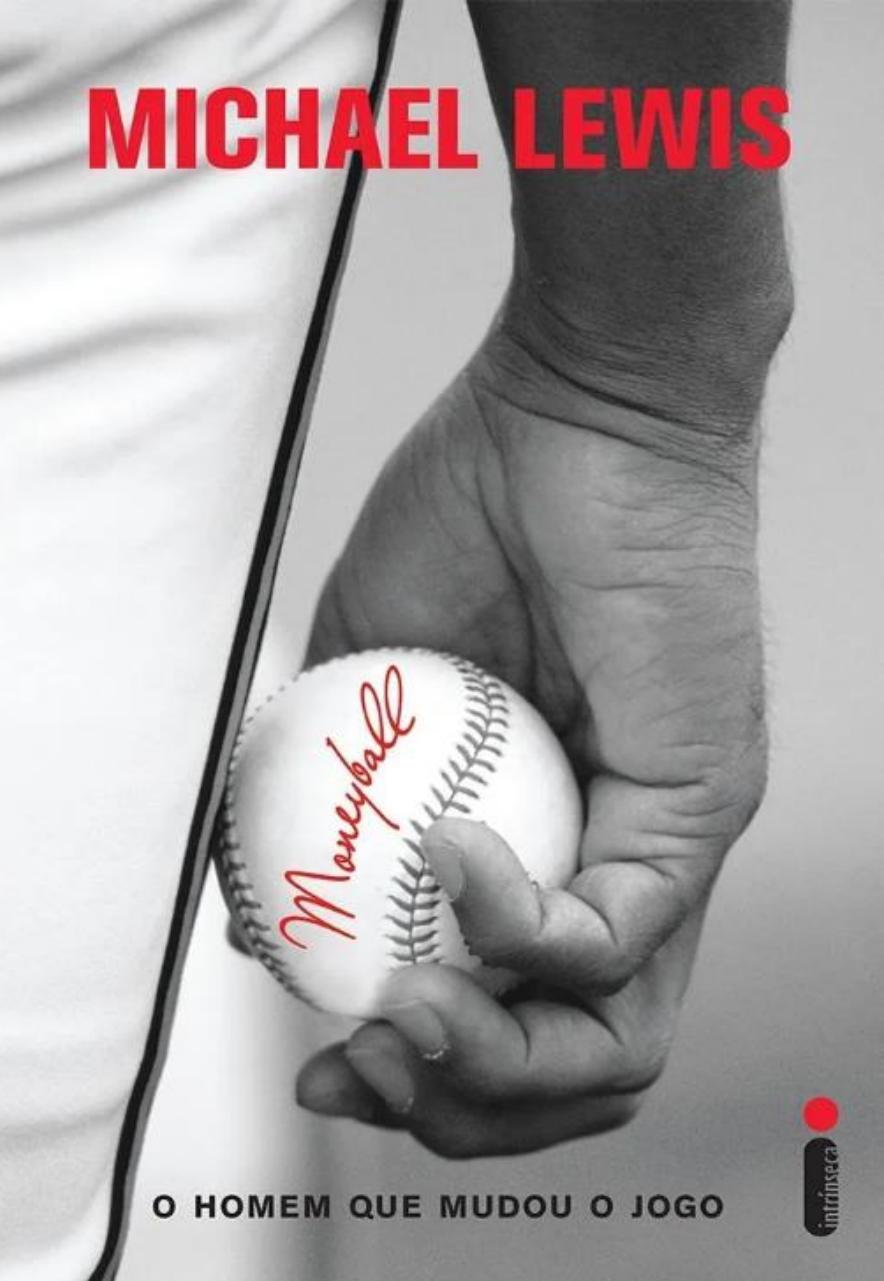
The International Journal of Computer Science in Sport (IJCSS) is published in association with the International Association of Computer Science in Sport (IACSS). It is a refereed electronic journal. Research results with an emphasis on the following topics regarding the application of Computer Science and Mathematics in supporting the development of theory and practice in sport are considered: Modelling (mathematical, informatics, biomechanical, physiological) Computer aided applications (software, hardware) Data acquisition and



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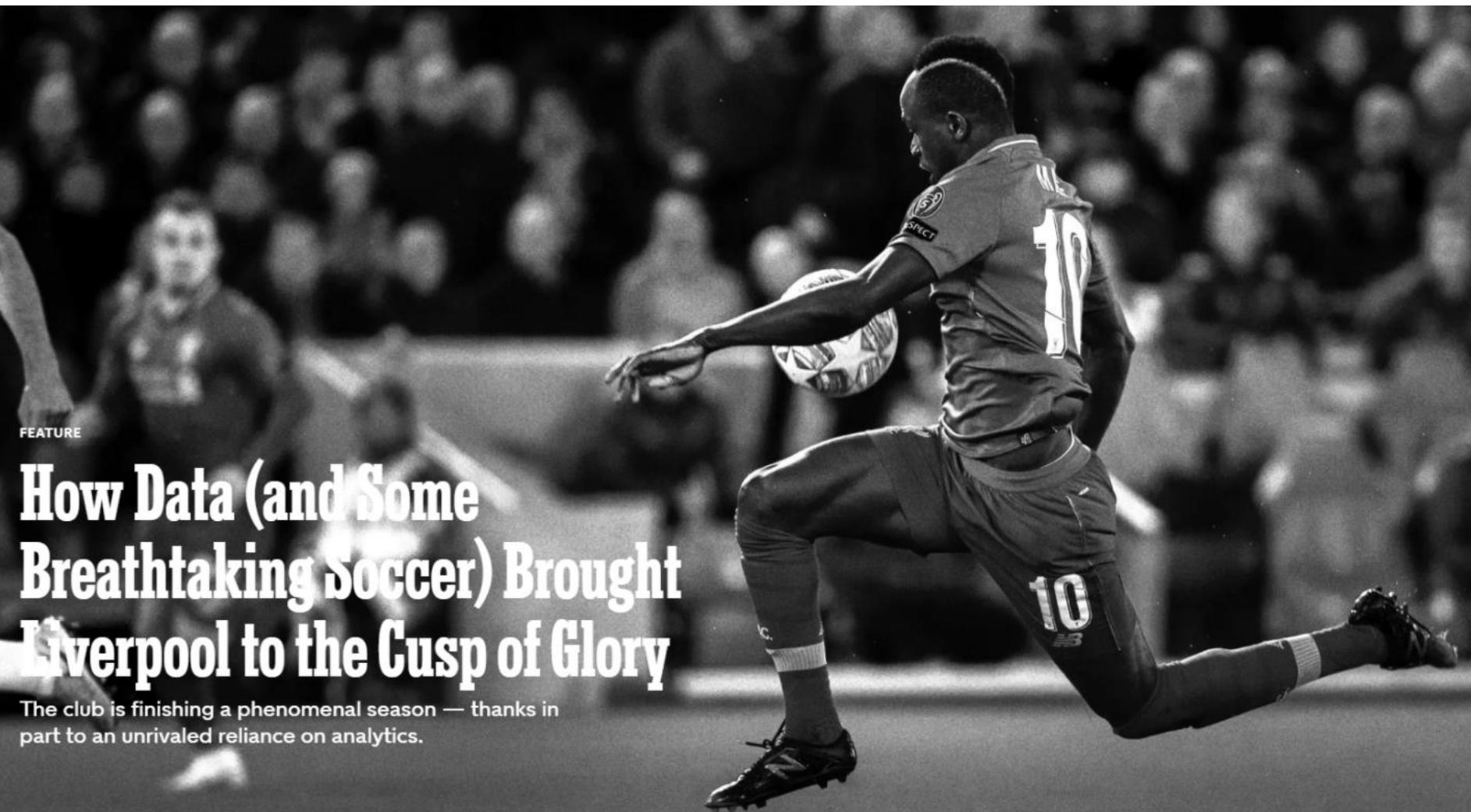
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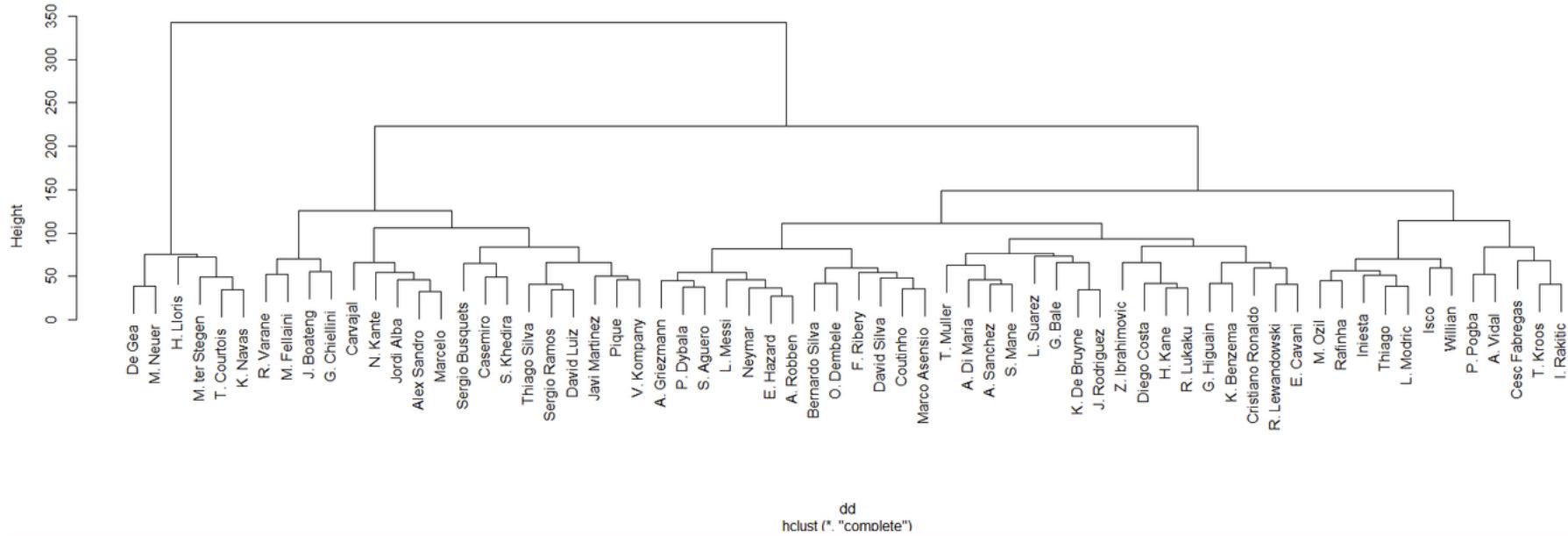


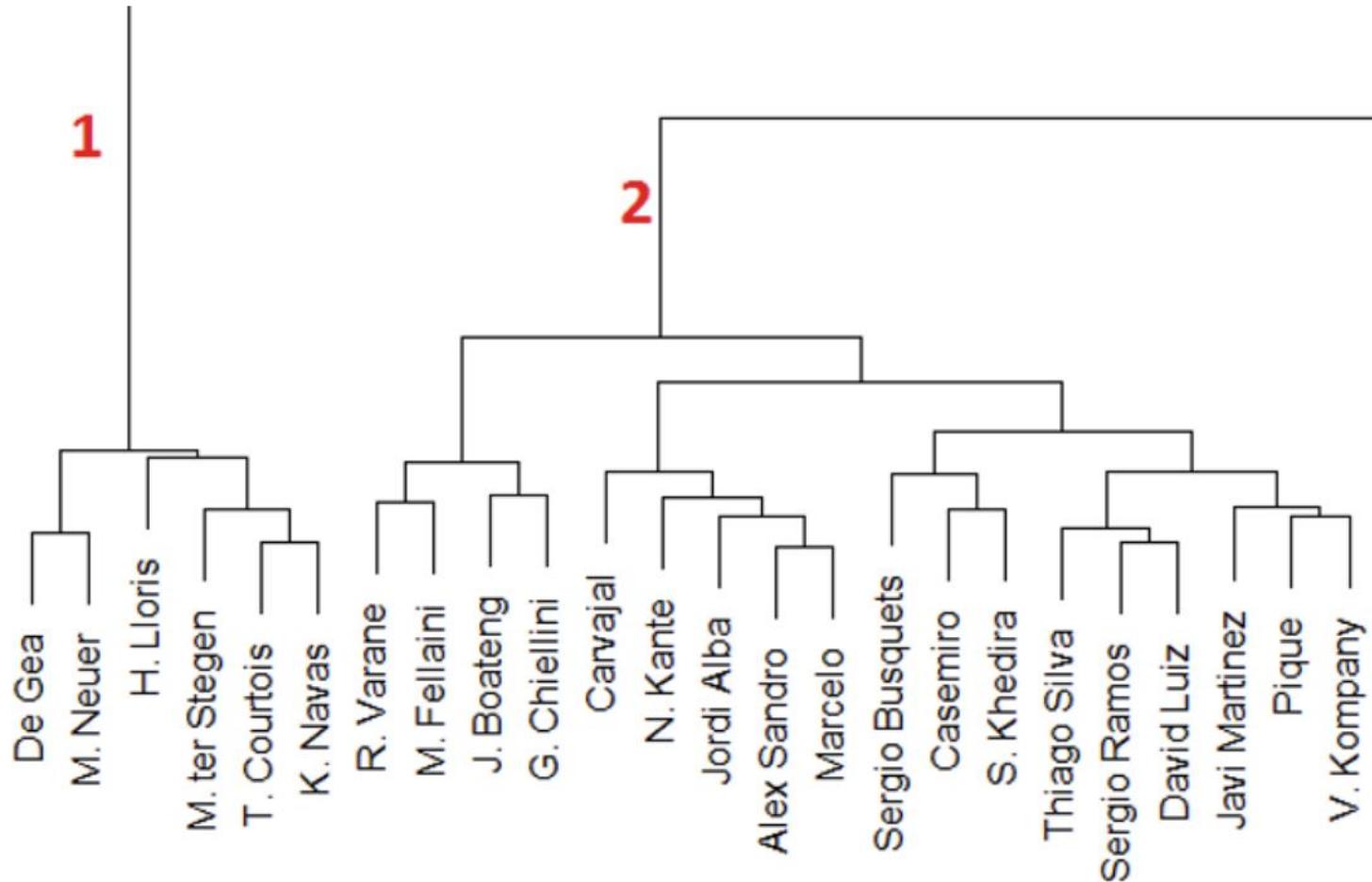
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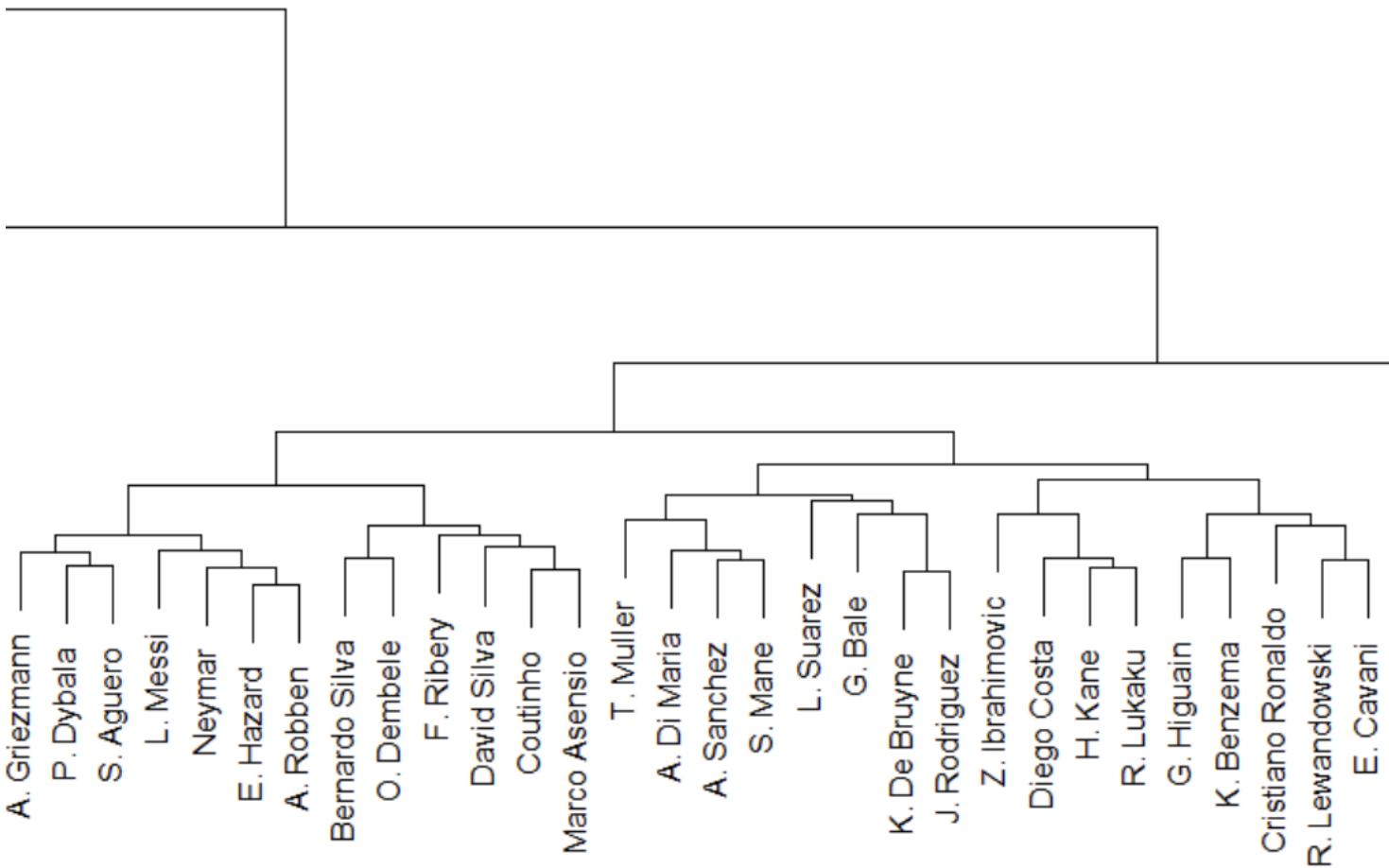
How Data (and Some Breathtaking Soccer) Brought Liverpool to the Cusp of Glory

The club is finishing a phenomenal season — thanks in part to an unrivaled reliance on analytics.

Liverpool's Sadio Mané during the team's Champions League semifinal against Barcelona on May 7.
Joachim Lademann for The New York Times

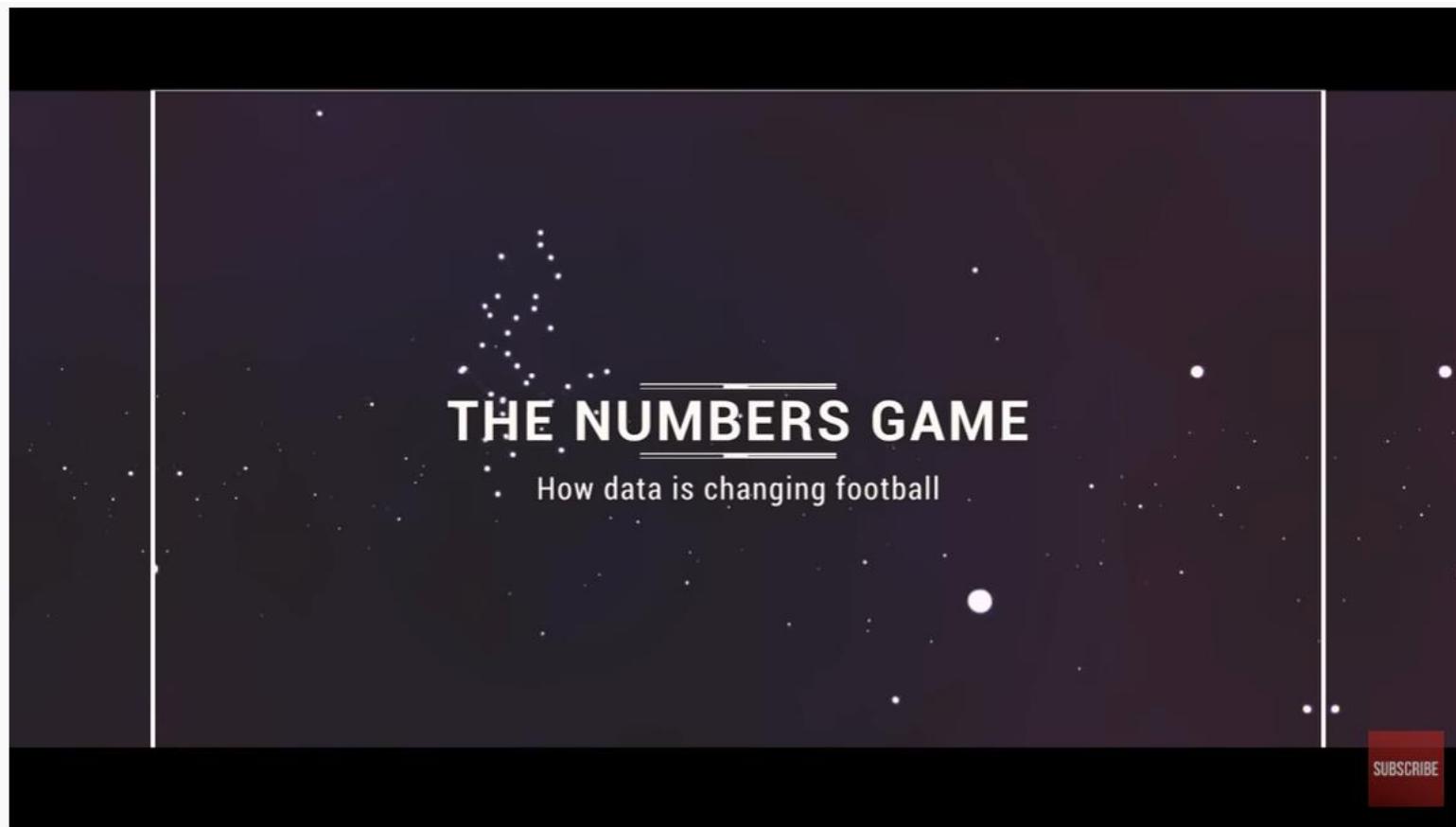








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The Numbers Game | How Data Is Changing Football | Documentary

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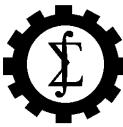
ESPORTE

Como a estatística ajudou a fazer 3 campeões: Palmeiras, Athletico e Grêmio





O futebol que se discute nas mesas-redondas tem cada vez mais estado longe do que se pratica nos campos, ao menos em termos estatísticos. Se a discussão é sobre "posse de bola" e como "Guardiola tem um time dominante", os clubes trabalham com uma gama enorme de índices específicos. "A gente vai além e pega o ritmo de passes dos jogadores. A gente fez isso muito com o Grêmio, eles eram uma máquina de passes. Passes bons para a frente, não ficar com a bola por muito tempo, jogar com a mesma qualidade na esquerda e na direita. E a gente entrega relatórios, por exemplo: vocês querem um acerto de 78% em passes para frente e nesse jogo foram 60%. Tem que melhorar."



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Powering Sports Coverage



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Hear from our clients as they discuss how we help them bring greater insight to fans.

▶ 01:16 **Ken Pomeroy on College Basketball Data and Fan Engagement**



KEN POMEROY
College Basketball Analytics Expert
KenPom.com



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SEP. 14, 2021, AT 10:00 AM

Possession Is The Puzzle Of Soccer Analytics. These Models Are Trying To Solve It.

By [John Muller](#)

Filed under [Soccer](#)





Soccer possession models are gaining steam

Key soccer possession models by publication year, with type of model and possession information

NAME	CREATOR	DEBUT	METHOD	WINDOW	OFF-BALL INFORMATION
Markov Chains	S. Rudd	2011	Markov chain	One possession	Defensive states tagged in event data
Possession-Based Model	N. Mackay	2016	Logistic regression and GAM	One possession	None
Expected Threat (xT)	K. Singh	2019	Markov-like	Next 5 actions (goal for)	None
Valuing Actions by Estimating Probabilities (VAEP)	KU Leuven DTAI	2019	Gradient-boosted trees	Next 10 actions (goal for or against)	Possession history proxies
Expected Possession Value (EPV)	J. Fernández et al.	2019	Multiple models	Next goal (for or against) or end of half	Full tracking data
Possession	Stats	2019	Gradient-boosted	Next 10 and so on	Possession



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Decomposing the Immeasurable Sport: A deep learning expected possession value framework for soccer

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1. Introduction

What is the right way to think about analytics in soccer? Is the sport about measured events such as passes and goals, possession percentages and traveled distance, or even more abstract notions such as mistakes (to quote Cruyff, "Soccer is a game of mistakes, whoever makes the fewer wins")? Analytical work to date has focused primarily on these more isolated aspects of the sport, while coaches tend to focus on the tactical interplay of all 22 players on the pitch. Soccer analytics is lacking from a comprehensive approach that can start to address performance-related questions that are closer to the language of the game. Questions such as: who adds more value? How and where is this value added? Are the teammates creating spaces of value? When and how should a backward pass be taken? How risky is a team attacking strategy? What is a player's decision-making profile?

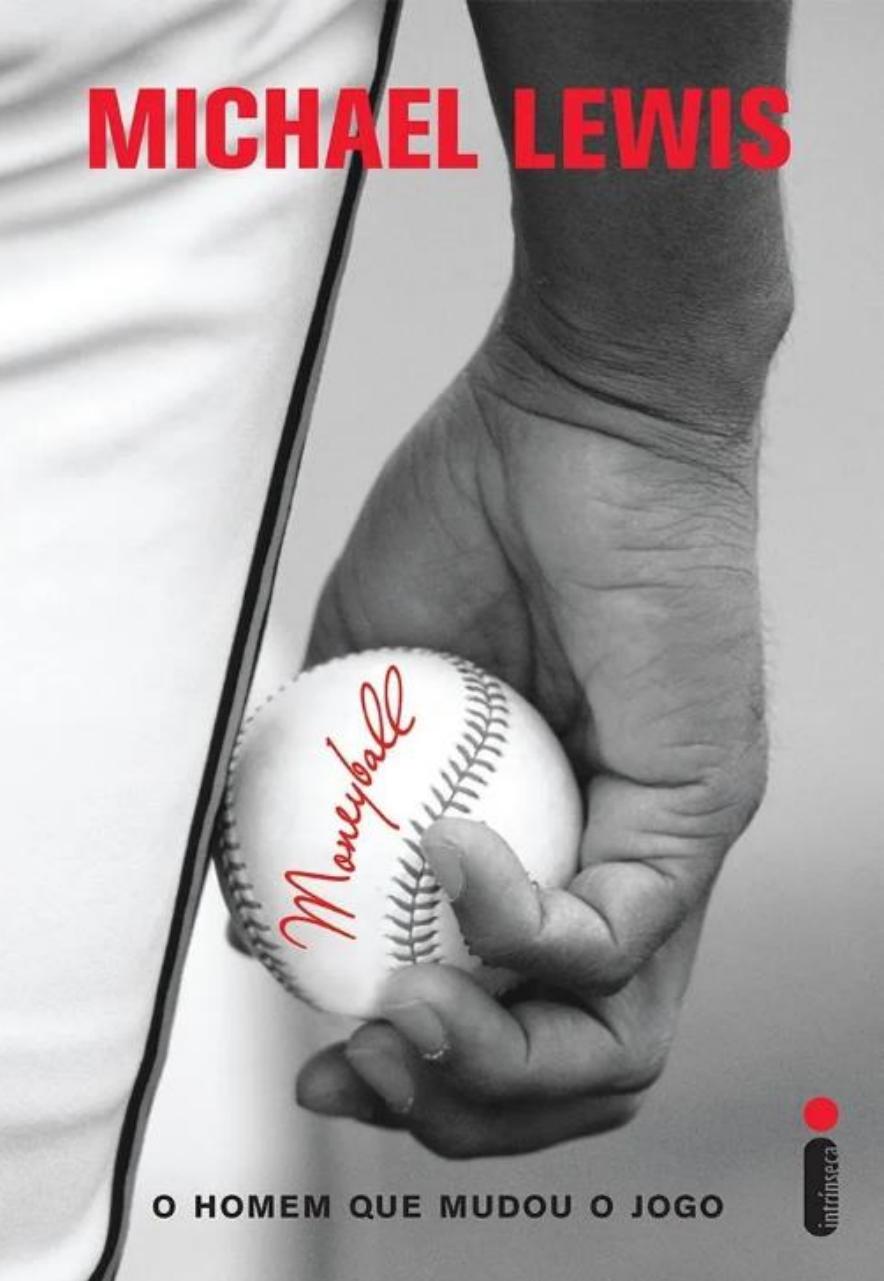
In order to make an impact on key decision-makers within the sport, soccer analytics



BASQUETE



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Como a Estatística
 está mudando os
 jogos da NBA

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Evolução da pontuação pela posição do
 arremesso da NBA de 2000 e 2020

The Evolution Of NBA Playoff Scoring
 Most Common Shot Locations In The NBA Playoffs, 2000 Vs. 2020
 By @KirkGoldsberry

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NBA



Advanced NBA Stats for Dummies: How to Understand the New Hoops Math

EHRAN KHAN

OCTOBER 18, 2013





How data analytics is revolutionizing the NBA

By [Petra](#)

Alumni

POSTED APR 21, 2020

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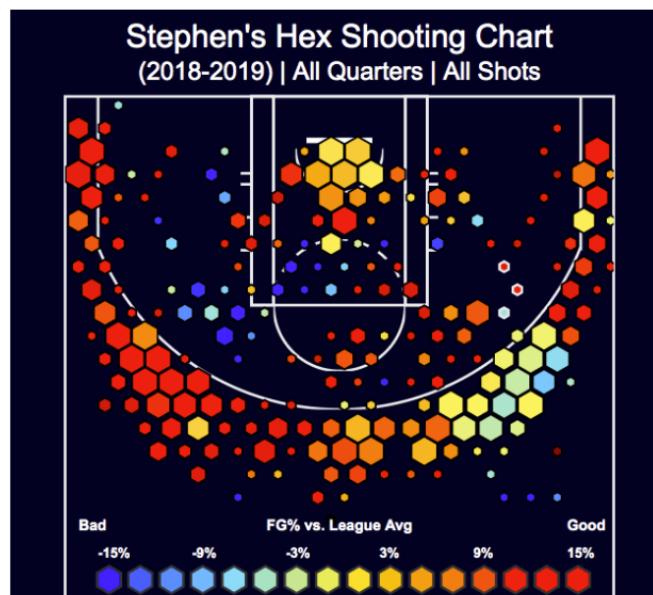
[AstraZeneca: AI in Drug Discovery & Development](#)



Professional basketball has looked very different over the past ten years thanks to the use of data analytics. It is almost as if these Analytics models have inputted the conventional NBA and outputted an entirely new game. A game where every team now has at least one data analyst. A game where every move is calculated with the aim to optimize for a winning strategy. A game where DATA is king. So how is data analytics being used in the context of the NBA? Is it really creating value or has it turned the basketball game from fun and eventful to predictable and boring?

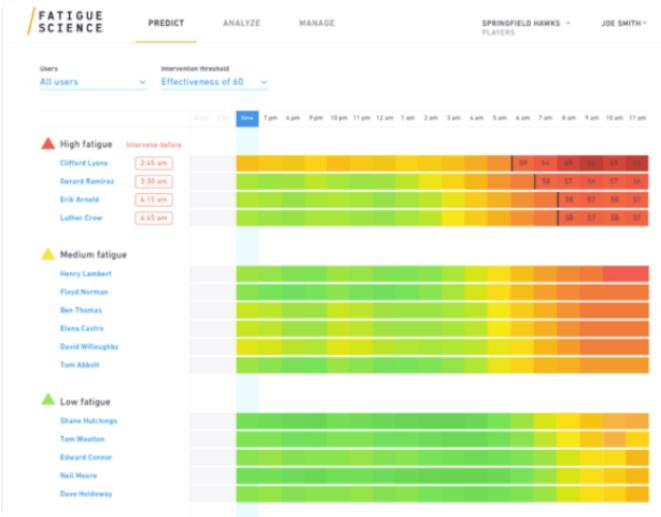


1. Designing winning strategies: the NBA has installed six cameras in every Basketball court to collect granular data on players' movements. This data is being analyzed by machine learning models to recommend the winning strategy accordingly. Historically, teams were only able to collect basic stats on their players like points scored and assists made, but today, and thanks to the video system installed, teams are now looking at more in-depth data such as the frequency of which players go forward with their right or left foot, or certain 'tells' players make before specific moves. This helped coaches better plan defensive strategies based on their opponents, decide on which players should be matched up against who, and recommend "smarter" offensive moves for their players such as how they should be positioned and how to better optimize for a three-point shot.





2. Predicting and avoiding player injury: teams have been collecting sophisticated data points about its players through wearables, sleep monitors, and even saliva samples to assess their fatigue level and predict their performance going forward. The revolutionary application of such data analytics was the “resting” of players even without “obvious” justifications in order to avoid injury. The idea is the more tired a player is, the more prone they are to injury. For example, studies have shown that the likelihood of being injured is less if players rest for 30 days after playing 30 straight games. Hence, NBA teams have been making tough decisions to rest key players to avoid injury (even when the fans don’t like it!).



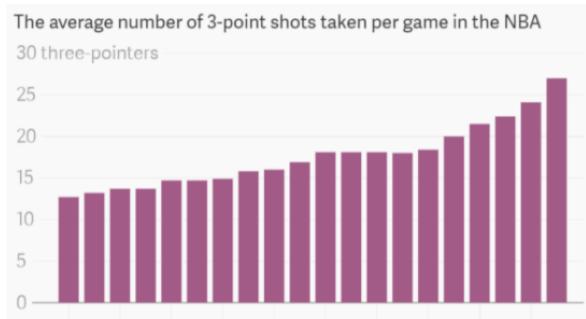
Example of fatigue report



3. **Scouting:** data analytics has become critical for scouting as coaches are now relying on predictive analytics when making draft selections. Drafting is a very important decision in the NBA as teams could be stuck with their expensive selection for years, so it is key that they minimize the risk as much as possible and analytics has been helping with this. Coaches now can easily look up video clips of players to analyze their tracked data (e.g. efficiency with which a certain player drives to the basket with their left hand) and even predict the kind of player they would be (e.g. probability of player becoming an All-Star).

Value capture:

Although there is no direct correlation between use of data analytics and winning, it is clear that teams have already started capturing value from use of data analytics. The biggest game changer to date is the rise of the three-point shot as a result of simple math. Data analytics models showed that three pointers have a 35% chance of going in and hence, could lead to more points than a two-point jump shot taken closer to the basket. As a result, the average 3-point shots taken per team has increased by 50% since 2012.





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Using Deep Learning to Understand Patterns of Player Movement in the NBA

Akhil Nistala, John Guttag

Track: Basketball

Abstract

In 2011, SportVU fundamentally changed the way that basketball can be analyzed. STATS SportVU utilized a six-camera system installed in basketball arenas to track the real-time positions of players, at 25 frames per second. In this paper, we demonstrate how we can apply deep learning techniques to this data to produce a queryable database of basketball possessions.

We trained an unsupervised machine learning pipeline that generates a representation, called a *trajectory embedding*, of how individual players move on offense. The representation is a 32-dimensional vector of floating-point numbers that captures the semantics of a single player's movement, such as locations of the endpoints, screen actions, court coverage, and other spatial features. We generated nearly 3 million trajectory-embeddings from three seasons of data (2013-2014, 2014-2015, 2015-2016).

We found that the Euclidean distance between trajectory-embeddings is an excellent indicator of the visual similarity of the movements they encode. For example, two different movements of a post-up in the right block will have nearby embeddings; a post-up in the right block and a screen action above the left wing will have distant embeddings. This result led to the Similar Possessions Finder, a queryable database of basketball possessions.

The Similar Possessions Finder can be used to quickly answer queries such as "How much more frequently did Andre Drummond establish position on the right block than on the left block during the 2015-2016 regular season?" and "Find all possessions from the 2014 playoffs in which Chris Paul ran a screen action in the high post that ended with DeAndre Jordan scoring."

1. Introduction

Our goal was to develop an automated framework to quantitatively examine and compare patterns of individual player movements on offense. This process currently entails a film analyst watching hundreds of hours of game footage, carefully examining each possession and taking notes on



VÔLEI



Vírus G: Descoberto o vilão da nova hepatite

SUPER INTERESSANTE

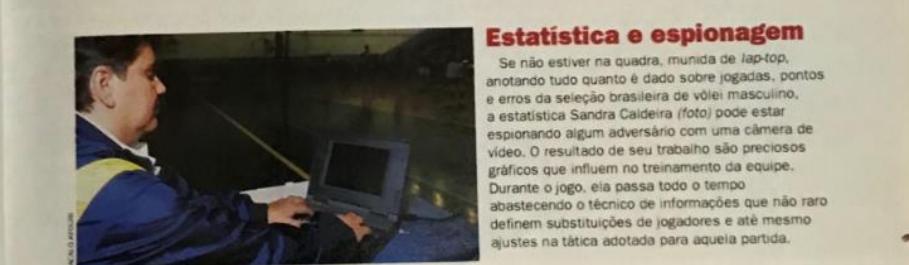
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O supernavio brasileiro no Polo Sul

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A FABRICAÇÃO DO ATLETA DE OURO

Os segredos dos computadores, da tecnologia e da química que constroem os campeões olímpicos

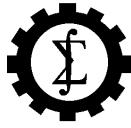
19 PÁGINAS A MAIS: Você vai ver 22 esportes em cores e alta



Estatística e espionagem

Se não estiver na quadra, munida de lap-top, anotando tudo quanto é dado sobre jogadas, pontos e erros da seleção brasileira de vôlei masculino, a estatística Sandra Caldeira (foto) pode estar espionando algum adversário com uma câmera de vídeo. O resultado de seu trabalho são preciosos gráficos que influem no treinamento da equipe. Durante o jogo, ela passa todo o tempo abastecendo o técnico de informações que não raro definem substituições de jogadores e até mesmo ajustes na tática adotada para aquela partida.







≡ MENU

ge



VÔLEI

BUSCAR

10/04/2014 09h00 - Atualizado em 10/04/2014 09h00

Avesso aos números e ex-boleiro, estatístico é arma do Osasco para semi

Com nome de volante, Fábio Simplício tentou ser jogador de futebol, odeia matemática e hoje é quem dá todas as informações para o técnico Luizomar de Moura

Por Guilherme Costa
Osasco, São Paulo



Fundamental. Esse adjetivo foi usado pelo treinador Luizomar de Moura e pelas titulares Thaisa e Adenízia quando perguntados sobre o trabalho de Fábio Simplício, estatístico da equipe do Osasco, que está invicto na Superliga feminina e disputa nesta sexta-feira a primeira partida da semifinal, diante do Sesi. A campeã olímpica Adenízia comparou o trabalho de Fábio com o do técnico Luizomar:

-O Fábio é essencial, 50% do jogo é dele e os outros 50% do Luizomar. Minha vida com o Fábio é muito mais fácil, sei de todas as probabilidades. Ele entra em contato com a gente durante a partida, passa as informações de todas as jogadoras adversárias- comenta a meio de rede titular da seleção brasileira e do Osasco.

TUDO SOBRE

Vôlei



BLOG: Vôlei masculino: primeiro ano de Renan no comando é positivo

em 18/09/2017



BLOG: Com três títulos e um vice, seleção feminina de vôlei fecha

em 11/09/2017



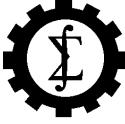
Evandro e André são confirmados campeões do Circuito Mundial 2017

em 04/09/2017

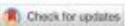
BLOG: Alerta: vôlei brasileiro termina sem medalhas nos Mundiais de categorias de base pela primeira vez em

em 28/08/2017

BLOG: Balanço do ano no



ESPORTES INDIVIDUAIS (ATLETISMO/NATAÇÃO)



Swimming performance index based on extreme value theory

Daniel T Gomes¹ and Lígia Henriques-Rodrigues²

Abstract

The International Swimming Federation has developed a points system that allows comparisons of results between different events. Such system is important for several reasons, since it is used as a criterion to rank swimmers in awards and selection procedures of national teams. The points system is based entirely on the world record of the correspondent event. Since it is based on only one observation, this work aims to suggest a new system, based on the probability distribution of the best performances in each event. Using extreme value theory, such distribution, under certain conditions, converges to a generalized Pareto distribution. The new performance index, based on the peaks over threshold methodology, is obtained based on the exceedance probabilities correspondent to the swimmers' times that exceed a given threshold. We work with 17 officially recognized events in 50 m pool, for each women and men, and considered all-time rankings for all events until 31 December 2016. A study on the adequacy of the proposed generalized Pareto distribution index and a comparison between the performances of Usain Bolt and Michael Phelps are also conducted.

Keywords

Aquatic sport, International Swimming Federation, performance analysis

Introduction

Competitive swimming has a non-subjective ranking system, based on times. When one analyzes the results of a given event, such criterion is free from arbitrariness and is the universal way to choose the "best (fastest) swimmers." However, for some reasons, it might be reasonable to compare performances in different events. For example, the winning time of the 100 m freestyle in a given competition is better than the winning time of the 200 m butterfly?

Obviously, the concept of "better" needs to be defined. Intuitively, a great performance is the one that, in its respective event, corresponds to a discrepant result in comparison to the others.

Such comparison is made by the International Swimming Federation (FINA) through a points system. It is important, since it is used to determine the winners of the World Cup.¹ It is also used by several national federations as the criterion to determine national teams, such as Brazil.²

In 2015, the FINA points system was used for the first time to select the best performances of that year. In 2016, Katie Ledecky (United States) and Adam Peaty

(Great Britain) were chosen the best performers of the year, by their performances in women's 800 m freestyle and men's 100 m breaststroke, respectively, in Rio de Janeiro Olympic Games.³

The FINA points system is based on what is called the *base times*.⁴ The base times are defined every year, based on the latest world record that was approved by FINA. The base times are defined with the cut date of 31 December. So, in a given event, let $T_i(t)$ be the time obtained by the swimmer i , in seconds, at the year t , and $B(t-1)$ the base time, which is the world record, in

Reviewer: John Einmahl (Tilburg University, Netherlands),
Ian G. McHale (University of Liverpool, UK),
Jonathan Tawn (Lancaster University, UK).

¹National School of Statistics, Brazilian Geography and Statistics Institute, Rio de Janeiro, Brazil

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STATISTICAL ANALYSIS: HOW FAST IS ADAM PEATY'S WORLD RECORD?



On Sunday, Adam Peaty became the first man to break 57 seconds in the 100 breaststroke. Could a swimmer be capable of a similar performance in another event? Current photo via "Rafael/Dorneyko Photography"

BY SWIMSWAM CONTRIBUTORS

July 25th, 2019

51

Industry, International, Records

Courtesy: Daniel Takota

A couple of days ago, **Adam Peaty** became the first man to break 57 seconds in the 100 breaststroke as he delivered an incredible 56.88.

He is also the only swimmer to ever break 58 and he has the 17 fastest performances of all time.





Adam Peaty MBE

2.022 Tweets



Tweets

Tweets e respostas

Mídia

Curtidas



Adam Peaty MBE  @adam_pe... · 43m ▾
I've never thought about how fast it would
be in another event, but this is a great
analysis 



SwimSwam  @swimswamn... · 8h
Statistical Analysis: How Fast is Adam
Peaty's World Record?
swimswam.com/statistical-an...

3

7

76

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Peaty v Bolt: Which is the greatest world record?

Using statistics to compare world records in athletics and swimming

Professor Takata calculated the likelihood of Peaty's world record being broken by a swimmer as 0.291%.

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Modeling the Training-Performance Relationship Using a Mixed Model in Elite Swimmers

MARTA AVALOS¹, PHILIPPE HELLARD², and JEAN-CLAUDE CHATARD³

¹*HEUDIASYC Laboratory, UMR CNRS 6599, Compiègne University of Technology, FRANCE;* ²*Research Department, French Swimming Federation, FRANCE; and* ³*Laboratory of Physiology, GIP Exercise, Faculty of Medicine, Saint-Etienne University, FRANCE*

ABSTRACT

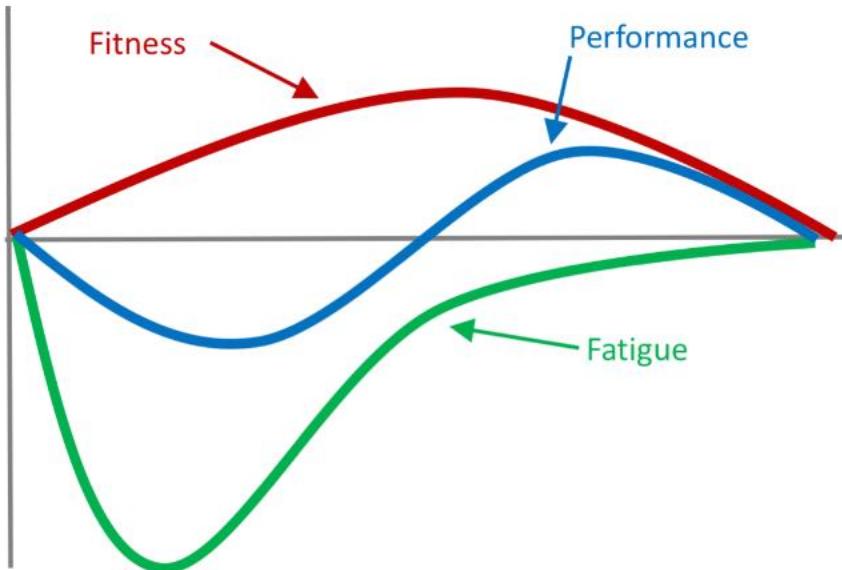
AVALOS, M., P. HELLARD, and J.-C. CHATARD. Modeling the Training-Performance Relationship Using a Mixed Model in Elite Swimmers. *Med. Sci. Sports Exerc.*, Vol. 35, No. 5, pp. 838–846, 2003. Purpose: The aim of this study was to model the relationship between training and performance in 13 competitive swimmers, over three seasons, and to identify individual and group responses to training. Methods: A linear mixed model was used as an alternative to the Banister model. Training effect on performance was studied over three training periods: short-term, the average of training load accomplished during the 2 wk preceding each performance of the studied period; mid-term, the average of training load accomplished during weeks 3, 4, and 5 before each performance; and long-term, weeks 6, 7, and 8. Results: Cluster analysis identified four groups of subjects according to their reactions to training. The first group corresponded to the subjects who responded well to the long-term training period, the second group to the long- and mid-term periods, the third to the short- and mid-term periods, and the fourth to the combined periods. In the model, the intersubject differences and the evolution over the three seasons were statistically significant for the identified groups of swimmers. Influence of short-term training was negative on performance in the four groups, whereas mid- and long-term training had, on the average, a positive effect in three groups out of four. Between seasons 1 and 3, the effect of mid-term training declined, whereas the effect of long-term training increased. The fit between real and modeled performances was significant for all swimmers ($0.15 \leq r^2 \leq 0.65$; $P \leq 0.01$). Conclusion: The mixed model described a significant relationship between training and performance both for individuals and for groups of swimmers. This relationship was different over the 3 yr. Personalized training schedules could be prescribed on the basis of the model results. Key Words: COACHING, EXERCISE, INTENSITY, MATHEMATICAL MODEL

The training-performance relationship is particularly important for elite sports coaches who search for reproducible phenomena useful for organizing the athlete's training program. Many authors have studied the relative influence of training (7,22,23,27) and found that reactions to training depend on volume, intensity, and frequency of the training sessions (7,16,23). Others have reported divergent results (4,9), perhaps related to the fact that delayed effects and interindividual differences were not taken into account.

For individual swimmers, mathematical models have been developed to describe the dynamic aspect of training and the consequences of succession of training loads over

(5,6) are based on two antagonistic functions, both calculated from the training impulse. Studies on cellular adaptability reactions to exercise (3) have demonstrated that the negative function can be assimilated to a fatiguing impulse. The positive function can be compared with a fitness impulse resulting from the organism's adaptation to training. Expressed as an exponential, the functions account for the decreasing impact of the training effect. When iterative training sessions are considered, the time course of performance is described by:

$$p_t = p_0 + k_a \sum_{\tau=0}^{t-1} e^{-(t-\tau)/\tau_W} - k_f \sum_{\tau=0}^{t-1} e^{-(t-\tau)/\tau_W} \quad (1)$$





Alan Couzens, M.Sc. (Sports Science)

"Devoted to the science of Maximal Athletic Development"

Why Neural Networks are better than the old Banister/TSS model at predicting athletic performance.

Alan Couzens, M.Sc.(Sports Science)

July 26, 2018

I received a lot of follow up qu's/discussion from this tweet on how I'm seeing [Neural Networks](#) consistently out-perform the [Banister model](#) (the model behind [Training Peaks' Performance Management Chart](#)) as a performance predictor for the vast majority of athletes....



DeepQB: Deep Learning with Player Tracking to Quantify Quarterback Decision-Making & Performance

Brian Burke, ESPN Analytics, brian.j.burke@espn.com

DeepQB is a proposed application of deep neural networks to player tracking data from over two full seasons of American professional football. This novel approach demonstrates the ability to successfully understand complex aspects of the passing game, most notably quarterback decision-making. It can assess and compare individual quarterback pass target selection based on a snapshot presented to the passer by the receivers and defenders. Assessments of quarterback decision-making are made by comparing actual target selection to that predicted by our model. The model performs well, correctly identifying the targeted receiver in 60% of cross-validated cases. When passers target the predicted receiver, passes are completed 74% of the time, compared to 55% when the QB targets any other receiver. This performance is surprisingly strong, given that the offense often conceals its intent by design, while defenses try not to allow any single receiver to be open. Further, quarterback passing skills separate and apart from his receivers and defense are isolated and assessed by comparing metrics of actual play success to the metrics of success predicted by the situation presented to the passer. This approach represents a new way for teams, media, and fans to understand and quantitatively assess quarterback decision-making, an aspect of the sport which has previously been opaque and inaccessible.

1. Introduction

Perhaps the most enigmatic and yet most important player attribute in all of American football is the decision-making abilities of quarterbacks. Although mental abilities are important for every position, quarterback is unique in that psycho-cognitive abilities rival physical abilities in regards to successful performance. Measurable and physical attributes are easily observed through the scouting process, but a professional quarterback's ability to process and exploit highly dynamic information during the course of a play is not well understood. Previously only relatively crude aggregate statistical methods - that cannot fully separate the quarterback's individual impact from those of his teammates, play design, and opponents - have existed to quantify this skill.

Early efforts to exploit football tracking data only scratched the surface of what is possible with such rich information. Typical applications of tracking data merely involved measuring the



You Cannot Do That Ben Stokes: Dynamically Predicting Shot Type in Cricket Using a Personalized Deep Neural Network

Will Gürpinar-Morgan, Daniel Dinsdale, Joe Gallagher,
Aditya Cherukumudi & Patrick Lucey

Track: Other Sports

Paper ID: 1548748

1. Introduction

The ability to predict what shot a batsman will attempt given the type of ball and match situation is both one of the most challenging and strategically important tasks in cricket.

The goal of each batsman is to score as many runs as possible without being dismissed. Batsmen can be dismissed in several ways, including being caught by fielders or having their wickets knocked over. While simple in principle, the type of shots and style of a batsman is greatly influenced by the format of the game. In short forms of the game such as T20 and One Day Internationals (the focus of this paper), batsmen are typically more aggressive since their team have a limited number of balls from which to score their runs (120 and 300 balls respectively).

Getting the right batsman vs bowler match-up is of paramount importance. For example, for the fielding team, the choice of bowler against the opposition star batsman could be the key difference between winning or losing. Therefore, the ability to have a predefined playbook (as in the NFL) which would allow a team to predict how best to set their fielders given the context of the game, the batsman they are bowling to and bowlers at their disposal would give them a significant strategic advantage.

In this paper, we present a personalized deep neural network approach which can predict the probabilities of where a specific batsman will hit a specific bowler and bowl type, in a specific game-scenario.

As a motivating example let us consider the 2019 Cricket World Cup Final between England and New Zealand, with England needing 8 runs from 2 balls to win. The ball was an attempted "heeler".



Baseball Predictions and Strategies Using Explainable AI

Joshua Silver (Singlearity, joshua.silver@singlearity.com)
Tate Huffman (Harvard University, thuffman@college.harvard.edu)

1. Abstract

Over the last decade, Major League Baseball has dramatically increased the amount of data it captures and makes available to the public. Meanwhile, there is a growing technology trend that applies AI to analyze massive amounts of data to build complex models that find relationships and meaning in the data. By marrying these two concepts together, we built a neural-network-based AI model called Singlearity-PA (pronounced single-arity-P-A) to solve one of the most fundamental questions in baseball: *How can we predict the outcome of a batter vs. pitcher plate appearance (PA)?*

We show how our model learned even the most subtle rules and strategies of the game, and is able to answer our batter vs. pitcher question with accurate and precise predictions. We demonstrate how to apply techniques to interpret and visualize Singlearity-PA's predictions to make the model's rationale understandable, and sharable for humans.

Finally, we provide open-source tools that allow for the readers' own experimentation and analyses.

2. Introduction and Motivation

Recently, new technologies and databases have rapidly increased the amount of available data in baseball. We now have many new statistics at our disposal. For instance, a single pitch at the major league level contains measurements for approximately 90 different parameters, with such varied data points as pitch information (including velocity, spin rates, and ball movement), batted-ball information (including exit velocity and launch angle) and fielder-position information. Baseball domain experts wishing to improve their abilities to forecast outcomes have pored over this data, looking to answer questions such as "How does a pitched ball spin rate affect pitcher performance



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Making Offensive Play Predictable - Using a Graph Convolutional Network to Understand Defensive Performance in Soccer

Michael Stöckl, Thomas Seidl, Daniel Marley & Paul Power | Stats Perform

1. Introduction

1.1 Measuring defensive quality in soccer

The art of good defending is to prevent something from happening before it has even happened. Virgil Van Dijk is considered one of the best defenders in world soccer as he has the ability to prevent a pass being made to an open attacker to shoot by forcing the ball carrier to pass somewhere else less dangerous. However, while we know this is great defending, in today's stats, Van Dijk would not receive any acknowledgement. A defender's contribution is simply measured by the number of tackles or interceptions they make. But what if we were able to measure actions that have been prevented before they were made?

The aim of a defense and a defender is to make offensive play predictable. For example, Jürgen Klopp's Liverpool, press the opposition with the aim of forcing them to give the ball away in specific areas of the pitch by limiting the number of passing options available in dangerous areas. If the art of good defending is to make play predictable, then it should be measurable. Given enough data, we should be able to predict where a player will pass the ball, the likelihood of that pass being completed and whether this pass will result in a scoring opportunity. It therefore stands that we should be able to measure if a defender forces an attacker to change their mind or to prevent an attacker from even becoming an option.

Figure 1 shows a situation from a match between Liverpool vs Bayern Munich in the 2018/19 UEFA Champions League that leads to Mané (red 10) scoring. Our model identifies that Milner (red 7) is the primary target for Van Dijk (red 4) in the first instance. However, due to the combination of Gnabry (blue 22) closing down Milner, Lewandowski (blue 9) closing down Van Dijk and Mané making an *active run*, behind the defence, Mané becomes both the most likely receiver and a high threat for scoring. This demonstrates our ability to model how players decision making is influenced and how a situation can move from low threat to high threat by the off-ball actions of attackers and defenders. [\[LINK TO VIDEO\]](#).

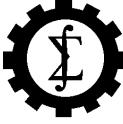


A utilização da estatística e da ciência de dados no esporte tem sido cada vez mais crescente, principalmente em termos da busca por melhoria de performance.



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Desafio: buscar as melhores ferramentas e, principalmente, manipular bases de dados enormes para extração de padrões e informações.



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Desafio: buscar as melhores ferramentas e, principalmente, manipular bases de dados enormes para extração de padrões e informações.

É um caminho sem volta: aqueles que continuarem abrindo mão da ciência em favor de opiniões e achismos estarão condenados ao ostracismo.



“In God we trust. All the others must bring data.”

William Edwards Deming



Daniel Takata



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danieltakata@yahoo.com.br



Obrigado!