Evaluating Baseball Metrics Using a Point-Mass Mixture Random Effects Model

New England Symposium on Statistics in Sports

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The greatest menace to big-time sports today is...a nonsense of numbers and the stupefying emphasis on meaningless statistics which is draining the color from competition.

-Stanley Frank, 1958

Numbers Are Good...And Old

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The Chicken Littles who complained that baseball's sky was falling in conveniently forgot that Earl Weaver kept batter-pitcher breakdowns on index cards, and that Whitey Herzog, who believed that defense won more games than statistics showed, used to sit in his office every day and chart every ball hit during his games. Or that the brilliant Branch Rickey used a Canadian statistician, Allan Roth, in the 1940s to help run the Brooklyn Dodgers. Or that all the way back to the 1860s, writers such as Henry Chadwick were fiddling around with new-fangled defensive statistics.

-Peter Gammons, 2004

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  - Bill James' Range Factor hearkens back to work by Henry Chadwick in 1870.

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  - Best prediction = league average.
- This suggests a **minimum threshold** for a metric: Players must perform **consistently** with respect to this metric over time.
- In other words, when predicting what a player will do, we'd rather know about his performance history on that metric than the league's performance.

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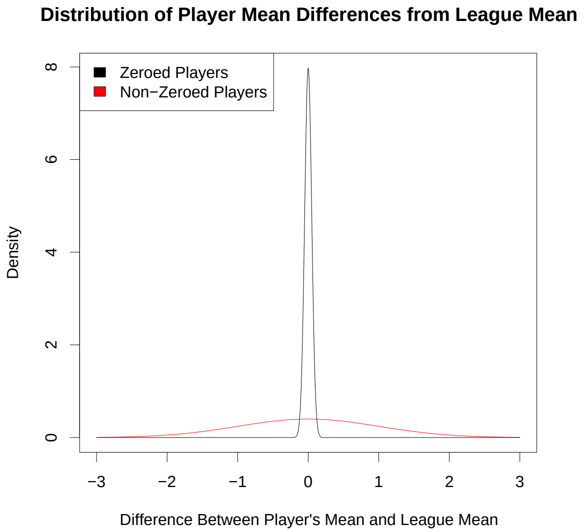
$\tau^2 \sim IG(\gamma_0, \delta_0)$	Player Variance

The Model in Pictures



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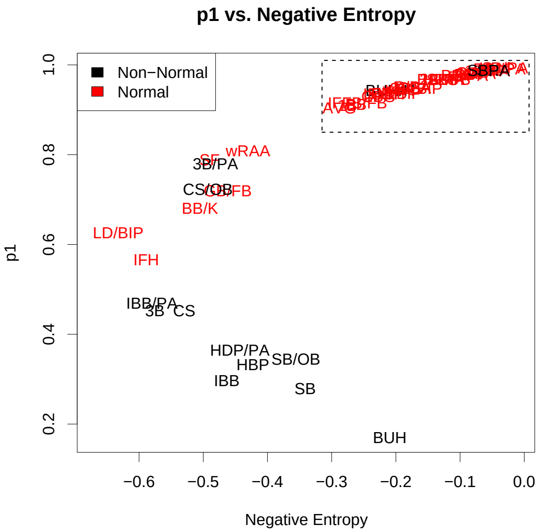
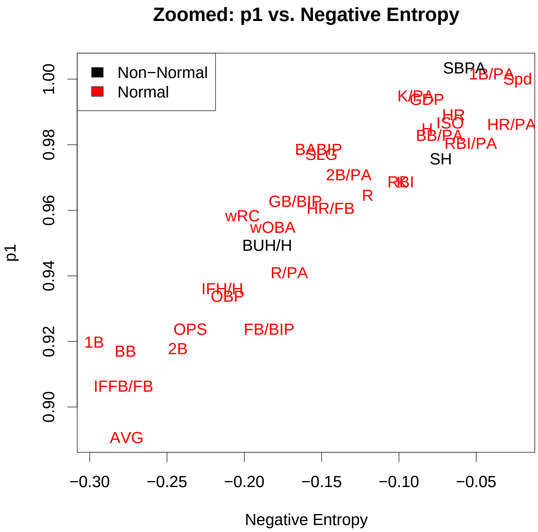
  - Data comes from **fangraphs.com**.

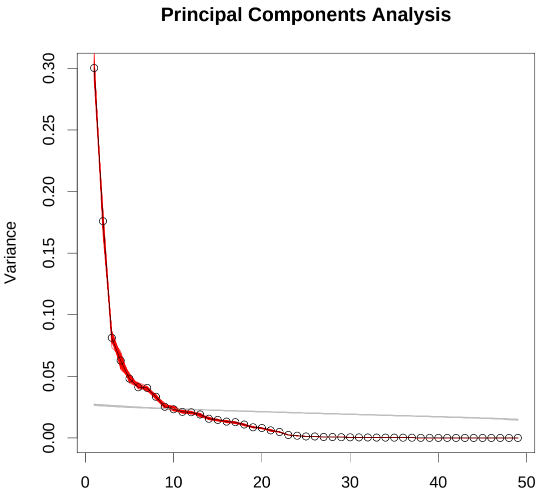
Clear Separation



Focus on High Signal Metrics



PCA: Metrics Have Signal But Are Redundant

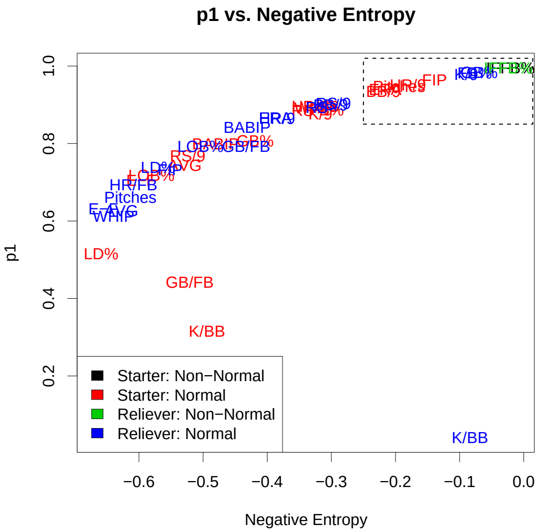


A Closer Look

ISO - Isolated Power			BB (walk) rate		
Player	Mean ($\mu + \alpha_i$) Estimate	SD	Player	Mean ($\mu + \alpha_i$) Estimate	SD
Mark McGwire	0.320	0.010	Barry Bonds	0.204	0.004
Barry Bonds	0.304	0.008	Gene Tenace	0.186	0.007
Ryan Howard	0.293	0.016	Jimmy Wynn	0.183	0.010
Jim Thome	0.287	0.009	Ken Phelps	0.176	0.011
Albert Pujols	0.281	0.011	Jack Cust	0.176	0.012
League Mean $\hat{\mu} = 0.142$			League Mean $\hat{\mu} = 0.087$		

Spd - Speed			K (strikeout) rate		
Player	Mean ($\mu + \alpha_i$) Estimate	SD	Player	Mean ($\mu + \alpha_i$) Estimate	SD
Vince Coleman	8.55	0.30	Jack Cust	0.388	0.018
Jose Reyes	8.22	0.40	Russell Branyan	0.376	0.021
Carl Crawford	8.14	0.36	Melvin Nieves	0.371	0.020
Willie Wilson	8.13	0.25	Rob Deer	0.351	0.010
Omar Moreno	7.89	0.31	Mark Reynolds	0.347	0.018
League Mean $\hat{\mu} = 4.11$			League Mean $\hat{\mu} = 0.166$		

A Continuum of Signal



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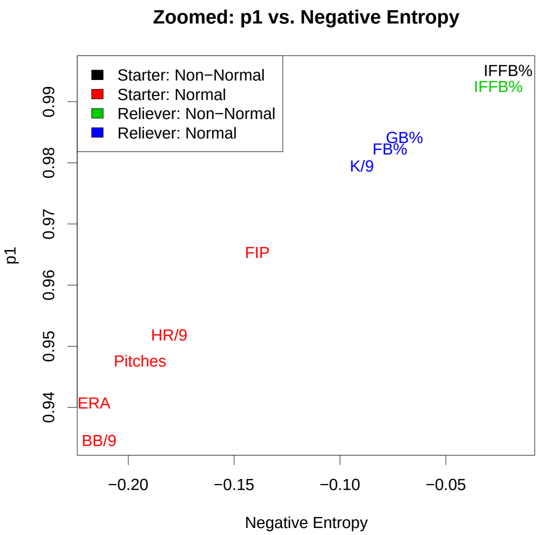

A Closer Look at Starters

FIP - Fielding Independent Pitching		
Player	**Mean** $(\mu + \alpha_i)$ **Estimate**	**SD**
Nolan Ryan	3.02	0.12
Pedro Martinez	3.03	0.14
Scott Elarton	5.28	0.24
J.R. Richard	3.06	0.18
Roger Clemons	3.13	0.10
League Mean $\hat{\mu} = 4.16$		

HR/9 - Home Run Rate		
Player	**Mean** $(\mu + \alpha_i)$ **Estimate**	**SD**
Scott Elarton	1.53	0.11
Jose Lima	1.48	0.09
Eric Milton	1.43	0.08
Brian Anderson	1.39	0.09
Rick Helling	1.38	0.09
League Mean $\hat{\mu} = 0.94$		

ERA - Earned Run Average		
Player	**Mean** $(\mu + \alpha_i)$ **Estimate**	**SD**
Jim Palmer	3.16	0.20
Pedro Martinez	3.17	0.19
Roger Clemons	3.22	0.15
Jose Rijo	3.25	0.24
Greg Maddux	3.27	0.14
League Mean $\hat{\mu} = 4.11$		

BB/9 - Walk Rate		
Player	**Mean** $(\mu + \alpha_i)$ **Estimate**	**SD**
Kazuhisa Ishii	5.10	0.35
Bobby Witt	4.85	0.17
Jose DeJesus	4.84	0.38
Daniel Cabrera	4.78	0.27
Bob Tewksbury	1.52	0.20
League Mean $\hat{\mu} = 3.14$		

A Closer Look at Relievers

GB% - Ground Ball Percentage		
Player	**Mean** $(\mu + \alpha_i)$ **Estimate**	**SD**
Cla Meredith	.662	.026
Bill Swift	.634	.026
Chad Bradford	.629	.020
Roger McDowell	.625	.014
Roy Corcoran	.623	.039
League Mean $\hat{\mu} = .449$		

FB% - Fly Ball Percentage		
Player	**Mean** $(\mu + \alpha_i)$ **Estimate**	**SD**
Troy Percival	.544	.016
Cla Meredith	.178	.026
Bill Swift	.188	.025
Carlos Marmol	.511	.028
Roger McDowell	.194	.014
League Mean $\hat{\mu} = .351$		

K/9 - Strike Out Rate		
Player	**Mean** $(\mu + \alpha_i)$ **Estimate**	**SD**
Brad Lidge	12.0	0.46
Rob Dibble	11.9	0.48
Billy Wagner	11.6	0.35
Octavio Dotel	11.4	0.45
Eric Gagne	11.2	0.52
League Mean $\hat{\mu} = 6.45$		

BB/9 - Walk Rate		
Player	**Mean** $(\mu + \alpha_i)$ **Estimate**	**SD**
Mitch Williams	6.42	0.26
Stephen Randolph	5.98	0.52
Mark Clear	5.90	0.25
Dennis Eckersley	1.54	0.24
Dan Quisenberry	1.56	0.21
League Mean $\hat{\mu} = 3.70$		

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- **Pitching:**
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  - For relievers, they relate to specialized roles (e.g., ground ball percentage).

Hitting Metrics I

1. Simple hitting totals and rates

Metric	Weight	Description	Metric	Weight	Description
1B	PA	singles	1B/PA	PA	single rate
2B	PA	doubles	2B/PA	PA	double rate
3B	PA	triples	3B/PA	PA	triple rate
HR	PA	home runs	HR/PA	PA	home run rate
R	PA	runs	R/PA	PA	run rate
RBI	PA	runs batted in	RBI/PA	PA	runs batted in rate
BB	PA	base on balls (walk)	BB/PA	PA	walk rate
IBB	PA	intentional walk	IBB/PA	PA	intentional walk rate
K	PA	strike outs	K/PA	PA	strike out rate
HBP	PA	hit by pitch	HBP/PA	PA	hit by pitch rate
BUH	H	bunt hits	BUH/H	H	bunt hit proportion
H	PA	hits	GDP	PA	ground into double play
SF	PA	sacrifice fly	SH	PA	sacrifice hit

Hitting Metrics II

2. More complicated hitting totals and rates

Metric	Weight	Description
OBP	PA⋆	on base percentage (OB/PA⋆)
AVG	AB	batting average (H/AB)
SLG	AB	slugging percentage
OPS	AB × PA⋆	OPB + SLG
ISO	AB	isolated power (SLG-AVG)
BB/K	PA	walk to strikeout ratio
HR/FB	PA	home run to fly ball ratio
GB/FB	BIP	ground ball to fly ball ratio
BABIP	BIP	batting average for balls in play
LD/BIP	BIP	line drive rate
GB/BIP	BIP	ground ball rate
FB/BIP	BIP	fly ball rate
IFFB/FB	FB	infield fly ball proportion
IFH	GB	in field hit
IFH/H	GB	in field hit proportion
wOBA	PA⋆	weighted on base average
wRC	PA	runs created based on wOBA
wRAA	PA	runs above average based on wOBA

PA⋆ = plate appearances minus sacrifice hits.

Hitting Results

Metric	$\widehat{p}_1$	Neg. Ent.
HR/PA	0.993	-0.034
RBI/PA	0.992	-0.040
Spd	0.991	-0.044
ISO	0.989	-0.052
SBPA	0.989	-0.057
SH	0.988	-0.057
1B/PA	0.987	-0.059
GDP	0.983	-0.080
K/PA	0.982	-0.074
HR	0.981	-0.083
RBI	0.980	-0.089
H	0.978	-0.098
K	0.977	-0.093
BB/PA	0.977	-0.095
R	0.974	-0.110
2B/PA	0.969	-0.129
BABIP	0.968	-0.130

Metric	$\widehat{p}_1$	Neg. Ent.
HR/FB	0.968	-0.121
SLG	0.968	-0.127
R/PA	0.952	-0.176
wOBA	0.949	-0.180
GB/BIP	0.949	-0.169
wRC	0.945	-0.193
BUH/H	0.943	-0.209
FB/BIP	0.937	-0.199
OBP	0.936	-0.213
IFH/H	0.936	-0.218
OPS	0.930	-0.227
2B	0.930	-0.235
IFFB/FB	0.916	-0.260
BB	0.912	-0.262
1B	0.910	-0.276
AVG	0.905	-0.289
wRAA	0.809	-0.430

Metric	$\widehat{p}_1$	Neg. Ent.
SF	0.789	-0.490
3B/PA	0.780	-0.483
CS/OB	0.723	-0.493
GB/FB	0.720	-0.462
BB/K	0.681	-0.505
LD/BIP	0.626	-0.633
IFH	0.567	-0.589
IBB/PA	0.470	-0.581
CS	0.453	-0.530
3B	0.453	-0.575
HDP/PA	0.366	-0.444
SB/OB	0.345	-0.356
HBP	0.333	-0.423
IBB	0.297	-0.463
SB	0.279	-0.341
BUH	0.170	-0.210

Pitching Metrics

Metric	Description
AVG	batting average against
BABIP	batting average in balls in play
FB%	fly ball percentage
GB%	ground ball percentage
LF%	line drive percentage
IFFB%	infield fly ball percentage
K/9	strikeouts per nine innings
BB/9	walks per nine innings
HR/9	home runs per nine innings
K/BB	strikeout to walk ratio
GB/FB	ground ball to fly ball ratio
HR/FB	home run to fly ball ratio
LOB%	left on base percentage
ERA	earned run average
FIP	fielding independent pitching (Tom Tango)
E-F	ERA - FIP
WHIP	walks and hits per inning
RS	run support
RS/9	run support per nine innings
Pitches	number of pitches thrown

Note: we weight by Innings Pitched (IP) for all metrics.

Pitching Results

Pitcher	Metric	$\widehat{p}_1$	Neg. Ent.
Reliever	IFFB%	0.995	-0.024
Starter	IFFB%	0.995	-0.021
Reliever	GB%	0.984	-0.069
Reliever	FB%	0.982	-0.076
Reliever	K/9	0.979	-0.090
Starter	FIP	0.965	-0.139
Starter	HR/9	0.952	-0.181
Starter	Pitches	0.948	-0.194
Starter	ERA	0.941	-0.216
Starter	BB/9	0.935	-0.219
Reliever	RS/9	0.904	-0.297
Reliever	BB/9	0.901	-0.301
Starter	HR/FB	0.896	-0.325
Reliever	RS	0.894	-0.323
Starter	WHIP	0.892	-0.325
Starter	FB%	0.888	-0.307
Starter	RS	0.886	-0.345
Starter	K/9	0.877	-0.317
Reliever	ERA	0.867	-0.387
Reliever	HR/9	0.865	-0.385

Pitcher	Metric	$\widehat{p}_1$	Neg. Ent.
Reliever	BABIP	0.843	-0.431
Starter	GB%	0.807	-0.419
Starter	BABIP	0.799	-0.480
Reliever	LOB%	0.794	-0.504
Reliever	GB/FB	0.793	-0.433
Starter	RS/9	0.769	-0.524
Starter	AVG	0.745	-0.530
Reliever	LD%	0.739	-0.570
Reliever	FIP	0.732	-0.551
Starter	LOB%	0.719	-0.581
Starter	E-F	0.705	-0.597
Reliever	HR/FB	0.694	-0.609
Reliever	Pitches	0.662	-0.613
Reliever	E-F	0.632	-0.655
Reliever	AVG	0.627	-0.629
Reliever	WHIP	0.613	-0.639
Starter	LD%	0.516	-0.659
Starter	GB/FB	0.442	-0.521
Starter	K/BB	0.317	-0.494
Reliever	K/BB	0.041	-0.084