Hidden in Plain Sight:

A case study into designing sophisticated statistical model grids that leverage student-credit hour production with revenue opportunities to uncover often overlooked students.

Randall Langston *Texas Woman's University*

Mark Hamner *Texas Woman's University*

Michael Stankey *Texas Woman's University*

AACRAO

28TH ANNUAL

STRATEGIC ENROLLMENT MANAGEMENT CONFERENCE

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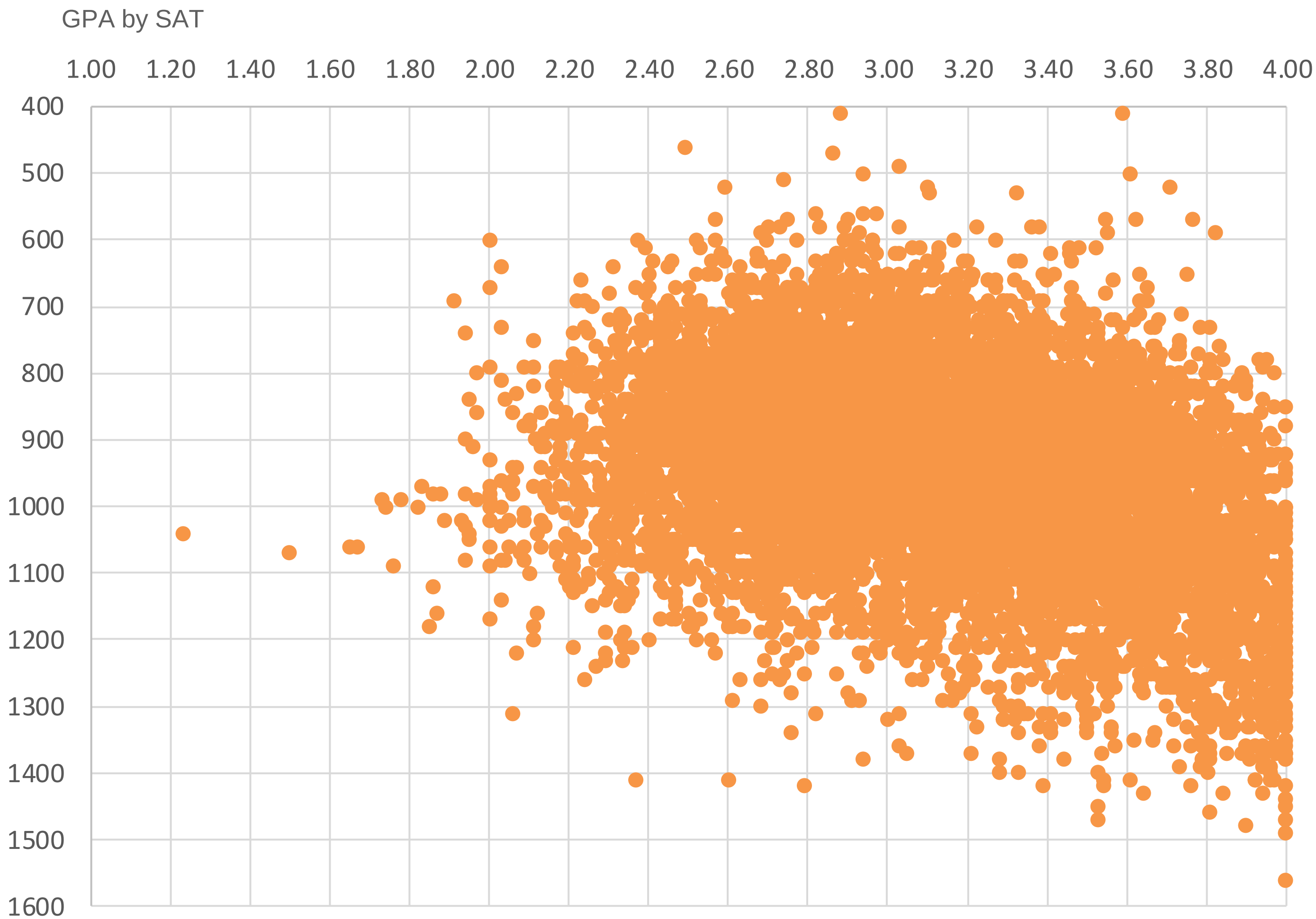
A case study into designing sophisticated statistical model grids that leverage student-credit hour production with revenue opportunities to uncover often overlooked students.

Randall *Vice President Enrollment Management*

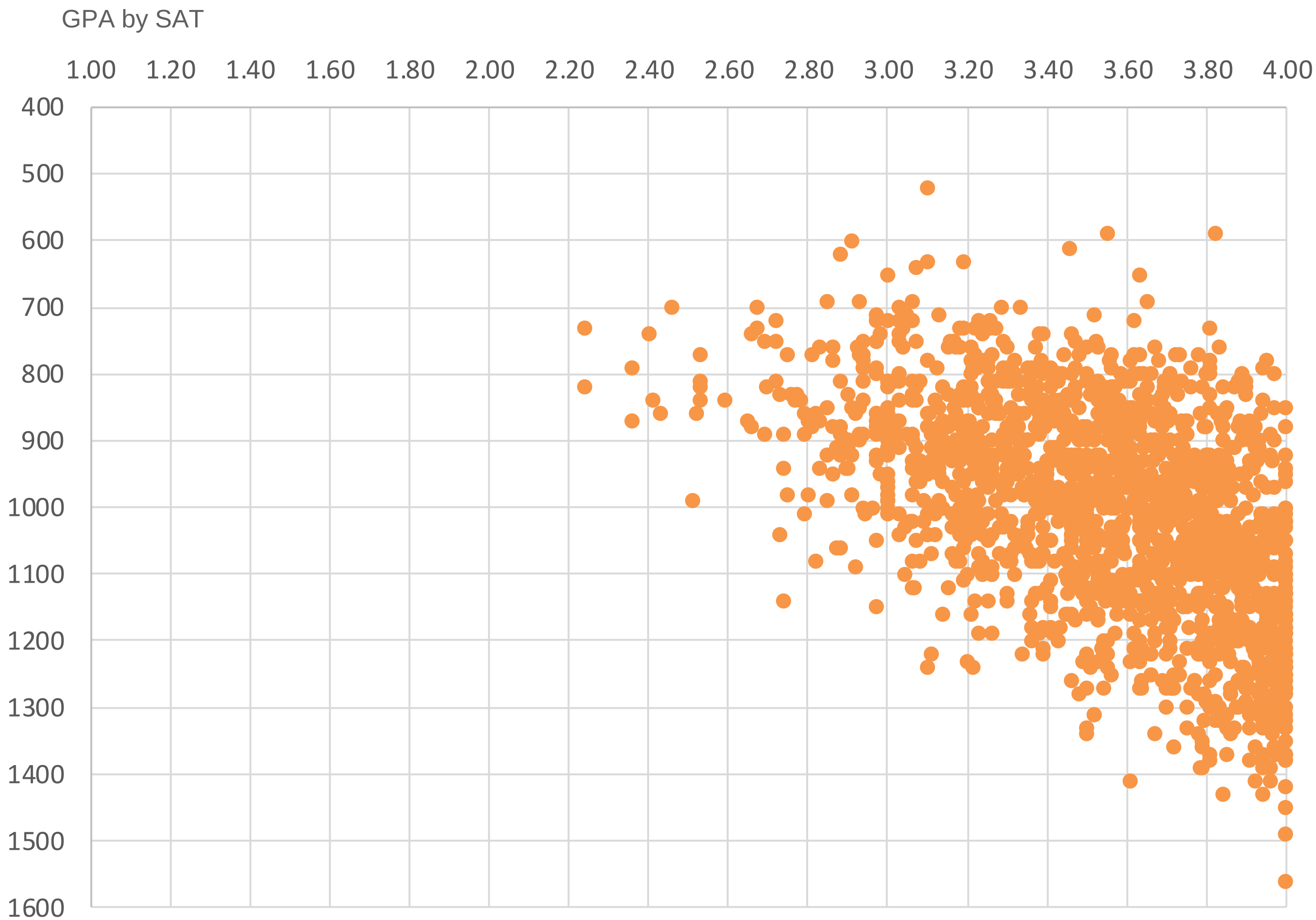
Mark *Vice Provost Institutional Research & Improvement*

Michael *Director of Analytics*



ALL

FTIC Applicants
FA13 to FA15

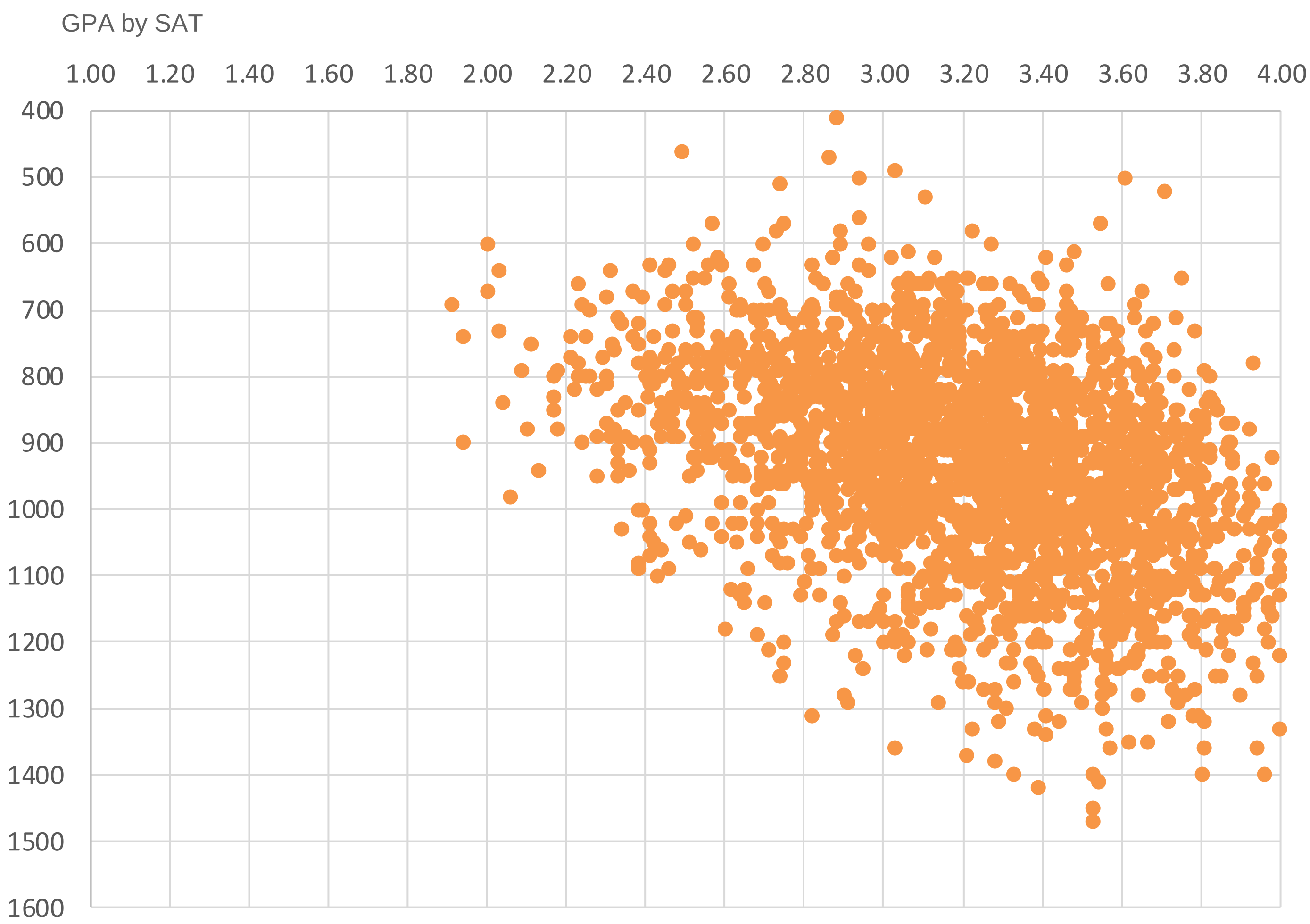


U1

FTIC Applicants
FA13 to FA15

Top 10% of Graduating Class

Admitted

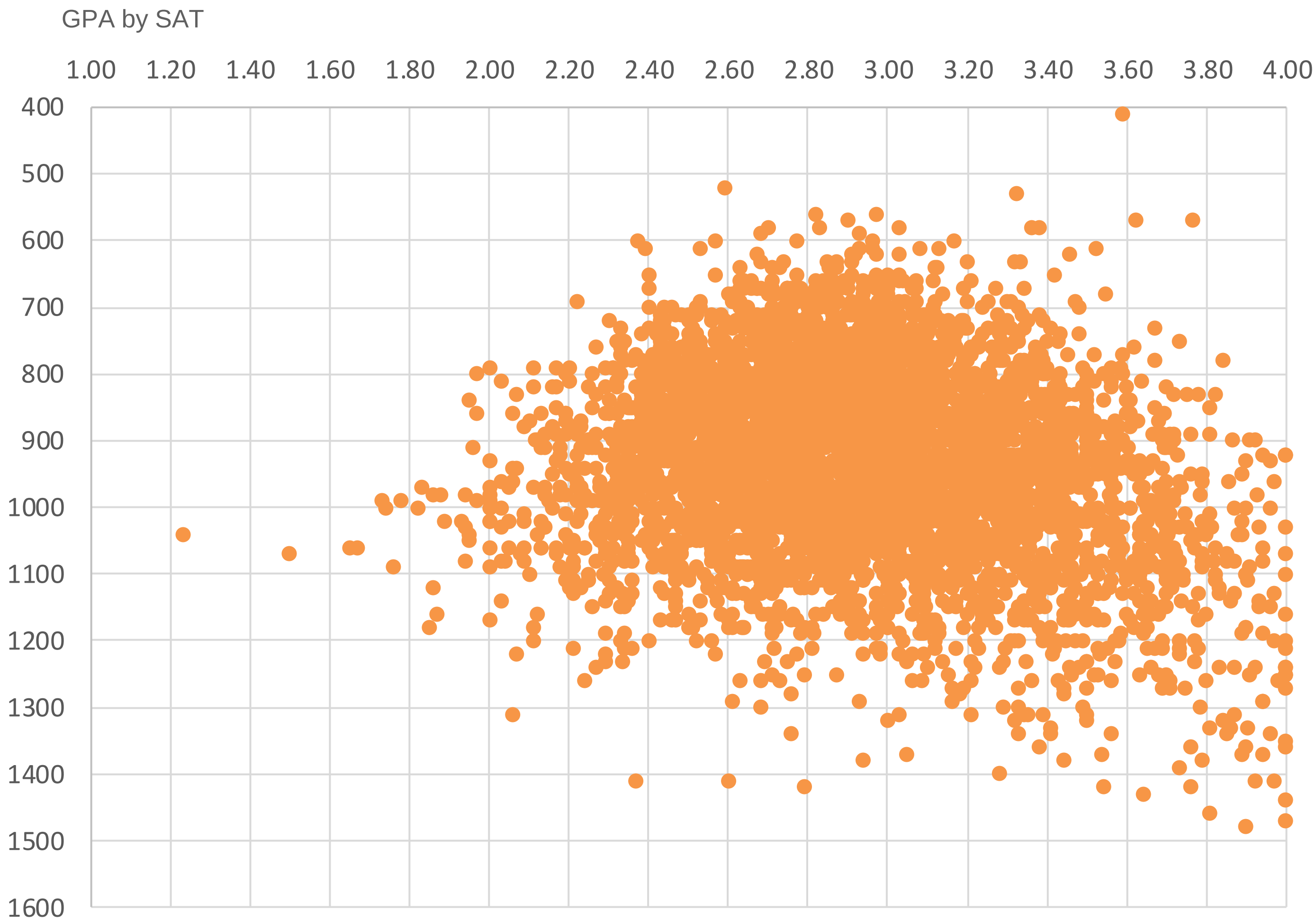


U2

FTIC Applicants
FA13 to FA15

Top 25% of Graduating Class

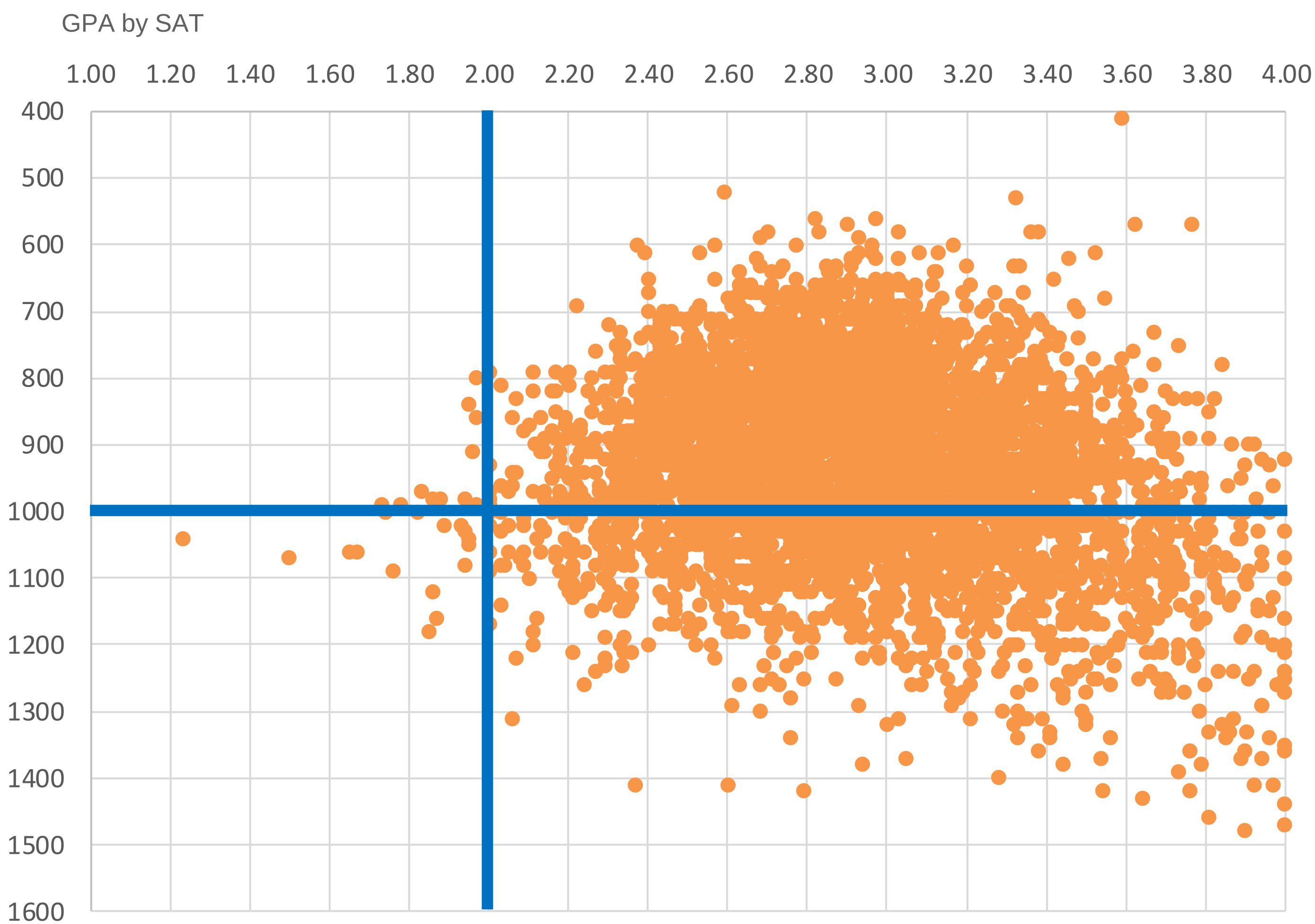
Admitted



U3+U12

FTIC Applicants
FA13 to FA15

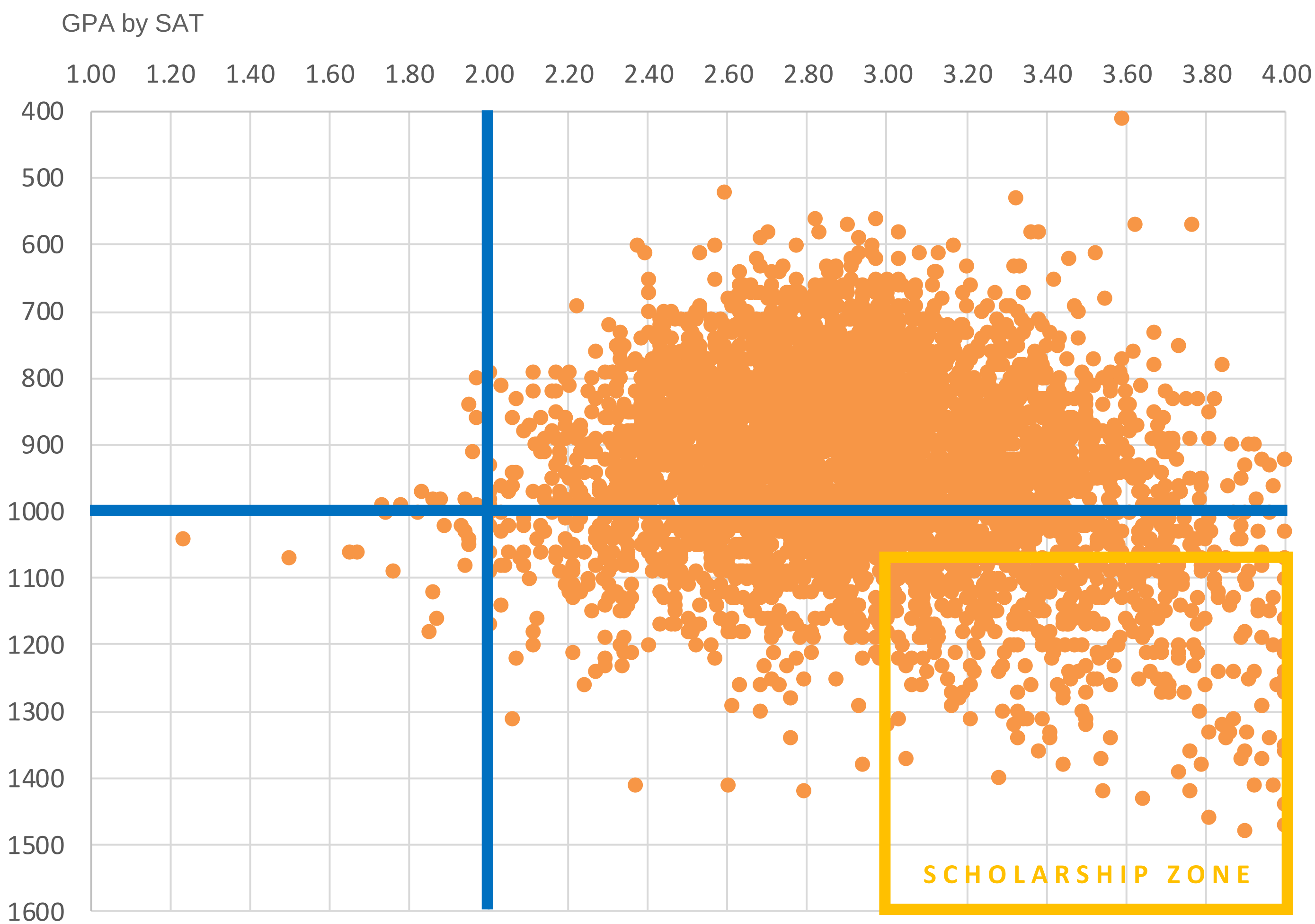
Students on whom we make admissions decisions.



U3+U12

FTIC Applicants
FA13 to FA15

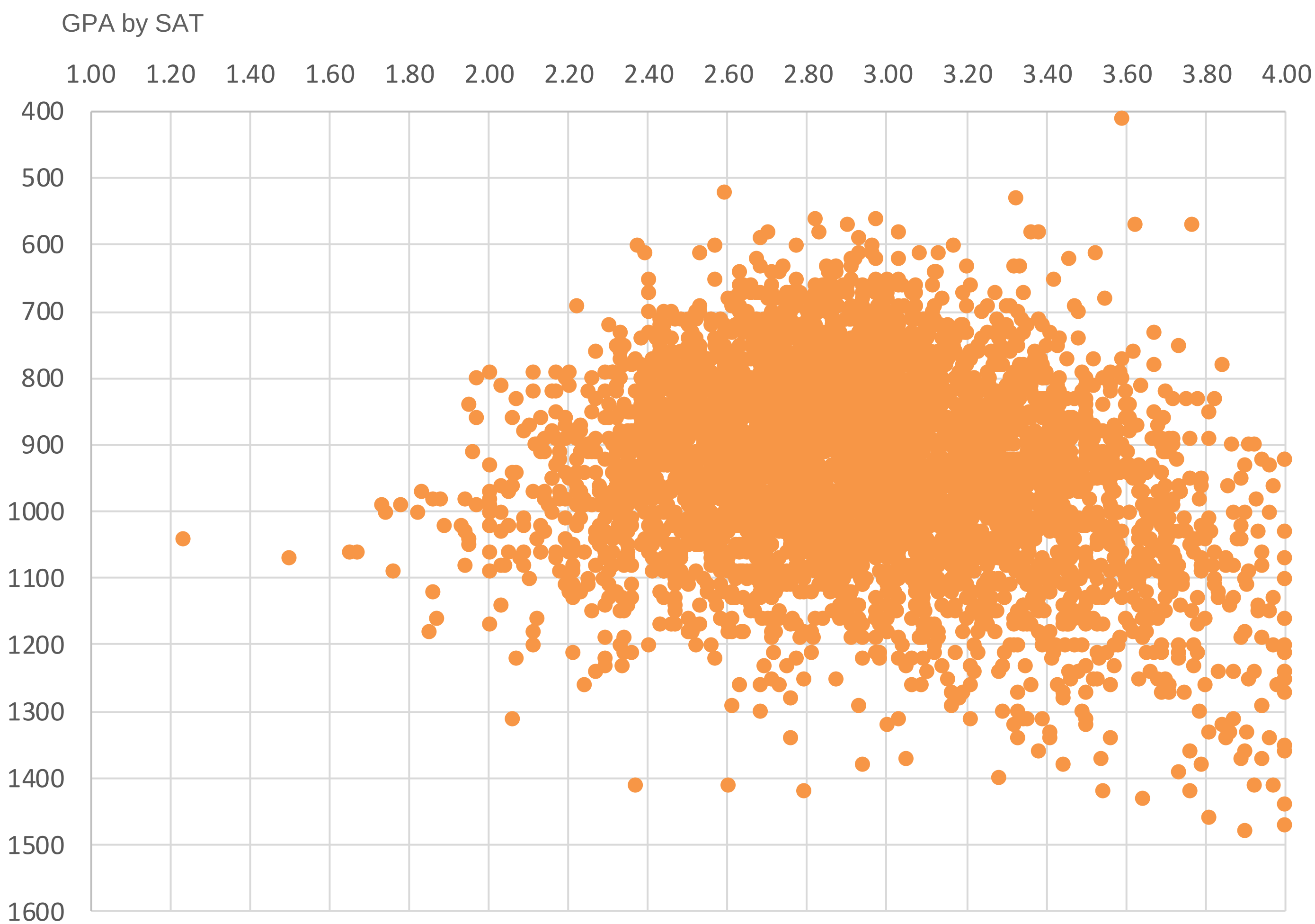
*Previous approach used the **"Flag of Finland"** to subdivide group into regular admits (U3) and provisionals (U12),*



U3+U12

FTIC Applicants
FA13 to FA15

*Previous approach used the **"Flag of Finland"** to subdivide group into regular admits (U3) and provisionals (U12), and focused scholarship awards on higher gpa and sat areas.*



U3+U12

FTIC Applicants
FA13 to FA15

Might there be a better way?

Nurse Educator

Successful Modeling of Factors Related to Recruitment and Retention of Prenursing Students

Jo-Ann Stankus, PhD, RN; Mark Hamner, PhD; Michael Stankey, PhD; and Peggy Mancuso, PhD, RN, CNM, CNE

ABSTRACT

Background: The traditional admission methodology used by many schools of nursing is the second-tier admission based on specified criteria. This method has been associated with a student body that is predominately female, white, and English speaking.

Problem: Rational judgment modeling (points assigned to criteria) used to evaluate applicants for admission into prenursing programs potentially overlooks students who do not fit into the traditional model.

Approach: This study compared predictive logistic regression with traditional rational judgment models to classify potential nursing school applicants.

Outcomes: A higher number of Hispanic and black prenursing students were identified for potential upper-level nursing program admission.

Conclusions: The use of logistic regression modeling can identify a more diverse student population. Advisors at both high school and university/college levels can use results of this model to help students determine their progress, identify academic weaknesses, and develop individual plans of action to help the students successfully complete the prenursing curriculum requirements.

Keywords: admissions, diversity, nursing students, predictive modeling, retention

Cite this article as: Stankus J-A, Hamner M, Stankey M, Mancuso P. Successful modeling of factors related to recruitment and retention of prenursing students. *Nurse Educ.* 2018. DOI: 10.1097/NNE.0000000000000579. [Epub ahead of print].

In the United States, nursing education is a high-stakes endeavor. The student expends money, time, and intellectual effort in the hopes of acquiring a rewarding career.[1-3] The educational institution deploys ever decreasing faculty and clinical resources in the hope of producing graduates who will be excellent practitioners.[4-6] Society expends taxpayer dollars to support universities and colleges in the hope that graduates will be nurses who provide care to our most vulnerable populations.[7] Current admission criteria tend to generate nursing student populations that are predominantly white and female, even in those states with diverse ethnic populations.[8,9] To maximize the benefits of nursing education, we must ensure that the students who are accepted into nursing programs represent the populations they will serve and can successfully address the rigors of the required academic work needed for successful graduation. To meet these objectives, this research project created an innovative modeling process using logistic regression to predict the future success of prenursing students who apply to nursing school through a second-tier admissions process.

Background

Admission to nursing programs today is no easy feat. Today's prenursing students grapple with the reality of a larger number of applicants for each available opening.[10] To compete for these openings, prenursing students must be academically equipped to meet the challenges of higher-education courses. Students who have successfully passed high school courses may not be adequately prepared for rigorous college/university science courses.[1,2,6,11] Students who come from lower socioeconomic status households are competing

Author Affiliations: Coordinator, RN BS/MS Program, and Assistant Professor (Dr Stankus), College of Nursing; Associate Provost of Institutional Research & Improvement (Dr Hamner); Director of Analytics (Dr Stankey); and Associate Dean for Research and Clinical Scholarship/Professor (Dr Mancuso), College of Nursing, Texas Woman's University, Denton.

The authors declare no conflicts of interest.

#SEM18

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Used Logistic Regression

to predict admission into upper level nursing program

and identify overlooked and undervalued students.

Nurse Educator

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Used Logistic Regression

to predict admission into upper level nursing program

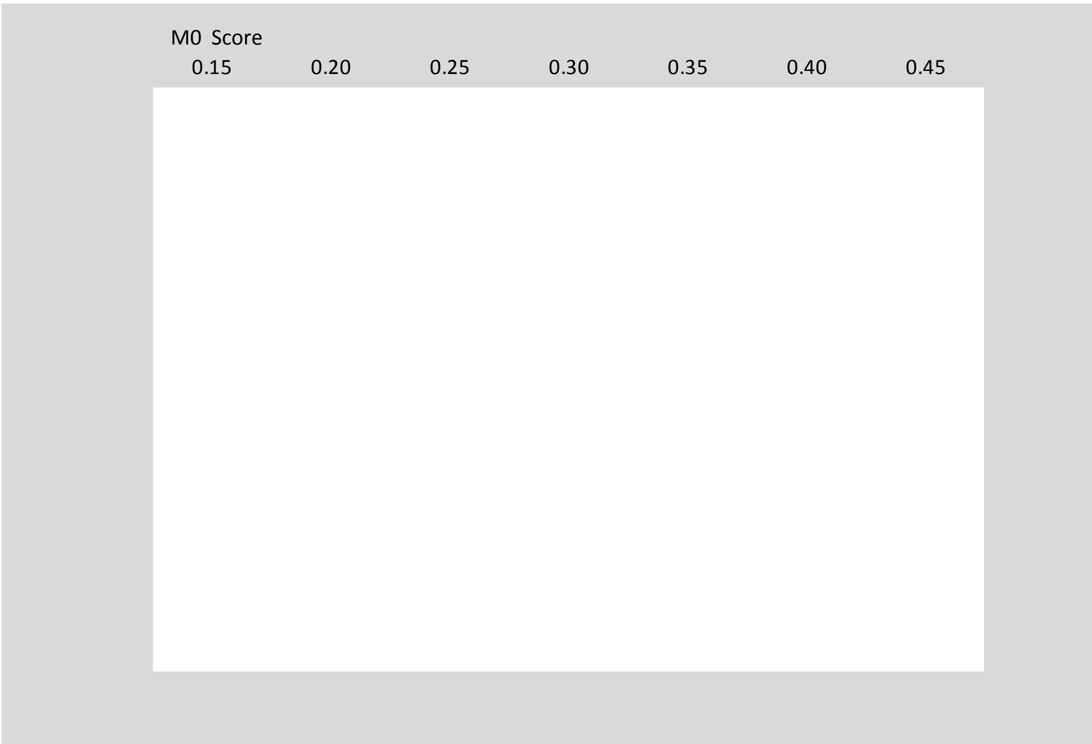
and identify overlooked and undervalued students.

What if we applied the same principle to the admissions grid

and used logistic regression scores on each axis?

Applications FA13-FA15

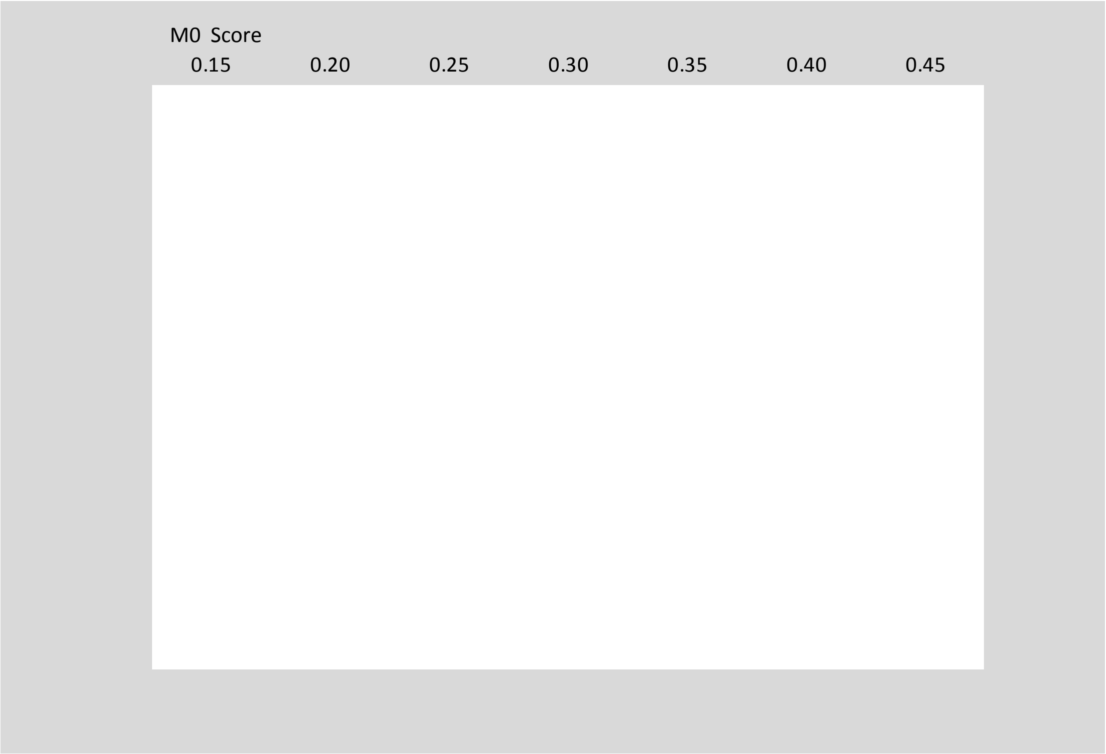
Applications FA13-FA15



MATRICULATION

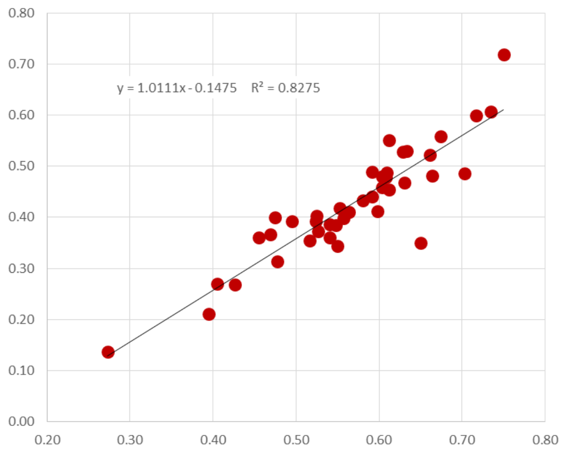
$$M0 = .002V - .001M - .121G - 0.863$$

Applications FA13-FA15



MATRICULATION

M0 = .002V – .001M – .121G – 0.863



Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20							
0.25							
0.30							
0.35							
0.40							
0.45							
0.50							
0.55							
0.60							
0.65							
0.70							
0.75							
0.80							
0.85							

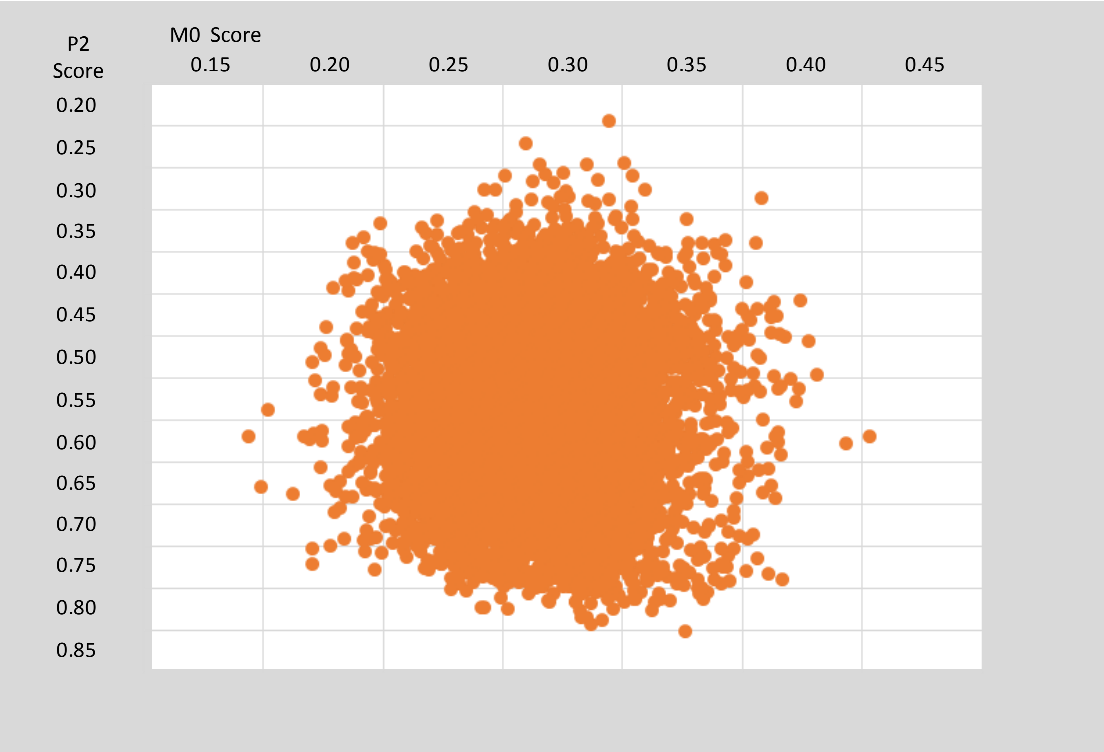
MATRICULATION

$$M0 = .002V - .001M - .121G - 0.863$$

$$P2 = .001V + .002M + .585G - 2.922$$

SECOND YEAR PERSISTENCE

Applications FA13-FA15



M A T R I C U L A T I O N

M0 = .002V − .001M − .121G − 0.863

P2 = .001V + .002M + .585G − 2.922

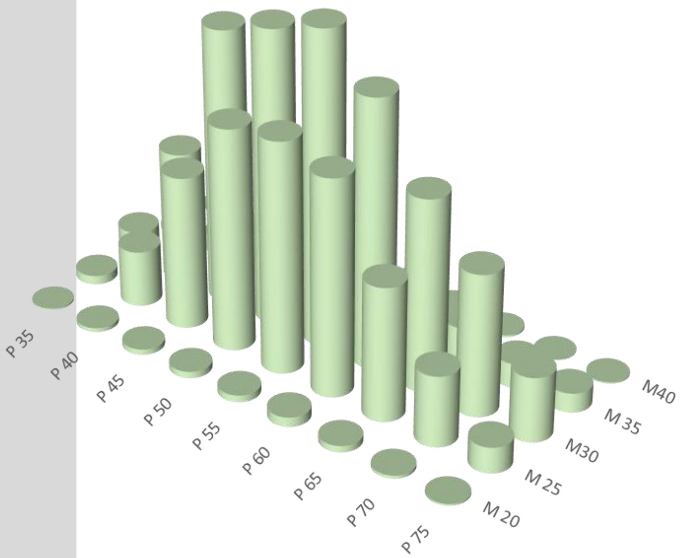
S E C O N D Y E A R P E R S I S T E N C E

Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1	.	.	.
0.25	.	.	.	4	1	.	.
0.30	.	.	2	20	3	1	.
0.35	.	4	26	85	10	1	.
0.40	.	12	165	386	51	1	.
0.45	.	16	449	805	119	10	.
0.50	.	19	650	862	146	8	.
0.55	.	20	675	917	151	11	.
0.60	1	28	634	785	128	8	2
0.65	1	19	392	564	109	6	.
0.70	.	9	208	416	72	2	.
0.75	.	5	76	190	57	4	.
0.80	.	.	5	26	14	.	.
0.85	.	.	.	.	1	.	.

Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1	.	.	.
0.25	.	.	.	4	1	.	.
0.30	.	.	2	20	3	1	.
0.35	.	4	26	85	10	1	.
0.40	.	12	165	386	51	1	.
0.45	.	16	449	805	119	10	.
0.50	.	19	650	862	146	8	.
0.55	.	20	675	917	151	11	.
0.60	1	28	634	785	128	8	2
0.65	1	19	392	564	109	6	.
0.70	.	9	208	416	72	2	.
0.75	.	5	76	190	57	4	.
0.80	.	.	5	26	14	.	.
0.85	.	.	.	.	1	.	.



Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1	.	.	.
0.25	.	.	.	4	1	.	.
0.30	.	.	2	20	3	1	.
0.35	.	4	26	85	10	1	.
0.40	.	12	165	386	51	1	.
0.45	.	16	449	805	119	10	.
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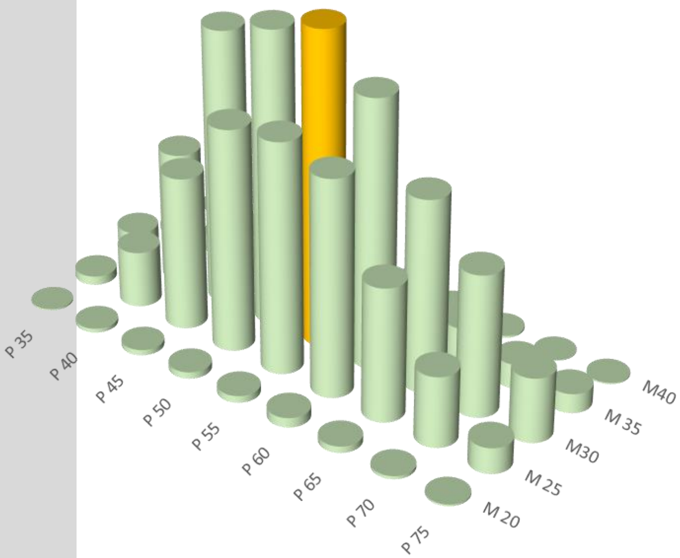
0.65	1	19	392	564	109	6	.
0.70	.	9	208	416	72	2	.
0.75	.	5	76	190	57	4	.
0.80	.	.	5	26	14	.	.
0.85	.	.	.	.	1	.	.



P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
0.50	.	0.333	0.563	0.523	0.480	0.000	.
0.55	.	0.000	0.620	0.560	0.558	0.667	.
0.60	.	0.600	0.676	0.646	0.818	0.333	1.000
0.65	.	0.500	0.606	0.635	0.629	0.333	.
0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
0.50	.	0.333	0.563	0.523	0.480	0.000	.
0.55	.	0.000	0.620	0.560	0.558	0.667	.
0.60	.	0.600	0.676	0.646	0.818	0.333	1.000
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0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
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0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

The Sweet Spot

P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
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0.55	.	0.000	0.620	0.560	0.558	0.667	.
0.60	.	0.600	0.676	0.646	0.818	0.333	1.000
0.65	.	0.500	0.606	0.635	0.629	0.333	.
0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

The Sweet Spot

Above average persistence rates are attractive,

M0 rates among applicants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	1.000	1.000	.	.
0.30	.	.	0.000	0.550	0.667	0.000	.
0.35	.	0.500	0.423	0.329	0.600	0.000	.
0.40	.	0.083	0.327	0.339	0.392	0.000	.
0.45	.	0.250	0.327	0.353	0.445	0.400	.
0.50	.	0.158	0.292	0.321	0.342	0.125	.
0.55	.	0.100	0.284	0.317	0.344	0.273	.
0.60	0.000	0.179	0.273	0.327	0.344	0.375	1.000
0.65	0.000	0.105	0.324	0.349	0.321	0.500	.
0.70	.	0.222	0.404	0.370	0.347	0.000	.
0.75	.	0.400	0.382	0.374	0.404	0.250	.
0.80	.	.	0.400	0.423	0.286	.	.
0.85	.	.	.	.	0.000	.	.

The Sweet Spot

Above average persistence rates are attractive, but below average matriculation rates are a concern and challenge.

M0 rates among applicants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	1.000	1.000	.	.
0.30	.	.	0.000	0.550	0.667	0.000	.
0.35	.	0.500	0.423	0.329	0.600	0.000	.
0.40	.	0.083	0.327	0.339	0.392	0.000	.
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0.65	0.000	0.105	0.324	0.349	0.321	0.500	.
0.70	.	0.222	0.404	0.370	0.347	0.000	.
0.75	.	0.400	0.382	0.374	0.404	0.250	.
0.80	.	.	0.400	0.423	0.286	.	.
0.85	.	.	.	.	0.000	.	.

Up here, the above average matriculation rates are a concern,

P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
0.50	.	0.333	0.563	0.523	0.480	0.000	.
0.55	.	0.000	0.620	0.560	0.558	0.667	.
0.60	.	0.600	0.676	0.646	0.818	0.333	1.000
0.65	.	0.500	0.606	0.635	0.629	0.333	.
0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

Up here, the above average matriculation rates are a concern, because they're associated with low persistence rates.

P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
0.50	.	0.333	0.563	0.523	0.480	0.000	.
0.55	.	0.000	0.620	0.560	0.558	0.667	.
0.60	.	0.600	0.676	0.646	0.818	0.333	1.000
0.65	.	0.500	0.606	0.635	0.629	0.333	.
0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

The Sour Spot

Up here, the above average matriculation rates are a concern, because they're associated with low persistence rates.

P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
0.50	.	0.333	0.563	0.523	0.480	0.000	.
0.55	.	0.000	0.620	0.560	0.558	0.667	.
0.60	.	0.600	0.676	0.646	0.818	0.333	1.000
0.65	.	0.500	0.606	0.635	0.629	0.333	.
0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

The Sour Spot

The Sweet Spot

Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1	.	.	.
0.25	.	.	.	4	1	.	.
0.30	.	.	2	20	3	1	.
0.35	.	4	26	85	10	1	.
0.40	.	12	165	386	51	1	.
0.45	.	16	449	805	119	10	.
0.50	.	19	650	862	146	8	.
0.55	.	20	675	917	151	11	.
0.60	1	28	634	785	128	8	2
0.65	1	19	392	564	109	6	.
0.70	.	9	208	416	72	2	.
0.75	.	5	76	190	57	4	.
0.80	.	.	5	26	14	.	.
0.85	.	.	.	.	1	.	.

The Sour Spot

The Sweet Spot

Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1	.	.	.
0.25	.	.	.	4	1	.	.
0.30	.	.	2	20	3	1	.
0.35	.	4	26	85	10	1	.
0.40	.	12	165	386	51	1	.
0.45	.	16	449	805	119	10	.
0.50	.	19	650	862	146	8	.
0.55	.	20	675	917	151	11	.
0.60	1	28	634	785	128	8	2
0.65	1	19	392	564	109	6	.
0.70	.	9	208	416	72	2	.
0.75	.	5	76	190	57	4	.
0.80	.	.	5	26	14	.	.
0.85	.	.	.	.	1	.	.

The Sour Spot

The Sweet Spot

Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1	.	.	.
0.25	.	.	.	4	1	.	.
0.30	.	.	2	20	3	1	.
0.35	.	4	26	85	10	1	.
0.40	.	12	165	386	51	1	.
0.45	.	16	449	805	119	10	.
0.50	.	19	650	862	146	8	.
0.55	.	20	675	917	151	11	.
0.60	1	28	634	785	128	8	2
0.65	1	19	392	564	109	6	.
0.70	.	9	208	416	72	2	.
0.75	.	5	76	190	57	4	.
0.80	.	.	5	26	14	.	.
0.85	.	.	.	.	1	.	.

The Sour Spot

Avg P2 = 42% (23% of applicants)

The Sweet Spot

Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1	.	.	.
0.25	.	.	.	4	1	.	.
0.30	.	.	2	20	3	1	.
0.35	.	4	26	85	10	1	.
0.40	.	12	165	386	51	1	.
0.45	.	16	449	805	119	10	.
0.50	.	19	650	862	146	8	.
0.55	.	20	675	917	151	11	.
0.60	1	28	634	785	128	8	2
0.65	1	19	392	564	109	6	.
0.70	.	9	208	416	72	2	.
0.75	.	5	76	190	57	4	.
0.80	.	.	5	26	14	.	.
0.85	.	.	.	.	1	.	.

The Sour Spot

Avg P2 = 42% (23% of applicants)

The Sweet Spot

Avg P2 = 78% (39% of applicants)

Applications FA13-FA15

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1	.	.	.
0.25	.	.	.	4	1	.	.
0.30	.	.	2	20	3	1	.
0.35	.	4	26	85	10	1	.
0.40	.	12	165	386	51	1	.
0.45	.	16	449	805	119	10	.
0.50	.	19	650	862	146	8	.
0.55	.	20	675	917	151	11	.
0.60	1	28	634	785	128	8	2
0.65	1	19	392	564	109	6	.
0.70	.	9	208	416	72	2	.
0.75	.	5	76	190	57	4	.
0.80	.	.	5	26	14	.	.
0.85	.	.	.	.	1	.	.

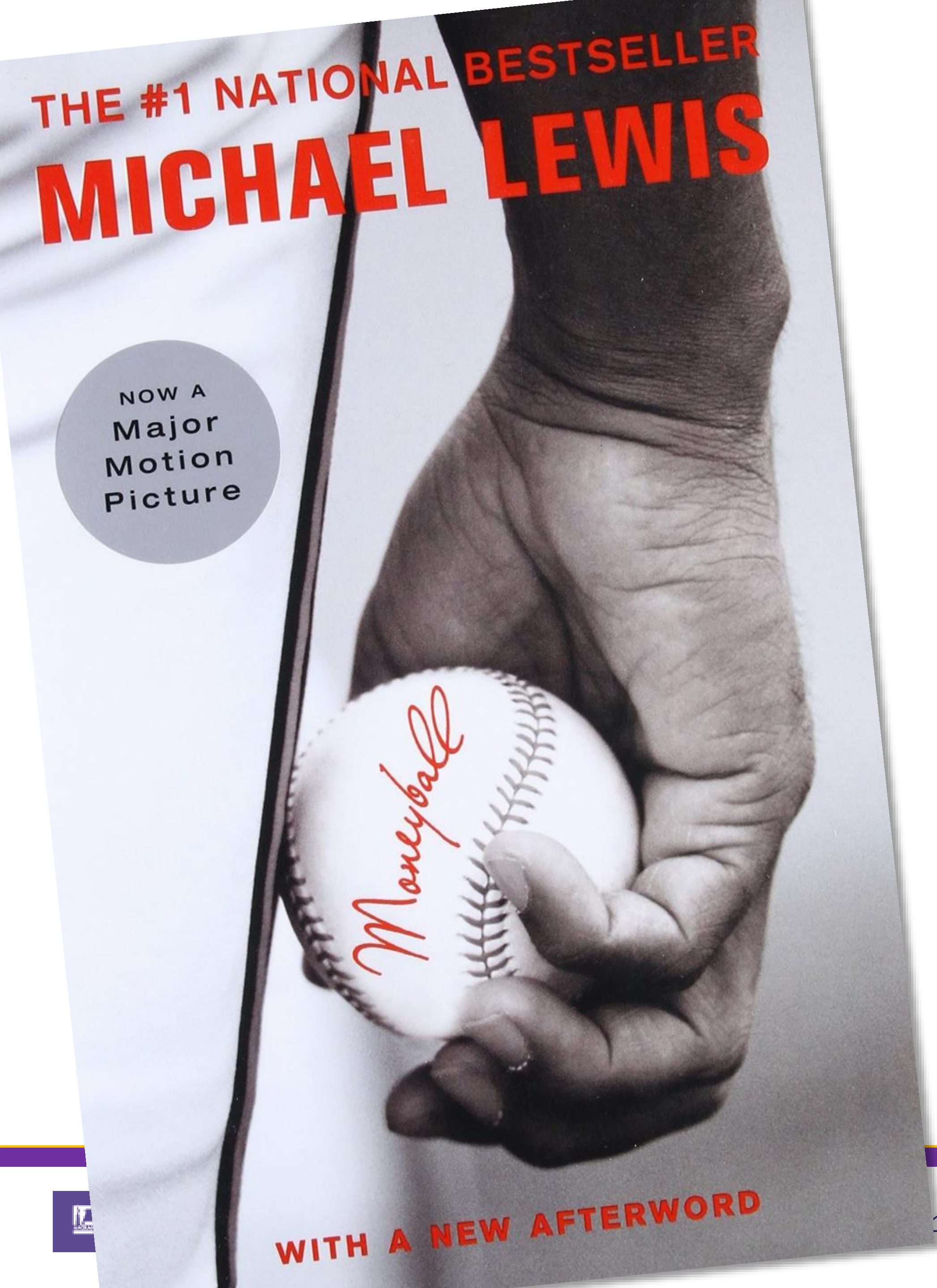
The Sour Spot

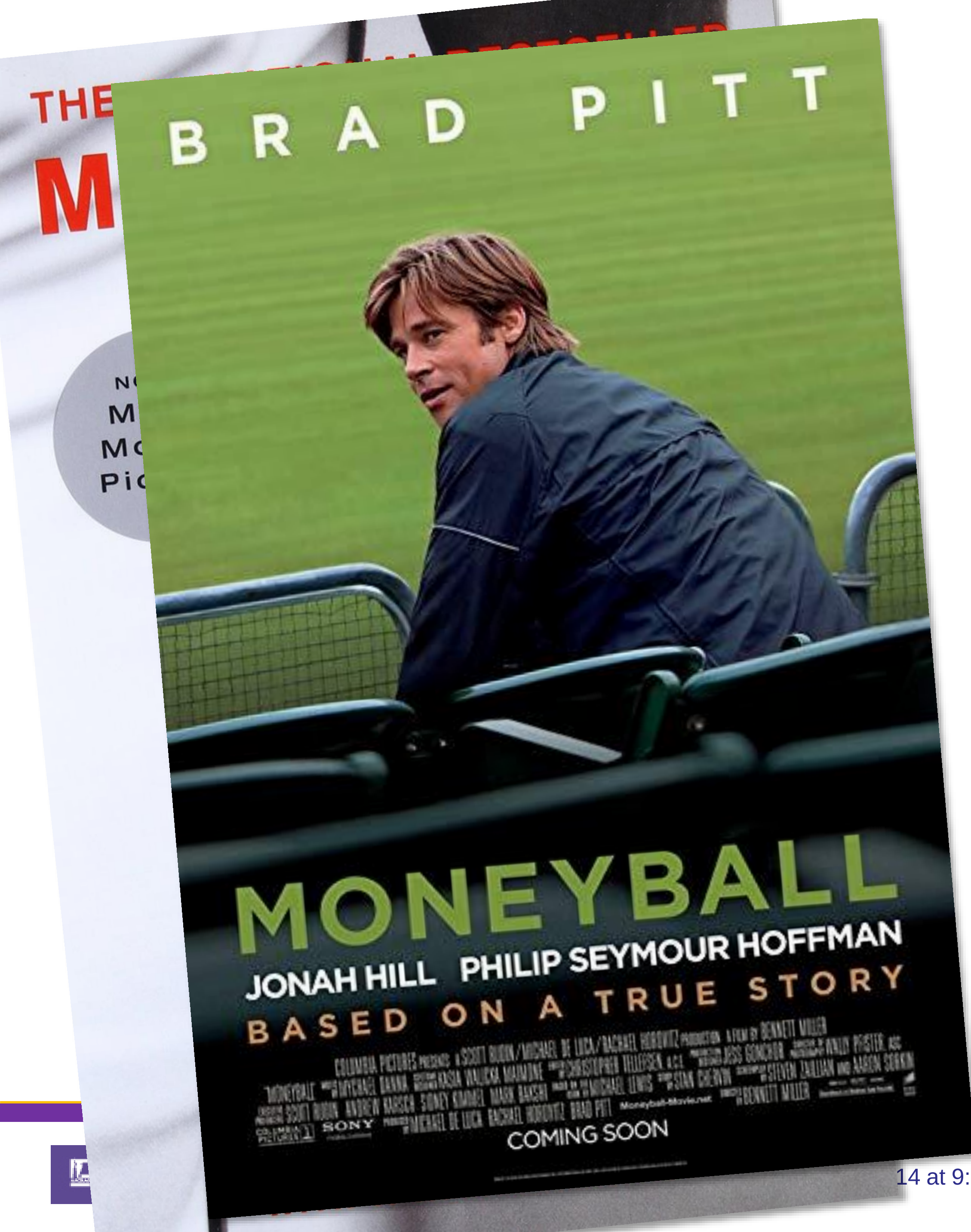
Avg P2 = 42% (23% of applicants)

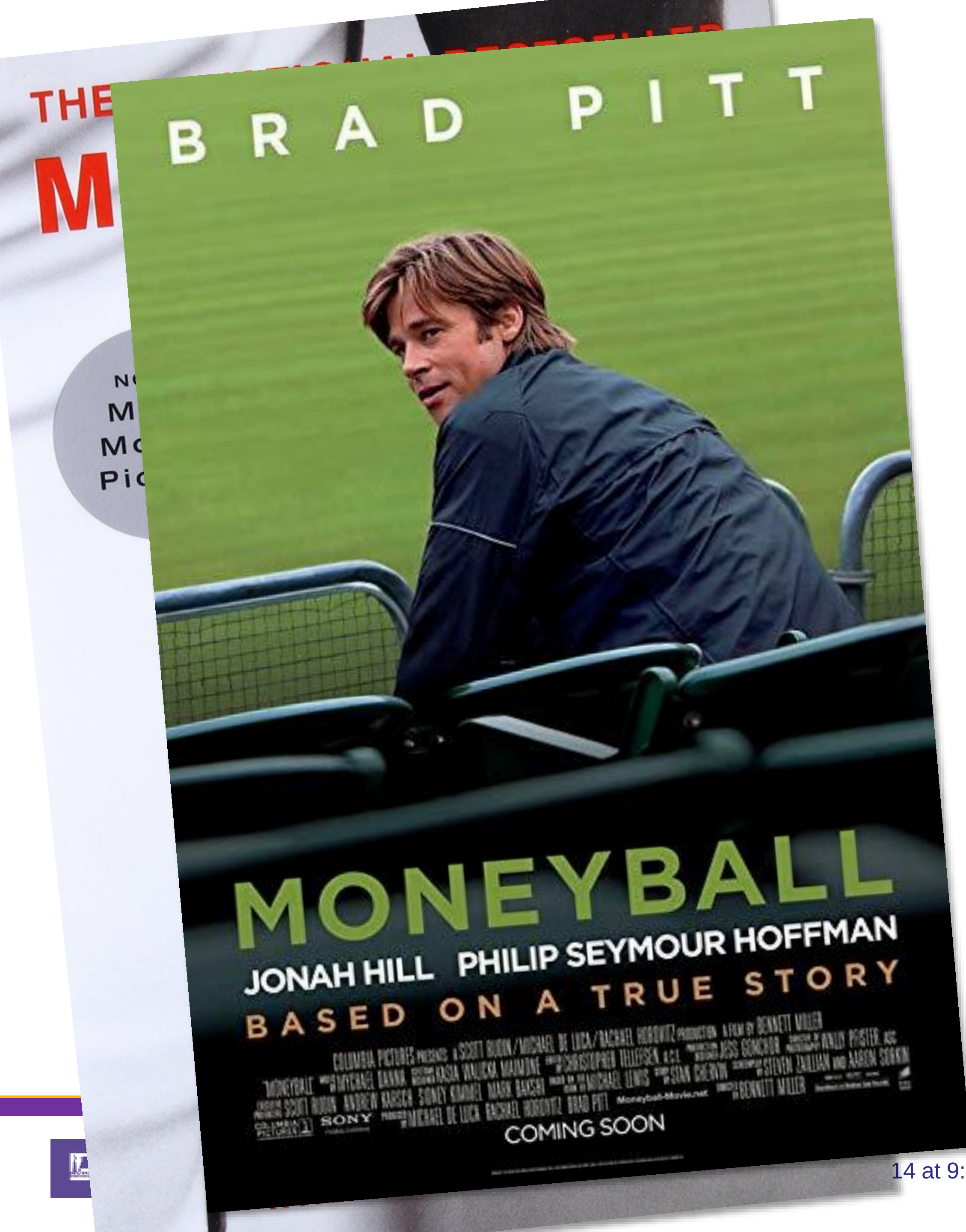
The Sweet Spot

Avg P2 = 78% (39% of applicants)

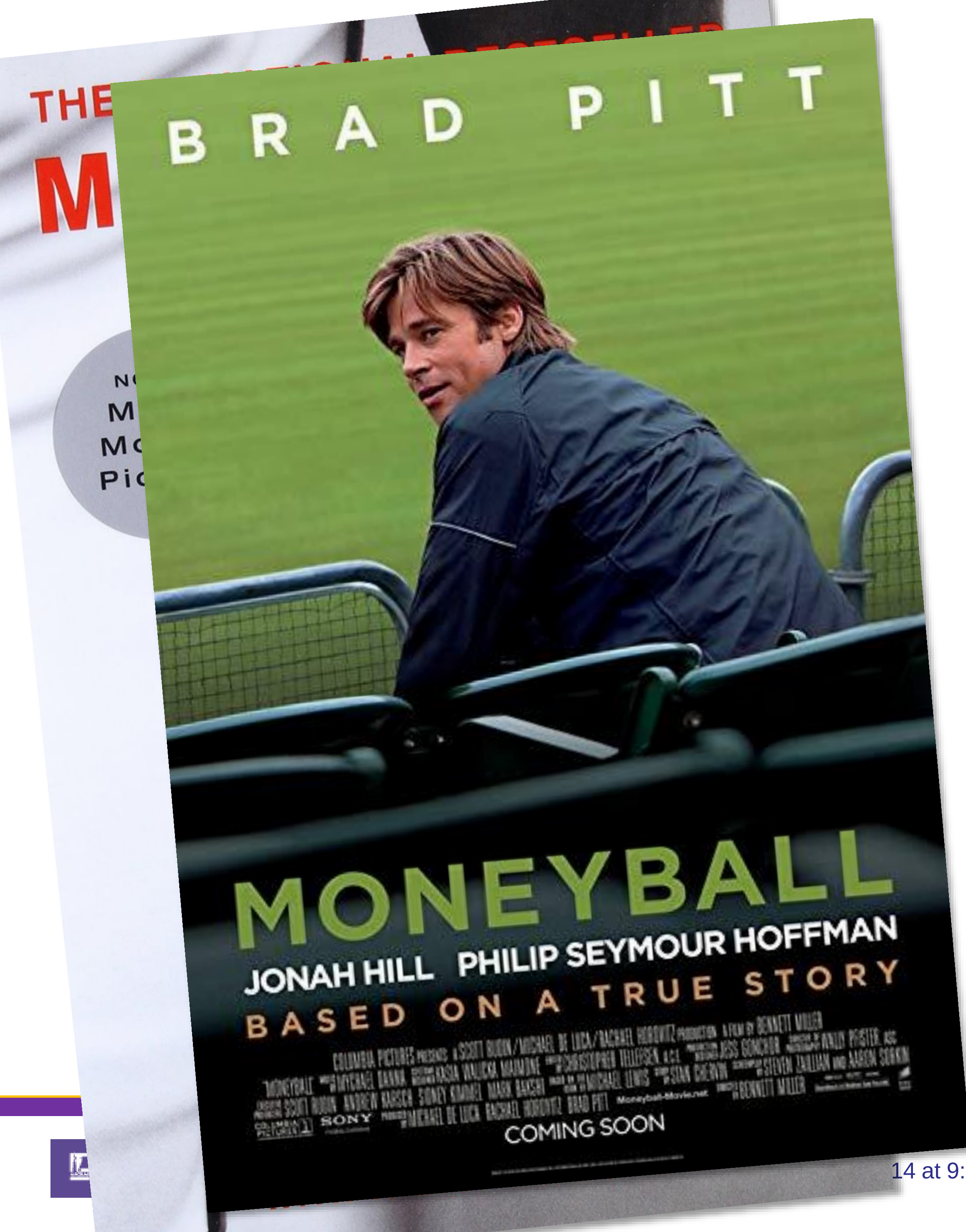
But is persistence enough?


THE #1 NATIONAL BESTSELLER
MICHAEL LEWIS
NOW A Major Motion Picture
Moneyball
WITH A NEW AFTERWORD


BRAD PITT
MONEYBALL
JONAH HILL PHILIP SEYMOUR HOFFMAN
BASED ON A TRUE STORY
COMING SOON

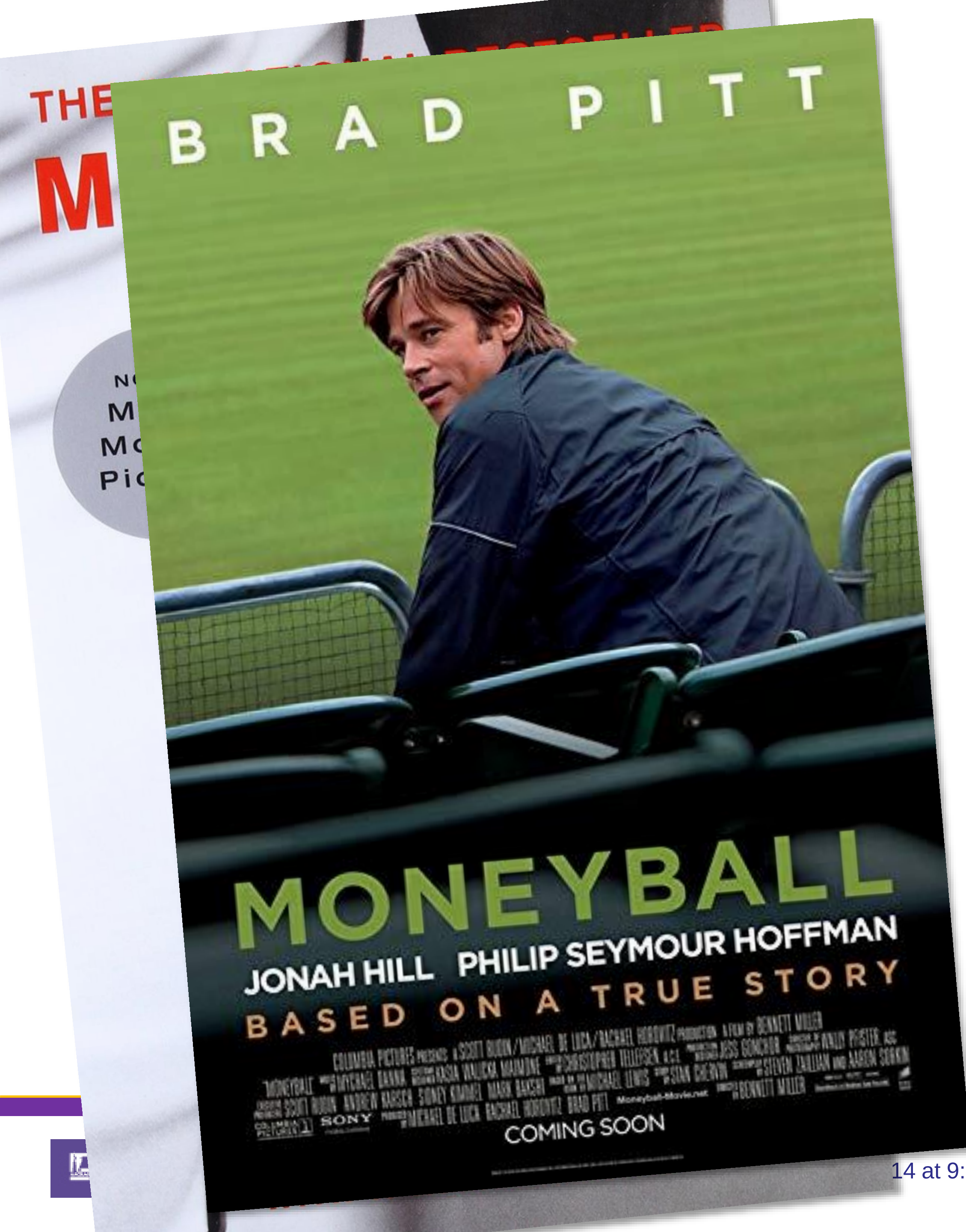


Moneyball **revolutionized the way major league baseball evaluates and rewards talent, moving away from traditional measures such as team batting average to more analytics-based metrics like OPS (on-base plus slugging), which correlate more closely to runs scored and wins.**



Moneyball revolutionized the way major league baseball evaluates and rewards talent, moving away from traditional measures such as team batting average to more analytics-based metrics like OPS (on-base plus slugging), which correlate more closely to runs scored and wins.

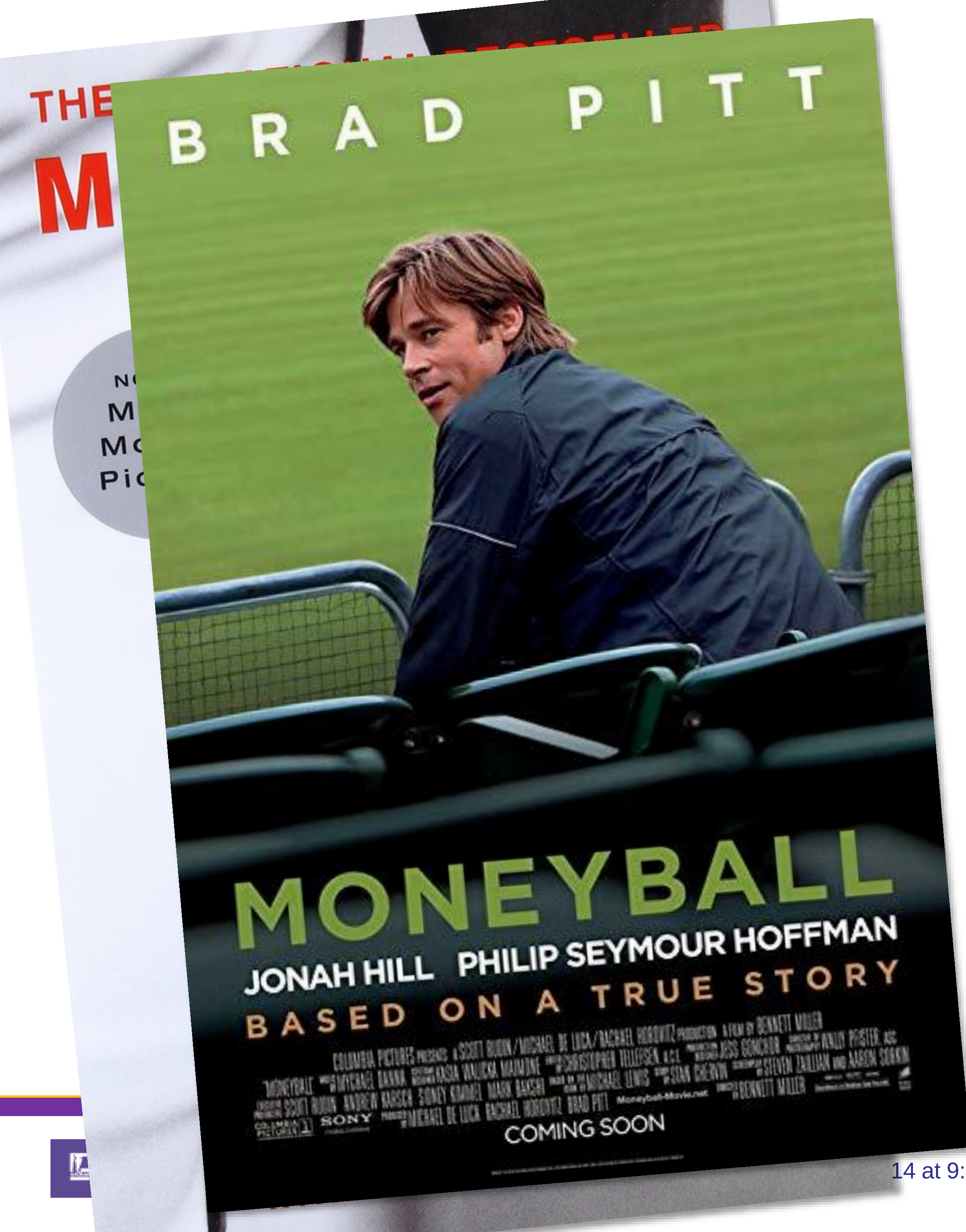
Modern day players are expected to get on base (i.e. persist) with more than just singles and walks.



Moneyball revolutionized the way major league baseball evaluates and rewards talent, moving away from traditional measures such as team batting average to more analytics-based metrics like OPS (on-base plus slugging), which correlate more closely to runs scored and wins.

Modern day players are expected to get on base (i.e. persist) with more than just singles and walks.

An occasional double or triple would be nice.

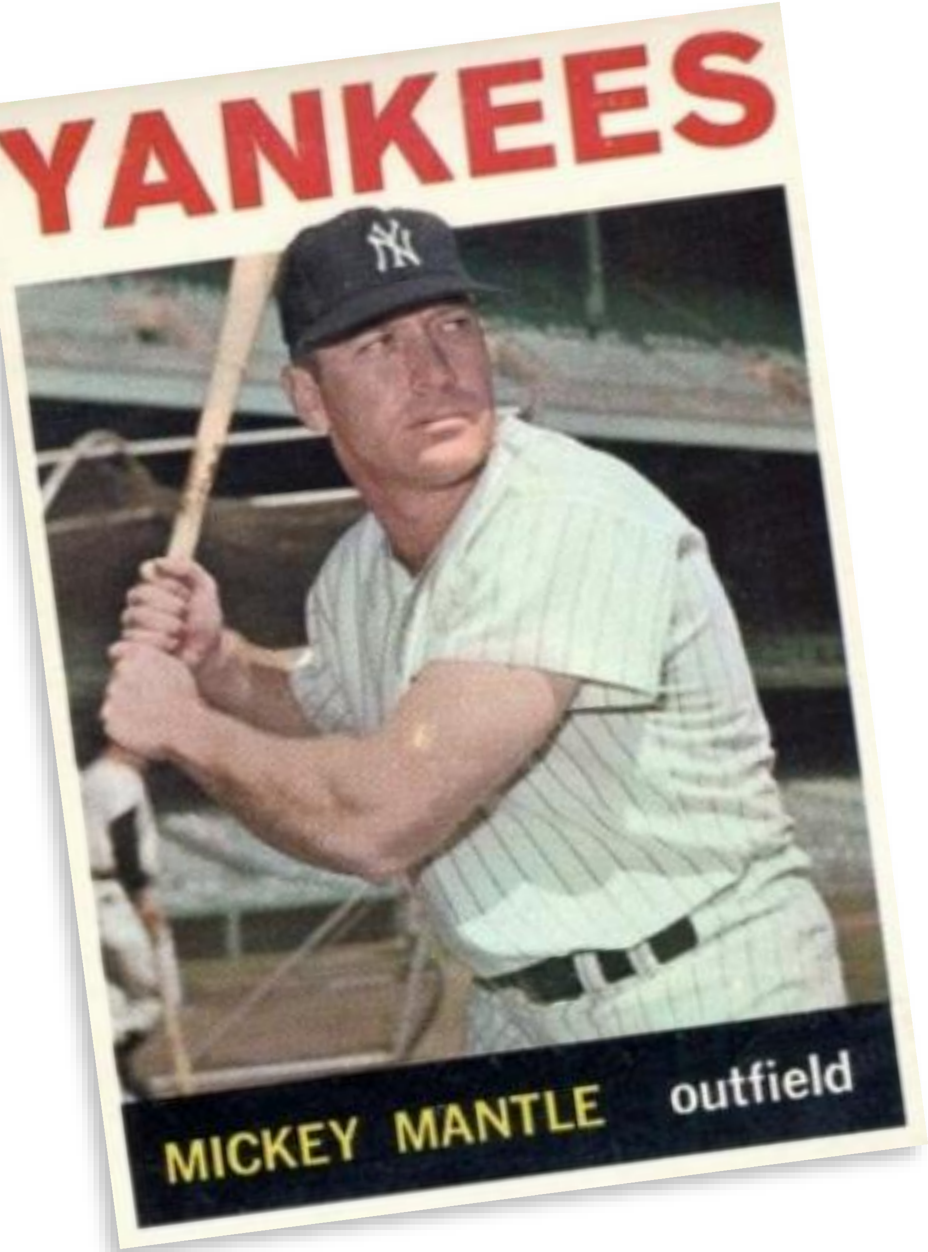


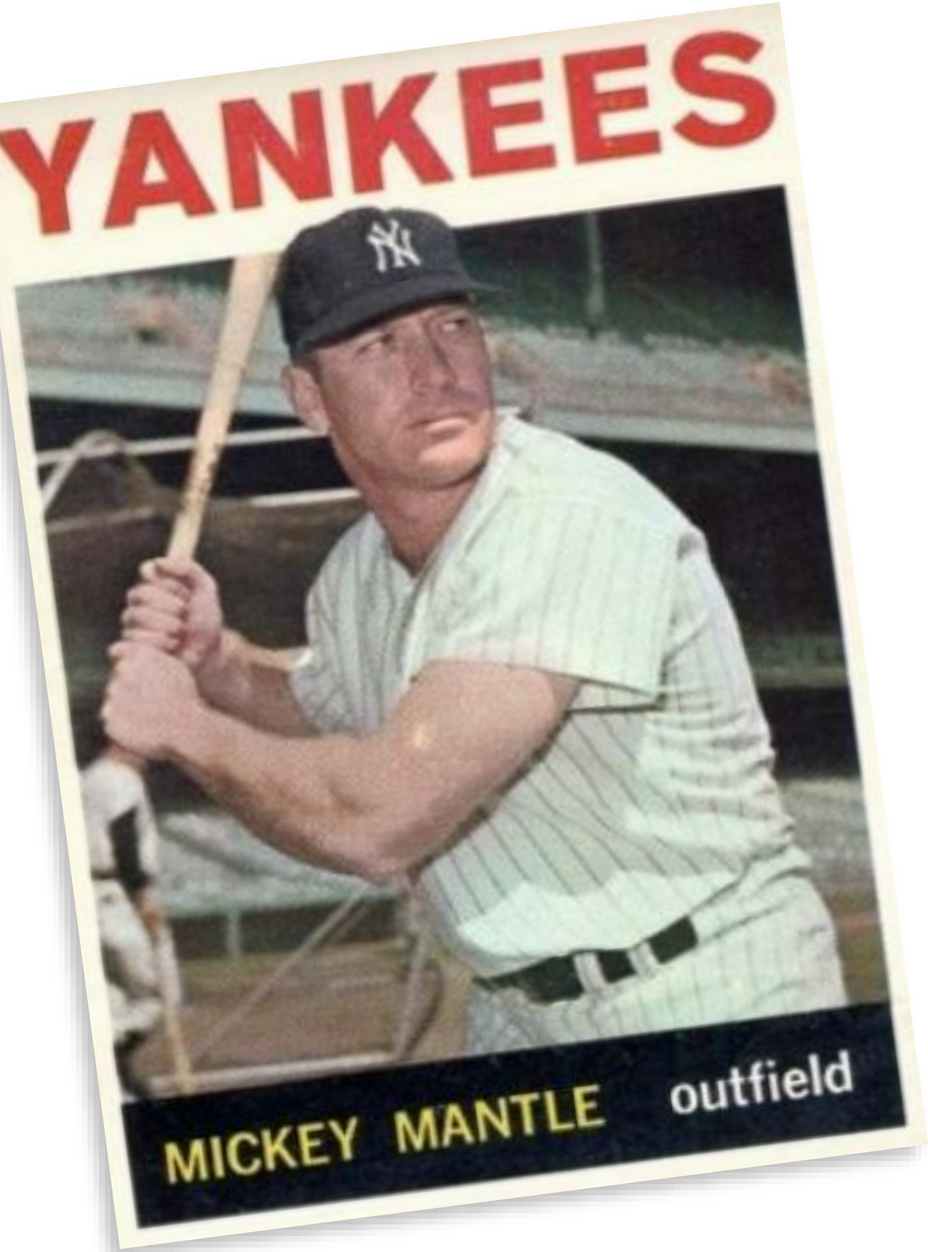
Moneyball revolutionized the way major league baseball evaluates and rewards talent, moving away from traditional measures such as team batting average to more analytics-based metrics like OPS (on-base plus slugging), which correlate more closely to runs scored and wins.

Modern day players are expected to get on base (i.e. persist) with more than just singles and walks.

An occasional double or triple would be nice.

Persist with power.


YANKEES
MICKEY MANTLE
outfield



OPS

Mickey Mantle **.977** **#11 Hall of Fame**

OPS

Mickey Mantle	.977	#11 Hall of Fame
Mike Trout	.990	#9 HOF lock

OPS

Mickey Mantle	.977	#11 Hall of Fame
Mike Trout	.990	$33 mm

OPS

Mickey Mantle	.977	#11 Hall of Fame
Mike Trout	.990	$33 mm
Marwin Gonzalez	.737	Top 1000 = .741

OPS

Mickey Mantle	.977	#11 Hall of Fame
Mike Trout	.990	$33 mm
Marwin Gonzalez	.737	$5 mm

OPS

Mickey Mantle	.977	#11 Hall of Fame
Mike Trout	.990	$33 mm
Marwin Gonzalez	.737	$5 mm

75% of the production for 15% of the cost.

OPS

Mickey Mantle	.977	#11 Hall of Fame
Mike Trout	.990	$33 mm
Marwin Gonzalez	.737	$5 mm
Babe Ruth	1.164	#1 Hall of Fame

OPS

Mickey Mantle	.977	#11 Hall of Fame
Mike Trout	.990	$33 mm
Marwin Gonzalez	.737	$5 mm
Babe Ruth	1.164	#1 Hall of Fame

Attract, Retain, Graduate Undervalued Students who

Persist with Power

P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
0.50	.	0.333	0.563	0.523	0.480	0.000	.
0.55	.	0.000	0.620	0.560	0.558	0.667	.
0.60	.	0.600	0.676	0.646	0.818	0.333	1.000
0.65	.	0.500	0.606	0.635	0.629	0.333	.
0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

P2 rates among matriculants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	0.750	1.000	.	.
0.30	.	.	.	0.545	0.500	.	.
0.35	.	1.000	0.455	0.357	0.167	.	.
0.40	.	1.000	0.333	0.519	0.400	.	.
0.45	.	0.000	0.551	0.454	0.566	0.250	.
0.50	.	0.333	0.563	0.523	0.480	0.000	.
0.55	.	0.000	0.620	0.560	0.558	0.667	.
0.60	.	0.600	0.676	0.646	0.818	0.333	1.000
0.65	.	0.500	0.606	0.635	0.629	0.333	.
0.70	.	1.000	0.750	0.786	0.920	.	.
0.75	.	1.000	0.759	0.845	0.783	1.000	.
0.80	.	.	1.000	0.818	1.000	.	.
0.85	.	.	.	.	.	.	.

P2 avg

.420

.780

SCH2 Two Year Semester Credit Hour Production per matriculant

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20							
0.25		.	.	.	.	.	
0.30		.	.	18	.	.	
0.35		47	20	15	10	.	
0.40		22	12	24	19	.	
0.45		.	26	23	32	.	
0.50		22	30	28	26	.	
0.55		.	34	31	32	29	
0.60		68	41	37	48	26	
0.65		38	43	43	40	35	
0.70		64	53	51	60	.	
0.75		74	62	58	50	78	
0.80		.	54	63	63	.	
0.85		.	.	.	.	.	

SCH2 avg

20

51

"Slugging" Percentage (actual SCH2 / expected SCH2)

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20							
0.25							
0.30				0.300	.	.	
0.35		0.783	0.325	0.253	0.160	.	
0.40		0.367	0.202	0.408	0.312	.	
0.45		.	0.428	0.376	0.534	.	
0.50		0.361	0.497	0.467	0.430	.	
0.55		.	0.572	0.514	0.528	0.475	
0.60		1.125	0.675	0.618	0.793	0.429	
0.65		0.625	0.724	0.710	0.661	0.575	
0.70		1.067	0.888	0.858	1.001	.	
0.75		1.233	1.029	0.967	0.835	1.300	
0.80		.	0.894	1.047	1.054	.	
0.85							

SLG avg

.333

.850

"Slugging" Percentage (actual SCH2 / expected SCH2)

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20							
0.25							
0.30				0.300	.	.	
0.35		0.783	0.325	0.253	0.160	.	
0.40		0.367	0.202	0.408	0.312	.	
0.45		.	0.428	0.376	0.534	.	
0.50		0.361	0.497	0.467	0.430	.	
0.55		.	0.572	0.514	0.528	0.475	
0.60		1.125	0.675	0.618	0.793	0.429	
0.65		0.625	0.724	0.710	0.661	0.575	
0.70		1.067	0.888	0.858	1.001	.	
0.75		1.233	1.029	0.967	0.835	1.300	
0.80		.	0.894	1.047	1.054	.	
0.85							

SLG avg	P2 avg
.333	.420
.850	.780

“Slugging” Percentage (actual SCH2 / expected SCH2)

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20							
0.25							
0.30				0.300	.	.	
0.35		0.783	0.325	0.253	0.160	.	
0.40		0.367	0.202	0.408	0.312	.	
0.45		.	0.428	0.376	0.534	.	
0.50		0.361	0.497	0.467	0.430	.	
0.55		.	0.572	0.514	0.528	0.475	
0.60		1.125	0.675	0.618	0.793	0.429	
0.65		0.625	0.724	0.710	0.661	0.575	
0.70		1.067	0.888	0.858	1.001	.	
0.75		1.233	1.029	0.967	0.835	1.300	
0.80		.	0.894	1.047	1.054	.	
0.85							

POWER SLG avg	+	PERSIST P2 avg	=	**OPS**
.333		.420		.753
.850		.780		1.630

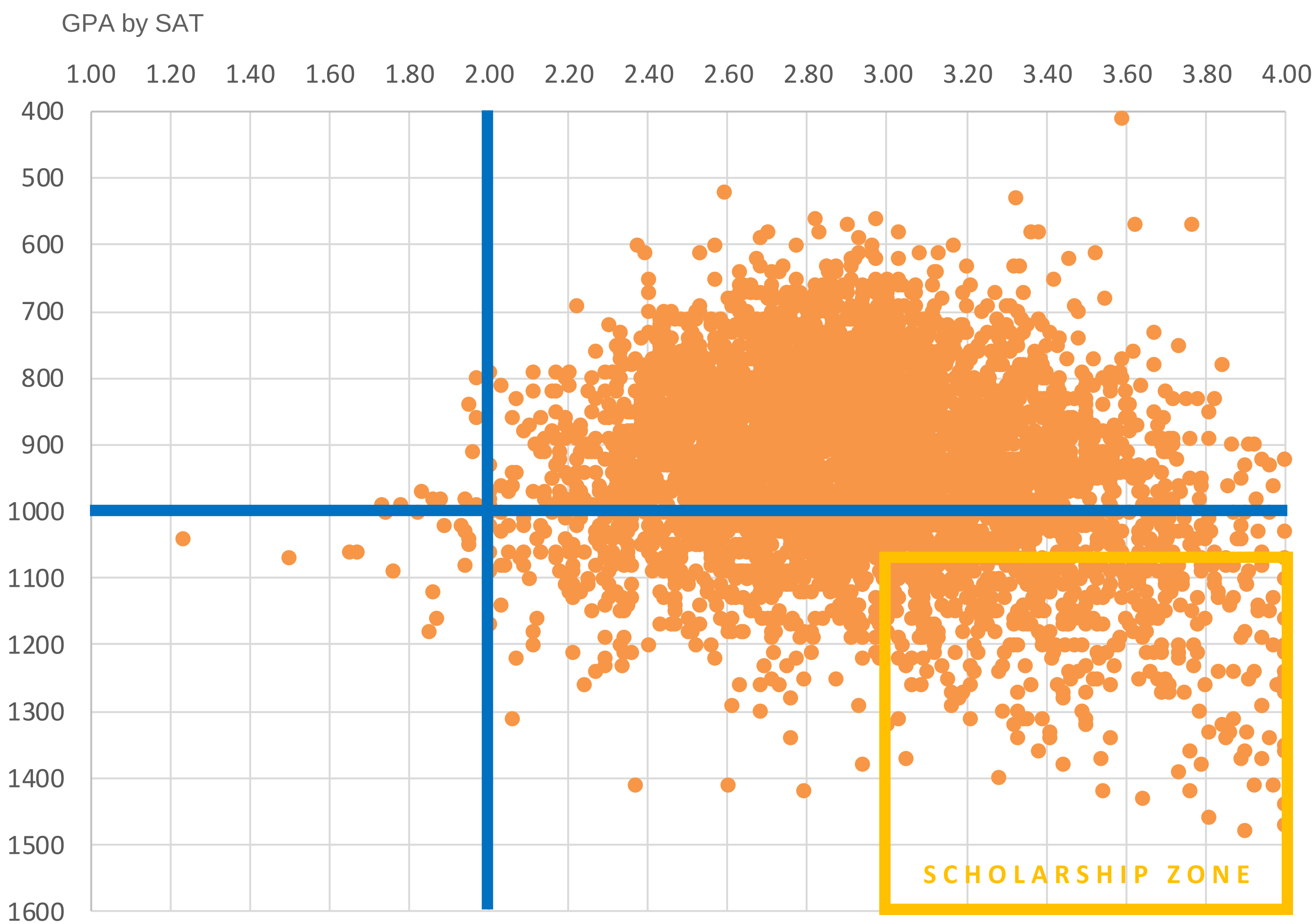
REVENUE per matriculant

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20							
0.25				.			
0.30				4957			
0.35		12943	5370	4177	2644		
0.40		6059	3346	6738	5160		
0.45		.	7068	6212	8818	.	
0.50		5967	8207	7715	7112	.	
0.55		.	9444	8496	8721	7849	
0.60		18589	11156	10219	13105	7091	
0.65		10327	11956	11735	10927	9501	
0.70		17625	14675	14173	16535		
0.75		20379	17011	15977	13792	21480	
0.80			14779	17294	17418		
0.85							

REV avg

$5,504

$14,050

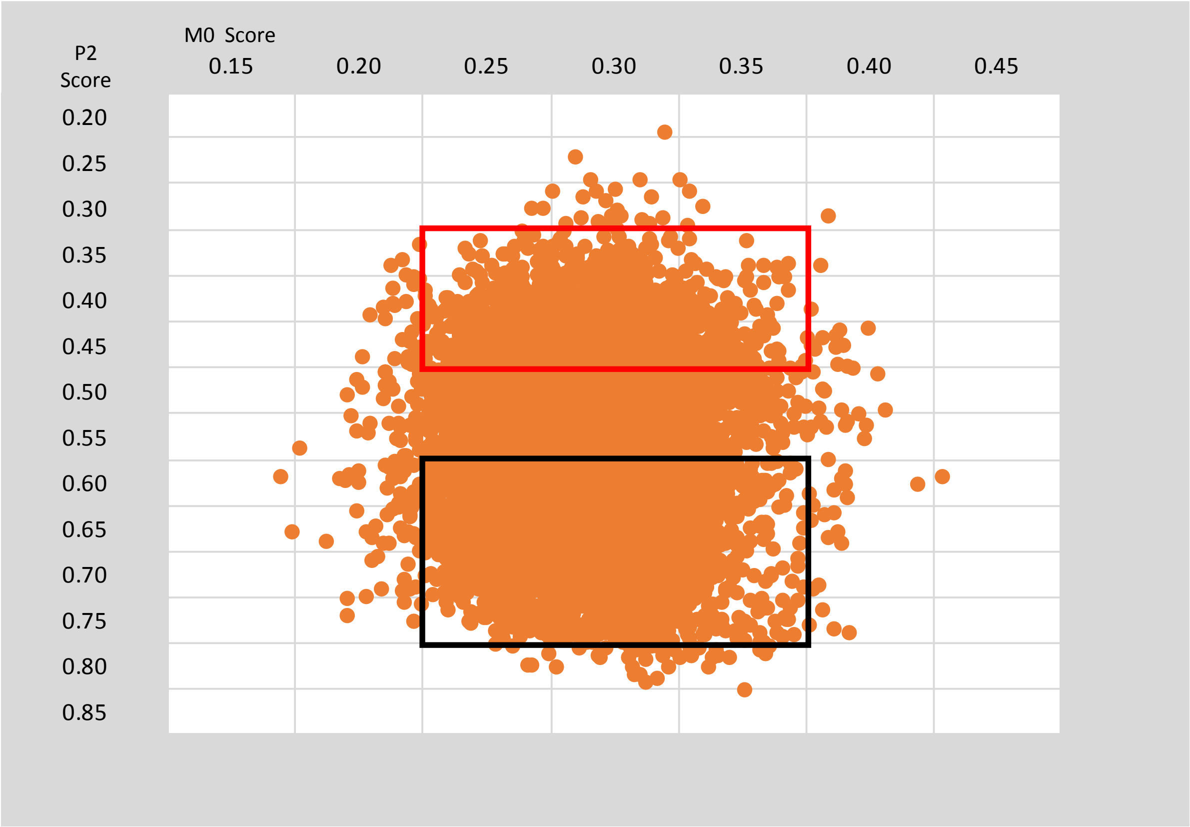


U3+U12

FTIC Applicants
FA13 to FA15

*Previous approach used the **"Flag of Finland"** to subdivide group into regular admits (U3) and provisionals (U12), and focused scholarship awards on higher gpa and sat areas.*

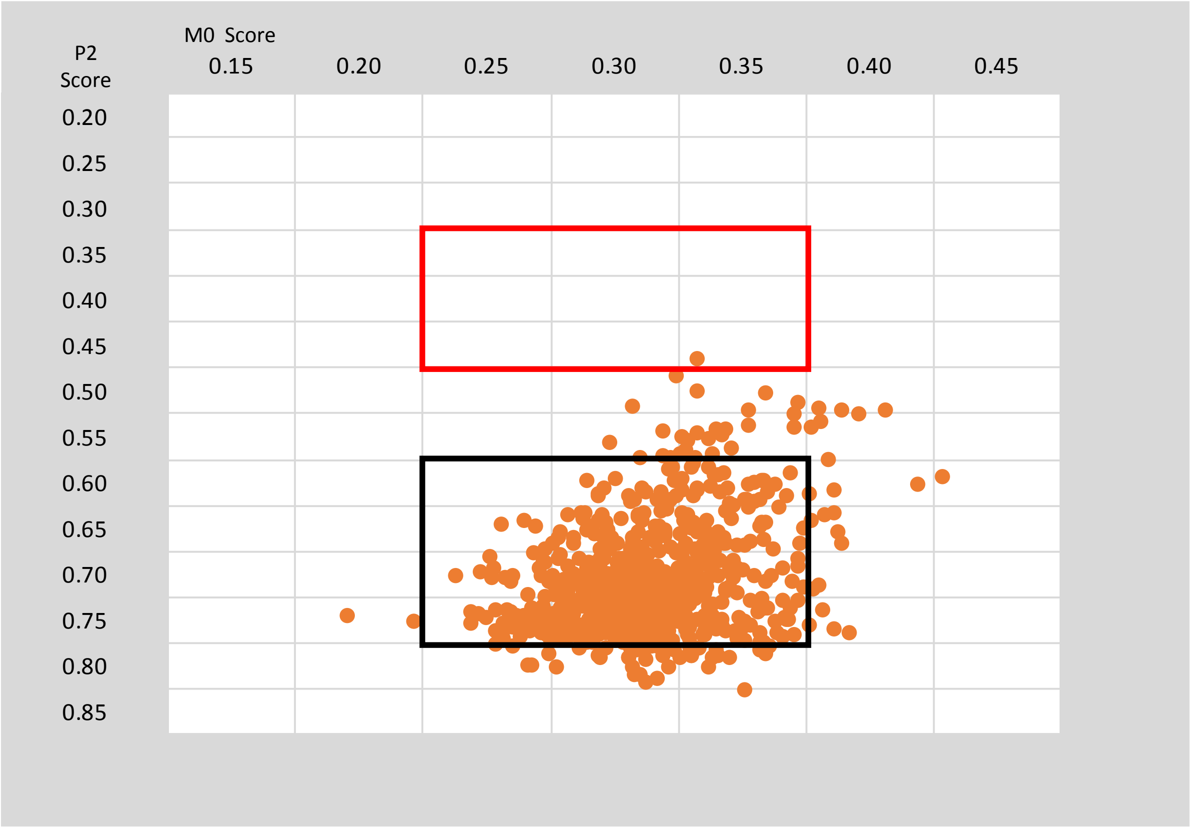
Applicants FA13-FA15



Applicants FA13-FA15

SAT 1700+

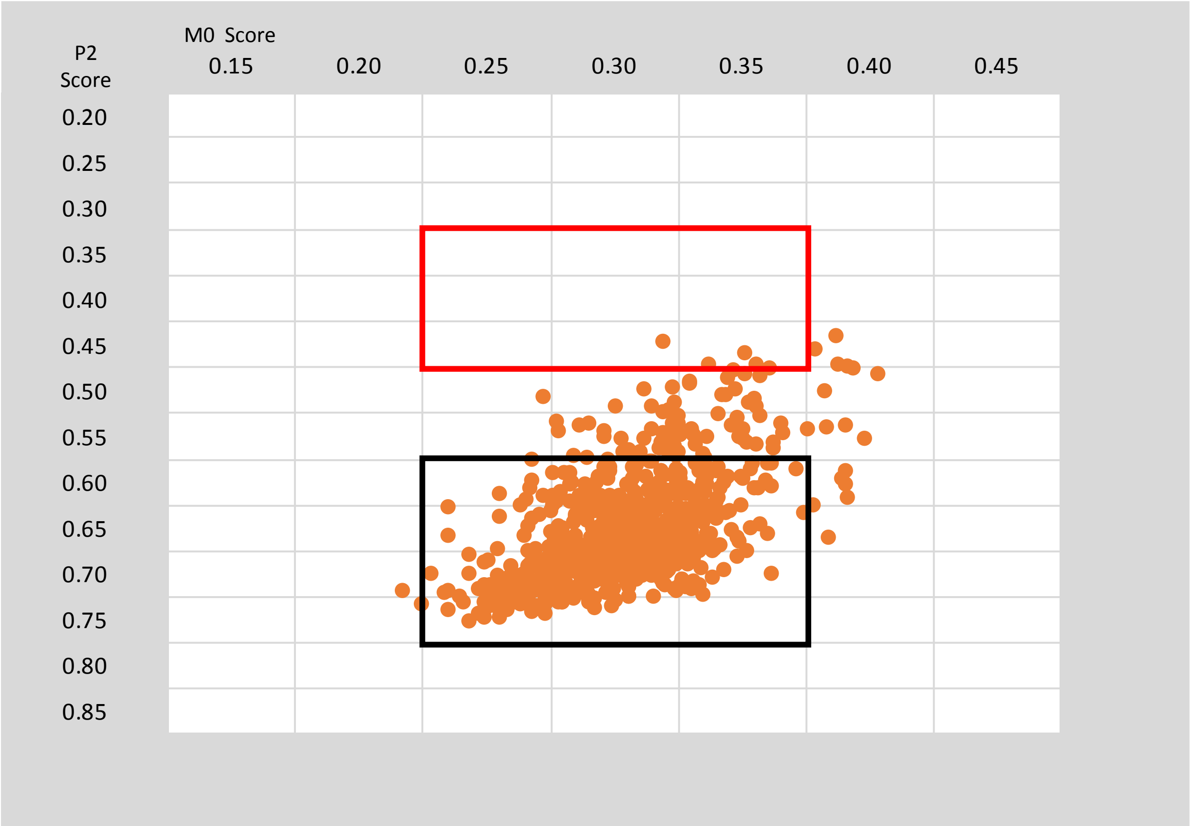
Highest scholarship
previously



Applicants FA13-FA15

SAT 1100-1169

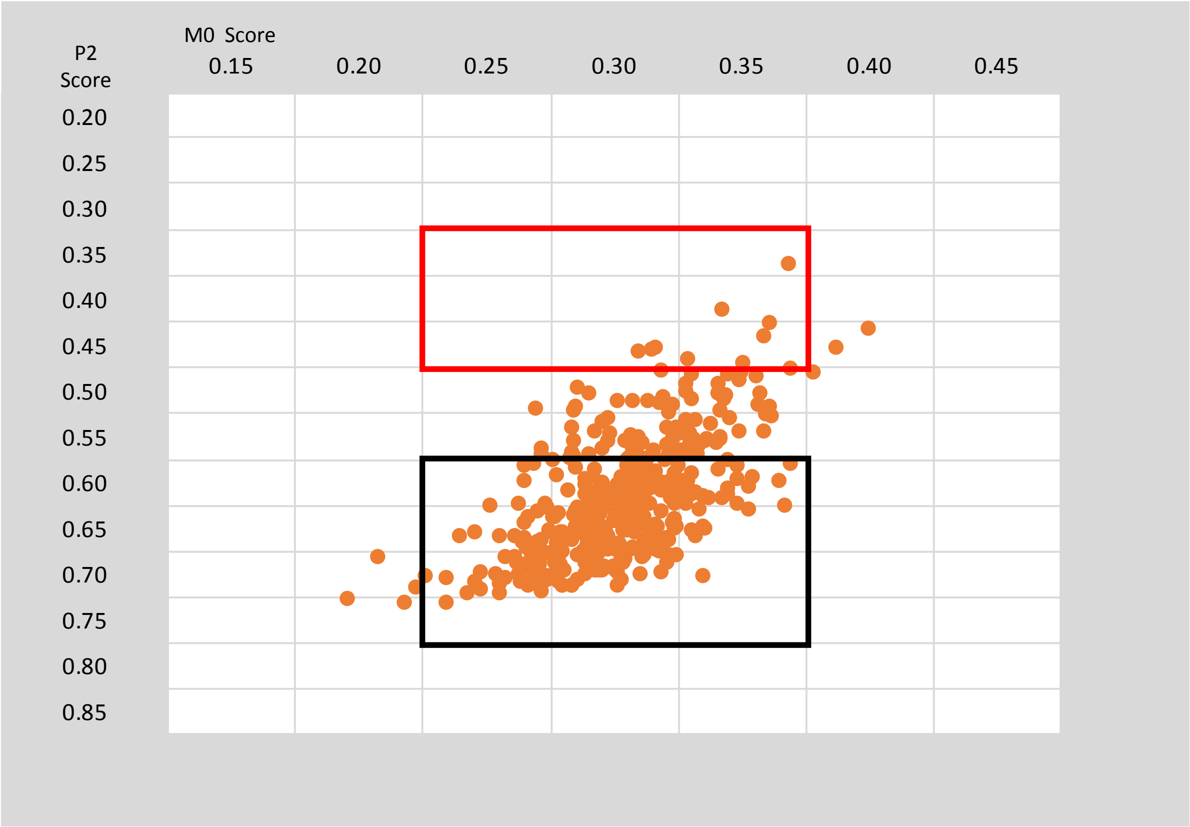
Middle scholarship
previously



Applicants FA13-FA15

SAT 1070-1099

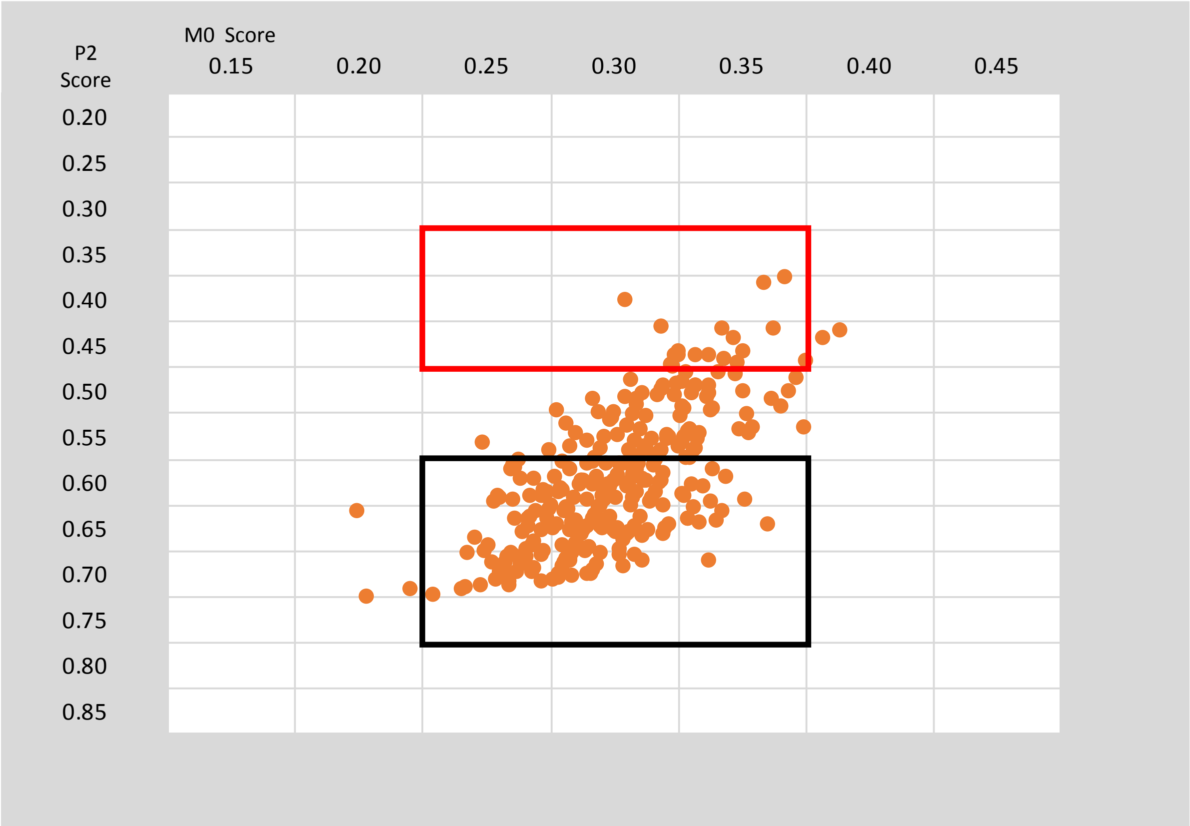
Lowest scholarship previously



Applicants FA13-FA15

SAT 1050-1069

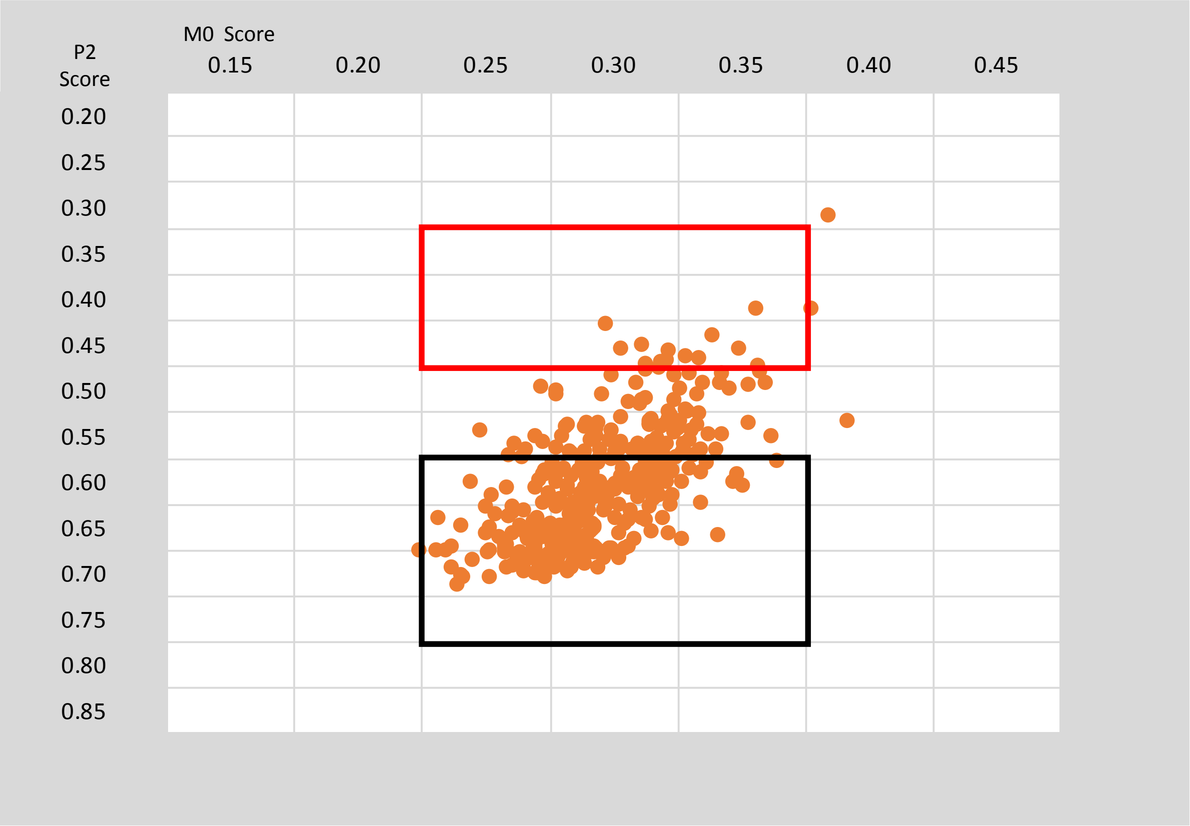
No scholarships
previously



Applicants FA13-FA15

SAT 1030-1049

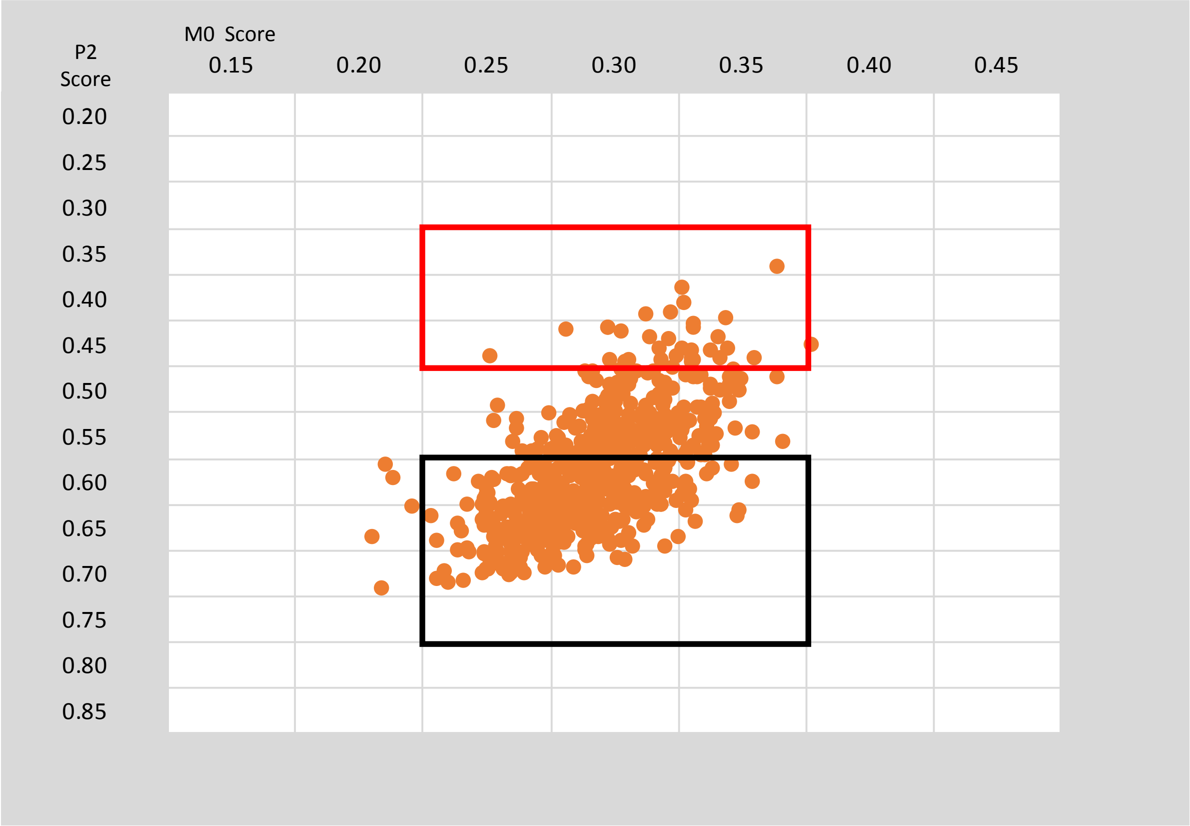
No scholarships previously



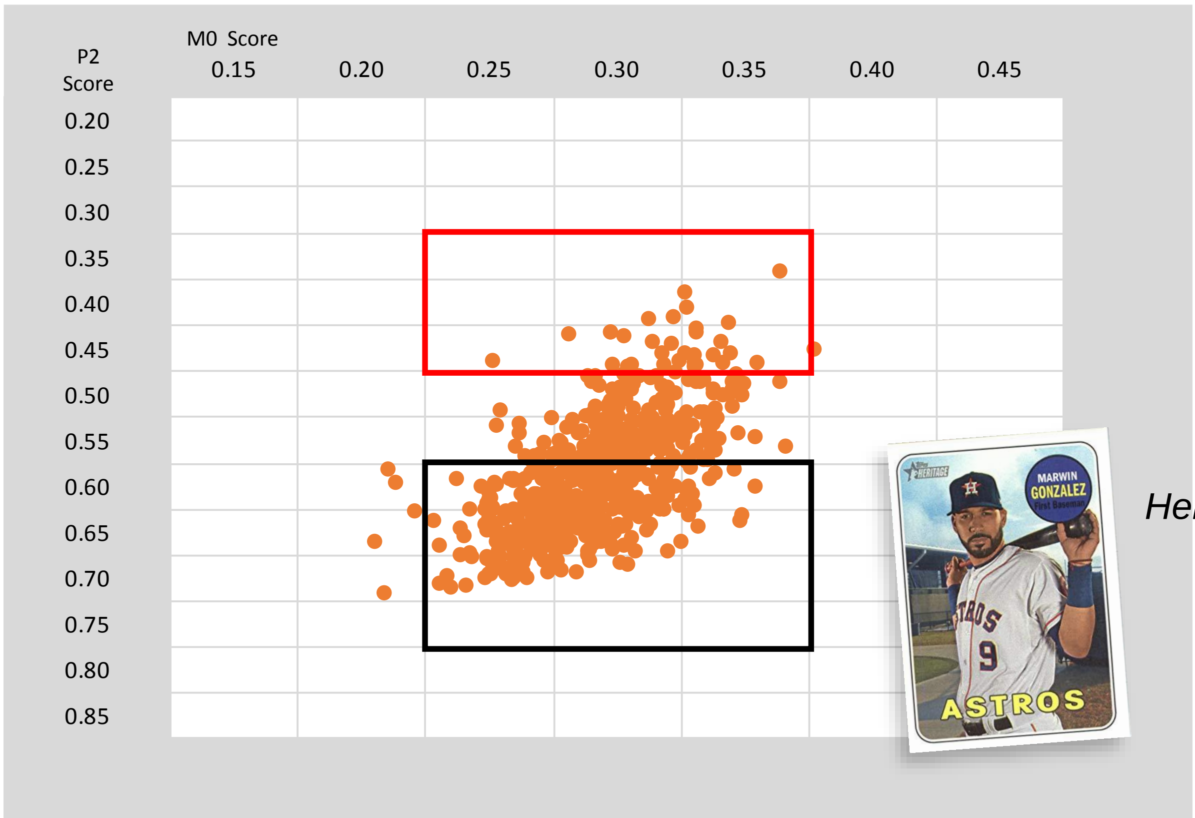
Applicants FA13-FA15

SAT 1000-1029

No scholarships
previously



Applicants FA13-FA15 *SAT 1000-1029*

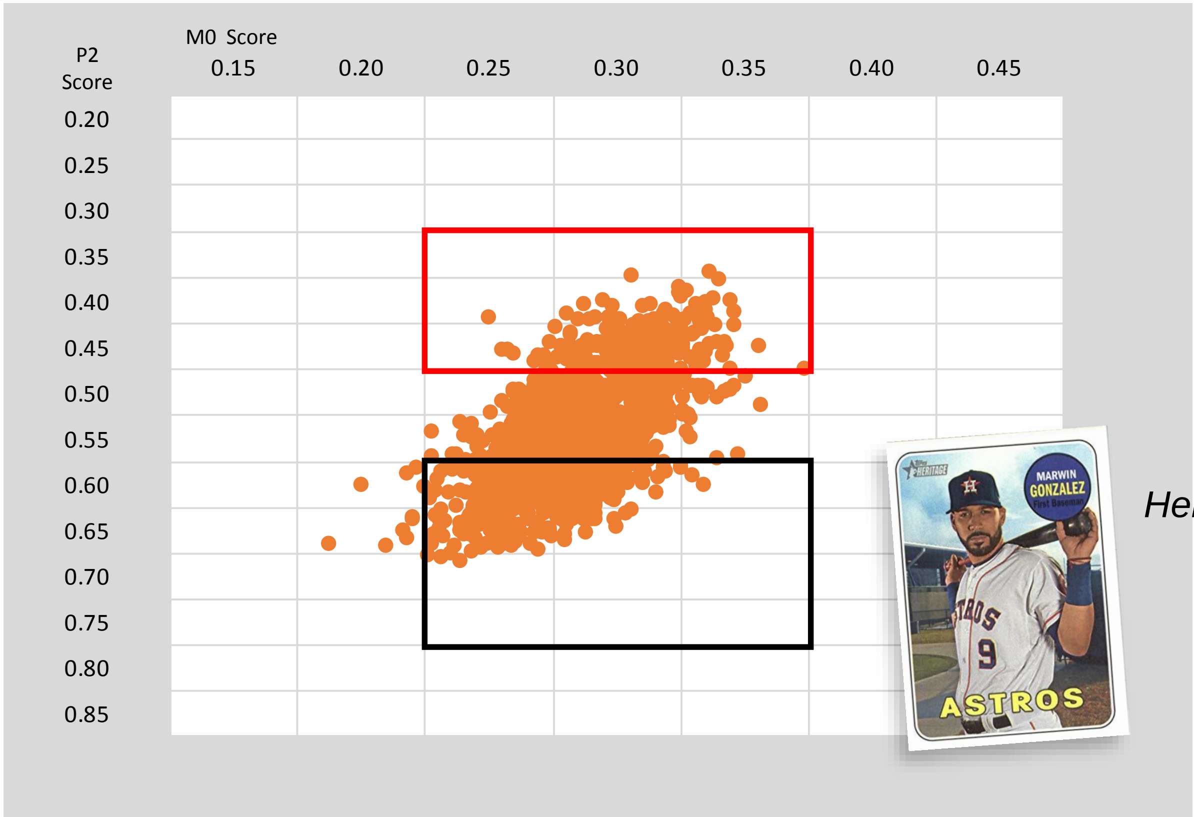


Hello, Marwin Gonzalez.

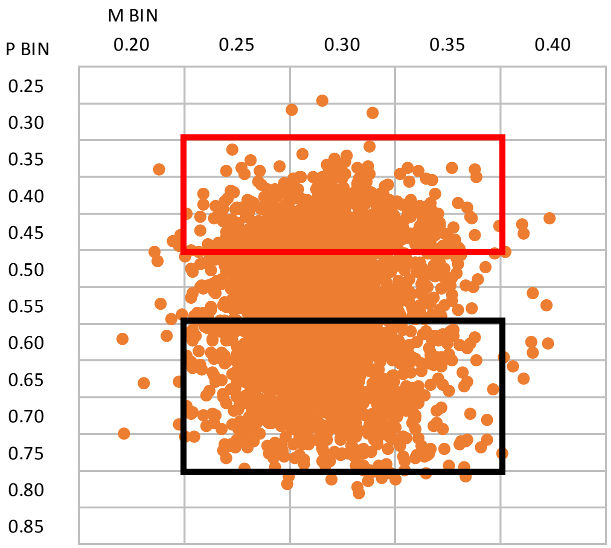
Applicants FA13-FA15

SAT 900-949

Provisional status
previously



Hello, Marwin Gonzalez.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P BIN
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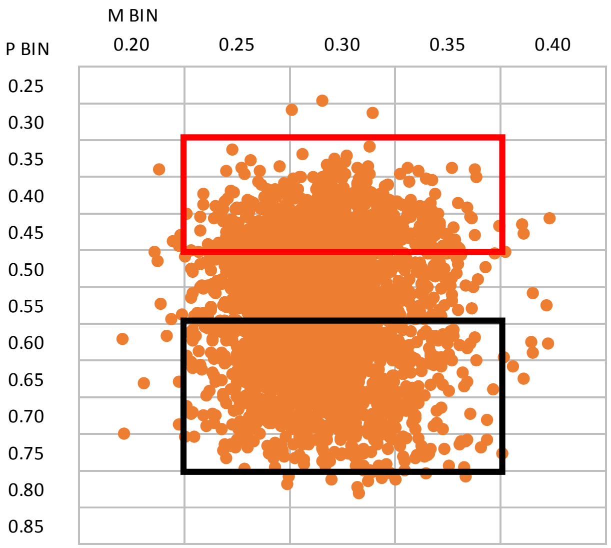
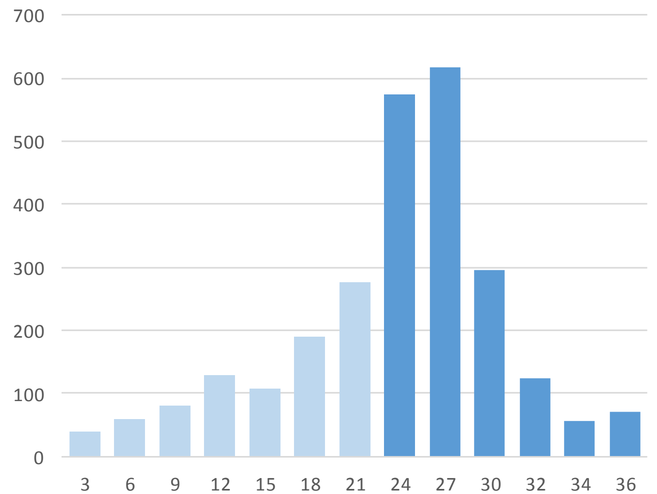
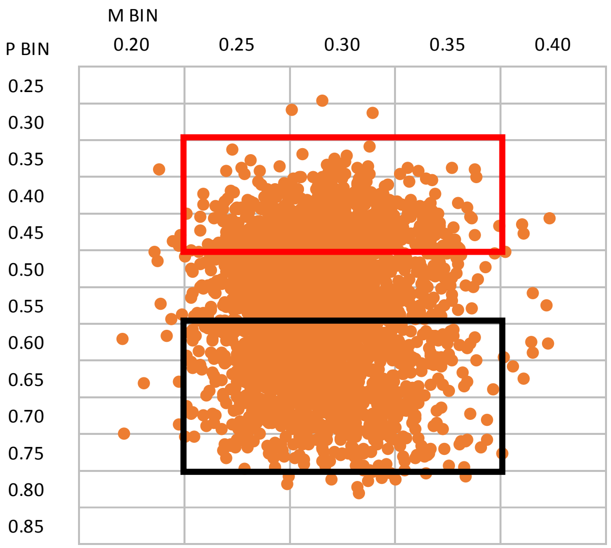
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85

N	24+	27+	30+
2622	0.664	0.445	0.209



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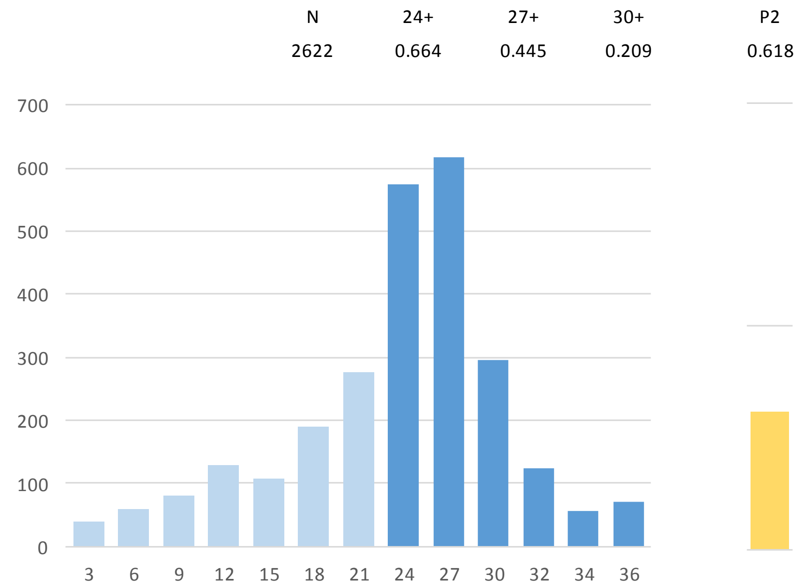
N
2622
24+
0.664
27+
0.445
30+
0.209
P2
0.618
700
600
500
400
300
200
100
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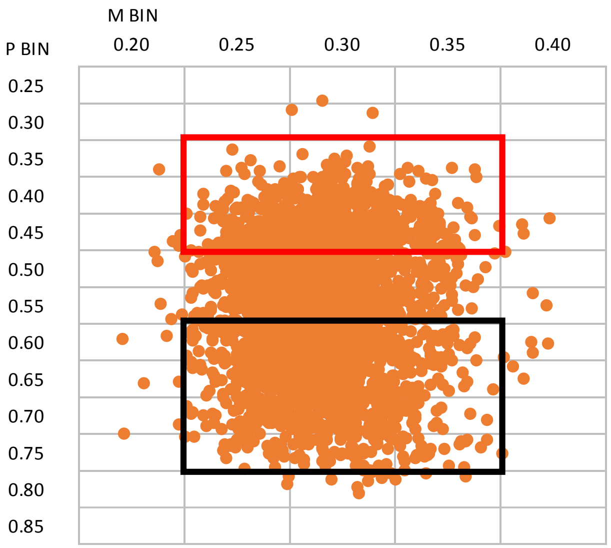
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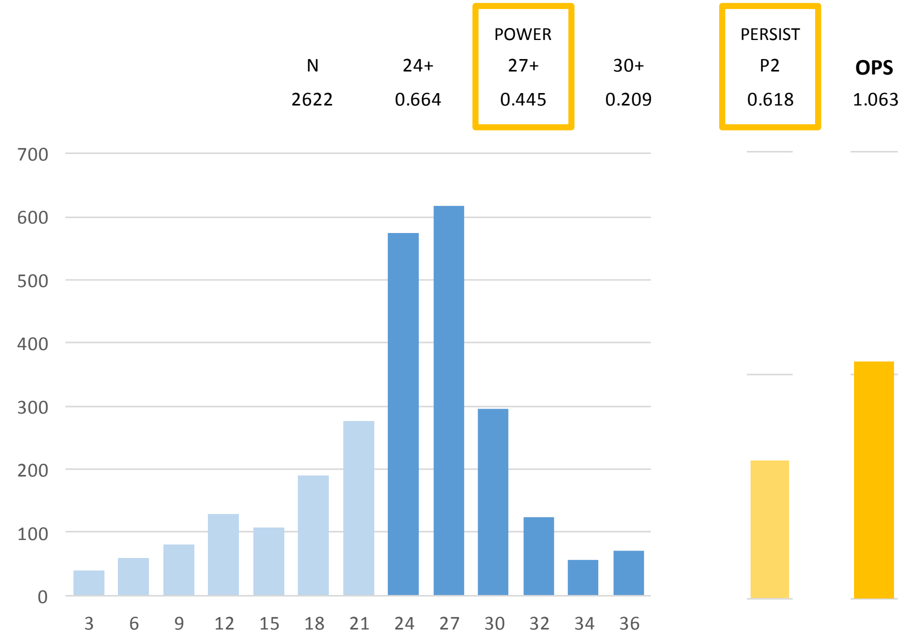
0.75
0.80
0.85


N
2622
24+
0.664
POWER
27+
0.445
30+
0.209
PERSIST
P2
0.618
OPS
1.063
700
600
500
400
300
200
100
0
3
6
9
12
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18
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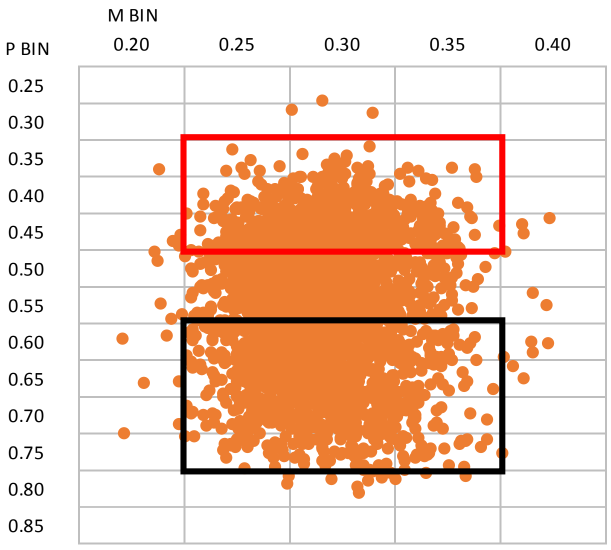
36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P BIN
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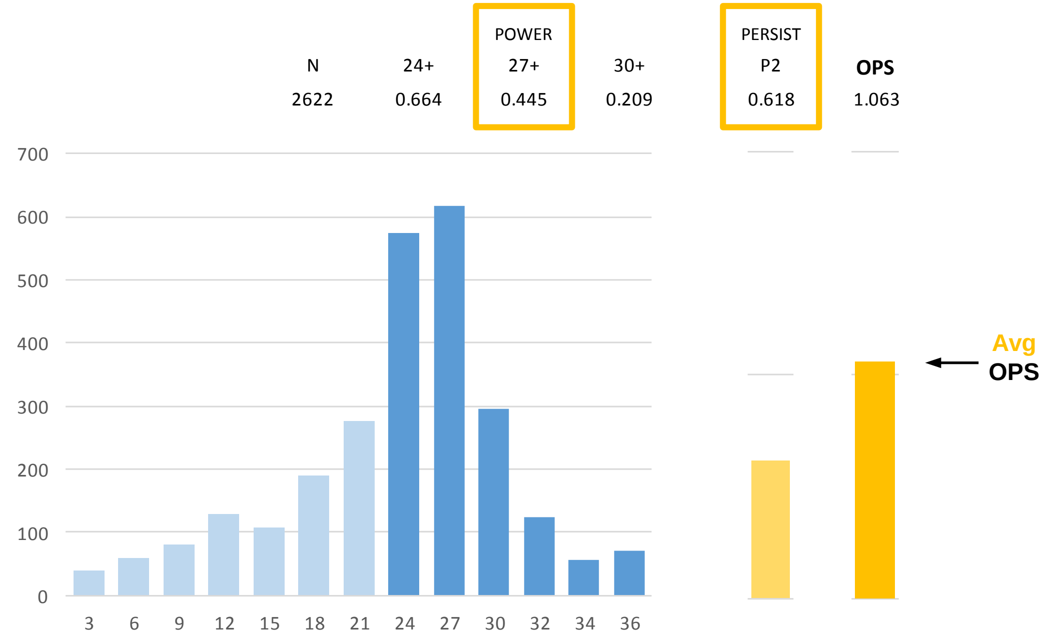
0.75
0.80
0.85


N
2622
24+
0.664
POWER
27+
0.445
30+
0.209
PERSIST
P2
0.618
OPS
1.063
Avg
OPS
0
100
200
300
400
500
600
700
3
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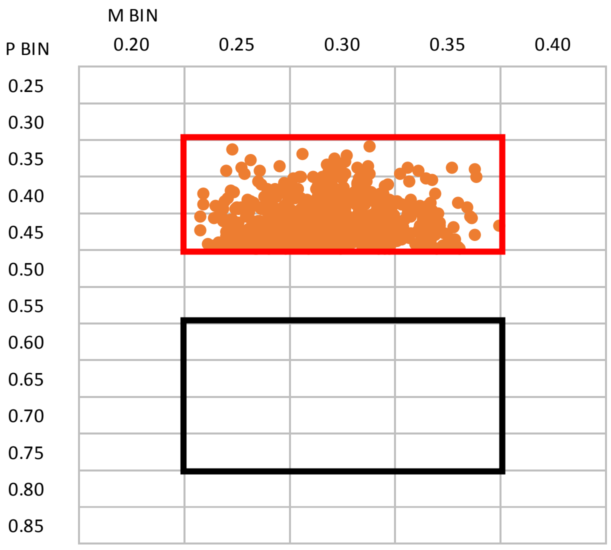

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0.40
P BIN
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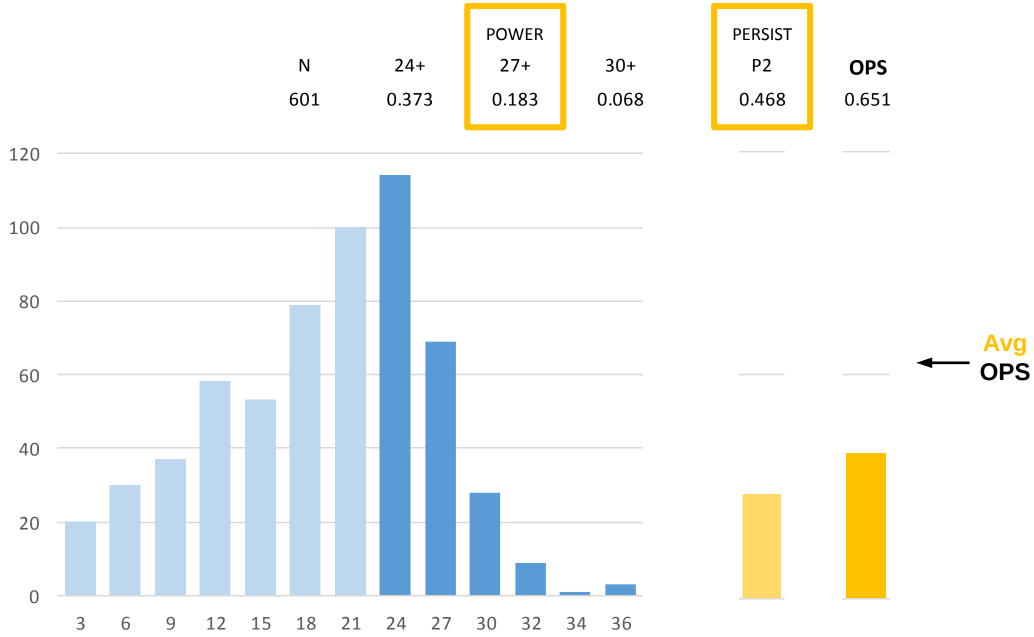
0.65
0.70
0.75
0.80
0.85



N
601
24+
0.373
POWER
27+
0.183
30+
0.068
PERSIST
P2
0.468
OPS
0.651
120
100
80
60
40
20
0
3
6
9
12
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18
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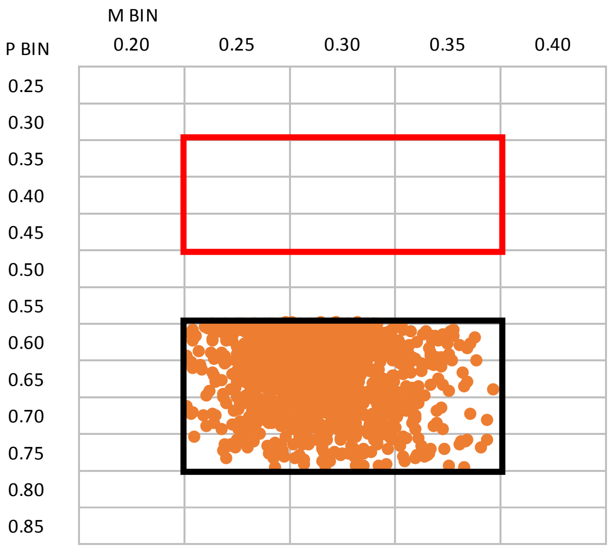
32
34
36
Avg
OPS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P BIN
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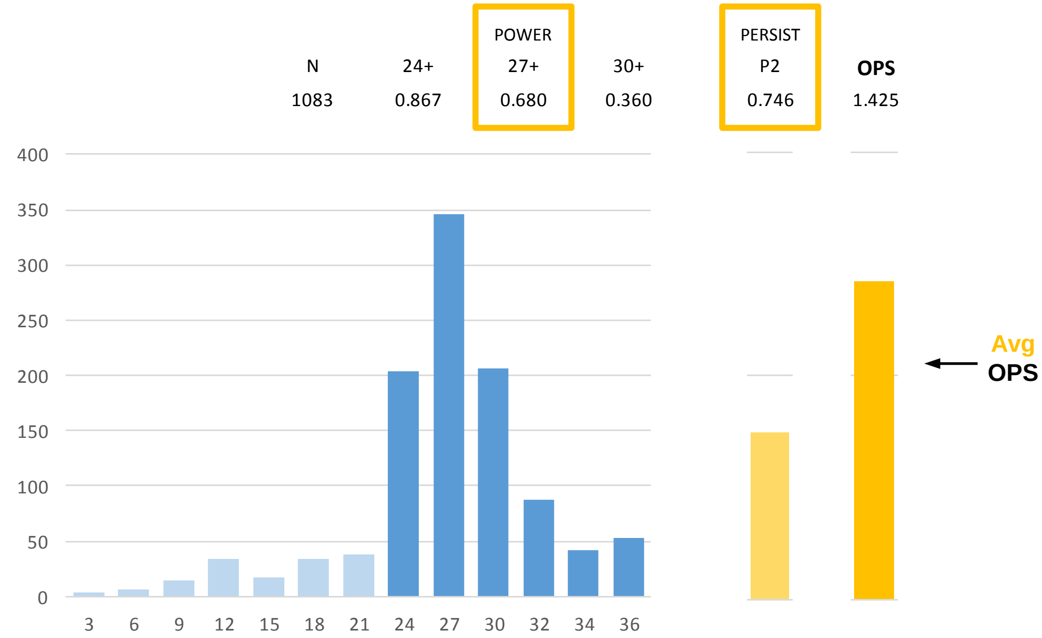
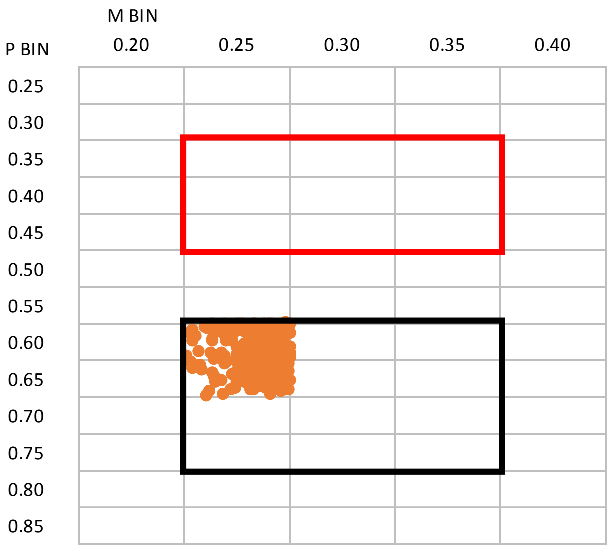
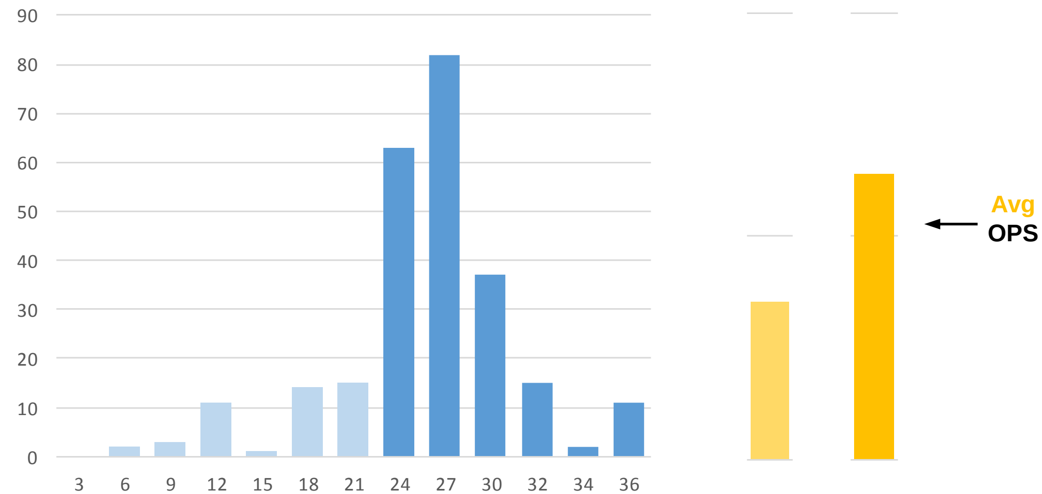
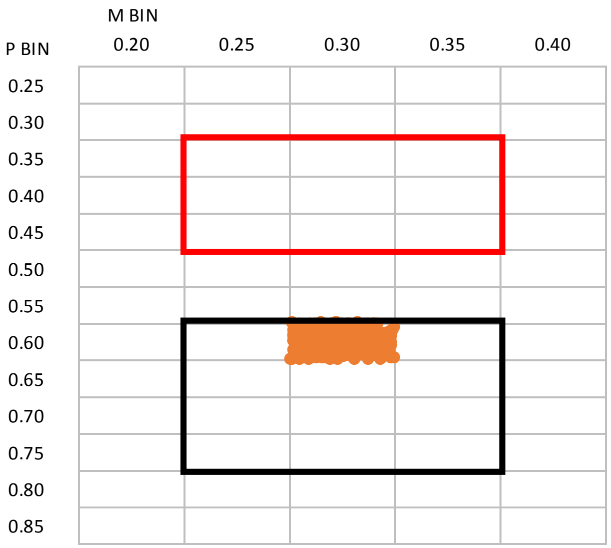
0.55
0.60
0.65
0.70
0.75
0.80
0.85


N
1083
24+
0.867
POWER
27+
0.680
30+
0.360
PERSIST
P2
0.746
OPS
1.425
400
350
300
250
200
150
100
50
0
3
6
9
12
15
18
21
24
27
30
32
34
36
Avg
OPS

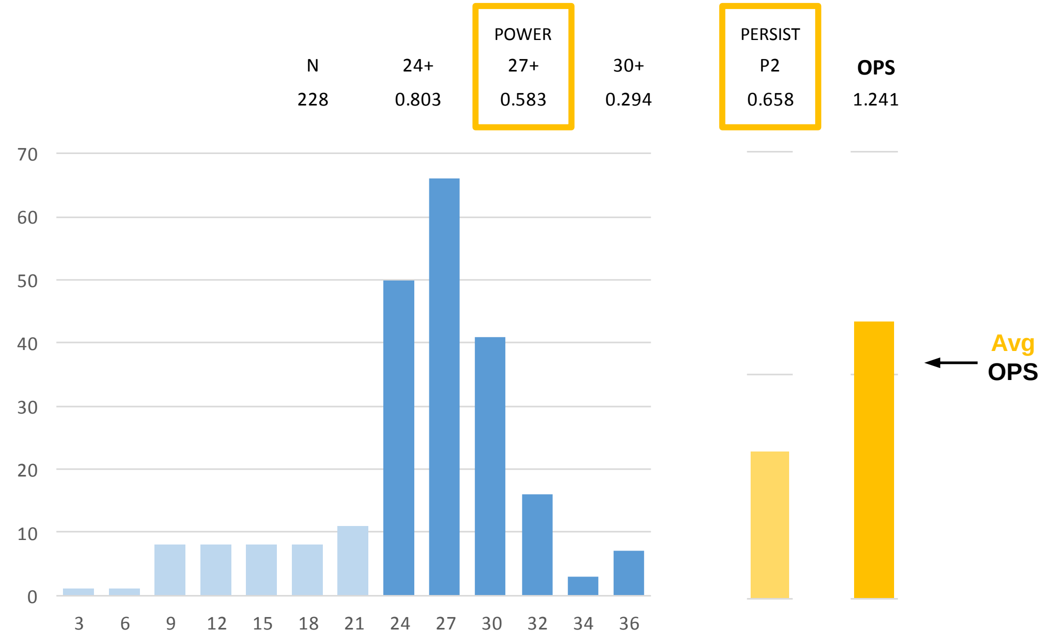
N	24+	POWER 27+	30+	PERSIST P2	OPS
256	0.820	0.574	0.254	0.704	1.278







M BIN
0.20
0.25
0.30
0.35
0.40
P BIN
0.25
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85



N
228
24+
0.803
POWER
27+
0.583
30+
0.294
PERSIST
P2
0.658
OPS
1.241
70
60
50
40
30
20
10
0
3
6
9
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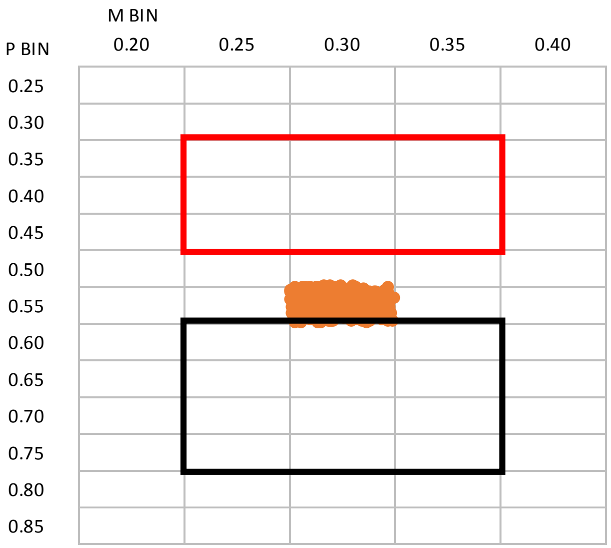
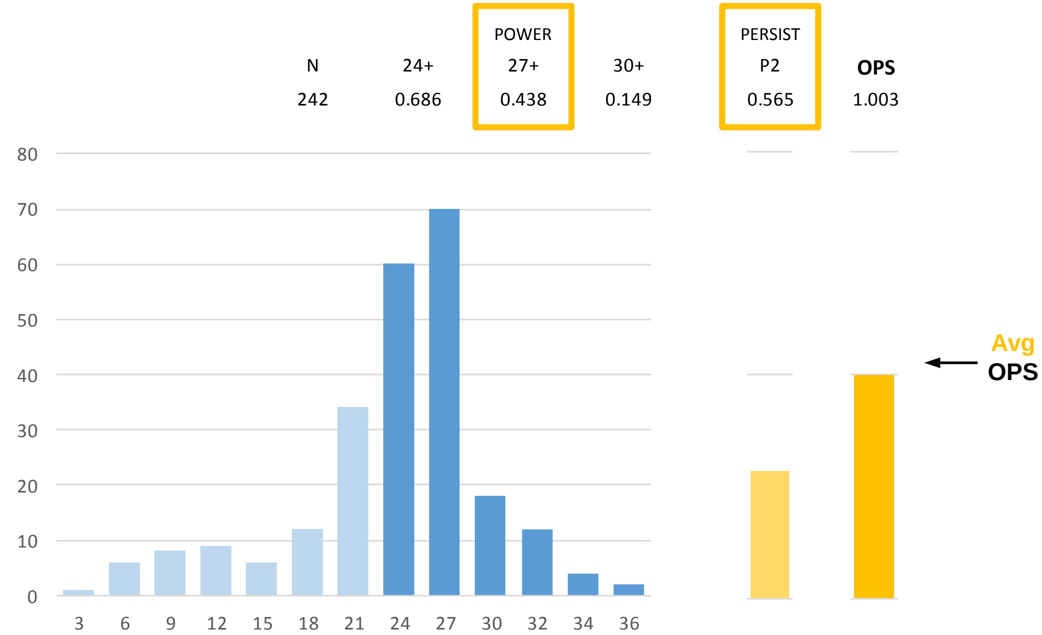
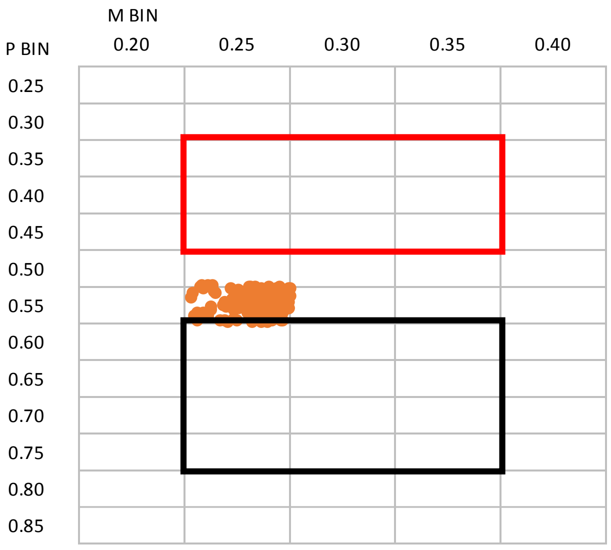
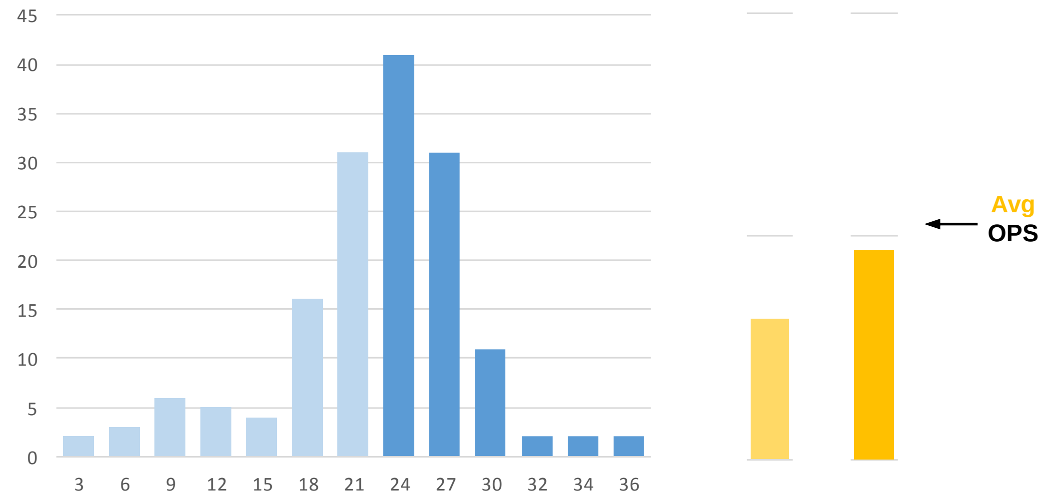
24
27
30
32
34
36
Avg
OPS

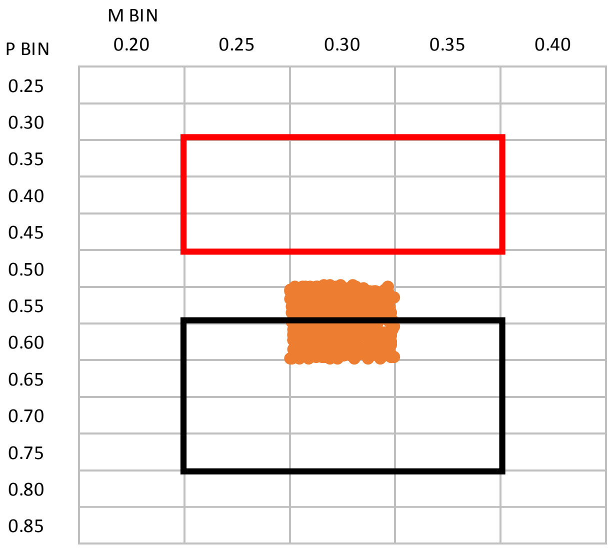

M BIN
0.20
0.25
0.30
0.35
0.40
P BIN
0.25
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85


N
242
24+
0.686
POWER
27+
0.438
30+
0.149
PERSIST
P2
0.565
OPS
1.003
80
70
60
50
40
30
20
10
0
3
6
9
12
15
18
21
24
27
30
32
34
36
Avg
OPS

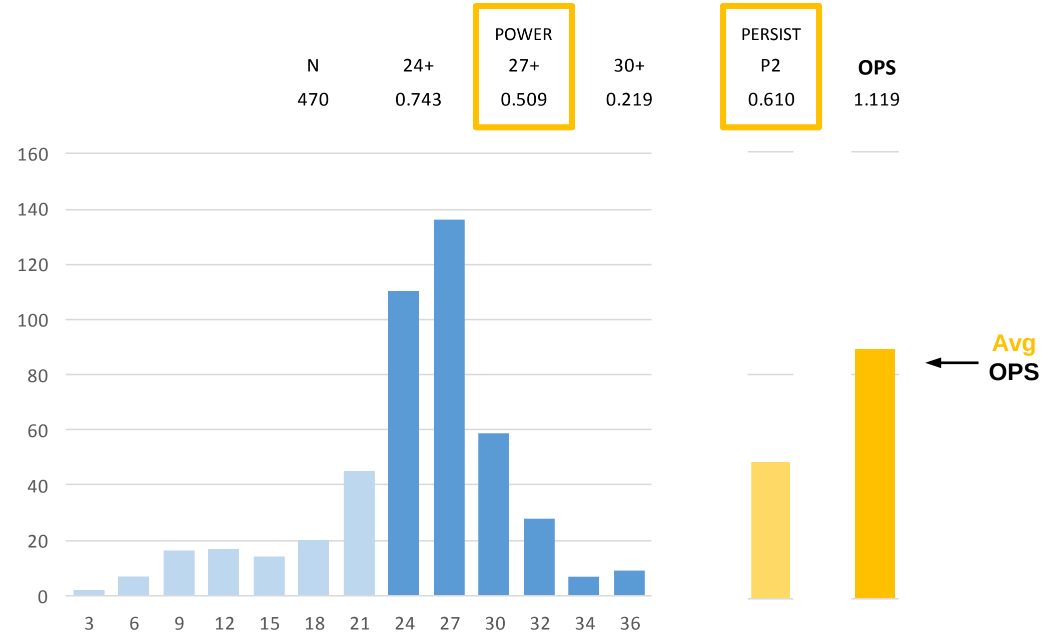


N	24+	POWER 27+	30+	PERSIST P2	OPS
156	0.571	0.308	0.109	0.629	0.937

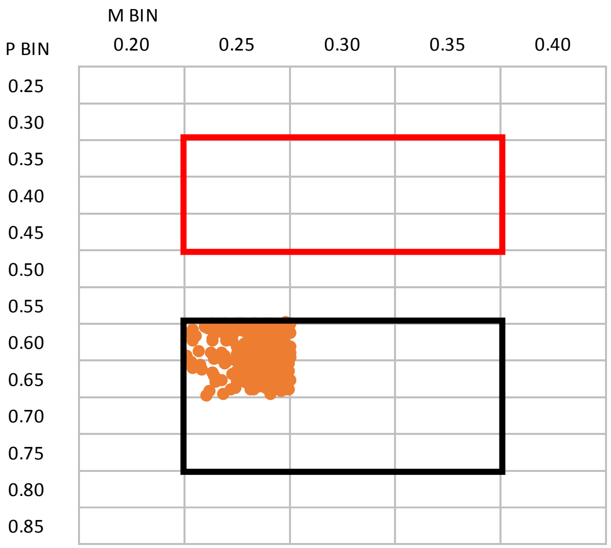


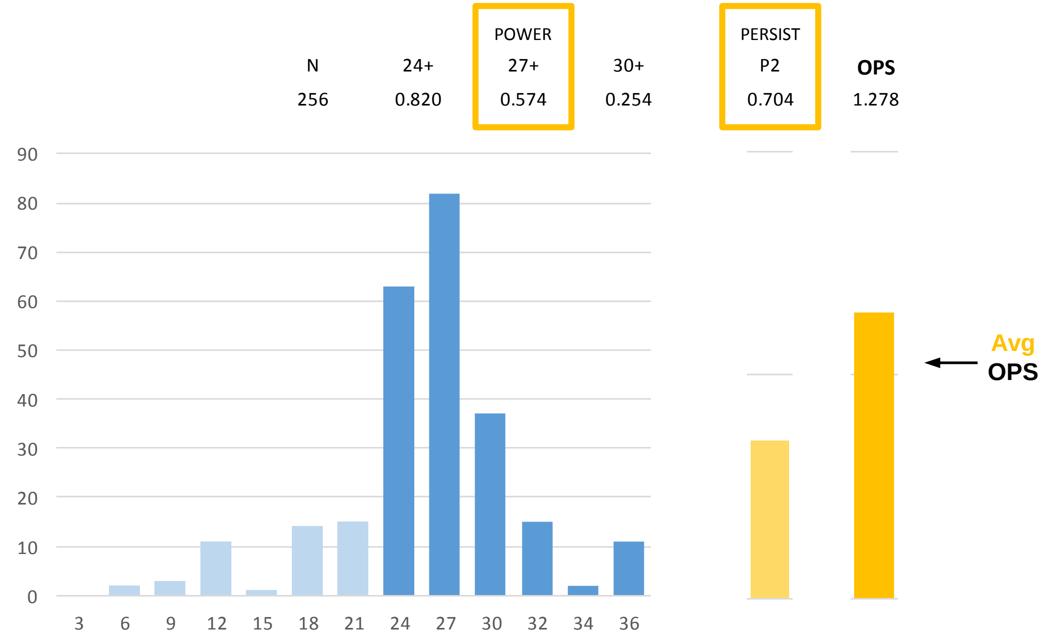


M BIN
0.20
0.25
0.30
0.35
0.40
P BIN
0.25
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85



POWER
PERSIST
N
24+
27+
30+
P2
OPS
470
0.743
0.509
0.219
0.610
1.119
160
140
120
100
80
60
40
20
0
3
6
9
12
15
18
21
24
27
30
32
34
36
Avg
OPS


M BIN
0.20
0.25
0.30
0.35
0.40
P BIN
0.25
0.30
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85


N
256
24+
0.820
POWER
27+
0.574
30+
0.254
PERSIST
P2
0.704
OPS
1.278
90
80
70
60
50
40
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0
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12
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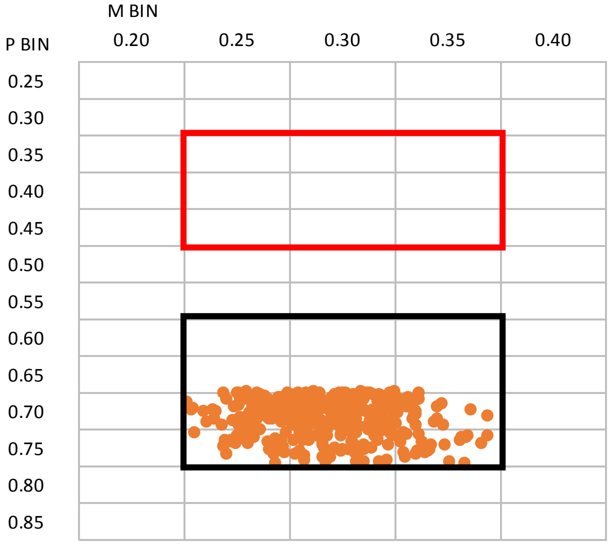
18
21
24
27
30
32
34
36
Avg
OPS



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0.20
0.25
0.30
0.35
0.40
P BIN
0.25
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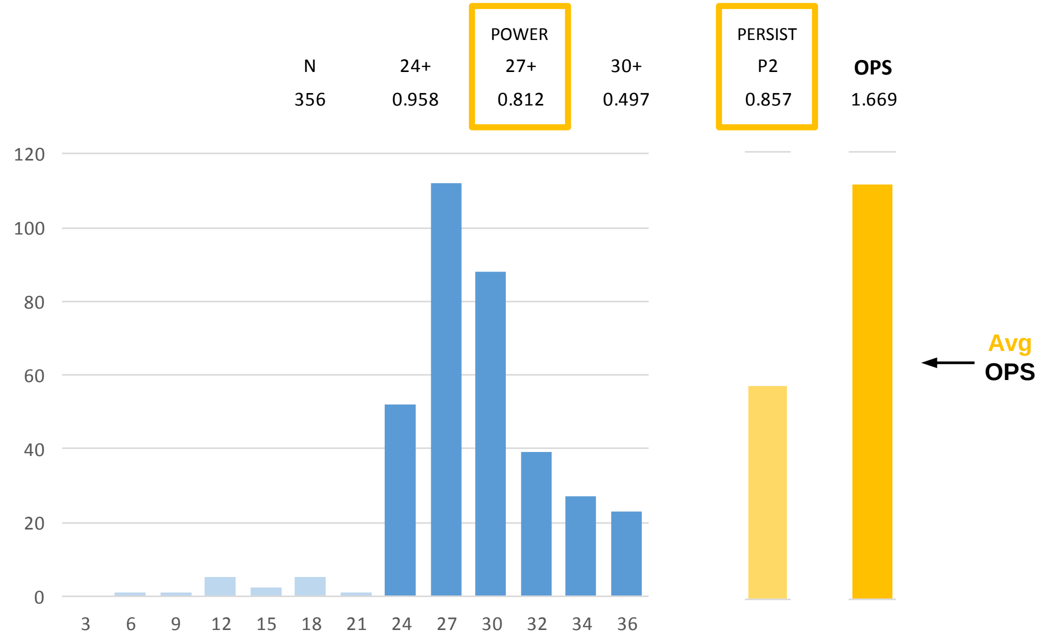
0.70
0.75
0.80
0.85



N
356
24+
0.958
POWER
27+
0.812
30+
0.497
PERSIST
P2
0.857
OPS
1.669
120
100
80
60
40
20
0
3
6
9
12
15
18
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27
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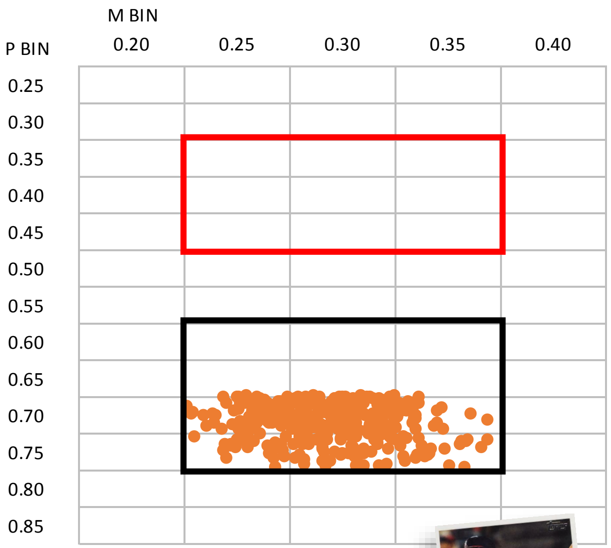
32
34
36
Avg
OPS


M BIN
P BIN
0.20
0.25
0.30
0.35
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0.25
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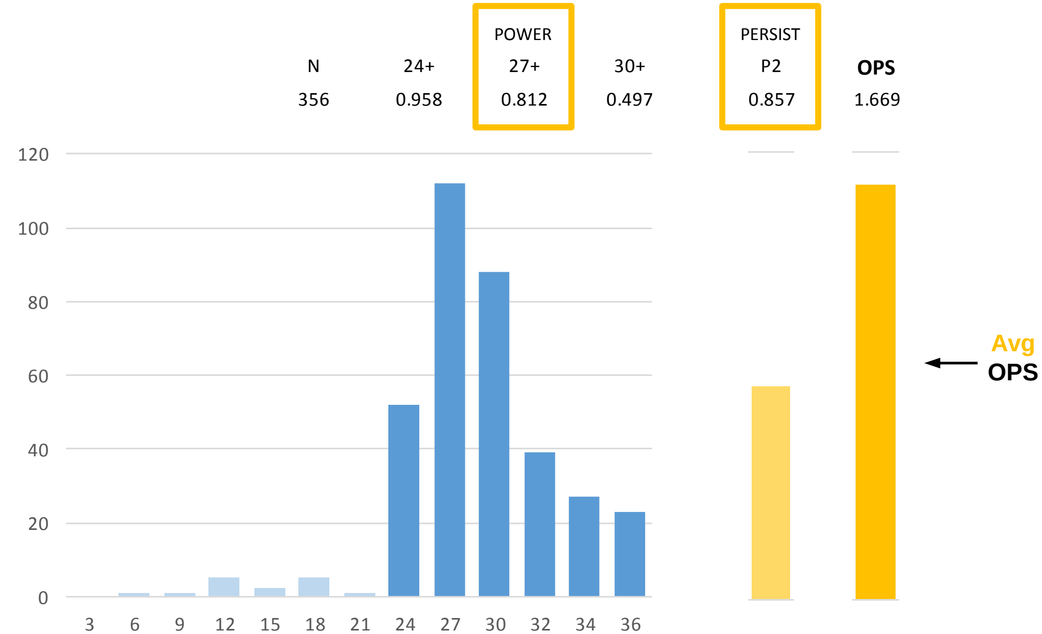
0.35
0.40
0.45
0.50
0.55
0.60
0.65
0.70
0.75
0.80
0.85


MIKE TROUT

Hello, $33mm.


N
356
24+
0.958
POWER
27+
0.812
30+
0.497
PERSIST
P2
0.857
OPS
1.669
120
100
80
60
40
20
0
3
6
9
12
15
18
21
24
27
30
32
34
36
Avg
OPS

M0 rates among applicants

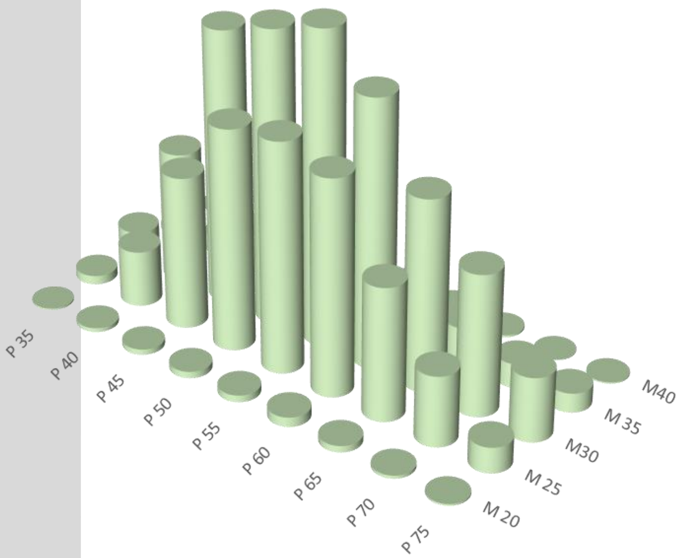
P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	1.000	1.000	.	.
0.30	.	.	0.000	0.550	0.667	0.000	.
0.35	.	0.500	0.423	0.329	0.600	0.000	.
0.40	.	0.083	0.327	0.339	0.392	0.000	.
0.45	.	0.250	0.327	0.353	0.445	0.400	.
0.50	.	0.158	0.292	0.321	0.342	0.125	.
0.55	.	0.100	0.284	0.317	0.344	0.273	.
0.60	0.000	0.179	0.273	0.327	0.344	0.375	1.000
0.65	0.000	0.105	0.324	0.349	0.321	0.500	.
0.70	.	0.222	0.404	0.370	0.347	0.000	.
0.75	.	0.400	0.382	0.374	0.404	0.250	.
0.80	.	.	0.400	0.423	0.286	.	.
0.85	.	.	.	.	0.000	.	.

The Sweet Spot

Above average persistence rates are attractive, but below average matriculation rates are a concern and challenge.

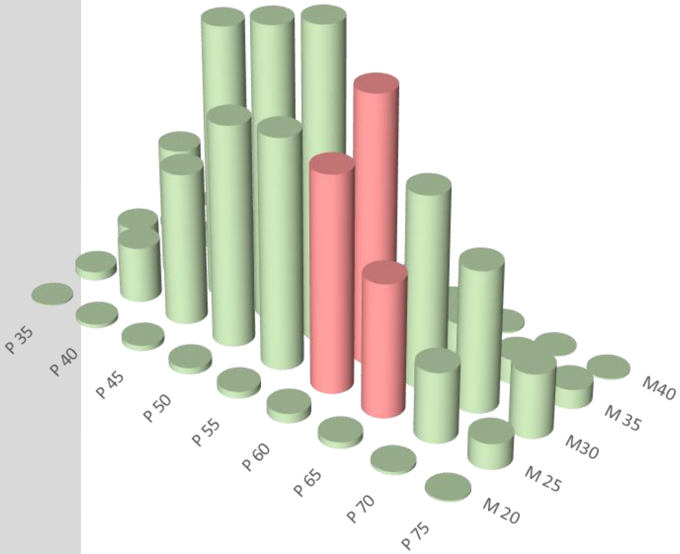
M0 rates among applicants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	1.000	1.000	.	.
0.30	.	.	0.000	0.550	0.667	0.000	.
0.35	.	0.500	0.423	0.329	0.600	0.000	.
0.40	.	0.083	0.327	0.339	0.392	0.000	.
0.45	.	0.250	0.327	0.353	0.445	0.400	.
0.50	.	0.158	0.292	0.321	0.342	0.125	.
0.55	.	0.100	0.284	0.317	0.344	0.273	.
0.60	0.000	0.179	0.273	0.327	0.344	0.375	1.000
0.65	0.000	0.105	0.324	0.349	0.321	0.500	.
0.70	.	0.222	0.404	0.370	0.347	0.000	.
0.75	.	0.400	0.382	0.374	0.404	0.250	.
0.80	.	.	0.400	0.423	0.286	.	.
0.85	.	.	.	.	0.000	.	.



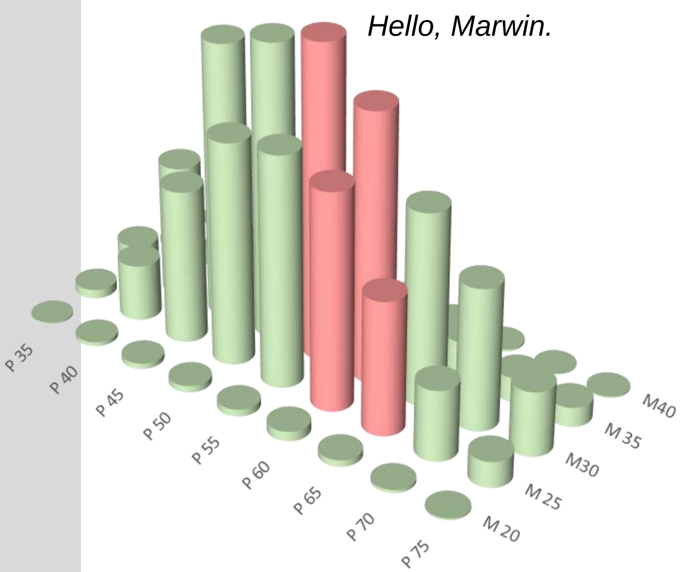
M0 rates among applicants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	1.000	1.000	.	.
0.30	.	.	0.000	0.550	0.667	0.000	.
0.35	.	0.500	0.423	0.329	0.600	0.000	.
0.40	.	0.083	0.327	0.339	0.392	0.000	.
0.45	.	0.250	0.327	0.353	0.445	0.400	.
0.50	.	0.158	0.292	0.321	0.342	0.125	.
0.55	.	0.100	0.284	0.317	0.344	0.273	.
0.60	0.000	0.179	0.273	0.327	0.344	0.375	1.000
0.65	0.000	0.105	0.324	0.349	0.321	0.500	.
0.70	.	0.222	0.404	0.370	0.347	0.000	.
0.75	.	0.400	0.382	0.374	0.404	0.250	.
0.80	.	.	0.400	0.423	0.286	.	.
0.85	.	.	.	.	0.000	.	.



M0 rates among applicants

P2 Score	M0 Score 0.15	0.20	0.25	0.30	0.35	0.40	0.45
0.20	.	.	.	1.000	.	.	.
0.25	.	.	.	1.000	1.000	.	.
0.30	.	.	0.000	0.550	0.667	0.000	.
0.35	.	0.500	0.423	0.329	0.600	0.000	.
0.40	.	0.083	0.327	0.339	0.392	0.000	.
0.45	.	0.250	0.327	0.353	0.445	0.400	.
0.50	.	0.158	0.292	0.321	0.342	0.125	.
0.55	.	0.100	0.284	0.317	0.344	0.273	.
0.60	0.000	0.179	0.273	0.327	0.344	0.375	1.000
0.65	0.000	0.105	0.324	0.349	0.321	0.500	.
0.70	.	0.222	0.404	0.370	0.347	0.000	.
0.75	.	0.400	0.382	0.374	0.404	0.250	.
0.80	.	.	0.400	0.423	0.286	.	.
0.85	.	.	.	.	0.000	.	.



Hidden in Plain Sight:

A case study into designing sophisticated statistical model grids that leverage student-credit hour production with revenue opportunities to uncover often overlooked students.

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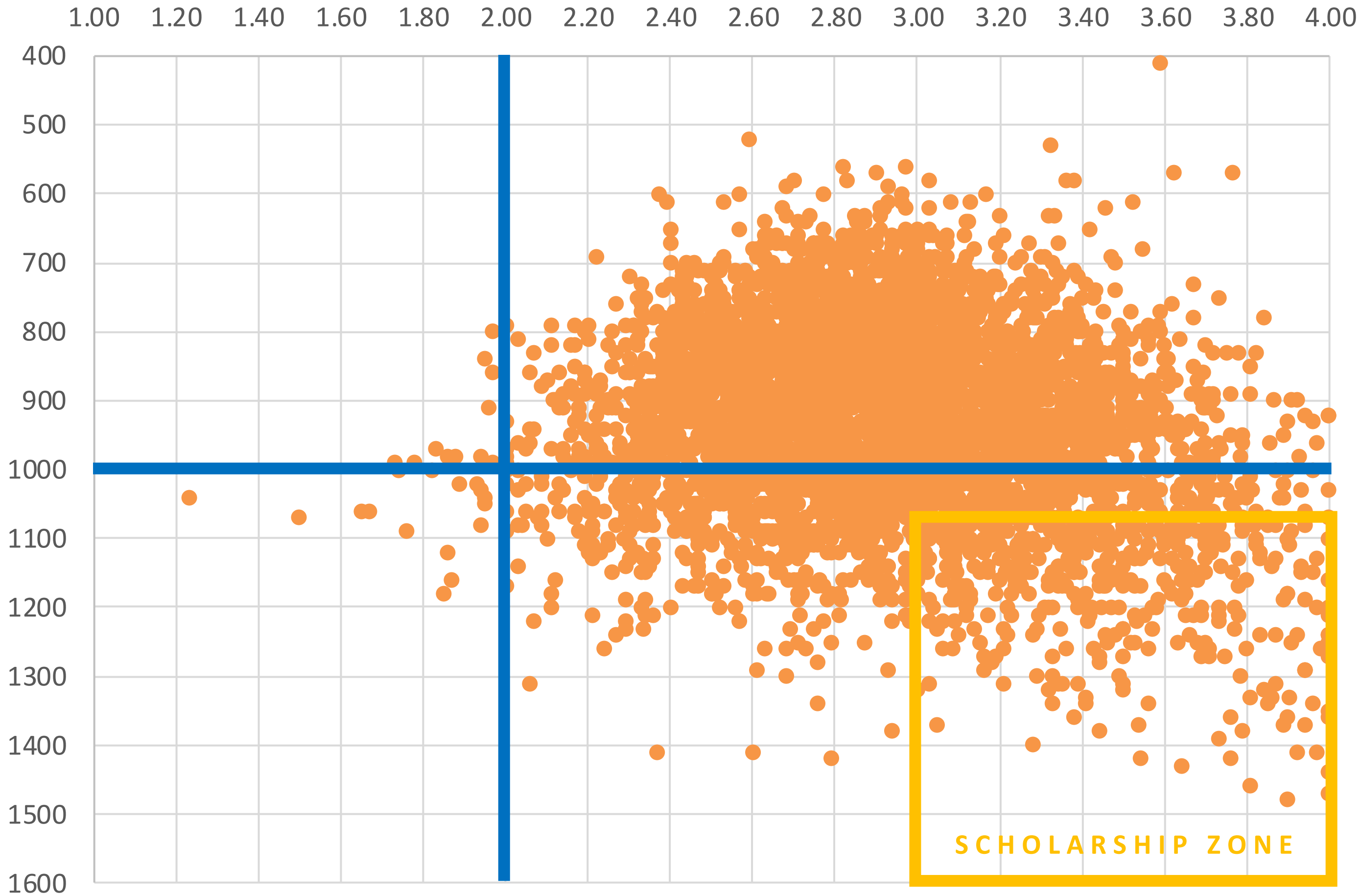
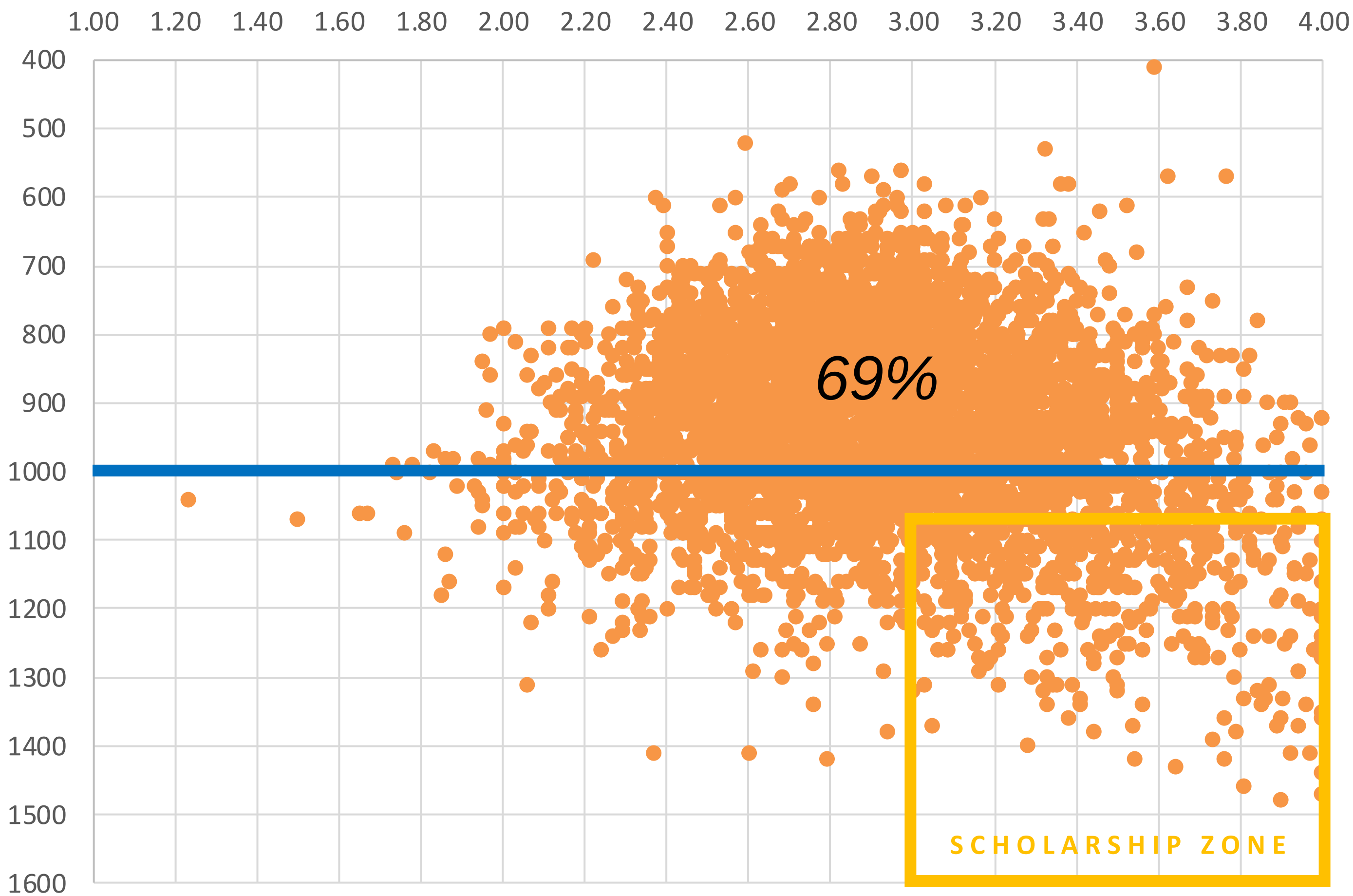


U3+U12

FTIC Applicants
FA13 to FA15

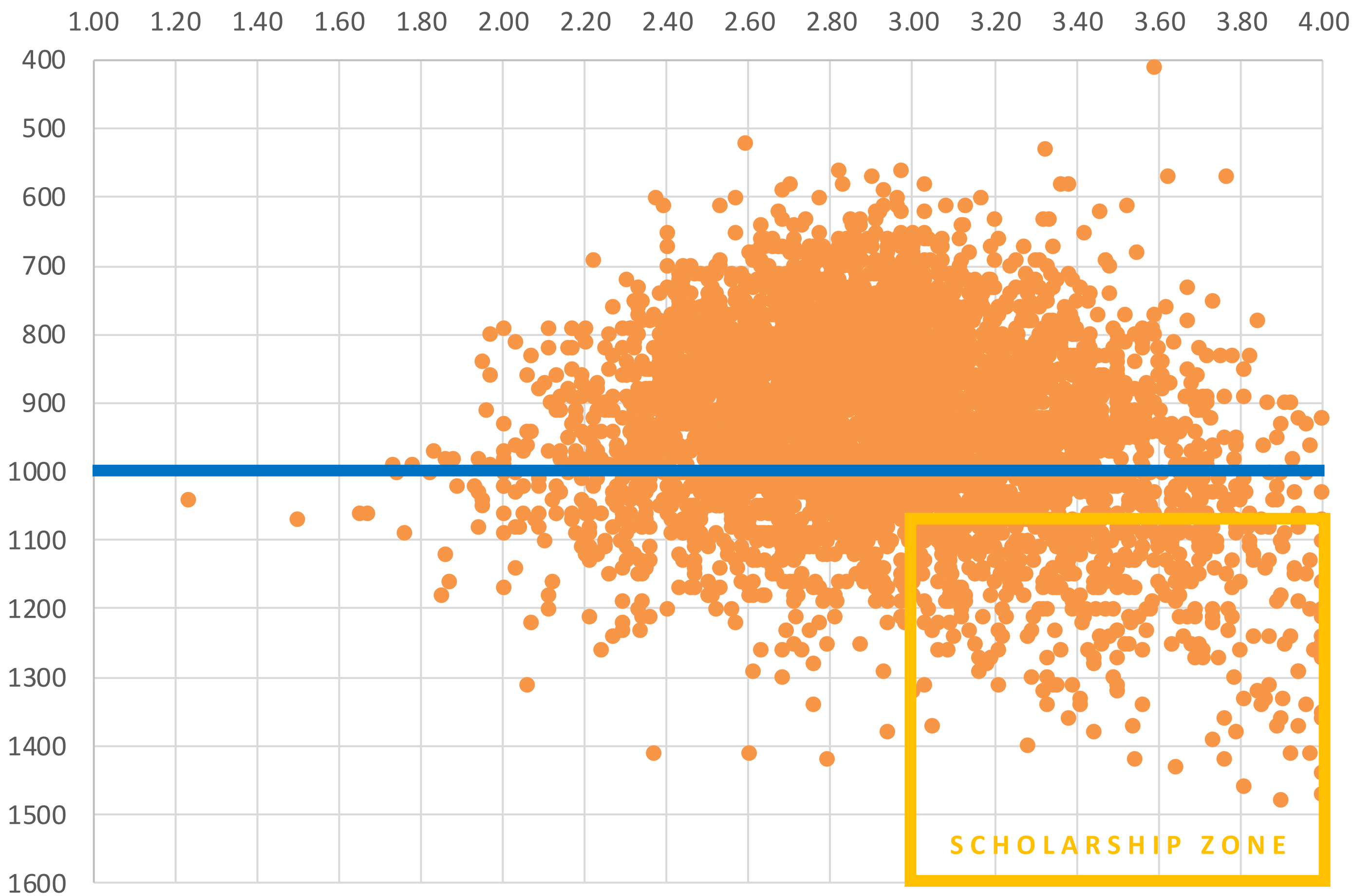
Previous approach used the ***"Flag of Finland"*** *to subdivide group into regular admits (U3) and provisionals (U12), and focused scholarship awards on higher gpa and sat areas.*



U3+U12

FTIC Applicants
FA13 to FA15

*But 69% of applicants got classified as "provisional" and the 2.00 GPA criterion did little to differentiate, which made it more **"Flag of Monaco"** in practice.*

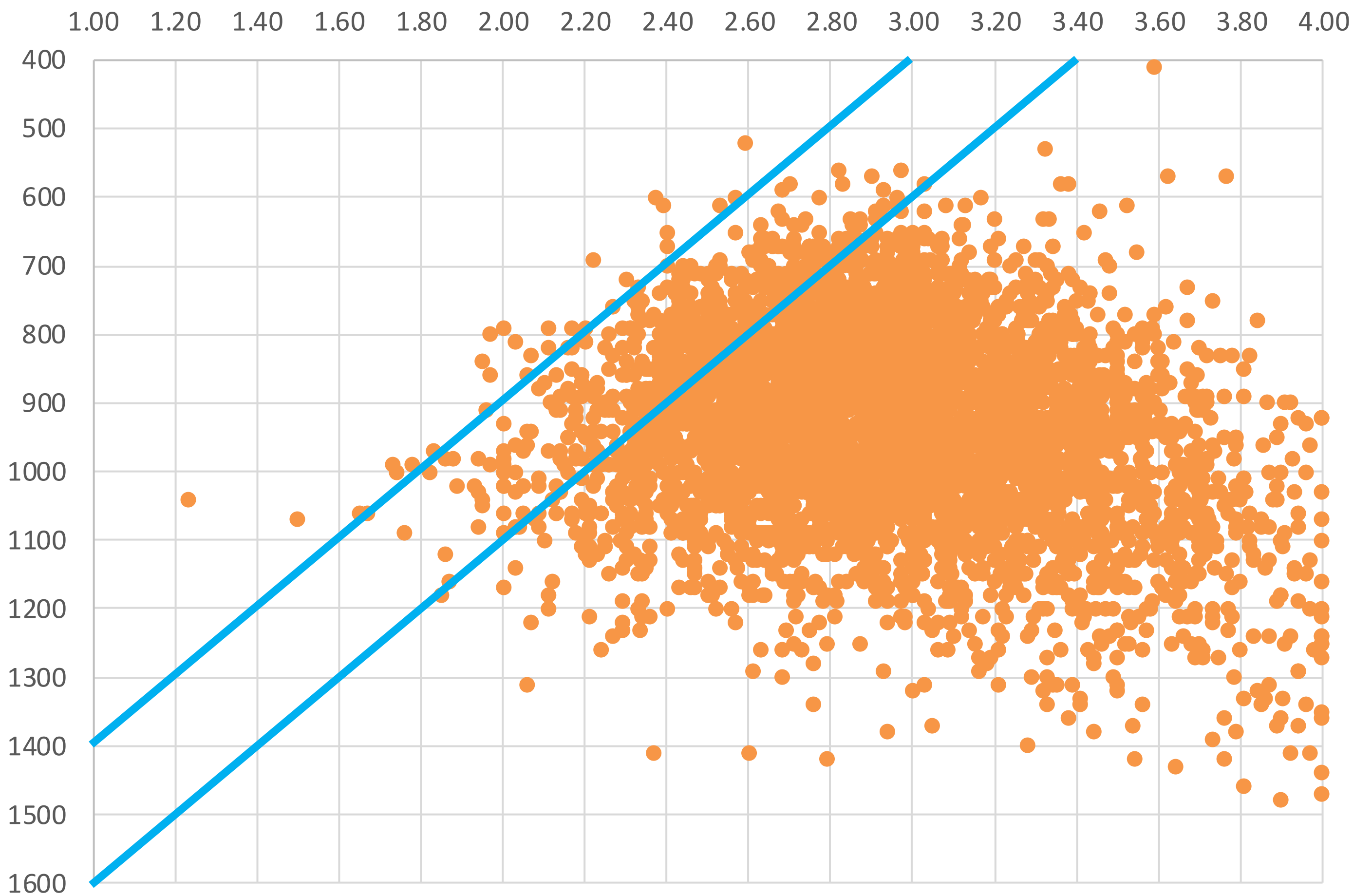


U3+U12

FTIC Applicants
FA13 to FA15

*But 69% of applicants got classified as "provisional" and the 2.00 GPA criterion did little to differentiate, which made it more **"Flag of Monaco"** in practice.*

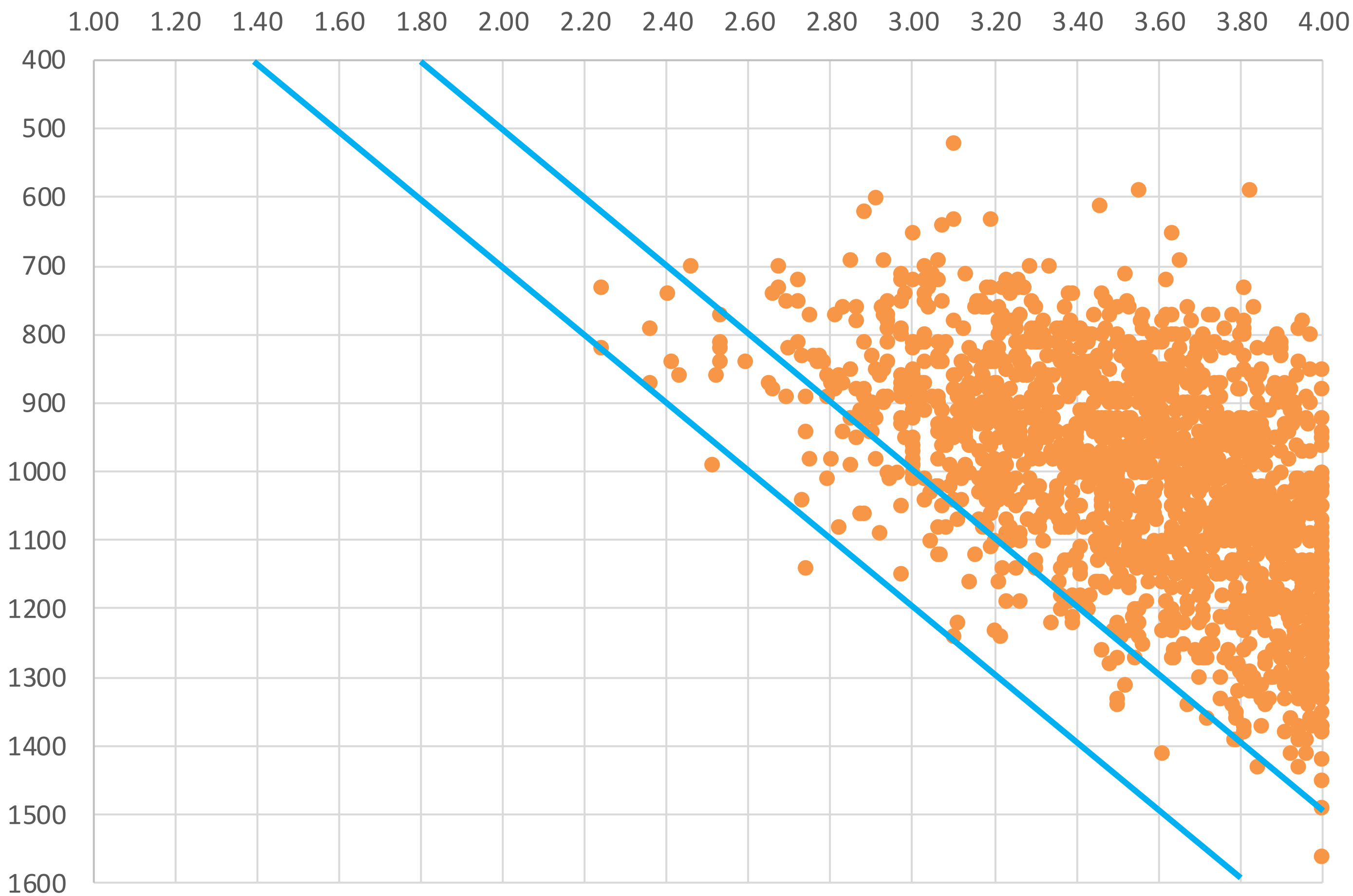
Wouldn't a different decision flag better fit the data?



U3+U12

FTIC Applicants
FA13 to FA15

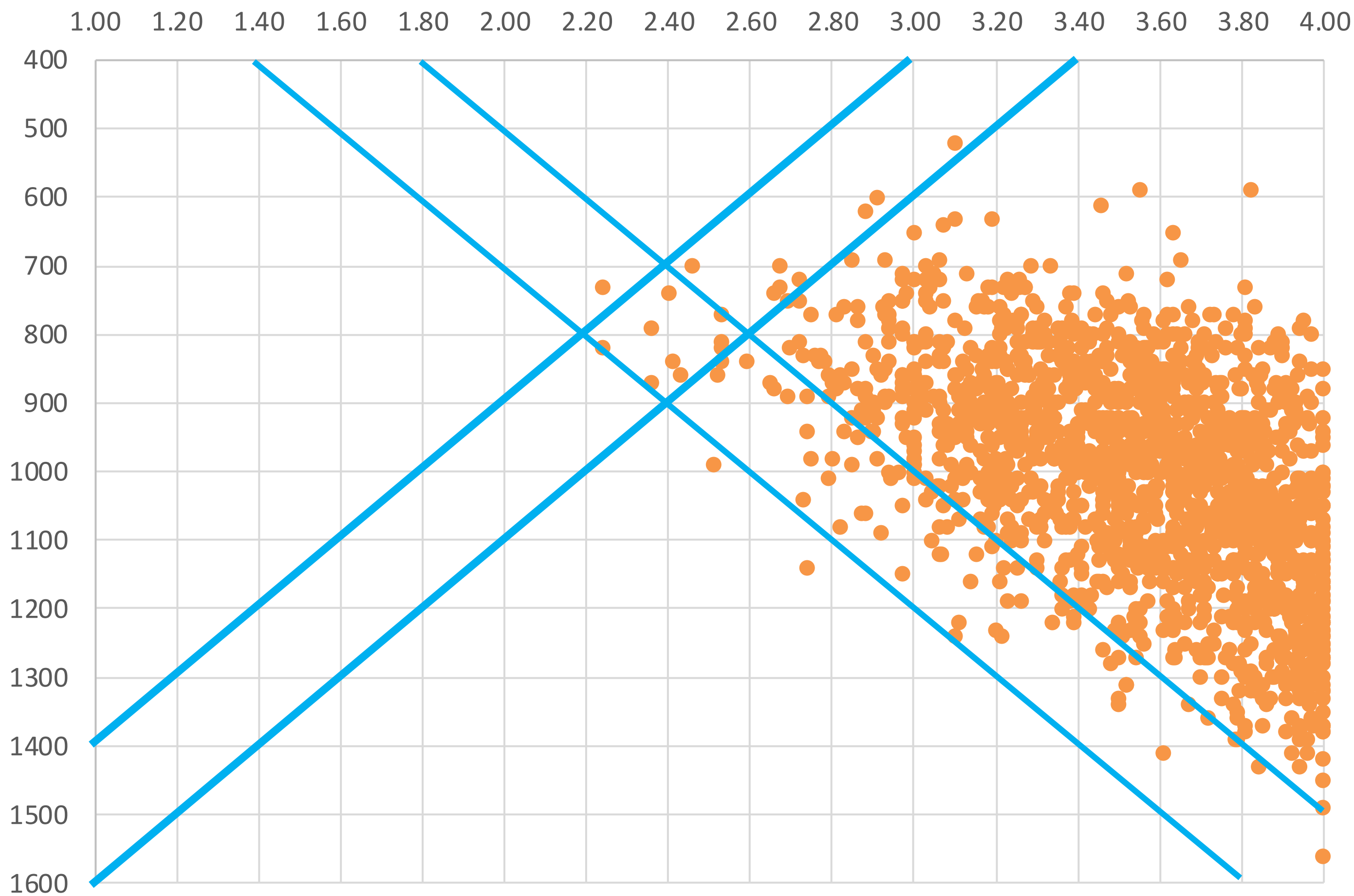
*What if we drew diagonals to capture the possible **"compensatory"** nature of performance, where students are known to overcome low SAT scores and earn high GPAs.*



U1

FTIC Applicants
FA13 to FA15

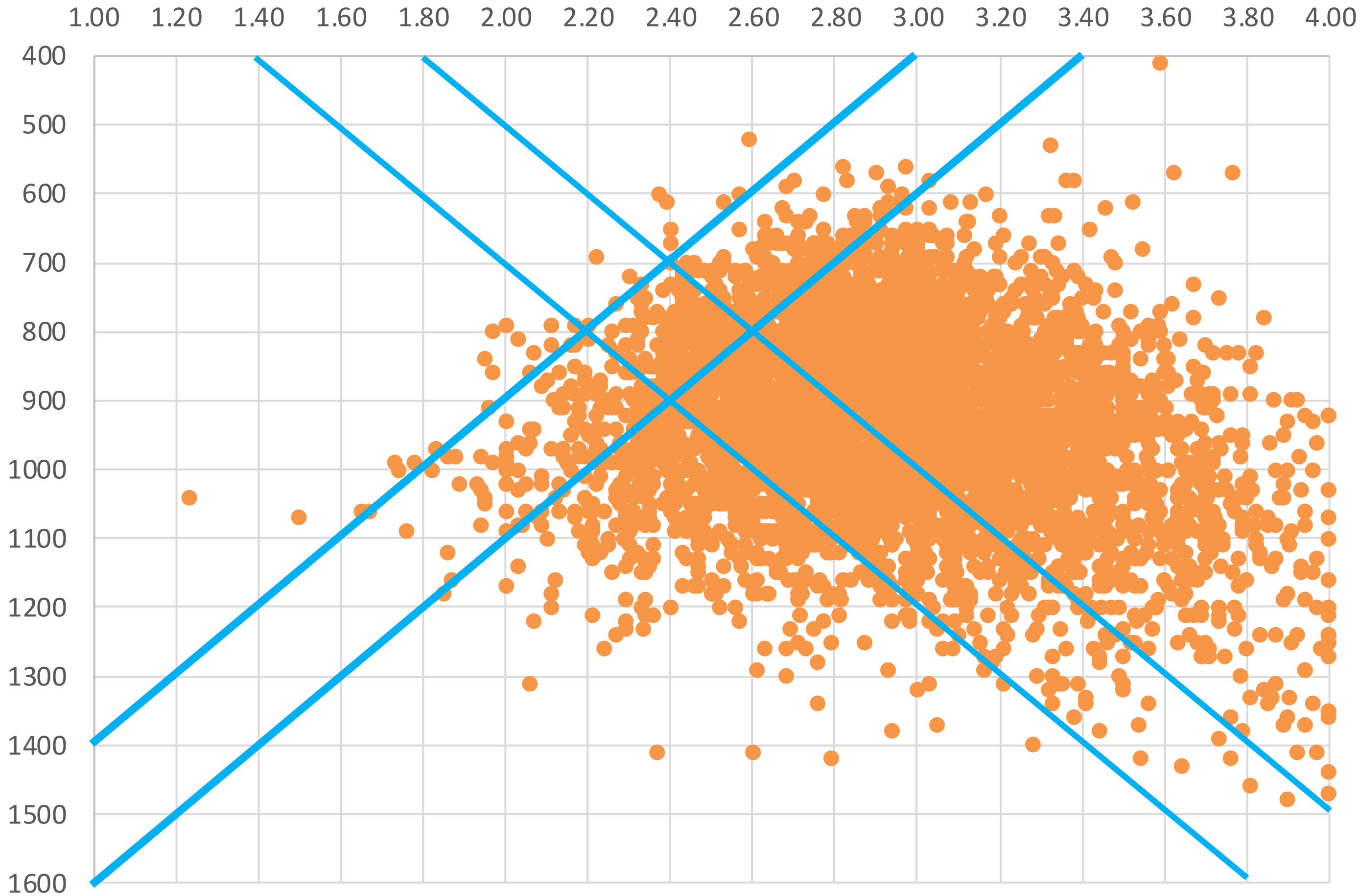
*And what if we added cross diagonals to reflect the **"expected"** nature of performance, where students with high SAT scores are expected to achieve high GPAs.*



U1

FTIC Applicants
FA13 to FA15

*We'd be left with a **"Flag of Scotland"** framework to perhaps better subdivide applicants into meaningful categories.*



U3+U12

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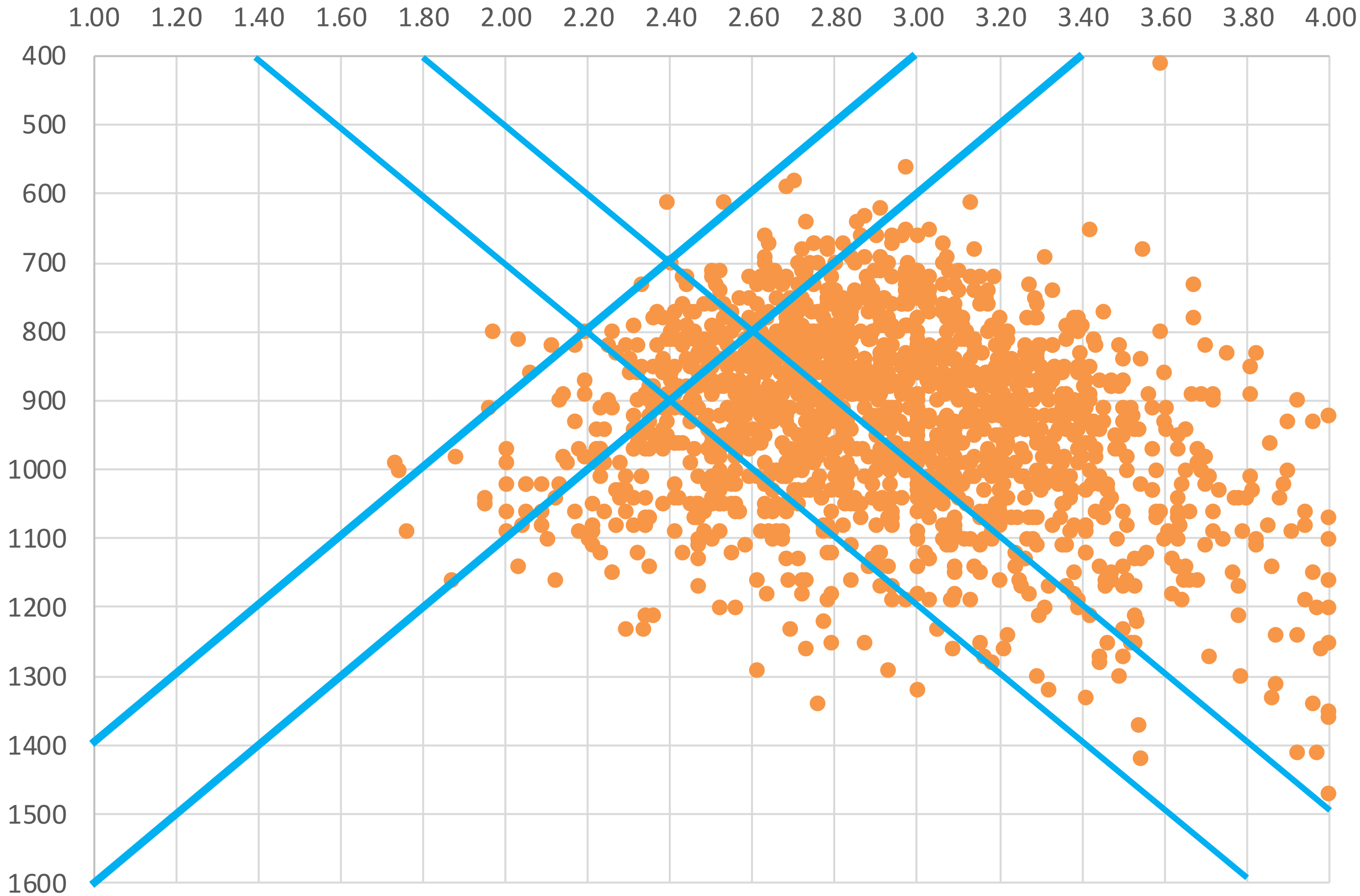
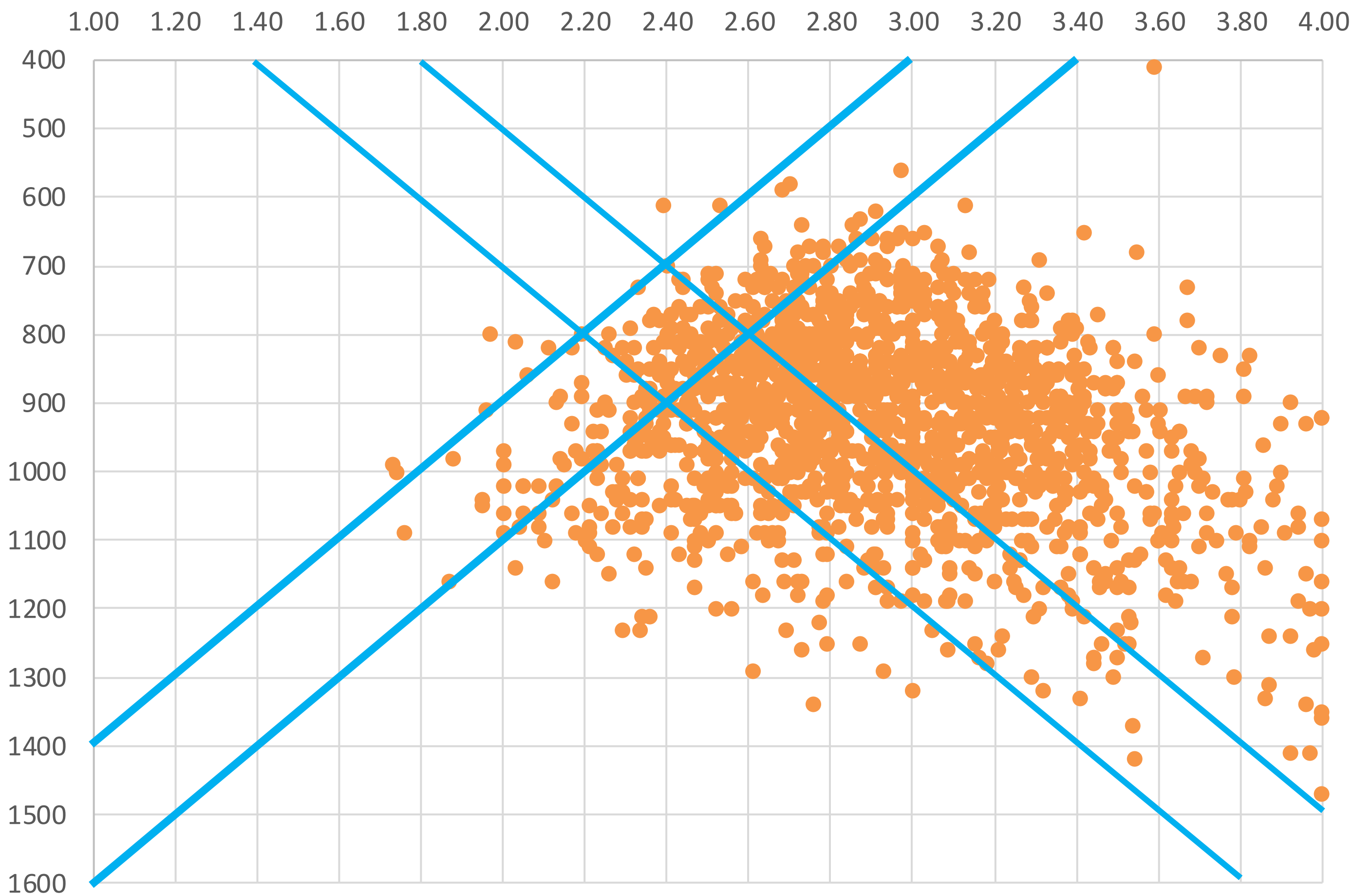


U3+U12

Matriculants
FA13 to FA15

The distribution of matriculated students follows a similar pattern, but to further subdivide into useful admissions categories, we need a good dependent variable.

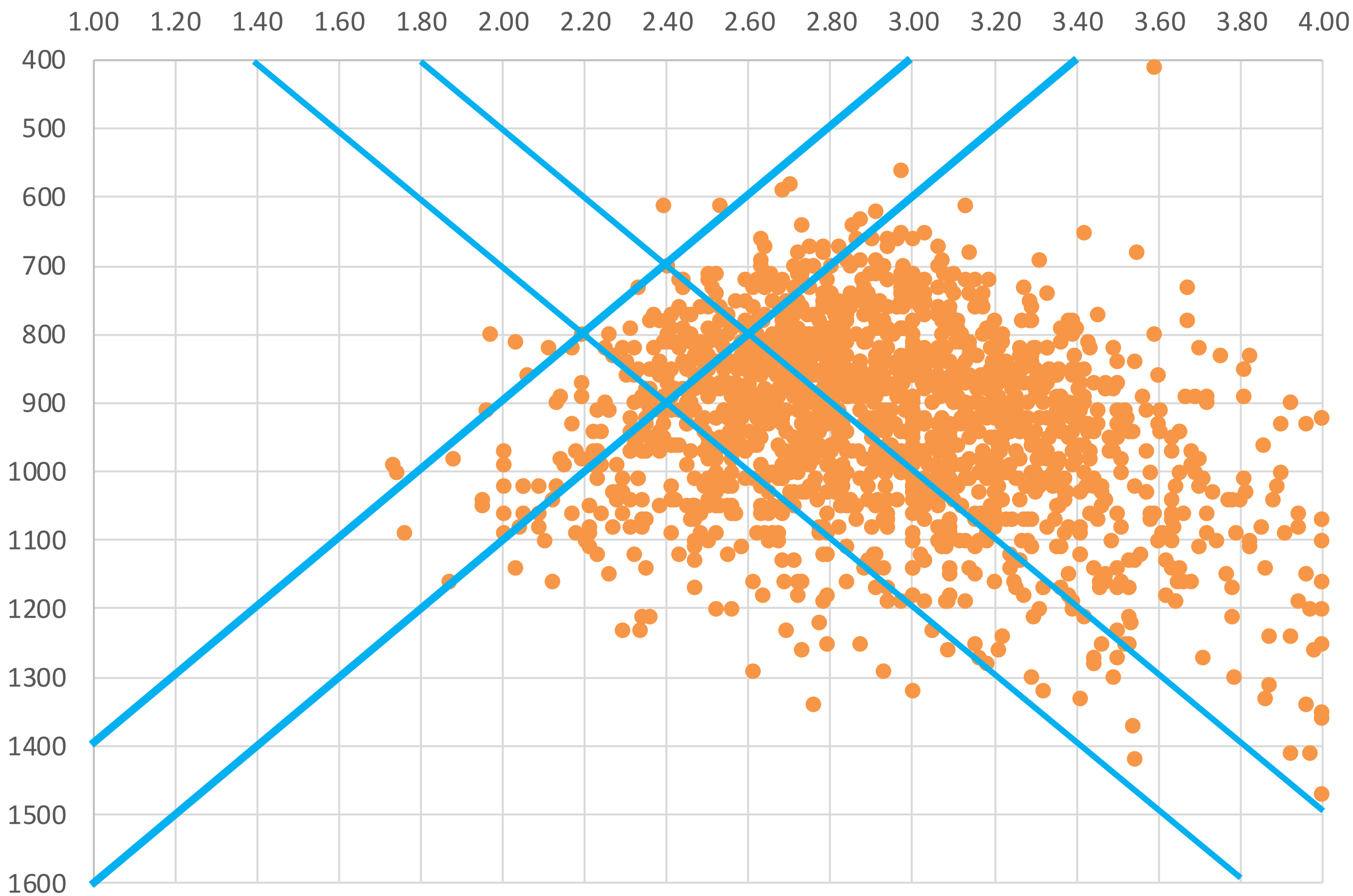


U3+U12

Matriculants
FA13 to FA15

The distribution of matriculated students follows a similar pattern, but to further subdivide into useful admissions categories, we need a good dependent variable.

like
OPS

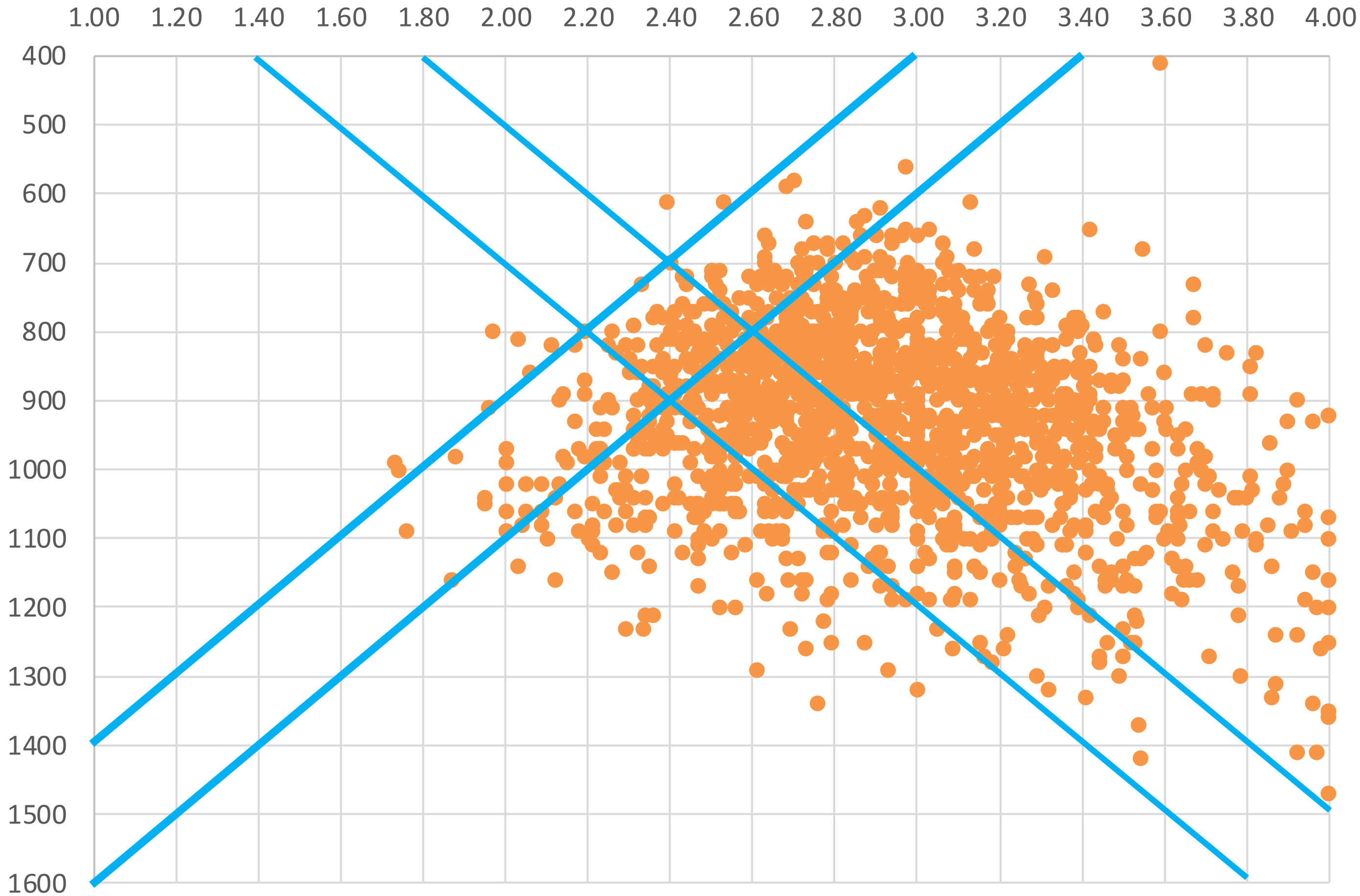


U3+U12

Matriculants
FA13 to FA15

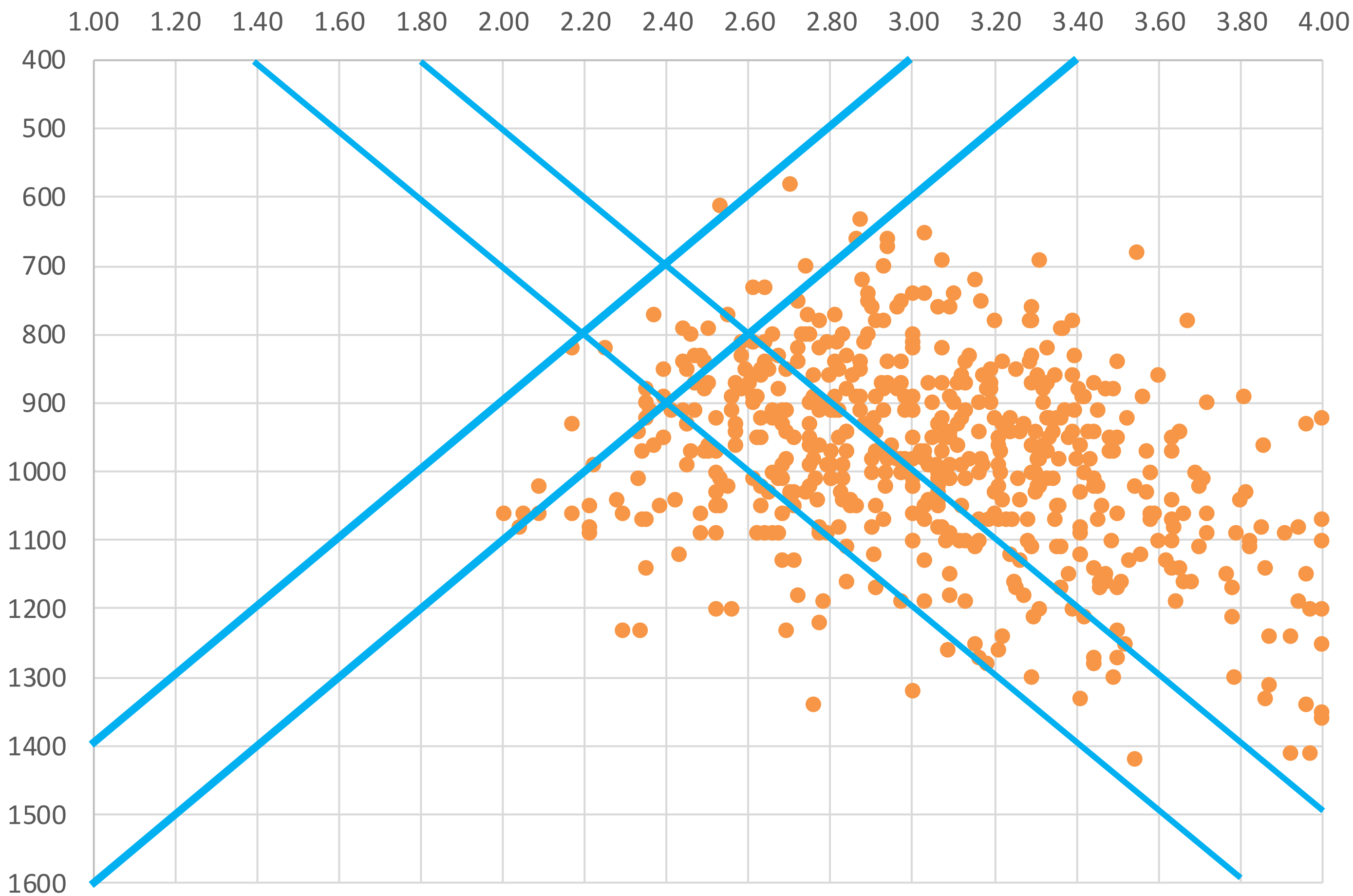
The distribution of matriculated students follows a similar pattern, but to further subdivide into useful admissions categories, we need a good dependent variable.

or even
SLG



U3+U12

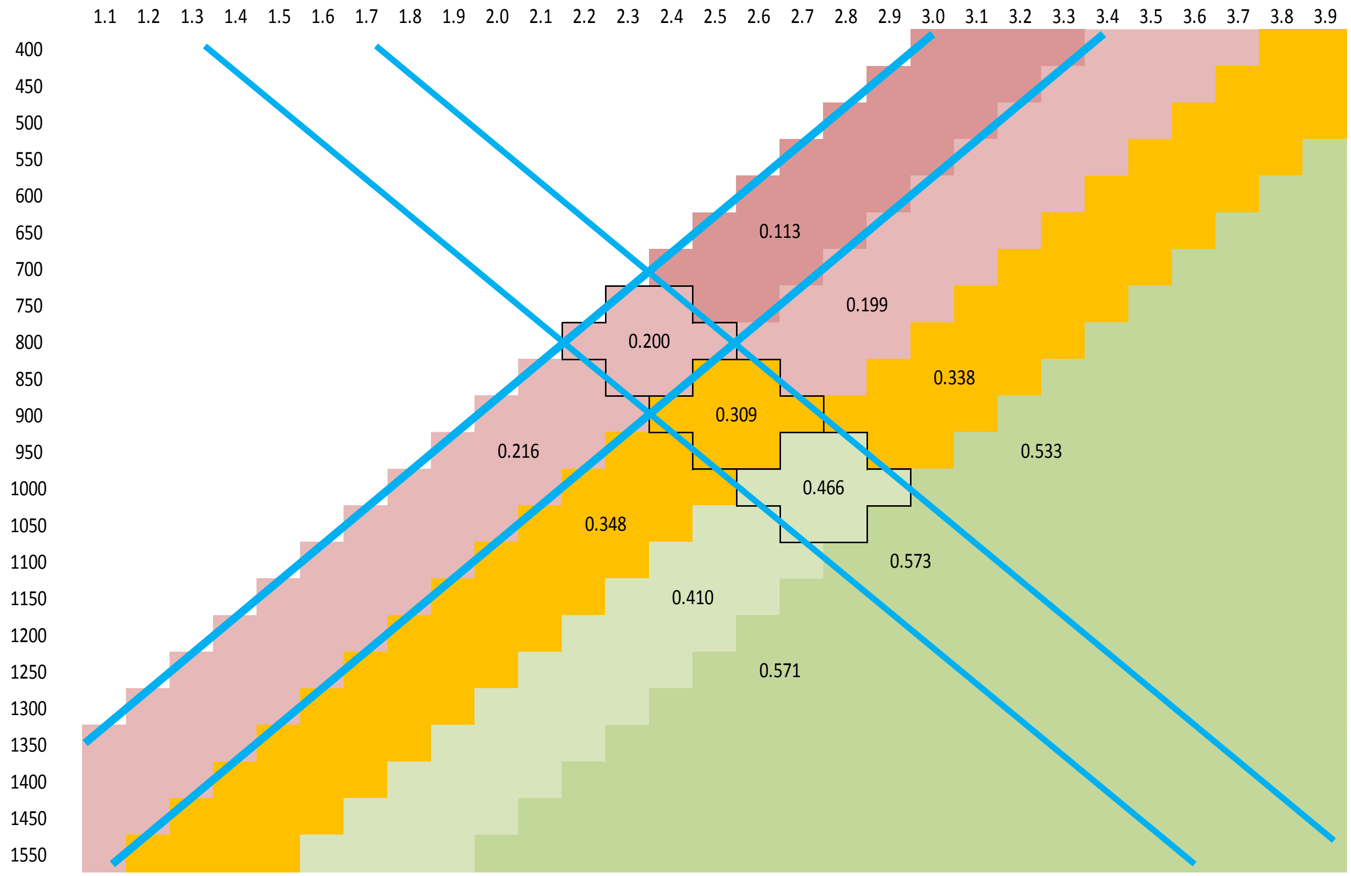
Matriculants
FA13 to FA15



U3+U12

SLG.850 Earners

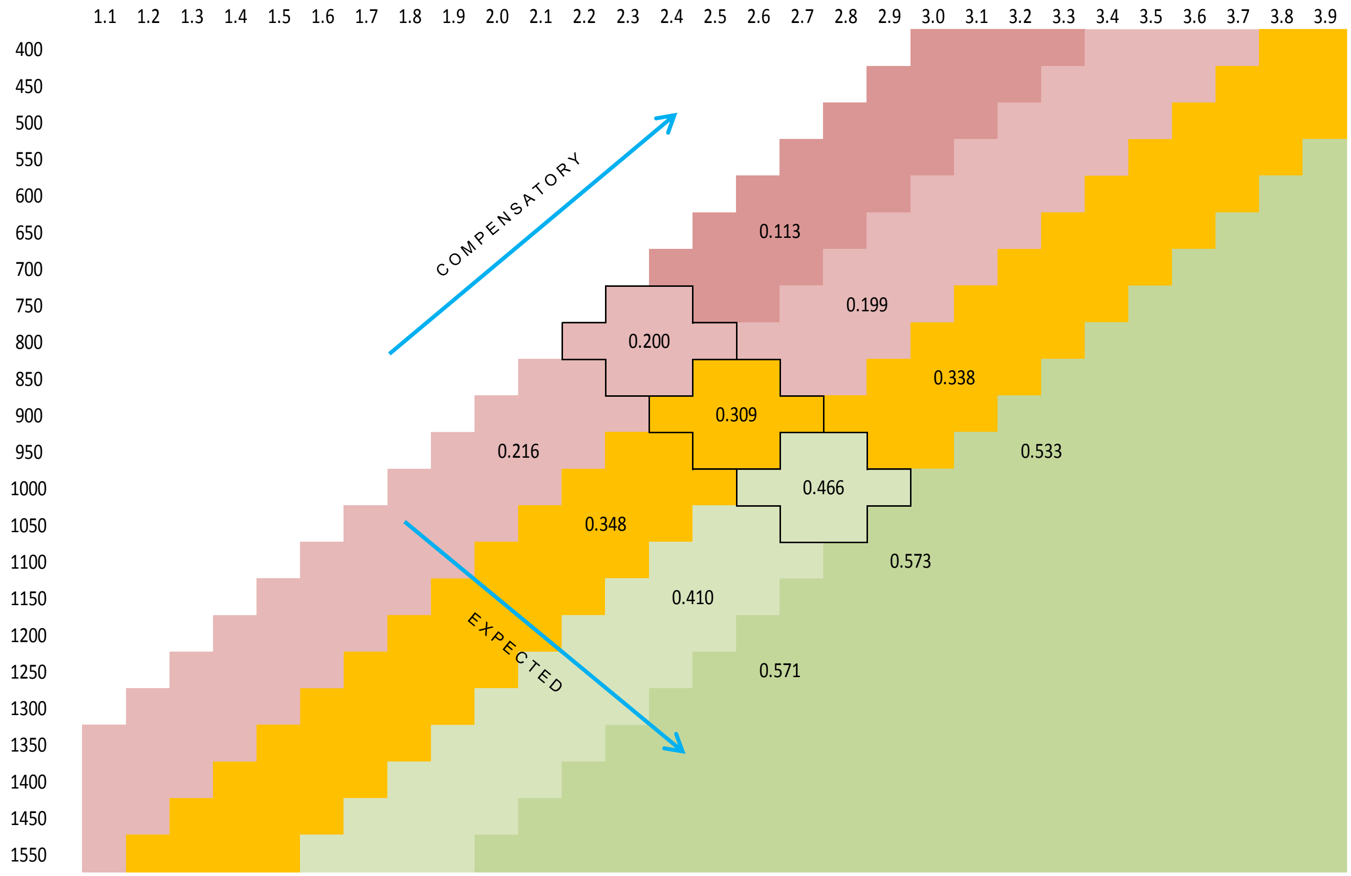
*Distribution of students who earned .850 of expected SCH in their first two years aligns nicely with the **"Flag of Scotland"** framework, but shifts down and to the right. To what extent does the SLG.850 rate vary by specific zone?*



U3+U12

SLG.850 Earners

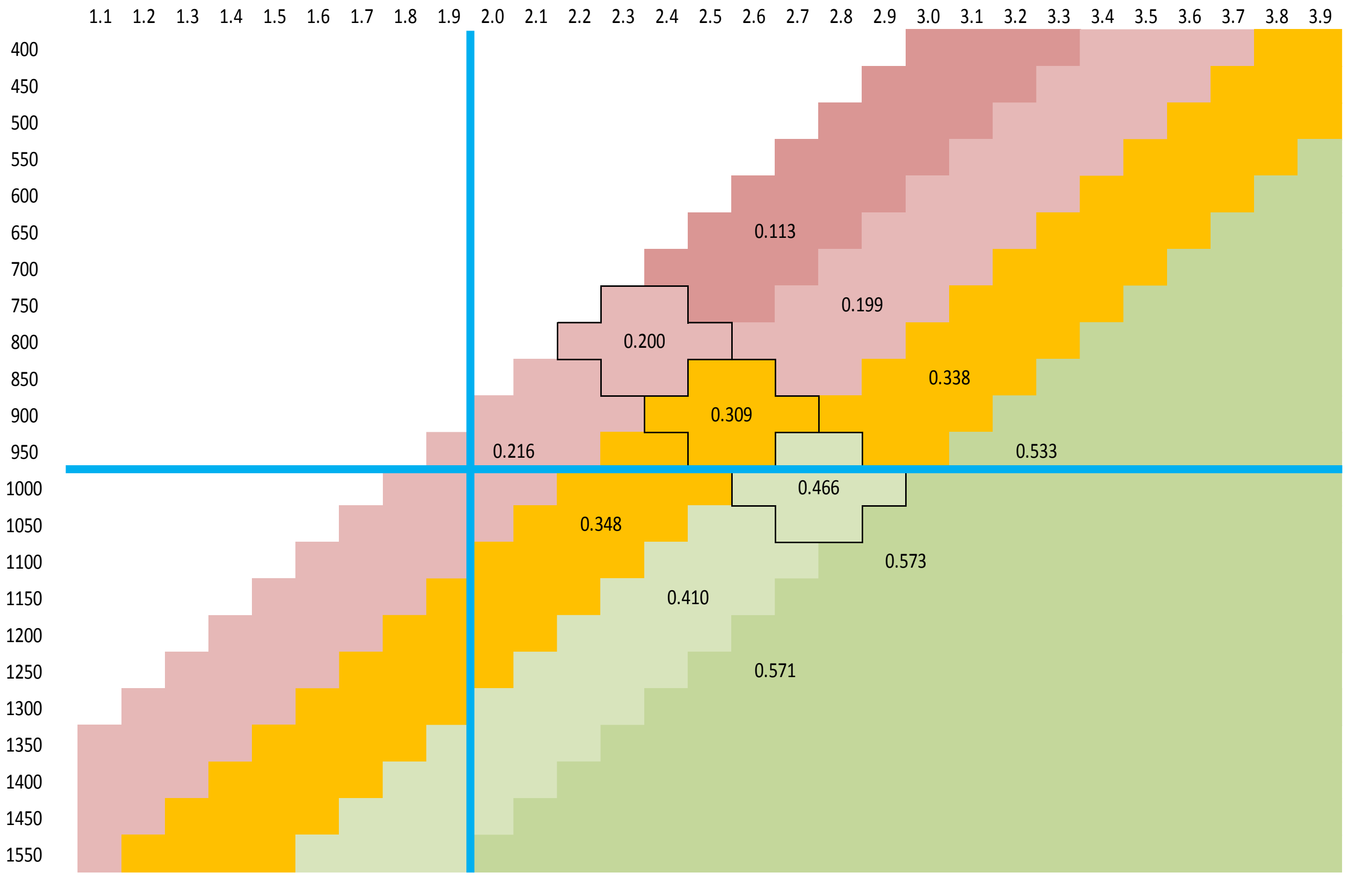
To find out, we drew more diagonal lines to create additional GPA by SAT zones, then calculated the SLG.850 rate for students in each zone.



U3+U12

SLG.850 Earners

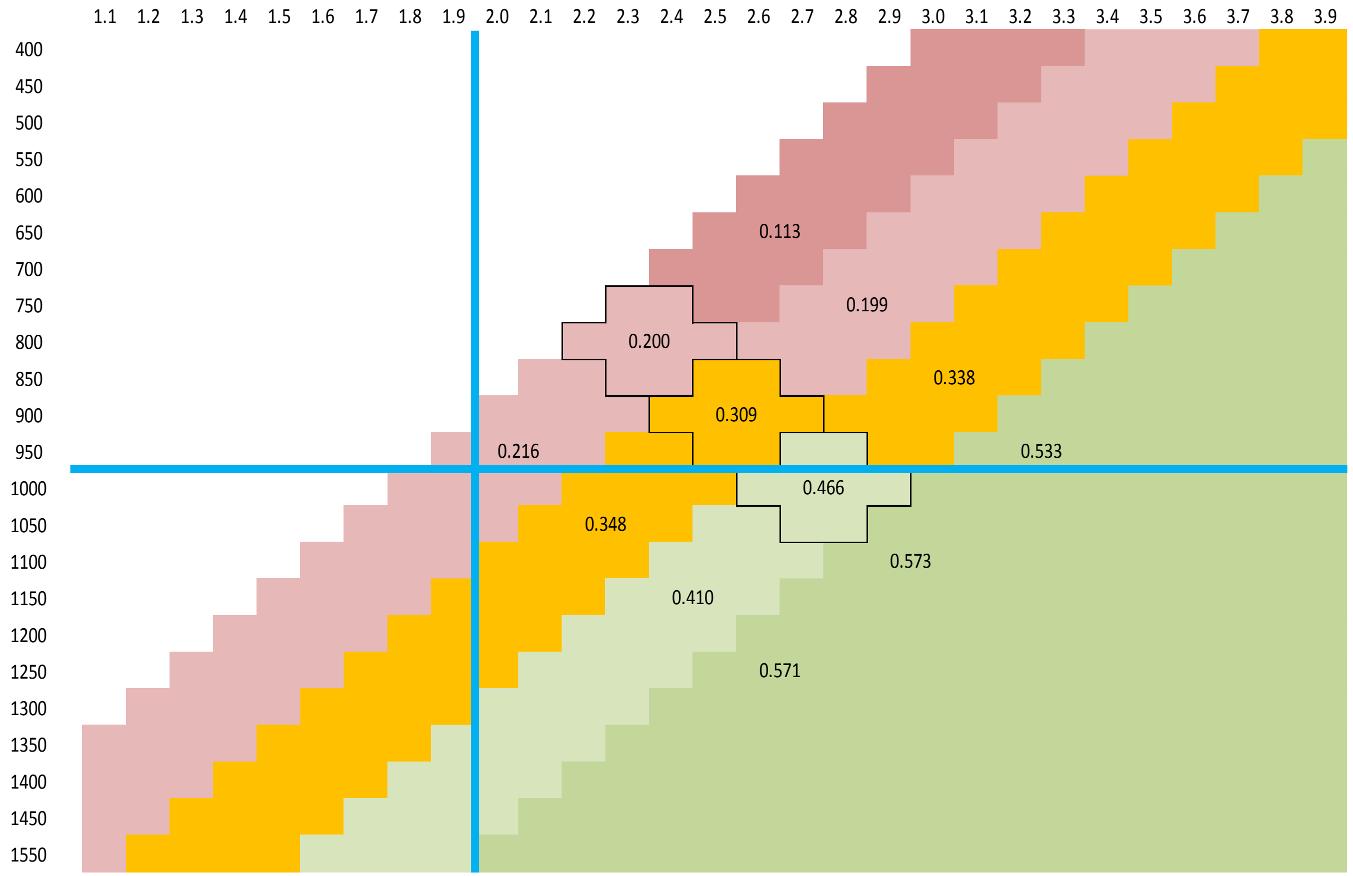
The results supported the existence of "compensatory" and "expected" diagonals, which served to identify SLG.850 performance zones.



U3+U12

SLG.850 Earners

The results also revealed a tremendous amount of misclassification when using the ***“Flag of Finland”*** *approach.*



U3+U12

SLG.850 Earners

*The results also revealed a tremendous amount of misclassification when using the **"Flag of Finland"** approach.*

These findings became the basis for a revised admissions and scholarship grid that incorporates diagonals.

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