An analysis of methods used to measure college football recruiting classes and assign star ratings to recruits

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Big picture problem

College football teams compete not only on the field, but in recruiting–trying to convince the best high school players to join their program. The players who choose to attend a given college in a given year are called that school's *recruiting class*. We ask:

How well can you predict the success of a college football team from the ratings of its recruits?

We use data from all major college programs (members of Power 5 conferences + Notre Dame) from 2016 to 2019.

Setup

How recruits are rated:

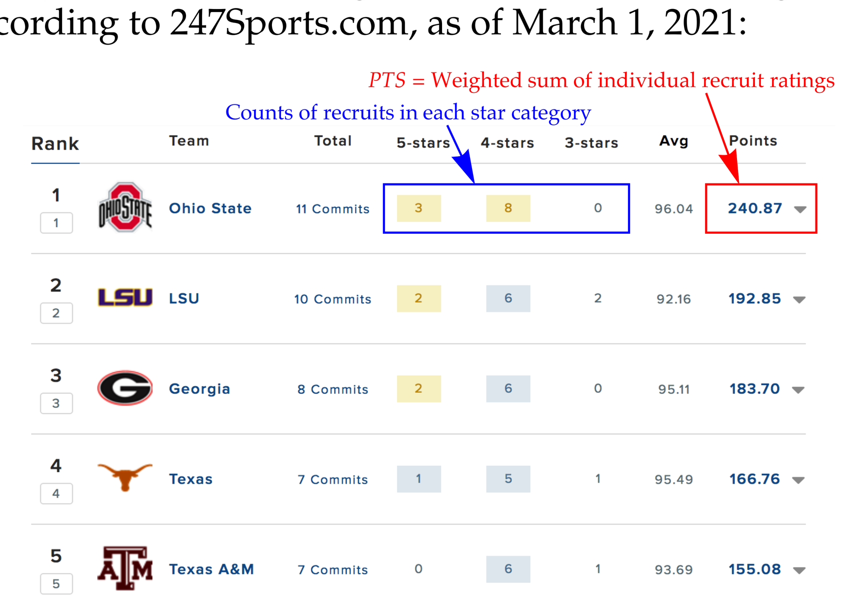
- Websites (such as ESPN.com, rivals.com, 247Sports.com, etc.) scout high school players and assign each recruit a numerical score.
- These scores are rescaled, then averaged to give a *composite rating* to each recruit, which is a number from .7 to 1.

How one predicts team success from recruit ratings:

Step 1: Compute an overall rating of each recruiting class. There are two standard methods:

1. Divide recruits into categories called 5★, 4★ 3★, and 2★, and for each class, record the number of recruits in each of these categories.
2. Assign to each class a single number called *PTS* (points), which is a weighted sum of the composite ratings of each recruit in the class.

Example: here are the highest-rated 2022 recruiting classes according to 247Sports.com, as of March 1, 2021:



Rank	Team	Total	5-stars	4-stars	3-stars	Avg	Points
1 (1)	Ohio State	11 Commits	3	8	0	96.04	240.87
2 (2)	LSU	10 Commits	2	6	2	92.16	192.85
3 (3)	Georgia	8 Commits	2	6	0	95.11	183.70
4 (4)	Texas	7 Commits	1	5	1	95.49	166.76
5 (5)	Texas A&M	7 Commits	0	6	1	93.69	155.08

Step 2: Study the correlation between the overall class rating from Step 1 and team success. We measure team success by

- Jeff Sagarin computer rating (denoted SAG), and
- number of games won (denoted $WINS$).

Prior research

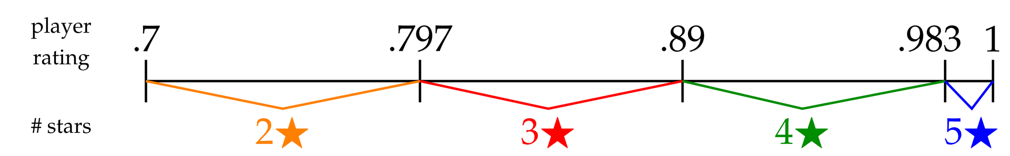
Langelett (2003), Dumond et al. (2008), Herda (2009), Bergman & Logan (2016) and Dronyk-Trosper & Stitzel (2017) all found positive correlation between overall class rating and team success.

But their research focuses on Step 2 from above. We focus on Step 1, which to our knowledge has not yet been studied.

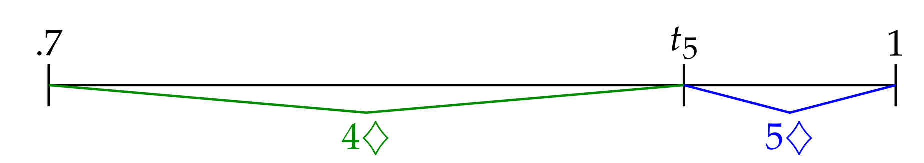
Optimal categorization of recruits into "types"

Here, we divide recruits into "types"; the quality of a class is based on the number of each type of recruit it has.

247Sports.com divides players into four types: 2★ to 5★:

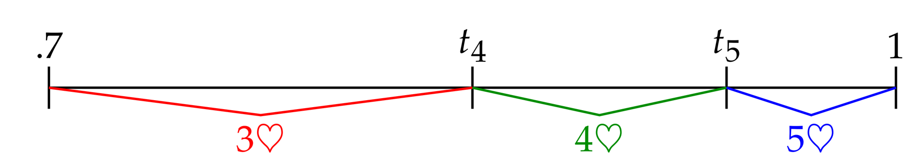


Our two-subset model: we divide players into two types, 5♢ and 4♢, based on a variable threshold t_5:



Specific goal: find t_5 so that the counts of players of each type is most strongly correlated with SAG.

Our three-subset model: we divide players into three types, 5♡, 4♡ and 3♡, based on variable thresholds t_4 and t_5:



Specific goal: find (t_4, t_5) so that the counts of players of each type is most strongly correlated with SAG.

Our models for estimating the quality of a recruiting class

Let $P_1, P_2, P_3, \dots$ be the ratings of recruits in a class, arranged from highest to lowest.

The overall class is rated by this weighted sum of the P_x's, called PTS:

$$PTS = 100 \sum_x w(m,b,x) \cdot \max\{P_x - f, 0\}$$

weight given to the x^{th} best recruit in the class

rating of the x^{th} best recruit in the class

We use *Gaussian* weight functions (bell curves), i.e.

$$w(m,b,x) = \exp\left(\frac{-(x-m)^2}{2b^2}\right),$$

where m and b are *mean* and *spread* parameters.

f is the *floor* of a recruit's possible rating; if any player's rating is $< f$, our formula resets this rating to f.

The current 247Sports.com model uses $f = .7$, $m = 1$, $b \approx 9$.

Our Model A: uses $f = .7$, $m = 1$, with b variable
Specific goal: find b so that the correlation between PTS and SAG is greatest.

Our Model B: uses $f = .7$, with m and b variable
Specific goal: find (m, b) so that the correlation between PTS and SAG is greatest.

Our Model C: f, m, b all variable
Specific goal: compute maximum correlation between PTS and SAG, as a function of f.

Results

Two-subset model: The optimal value of t_5 is .9184.

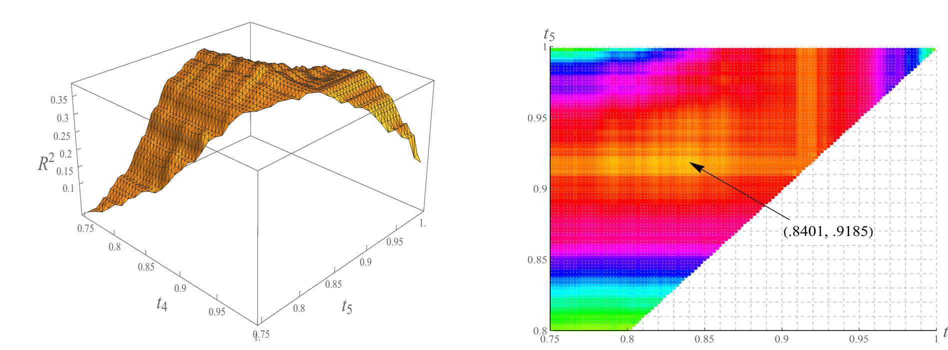
Using this threshold to split players into 5♢ and 4♢ groups:

	5♢	4♢
% of recruits	14.1%	85.9%
change in SAG per recruit	1.718***	−0.348***
additional wins per recruit	0.249***	−0.113***

*** $p < .001$

- These regression coefficients have stronger significance than analogous coefficients coming from traditional star ratings.
- The correlation between counts from our model and team success is 9.2% higher than counts coming from traditional star ratings.

Three-subset model: Optimal values: $t_4 = .8401$, $t_5 = .9185$.



Using t_4 and t_5 to split players into 5♡, 4♡ and 3♡ groups:

	5♡	4♡	3♡
% of recruits	14.1%	60.8%	25.1%
change in SAG per recruit	1.064***	−0.190	−0.588**
additional wins per recruit	0.225***	−0.077	−0.167*

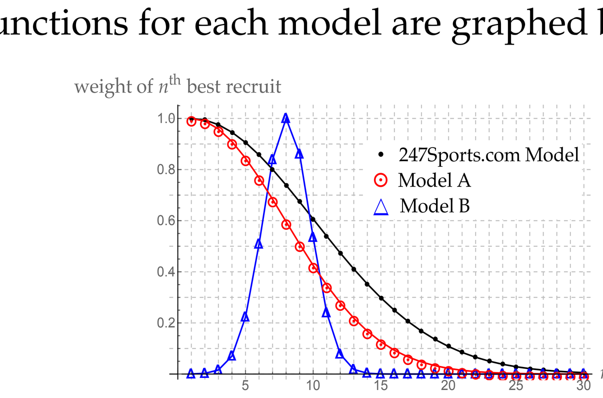
* $p < .1$; ** $p < .01$; *** $p < .001$

- Regression coefficients are less significant than in our two-subset model, but stronger than analogous coefficients coming from traditional star ratings.
- Correlation between counts in this model and team success is 9.5% higher than counts coming from traditional star ratings.

Models A and B: Optimal values of m and/or b are given in this chart:

	247Sports	Model A	Model B
m	1	1	8.038
b	9	6.882	1.752
% of variance in SAG predicted by model	33.8%	34.5%	36.1%

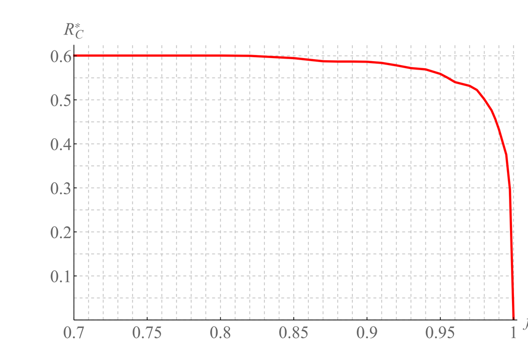
Weight functions for each model are graphed below:



- In Model B, we obtain a much "skinnier" weight function, allowing us to take substantially less information into account.
- In particular, we can effectively ignore the ratings of players outside the top 12 of each recruiting class while making the model more predictive of team success.

Results (continued)

Model C: The maximum correlation between class rating and team success does not severely decrease until the floor f is raised to about .94:



This means that by taking into account only the particular ratings of the top 5.6% of all recruits, we can predict team success 90% as well as someone who considers the particular ratings of all recruits.

Conclusions

- Fewer players should be categorized as "blue chip" than are currently.
- Dividing players into two groups (5♢ and 4♢), based on whether their rating is above or below .9184, is useful for predicting team success.
- Dividing players into more than two groups (like 5★, 4★, 3★, etc.), or otherwise trying to distinguish the ratings of non-elite players is of limited additional value in predicting team success.
- There is positive correlation between Gaussian weighted sums of individual player ratings and team success.
- The weighted sums currently used by 247Sports.com take an unnecessary amount of information into account: sums constructed with a smaller spread parameter produce a weighted total more correlated with team success.
- One only needs to incorporate the ratings of a small percentage of the most elite recruits to produce a model that is almost as predictive as a similar model taking the rating of all players into account.

References

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