A Bayesian Home Run: Modeling a Successful Baseball Season

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Problem Statement:

Since the 1800s, baseball has been a prominent feature of the American sports scene. Sports bring people together, and there is arguably no sport more universally understood and enjoyed in the United States than baseball. Everyone has a stake in the game, from the players and managers to the fans and the residents of the teams' cities. While the fans have an emotional stake, players, managers, and franchise owners and employees stake their livelihood on their team's success. Outside of the team itself, many Americans have a monetary stake in a given team's success due to the prevalence of sports betting. Regardless of the driving force behind their interest, the undeniable truth is that millions of Americans follow major league baseball religiously each season, and the success of their favored team has a real impact on their lives.

For any invested party, the ability to determine the success level of a given team for a given season is an invaluable asset. Through our analysis, we are seeking to determine the success rate of a team based on their game by game performance statistics. We will look at a series of in-game statistics from across several seasons, and we will investigate which of these statistics serve as useful predictors for the success rate of a baseball team. We will parse down to the most valuable predictors, and then we will determine how these predictors affect success rate. At the conclusion of our analysis, we aim to have constructed a model that will return an accurate report of a team's seasonal success rate based on their in-game performance. In practice, this model could be used effectively in the postseason and the leadup to the world series– with a season's worth of gameplay statistics, running two teams' information through the model should indicate which team is more likely to win the series.

Data Description:

For this analysis, we will be using a baseball database compiled by Sean Lahman. The database is extremely extensive, but we will be honing in on one specific data table for our analysis. The Teams data table provides a plethora of team-wide statistics from a wide range of seasons, dating back to the 1800s. The dataset includes many useful statistics: yearID, representing the year of the observation; lgID, representing league; teamID, representing team; franchID, representing franchise; divID, representing division; Rank, representing the teams final ranking at the end of the season; G, representing total games played in the season; Ghome, representing number of home games; W, representing wins; L, representing losses; DivWin, a binary variable representing whether the team won their division; WCWin, a binary variable representing whether the team won the Wild Card; LgWin, a binary variable representing whether the team won their league; WSWin, a binary variable representing whether the team won the World Series; R, representing the number of runs scored; AB, representing the number of at bats; H, representing the number of hits by batters; 2B, representing the number of doubles; 3B, representing the number of triples; HR, representing the number of home runs; BB, representing the number of walks; SO, representing the number of strikeouts; SB, representing the number of stolen bases; CS, representing the number of times the team was caught stealing; HBP, representing the number of times a batter was hit by a pitch; SF, representing the number of sacrifice flies; RA, representing the number of opponent runs scored; ER, representing the number of earned runs allowed; ERA, representing the earned run average; CG, representing the number of complete games; SHO, representing the number of shutouts; SV, representing the number of saves; IPOuts, representing the number of outs pitched; HA, representing the number of hits allowed; HRA, representing the number of home runs allowed; BBA, representing the number of walks allowed; SOA, representing the number of strikeouts by pitchers; E, representing the number of errors; DP, representing the number of double plays; FP, representing the fielding percentage; name, representing the team's full name; park, representing the name of the team's home ballpark; attendance, representing the home attendance total; BPF and PPF, representing the three-year park factor for batters and pitchers, respectively; and finally several teamID variables linking the Teams dataset to other datasets.

Exploratory Data Analysis:

First, we take a look at the top 10 winningest teams in our database (which now ranges from 2005 to 2015), as well as the teams with the least wins to see if anything stands out.

There are some interesting quick, eye-test observations from the data: The 4th "best" team (with the 4th most wins) in the dataset scored less runs than the 4th "worst" team. Additionally, the winningest teams are significantly "better" in the field, with only 2 teams entering triple digits in Errors (versus all 10 of the worst teams.) We also found that teams who strike out less and walk more tend to rack up more wins. Patience is a virtue.

Figure 1.1

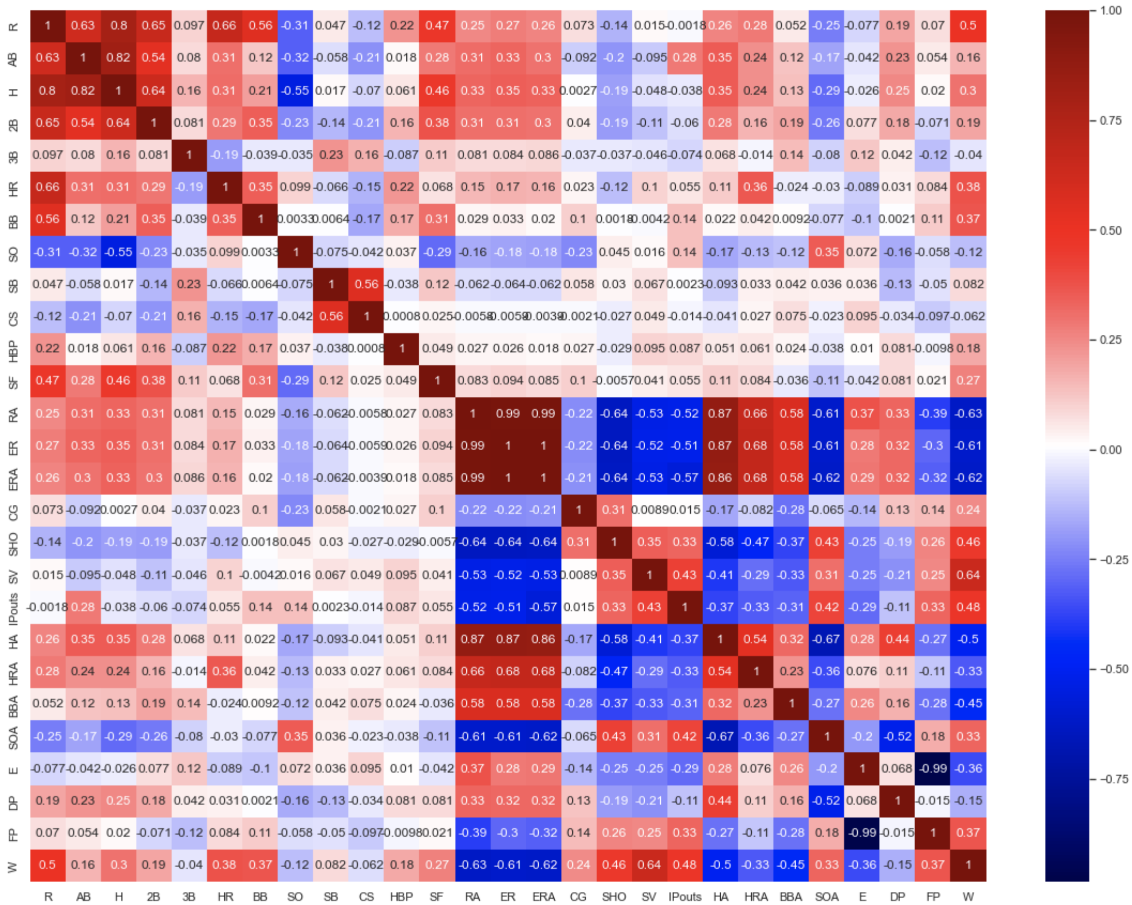
	R	AB	H	2B	3B	HR	BB	SO	SB	CS	...	SV	IPouts	HA	HRA	BBA	SOA	E	DP	FP	W
2612	915	5660	1604	325	21	244	663	1014.0	111.0	28.0	...	51	4350	1386	181	574	1260	86	131	0.985	103
2675	713	5579	1409	258	38	153	539	1024.0	96.0	24.0	...	47	4431	1320	120	404	1299	74	135	0.988	102
2578	765	5540	1486	274	25	159	481	987.0	129.0	48.0	...	66	4354	1455	160	457	1106	91	159	0.985	100
2800	647	5484	1386	288	39	137	506	1267.0	69.0	38.0	...	62	4394	1359	123	477	1329	96	159	0.984	100
2500	805	5538	1494	287	26	170	534	947.0	83.0	36.0	...	48	4337	1399	153	443	974	100	196	0.984	100
2479	741	5529	1450	253	23	200	435	1002.0	137.0	67.0	...	54	4427	1392	167	459	1040	94	166	0.985	99
2757	773	5652	1464	304	31	155	492	1266.0	81.0	39.0	...	46	4448	1307	126	504	1342	83	127	0.986	98
2796	697	5631	1462	292	27	140	461	1322.0	98.0	45.0	...	54	4469	1392	110	453	1338	122	177	0.981	98
2714	731	5615	1468	301	25	194	479	1325.0	105.0	35.0	...	51	4405	1296	129	497	1325	94	134	0.985	98
2718	853	5651	1566	363	29	178	581	1308.0	123.0	19.0	...	33	4362	1366	156	524	1294	80	142	0.987	97

Figure 1.2

	R	AB	H	2B	3B	HR	BB	SO	SB	CS	...	SV	IPouts	HA	HRA	BBA	SOA	E	DP	FP	W
2725	610	5457	1307	266	16	148	426	1535.0	110.0	61.0	...	32	4320	1530	191	616	1084	125	168	0.979	51
2695	583	5407	1276	238	28	146	463	1365.0	105.0	46.0	...	31	4270	1493	173	540	1170	118	132	0.981	55
2666	615	5598	1442	309	28	95	401	1164.0	118.0	33.0	...	25	4305	1477	188	560	1191	116	140	0.981	56
2487	701	5503	1445	289	34	126	424	1008.0	53.0	33.0	...	25	4240	1640	178	580	924	125	163	0.979	56
2646	587	5386	1303	276	27	126	463	1207.0	87.0	36.0	...	31	4235	1567	167	538	1026	127	120	0.979	57
2624	710	5493	1416	271	38	156	617	1208.0	73.0	40.0	...	33	4273	1533	173	629	911	143	155	0.977	59
2594	641	5491	1376	269	26	117	534	1095.0	81.0	43.0	...	28	4302	1496	190	588	1063	123	143	0.980	59
2690	613	5411	1297	265	36	137	447	1235.0	94.0	45.0	...	28	4241	1399	175	573	1128	105	148	0.982	61
2648	513	5409	1274	227	16	101	459	1184.0	142.0	39.0	...	38	4314	1402	157	452	973	110	145	0.982	61
2531	689	5474	1395	267	33	190	441	1106.0	134.0	52.0	...	33	4261	1600	180	606	979	116	156	0.981	61

Using an eye test from which variables look to have a particularly strong correlation (for or against) Wins, we can examine them further in a pairplot. We tended to skip over some that overlap or were redundant (such as Runs Allowed vs. Earned Runs Allowed.)

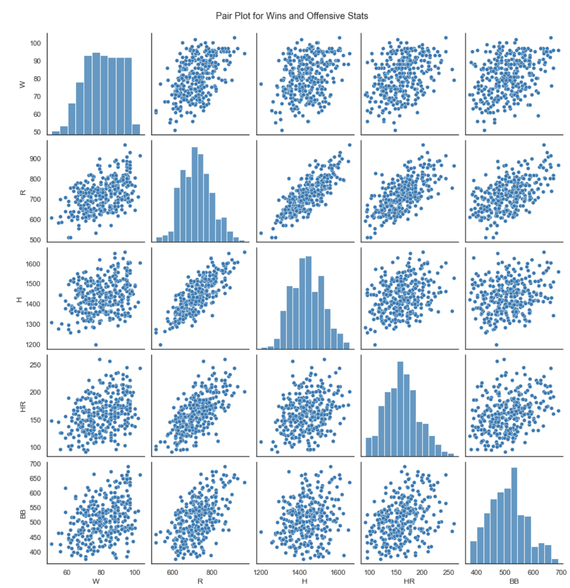
Figure 1.3

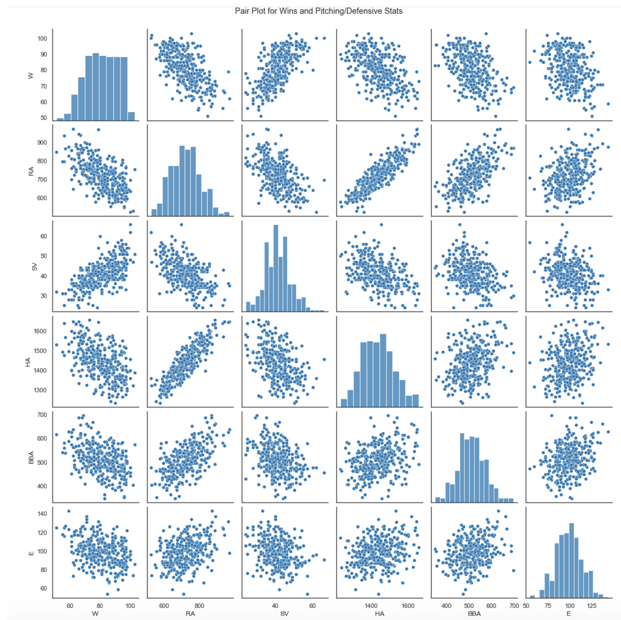


On the offensive side of the ball, Wins and Runs have the strongest correlation of the variables chosen. Interestingly, Home Runs just edge out Walks in correlation to Wins. Hits have a noticeable correlation with Wins, but the lowest amongst the group.

Overall, the pitching and defensive stats appeared to show stronger correlation with a baseball team's Wins. Saves had the strongest positive correlation with Wins, while Runs Allowed had the strongest negative correlation. This is no surprise, as in order to qualify for a Save, a pitcher must "enter the game with a lead of no more than three runs and pitch at least one inning; or enter the game with the tying run in the on-deck circle, at the plate or on the bases" according to MLB rules. This links save situations very closely to a team winning their game. On the other hand, letting the other team score a large amount of runs is typically not conducive to winning a game. Runs Allowed was followed by Hits Allowed, Walks Allowed, and Errors in terms of negative correlation.

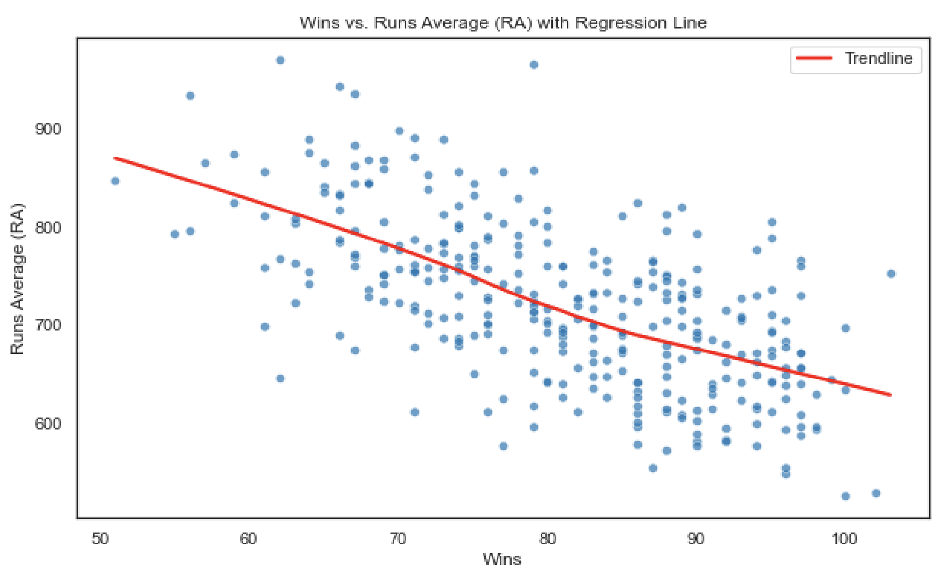
Figure 1.4 and Figure 1.5





We can see in Figure 1.6 the importance of runs and good pitching/defense in the following figure. As the amount of runs allowed by pitchers and the defense decreases, we see a significant trend towards winning more games.

Figure 1.6



Feature Selection:

	Feature	Importance
0	R	0.050062
2	H	0.044946
17	SV	0.044466
6	BB	0.041979
21	BBA	0.041491
5	HR	0.041431
12	RA	0.040797
18	IPouts	0.040560
1	AB	0.040361
8	SB	0.039865
20	HRA	0.039417
24	DP	0.038993
23	E	0.038596
4	3B	0.038333
22	SOA	0.038266

The main task that needs to be tackled before the final phase of model building is variable selection. With such a comprehensive dataset, parsing down the variables is extremely important for model performance and overall success. For this preliminary data work, we decided to use a random forest model to determine variable importance. We limited the variables included in the model to those that were collected on a game-by-game basis: R, AB, H, 2B, 3B, HR, BB, SO, SB, CS, HBP, SF, RA, ER, ERA, CG, SHO, SV, IPouts, HA, HRA, BBA, SOA, E, DP, FP, and W. To set up our random forest model, we created a training set and a test set in our data, where the training set was a random 70% split of the data and the test set was the remaining 30%. We set the value to be predicted as W, number of wins, as this will be our ultimate determinant of success in a given season. We ran the random forest model and updated the number of estimator trees from the default value of 100 to 200, so that we could have a higher level of accuracy. We also made sure to run it on the criterion specified by the Gini coefficient. We then fit the random forest model to our training data and extracted the relevant feature importances from to determine which features were most useful in determining the number of wins per season based on the Gini coefficient impurity. Figure 1.7 (left) shows the fifteen most useful predictors and their respective importances.

Based on the random forest model variable importances, we chose to include the 5 most useful predictors in our final model. We decided to select 2 offensive-based stats (R and H), 2 pitching-based stats (SV and RA), and one defensive-based stat (E) to diversify and more fully capture the different aspects of the game. With this predictor set, the model will determine number of wins in a given season based on the following predictors: R, with an importance of .050062; H, with an importance of .044946; SV, with an importance of .044466; RA, with an importance of 0.040797; and E, with an importance of 0.038596. With this predictor set, we believe that our final model will predict the number of wins per season with a high level of accuracy.

Model Description:

For our final analysis, we chose to construct a hierarchical Bayesian regression model with the following equation:

Wins $=\alpha+\beta*runs+\gamma*hits+\delta*saves+\varepsilon*runsallowed+\zeta*errors$

where:

β represents the effect of runs for the team, indicating how much the number of Wins is expected to change with a one-unit increase in runs while keeping other variables constant.

γ represents the effect of hits for the team, indicating how much the number of Wins is expected to change with a one-unit increase in hits while keeping other variables constant.

δ represents the effect of saves for the team, indicating how much the number of Wins is expected to change with a one-unit increase in saves while keeping other variables constant.

ε represents the effect of runs allowed for the team, indicating how much the number of Wins is expected to change with a one-unit increase in runs allowed while keeping other variables constant.

ζ represents the effect of errors for the team, indicating how much the number of Wins is expected to change with a one-unit increase in errors while keeping other variables constant.

α represents the hierarchical effect as well as the overall intercept, representing the baseline level of Wins at the mean levels of all variables.

Prior Rationale:

μ is set to follow a normal distribution with mean 0 and a large standard deviation of 10000. σ is set to follow a Half-Cauchy distribution with scale parameter 5. An offset is drawn from a normal distribution with mean 0 and standard deviation 1. The shape is 330. The coefficient α is then determined as the sum of μ and each element of the offset vector multiplied by σ. The motivation behind using such wide priors for α is due to the lack of clear information or strong prior beliefs about its values. By employing these large priors, the model can maintain flexibility and allow for a more general representation of the posterior distributions.For the remaining coefficients, the prior information is as follows:

An offset is drawn from a normal distribution with mean 0 and standard deviation 1. The coefficient of interest is determined as the value of the offset. These priors are chosen similarly to the α priors because there is limited prior information about the data. There is no need for a shape input since the coefficients have similar structure.

Overall, these prior choices aim to account for uncertainty and avoid imposing strong assumptions on the coefficient values, allowing the model to be more flexible in representing the data's behavior.

Findings:

Figure 1.8

	index	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
0	mu_a	56.298	4.197	48.409	64.787	0.208	0.158	502.0	158.0	1.01
333	delta_saves	0.455	0.032	0.396	0.516	0.002	0.001	474.0	147.0	1.01
331	beta_runs	0.090	0.004	0.082	0.097	0.000	0.000	469.0	191.0	1.01
332	gamma_hits	-0.000	0.004	-0.007	0.007	0.000	0.000	747.0	319.0	1.01
335	zeta_errors	-0.002	0.013	-0.027	0.021	0.000	0.000	1367.0	2466.0	1.00
334	epsilon_runs_allowed	-0.082	0.003	-0.087	-0.076	0.000	0.000	408.0	134.0	1.01

We pulled a few key takeaways from our summary table: Consistent r-hat values around 1 suggest that our sampler performed well, meaning that the sampler has explored the parameter space effectively and provides reliable estimates for the model parameters. The ESS values also indicate that the chains look to have converged well for these parameters. Additionally, standard deviation values appear to have remained relatively low across the parameters.

Results:

Our hierarchical Bayesian model was used to test the variables influencing team performance in baseball. The estimated mean baseline level of a team's wins, mu_a, represented the expected number of wins at the average levels of all the variables that were included in our model: runs, hits, saves, runs allowed, and errors. The resulting mean was approximately 56.3, with a moderate standard deviation of 4.197.

The effects of specific variables on team wins were also determined. The number of saves was found to have the greatest positive effect, with an estimated effect size of 0.455 and relatively low uncertainty (a standard deviation of 0.032). Similarly, runs scored demonstrated a positive impact, with an effect size of 0.090 and low uncertainty (a standard deviation equal to 0.004).

Interestingly, hits seemed to have a negligible effect on wins, with the estimated effect being close to zero.

On the other side, errors were associated with a slight negative impact as the effect size was -0.002, but the uncertainty in this estimate was relatively higher (with a standard deviation of 0.013). Unsurprisingly, runs allowed exhibited the strongest negative effect, with a notable effect size of -0.082 and low uncertainty (standard deviation = 0.003). These findings provide insights into the factors driving team performance and could inform strategies for optimizing team success in baseball.

Discussion:

Based on our model, the selected pitching stats seem to play a larger role in determining the outcome of the game than the selected offensive stats. The positive effect of saves on wins suggests that teams which are more successful in preserving their tight leads and securing victories in close games tend to have a higher overall win count. This emphasizes the critical role of a strong bullpen and effective closing pitchers in securing wins for a baseball team. Similarly, the negative effect of runs allowed reinforces the critical role of strong pitching and effective defensive strategies. The model suggests that teams which can limit their opponents' scoring are more likely to secure victories, indicating that a solid pitching rotation and reliable defense are important aspects of success for a baseball team.

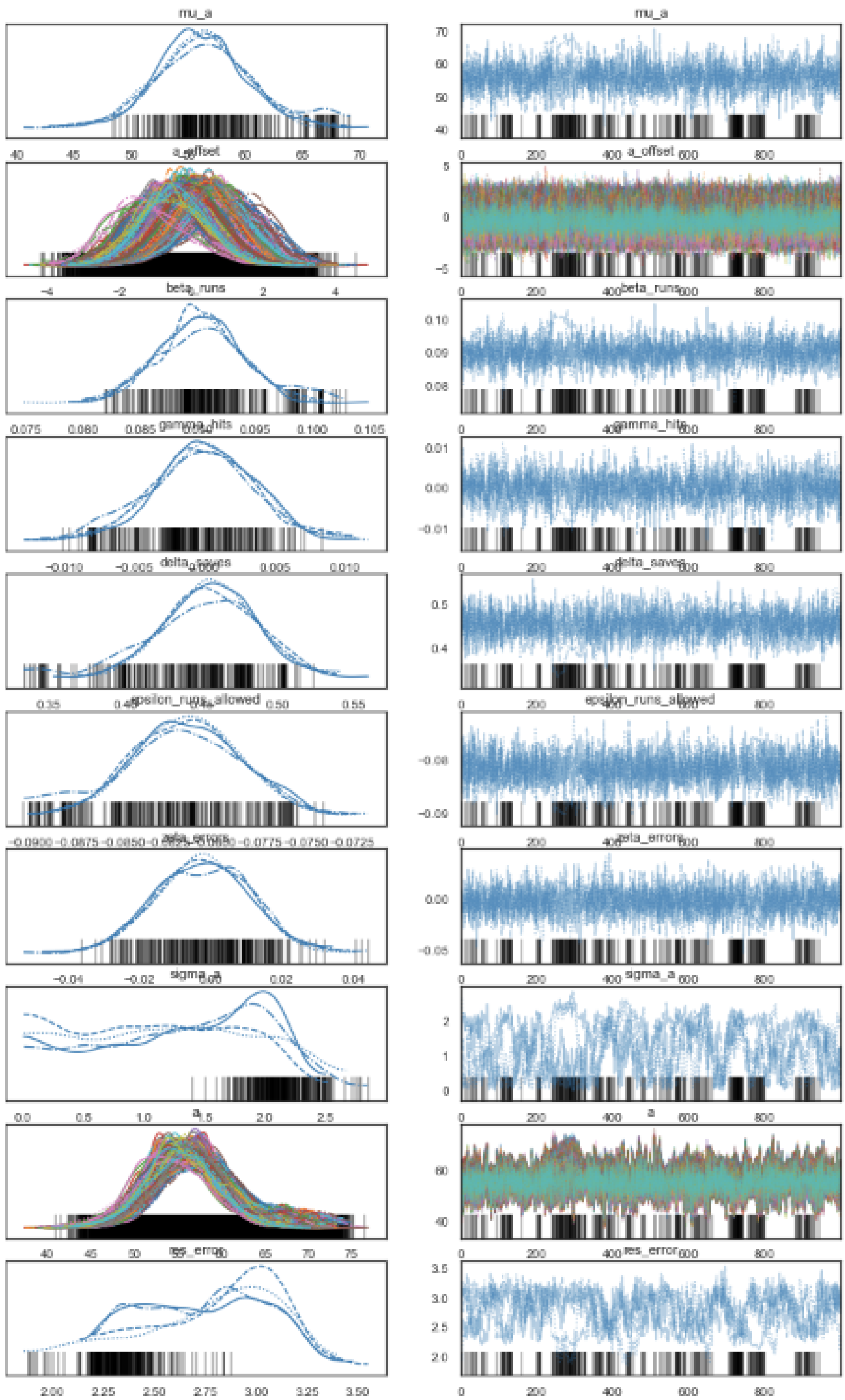
Of course, that does not mean that offense is completely worthless. The positive effect of runs scored emphasizes the significance of offense in driving team success. Teams that can consistently score runs are more likely to secure wins, indicating the importance of a well-rounded batting lineup and effective run-scoring strategies. These run-scoring strategies can come in many ways - as evidenced by the finding that hits have a negligible effect on wins in our model. The finding suggests that numerous methods for getting on base can contribute to run scoring strategies and that the quality of hits may be more important than the quantity of hits when it comes to winning games.

Overall, our model appears to give useful insight into the strategies that go into creating a successful, winning baseball team. In future analyses on this data, we would consider branching out into the different types of data offered in different data tables of the baseball database. For example, it would be interesting to investigate the effect of salary on team success, or the effect of individual player awards across the league on each team’s success in a given season.

Appendix:

For relevant code, see accompanying python notebook.

Trace Plots:



Forest plot preview: