



Butts in Seats

A Data-Driven Look at Major League Baseball
Attendance

Paul Giesting, PhD
Metis New York DS23

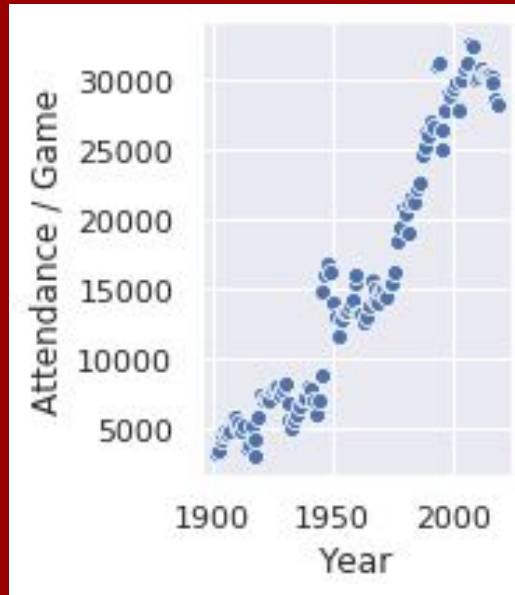
Baseball Attendance in the 21st Century

The Problem

After a century of increase, game attendance is slipping.

This is partly a side effect of different stadium and revenue design, but let's consider whether the game itself is contributing.

The Data



The Approach

Baseball has more things to count than any other sport, and a longer history to boot.

Let's put that data to work.

Workflow

Import & parse

Get the data imported and converted to a usable form.

Visualize & judge

Not every stat can be used or is equally useful.

After inspection, dead ball era data is [sigh] not valuable for this project.

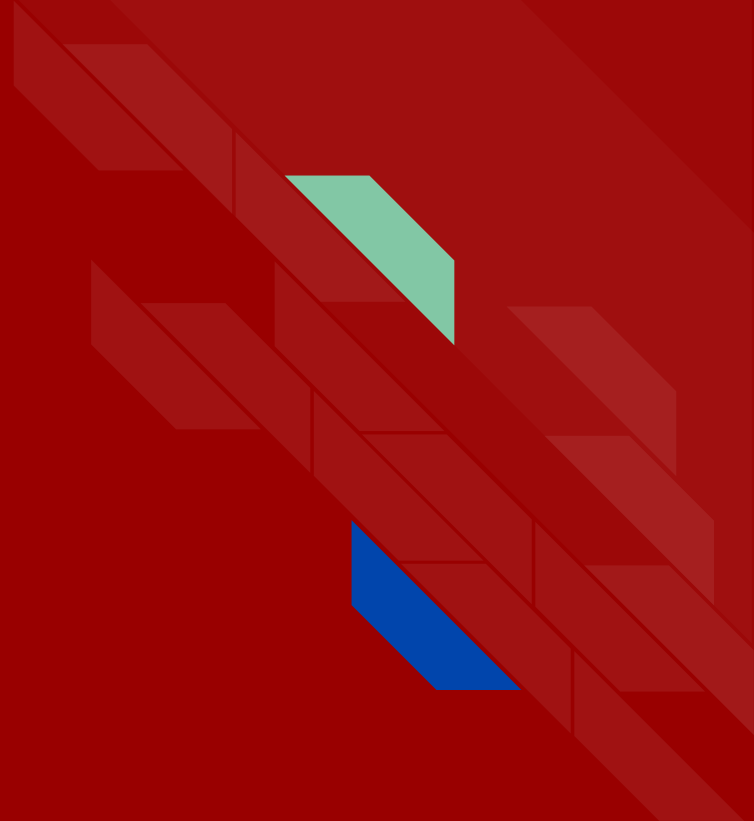
A curated set of statistics were evaluated and cut down to create a model.

Model & ponder

LassoCV: repeated train-test splits, checking the number of times different features are removed.

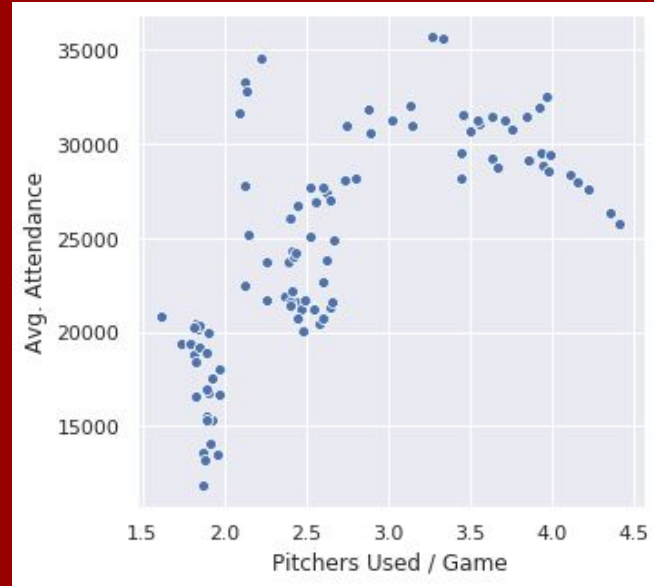
Statsmodels: feature p -values, kicking the worst stats off the island, iterate to stabilization.

The Insights



Strategy

Reinforcing Conclusions

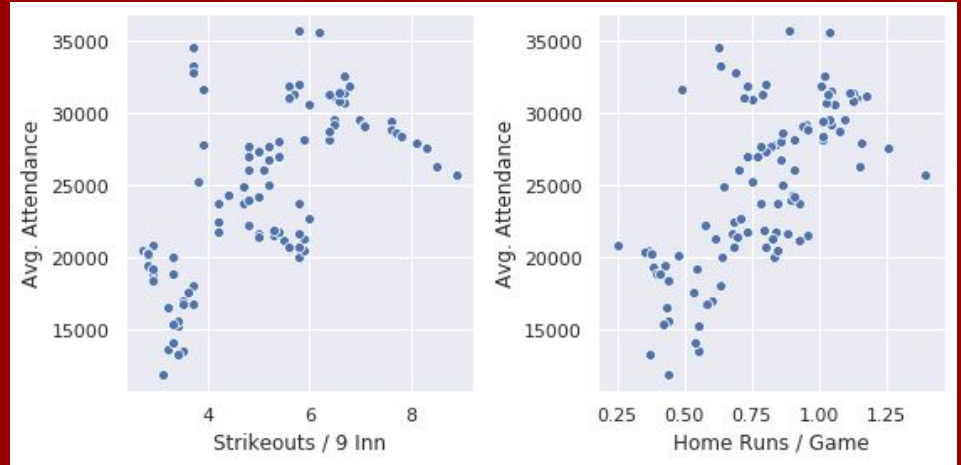


Pitching changes:

- The game has passed a tipping point.

Strategy

Usable Insights

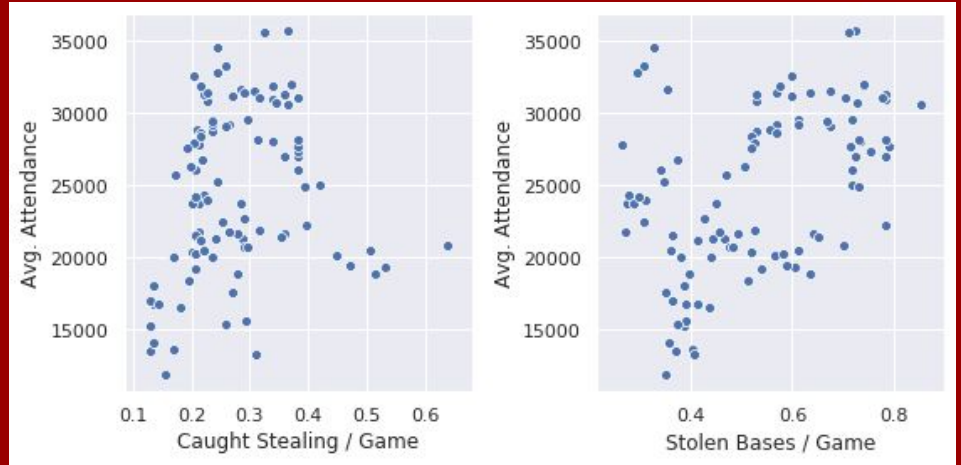


Strikeouts and home runs:

- Do fans want to wait around for the Three True Outcomes?
- Idea: Reverse the trend of short outfield fences.

Strategy

Rethinking Culture



Stolen bases:

- Base stealers *and* catchers are heroes to the fans.
- Culture / scouting changes.

The game has passed a tipping point. Too much of two good things.

Steals are exciting, even... especially... when a team's favorite catcher makes the play.

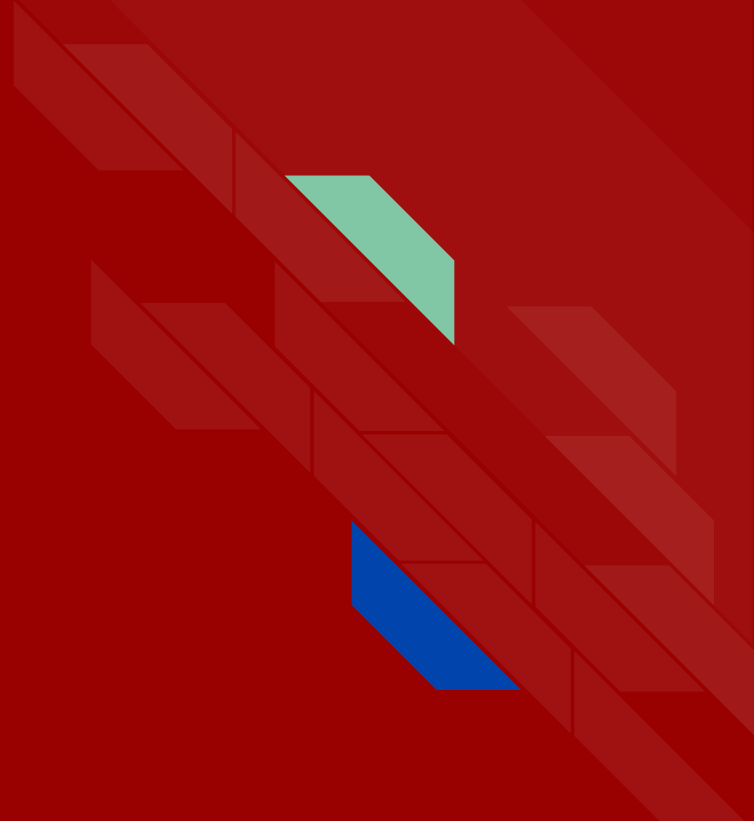
The data suggest that fans want action and visible strategy, even if strategically it's unwise.



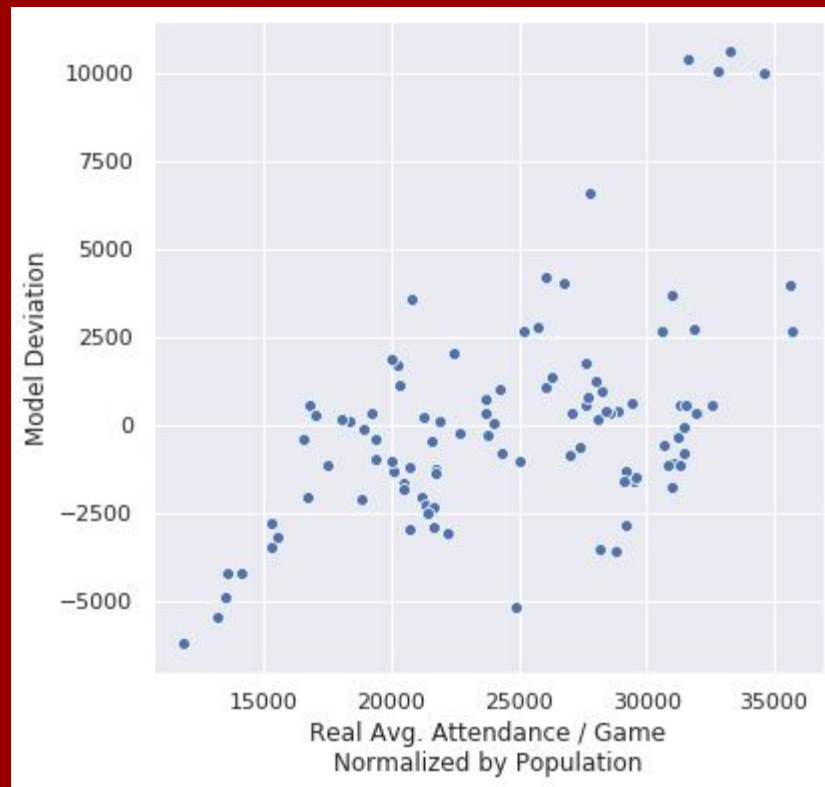
This is also past a tipping point. Intervention was wise.

Today's fielders have been perfecting their craft for a lifetime, and the fans appreciate it.

Appendix



Model Quality



Main Model

OLS Regression Results

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=====
Dep. Variable:          y      R-squared:          0.724
Model:                  OLS    Adj. R-squared:       0.712
Method:                 Least Squares  F-statistic:        62.33
Date:                   Thu, 16 Apr 2020  Prob (F-statistic):  9.67e-26
Time:                   23:43:22  Log-Likelihood:     -372.88
No. Observations:      100      AIC:               755.8
Df Residuals:          95      BIC:               768.8
Df Model:               4
Covariance Type:       nonrobust
=====

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=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          -115.6298      18.879      -6.125      0.000      -153.109      -78.151
S09             -12.9784       2.486      -5.220      0.000      -17.915      -8.042
Pitchers/G      145.4968      16.835       8.643      0.000      112.075      178.918
PitG^2          -17.4525       2.382      -7.327      0.000      -22.181      -12.724
CS/G            32.9747      11.316       2.914      0.004       10.510       55.439
=====

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Omnibus:          35.735      Durbin-Watson:      0.551
Prob(Omnibus):    0.000      Jarque-Bera (JB):   77.947
Skew:             1.367      Prob(JB):           1.19e-17
Kurtosis:         6.351      Cond. No.           263.
=====

```

Alternative Model
with HR,
Bunts,
Fld%

OLS Regression Results

```
=====
Dep. Variable:          y      R-squared:          0.763
Model:                  OLS    Adj. R-squared:       0.748
Method:                 Least Squares    F-statistic:        49.92
Date:                  Thu, 16 Apr 2020    Prob (F-statistic):   5.63e-27
Time:                  19:36:08    Log-Likelihood:      -365.26
No. Observations:      100    AIC:                 744.5
Df Residuals:          93    BIC:                 762.8
Df Model:               6
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	-1907.1394	364.545	-5.232	0.000	-2631.054	-1183.225
HR/G	29.6711	9.542	3.109	0.002	10.722	48.620
Pitchers/G	16.0803	5.944	2.705	0.008	4.277	27.884
S09^2	-1.2423	0.215	-5.773	0.000	-1.670	-0.815
SH^2	12.8740	5.030	2.560	0.012	2.886	22.862
Fld^2	2033.2049	392.044	5.186	0.000	1254.682	2811.727
CS/G	48.6562	11.090	4.387	0.000	26.634	70.679

```
=====
Omnibus:                33.816    Durbin-Watson:         0.747
Prob(Omnibus):          0.000    Jarque-Bera (JB):      81.257
Skew:                   1.234    Prob(JB):              2.27e-18
Kurtosis:               6.662    Cond. No.              1.83e+04
=====
```

Outlier Years

Alternative Model
with HR, Bunts,
Fld%

	Att	AttP	Diff
1933	39.544513	58.736799	-19.192286
1943	44.098289	69.470340	-25.372051
1946	105.481293	70.252783	35.228510
1947	110.934573	86.323748	24.610825
1948	115.337925	79.269745	36.068180
1949	109.270058	83.608718	25.661340
1981	82.978167	97.883077	-14.904910
1988	103.218814	91.624403	11.594411
1989	106.142128	89.182330	16.959798
1993	119.128963	102.510133	16.618830
1994	118.785391	103.667513	15.117878
2003	95.932577	110.367523	-14.434946

Linear features only.
(A last minute addition to show where I wanted to go.)

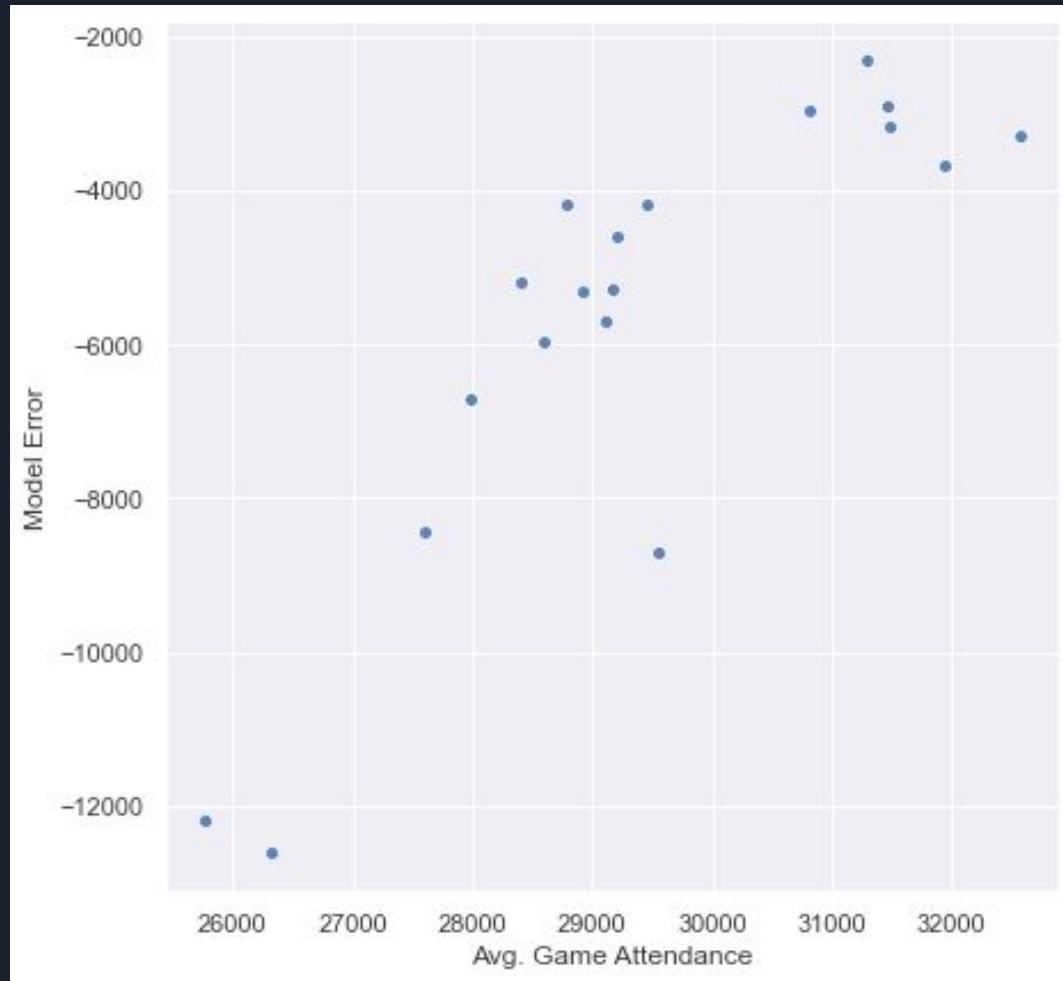
OLS Regression Results						
=====						
Dep. Variable:	Att	R-squared:	0.796			
Model:	OLS	Adj. R-squared:	0.776			
Method:	Least Squares	F-statistic:	40.61			
Date:	Fri, 17 Apr 2020	Prob (F-statistic):	1.05e-22			
Time:	09:14:58	Log-Likelihood:	-290.54			
No. Observations:	81	AIC:	597.1			
Df Residuals:	73	BIC:	616.2			
Df Model:	7					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	-4832.6800	964.096	-5.013	0.000	-6754.120	-2911.240
Year	0.3959	0.177	2.238	0.028	0.043	0.748
SH/G	39.3055	11.103	3.540	0.001	17.176	61.435
SO9	-11.2172	2.655	-4.224	0.000	-16.509	-5.925
CS/G	94.0683	17.449	5.391	0.000	59.293	128.844
3B/G	188.7290	39.988	4.720	0.000	109.034	268.424
A/G	-39.1350	7.109	-5.505	0.000	-53.303	-24.967
Fld%	4634.9524	1065.883	4.348	0.000	2510.651	6759.253
=====						
Omnibus:	4.116	Durbin-Watson:	1.244			
Prob(Omnibus):	0.128	Jarque-Bera (JB):	3.503			
Skew:	0.498	Prob(JB):	0.174			
Kurtosis:	3.212	Cond. No.	2.71e+06			
=====						

Predictive Model:
Calibrated on
20th century data.

Systematically
overpredicts 21st
century data.

- Culture is shifting.
- Stadiums & revenue models are shifting.



Periodicity: Batting Average

