Predicting Saves from Past Performance

“Closers are one of the most volatile positions in fantasy baseball…Each year, closers drop like flies and many MLB teams make in-season changes due to injuries or poor performance.”

https://www.rotoballer.com/mlb-saves-closers-depth-charts/226767

Hello!

My name is

Ethan Feldman

I am here today to talk about how we can leverage data to better understand future baseball performance

Agenda

- Methods and Data
- Models, Observations, and Error
- Predictions and Recommendations

Where did the data come from?

BASEBALL REFERENCE

python™

jupyter

matplotlib

scikit learn

What do we want to talk about with saves?

- Saves are very difficult to accurately predict
  - Injuries (occurring and recovering from)
  - ‘Position’ change

- The highest valued indicators are:
  - Opportunity
  - “Commanding a game”

Baseline Metric

How'd they do last year?

Let’s build a very simple model with one feature

The dotted line represents accurate predictions

- Below the line represents underpredictions
- Above the line represents over predictions

Really gives a lower bound on predictions

- Really constrains our predictions
- This linear model accounts for about 29.4% of the variability in actual saves
- Has an average error of about 14 saves

Can we improve?

Let’s include more features

After employing regularization and feature engineering

The dotted line represents accurate predictions

- Below the line represents underpredictions

- Above the line represents over predictions

After employing regularization and feature engineering

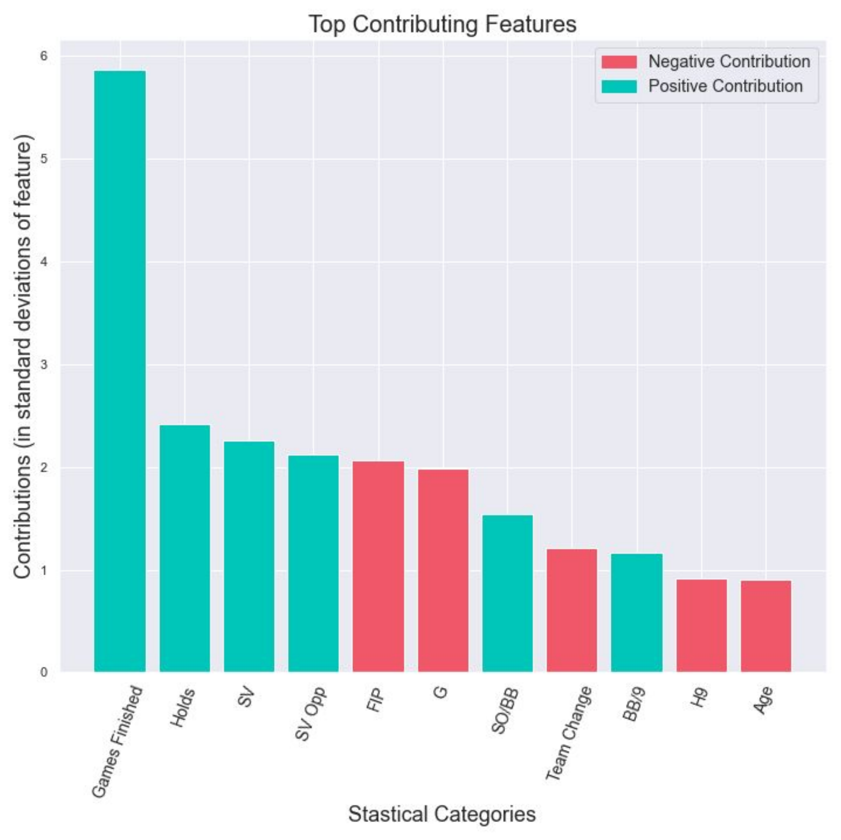
- Points less constrained, fall closer to true values on average
- This model accounts for about 41.6% of the variability in actual saves
- Has an average error of about 10 saves in either direction

Big factors

Which features contribute most?

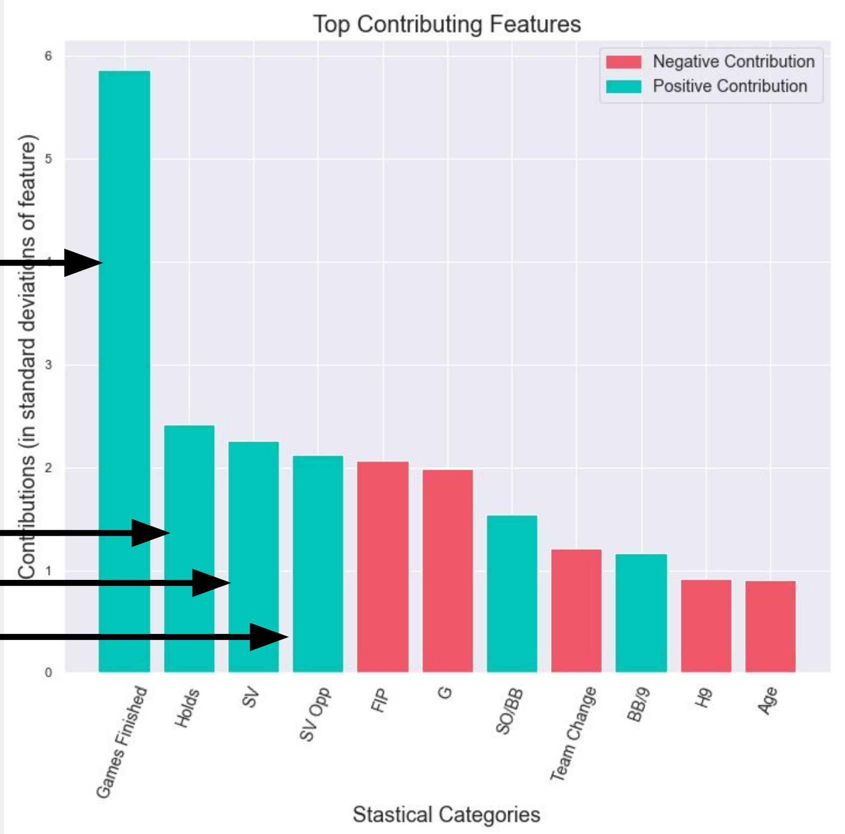
Why do we see so much error?

Which features contributed most heavily in our model?



Pitchers in higher leverage situations saw more saves

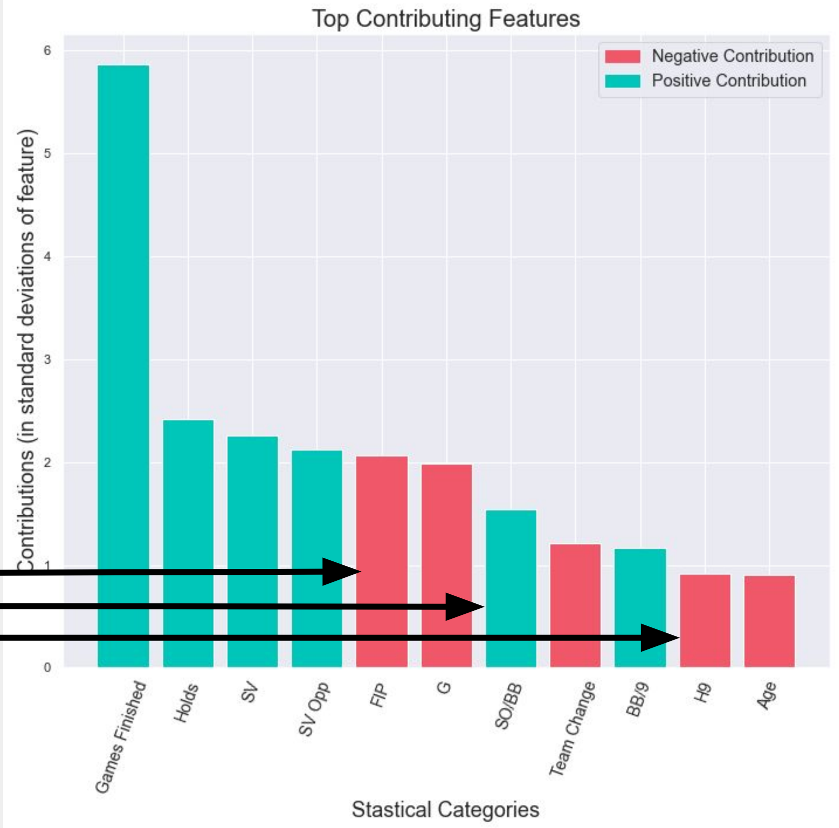
Opportunity
Opportunity
Opportunity



More success with less chance (balls in play) or mistakes

Pitchers Who "Control The Game"

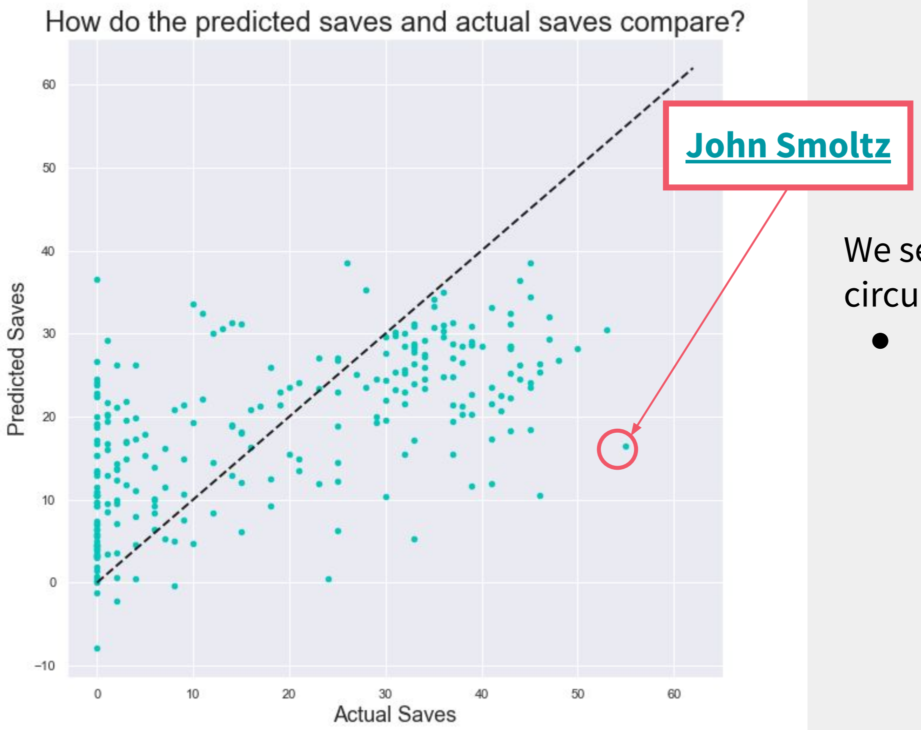
- **Lower FIP**
- **Higher SO/BB**
- **Fewer Hits**
- **More SO**



Can we identify traits of players further from the line?

We see large error values in a few main circumstances:

Positional change accounted for many large errors



We see large error values in a few main circumstances:

- Players transition from starter one year to closer the next (John Smoltz)

Injuries added large error for some players

We see large error values in a few main circumstances:

- Players transition from starter one year to closer the next (John Smoltz)
- Players become or return from injury (Duane Ward)

Short lived success for closers

We see large error values in a few main circumstances:

- Players transition from starter one year to closer the next (John Smoltz)
- Players become or return from injury (Duane Ward)
- High volatility and short careers as closers (Go to zero)

Big Takeaways

What we learned here

What can we say about predicting saves?

- Saves are very difficult to accurately predict
  - Unexpected Twists such as:
    - Pitchers transition quickly from starter to closer
    - High frequency of injury

- The highest valued indicators are:
  - Opportunity (games finished, holds, etc)
  - “Commanding a game” (SO/BB, fewer hits, etc)

Next Steps

How might we gain more insight?

Based on these findings, next steps would include:

- Dig deeper into metrics for pitchers who dominate
  - Velocity, spin rate, swing/miss%, etc
- Do any of the above stats or others project injury?
- Is there a way to predict opportunity?
  - Managers, teams, strength of teammates, etc.
- Is a linear model appropriate? Maybe classification?

Thanks!

Any questions?

You can find me at:

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Appendix

But let’s pretend

What would our model predict for the 2020 shortened season (60 of 162 games)?

“Wins may be the most challenging part of fantasy baseball to figure out, but closers are the most frustrating.”

https://www.si.com/mlb/2020/02/22/fantasy-baseball-the-save-game

What did our model say about 2020?

Name	Tm	Predictions 2020	Shortened 2020
Brad Hand	CLE	9.706878	16
Liam Hendriks	OAK	10.582459	14
Josh Hader	MIL	12.635866	13
Alex Colomé	CHW	7.986627	12
Brandon Kintzler	CHC	3.515879	12
Ryan Pressly	HOU	7.578048	12
Kenley Jansen	LAD	10.028261	11
Trevor Rosenthal	TOT	1.550649	11
Mark Melancon	TOT	4.944614	11
Daniel Hudson	TOT	4.598647	10
Taylor Rogers	MIN	11.192820	9
Zack Britton	NYY	5.819833	8
Raisel Iglesias	CIN	10.236867	8
Greg Holland	ARI	4.885251	6
Edwin Díaz	NYM	7.752255	6
Sergio Romo	TOT	6.863781	5
Andrew Miller	STL	4.420868	4
Aroldis Chapman	NYY	11.012168	3
Craig Kimbrel	CHC	2.090575	2
Wade Davis	COL	4.241749	2

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Felipe Vázquez	PIT	10.784351	0
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Injuries/ Leave

Team Change

Converted Stater

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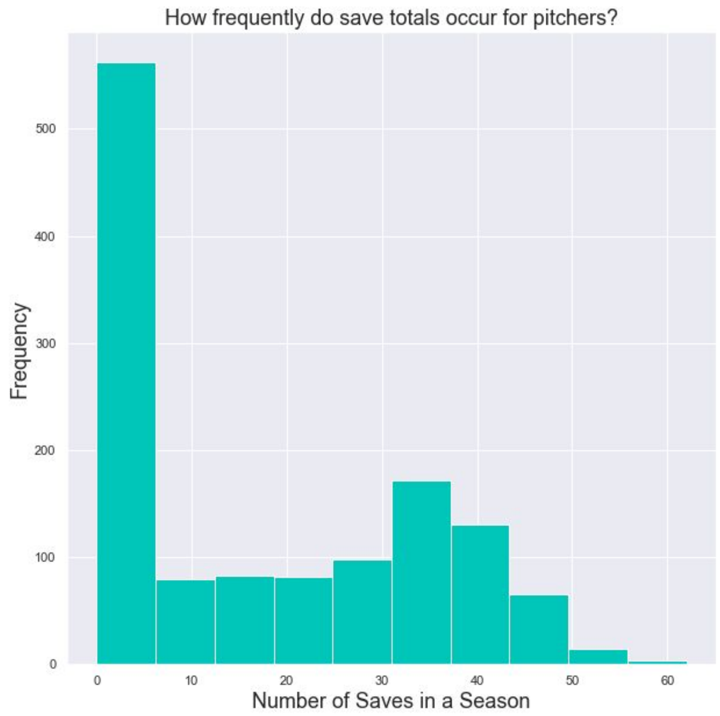
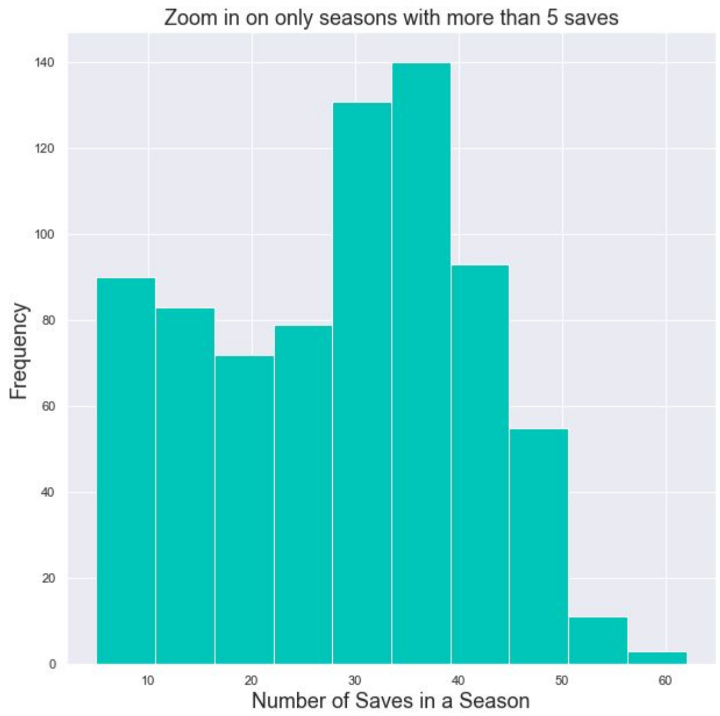
Ridge Regression Coefficients

Feature	Coefficient
Games Finished	**5.87**
Holds	**2.42**
Saves	**2.27**
Save Opportunity	**2.12**
FIP	**-2.07**
Games	**-1.99**
SO/BB	**1.54**
Team Change	**-1.21**
BB/9	**1.17**

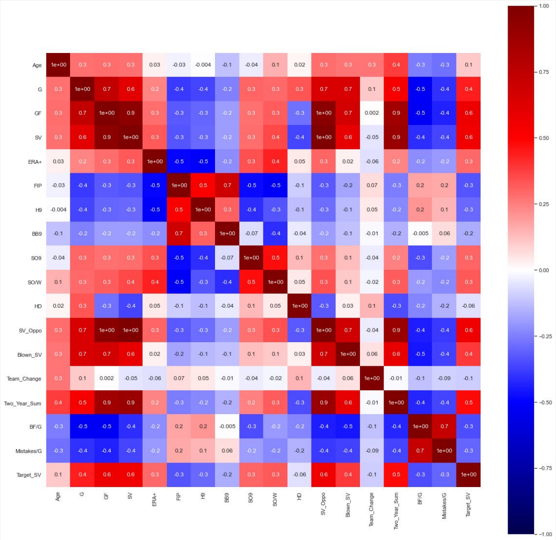
Feature	Coefficient
Hits/9	**-.92**
Age	**-.90**
Two Year Sum SV	**-.6**
Blown Saves	**-.51**
Mistakes/G	**-.40**
BF/G	**-.28**
ERA+	**-.21**
SO/9	**.21**

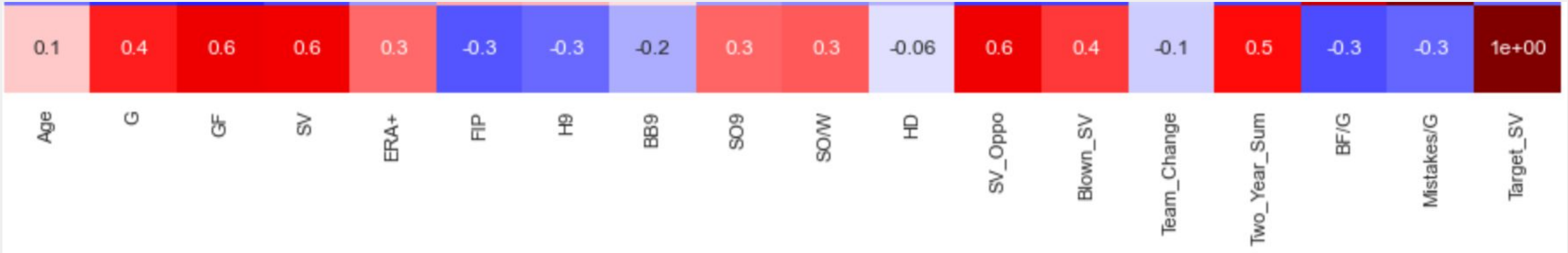
How do saves break down over the years?





How does our smaller subset of features correlate?





Some assumptions about data

- Data drawn from players careers who have had at least one top ten finish of saves since 1985
- Final seasons of careers used as target, but never predictions
- 2020 not used as target for anyone