STATS 601

Caught Looking: Analyzing Variations in Umpire Strike Zones

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MOTIVATION

In baseball, the home plate umpire is tasked with calling every pitch a ball or strike, unless the batter swings

MLB provides PITCHf/x data which includes information about every pitch such as location, umpire's call, speed, game situation, etc.[3]

We want to use this data to see how close umpires come to calling the true strike zone

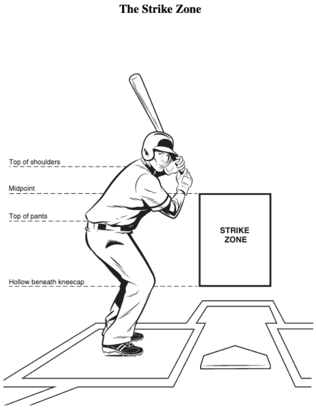


Figure: Official MLB strike zone[2]

Motivation

A brief detour into the rules of baseball

- If a batter gets 3 strikes before 4 balls, he is out. Otherwise he gets to walk to first base
- Therefore, the ball/strike call is more consequential in certain situations, leading umpires to possibly expand or shrink their strike zones

Our primary question is whether different umpires have different strike zones in counts with [0, 1] strikes, 2 strikes, [0, 2] balls, 3 balls. We consider umpires with at least 30 games behind the plate in 2018.

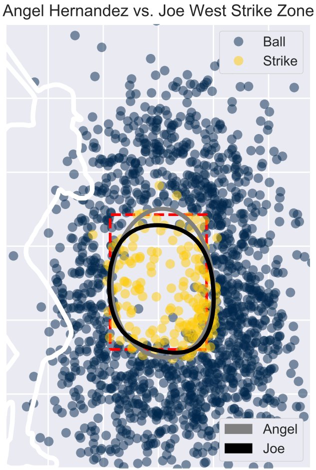
Motivation
Actionable items

- Evaluating umpire ability to determine who gets promotions, playoff assignments, etc.
- Assessing the need for automatic strike zone calls/robot umpires
- Delivering insights to pitchers and batters

This is a problem of interest to league officials, teams, and fans alike

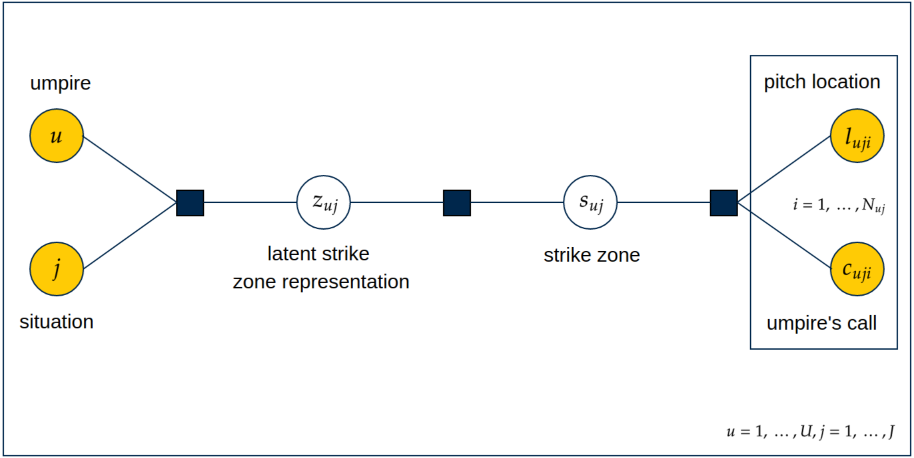
Motivation
Quantifying Differences in Strike Zones

The plot on the right shows that Angel Hernandez and Joe West have different strike zones in counts with 2 strikes and <3 balls, but we need to develop a method to quantify the difference



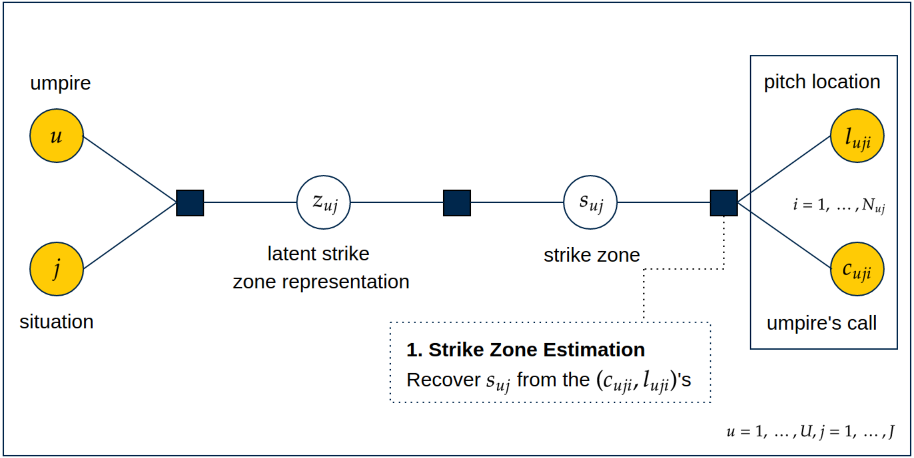
Motivation

A graphical depiction of our problem



Motivation

A graphical depiction of our problem



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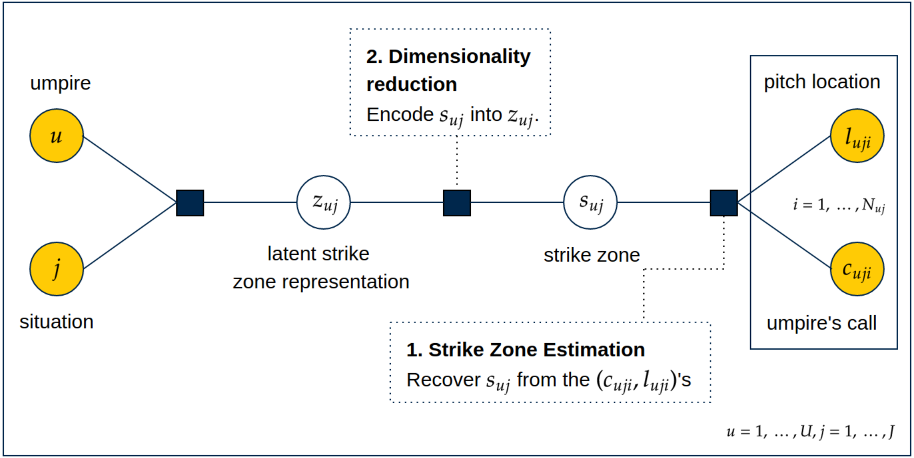
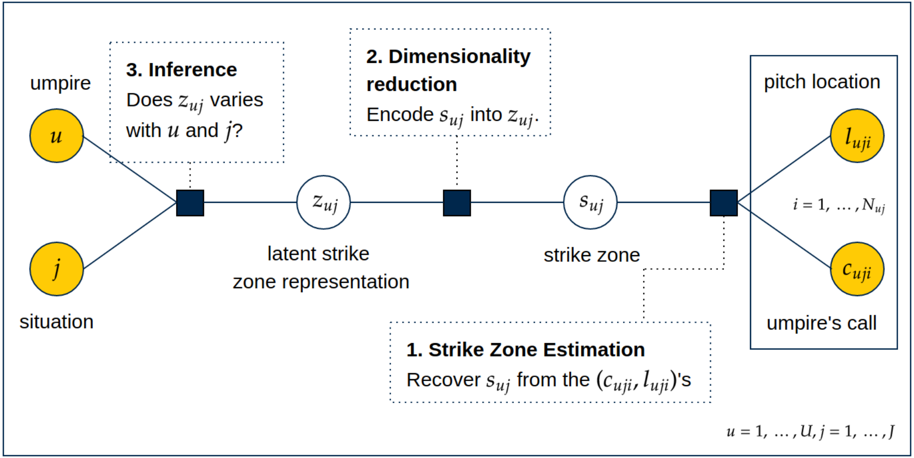


Motivation

A graphical depiction of our problem



CLASSIFICATION

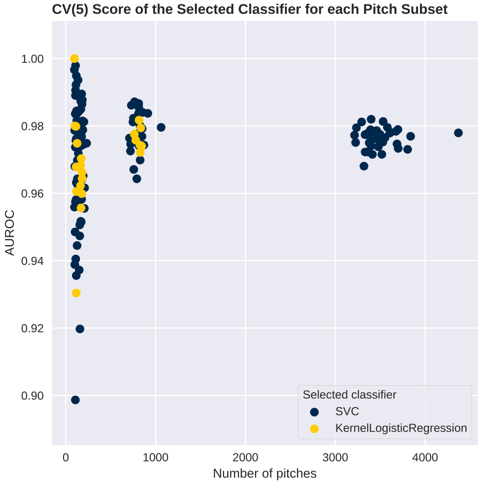
Classification

Choosing a model to learn each umpire's strike zone

- We want to learn the strike zone boundary for each umpire in a variety of game situations
- Challenge is finding good boundary for specific game situations, where sample size may be small, without overfitting
- Some methods we tried included
  - **Kernel Logistic regression**
  - Logistic GAM
  - Neural network
  - **Kernel SVM**
  - Tree-based methods (AdaBoost, CART, Random Forest, Gradient Boosting)

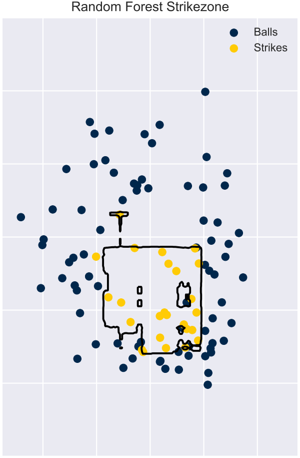
Classification
Cross validation results

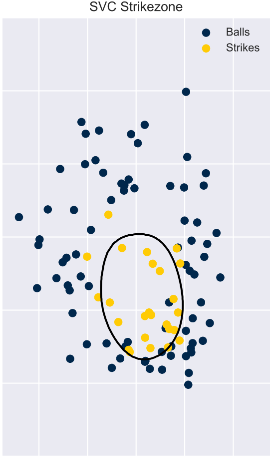
As some umpire/situation combinations have small sample size, we use cross validation to determine the best classifier (and tune them) for each subsample of the data
We use the AUROC score since it is less sensitive to unbalanced classes.



Classification
Comparison of Kernel and Ensemble methods

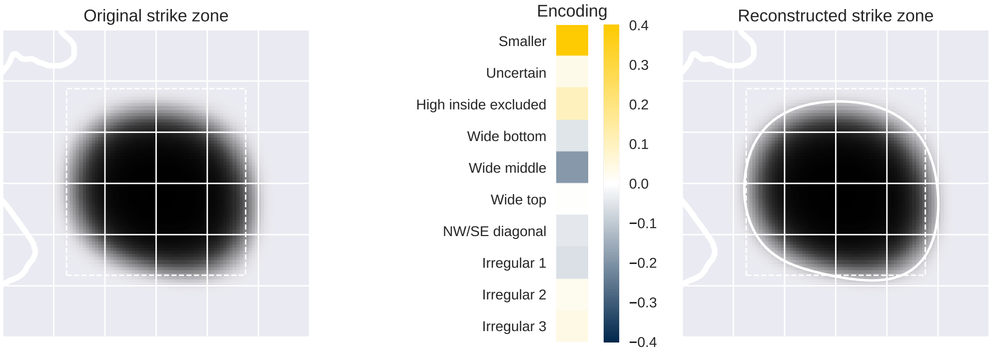
Although these methods have similar error rates, SVC produces a more realistic boundary





DIMENSIONALITY REDUCTION

Dimensionality Reduction
Encoding



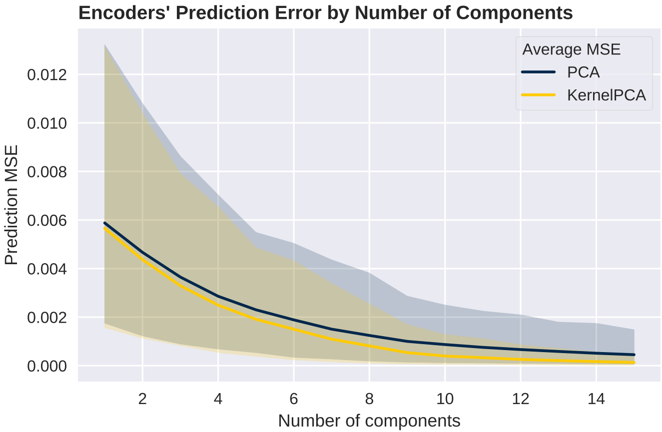
Dimensionality Reduction
Model and number of components selection

PCA and Kernel PCA

- **orthogonal** embeddings are desirable for inference

CNN Autoencoder

- Natural choice for image encoding
- Similar prediction error
- **non-orthogonal** embeddings



Dimensionality Reduction
Component interpretation

Component	Interpretation
1	Overall size
2	Overall uncertainty
3	High inside
4	Lower width
5	Middle width
6	Upper width
7	Diagonal direction
8	Irregular shape 1
9	Irregular shape 2
10	Irregular shape 3

Visualization app

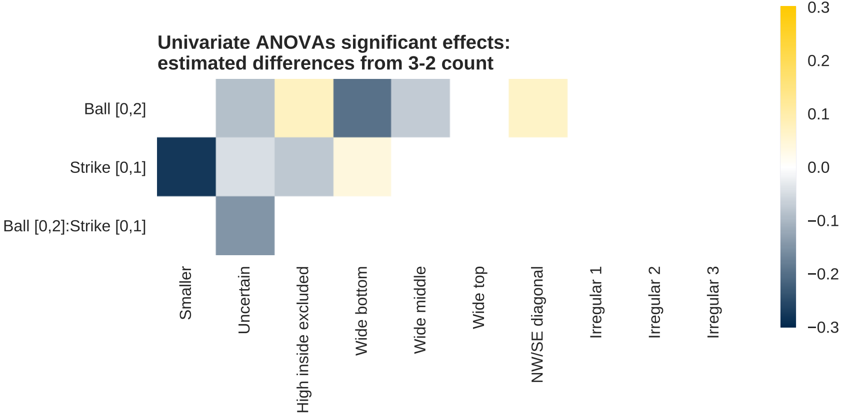

INFERENCE

Model : components $\sim$ umpire + ball count $*$ strike count

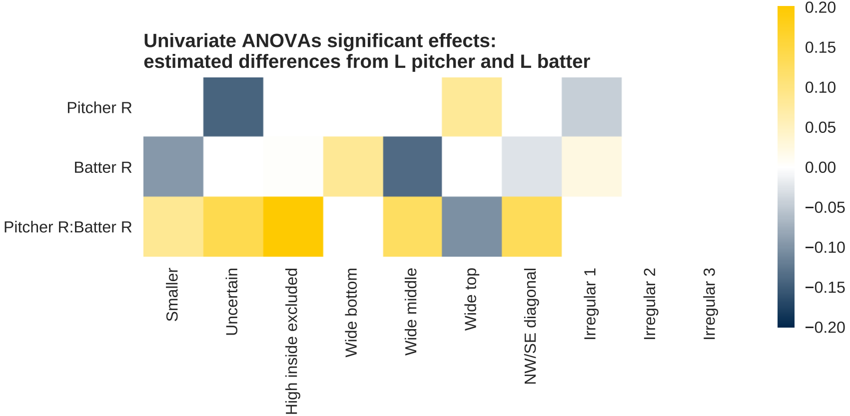
MANOVA results

Term	Wilks' Lambda	Num. df	Den. df	F value	p-value
Umpire	0.0142	380	1046	1.51813	1.80e-07
Ball count	0.4112	10	105	15.0334	2.65e-16
Strike count	0.3534	10	105	19.0555	1.74e-19
Ball count:Strike count	0.7675	10	105	3.1805	0.0013

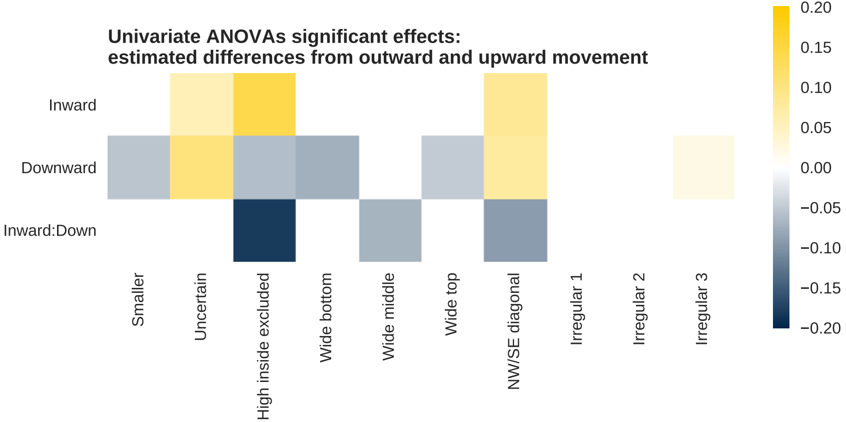
$$\text{Model : component} \sim \text{umpire} + \text{ball count} * \text{strike count}$$



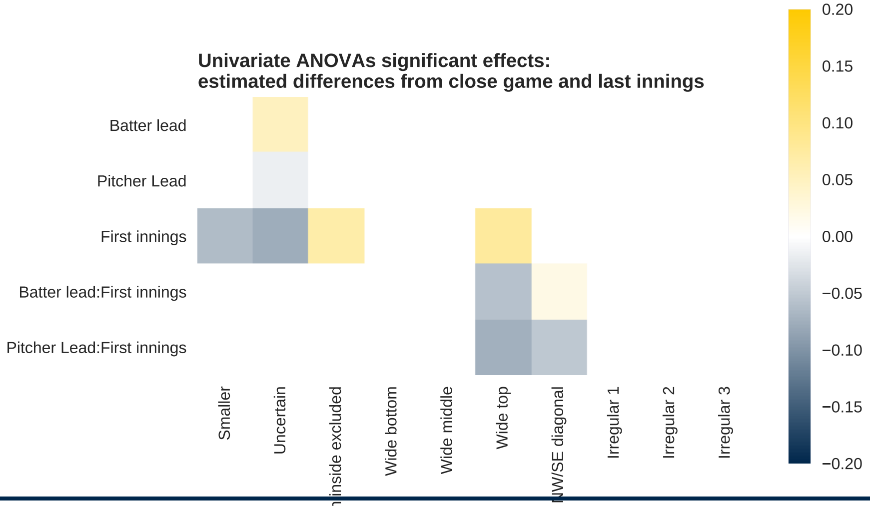
$$\text{Model : component} \sim \text{umpire} + \text{batter} * \text{pitcher}$$



$$\text{Model : component} \sim \text{umpire} + \text{horiz. move} * \text{vert. move}$$



Model : component $\sim$ umpire + score $*$ inning

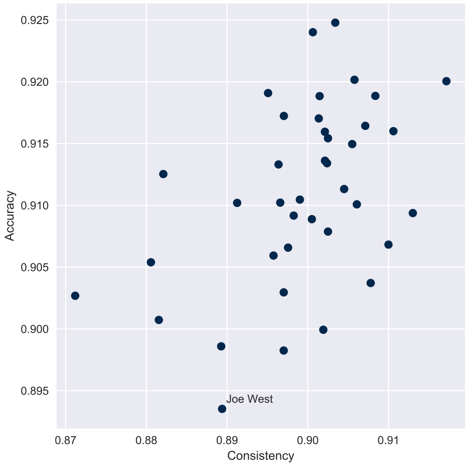



RANKING UMPIRES
Dodgers
7

Ranking Umpires

A metric that accounts for consistency and accuracy

- Umpires are frequently ranked by overall accuracy, but our classification procedure allows for umpires to be ranked on consistency, i.e., how similar is an umpire’s strike zone across different game situations?
- We construct umpire ratings that weight consistency and accuracy 25%/75%, respectively.



Ranking Umpires

How do we compare to Bloomberg's "Umpire Auditor"?

Our top 5 umpires from 2018

1. Mark Wegner
2. Vic Carapazza
3. Pat Hoberg
4. John Tumpane
5. Alfonso Marquez

Bloomberg's top 5[1]

1. Mark Wegner
2. Pat Hoberg
3. Alfonso Marquez
4. Nic Lentz
5. Sam Holbrook

And the worst, according to our scoring, is **"Country Joe" West**.

CONCLUSION

Conclusion

Findings

- Low-dimensional encoding of strike zones
- Balls and strikes count has a measurable effect
- Variability between umpires

Remarks

- Sequential analysis
- Principal component regression
- Multiple testing

Further analyses

We also considered the following situations:

- Pitcher arm (L/R) and batter stand (L/R)
- Score and inning
- Pitch movement (up/down and inward/outward)

Most yield positive results (omitted for brevity)

Analysis of the variability between umpires

THANK YOU!

References

[1] *2018 Umpire Ranking.* URL: https://www.bloomberg.com/businessweek/graphics/baseballs-worst-call-of-the-day/#/umpires/ranking/2018 (visited on 04/18/2020).

[2] *2019 MLB Official Rule Book.* URL: https://content.mlb.com/documents/2/2/4/305750224/2019_Official_Baseball_Rules_FINAL_.pdf (visited on 04/17/2020).

[3] Paul Schale. *MLB Pitch Data 2015-2018.* 2019. URL: https://www.kaggle.com/pschale/mlb-pitch-data-20152018.


QUESTIONS?