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The Ultimate Analysis

Predicting an ultimate frisbee player's effectiveness on the field

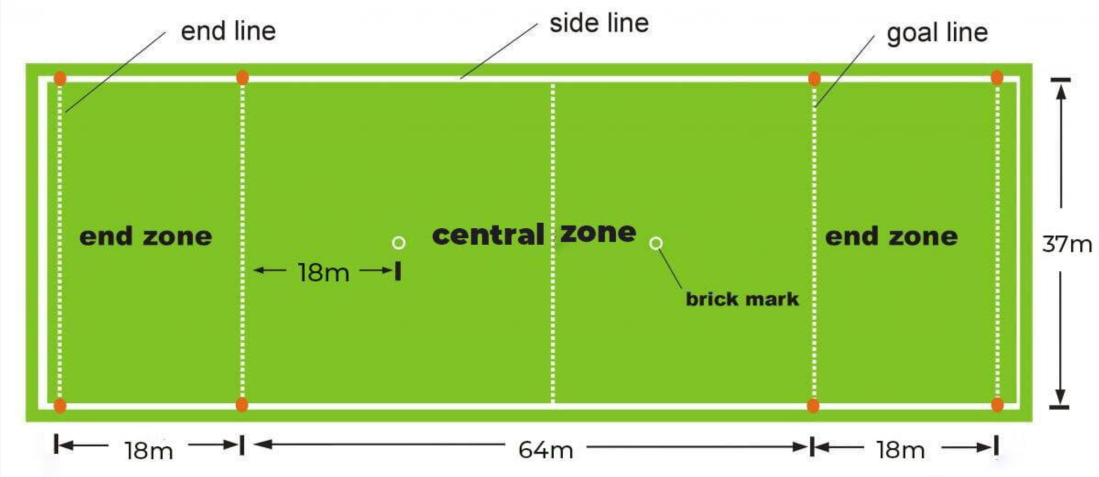
A primer on Ultimate

Non-contact sport (7v7)

Passing disc to score in the end zone (1 point)

Combines elements of soccer and football

Self-officiated



Ultimate at Vassar

Long history of Ultimate at Vassar

Mixed, women’s, and men’s teams

~110 players each year

Self-coached and student-run

Research goals

Rationale : We collect a small amount of stats each game, but do not have the resources to keep track of player impact

Goal : To quantify individual player impact based on a small collection of statistics

THE DATA

15 variables, 1665 rows which correspond to individual players

SOURCE: USA Ultimate, uploaded to Kaggle.com

ABOUT: Division 1 & 3 Men & Women's College Ultimate Frisbee Championships 2024

CLEANING/WRANGLING: Minimal, data was already clean and tidy, no missing values

Outcome: +/- score per game

the difference between the points scored for the team and the points against the team while the player is on the field, used to measure a player’s effectiveness

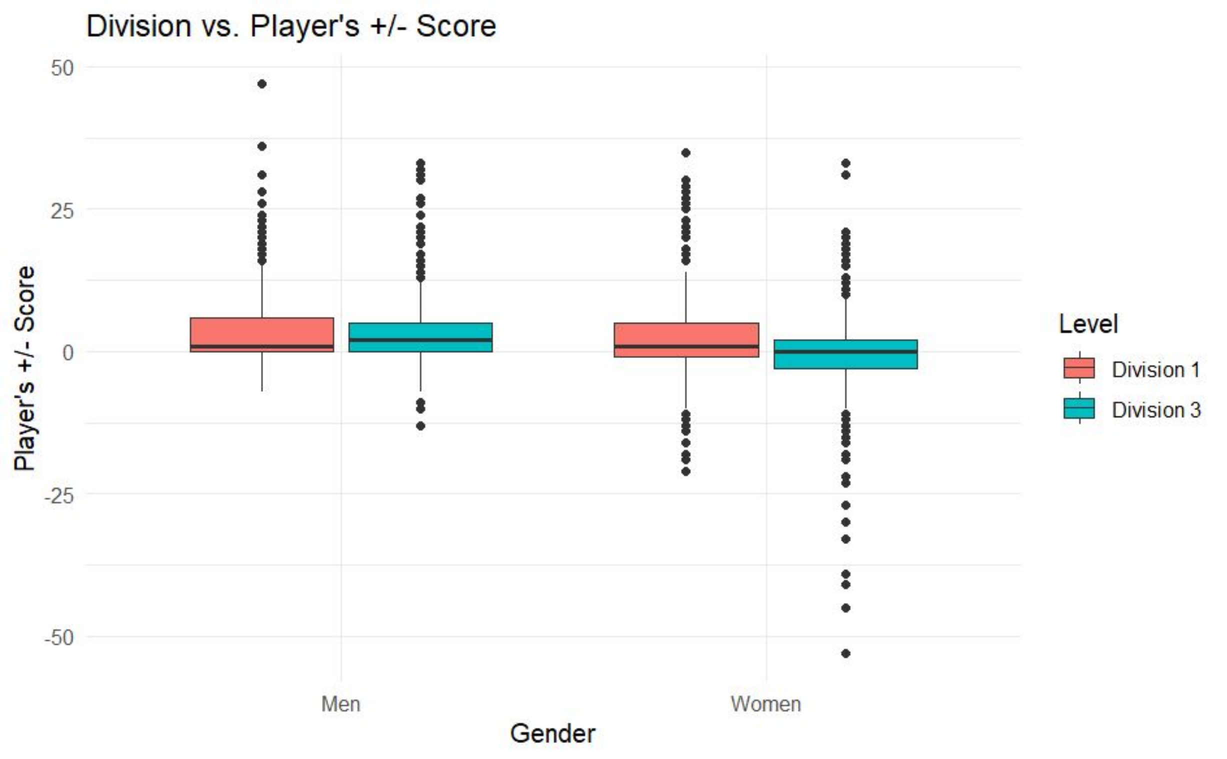
CODEBOOK

Player = name of player
Level = "Division 1", "Division 3"
Gender = "Women", "Men"

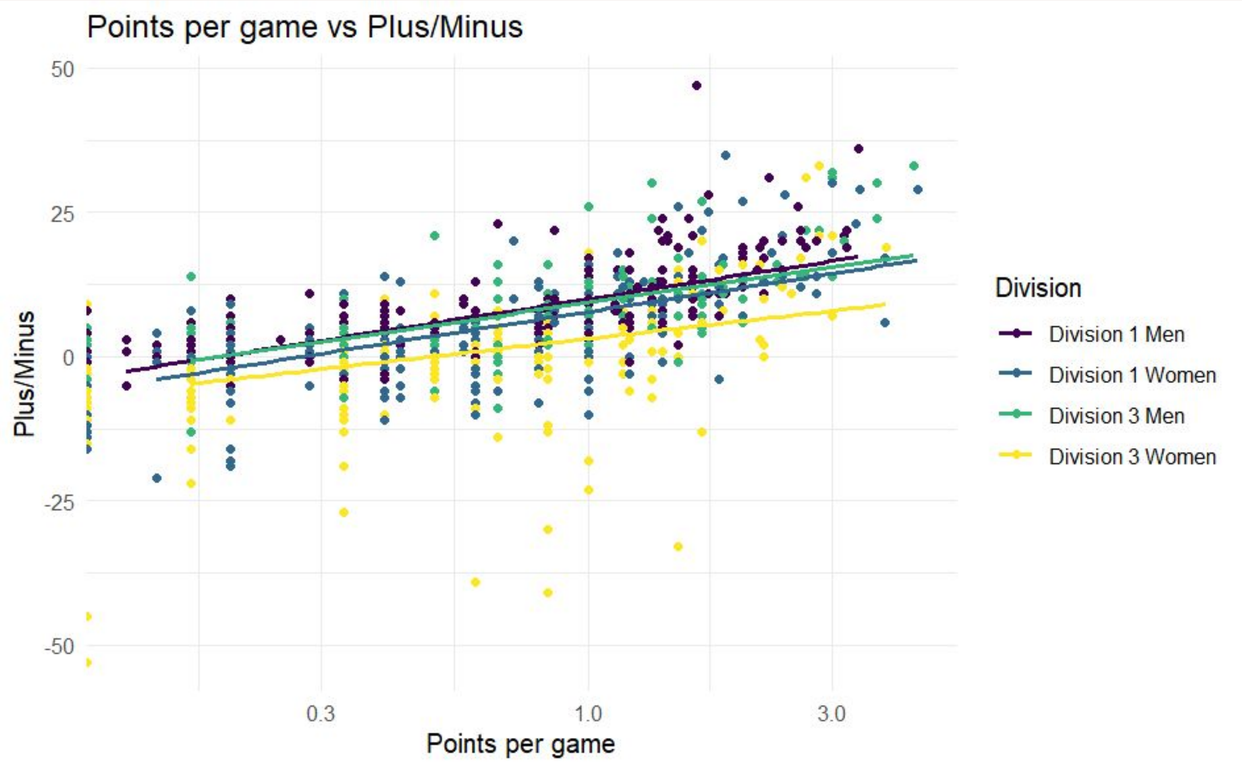
Turns = # turnovers player threw
Ds = # defensive blocks player made
Assists = # assists player threw
Points = # points player scored
plus_minus = player's +/- score

team_games = # games played
turns_per_game = avg turnovers per game
ds_per_game = avg defensive blocks per game
ast_per_game = avg assists per game
pts_per_game = avg points per game
pls_mns_per_game = avg +/- per game

EDA

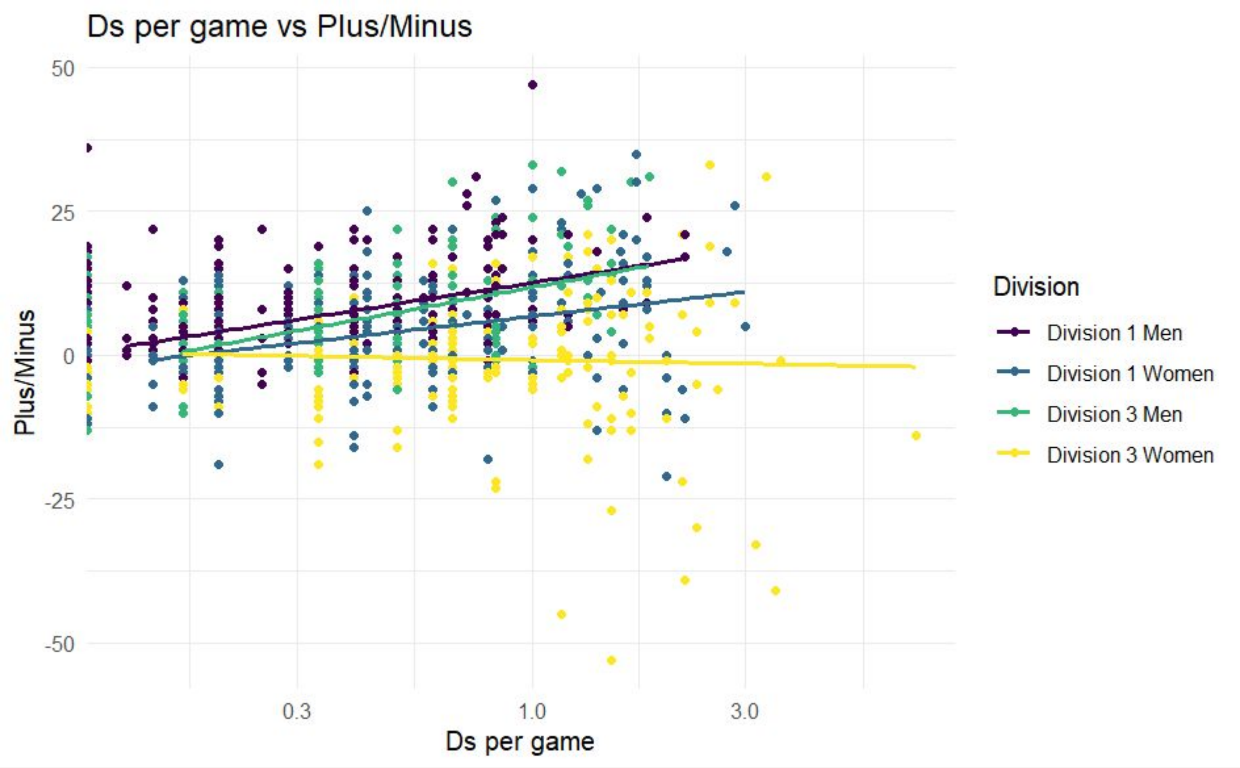

Division vs. Player's +/- Score
50
25
0
-25
-50
Player's +/- Score
Men
Women
Gender
Level
Division 1
Division 3

EDA

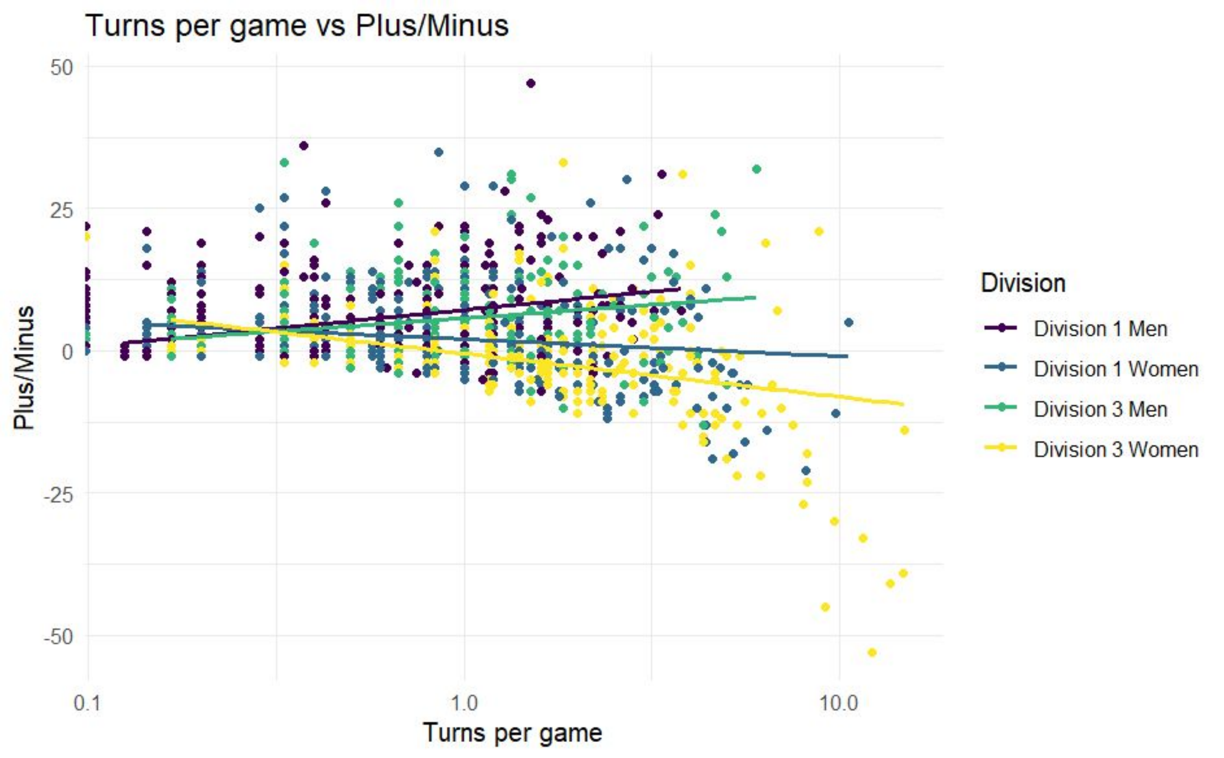


Points per game vs Plus/Minus
50
25
0
-25
-50
Plus/Minus
0.3
1.0
3.0
Points per game
Division
Division 1 Men
Division 1 Women
Division 3 Men
Division 3 Women

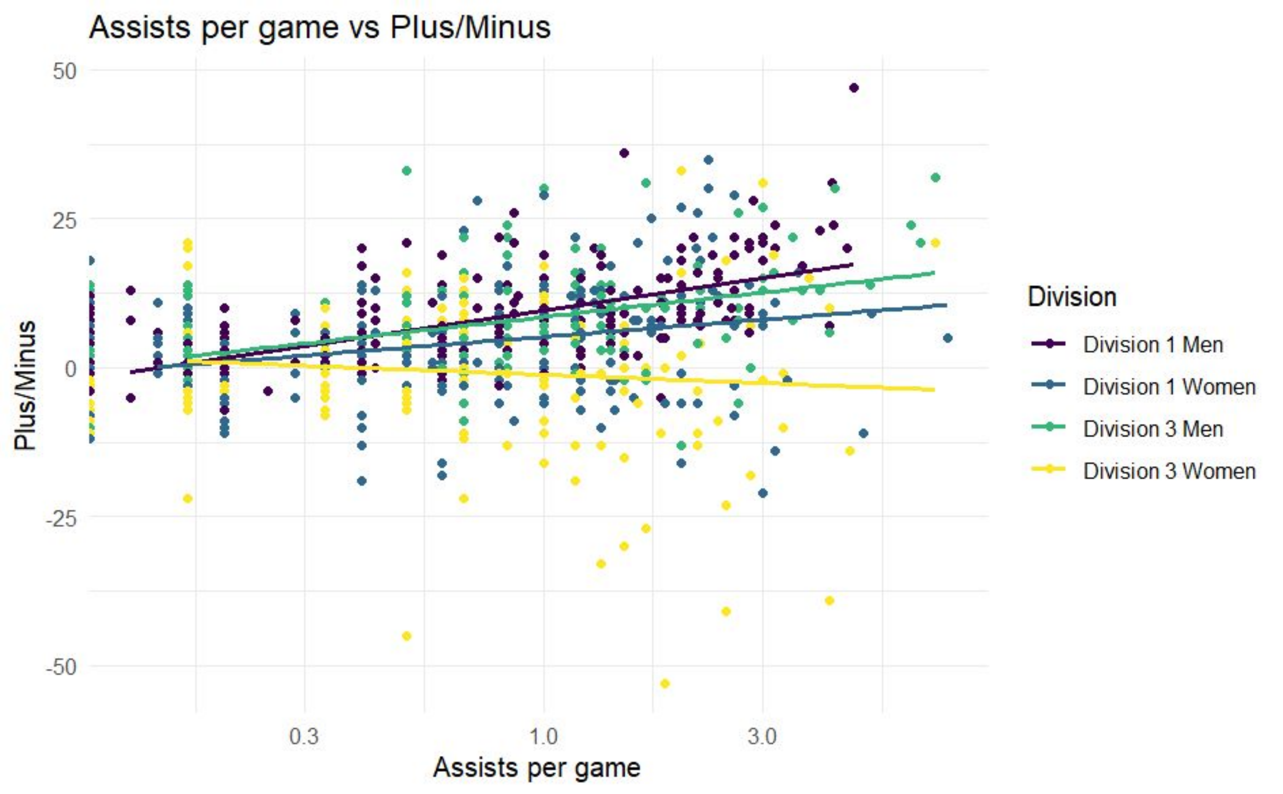
EDA


Ds per game vs Plus/Minus
50
25
0
-25
-50
Plus/Minus
0.3
1.0
3.0
Ds per game
Division
Division 1 Men
Division 1 Women
Division 3 Men
Division 3 Women

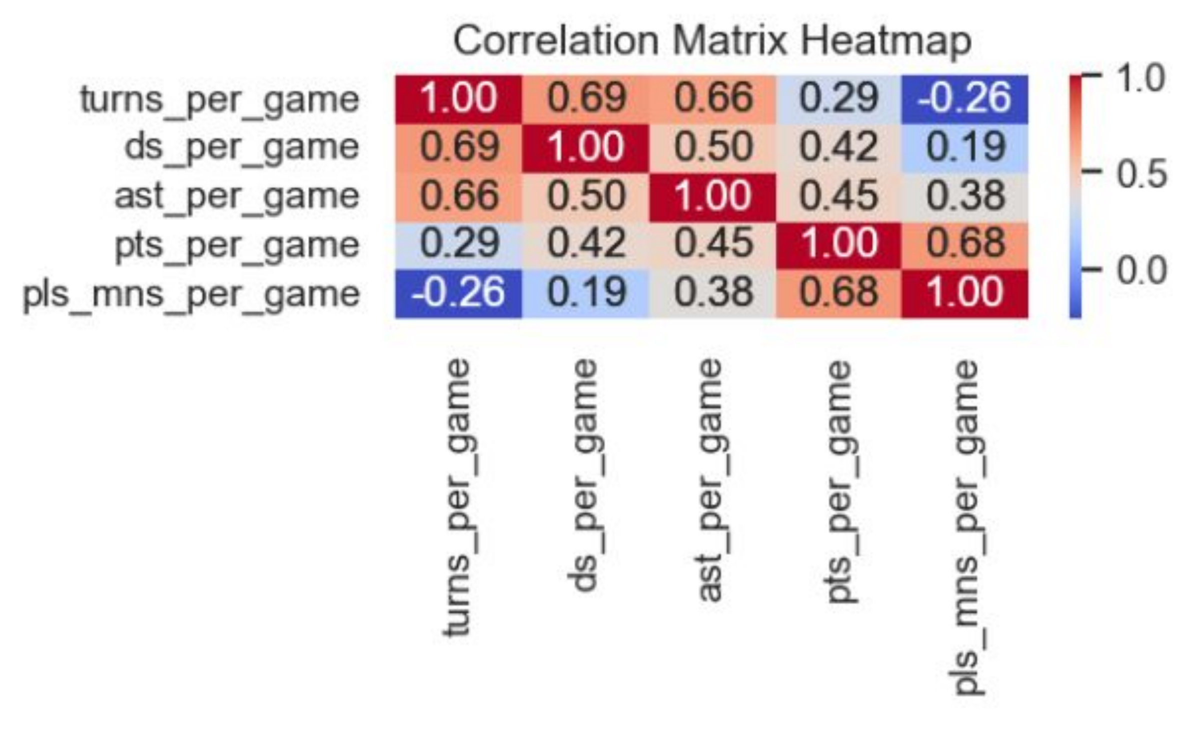
EDA


Turns per game vs Plus/Minus
50
25
0
-25
-50
Plus/Minus
0.1
1.0
10.0
Turns per game
Division
Division 1 Men
Division 1 Women
Division 3 Men
Division 3 Women

EDA


Assists per game vs Plus/Minus
50
25
0
-25
-50
Plus/Minus
0.3
1.0
3.0
Assists per game
Division
Division 1 Men
Division 1 Women
Division 3 Men
Division 3 Women

EDA


Correlation Matrix Heatmap
turns_per_game
ds_per_game
ast_per_game
pts_per_game
pls_mns_per_game
1.00 0.69 0.66 0.29 -0.26
0.69 1.00 0.50 0.42 0.19
0.66 0.50 1.00 0.45 0.38
0.29 0.42 0.45 1.00 0.68
-0.26 0.19 0.38 0.68 1.00
1.0
0.5
0.0

Modeling methodology

Outcome (scaled): plus/minus score per game

Explanatory variables (scaled):
1. Turns per game
2. Points per game
3. Ds per game
4. Assists per game

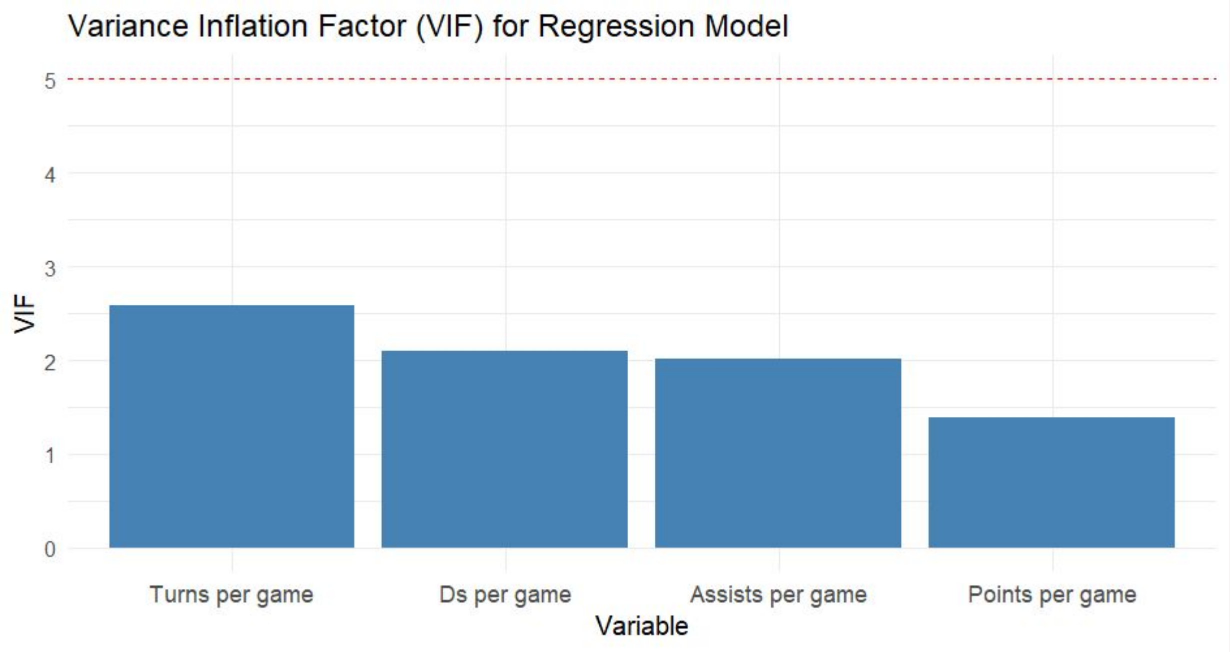
Models: Linear, Ridge, and Lasso for each division/gender grouping

Diagnostics: 5-fold cross validation, R^2, RMSE

Linear Regression Results

	Division 1		Division 3	
	Men	Women	Men	Women
n	521	452	372	320
Cross-validated R^2	1.00	1.00	1.00	1.00
Cross-validated RMSE	0.00	0.00	0.00	0.00

Assessing multicollinearity

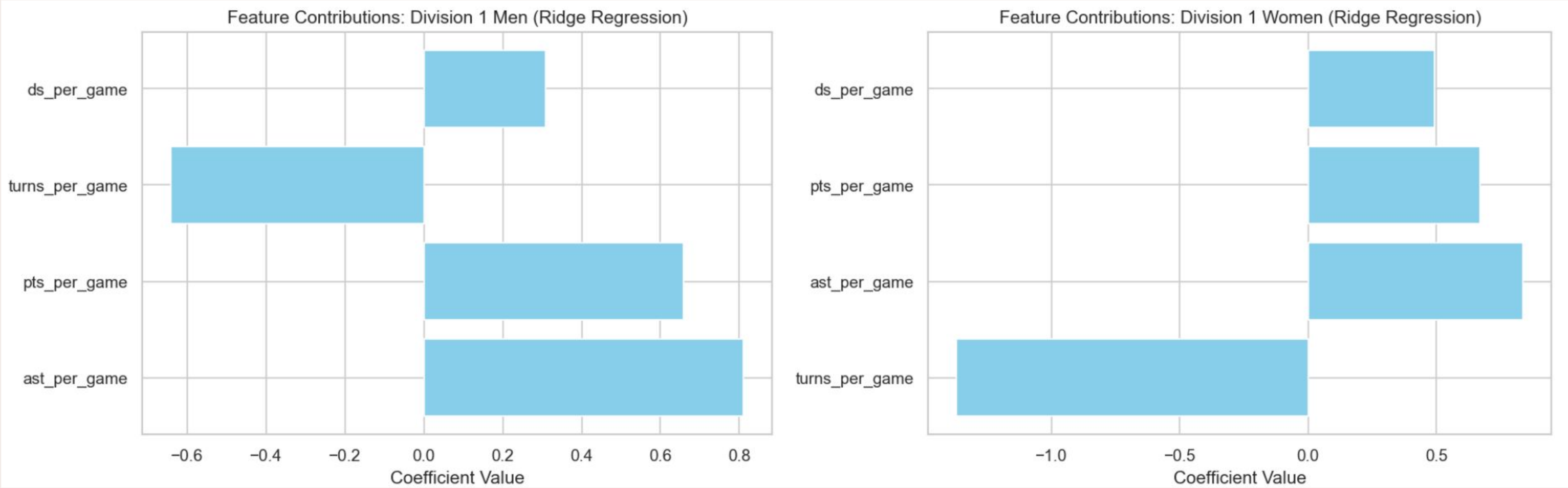


No apparent multicollinearity!

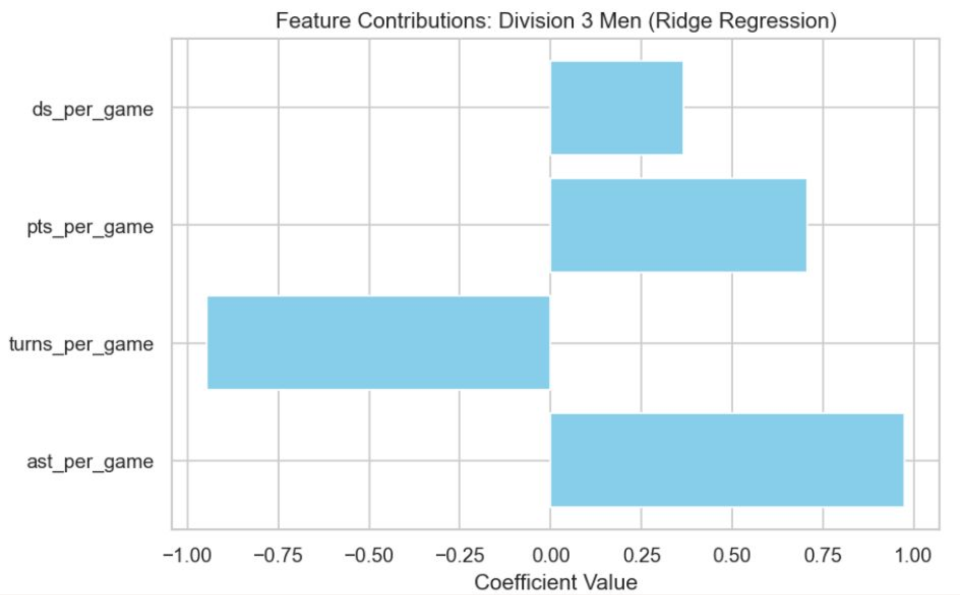
Ridge Regression Results

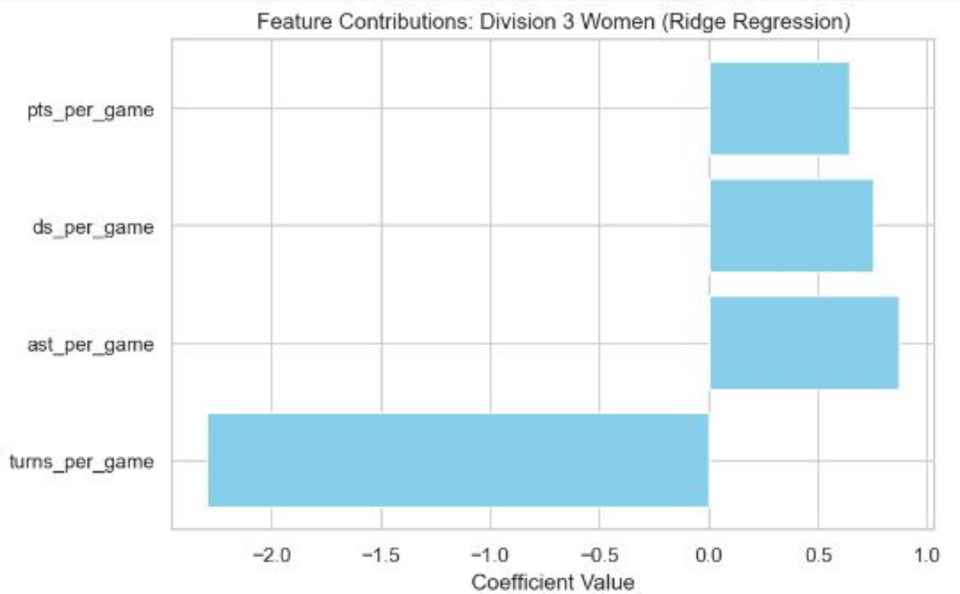
	Division 1		Division 3	
	Men	Women	Men	Women
n	521	452	372	320
Cross-validated R^2	0.999	0.999	0.997	0.995
Cross-validated RMSE	0.01	0.02	0.02	0.05

Ridge Regression Results



Ridge Regression Results





Lasso Regression Results

	Division 1		Division 3	
	Men	Women	Men	Women
n	521	452	372	320
Cross-validated R^2	1.00	1.00	1.00	1.00
Cross-validated RMSE	0.001	0.001	0.001	0.001

Best alpha: 0.001

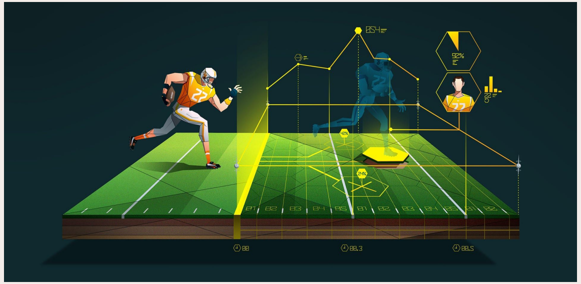
Example Application

Player A
Division 1, Male

Turns per game: 2.5
Ds per game: 1.0
Assists per game: 4.0
Points per game: 2.0

Predicted Plus/Minus per game:

Ridge: 4.49
Linear: 4.50
Lasso: 4.49



Limitations

- Small feature set: Split model into four categories (women's and men's D-Ⅰ and D-Ⅲ)
- Potential data imbalance: Model performance depends on number of observations in group
- Unrealistic R^2 value: Many models had an R^2 value of 1

Ethical considerations

Benefits:

- Enhanced performance insights: Provide data-driven insights
- Objective evaluation: Reduces subjective bias in player evaluations

Risks:

- Privacy concerns: Public and anonymous yet questions on consent and extent to which athletes are aware of their data being used
- Potential for misuse: Model used without broader outlook on athlete potential
- Bias and fairness: If the data contains bias, model perpetuates it

Future steps

- Broader dataset: Need more than just college-level data for model to have larger applicability
- Testing: Run model on actual data collected at Vassar
- R^2 value: Fix the R^2 value

Conclusion

- Research aim: Predict player plus-minus using 4 individual player stats
- Best model - all have about an equal R^2 of 1
- Results suggest plus-minus can be predicted from the variables used
- Player stats can be collected but plus-minus is hard to calculate, this model offers an accurate calculation.

Thank you!