AUDL* Ultimate Frisbee – Win Prediction Modeling

** Prior to the 2024 season, the AUDL re-branded as UFA. This presentation encompasses the 2012-2023 seasons, and will keep nomenclature consistent with the report.*

Project Repository

Presentation | Report

Contents

Project Summary

regression model predicts home margin from game summary statistics

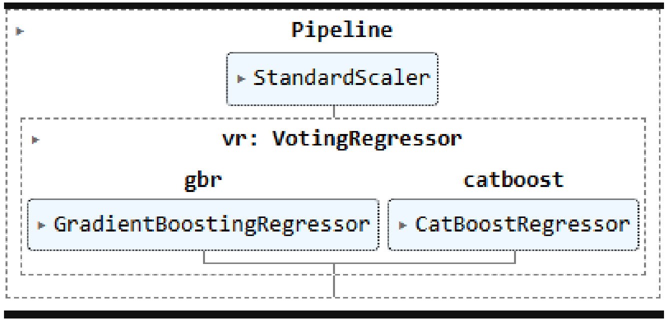
AUDL statistics


```
{
    "awayTeam": "LA Aviators",
    "homeTeam": "Salt Lake Shred",
    "awayTeamStats": {
        "completions": 268,
        "throwingAttempts": 292,
        "hucksCompleted": 8,
        "hucksAttempted": 12,
        "blocks": 3,
        "turnovers": 24,
        "oLineScores": 12,
        "oLinePoints": 27,
        "oLinePossessions": 34,
        "dLineScores": 1,
        "dLinePoints": 15,
        "dLinePossessions": 4,
        "redZoneScores": 11,
        "redZonePossessions": 18
    },
    "homeTeamStats": {
        "completions": 233,
        "throwingAttempts": 244,
        "hucksCompleted": 11,
        "hucksAttempted": 14,
        "blocks": 11,
        "turnovers": 11,
        "oLineScores": 13,
        "oLinePoints": 15,
        "oLinePossessions": 18,
        "dLineScores": 12,
        "dLinePoints": 27,
        "dLinePossessions": 20,
        "redZoneScores": 15,
        "redZonePossessions": 16
    }
}
```


Processed data

	3101
game	2023-05-19-LA-SLC
date	2023-05-19 19:00:00+00:00
home	Shred
away	Aviators
home_score	25
away_score	13
home_completions	233
away_completions	268
home_throws	244
away_throws	292
home_blocks	11
away_blocks	3
home_turnovers	11
away_turnovers	24
home_completion_rate	0.954918
away_completion_rate	0.917808
comp_rate_diff	0.03711
block_turnover_diff	21
home_win	True
home_margin	12

Regression Model



home_margin prediction

```python
gid = '2023-05-19-LA-SLC'
print('model predicted home margin\n',
round(final_model.predict(data[\
data.game==gid].iloc[:,6:-2])[0]))
```

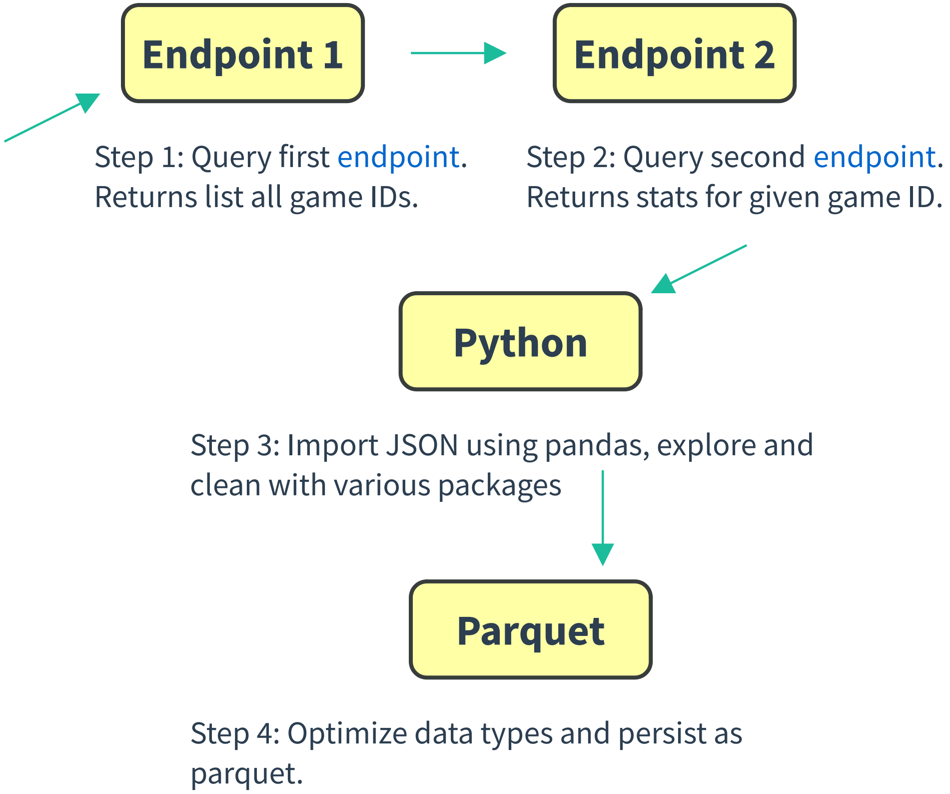
```
model predicted home margin
 12
```

Project Overview

- **Problem Statement: Can the AUDL and its teams leverage the league's existing data streams to create useful models?**
  - Eleven seasons of the game summary data was collected to develop models which predict the difference in score between home and away team
    | Home Margin |
- **Outcomes:**
  - Final regression model achieved R^2 ~ 0.85, mean absolute error ~ 1.7.
    - Classification model: 94% accuracy for winning team prediction
  - Model feature importance provides game management insights
  - Fixable data quality issues identified, rationale for cleaning efforts.

Data Wrangling

- AUDL website provides REST API for statistics
- Collection of endpoints used to gather each game's summary data
- Imported data was thoroughly explored and cleaned.
- Game records reduced from 1,604 on import to 1,521 after cleaning. Cleaning process detailed in project report.



Target Definition, Feature Selection

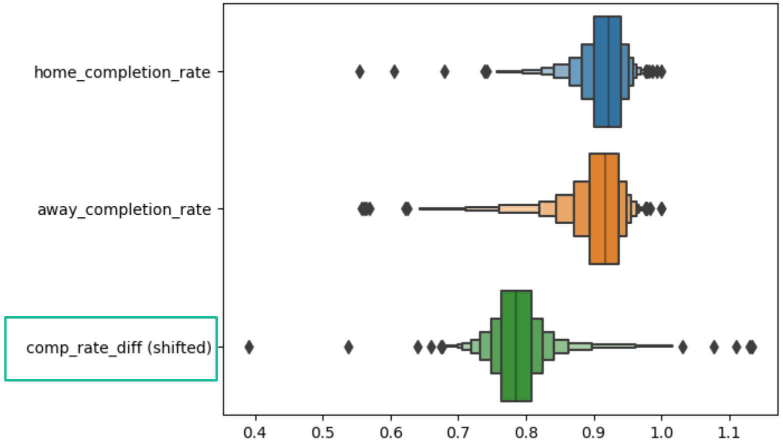
- Target: **home margin** = home_score – away_score
- Some data features allow exact analytical determination of **home margin** and were dropped
- Remaining features (for both home and away teams):
  - Throws, Completions, Blocks, Turnovers
- Categorical features used to group data, but not for modeling

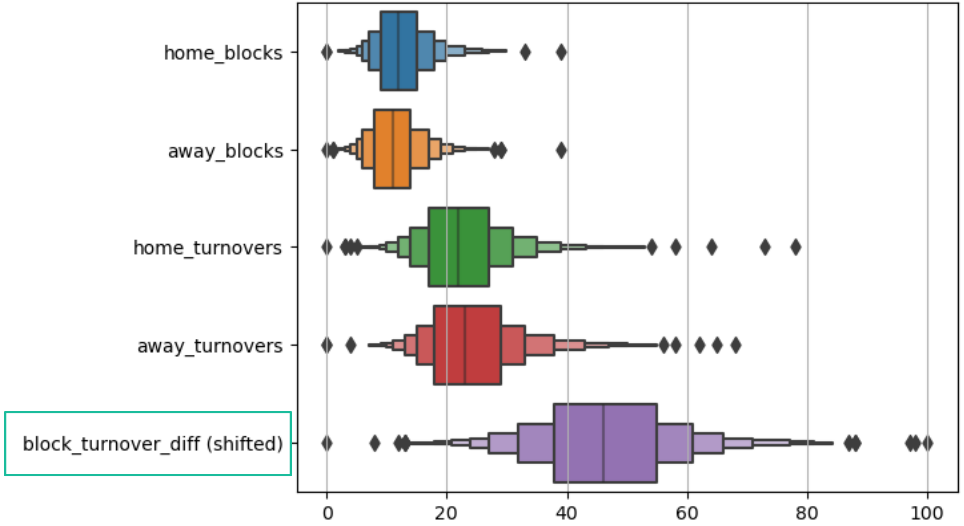
	1545	2180
game	2016-07-02-TOR-MTL	2014-07-26-MAD-SJ
date	2016-07-02 19:00:00+00:00	2014-07-26 19:00:00+00:00
week	14	championship
home	Royal	Spiders
away	Rush	Radicals
home_score	18	23
away_score	29	20
away_completions	237	265
away_throws	252	286
away_hucks_completed	-1	-1
away_hucks	-1	-1
away_blocks	15	16
away_turnovers	15	21
away_o_scores	17	15
away_o_points	20	25
away_o_possessions	22	33
away_d_scores	12	5
away_d_points	31	22

Sample data before cleaning steps, not all features shown. Values of "-1" indicate missing data.

Feature Engineering

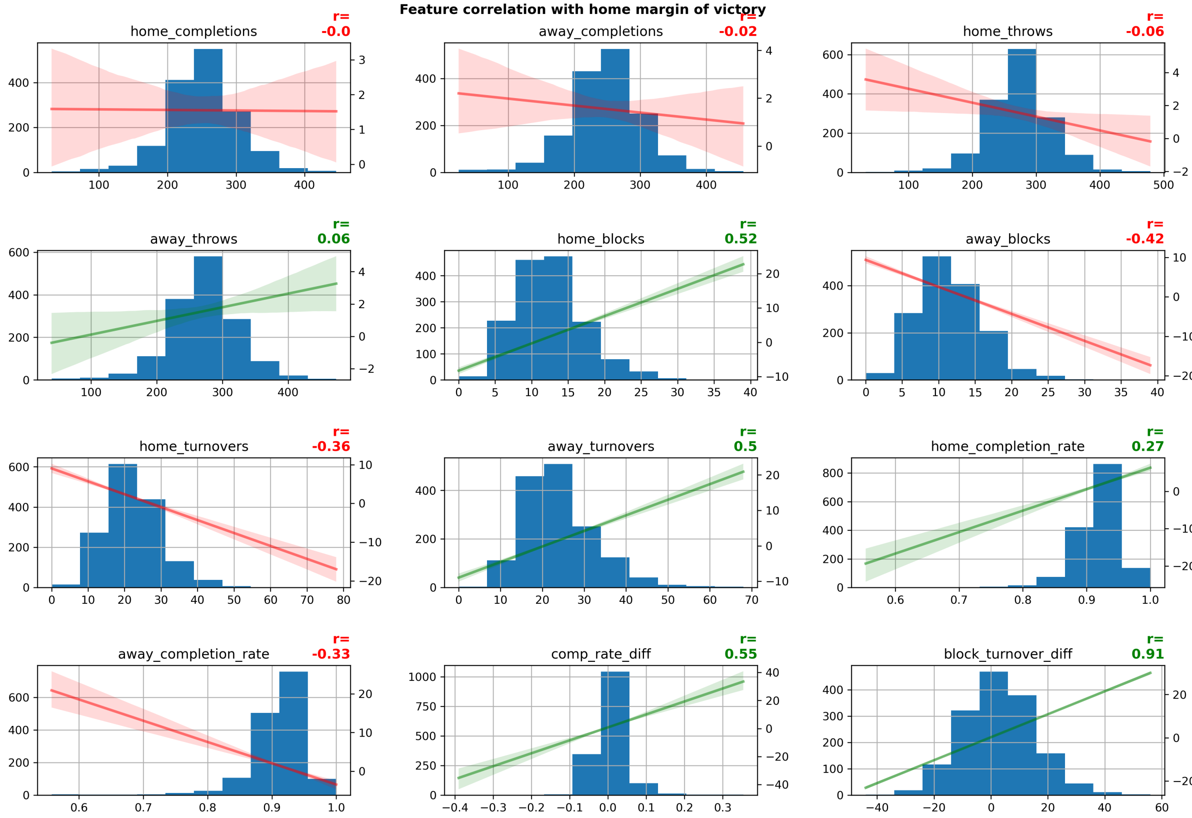
- **Each basic feature was used as a component for engineered features:**
  - Completion rate, completion rate difference
  - Block+Turnover difference
- **Engineered features were distributed more normally and had higher target correlation than their component features**





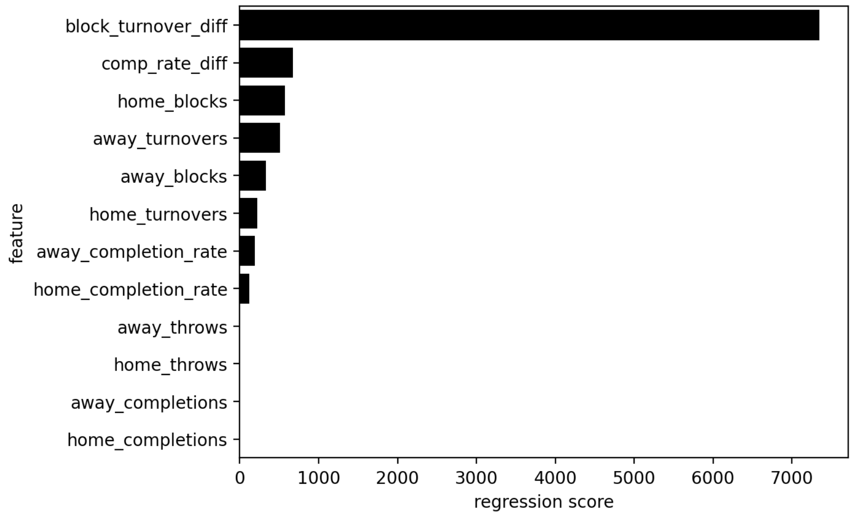
Data for Modeling Summary:

features capturing change of possession correlate strongly with target



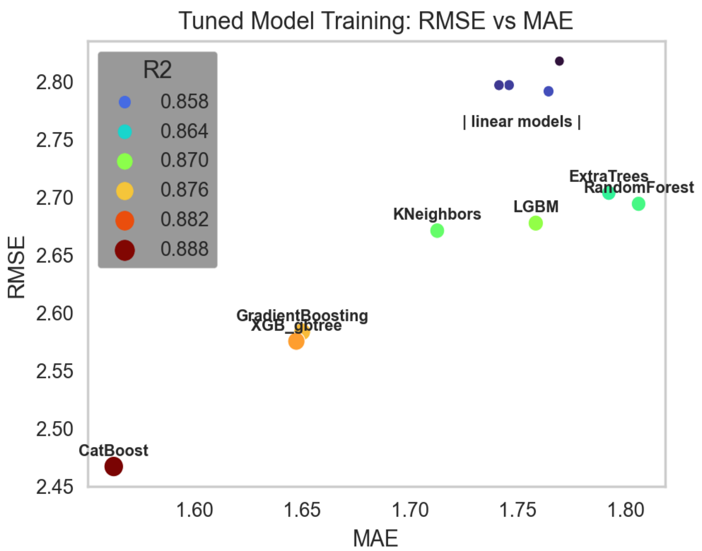
x-axis: feature values *left y-axis: histogram bin count* *right y-axis: home margin*

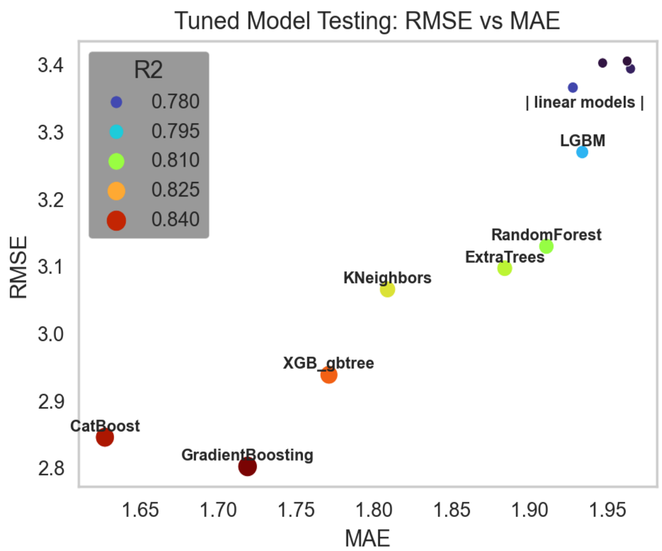
- Feature distributions, correlation coefficient with **home margin**
- Feature importance via p-value scores scored via *f_regression*



Model Selection, Hyperparameter Tuning

better models are ↙ | testing results (right) used for final evaluation and shown in table





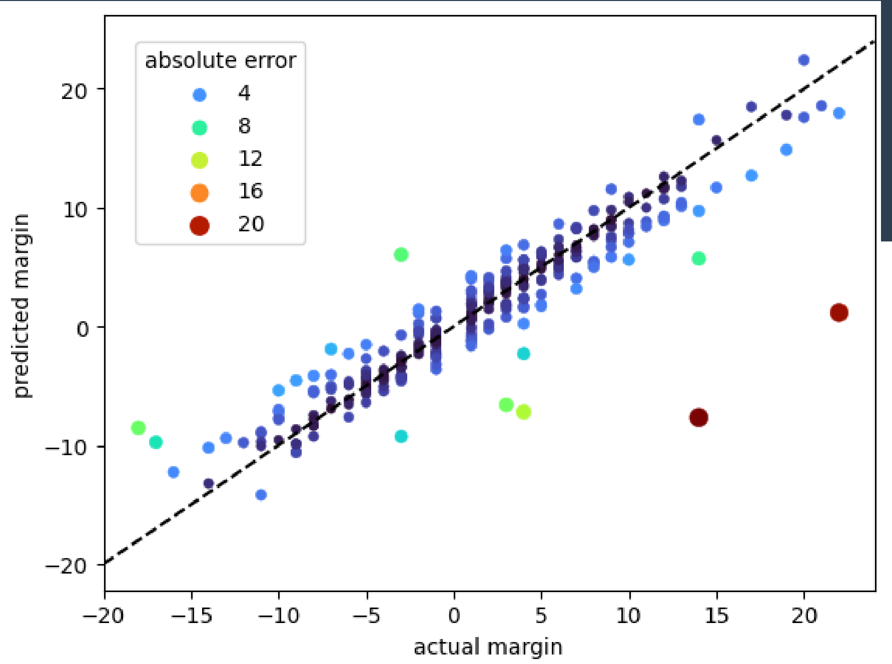
Tuned test scores

	R2	RMSE	MAE	MAPE
voting_GBR-Cat	0.849	2.789	1.644	0.438
GradientBoostingRegressor	0.847	2.801	1.719	0.459
voting_GBR-Cat-XGB	0.847	2.809	1.663	0.449
CatBoostRegressor	0.843	2.845	1.627	0.435
XGBRegressor	0.832	2.938	1.771	0.496
KNeighborsRegressor	0.817	3.065	1.809	0.504

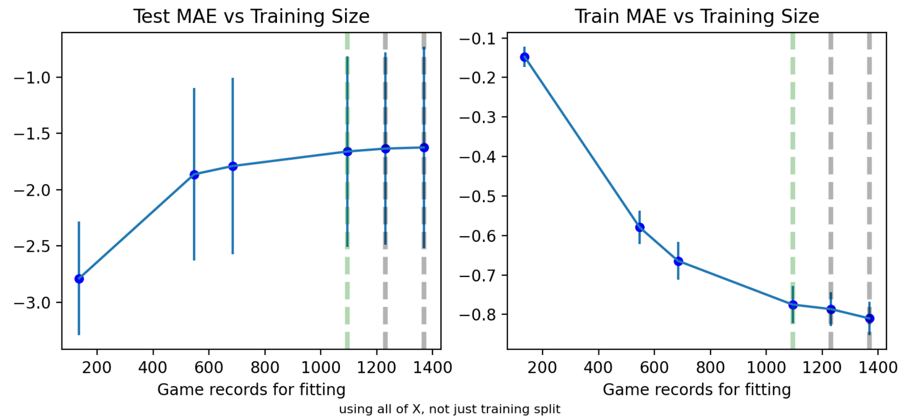
- 22 regression models were evaluated and tuned.
  Top models' tuned performance is shown for the training and test splits below.
- Combinations of the top three models were blended into a voting regressor.
- Final model: GradientBoosting+CatBoost blend

Final Model

residual analysis, data quality/quantity



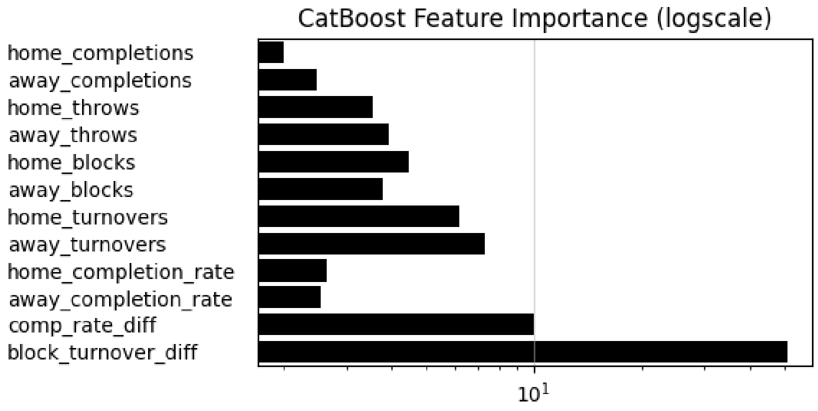
- **Model's worst two predictions were games that should have been removed during data cleaning.**
  [2013-05-04-DC-NY, 2018-07-14-DET-PIT]
  - Higher error for 2012, 2013 seasons when bookkeeping was more suspect. Model error is not independent of team

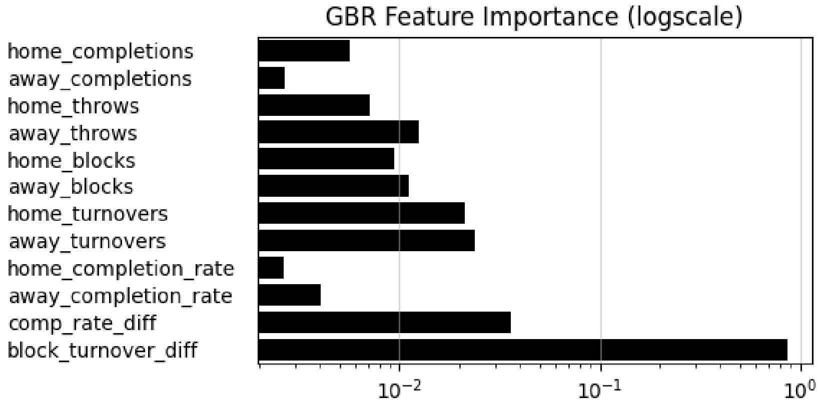


- Learning curve analyses indicate model performance slightly limited by dataset size
- Retroactive data fill ins / cleaning could add 83 games to the dataset. Data collection pipeline can be adapted for online data retrieval, continuously update as games are played.

Model Applications

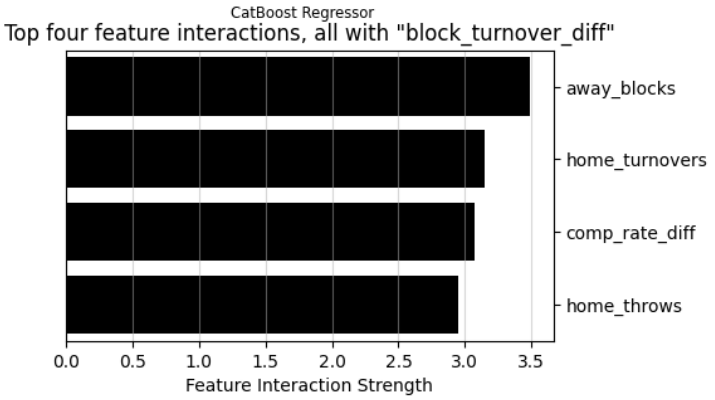
utilize feature importance to develop strategy





- Model feature importance provides context for most important factors to improve score margin.
- Feature interactions could allow a coach to have a numerical basis of focus:

The four strongest interactions the block_turnover_diff involve forcing turns on defense and maintaining possession on offense. It may be more advantageous to aggressively go for blocks on defense, instead of forcing more difficult throws.



Model Refinement, Future work

- Incorporate classification model into regression model pipeline, may help predict correct +/- for games with narrow margins.
- Descriptive features such as “week” and “team” can be encoded and included in the model. Team identity should improve performance, based on the variation in their residuals.
  - Match-up specific models can be used to establish odds for upcoming games
- The data pipeline can be adapted to other available AUDL data streams, allowing the expansion of current work and many new applications.
  - Bring back dropped features for other applications.
    Incorporate individual player statistics. Event-by-event data (with field coordinates).

Project Implications

- **AUDL Data Streaming and Cleaning**
  - Methodology provided for collecting and cleaning AUDL data from API to model training. Can be adapted for online learning.
  - Data integrity issues identified, worth retroactive cleaning and/or imposing more stringent data collection standards.
- **Winning contribution of game features (throws, catches, turnovers)**
  - Model provides quantification of a team/player’s statistics and could be used to develop strategy and to better analyze previous results
- **Basis for team match-up evaluation and odds prediction**

Acknowledgments

- **Aditya Bhattacharya**
  Thank you for your mentorship and guidance throughout the project!
- **AUDL/UFA**
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  The guided capstone project served as a useful guide for this project.

Questions?