Machine Learning
WNBA Prediction Task

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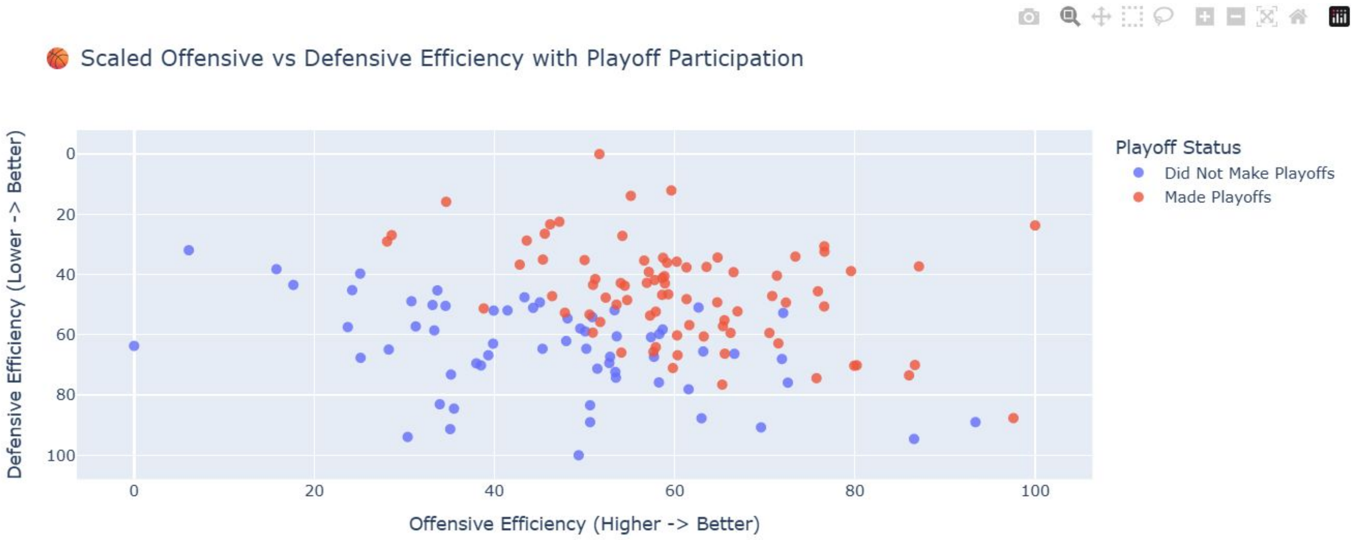
Domain Description

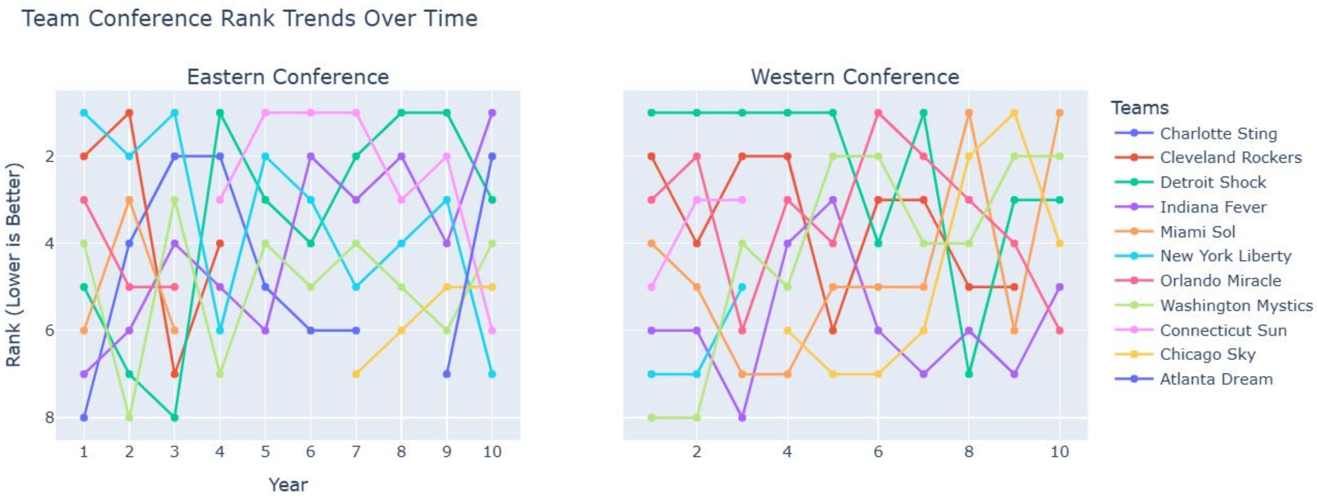
This project analyzes **10 years of WNBA data**, including **player**, **team**, **coach**, and **game statistics.** Basketball seasons are structured in two phases: a **regular season**, where teams compete to maximize wins, and a **playoff stage**, where top teams face off in knockout matches for the championship.

Exploratory Data Analysis



The scatter plot shows that playoff teams cluster in the upper-left, combining strong offense and elite defense, while non-playoff teams are more dispersed and typically weak in at least one area. This highlights that balanced performance on both ends is key to reaching the postseason.

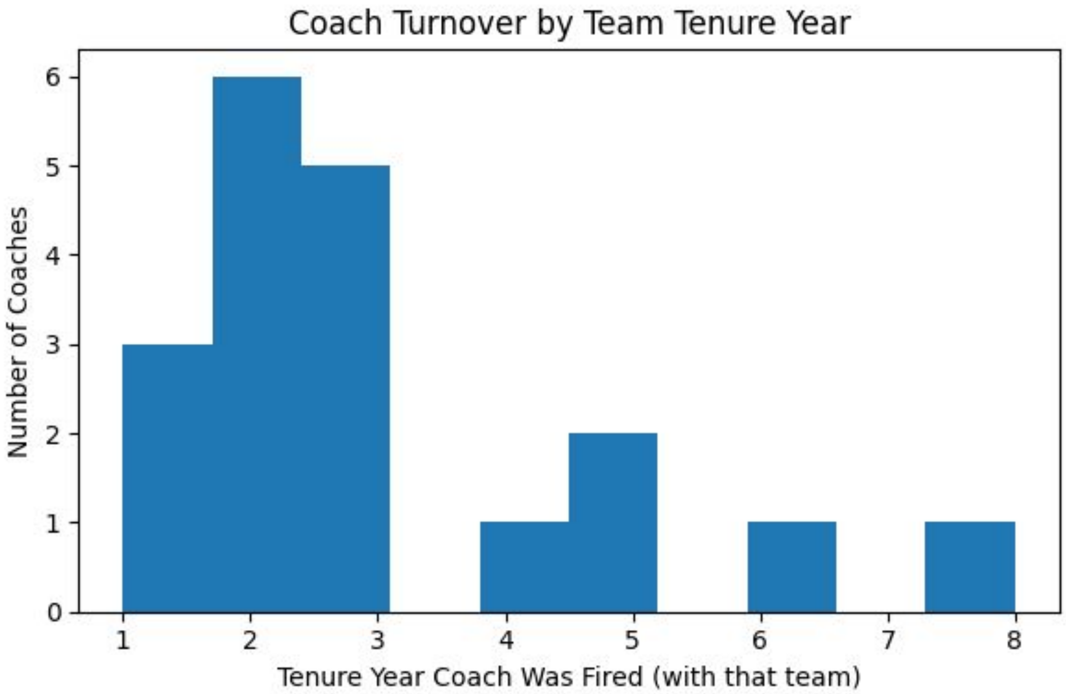
Exploratory Data Analysis



The final time-series plot highlights strong competitive volatility and league parity over the past 10 years. While teams occasionally reach peaks of 25–27 wins, no team sustains dominance, with frequent year-to-year swings in both wins and rankings. These fluctuations indicate an unstable competitive landscape with limited long-term consistency across teams.

Exploratory Data Analysis

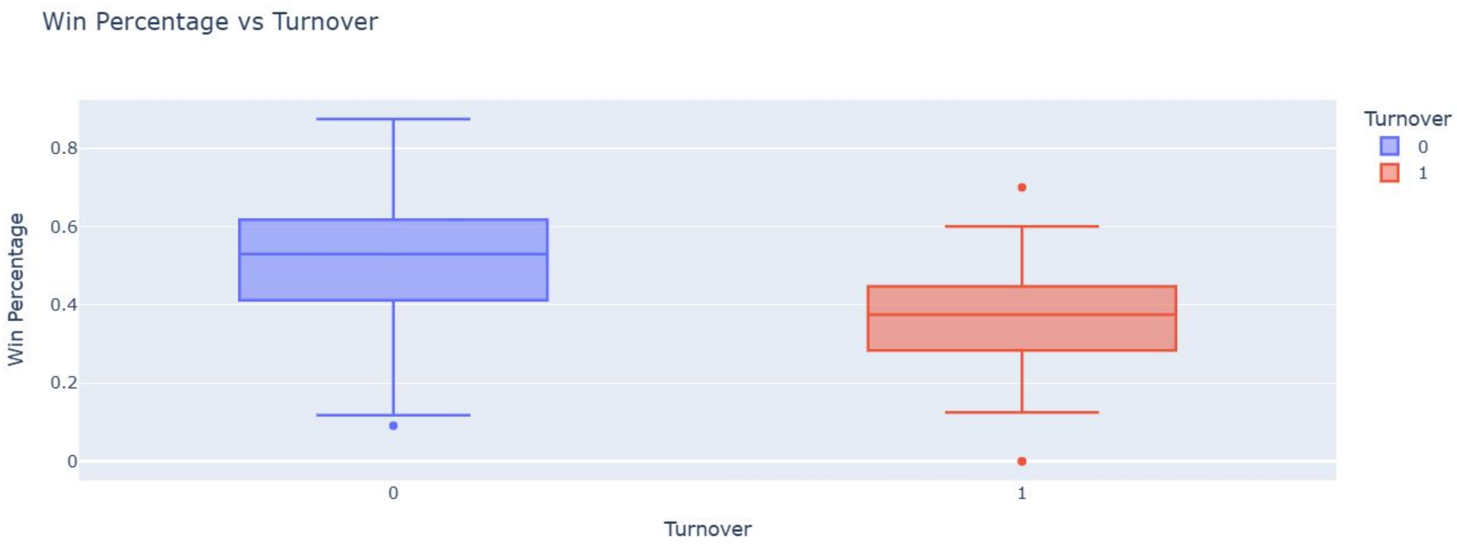
The histogram reveals that coaches in their first three years face the highest turnover rates, highlighting that short-tenured coaches are most vulnerable to organizational changes.



Exploratory Data Analysis

This analysis examines how a player's yearly performance correlates with their teammates' average performance. Most players show negative correlations, indicating that high-usage or star players often see teammates' stats dip when they excel. Positive correlations, though less common, highlight role players who thrive in strong, cohesive teams. Overall, individual excellence can slightly come at the expense of teammates' production, while a few players' success aligns closely with team performance.

Exploratory Data Analysis



The boxplot of Win Percentage vs. Turnover shows that retained coaches generally have higher win rates, while dismissed coaches cluster at the lower end. A few outliers exist, such as a coach with ~10% wins who was retained and another with ~70% wins who was dismissed.

Exploratory Data Analysis

playerID	year	tmID	prev_year_team_rank
stileja01w	2	POR	7
catchta01w	3	IND	6
fordch01w	4	DET	8
tauradi01w	5	PHO	7
johnste01w	6	WAS	4
augusse01w	7	MIN	6
pricear01w	8	CHI	7
parkeca01w	9	LAS	7
mccouan01w	10	ATL	7

The tables shows the previous season ranks of the teams that the rookies of the year entered on a relation. Since just one rookie of the year had a team that made the playoffs we can assume that the worst teams in the year before get the best rookies something that is plausible because of the draft made by the WNBA that the worst teams get the best picks.

Predictive Data Mining Problem

Leverage rich historical team, player, and coaching data to **anticipate the storyline of the upcoming WNBA season**, including:

- **Projected final conference standings**, highlighting contenders and potential risers
- **Team-level probabilities of coaching changes**, identifying organizations at risk of turnover
- **Predicted winners of major individual awards**, revealing likely stars and breakout narratives

Together, these forecasts move beyond raw statistics to deliver **actionable insights into performance, stability, and season-defining outcomes**.

Data Preparation

- Deleted Columns with **Unique Values**
- Deleted Players without **Birthdate** or **Position**
- Processed outliers in **height** and **weight** from the dataset **“players”** putting those values with the average of the position with the highest values (order by position Center -> Forward -> Guard)
- Fixed **Incorrect Award** name: Kim Perrot Sportsmanship -> Kim Perrot Sportsmanship Award
- Fixed missing values in the playoffs rounds in the **“teams”** dataset getting this missing information from the series_post dataset
- Removed irrelevant columns such as: **“arena”**, **“lgID”**, etc
- Format Standardization of **height** (feet to cm) and **weight** (pounds to kilograms)
- Data Transformation of the playoffs labels in the **“teams”** dataset: **“L”** -> **0** & **“W”** -> **1**, and the **“confID”**: **“EA”** -> **0** & **“WE”** -> **1**
- Teams and colleges were transformed into numerical representations so they could be used in prediction models
- Feature Engineering of the **wins** and **losses** to **win percentage**

Data Preparation: Created and Used Features in the Prediction Task

For **MVP** award: Previous years' overall scores (1, 2, and 3 years back) which capture sustained excellence in performance.

For **DPOTY** award: Defense scores from the previous 3 years, focusing specifically on defensive metrics rather than overall performance.

For **ROTY** award: Team ID, college background, and previous team ranking. Since rookies have no prior WNBA history, we rely on team context and college pedigree.

For **MIP** award: Overall scores from previous years, minutes played, minutes category, and whether the player has won before. These features capture both improvement trajectory and opportunity.

For **KPSA** award: Previous sportsmanship score, as this award tends to recognize consistently exemplary behavior.

For **SWOTY** award: Overall scores from previous years, games played/started statistics, and starting percentage. These features identify high-performing non-starters.

Data Preparation: Created and Used Features in the Prediction Task

For **FMVP** award: Individual and team performance metrics over multiple years (weighted by recency). This captures both player excellence and team success needed to reach the Finals.

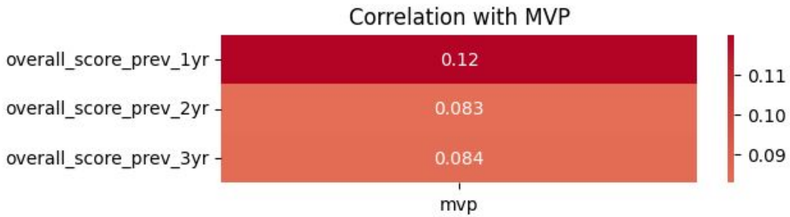
For **ASGMVP** award: Overall scores from previous years, as All-Star MVP often goes to established stars who excel in the showcase format.

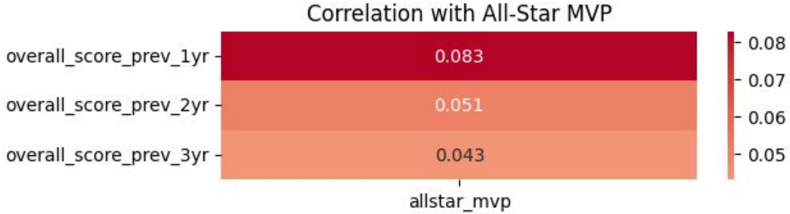
For **COTY** award: Previous team win rates (regular and postseason), merged performance, and year-over-year changes. These capture both sustained success and improvement narratives.

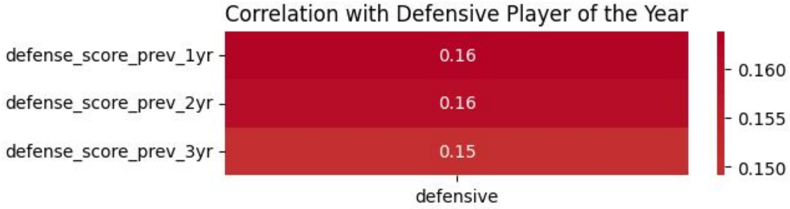
For **Coach Turnover**: Previous team and coaching performance metrics, including coach tenure, recent and historical team win rates, coach-specific win rates, and prior organizational turnover. These features capture both short-term instability signals and longer-term performance trends.

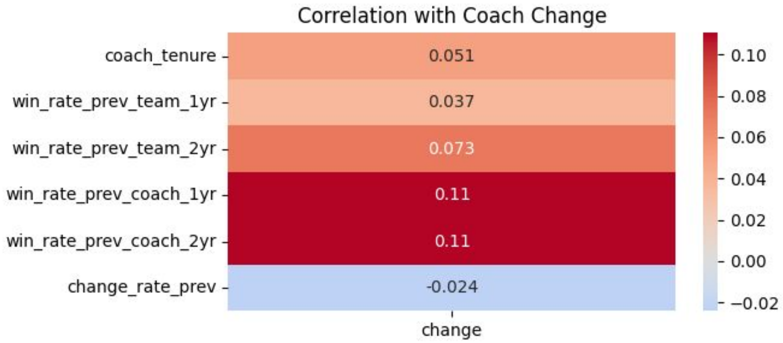
For **Team Rankings**: Feature weights are assigned based on Spearman correlation analysis, with recent performance prioritized through temporal weighting (70% last year, 15% year before, 10% two years prior, 5% earliest). Defensive metrics receive the highest weight, followed by overall and offensive performance, alongside playoff and win-rate signals to capture both recent success and longer-term trends.

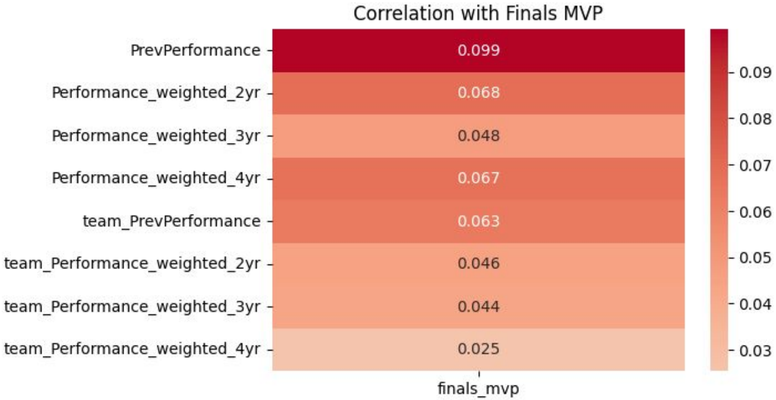
Data Preparation: Correlation of Used Features in the Prediction Task











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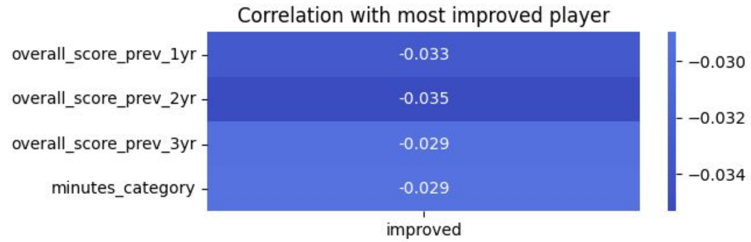
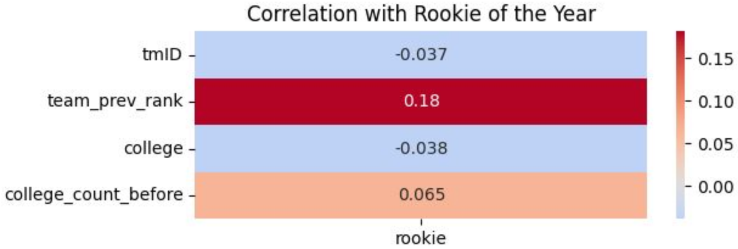
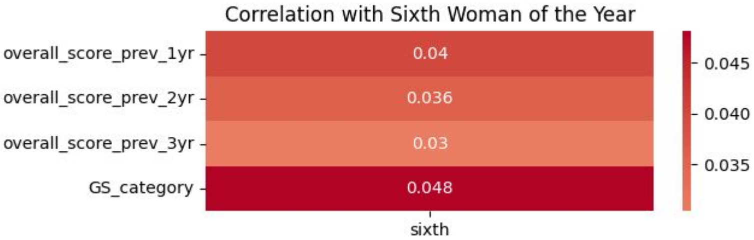
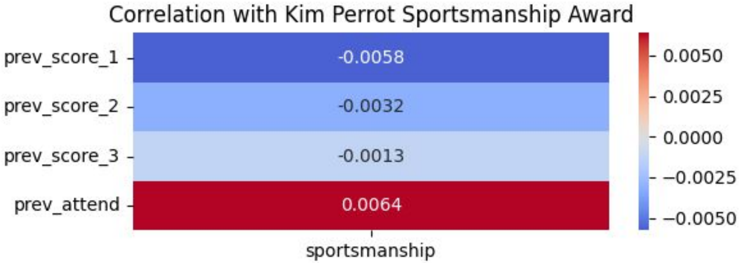
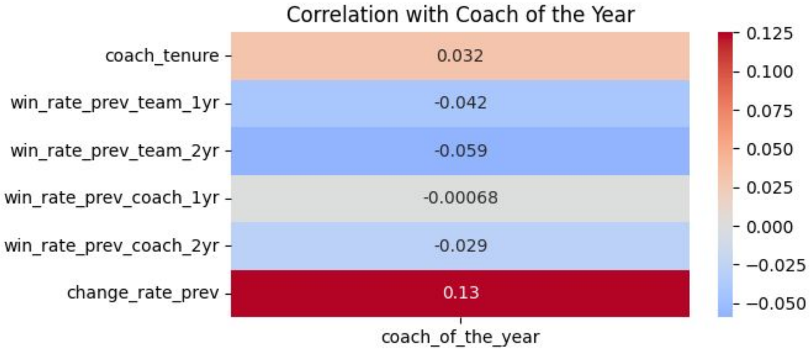


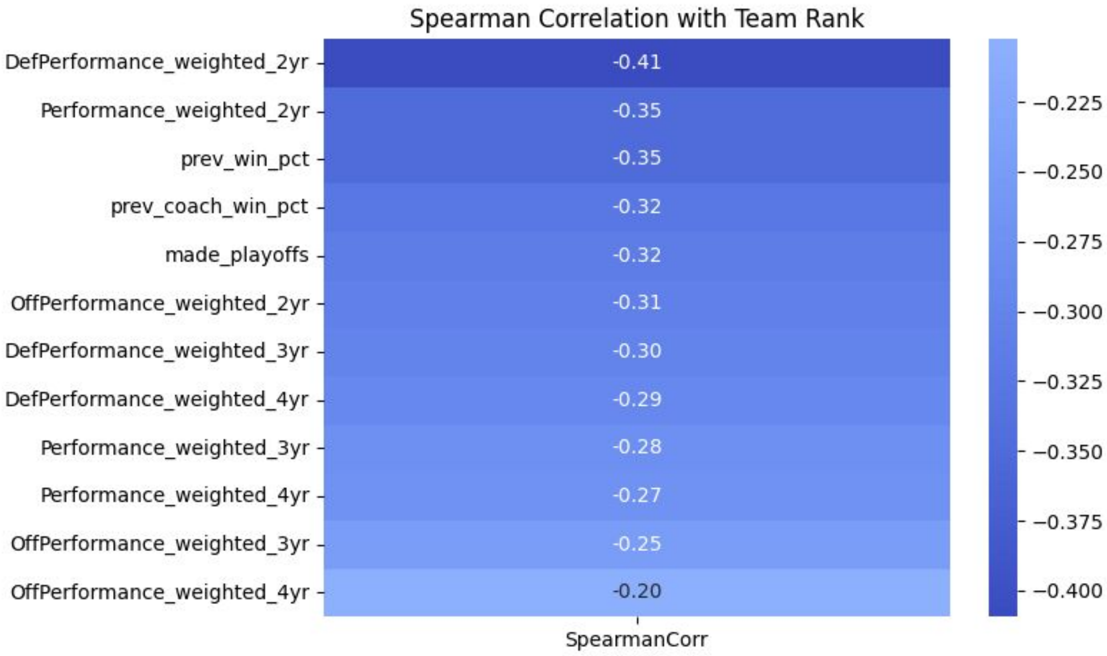








Data Preparation: Correlation of Used Features in the Prediction Task



Experimental Setup: Awards

Models

- **Logistic Regression**: Linear baseline for interpretability and comparison. Uses L2 regularization (C=1.0), balanced class weights, LBFGS solver, max_iter=1000, with standardized features to handle class imbalance and ensure stable training.
- **XGBoost**: Powerful non-linear model to capture complex feature interactions. Configured conservatively (learning_rate=0.05, max_depth=5, n_estimators=500, subsample=0.8, colsample_bytree=0.7) to reduce overfitting and improve generalization.
- **CatBoost**: Gradient boosting model designed for categorical features. Uses shallow trees (depth=4), low learning rate (0.05), 500 iterations, and multiclass log loss.

Metrics

- **Hit@1**: Fraction of cases where the true winner is ranked first
- **Hit@3**: Fraction of cases where the true winner appears in the top 3
- **MRR**: Average inverse rank of the true winner (rewards higher ranks)

For each award, we train models on 4 years of historical data and predict the winner for specific target years.

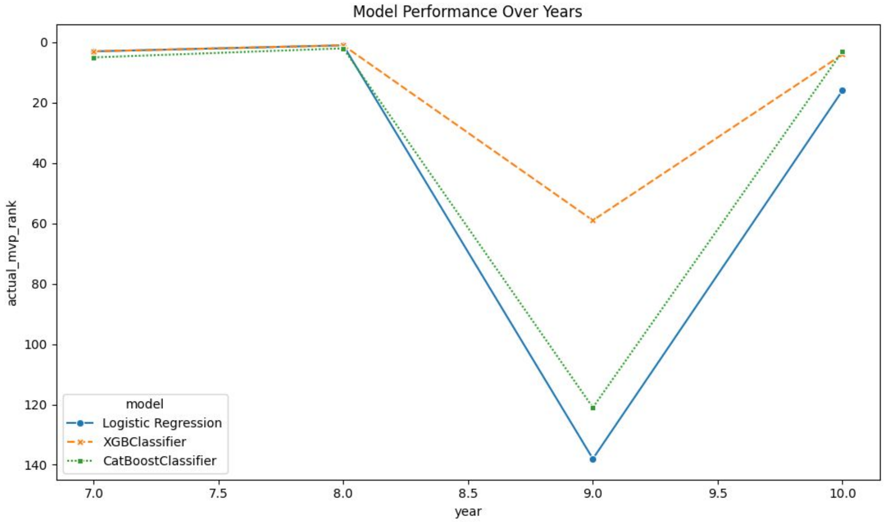
Results: MVP Award

Winner Ranking Performance

- High volatility across years: models perform well in early years (7-8) but drop in year 9 due to a rookie winner.
- Logistic Regression is most consistent (ranks 1-18, excluding year 9).
- XGBClassifier recovers strongly in year 10 (rank 2).
- CatBoost improves in year 10 (rank 4).

Performance Metrics

- **Hit@1**: Logistic Regression & XGBClassifier 25%, CatBoost 0% → MVP selection involves factors beyond previous scores.
- **Hit@3**: All models 50% → reliably identify the top candidate pool.
- **MRR**: XGBClassifier 0.400, Logistic Regression 0.351, CatBoost 0.260 → XGBoost provides best overall ranking balance.

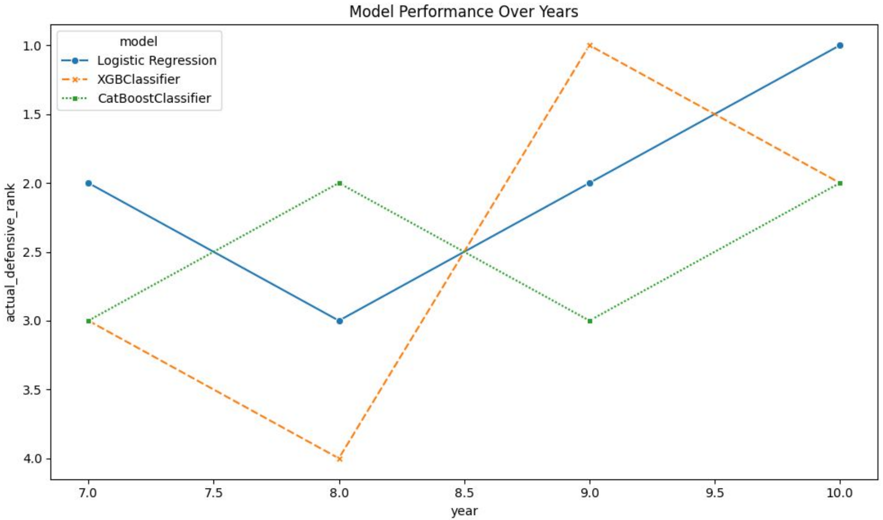


	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.00	0.5	0.260
1	Logistic Regression	0.25	0.5	0.351
2	XGBClassifier	0.25	0.5	0.400

Results: DPOTY Award

Winner Ranking Performance

- Models are more consistent than MVP predictions.
- **Logistic Regression**: ranks 1-2 across all years → very stable.
- **XGBClassifier**: ranks 1-4, strong early performance but more variable.
- **CatBoost**: steady ranks 3-4 across years.
- All models generally keep winners in top 4 → defensive performance is more predictable.



Performance Metrics

- **Hit@1**: Logistic Regression & XGB 25%, CatBoost 0% → competitive given subjectivity.
- **Hit@3**: Logistic Regression 100%, XGB & CatBoost 75% → strong identification of top defensive players.
- **MRR**: Logistic Regression 0.583, XGB 0.521, CatBoost 0.312 → defensive awards more predictable than MVP.

	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.00	1.00	0.417
1	Logistic Regression	0.25	1.00	0.583
2	XGBClassifier	0.25	0.75	0.521

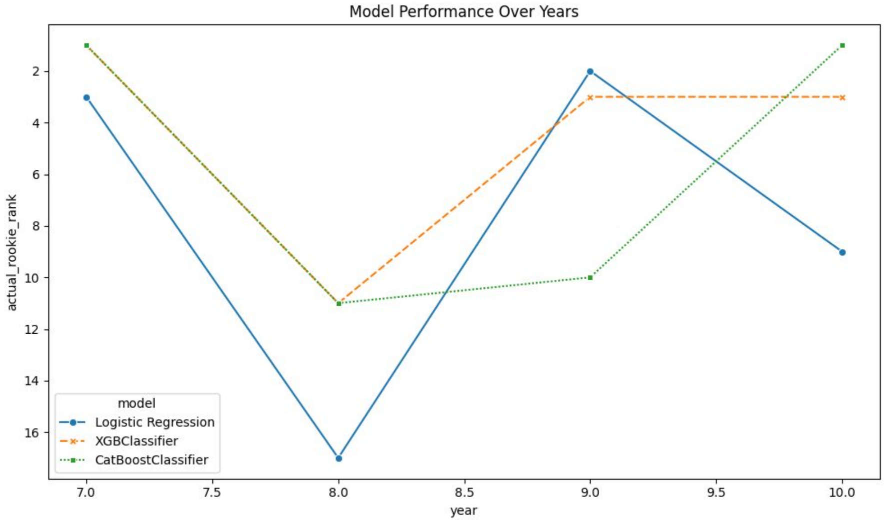
Results: ROTY Award

Winner Ranking Performance

- Performance is inconsistent due to a small candidate pool (~10 rookies).
- **XGBClassifier**: rank 1 in year 7, ranks 3-11 otherwise → most promising overall.
- **CatBoost**: ranks 1-12, excellent in year 7 (1) and strong in year 8 (9).
- **Logistic Regression**: more volatile, rank 2 (year 7) to 17.

Performance Metrics

- **Hit@1**: CatBoost 50%, XGB & Logistic Regression 0% → CatBoost best at predicting top rookie.
  Hit@3: XGB 75%, CatBoost & Logistic Regression 50% → models struggle with limited pool.
  MRR: CatBoost 0.548, XGB 0.439, Logistic Regression 0.251 → CatBoost excels at modeling complex factors for rookie success.



	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.50	0.50	0.548
1	Logistic Regression	0.00	0.50	0.251
2	XGBClassifier	0.25	0.75	0.439

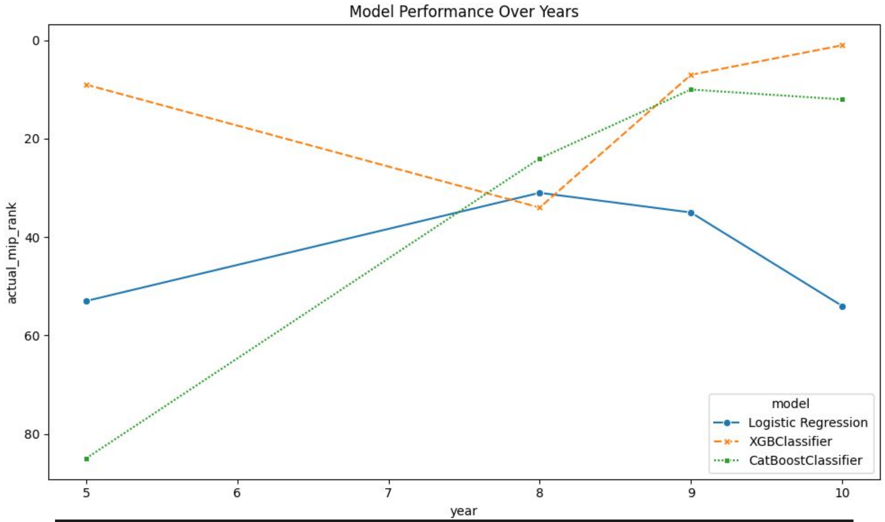
Results: MIP Award

Winner Ranking Performance

- Extremely difficult award; all models struggle.
- **CatBoost**: ranks 10–98, poor early performance.
- **Logistic Regression**: consistently low, ranks 36–51.
- **XGBClassifier**: highly variable, rank 1 in year 10 but 25–35 in other years.
- High variance shows improvement is hard to predict from statistics alone.

Performance Metrics

- **Hit@1**: XGB 25%, CatBoost & Logistic Regression 0% → reflects narrative-driven nature.
- **Hit@3**: XGB 25%, CatBoost & Logistic Regression 0% → models fail to capture improvement trends.
  MRR: XGB 0.321, CatBoost 0.059, Logistic Regression 0.025 → historical stats poorly predict "most improved" award.



	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.00	0.00	0.059
1	Logistic Regression	0.00	0.00	0.025
2	XGBClassifier	0.25	0.25	0.321

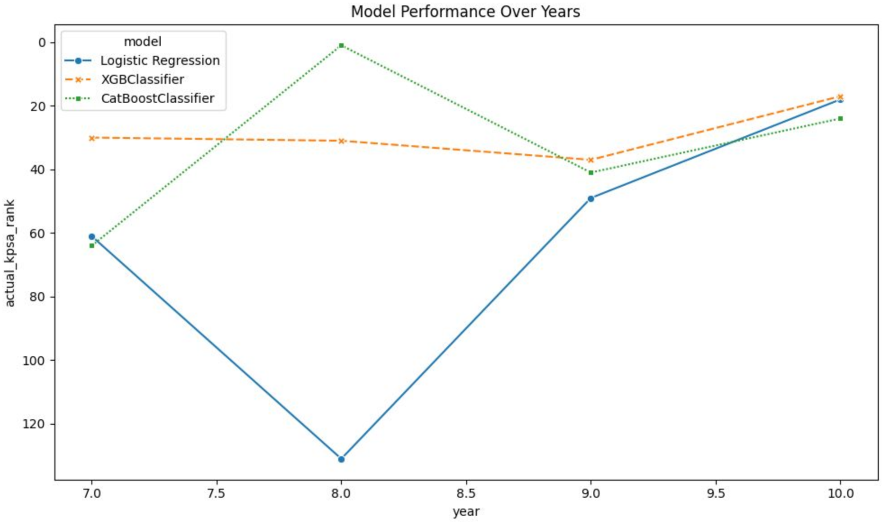
Results: KPSA Award

Winner Ranking Performance

- Moderate consistency with high year-to-year variation.
- **XGBClassifier**: ranks 20–31 → most stable overall.
- **Logistic Regression**: highly variable, 20–132; catastrophic year 8 (132) but recovers.
- **CatBoost**: ranks 30–54; poor year 8 performance mirrors Logistic Regression.

Performance Metrics

- **Hit@1**: CatBoost 25%, Logistic Regression & XGB 0% → some predictive signal.
- **Hit@3**: CatBoost 25%, others 0% → marginally captures pattern.
- **MRR**: CatBoost 0.270, XGB 0.039, Logistic Regression 0.025 → award remains difficult to predict from historical data.



	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.25	0.25	0.270
1	Logistic Regression	0.00	0.00	0.025
2	XGBClassifier	0.00	0.00	0.038

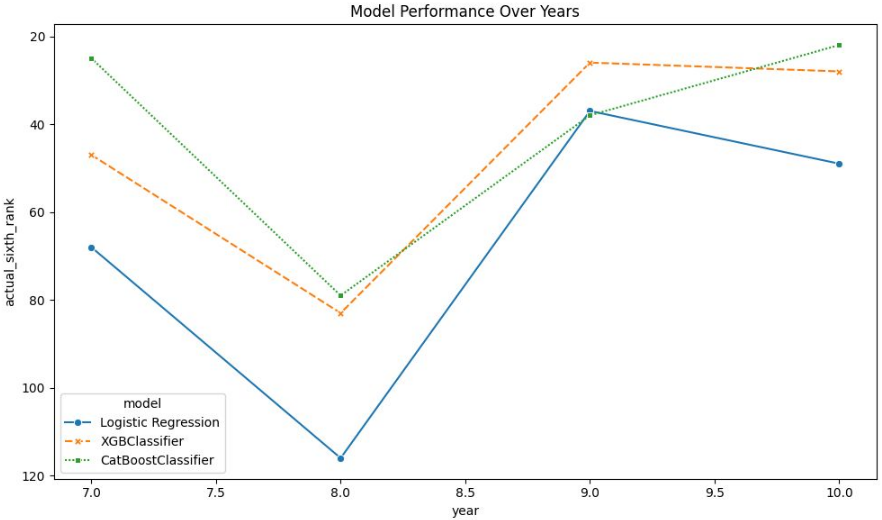
Results: SWOTY Award

Winner Ranking Performance

- All models struggle with highly inconsistent rankings.
- **XGBClassifier**: ranks 37–91, poor year 7 (91).
- **Logistic Regression**: ranks 27–61, moderate volatility.
- **CatBoost**: ranks 20–62, best among tree models but still variable.

Performance Metrics

- **Hit@1**: 0% for all models → cannot predict exact winners.
- **Hit@3**: 0% for all → winners not in top 3.
- **MRR**: CatBoost 0.031, XGB 0.027, Logistic Regression 0.018 → sixth player selection driven by role, team context, and narrative, not captured by raw stats.



	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.0	0.0	0.031
1	Logistic Regression	0.0	0.0	0.018
2	XGBClassifier	0.0	0.0	0.027

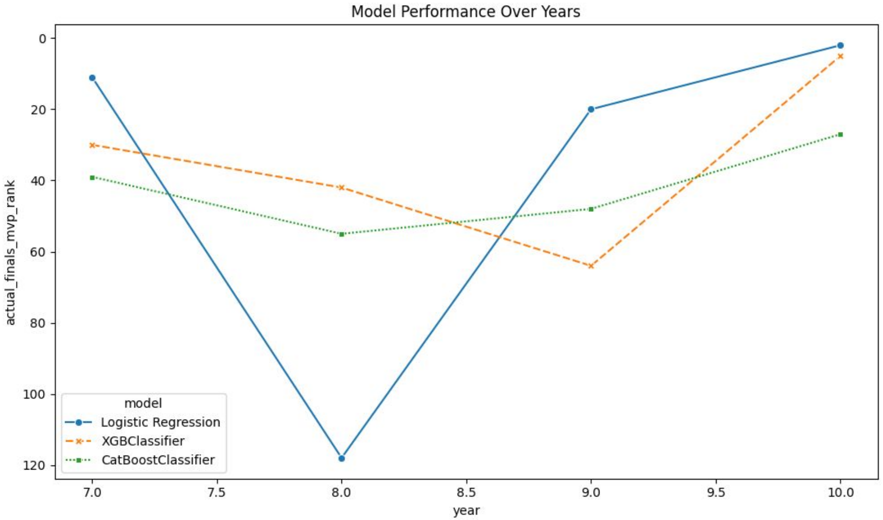
Results: FMVP Award

Winner Ranking Performance

- Dramatic year-to-year variation in rankings.
- **Logistic Regression**: ranks 2–118; catastrophic year 8 (118).
- **XGBClassifier**: ranks 5–64; best in year 10 (5), poor in year 9 (64).
- **CatBoost**: ranks 33–63; most consistent but never top-tier.

Performance Metrics

- **Hit@1**: 0% for all → Finals MVP unpredictable from historical metrics.
- **Hit@3**: Logistic Regression 25%, XGB & CatBoost 0% → top-3 prediction largely fails.
- **MRR**: Logistic Regression 0.162, XGB 0.068, CatBoost 0.025 → historical performance has limited predictive power; series-specific performance dominates.



	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.0	0.00	0.025
1	Logistic Regression	0.0	0.25	0.162
2	XGBClassifier	0.0	0.00	0.068

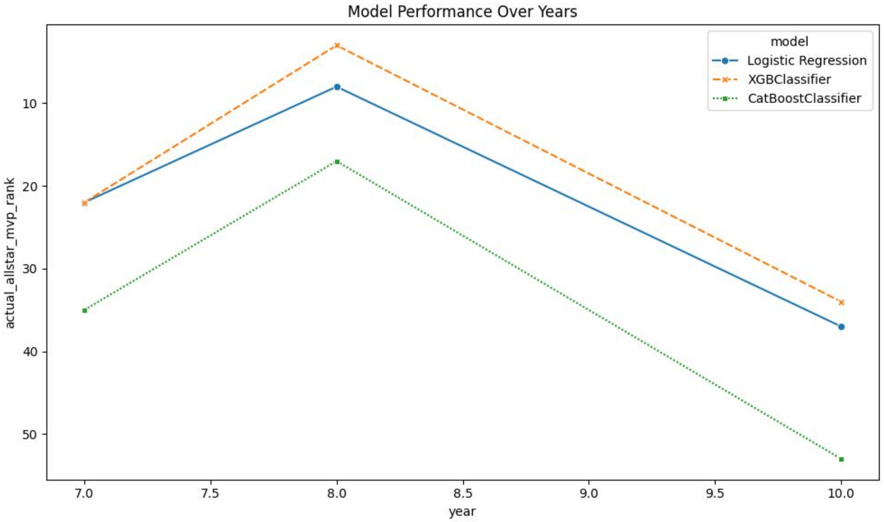
Results: ASGMVP Award

Winner Ranking Performance

- Rankings concentrated in mid-to-low ranges (3–61).
- **XGBClassifier**: best performer, rank 3 in year 8, rank 24 in year 10 → improving over time.
  Logistic Regression: ranks 8–37; best in year 8 (8), declines in year 10 (37).
- **CatBoost**: ranks 45–61; highly volatile, worst in year 7 (61).

Performance Metrics

- **Hit@1**: 0% for all → All-Star Game MVP cannot be predicted from regular season stats.
- **Hit@3**: XGB 33%, Logistic Regression & CatBoost 0% → XGB shows limited candidate identification.
- **MRR**: XGB 0.135, Logistic Regression 0.066, CatBoost 0.035 → confirms exhibition performance doesn't follow season patterns.



	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.0	0.000	0.035
1	Logistic Regression	0.0	0.000	0.066
2	XGBClassifier	0.0	0.333	0.136

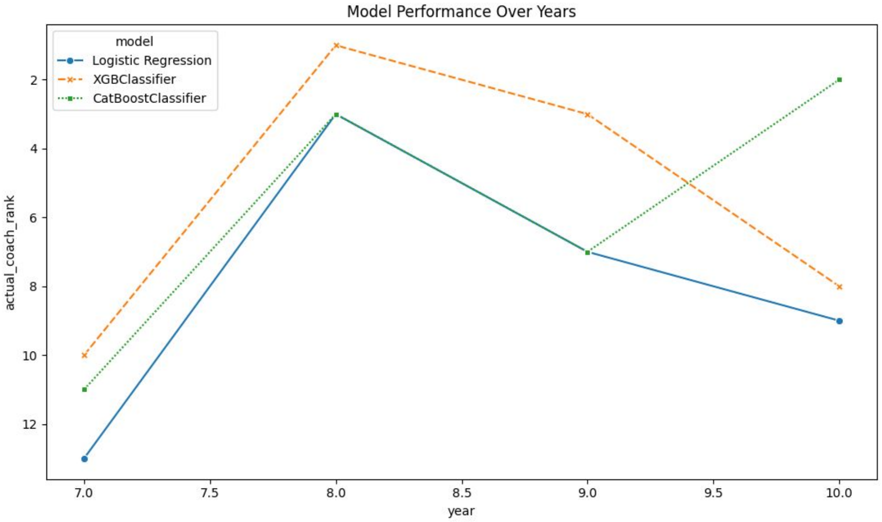
Results: COTY Award

Winner Ranking Performance

- Rankings vary despite small candidate pool (13–14 coaches/year).
- **XGBClassifier**: ranks 1–10; perfect rank 1 in year 8, strong year 10 (8).
- **Logistic Regression**: ranks 3–13; poor year 7 (13) but recovers to 3 in year 10.
  CatBoost: ranks 3–10; competitive with notable year 8 success (3).

Performance Metrics

- **Hit@1**: XGB 25%, CatBoost & Logistic Regression 0% → exact winner prediction is challenging.
  Hit@3: XGB 50%, CatBoost 50%, Logistic Regression 25%.
- **MRR**: XGB 0.390, CatBoost 0.267, Logistic Regression 0.166 → gradient boosting captures complex interactions informing COTY voting.



	model	hit@1	hit@3	MRR
0	CatBoostClassifier	0.00	0.50	0.267
1	Logistic Regression	0.00	0.25	0.166
2	XGBClassifier	0.25	0.50	0.390

Experimental Setup: Coach Turnover

Models

- **LightGBM**: Leaf-wise GBDT with shallow trees (max_depth=4, num_leaves=15), learning_rate=0.05, 300 estimators. Subsampling and scale_pos_weight handle overfitting and class imbalance.
- **CatBoost**: Ordered boosting with symmetric trees (depth=4, 300 iterations, learning_rate=0.05). Natively handles categorical features and balances classes automatically.
- **XGBoost**: Level-wise boosting (max_depth=4, 300 estimators, learning_rate=0.05) with strong regularization, scale_pos_weight for imbalance, optimized for AUC-PR.
- **Ensemble**: Average ranks from all models, normalize final score to [0,1].

Metrics

- **Recall@K**: % of actual coaching changes captured in the top K predictions
- **Precision@K**: % of top K flagged teams that truly changed coaches
- **Lift@K**: Performance vs. random selection (Lift > 1 indicates added value)

We train models on 4 years of historical data and predict the winner for specific target years.

Results: Coach Turnover

Model	K	Recall@K	Precision@K	Lift@K	Hits	Year
LightGBM	3	100.0%	33.3%	4.67	1	7
CatBoost	3	100.0%	33.3%	4.67	1	7
XGBoost	3	100.0%	33.3%	4.67	1	7
Ensemble	3	100.0%	33.3%	4.67	1	7
LightGBM	5	100.0%	20.0%	2.80	1	7
CatBoost	5	100.0%	20.0%	2.80	1	7
XGBoost	5	100.0%	20.0%	2.80	1	7
Ensemble	5	100.0%	20.0%	2.80	1	7
LightGBM	8	100.0%	12.5%	1.75	1	7
CatBoost	8	100.0%	12.5%	1.75	1	7
XGBoost	8	100.0%	12.5%	1.75	1	7
Ensemble	8	100.0%	12.5%	1.75	1	7

Model	K	Recall@K	Precision@K	Lift@K	Hits	Year
LightGBM	3	0.0%	0.0%	0.00	0	8
CatBoost	3	0.0%	0.0%	0.00	0	8
XGBoost	3	0.0%	0.0%	0.00	0	8
Ensemble	3	0.0%	0.0%	0.00	0	8
LightGBM	5	0.0%	0.0%	0.00	0	8
CatBoost	5	0.0%	0.0%	0.00	0	8
XGBoost	5	0.0%	0.0%	0.00	0	8
Ensemble	5	0.0%	0.0%	0.00	0	8
LightGBM	8	0.0%	0.0%	0.00	0	8
CatBoost	8	0.0%	0.0%	0.00	0	8
XGBoost	8	0.0%	0.0%	0.00	0	8
Ensemble	8	0.0%	0.0%	0.00	0	8

Model	K	Recall@K	Precision@K	Lift@K	Hits	Year
LightGBM	3	0.0%	0.0%	0.00	0	9
CatBoost	3	0.0%	0.0%	0.00	0	9
XGBoost	3	0.0%	0.0%	0.00	0	9
Ensemble	3	0.0%	0.0%	0.00	0	9
LightGBM	5	0.0%	0.0%	0.00	0	9
CatBoost	5	100.0%	20.0%	2.80	1	9
XGBoost	5	0.0%	0.0%	0.00	0	9
Ensemble	5	0.0%	0.0%	0.00	0	9
LightGBM	8	0.0%	0.0%	0.00	0	9
CatBoost	8	100.0%	12.5%	1.75	1	9
XGBoost	8	0.0%	0.0%	0.00	0	9
Ensemble	8	0.0%	0.0%	0.00	0	9

Model	K	Recall@K	Precision@K	Lift@K	Hits	Year
LightGBM	3	0.0%	0.0%	0.00	0	10
CatBoost	3	33.3%	33.3%	1.44	1	10
XGBoost	3	66.7%	66.7%	2.89	2	10
Ensemble	3	66.7%	66.7%	2.89	2	10
LightGBM	5	66.7%	40.0%	1.73	2	10
CatBoost	5	66.7%	40.0%	1.73	2	10
XGBoost	5	66.7%	40.0%	1.73	2	10
Ensemble	5	66.7%	40.0%	1.73	2	10
LightGBM	8	100.0%	37.5%	1.62	3	10
CatBoost	8	66.7%	25.0%	1.08	2	10
XGBoost	8	66.7%	25.0%	1.08	2	10
Ensemble	8	66.7%	25.0%	1.08	2	10

Results: Coach Turnover

- CatBoost and XGBoost demonstrate the most consistent performance across years, while LightGBM shows higher variance, performing well in some seasons but struggling in others. The ensemble approach provides a stable middle-ground by combining the strengths of individual models.
- In terms of ranking quality, CatBoost and the ensemble consistently place actual coaching turnovers within the top 3–5 positions. Even when exact probabilities are uncertain, the models successfully identify high-risk teams, with actual changes clustering near the top of the rankings, indicating strong discrimination.
- Lift analysis further highlights the practical value of the models: all achieve a Lift@5 greater than 2.0 in most years, meaning that flagging the top five teams is more than twice as effective as random selection.
- Overall, CatBoost offers the best balance of performance, reliability, and ease of use. While rare organizational events cannot be predicted perfectly, CatBoost effectively concentrates risk in its top predictions, delivering actionable insights for proactive planning. The roughly 40% Top-3 hit rate represents a substantial improvement over baseline methods.

Experimental Setup: Teams Ranking

Models

- **Extra Trees Regressor**: Ensemble of 200 shallow trees (max_depth=4, min_samples_split=2) to reduce variance while preventing overfitting on small datasets. Good for robust predictions with limited data.
- **Random Forest Regressor**: Similar to Extra Trees but uses max_features='sqrt' to decorrelate trees. Handles non-linear relationships well and generalizes effectively on small datasets.
- **Gradient Boosting Regressor**: Sequentially builds 200 trees (max_depth=3) with learning_rate=0.05 and subsample=0.8, correcting previous errors while controlling overfitting. Good for capturing complex patterns.
- **Ridge Regression**: Linear model with L2 regularization (alpha=1.0) serving as a simple, robust baseline. Prevents overfitting while providing interpretable results.

Metrics

- **MAE (Mean Absolute Error)** – Average ranking error.
- **Accuracy** – Proportion of exact rank matches.
- **AUC** – Assesses model's ability to separate ranks using a binarized approach.

We train models on 4 years of historical data and predict the winner for specific target years.

Results: Teams Ranking

Rank	year	model	Avg_MAE	Avg_Accuracy	Avg_AUC
1	7	GradientBoosting	1.714	28.57%	0.583
2	7	RandomForest	1.714	28.57%	0.583
3	7	ExtraTrees	1.857	21.43%	0.542
4	7	Ridge	1.857	14.29%	0.500

Rank	year	model	Avg_MAE	Avg_Accuracy	Avg_AUC
1	9	ExtraTrees	2.000	28.57%	0.583
2	9	GradientBoosting	2.143	21.43%	0.542
3	9	RandomForest	2.000	14.29%	0.500
4	9	Ridge	2.143	14.29%	0.500

Rank	year	model	Avg_MAE	Avg_Accuracy	Avg_AUC
1	8	ExtraTrees	1.619	39.29%	0.642
2	8	Ridge	1.762	25.00%	0.558
3	8	RandomForest	1.786	15.48%	0.500
4	8	GradientBoosting	2.405	8.33%	0.458

Rank	year	model	Avg_MAE	Avg_Accuracy	Avg_AUC
1	10	RandomForest	1.262	39.29%	0.642
2	10	ExtraTrees	1.262	30.95%	0.592
3	10	GradientBoosting	1.571	29.76%	0.583
4	10	Ridge	1.405	23.81%	0.550

Results: Teams Ranking

Overall Performance

- Moderate but inconsistent performance across years
- AUC ≈ **0.55–0.65**, indicating meaningful discrimination between strong and weak teams

Model Comparison

- Best model varies by year (RF, ExtraTrees, GB each excel in different seasons)
- **Ridge Regression underperforms**, showing linear models are insufficient

Accuracy & Error

- Exact rank accuracy is low (**8–39%**)
- Best years show **MAE ≈ 1–1.5 ranks**, meaning predictions are usually close

Key Takeaway

- Models outperform random baseline and capture **ranking trends**
- Useful for identifying likely improvement or decline, but **exact ranks remain difficult to predict**

Season 11 Prediction: Awards

For the season 11 award prediction the model that had the best results on the predictions of the others years was used.
Models for each award:

1. **Most Valuable Player** (Logistic Regression)
2. **Defensive Player Of The Year** (Logistic Regression)
3. **Rookie of The Year** (CatBoostClassifier)
4. **Most Improved Player** (XGBClassifier)
5. **Kim Perrot Sportsmanship Award** (CatBoostClassifier)
6. **Sixth Woman of The Year** (CatBoostClassifier)
7. **Finals Most Valuable Player** (Logistic Regression)
8. **All-Star Game Prediction** (Logistic Regression)
9. **Coach of the Year** (XGBClassifier)

Season 11 Prediction: Awards

Most Valuable Player

MVP PREDICTION FOR YEAR 11

ID	Probability	Rank
jacksla01w	0.907363	1.0
catchta01w	0.905549	2.0
swoopsh01w	0.863375	3.0
pierspl01w	0.795749	4.0
thompti01w	0.775144	5.0
milleke01w	0.770884	6.0
taylope01w	0.754751	7.0
pricear01w	0.749766	8.0
augusse01w	0.749310	9.0
whaleli01w	0.746111	10.0

Defensive Player of The Year

DPOTY PREDICTION FOR YEAR 11

ID	Probability	Rank
parkeca01w	0.900995	1.0
catchta01w	0.878657	2.0
jacksla01w	0.835882	3.0
dupreca01w	0.766746	4.0
anosini01w	0.389660	5.0
brunsre01w	0.381818	6.0
fowlesy01w	0.381558	7.0
lyttlsa01w	0.337236	8.0
mcwilta01w	0.325594	9.0
swoopsh01w	0.267842	10.0

Rookie of the Year

ROTY PREDICTION FOR YEAR 11

ID	Probability	Rank
bjorkan01w	0.517443	1.0
charlti01w	0.030449	2.0
greenka01w	0.030449	2.0
hightal01w	0.010768	3.0
moorema01w	0.009487	4.0
brelaje01w	0.003721	5.0
thomaja01w	0.002505	6.0
chriska02w	0.002417	7.0
cheekjo01w	0.002300	8.0
chriska02w	0.002040	9.0

Season 11 Prediction: Awards

Most Improved Player

```
==================================
MIP PREDICTION FOR YEAR 11
==================================
         ID  Probability  Rank
parisco01w     0.029776   1.0
januabr01w     0.029305   2.0
 holtam01w     0.023582   3.0
ajavoma01w     0.021779   4.0
snellbe01w     0.014201   5.0
sanfona01w     0.009654   6.0
bonnede01w     0.008975   7.0
mccouan01w     0.008975   7.0
montgre01w     0.008975   7.0
zellosh01w     0.008975   7.0
```

Kim Perrot Sportsmanship Award

```
==================================
KPSA PREDICTION FOR YEAR 11
==================================
         ID  Probability  Rank
hammobe01w     0.062858   1.0
bobbish01w     0.026365   2.0
thompti01w     0.010938   3.0
thorner01w     0.005622   4.0
dupreca01w     0.005574   5.0
quinnno01w     0.005574   6.0
mazzake01w     0.004771   7.0
 cashsw01w     0.004769   8.0
hodgero01w     0.004161   9.0
 birdsu01w     0.003603  10.0
```

Sixth Woman of The Year

```
==================================
SWOTY PREDICTION FOR YEAR 11
==================================
         ID  Probability  Rank
kraayca01w     0.123037   1.0
 cashsw01w     0.028527   2.0
willile01w     0.022942   3.0
beviltu01w     0.018786   4.0
currimo01w     0.012036   5.0
cantydo01w     0.007754   6.0
penicti01w     0.006629   7.0
swoopsh01w     0.002853   8.0
milleke01w     0.002219   9.0
carsoes01w     0.001944  10.0
```

Season 11 Prediction: Awards

Finals Most Valuable Player

FMVP PREDICTION FOR YEAR 11

ID	Probability	Rank
mccouan01w	0.617974	1.0
anosini01w	0.491309	2.0
catchta01w	0.423408	3.0
jacksla01w	0.421527	4.0
tauradi01w	0.414092	5.0
augusse01w	0.378879	6.0
bonnede01w	0.373992	7.0
parkeca01w	0.268274	8.0
pondeca01w	0.256420	9.0
hammobe01w	0.231951	10.0

All-Star Game Most Valuable Player

ASGMVP PREDICTION FOR YEAR 11

ID	Probability	Rank
jacksla01w	0.993183	1.0
catchta01w	0.988842	2.0
tauradi01w	0.981688	3.0
augusse01w	0.973069	4.0
youngso01w	0.950470	5.0
dupreca01w	0.946052	6.0
pondeca01w	0.943036	7.0
douglka01w	0.929293	8.0
whaleli01w	0.923183	9.0
hammobe01w	0.918077	10.0

Coach of The Year

COTY PREDICTION FOR YEAR 11

ID	Probability	Rank
meadoma99w	0.770409	1.0
thibami99w	0.284675	2.0
richano99w	0.228029	3.0
aglerbr99w	0.112508	4.0
hugheda99w	0.088486	5.0
dunnli99wc	0.045420	6.0
gaineco01w	0.041364	7.0
chatmda99w	0.023973	8.0
whisejo99w	0.008486	9.0
gilloje01w	0.004885	10.0

Season 11 Prediction: Coach Turnover and Team Rankings

For the Season 11 award prediction, the model that achieved the best results on predictions for previous seasons was selected. Accordingly, **XGBClassifier** was used for the Coach Turnover Prediction, and **Random Forest Regressor** was employed for the Team Rankings Prediction.

While the coach model originally outputs the probability of a coach being replaced, the current task requires predicting the actual outcome rather than just the probability. To address this, predictions from previous seasons were analysed, and a threshold of **0.25** was determined for the XGBClassifier to classify whether a coach would be changed.

Season 11 Prediction: Coach Turnover and Team Rankings

```
==================================================
COACH TURNOVER PREDICTION FOR YEAR 11
==================================================
No coach turnovers predicted for year 11
```

This indicates that no coaches reached the 0.25 probability threshold for being replaced.

East Conference Ranking

tmID	Predicted_Rank
IND	1
WAS	2
CHI	3
ATL	4
NYL	5
CON	6

West Conference Ranking

tmID	Predicted_Rank
SAS	1
SEA	2
LAS	3
PHO	4
TUL	5
MIN	6

Conclusions

- Model accuracy in predicting final team rankings is **reasonable** for years 7 and 10, given the **high** inter-season volatility observed in WNBA team performance.

- Some awards had bad data to predict from such as **Kim Perrot Sportsmanship Award** because there are a lot of things that aren't statistics such as *trash talk* and faking a foul that count for that award.

- In general with the data we had the predictions are pretty good. Since we don't have the statistics of the year to be predicted some things such as injuries or retirements can lead to errors that our predictions don't account for.

Limitations

- The **limited** number of observations **restricts** the capacity of complex models to learn robust patterns and necessitates regularization strategies.
- The **high temporal variability** and **frequent shifts** in team rankings introduce **noise**, making stable predictive modeling highly **challenging**.
- The **paucity** of suitable or diverse data for the test set **limits** the robustness and representativeness of the final model evaluation.