MULTIVARIATE ANALYSIS

CLASSIFICATION STUDY OF NBA PLAYER PROFILES

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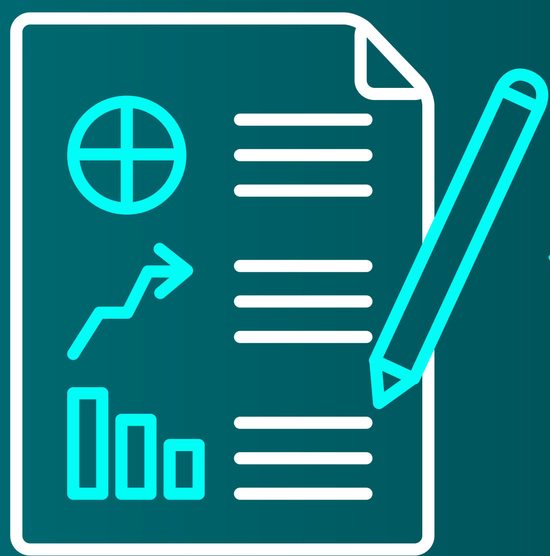
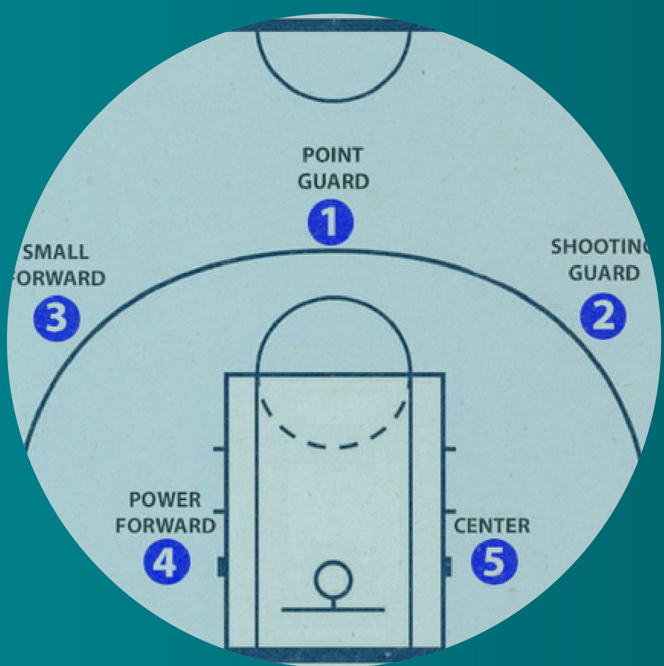
WHY THIS STUDY?

- Understand what performance leads to major NBA recognition
- Classify player positions using career stats
- Use interpretable statistical models





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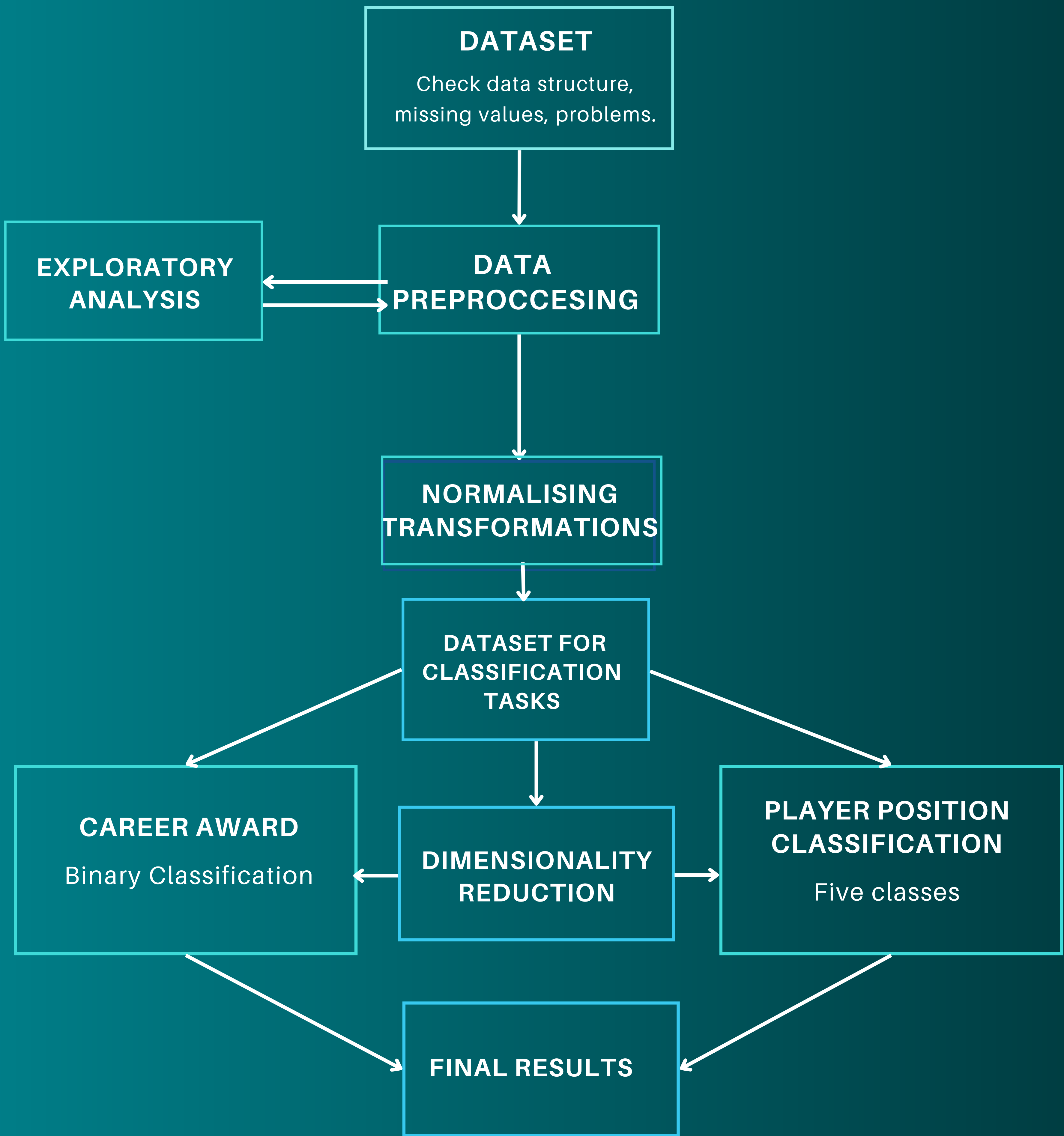
METHODOLOGY



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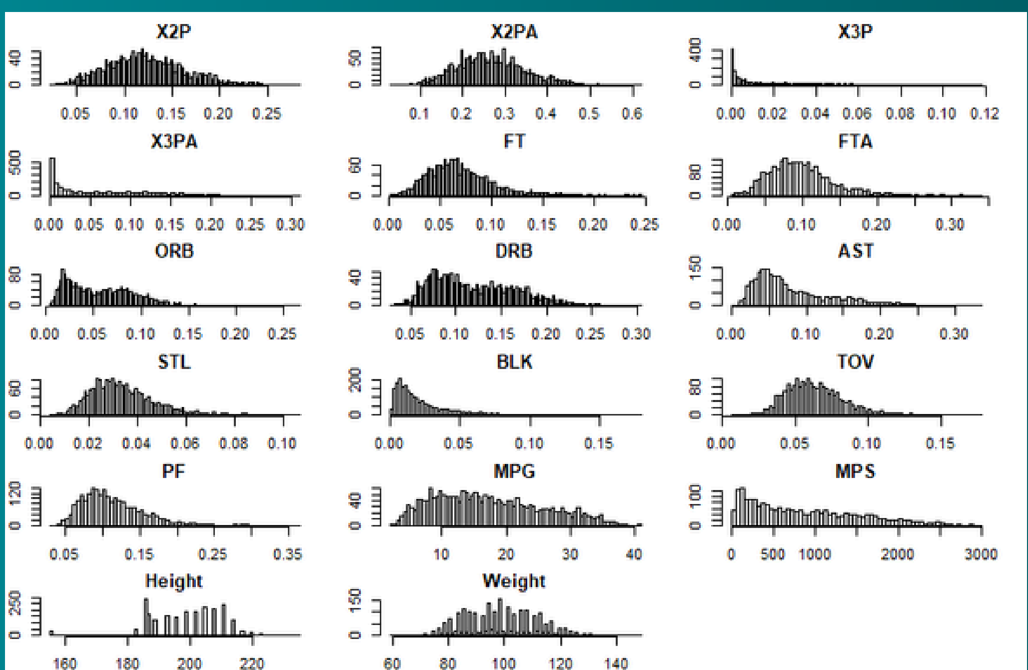
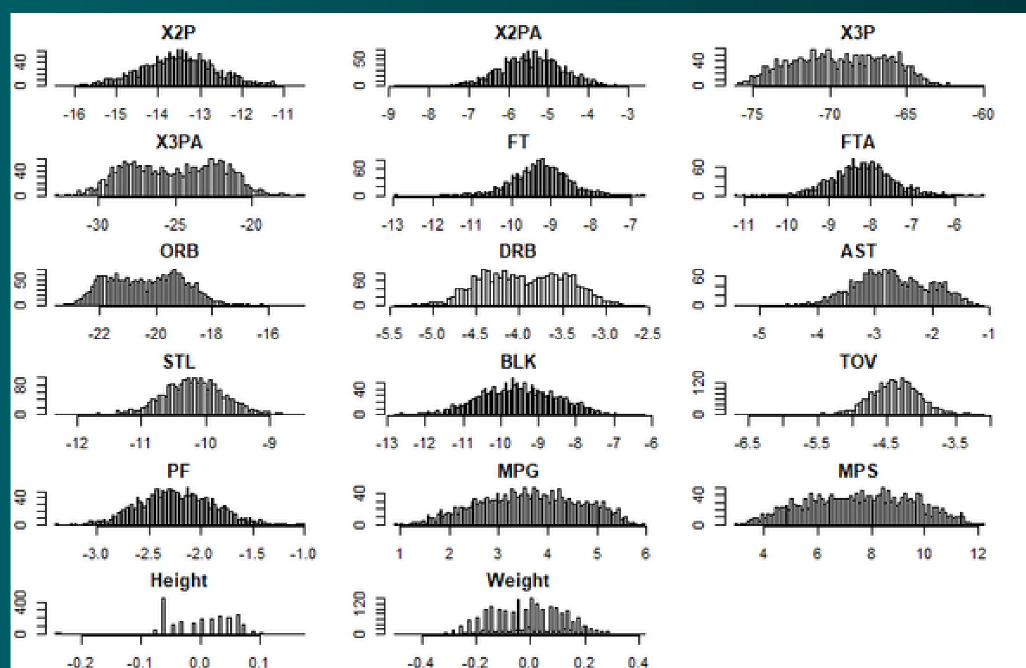
PREPROCESSING STEPS AND FEATURE TRANSFORMATION

- Aggregate per-player lifetime stats
- Drop players with <60 minutes or <10 games
- Normalize using per-minute stats (e.g., X2P/MP)

- Applied log-like transform to improve normality
- Constructed features: MPG, MPS, action rates
- Dropped categorical or poorly-behaved features



Before Transformation



After transformation

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WHY DO WE USE THE TRANSFORMATIONS?

- To make the predictors better resemble a multivariate normal (MVN) distribution — a key assumption for methods like LDA and QDA.

WHAT TRANSFORMATION WAS APPLIED?

- A log-like monotonic transformation of the form:

$$f(x) = c(x-1) + log(x)$$

- ***log(x)***: Reduces positive skewness (common in count-based sports stats).
- ***c(x−1)***: Adds a linear scaling factor to adjust for the level of skewness in each variable.
- ***c*** is not fixed: It was tuned per feature by minimizing the Anderson-Darling (AD) test statistic (a test for normality).
- The transformation ensures positivity (by adding 1 to counts), which is important before applying log.

WHY NOT JUST USE LOG(X)?

- Because not all features had the same skewness — a fixed transformation would not equally improve all distributions. So, a data-adaptive approach was used:
- c ∈ (0,10^5] was optimized via Brent's method (a global minimization algorithm).
- Some features (e.g., X2P, STL) passed the AD test after transformation.

WHAT ABOUT HEIGHT AND WEIGHT?

- These were transformed with log(x/x), effectively centering around 0. This removes strict positivity without changing interpretability or affecting results (translation-invariant).

RESULTS OF THE TRANSFORMATIONS

- Features became more symmetric and less skewed.
- PCA retained more variance post-transformation (e.g., 33.7% vs. 31.0% in PC1).
- Improved compatibility with Gaussian-based methods like LDA/QDA.

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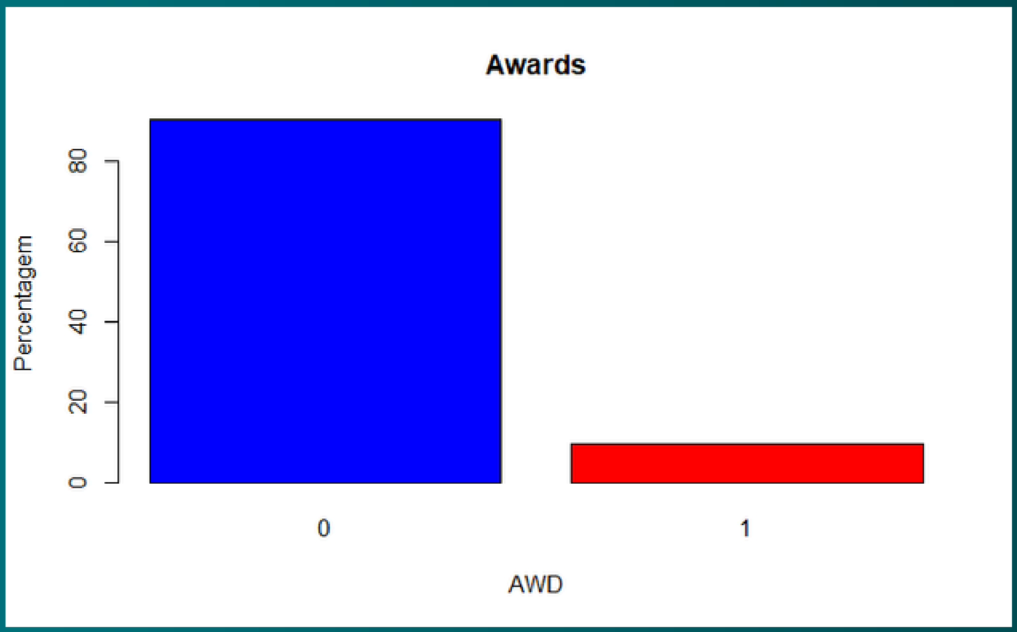
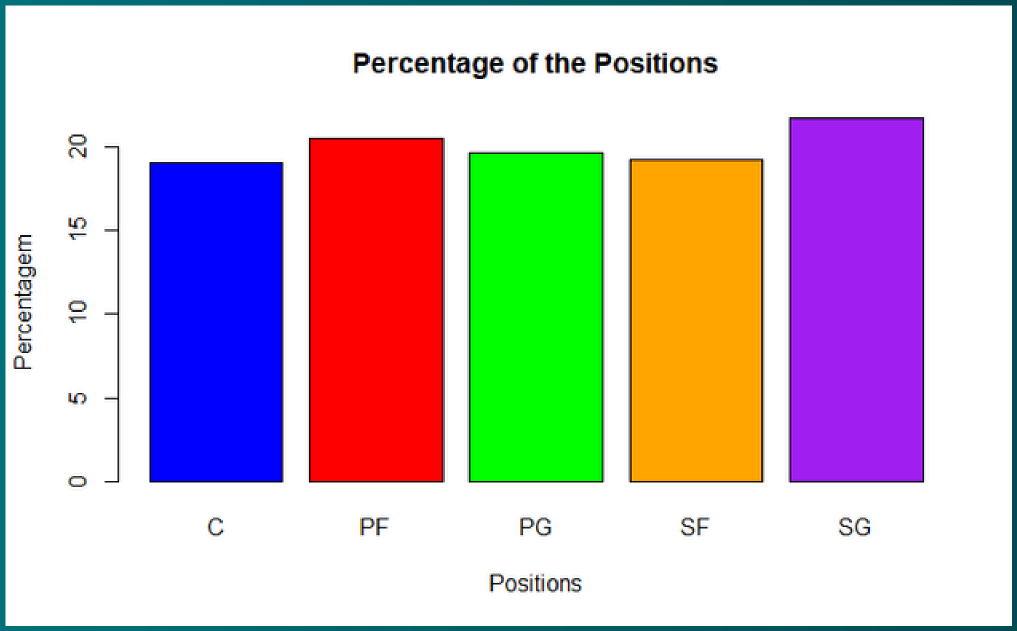
WHAT ARE WE PREDICTING?

- AWD: Award recipient? (Yes/No, 9.74% positive).
- Pos: Player position (C, PF, SF, SG, PG).



Award Proportion (Imbalanced).



Positions Proportion

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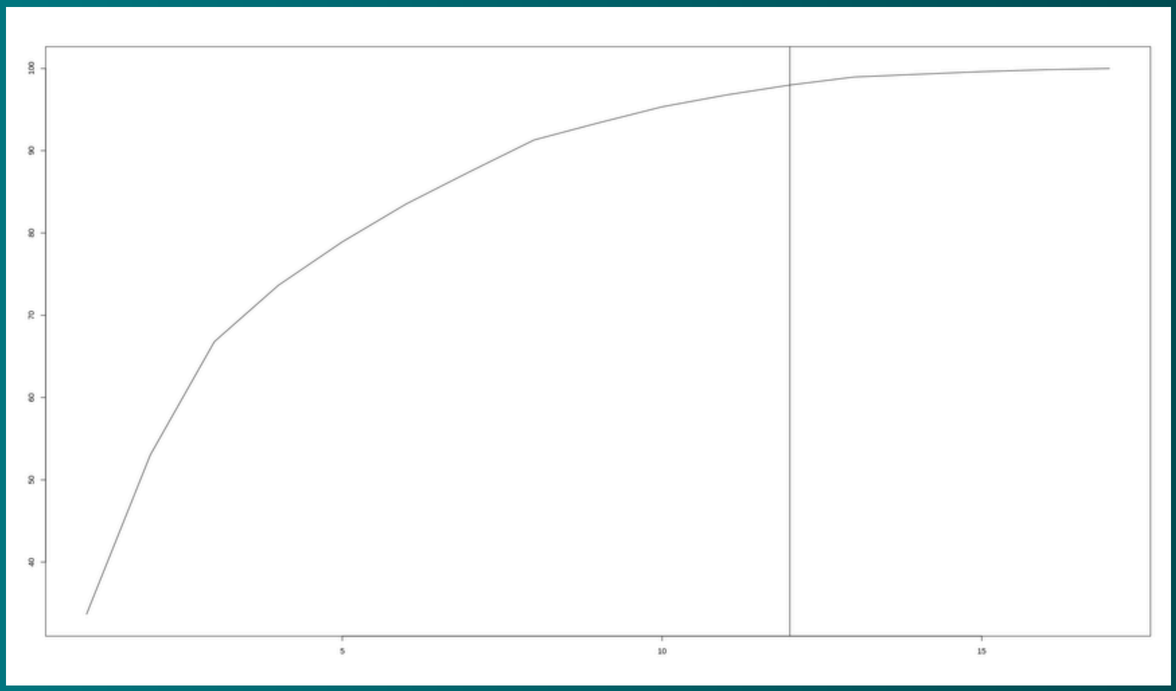
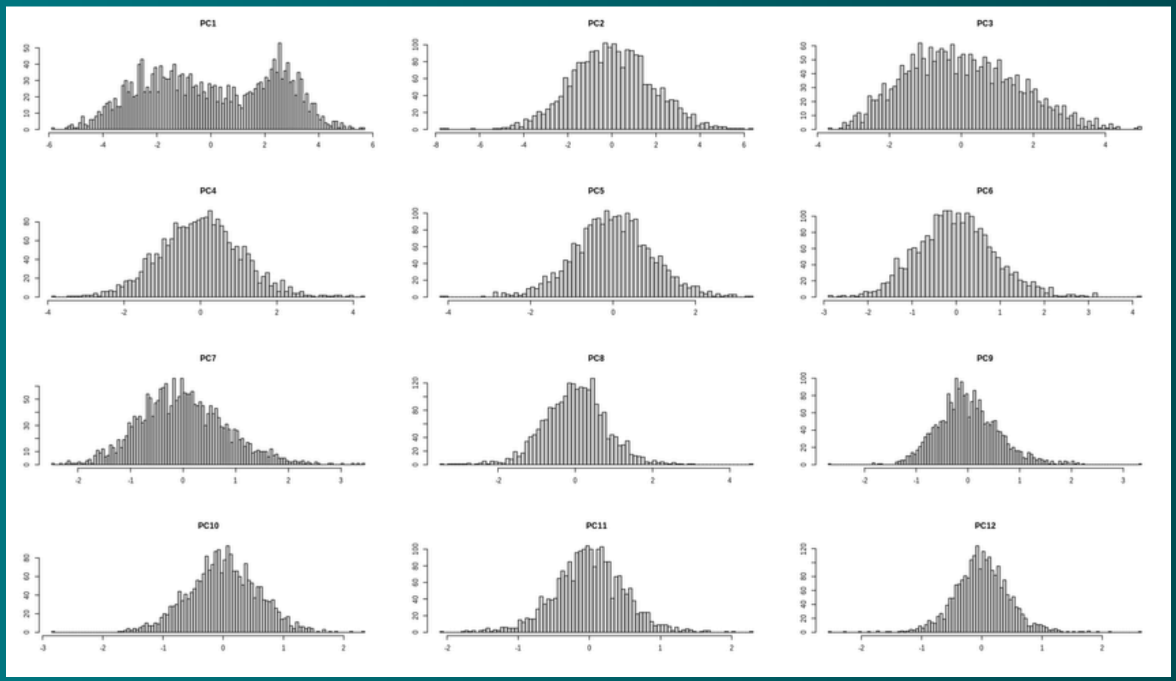
PRINCIPAL COMPONENT ANALYSIS (PCA)

- Reduced to 12 PCs, preserving 98% of variance
- Improved performance and interpretability
- Used in both transformed and untransformed datasets.



Cumulative Var% with v-line at 12 PCs



histograms of the retained PCs.

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CLASSIFICATION MODELS USED

LDA – Linear Discriminant Analysis

- Assumes features are normally distributed within each class.
- Assumes equal covariance across classes (linear boundaries).
- Works well when features are continuous and classes are well-separated.
- Best performer in this study.
- Use when interpretability matters.

QDA – Quadratic Discriminant Analysis

- Similar to LDA but allows different covariances per class.
- More flexible boundaries (curved decision surfaces).
- May overfit with small or high-dimensional data.
- Use when classes may have different spreads.

k-NN – k-Nearest Neighbors

- Non-parametric, no training needed.
- Classifies based on the majority class among k closest data points.
- Sensitive to feature scaling and high dimensionality.
- Simple, but suffers with noisy or sparse data.

Naive Bayes

- Assumes all features are conditionally independent given the class.
- Fast and simple, works well with text or categorical data.
- Assumption often violated in real datasets like this one.
- Lightweight, but less accurate with correlated features.

Evaluation:

- All methods were compared using:
- Stratified 10-fold cross-validation
- F1-score, Accuracy, Confusion Matrix

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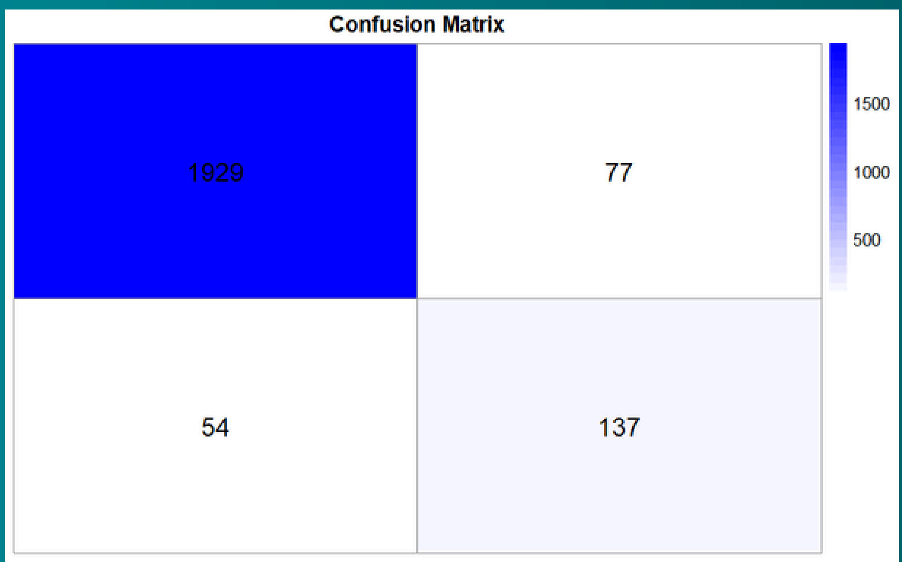
RESULTS: AWARD PREDICTION (AWD)

Metric / Method	LDA	QDA	kNN	Naive Bayes
Accuracy	0.9404	0.8812	0.9294	0.8994
F1-Score	0.8215	0.7501	0.7382	0.7765

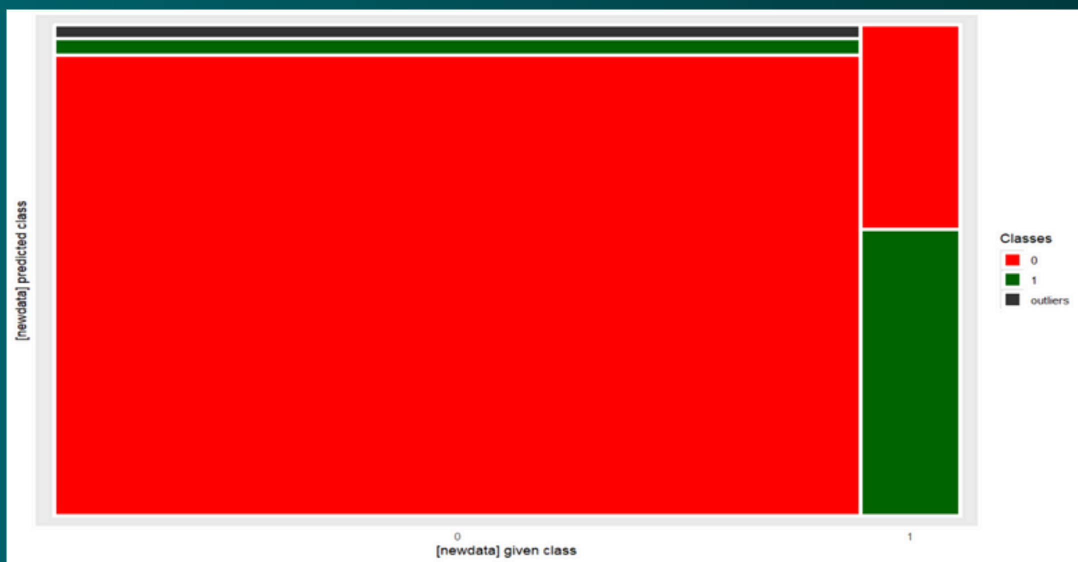
Classifcation Results without Dimension Reduction

Metric / Method	LDA	QDA	kNN	Naive Bayes
Accuracy	0.9335	0.9099	0.9030	0.9281
F1-Score	0.7870	0.7601	0.6975	0.7664

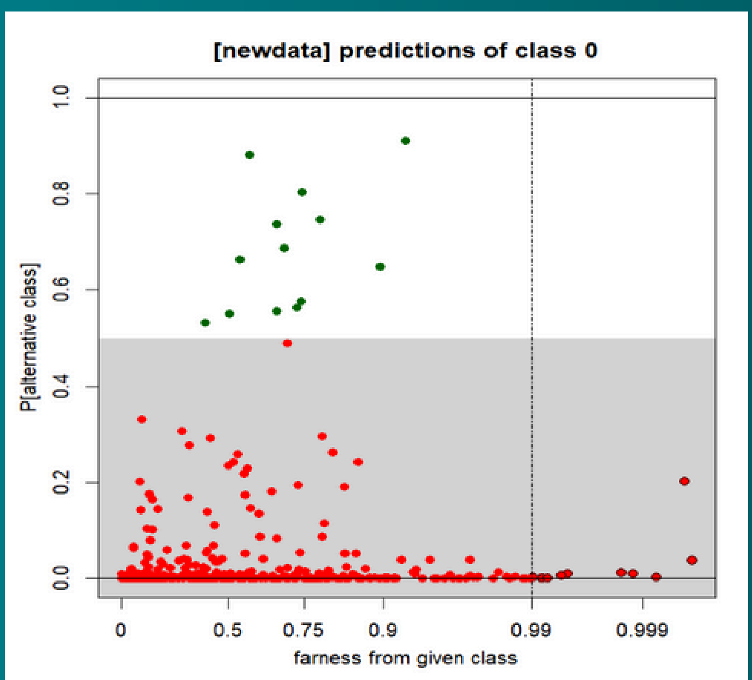
Classifcation Results with PCA



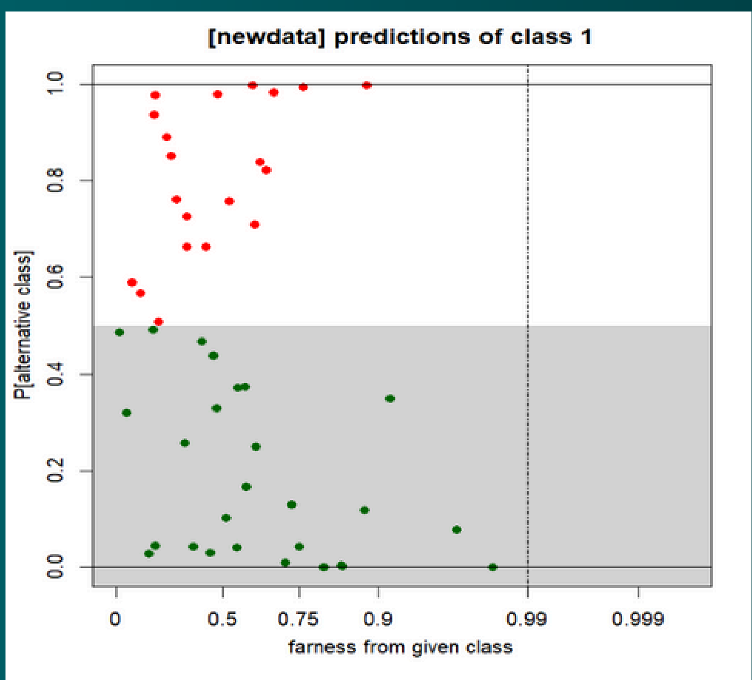
Confusion Matrix for LDA and Full Dataset



Stacked mosaic plot of a classification with LDA and Full Dataset



Classmap for class 0.



Classmap for class 1.

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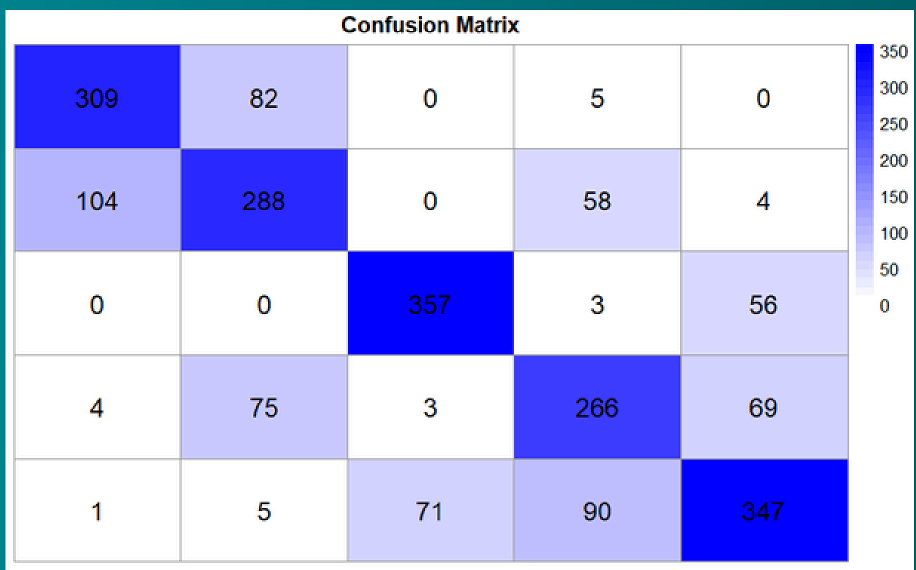
RESULTS: PLAYER POSITION PREDICTION

Metric / Method	LDA	QDA	kNN	Naive Bayes
Accuracy	0.7132	0.6941	0.7069	0.6982
F1-Score	0.7140	0.6886	0.7060	0.6941

Classifcation Results without Dimension Reduction

Metric / Method	LDA	QDA	kNN	Naive Bayes
Accuracy	0.7069	0.7212	0.6441	0.6468
F1-Score	0.7072	0.721	0.6398	0.6415

Classifcation Results without Dimension Reduction



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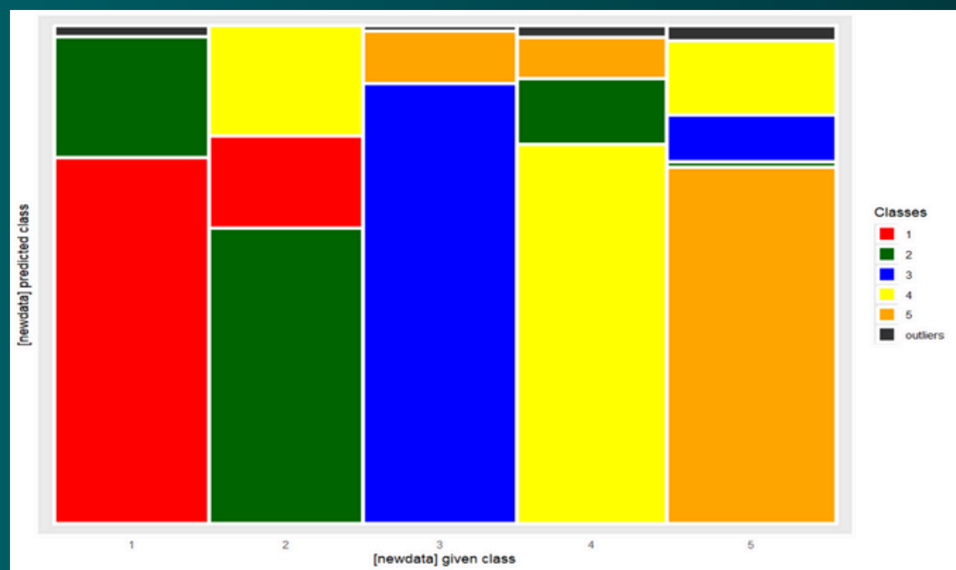

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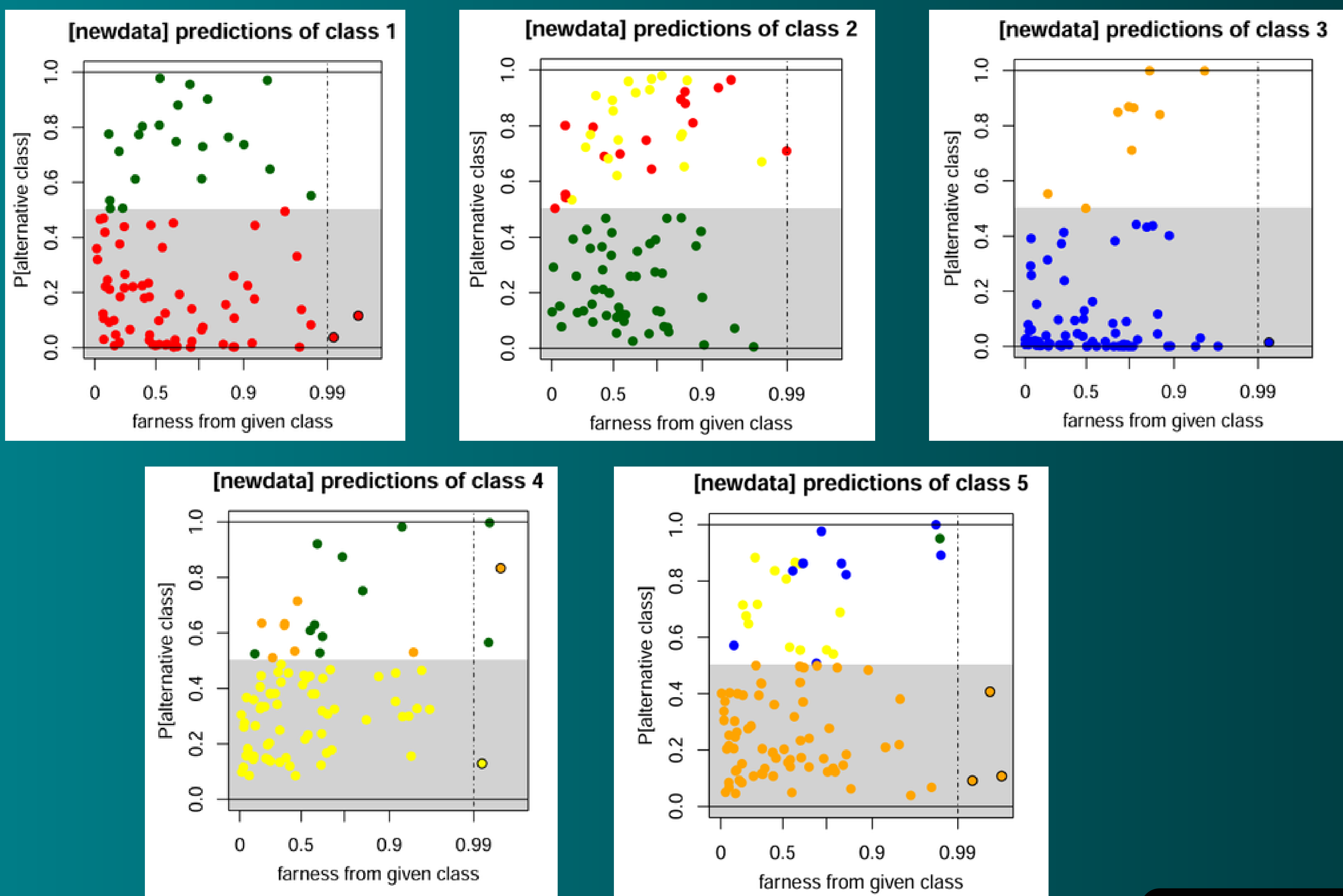

Classmaps

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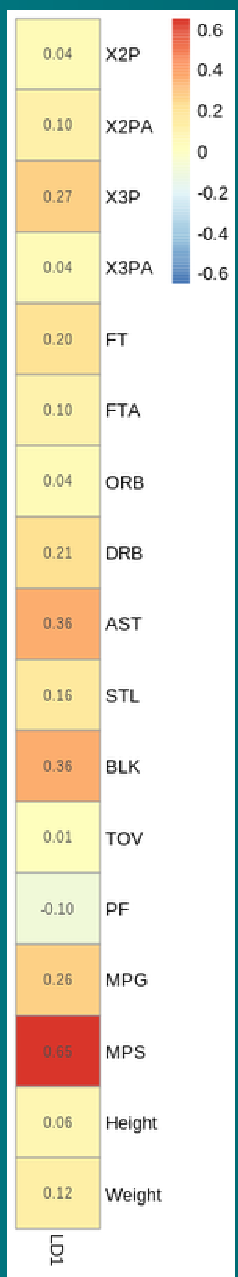
RESULTS: CLASSIFICATION (LDA)

- Importance of playing a significant number of matches and minutes for recognition.
- Higher useful action rates (e.g., assists, rebounds) increase likelihood of receiving awards.
- Anthropometric parameters do not impact award classification

- First linear discriminant highlights assists and rebounds as key classification features.
- Centers and Forwards (SF-PF) typically have fewer assists and more rebounds than guards
- Weight is a significant factor; Centers and Forwards generally weigh more than guards.
- Centers likely incur more fouls, leading to more FT executions due to physical play in tight spaces.



LDA discriminant coefficients Awards

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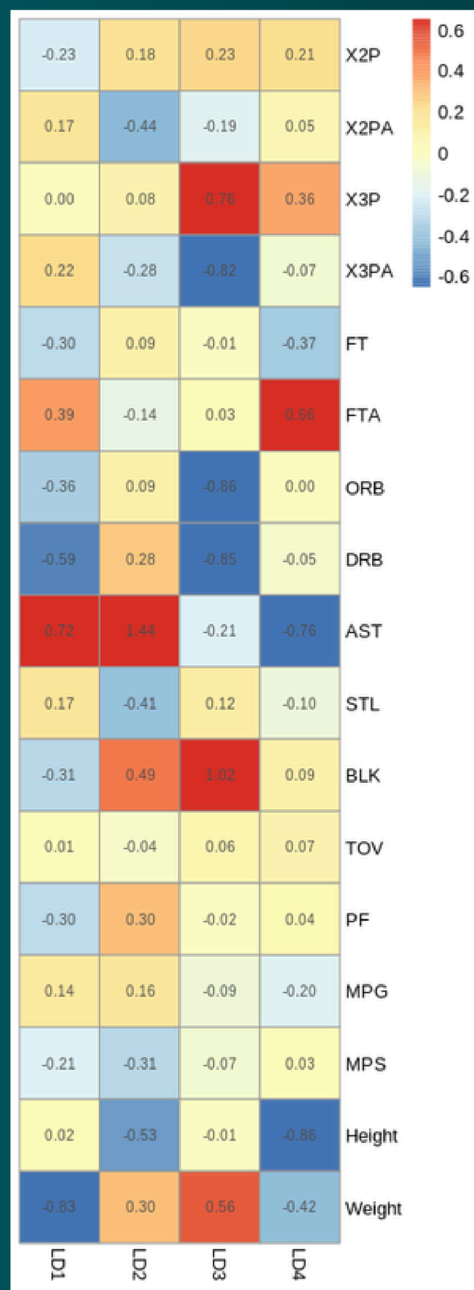

LDA discriminant coefficients Positions

CONCLUSIONS & FUTURE WORK

- Best performance classification methods: LDA and QDA.
- Handling Imbalance: downsampling.
- Features were constructed to better distinguish between aspects of the target classes
- Technical departures from model assumptions were addressed without losing much transparency
- PCA did not improve results but confirmed existence of a reduced efficient subset of feature info
- The data appears sufficient for establishing the relationships of interest despite being basic
- Future work and recommendations: include additional features like advanced statistics (e.g., plus-minus, win shares) and contextual data (e.g., team performance); apply machine learning methods that target prediction performance rather than parsimony

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