NBA Player Role Prediction

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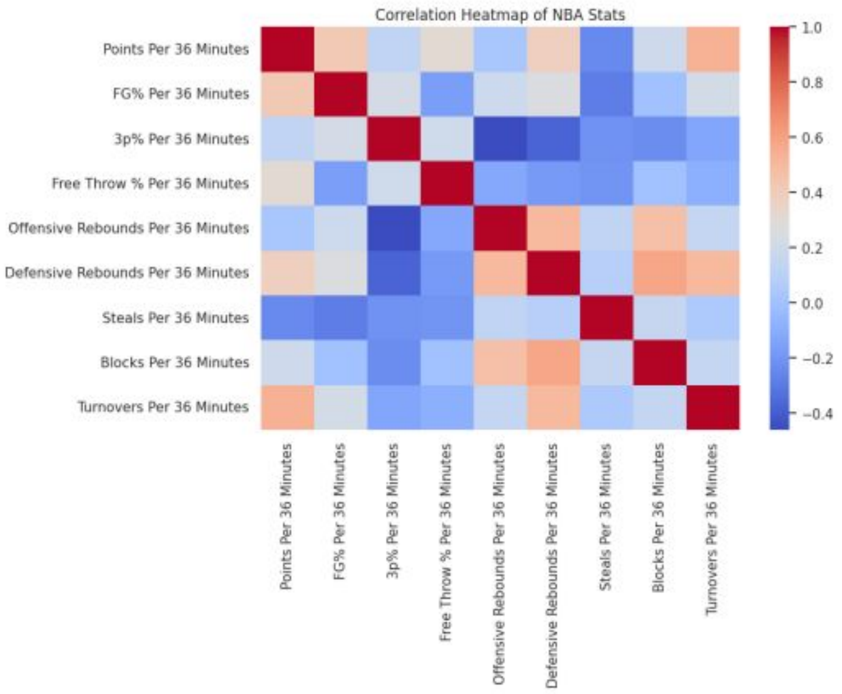
Python libraries and Tools

- pandas
- numpy
- matplotlib
- seaborn
- collections
- scikit-learn
- tensorFlow

Classifying and Data Gathered

- The National Basketball Association (NBA) numbers are complex and linked together - so comparing athletes and spotting their roles is difficult.
- Our goal is to classify NBA players (including 2025 rookies) into player archetypes using per–36-minute statistics, which demonstrates a probability-style project.
- We start from 10 archetypes (Shot Creator, 3-Point Specialist, Stretch 5, etc.) and, due to limited samples taken from the top players in the league currently. The archetypes are split into 3 broader categories. (Offensive, Defensive, and Playmaker)

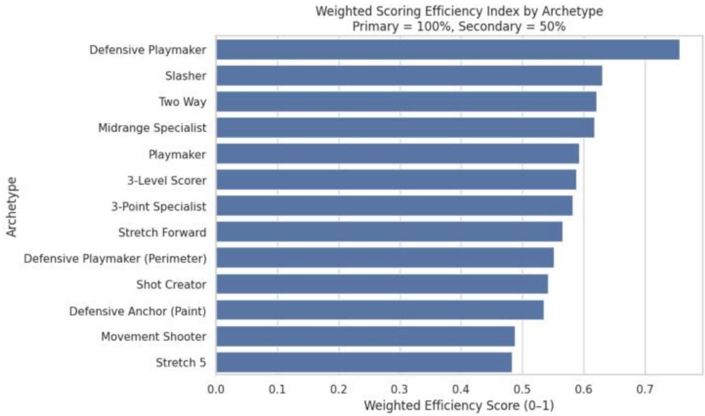


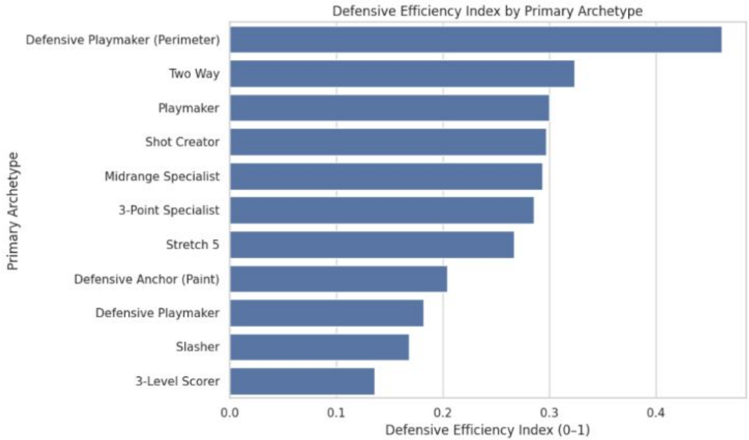
Why it Matters

- **Role/archetype labels summarize strengths** more clearly than raw stat tables rather than relying on just points put up per the 36 minutes there are more categories or objectives to basketball than meets the eye.
- **Correlation patterns** show which stats move together, helping identify what features are crucial to demonstrate whether a person is seen more as an offensive or defensive player whether it may be blocks/steals or offensive rebounds/high 3 point percentage.
- Real modeling constraint: class imbalance (especially Playmaker) can hurt classification performance, motivating broader group labels.

Data Snapshot

- For data tracking we utilized the NBA's stats per-36-minutes as this allows us to keep track of different play-times rather than stats per-game. With stats per-36-minutes we can get a good estimate of bench players for example who scores 12 points in 18 minutes, we can then assume their points per 36 is 24 points.
- Features that we used through this process are points, blocks, assists, FG%, 3p%, Free Throw%, Offensive/Defensive rebounds, turnovers, steals, and personal fouls.
- We reduce complexity by engineering combined metrics (e.g., **Scoring Efficiency Index** and **Defensive Efficiency Index**) to better capture structure.





Data source & Scope

- **Data source:** Basketball-Reference “2025 NBA Player Stats: Per 36 Minutes” (player per-36 table).

  https://www.basketball-reference.com/leagues/NBA_2026_per_minute.html

- **Why per-36?** Per-36 stats normalize production by playing time (stat/minutes × 36), letting you compare bench vs starters more fairly.
- **Scope:** Our report states the dataset includes **NBA players + 2025 rookies** and uses **per–36-minute statistics**.

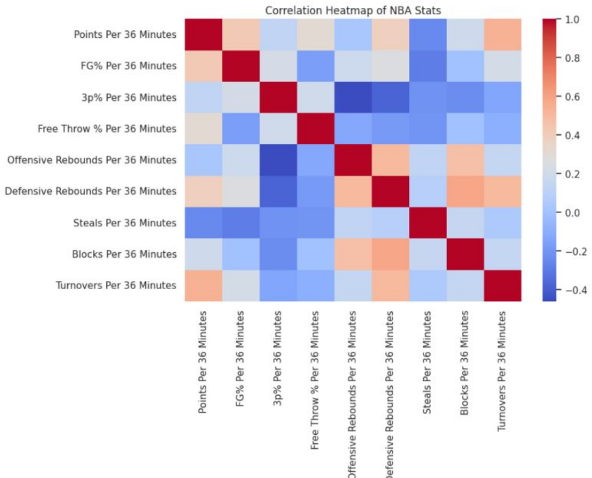
Dataset Features

- **9 numeric features used**
  - Points, assists, steals, blocks
  - FG%, 3P%, FT%
  - Offensive rebounds, defensive rebounds
  - Turnovers

  (This can be best demonstrated through the correlation heatmap for how one compliments the other.)
- **Target labels:** 11 archetypes

Archetype	Description
Shot Creator	Creates their own shots using dribbles, stepbacks, and pull-ups. High unassisted FG%, high isolation frequency.
Playmaker	Creates shots for teammates. High AST%, high potential assists, heavy pick-and-roll ball-handler usage.
Slasher	Attacks the rim using speed and athleticism. High drives per game, rim frequency, and free-throw rate (FTr).
Two Way	Strong offensive and defensive impact. Balanced scoring with strong defensive metrics (stocks, DFG%, DBPM).
Defensive Playmaker (perimeter)	Focus on defense outside of the 3pt line and specialize in stopping the other teams best guards.
Defensive Anchor	Protects the interior. High block rate, strong rim deterrence, low opponent FG% at the rim.
Defensive Playmaker	Creates turnovers and pressure on the ball. High steal rate, deflections, and on-ball impact.
Midrange Specialist	High midrange volume and efficiency. Pull-up twos, elbow jumpers, and fadeaways.
3-Point Specialist	High 3PA rate and accuracy. Catch-and-shoot threat that provides spacing gravity.
3-Level Scorer	Efficient at the rim, midrange, and from three. Versatile scoring profile across all zones.
Stretch 5	A center who stretches the floor with three-point shooting. Pops instead of rolls; high 3PA rate for a big.

Table 1: Descriptions of NBA Archetypes Used in the Project



Cleaning & Preprocessing

- **Coerce numeric columns:** Convert stat columns to numeric using pd.to_numeric(..., errors="coerce") to safely handle bad/missing entries.
- **Handle missing values:** Drop rows with missing key stat fields before building indices (e.g., dropna(subset=eff_features)) so normalization/index math is valid.
- **Standardization for comparisons:** Compute **z-scores** for each numeric feature to compare “above/below league average” by archetype in a common scale.
- **Label cleanup:** Strip whitespace on archetype strings (primary/secondary) to avoid duplicate categories from formatting inconsistencies.

Feature Engineering

- **Offensive (Scoring) Efficiency Index:** Min-max normalize Points + FG% + 3P% + FT%, then average to get one offense “score.”
- **Weighting primary vs secondary archetype:** Primary contributes **100%**, secondary contributes **50%** so hybrid players influence both profiles.
- **Defensive Efficiency Index:** Normalize defensive rebounds, blocks, steals, then average for one defense “score.”
- **Motivation:** Reduce complexity by combining shooting-related %’s into offense efficiency and defense stats into defense efficiency.

What We Predict

- **Prediction target:** player **role group label** from stats. We ultimately predict **Offensive vs Defensive** (binary classification: 0 = Defensive, 1 = Offensive).
- **Why not 3 classes?** When we tried **Offensive / Defensive / Playmaker**, both models were ~**50% test accuracy** because the Playmaker class had **very few labeled examples** and models biased toward the majority class.
- **Final framing:** after removing Playmaker and collapsing to **Offensive vs Defensive**, performance improves (KNN ~0.75 accuracy; neural net ~0.86 accuracy).
- **Why this matters:** with **only six engineered features**, the efficiency indices contain enough signal for simple models to separate offense vs defense roles.

Method 1: K-Nearest Neighbors (KNN)

- **Model idea:** classify a player by the **majority label among the k most similar players** in feature space (distance-based).
- **Why KNN here:** it's a strong, simple baseline for **small, tabular, low-dimensional** numerical data (no heavy training).
- Key parameters used:
  - n_neighbors = 3 (final choice)
  - **Distance metric:** default **Euclidean**
  - **Train/test split:** test_size=0.2, random_state=42, with **stratification**
- **Why k = 3:** we tuned **k = 1..15**, saw an "elbow" with best performance around **k = 3–4**, and chose **k = 3** to keep neighborhoods local while maintaining high accuracy.

Method 2: Shallow Neural Network

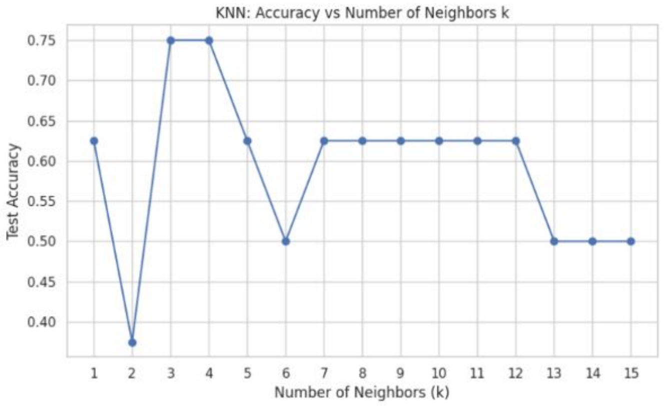
- **Model idea:** learn a **nonlinear decision boundary** between Offensive vs Defensive using a small feed-forward network.
- **Why choose it:** with engineered indices, a small network can model interactions between features and performed best in our tests.
- Architecture + training parameters:
  - Dense layers: **32 (ReLU)** → **16 (ReLU)** → **softmax output**
  - Optimizer: **Adam**; Loss: **categorical cross-entropy**
  - batch_size = 8, epochs = 50, validation_split = 0.1
  - Adam default learning rate **α ≈ 0.001**; (ReLU hidden, softmax output)
- **Hyperparameter reasoning:** validation accuracy stabilized after ~**15–20 epochs**, so training to 50 epochs ensured convergence without obvious overfitting on this small dataset.

Evaluation Setup & Metrics Reported

- We evaluated two models: **KNN (k = 3)** and a small **feed-forward “MLP”** network.
- We report **Accuracy, Macro Precision, Macro Recall (Sensitivity), Macro F1**, plus **Confusion Matrices**.
- Two regimes emerged:
  - **3-class** (Offensive / Defensive / Playmaker): ~**50%** test accuracy for both models (class imbalance + few Playmaker labels).
  - **Binary** (Offensive vs Defensive) after removing Playmaker: performance improves substantially.

KNN Results

- With Playmaker (3-class):
  - Accuracy **0.50**, Precision **0.39**, Recall **0.39**, F1 **0.38**.
- After removing Playmaker
  - Accuracy **0.75,** Precision **0.4889**, Recall **0.5556**, F1 **0.5185**
- Classification report highlights the weakness of the rare class (Playmaker has **0.00** precision/recall/F1 with support 1 in the shown output).



Neural Net Results

- With Playmaker (3-class):
  - Accuracy **0.50**, Precision **0.17**, Recall **0.33**, F1 **0.22**.
  - Notes: model **favors Offensive**, and Playmaker recall is very low due to difficulty + imbalance.
- After removing Playmaker
  - Accuracy **0.86,** Macro Precision **0.88**, Macro Recall **0.88**, Macro F1 **0.86**
- Confusion matrix (rows = true [Defensive, Offensive], cols = predicted):
  -

3	0
1	3

Side-by-Side Summary

- Table 2 (Offensive vs Defensive, before PCA):
  - **KNN (k=3):** Accuracy **≈ 0.75**, Macro Precision **≈ 0.49**, Macro Recall **≈ 0.56**, Macro F1 **≈ 0.52**
  - **Neural net:** Accuracy **≈ 0.86**, Macro Precision **≈ 0.88**, Macro Recall **≈ 0.88**, Macro F1 **≈ 0.86**
- **Takeaway:** once Playmaker is removed, the engineered efficiency features provide enough signal for both models, with the neural net strongest overall.

PCA Ablation

- After applying PCA (2 components), **both models lose performance**:
  - KNN drops to about **0.57** accuracy
  - Neural net drops to about **0.43** accuracy
- Reason given: PCA maximizes variance, which **doesn’t necessarily align** with the best separation direction for Offensive vs Defensive, and with only **six engineered features**, PCA mostly discards useful information.

Conclusion

- Built a pipeline to **classify NBA players into archetype-based role groups** using **per–36-minute stats** (including 2025 rookies).
- Engineered compact features like **Scoring Efficiency Index** and **Defensive Efficiency Index** to reduce feature complexity while preserving signal.
- Trained and evaluated **KNN** and a small **neural network (MLP)** to predict **Offensive vs Defensive** roles, and compared results across accuracy/precision/recall/F1 + confusion matrices.

Key Results

- 3-class prediction (Offensive/Defensive/Playmaker) struggled (~**50% accuracy**) largely due to **class imbalance** and too few Playmaker examples.
- After removing Playmaker and using **binary classification**, performance improved:
  - **KNN: ~0.75 accuracy**
  - **Neural net (MLP): ~0.86 accuracy**, with only **1 error** in the shown confusion matrix.
- PCA (2 components) **reduced** accuracy for both models, suggesting PCA compression removed useful separation information for this task.

Limitations & Next Steps

- Limitations
  - **Class imbalance** (especially Playmaker) caused biased predictions and weak minority-class metrics.
  - Using a small, engineered feature set (6ish features after indices) may miss nuanced role signals (spacing, usage, defensive versatility).
- Next Steps
  - **Fix class imbalance:** get more Playmaker labels or use **class weights / oversampling**.
  - **Broaden + validate:** add more features and test across **multiple seasons**.
  - **Try stronger tabular models:** e.g., logistic regression / random forest / boosting, then compare against KNN