**Analyzing Success Factors for NBA Game ‘Personality’ Clusters**

Basketball

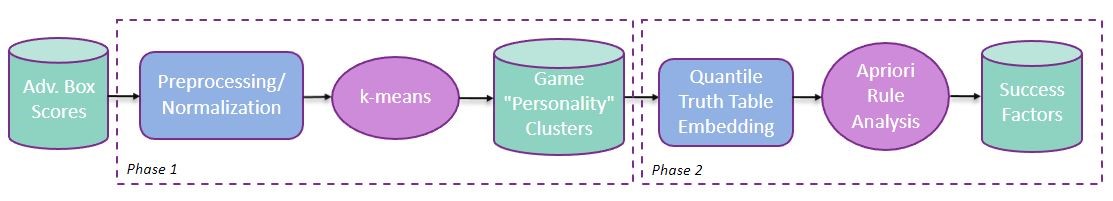
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**1. Introduction**

“This is gonna be a slugfest.” - Nick Nurse, ahead of the Raptors 2022 Eastern Conference Playoff’s matchup against the 76’ers [1]. This assertion touches on a conventional wisdom: NBA games have personalities of their own. In this paper, we use k-mean clustering and apriori rule analysis to examine advanced box scores from NBA games and identify these personality types and the key success factors to winning each type.

**2. Methods**

This research is conducted using a pipeline with two phases: k-means clustering, and apriori association mining, as illustrated in Figure 1.



Previous clustering research in the NBA has focused on play-action [2], player archetypes [3], and historical eras [4]. This is, to the best of our knowledge, the first examination of game personality clustering.

**Clustering**

We implement a k-means clustering algorithm to group games using in-game statistics collected from advanced box-scores from the 2014-2018 NBA regular seasons. Normalization is performed on numeric features to avoid scale bias. To avoid redundancy, only entries for the home team are considered. Elbow plots and silhouette scores suggest an ideal cluster set of 4, and labels are assigned to the box-score entries.

**Association Mining**

For our analysis, we broke each statistical category into quantiles. We then created a truth-table where the rows represent the individual games in the box-score, and the columns contain Boolean values indicating whether the quantile threshold for that statistical category was overcome. The embedded data was passed per cluster to the apriori algorithm to determine which success factors most impacted winning.

**3. Results**

**Clustering**

The four resulting game clusters were then condensed into feature averages and compared to assess the ‘personality’ of each. We then associated the trends in each to one of four colloquial labels from the NBA vernacular: track meet, shooting clinic, blowout, slug fest. Notably, three of the four clusters include a positive scoring margin, lending credence to the theory of home court advantage. Table 1 contains feature summaries for home and away teams of each cluster.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Cluster Label | Score | Field Goals | 3 Point % | Assists | Boards | Fouls | Win % |
| ‘Track Meet’ | 113-112 | 40.3-39.8 | .364-.359 | 23.4-22.5 | 44.6-43.7 | 23.6-24.5 | .561-.439 |
| ‘Shooting Clinic’ | 102-111 | 38.2-42.3 | .342-.428 | 22.1-26.0 | 40.7-42.5 | 17.8-19.5 | .228-.772 |
| ‘Blowout’ | 114-99 | 43.7-37.3 | .433-.326 | 27.9-21.3 | 44.6-40.4 | 18.7-17.9 | .932-.068 |
| ‘Slug Fest’ | 95-93 | 35.4-34.8 | .314-.304 | 20.2-19.1 | 45.8-44.6 | 19.3-20.2 | .596-.404 |

**Association Mining**

The rules targeting outcome were extracted and sorted by lift (how impactful the rule was within the personality cluster). Our approach is unsupervised, thus unaware that the team with the highest score wins therefore, we manually filter out noisy rules like: Knicks outscored Lakers. These rules provide game insights that we believe, if utilized by a domain expert, would provide a strategic advantage. Table 2 contains a sample of top rules for each cluster.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Cluster | Rule | Confidence | Lift | Cluster | Rule | Confidence | Lift |
| 1 | Opp.FieldGoalsAttempts > 93, OppFieldGoals > 43, TotalFouls > 27 | .928 | 1.19 | 3 | Blocks > 7, Opp.FieldGoalsAttemps > 91, TotalFouls > 22 | .936 | 1.21 |
| 1 | FreeThrows > 28, X3PointShots > 32,  TotalFouls > 27 | .877 | 1.12 | 3 | Turnovers > 16, Opp.3PointShots > 11, Opp.FieldGoalsAttempts > 91 | .908 | 1.17 |
| 2 | Opp.FreeThrows > 18, Opp.3PointShots > 15, Opp.FieldGoalsAttempts > 90 | .898 | 1.16 | 4 | Steals > 10,  TotalFouls > 22 | .925 | 1.18 |
| 2 | Turnovers > 16,  TotalFouls > 21 | .914 | 1.18 | 4 | Turnovers > 17, Opp.FieldGoalsAttempts > 89 | .909 | 1.16 |

**4. Conclusion**

This paper presents a novel approach to examining key success factors within different personality trends of NBA games. We believe this technique has cross-domain appeal in other sports, markets, and industries.

**References**

[1] A. Rose, "Raptors Need to Avoid 'Slugfest' by Dictating Tempo to 76ers", *Sports Illustrated Toronto Raptors News, Analysis and More*, 2022. [Online]. Available: https://www.si.com/nba/raptors/news/toronto-raptors-slugfest-transition-offense-philadelphia-76ers-playoffs.

[2] D. Stephanos, G. Husari, B. Bennett, M. Harrisson and E. Stephanos, “Using Hex Maps to Classify & Cluster Dribble Hand-Off Variants in the NBA,” in *Proceedings of the MIT Sloan Sports Analytics Conference*, 2022.

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