



“How to Get an Open Shot”: Analyzing Team Movement in Basketball using Tracking Data

Patrick Lucey, Alina Bialkowski, Peter Carr, Yisong Yue and Iain Matthews
Disney Research, Pittsburgh, PA, USA, 15213

Email: [patrick.lucey](mailto:patrick.lucey@disneyresearch.com), [alina.bialkowski](mailto:alina.bialkowski@disneyresearch.com), [peter.carr](mailto:peter.carr@disneyresearch.com), [yisong.yue](mailto:yisong.yue@disneyresearch.com), [ianm](mailto:ianm@disneyresearch.com)@disneyresearch.com

Abstract

In this paper, we use ball and player tracking data from STATS SportsVU from the 2012-2013 NBA season to analyze offensive and defensive formations of teams. We move beyond current analysis that uses only play-by-play event-driven statistics (i.e., rebounds, shots) and look at the spatiotemporal changes in a team’s formation. A major concern, which also gives a clue to unlocking this problem, is that of permutations caused by the constant movement and interchanging of positions by players. In this paper, we use a method that represents a team via “role” which is immune to the problem of permutations. We demonstrate the utility of our approach by analyzing all the plays that resulted in a 3-point shot attempt in the 2012-2013 NBA season. We analyzed close to 20,000 shots and found that when a player is “open” the shooting percentage is around 40%, compared to a “pressured” shot which is close to 32%. There is nothing groundbreaking behind this finding (i.e., putting more defensive pressure on the shooter reduces shooting percentages) *but finding how teams get shooters open is*. Using our method, we show that the amount of defensive role-swaps are predictive of getting an open-shot and this measure can be used to measure the defensive effectiveness of a team. Additionally, our role representation allows for large-scale retrieval of plays by using the tracking data as the input query rather than a text label - this “video Google” approach allows for quick and accurate play retrieval.

1 Introduction

A central theme in Dean Oliver’s book *Basketball on Paper* [1], is to “understand the team first and its players second...because it is the team that wins and loses, not individuals...”. Traditionally, team statistics such as offensive and defensive efficiency ratings, have been estimated from event-driven play-by-play data (e.g., shooting percentages, rebounds, turnovers etc.). While these team ratings have been used to good effect, the sparse nature of the play-by-play data means that these statistics only tell a partial story of what is occurring in a game (i.e., it can tell us *what* is happening, but not *where* and *how*). However, with the recent full deployment of optical tracking systems in the NBA using STATS SportsVU [2], a better and deeper story of how teams operate can be obtained because the ball and all players are tracked at 25 frames-per-second.

Many recent works have used the STATS SportsVU data for improved analysis. Maheswaran et al., [3] used the data to investigate the optimal placement of players to obtain a rebound. Goldsberry [4] used the data to rank the best shooters in the NBA using “CourtVision”, and more recently used it to rank individual defenders [5]. Maymin [6] used the data to explore burst locations on the court where players tend to accelerate, while Wiens et al., [7] looked at which situations teams should go for an offensive rebound or not. Although interesting, none of these works have focused on using the data to describe *how* teams operate as a unit. This is because tracking data is highly complex with players randomly moving resulting in an infinite number of possible permutations, making comparisons impossible. As Phil Jackson notes in his recent book *Eleven Rings* [14] “basketball is a dynamic game of chess in which all pieces are in motion...”, but it is through this dynamic motion that space and scoring chances are created. In this paper, we present a method which can normalize against the vast number of possible permutations by enforcing a role-representation. To show the utility of our approach, we analyze all the 3-second plays leading up to every three-point attempt in the 2012-2013 NBA season and show that how a team’s defensive formation moves is predictive of whether or not they give up an open shot or not.

Based on the STATS SportsVU tracking data for the 2012-13 NBA season, we define an “open” shot as one in which the defender closest to the shooter is at least 6 feet away at the time of release (Section 2). We then build on our recent work in team analysis [8-11], and automatically infer the position or “role” (e.g., point-guard, center, power-forward etc.) that each player is fulfilling at every time instant (Section 3). Using both the tracking data and role assignments, we identify indicative factors of a shooter getting open for a three-point shot (Section 4). Finally, we show role information is critical for efficient, accurate and intuitive retrieval of similar plays (Section 5). We applied our techniques to the STATS SportsVU tracking data from the recent 2012-13 NBA season, and analyzed close to 20,000 spatiotemporal sequences of three-point attempts.

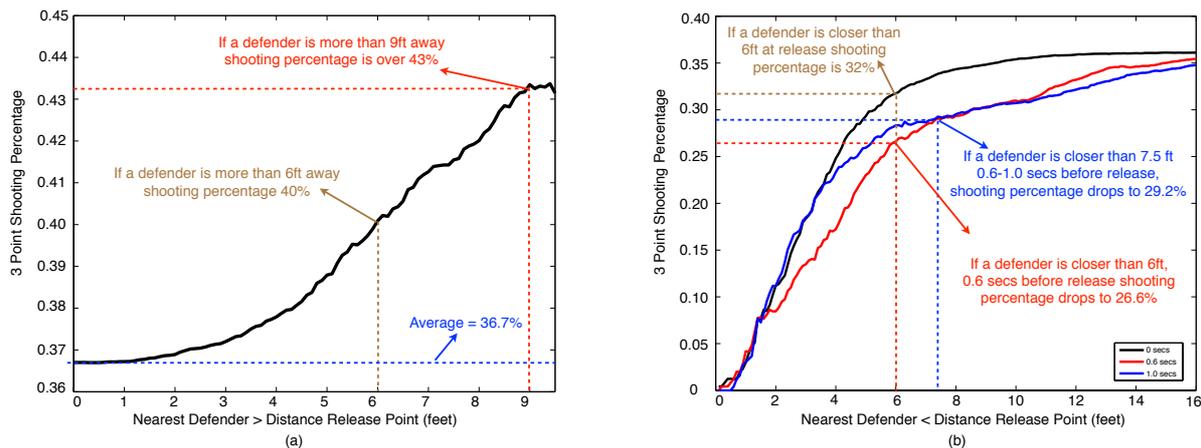


Figure 1. (a) As the distance of the nearest defender to the shooter increases, so does the 3-point shooting percentage. When the defender is more than 6 feet away, the shooting percentage is 40%, and increases to over 43% when the defender is more than 9 feet away at the release point. (b) Conversely, when the defender is closer to the defender the shooting percentage drops. When a defender is within 6 feet, the shooting percentage is approximately 32.5%. However, when a defender is within 6 feet 0.6 seconds before the shot it drops to 26.6%.

2 “Open” vs “Pressured” Shots

A recent study by Weil [13] showed that there was a strong relationship between field-goal shooting percentage and defender proximity (i.e., further a defender was away, the higher the shooting percentage was), where he used over 60 games of STATS SportsVU tracking data. In our work, we used an order of magnitude more games (600) across 13 NBA teams which had the system installed in their arenas and analyzed the 3-second segment of play which occurred before the release-point of each attempt (we chose 3 seconds because in [16] it is noted that this is the optimal time for a player to get open). Overall, we analyzed 19,386 three-point attempts from 13 different teams and the shooting average for the shots analyzed was 36.7%.

In Figure 1(a), we can see how the shooting average varies as the distance to the nearest defender increases - specifically we can see that when a defender is 6 or more feet away, the shooting percentage hovers above 40% while it peaks to over 43% when a defender is more than 9 feet away at the release point of the shot. Conversely in Figure 1(b), we see that when a defender is within 6 feet of the shooter at the time of release, the shooting percentage drops down to 32%. It drops even further when we look back at where the defender before the release point. For example, it drops to 29.2% when a defender is within 7.5 feet 0.6 to 1 second prior to the release point, and further drops to 26.6% when a defender is within 6 feet 0.6 seconds prior to the shot release. Even though these findings are interesting, there is nothing really compelling about them as it reinforces the conventional wisdom that putting pressure on the shooter will reduce their shooting percentage. However, *finding the ways teams get shooters open in interesting*. Before doing this, we first have to define what an “open” and “pressured” shot is. Looking at the black curve of Figure 1(b), there seems to be a knee-point occurring at 6 feet which suggests a good threshold. From this, we define an “open” shot as having a defender at least 6 feet away from the shooter and a “pressured” shot as having a defender at least 6 feet from the shooter at the time of release. Although the positional data does not give us the context necessary to be definitive (i.e., we don’t know if the defender has his arm up or whether he is jumping?), but based on the volume of data we have analyzed it suggests that this is a reasonable approximation.

Table 1 shows the offensive and defensive three-point shooting percentages of each team. Offensively (Table 1(a)), the Golden State Warriors have the best 3 point shooting percentage, averaging 42.13% while the Minnesota Timberwolves are the worst shooting team with 30.08%. The Warriors also shoot very well under pressure with only a difference of 2.90% between their “open” and “pressured” attempts. Apart from the Philadelphia 76’ers, the range in difference between “open” and “pressured” shots varies considerably from 3-11% (Cleveland shoot over 40% when open but 30% when they are pressured). A similar trend is found when analyzing the defense of each team (Table 1(b)) where the shooting percentage varies from 2% to under 15% (teams playing the Timberwolves shoot over 40% when open but around 27.5% when under pressure - with more than half the shots being open they would be well advised to put more pressure on the opposition shooters). In terms of the number of open shots teams get, San Antonio get more than 60% of their 3-point attempts open while Toronto get less than 40%. Defensively, the Orlando Magic give up more than 62% open shots while the Warriors give up about 51%.

Home Team Name	Offense						
	Rank	Avg Shot%	# Att	% of Shots Open	Shot % when Open	Shot % when Press	Shot % Diff
Golden State	1	42.13	743	51.95	43.52	40.62	2.90
San Antonio	2	39.81	957	60.29	44.02	33.42	10.60
Dallas	3	39.54	741	55.06	41.67	36.94	4.73
Washington	4	39.09	637	56.99	43.80	32.85	10.95
New York	5	38.23	1177	58.79	41.76	33.20	8.56
Philadelphia	6	37.17	374	59.63	37.67	36.42	1.25
Houston	7	36.79	1128	52.39	38.58	34.82	3.76
Orlando	8	35.97	670	51.94	39.37	32.30	7.07
Toronto	9	35.66	760	39.47	40.00	32.83	7.17
Milwaukee	10	35.49	744	52.15	39.95	30.62	9.33
Cleveland	11	34.53	614	42.67	40.46	30.11	10.35
Phoenix	12	34.25	660	51.82	37.43	30.82	6.61
Minnesota	13	30.08	655	59.54	33.59	24.91	8.68

(a)

Home Team Name	Defense						
	Rank	Avg Shot%	# Att	% of Shots Open	Shot % when Open	Shot % when Press	Shot % Diff
New York	1	34.19	936	58.65	38.80	27.65	11.15
Washington	2	34.22	827	58.52	35.95	31.78	4.17
Philadelphia	3	34.45	415	54.70	37.00	31.38	5.62
Golden State	4	35.34	900	51.33	36.80	33.79	3.01
Minnesota	5	35.20	696	52.44	42.19	27.49	14.70
Milwaukee	6	35.40	695	60.14	38.52	30.69	7.83
Toronto	7	35.63	668	56.29	40.16	29.79	10.37
San Antonio	8	36.09	823	55.16	38.99	32.52	6.47
Dallas	9	37.56	788	53.55	40.76	33.88	6.88
Cleveland	10	37.86	655	56.34	38.75	36.71	2.04
Phoenix	11	38.13	640	51.72	41.39	34.63	6.76
Orlando	12	38.92	745	62.15	41.90	34.04	7.86
Houston	13	39.07	883	56.17	43.55	33.33	10.22

(b)

Table 1. The shooting percentages of each team (a) offensively and (b) defensively. In the last column the difference in shooting percentages between open and pressured shots is given.

3 Representing Team Formation using Player Role

Before we look at the factors that can help describe how a team gets an open shot, we first need a representation of a team's formation. A common language used in team sports is one of role or position within a formation. In basketball, a team is made up of 5 positions: point-guard (PG), shooting-guard (SG), small-forward (SF), power-forward (PF) and center (C). Even though each of these players have a specific role, due to the dynamic nature of the game, these players will dynamically interchange or swap roles which is the major obstacle hindering work in this area as the number of permutations is enormous. For example in Figure 2, we have two snapshots of identical plays where Harden drives to the basket and passes it to the right corner. The only difference is that Douglas and Anderson swap positions, where Douglas gets the ball in (a) and Anderson gets it in (b).

For a computer to understand these plays, it needs a common language or "feature representation" which allows comparisons to be made. If we use static role ordering consisting of the ball as feature 1, the PG (Morris) as feature 2, SG (Harden) as feature 3, C (Smith) as feature 4, SF (Douglas) as feature 5 and PF as feature 6 (Anderson), we can see when Douglas and Anderson switches position the computer will see this as totally different as the important features (highlighted in blue) do not correspond. This highlights the problem associated with representing team plays as an enormous number of permutations exist. In the example shown, there are 120 (or 5!). If we include the defending team there are 14,400 (or 120^2) possible permutations just for this play and this number explodes when substitutions and different teams are included making play comparisons intractable. However, if we choose a representation which is "dynamic" and not "static", we can update the representation so they correspond to dynamically changing role and not the pre-defined role. This ensures that fair comparisons can be made (i.e., when Douglas and Anderson swap positions, our feature representation also updates). To dynamically update the feature representation, we devised a method which leverages our recent work in player tracking [8] which assigns the player role of each player in every frame. First of all, we get the player locations with a team. We then calculate the cost matrix of the current player positions to our templates (defined by an expert human) and then we use the Hungarian algorithm [12] to make the role assignment for that frame (see [8] for full details). Even though different formations exist, we chose one global role ordering scheme so that we could use the entire set of data. This is shown in Figure 2(c).

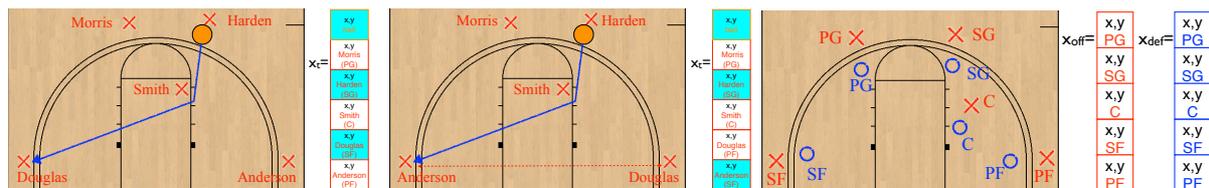


Figure 2. (a) Harden drives to the basket and passes to Douglas in the corner. (b) Harden does the same thing but passes to Anderson who has changed positions with Douglas - a computer will see these plays differently as it does not know they have changed positions. (c) We use the role-labeling convention so the relative positions are maintained.



4 Factors That Lead to an Open Shot

To determine how teams get an open three-point shot, we extracted a host of team factors from the player and ball tracking data. The factors we analyzed were:

- **Team Area Difference (offensive and defensive):** Team spacing and how it varies over time can give an indication of key dynamics that lead to an open shot. To calculate the area of a team, we calculated the area of the polygon that consisted of the players on the court. We then calculated the change of the area over the 3 seconds.
- **Average Team Distance (offensive and defensive):** We calculated the distance that each player moved over the 3 second window preceding the shot and then calculated the mean of those distances.
- **Max Distance (offensive and defensive):** A player driving to the basket or cutting baseline could be a key factor is getting an open shot - to see if this was the case we looked at the maximum distance moved by a player in a team over the 3 second window.
- **Average Team Velocity (offensive and defensive):** We calculated the distance that each player moved over the 3 second window preceding the shot and then calculated the mean of those distances.
- **Max Velocity (offensive and defensive):** A player driving to the basket or cutting baseline could be a key factor is getting an open shot - to see if this was the case we looked at the maximum distance moved by a player in a team over the 3 second window.
- **Average Team Acceleration (offensive and defensive):** We calculated the distance that each player moved over the 3 second window preceding the shot and then calculated the mean of those distances.
- **Max Acceleration (offensive and defensive):** A player driving to the basket or cutting baseline could be a key factor is getting an open shot - to see if this was the case we looked at the maximum distance moved by a player in a team over the 3 second window.
- **Dribbles (offensive):** Determined from the optical tracking data where the player closest to the ball (and is within 3.5 feet) has been closest for 5 or more frames and the ball drops lower than 1.5 feet and is within the boundaries of the court.
- **Passes (offensive):** Determined from the optical tracking data where a player registers a touch, defensive or offensive rebound; or the ball travels away from passer; or a receiver, who is on the same team as the passer, registers a touch and there were no events registered in between the passer's touch and the receiver's touch.
- **Possessions (offensive):** Determined from the optical tracking data where a player touches the ball during the offensive play for more than 5 consecutive frames.
- **Role-Swaps (offensive and defensive):** Using our dynamic method of determining the role of a player based on the template shown in Figure 2(c), we can detect at the frame-level when players switch roles within the team formation. The role-swap measure is a count of how many swaps there are in the 3 seconds before the release point of a shot.

To see which factors could discriminate between an open and pressured shot we conducted a series of experiments where we tested each of these shot factors. The experiments consisted of a series of an unpaired t-test's comparing the open versus pressured spatiotemporal examples in the dataset. The mean values for each of the measures for both the offense and defense for each of the factors are given in Table 2. In the last row of the table, we have shown the p-values which show factor significance (i.e., the differences between the open and pressured shots for each factor). The significant shot factors are highlighted in the gray (those with p-values < 0.01). At the event-level, it can be seen that to get an open shot teams should dribble less and share the ball more, with more dribbling leading to pressured shots and more possessions leading to open shots. In terms of measuring team factors (i.e., area difference, distance, velocity, acceleration and role-swaps), only the defensive team factors were significant.

FACTOR	Area Diff (ft ²)		Average Distance (ft)		Max Distance (ft)		Average Velocity (ft/frame)		Max Velocity (feet/frame)		Average Acceleration (ft/frame ²)		Max Acceleration (ft/frame ²)		Dribble	Pass	Poss	Role-Swaps	
	Off	Def	Off	Def	Off	Def	Off	Def	Off	Def	Off	Def	Off	Def	Off	Off	Off	Off	Def
Open	95.38	48.99	83.76	83.95	27.86	25.30	0.075	0.075	0.205	0.206	0.004	0.0057	0.0485	0.0731	1.32	0.74	1.26	3.19	4.67
Pressure	81.18	40.36	80.55	73.48	26.60	22.74	0.072	0.065	0.215	0.195	0.004	0.0050	0.0656	0.0752	1.58	0.58	0.96	2.96	3.71
p-value (difference)	0.231	0.118	0.150	9.70E-05	0.032	4.08E-06	0.150	9.74E-07	0.603	0.386	0.783	2.11E-05	0.1923	0.2797	0.0024	0.095	1.22E-05	0.1929	8.35E-06

Table 2. Analysis of the various factors that occur during the 3 second window before a three-point shot. The columns in gray highlight the factors which are significant.

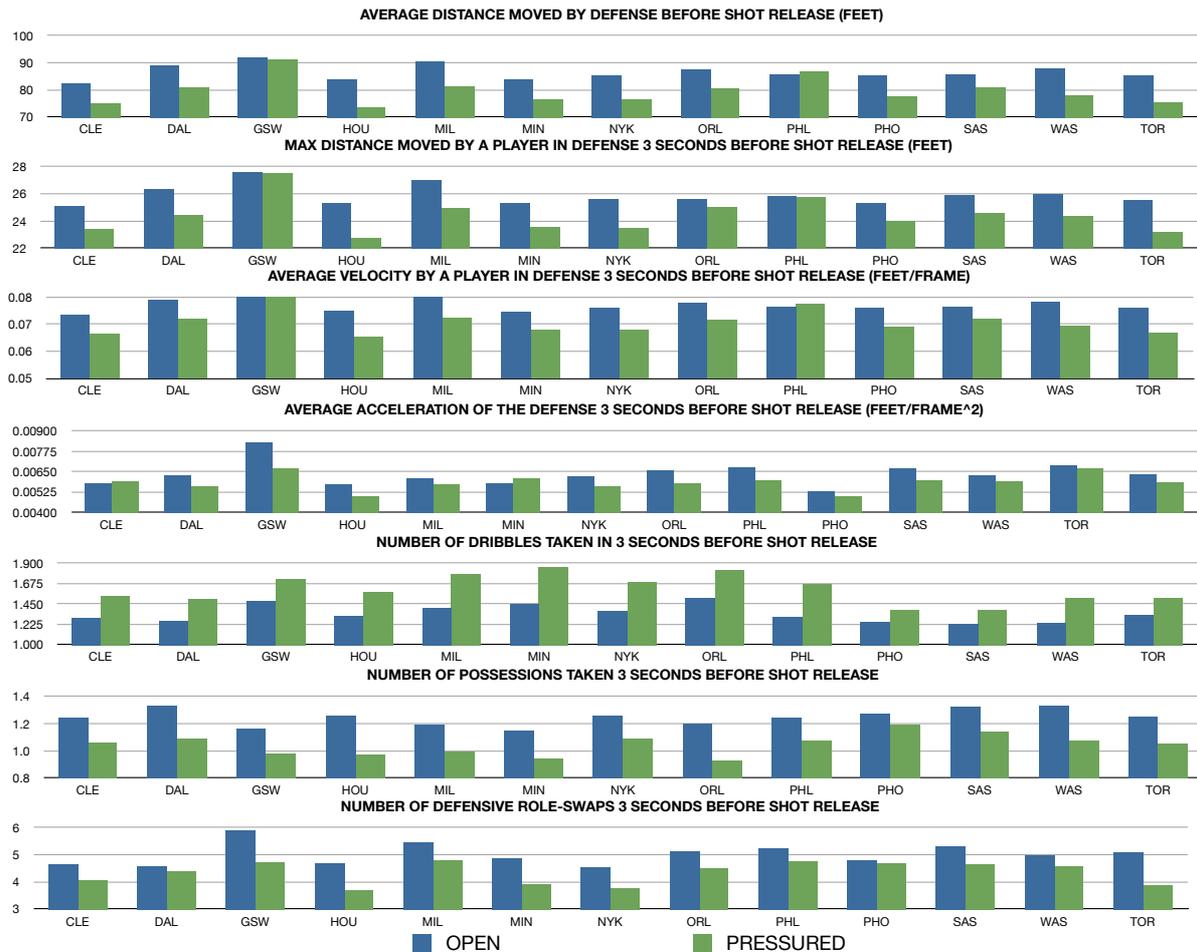


Figure 3. Team-by-team comparison of the various significant factors which lead to an open shot: (a) average distance moved defensively, (b) maximum distance moved by a defensive player, (c) average acceleration of the defensive team, (d) number of dribbles taken by the offensive team, (e) number of possessions taken by the offensive team, and (f) the number of defensive role-swaps.

Specifically, the less distance the defensive team moved in the 3 seconds prior to the shot release the more likely they were to put pressure on the shot. Derivations on the distance factor such as velocity and acceleration also back this up. To understand why, we need to look at the number of defensive role-swaps (which was also very significant). These findings are quite intuitive when we look at all these factors together, as when defensive players swap roles it means that they have to travel more distance and at a quicker speed to follow their attacking player (it also signals that they are playing man-to-man coverage). When defensive players have to move out of their defensive formation, it also means that more space is created for the offensive team as the defensive structure becomes unstable. On the flip-side, if the defensive player “passes” on their assignment and maintains their place in the formation not as much space is available to the offensive team. This is a major reason why none of the offensive team factors were significant, as they can move as much as they like but if it does not cause any disruption to the defense then open shots will not be available. Even though not directly measured, the number of role-swaps, distance travelled as well as dribbles and possessions essentially encodes the effectiveness of other high-level factors such as “pick-and-rolls” and “double or triple teaming” (pick-and-roll and double or triple teaming events were not contained in the dataset). In Figure 3, we show the team-by-team analysis for each of the significant factors when the team is attacking (the defensive charts are given in Appendix A). While it is evident that there is a global trend (i.e. there is a clear discrepancy between open and pressured variable for each factor), the characteristic of each team also emerges from these plots, which can again suggest what type of defensive system they are playing. For instance, the Golden State Warriors tend to make teams move more which is shown by the average and maximum distance factors as well as the number of role-swaps, while Houston tend not to be as mobile.

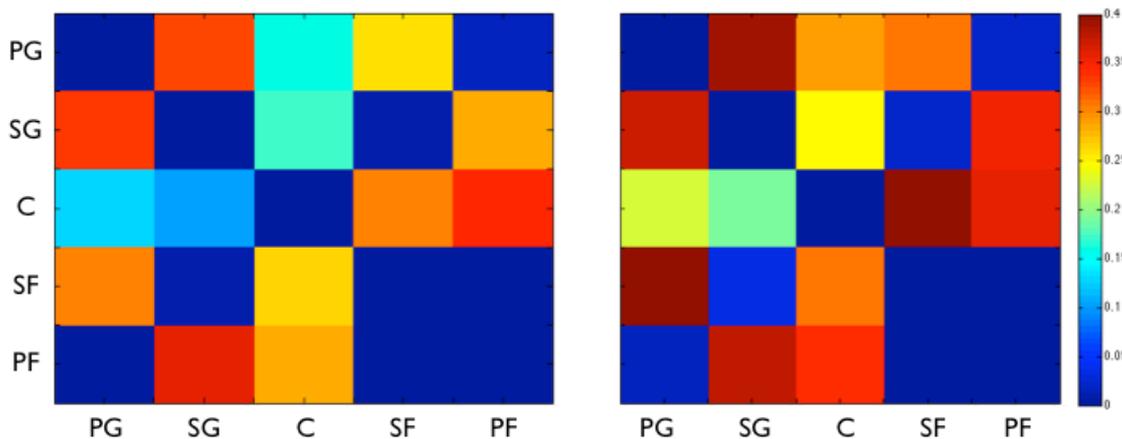


Figure 4. Transition matrices showing the proportion of defensive role-swaps that occur between different roles on the court for (left) pressured, and (b) open shots. On the vertical are the starting roles the players are in and on the horizontal are the role that they transitioned to.

The role-swap measure also gives an insight into the relative defensive motion patterns that cause a team to get an open shot. An example of this is shown in the transition matrices given in Figure 4, which shows which role-swaps cause the most confusion to the team formation to cause an (a) pressured shot and (b) open shot. The first thing to note is that the most common role-swaps occur between players who are closest in proximity to each other (i.e., PG-SG, PG-SF, SG-PF and the C with all positions (it is in the center of all)). The other obvious thing is the increased in defensive role-swaps that occur when a team gets an open shot compared to a pressured shot which was described before. The last thing to note is that there are significantly more swaps involving the center (C), which suggests that the offensive team try to draw the perimeter men closer to the basket while drawing the bigger men out to the perimeter. As the big men (normally located in the middle) or generally less mobile than other players this specific tactic makes a lot of sense.

5 Retrieving Plays using Tracking Data

Although player and ball tracking data is fast becoming the norm in professional sports, retrieving and analyzing team behaviors is still a heavily humanized endeavor. For example, in basketball, retrieval and analysis normally occur by having a coach or analyst input a query such as “3-point-shots” or “pick-and-roll”, followed by more specific items such as “defensive match-up” and even an approximate spatial location if the annotation is sophisticated enough to support it. Despite the existence of analysis solutions like Synergy Sports [17], where video clips of plays are associated with event-driven stats, the granularity of analysis is limited by the use of manually defined tags i.e., text labels which describe the event/play of interest. This limitation is particularly evident in continuous sports like basketball where a prohibitive number of tags would be required to describe the location, direction and speed of all players on the court coinciding with a particular event. However, given that all games are being digitized, instead of using a text tag a more intuitive and accurate method would be to use a visual tag, where the user would input the start and end time of the video of the play of interest. This idea is similar to that of “Video Google” which was first proposed back in 2003 [15] and the system would then return all plays which are similar to that play.

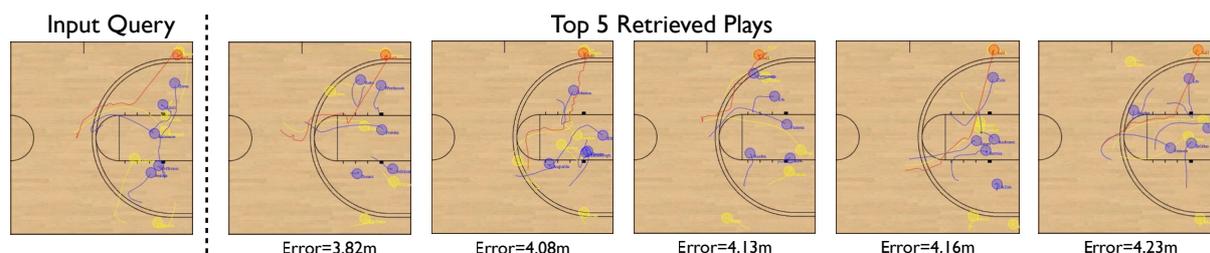


Figure 5. Players and Ball: Given the input query with the ball and players, we show the top five retrieved plays. The error measure was a weighted L-infinity norm, with the players and ball following the same paths.



Our specific goal was: *given an input play query, can we find all similar plays in the database?* This raises the question: *what makes a play similar?* This is a very subjective task as it depends almost entirely on the user. For example, a coach could find a 3-second play of interest and is interested in finding all plays in the database that have the same: a) ball movement, b) movement of the ball and the ball-handler, c) movement of the attacking team, or d) movement of all offensive and defensive players as well as the ball. These are just a few examples, but there are numerous queries which could extend to player identity, defensive match-up etc. Regardless of the query, when dealing with multiple players the bottleneck to solve is that of permutations (see Section 3) and using our role-representation we can circumvent this issue. An example is shown in Figure 5, where we have an input query on the left and we are interested in retrieving all plays which had the same motion of all offensive players and the ball. When using the dynamic role representation, we can see that we retrieve plays which look similar to the input query (the dominant mode is the player driving to the basket and then passing the ball to the corner for the shot (red is the ball)).

6 Summary

In this paper, we moved beyond current analysis that only use play-by-play statistics and looked at the spatiotemporal changes in a team's formation that lead to an open three-point attempt (i.e., a defender being at least 6 feet away from the shooter at the time of shot release). A major bottleneck with dealing with spatiotemporal tracking data is the sheer number of possible permutations that exist due to the constant motion and swapping of players. To counter this issue, we presented a dynamic method of representing team behaviors that assigns each player a role (e.g. point-guard, shooting-guard, center, small-forward or power-forward) at every frame so that each player has a role-label at every frame to maintain the structure of formation of the team. We analyzed close to 20,000 three-second spatiotemporal sequences of team behaviors before a three-point attempt was made from the 2012-2013 NBA season. From the data which was provided by STATS SportsVU, we compared many different offensive and defensive team factors, such as team area, distance ran, velocity, acceleration, dribbles, possessions and passes - as well as our new role-swaps measure. We showed that only the defensive team factors such as team distance, velocity, acceleration and role-swaps were predictive of the offensive team getting an open shot (in addition to dribbles and possessions), and showed that the type of role-swaps that occur are also informative of how a team gets an open shot (e.g. point-guard switching with the small-forward). Additionally, we showed that our role-representation is conducive to large-scale play retrieval which can greatly improve the speed and accuracy through the use of a visual query. While these findings may be quite intuitive for a coach and player, this work shows the tremendous value that spatiotemporal tracking data has as it enables deeper and better understanding of team behaviors to occur at a quantifiable level.

Acknowledgements

We would like to thank Brian Kopp and the STATS team for their help and support for this work.

References

- [1] D. Oliver, "Basketball on Paper: Rules and Tools for Performance Analysis", Potomac Books, 2004.
- [2] STATS SportsVU. <http://www.sportvu.com>
- [3] R. Maheswaran, Y. Chang, A. Henehan and S. Danesis, "Deconstruction the Rebound with Optical Tracking Data", in MIT Sloan Sports Analytics Conference, 2012.
- [4] K. Goldsberry, "CourtVision: New Visual and Spatial Analytics for the NBA", in MIT Sloan Sports Analytics Conference, 2012.
- [5] K. Goldsberry and E. Weiss, "The Dwight Effect: A New Ensemble of Interior Defense Analytics for the NBA", in MIT Sloan Sports Analytics Conference, 2013.
- [6] P. Maymin, "Acceleration in the NBA: Towards an Algorithmic Taxonomy of Basketball Plays", in MIT Sloan Sports Analytics Conference, 2013.
- [7] J. Wiens, G. Balakrishnan, J. Brooks and J. Guttag, "To Crash or Not To Crash: A Quantitative Look at the Relationship Between Offensive Rebounding and Transition Defense in the NBA", in MIT Sloan Sports Analytics Conference, 2013.
- [8] P. Lucey, A. Bialkowski, P. Carr, S. Morgan, I. Matthews and Y. Sheikh, "Representing and Discovering Adversarial Team Behaviors using Player Roles", in CVPR, 2013.
- [9] X. Wei, L. Sha, P. Lucey, S. Morgan and S. Sridharan, "[Large-Scale Analysis of Formations in Soccer](#)", in DICTA, 2013.
- [10] P. Lucey, A. Bialkowski, P. Carr, E. Foote and I. Matthews, "Characterizing Multi-Agent Team Behavior from Partial Team Tracings: Evidence from the English Premier League", in AAAI, 2012.

- [11] P. Lucey, D. Oliver, P. Carr, J. Roth and I. Matthews, "Assessing Strategy using Spatiotemporal Data", in KDD, 2013.
- [12] H. W. Kuhn, "The Hungarian Method for the Assignment Problem", in Naval Research Logistics Quarterly, vol. 2, no 1-2, pp. 83-97, 1955.
- [13] S. Weil, "The Importance of Being Open: What Optical Tracking Data Can Say About NBA Field Goal Shooting", in MIT Sloan Sports Analytics Conference, 2011.
- [14] P. Jackson and H. Delehanty, "Eleven Rings", The Penguin Press, 2013.
- [15] J. Sivic and A. Zisserman, "Video Google: A Text Retrieval Approach to Object Matching in Videos", in ICCV, 2003.
- [16] G. Gandolfi and National Basketball Coaches Association, "NBA Coaches Playbook: Techniques, Tactics and Teaching Points", Human Kinetics, 2009.
- [17] Synergy Sports, <http://corp.synergysportstech.com>

Appendix A Defensive Analysis of Factors Leading to Open Shots

In Figure 3, we showed how each team attacked against defense (i.e. all teams visiting the team of interest). Here we compare the significant factors for each team when they are defending (i.e. how they defend when the opposition are attacking). The plots are shown in Figure 6.

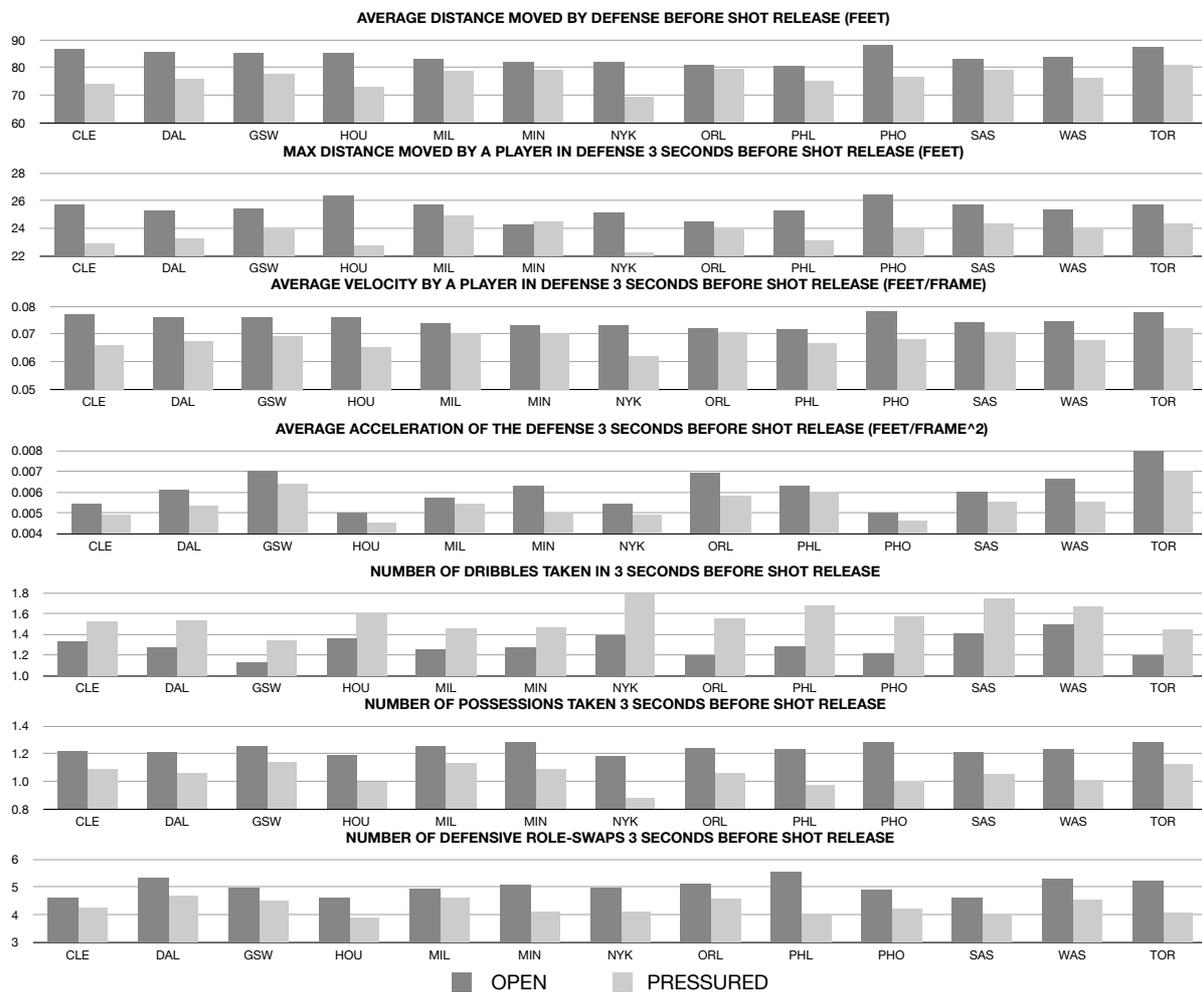


Figure 6. Team-by-team comparison of the various significant factors which lead to an open shot: (a) average distance moved defensively, (b) maximum distance moved by a defensive player, (c) average acceleration of the defensive team, (d) number of dribbles taken by the offensive team, (e) number of possessions taken by the offensive team, and (f) the number of defensive role-swaps.