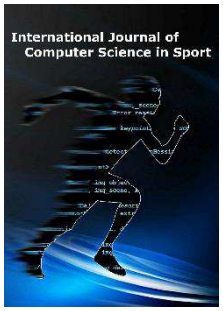
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Modeling the extra pass in basketball – an assessment of one of the most crucial skills for creating great ball movement

Bence Supola[1], *Thomas Hoch*[2] *& Arnold Baca*[3]

[1]*Department of Sport Science, University of Vienna, Vienna, Austria*

[2]*Software Competence Center Hagenberg GmbH, Hagenberg, Austria*

[3]*Centre for Sport Science and University Sports, University of Vienna, Vienna, Austria*

Abstract

NBA teams rely heavily on their star players, though an ever-increasing tendency shows that proper ball movement is key for building a successful offense. According to experts, one of the most crucial individual contributions for this aspect is 'making the extra pass' – meaning to pass on a decent shooting opportunity to create an even better one. However, judging this ability is subjective, even a precise definition is missing. In this analysis, we conceptualize the event and design a method to measure this skill on an individual player level. Using this model, we analyze directly assisted shots – whether they could have been turned down to make the extra pass. In-season statistics are used to calculate the scoring efficiency of the player from the particular zone given the distance of the closest defender. Our method helps to automatically find individual situations where the extra pass could have been played to gain a margin in Expected Points and scaled up to a whole season, we are able to identify which areas of the court are the most often overlooked. By detecting these missed opportunities of extra passes, experts can easily point out situations where better teamwork can lead to better scoring opportunities.

KEYWORDS: EXTRA PASS, BALL MOVEMENT, BASKETBALL, PLAYER TRACKING, SECONDARY ASSIST

Introduction

Great ball movement is the most obvious sign of successful teamwork in basketball and is seen as one of the key performance factors in offense – despite the strong dependency on the production of the star players (Martin, n.d.) in the National Basketball Association (NBA). The tendency of an increasing efficiency in ball movement has also been observed in the International Basketball Federation (FIBA) basketball (Stavropoulos, 2020). Besides the great value by creating unpredictability in the offense (D'Amour et al., 2015), moving the ball properly has great potentials to strengthen the team spirit.

Several studies showed the importance of assists already (García et al., 2013; Ibánez et al., 2008; Melnick, 2001), and secondary assisted (two-pass) actions in general (Supola, Hoch, & Baca, 2022). Two-pass actions also proved to be highly effective in the special case of pick and rolls (Marmarinos et al., 2016) resulting in further increase of Expected Points compared to self-created or only assisted (one-pass) actions.

In this light, it is no surprise that experts conceive the ability to make the extra pass (meaning literally an extra pass which follows a potential assist to create an even better shot from a situation that itself was already a decent scoring opportunity) as one of the most crucial skills a player can bring to create better ball movement – and being a needed pillar to 'playing the right way' (Colás & Colas, 2012). However, assessing these situations depends on the subjectivity of the coach, as not even the exact meaning of the extra pass is defined. Even more pressingly, there is no method to count the number of these opportunities, so the judgement of the players in this regard is completely left to the intuition of the coaches.

To overcome the above-mentioned burdens, we conceptualized these actions and – by using positional information from the SportVU dataset – we modeled the passing windows as well as the expected movement of the closest defender to the potential shooter. Having a forecast for the circumstances of these situations, we converted them into Expected Points by accounting for individual scoring skills given the closest defender distance and the shooting area. Putting it all together, our model can assess whether an extra pass would yield more Expected Points than the direct shot.

The contribution of this paper is severalfold, as we give a concise definition to identify the extra pass situations and provide a mathematical model to operationalize it. By putting this model into action, we could also demonstrate its benefits for game analysis: Besides its potential use for actual game scouting, the method gives general insights on areas of the court that are frequently overlooked and a breakdown of player decision making – how many shots were taken correctly, and how often could a player have sacrificed their own shots in order to create a better opportunity for a teammate?

Methods

Even though there is no exact statement of meaning for the extra pass in the current basketball literature, we argue that our interpretation as creating an even better shooting opportunity by playing one more pass resonates well with the expert opinion. This notion is also confirmed by a senior NBA reporter describing the philosophy of Gregg Popovich, the winningest coach of NBA history: "Popovich's theory of an extra pass turning a good shot into a great shot is a staple of modern NBA offenses." (Zillgitt n.d.)

First, lacking an official definition of the extra pass, we defined it rigorously according to the common understanding in the basketball world: *An extra pass is a pass that is given by a player, who has a realistic and immediate shooting opportunity upon receiving the ball but decides to*

turn it down to utilize an even better scoring chance for a teammate. This happens by passing the ball without wasting any time – as in general these opportunities are already existing in the moment of ball reception.

We emphasize the notion that these situations are generally not the ones that develop in the given moment (and require great skill to percept their coming), but much more the already existing ones, where players without the ball are oftentimes static and only waiting for the pass, ready to shoot. In most of these situations, the defense is scrambling, and the required skill to recognize these openings is rather to know where the players are positioned – along with knowing which players are positioned in those particular spots.

By creating the exact definition, we were able to extract the situations that we wanted to assess, whether an extra pass should have been played instead of the taken shots. For this process, we used the SportVU dataset that is available on the internet (Johnson, 2015) and includes time-sampled (25 FPS) moment-to-moment, high-resolution positional records from the first half of the 2015–2016 NBA season. The data is a reduced, raw version of the information that provides the source for the tracking statistics in the NBA and is also used for analytical research by the teams (Robertson, 2017). A more detailed description about the impact and usage of the SportVU data can be found in (Stephanos et al., 2021). As this particular data set does not include event labels, we extracted them by a rule-based system that is described in detail by (Supola et al., 2022).

For a more homogenous and accurate scope of actions, we first filtered the sequences for half court offenses (ball possession with a minimum length of two seconds on the offensive halfcourt, with the restriction that the ball must come to a stop on the x-y axis at any point). Then, we filtered all these actions for potential assists (passes that led to a shot – made or missed) that were immediately followed by the shot (with the shooting motion starting in maximum 0.5s after receiving the ball). We obtained 15,479 such actions occurring in half court offenses, and these are the basis for the extra pass analysis carried out by using the model that we describe later.

To determine whether an extra pass yields an appealing option, we compared the Expected Points by simulating the extra pass actions. The overall model comprises several steps (Figure 1) that will be described next.

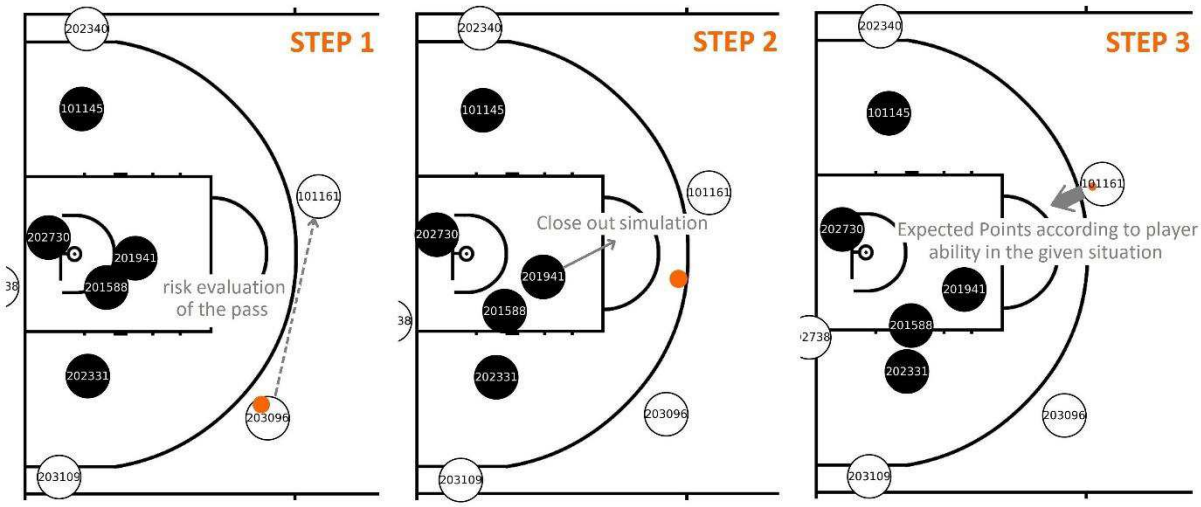


Figure 1. Schematic diagram of the methodical steps to simulate the extra pass situations

Passing windows

First, we had to assess which players are open from a given ball position by determining how

the defense can affect the passing lanes. For this purpose, we used a similar approach as Lee (2015), where he computed pass congestion over the course of the whole passing action. High congestion values indicate situations where the likelihood of a pass interception is strongly increased. The detailed calculation of the score is as follows:

The distances of the defenders closer than 15ft (4.57m) to the passing path were plugged into equation 1 (where *d* denotes the distance to the passing path, *i* the defender and *n* the number of defenders closer than 15ft between the passer and the receiver):

$$\gamma = \sum_{i=1}^{n} \frac{(15-d_i)^2}{225} \quad (1)$$

As we can only use a split of a second to decide whether to pass or not (the player should waste no time to qualify for an extra pass), we used only the one frame at receiving the ball for our congestion metric – and the defenders are weighted proportionally to their relative closeness of the receiver (position projected onto the passing lane, see Figure 2). We chose this weighting because the closer the defenders are to the receiver, the more time they have for adjusting and creating danger for the success of the pass.

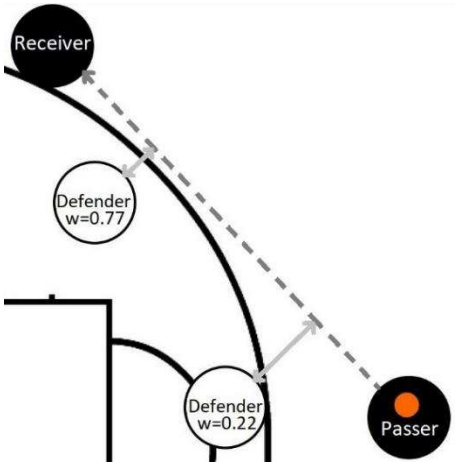


Figure 2. Pass congestion based on one frame; the distance of the defenders is measured to the passing path and weighted by how close they are to the receiver

To get a probability metric, which determines at last whether the pass is possible, we converted these congestion scores by dividing the pass attempts according to made (successful) passes and turnovers (unsuccessful passes). We split these categories further on every 10th percentile according to their congestion scores and observed the distribution of them.

Because the data set would be highly unbalanced in terms of successful and turnover passes, we used equal-sized label sets (1431 passes each) to create the probabilities. This means that the model is punishing congested passing lanes much stricter than it is expected in real situations. However, this overly cautious behavior is highly welcomed, as the purpose of the model is to show better shooting opportunities than the direct one – meaning that even a low turnover risk would be inappropriate (as it could even lead to negative Expected Points instead of the already existing decent shooting opportunity).

With this notion, we used the intersection point where turnovers start to dominate in order to

determine the congestion threshold. A player with a score above this threshold is not considered as a potential extra pass destination (Figure 3).

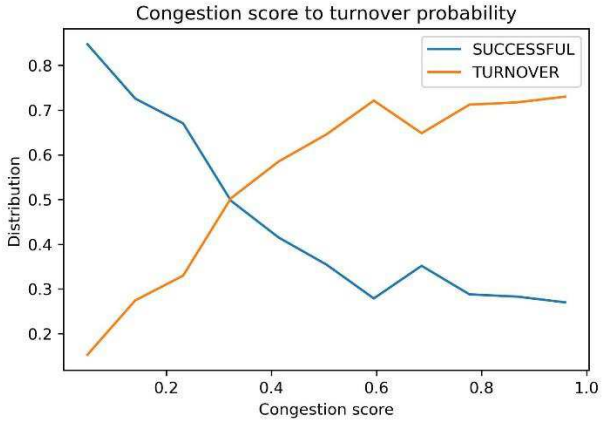


Figure 3. Turning congestion scores into probabilities by using equal sized label groups

Movement of the defense during the pass

After finding the passes that lead to a potential shooter, we needed to estimate the exact situational parameters of the shot that is expected to happen after the extra pass. Terner and Franks (2020) showed that shooting performance varies strongly according to the closest defender distance given a particular area. To determine the position of the closest defender at the moment of shooting, we assumed that the defense is doing its best to challenge this shot. This assumption brings two notions with it:

1. The closest defender to the shooter at the starting moment of the pass is committed to challenging the shot;
2. This player is closing out to the shooter during the pass as fast as he or she can.

To make the second point relevant, we need to compute the distance that this defender is able to cover during the ball on its way to the shooter. For that, we need the pass duration and the speed of the close out.

- First, we took a regression model to create the relationship between pass distance and pass duration. Although we could have used a model based on physics, we found the data-based approach more realistic for game situations in general.
- As the close out speed is highly dependent on the distance to be covered (speeding up takes time, eventually slowing down as well), we also used a regression model for the relationship between the defender-shooter distance and the average (over the particular run) close out speed of the defender.

Using these two estimations, we became able to approximate the distance of the closest defender at the moment of shooting. However, the speed of passes (and therefore their duration – computed in the 1st step) vary strongly according to the need of the situation. A simple linear regression model can yield the average durations given the distances, but this can be insufficient because the mean is pulled towards the long tail of the distribution as we can see in Figure 4 (red line on the right plot), where the plot shows the distribution of the pass duration for the average distance (5.89m [19.32ft]; plus-minus 0.15m – corresponding to 0.5ft – as a range). To overcome this problem, we ran the model on assisted shot attempts, where the receiving player is stand-waiting for the ball during the pass time (on one hand, because it corresponds to typical extra pass situations defined at the beginning of the section; on the other hand, the congestion model can assess whether a teammate is open at the moment but unable to recognize the possibility of

getting open by the time the ball reaches its destination). We split the results of assisted shooting sequences to tuning and validation sets (70-30%) and used only the results of actions where the shooter had at least 30 attempts from that area (1,312 and 554 actions respectively). We fit the model (the quantile parameter, q) using a 2nd order quantile regression (Koenker & Hallock, 2001) to the real Expected Points (EP), and the best setting was reached at a q value of 0.15 (tuning set – EP: 0.9923, Actual Average Point Per Possession: 0.9924; validation set – EP: 0.9951, Actual APPP: 0.9946), and used this as an upper range for the expected pass speeds in the analysis. The lower range was defined by using the median (q=0.5) for the quantile regression – as Figure 4 demonstrates, these boundaries also enclose the majority of the passes, including the modus (and allows situations, where the player is not in a position to play a faster-than-average pass).

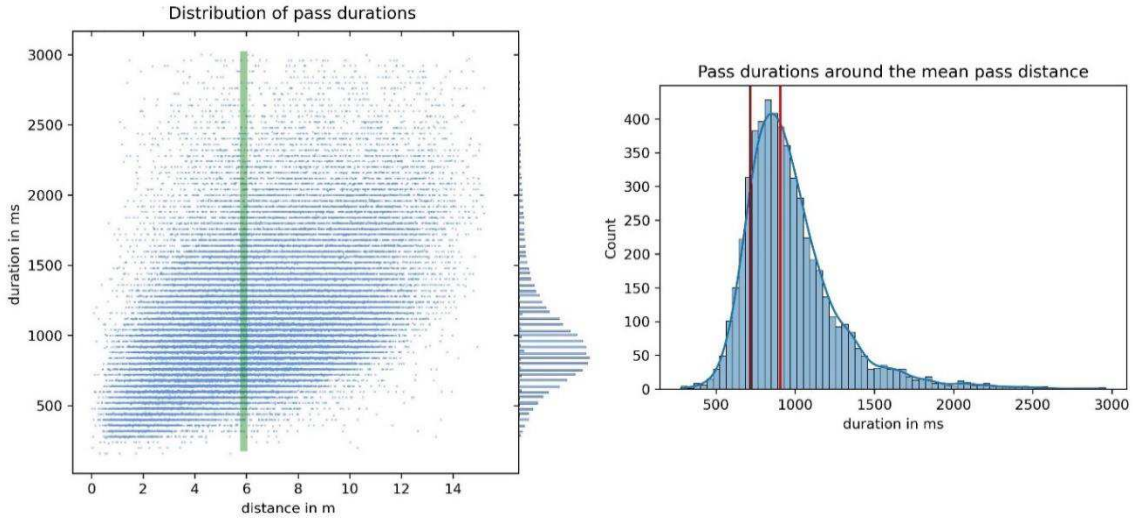


Figure 4. Left – Distribution of pass durations according to their distances; Right – Histogram of pass durations around the average distance passes (in a range of 0.30 meter – corresponding to 1ft)

Expected points of the (potential) shot

To compute the EP of a potential shot we needed the exact circumstances – described earlier – and the shooting ability of the player. These factors are not independent of each other; therefore, we assessed the performance of all players individually per area and particular defender distance.

To assess the shooting abilities depending on these factors, we collected all the shots of the players in the given areas – which we defined as Mid-range, Corner 3 and Arc 3 (Figure 5). Areas under the basket (Restricted area and Close-range) were excluded because they are much less typical to come into question for extra passes; there are multiple defenders around, and the situation changes much quicker. Also, in these areas, the relationship between the shooting accuracy and the closest defender distance is less direct, as many times the closest defender is behind the shooting player and unable to alter the shot as much as somebody on the front.

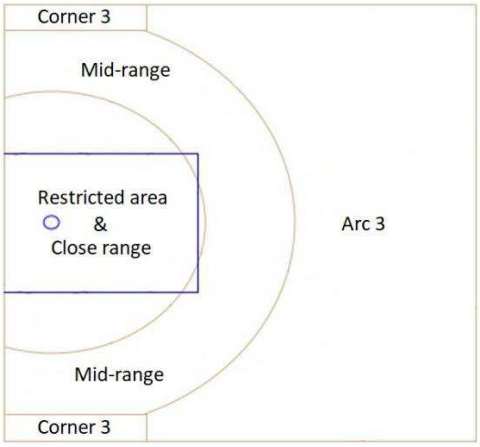


Figure 5. The areas of the half court. We defined mid-range as 2-pointers at least 4.57m (15ft) away from the basket - making these shots more homogenous than using the traditional 'outside the paint' definition.

We proceeded with the following steps:

1. We computed the shooting performance of the player for the median (45th-55th percentile), the minimum (0th-10th percentile) and the maximum (90th-100th percentile) defender distances in the given area. However, given the large variance of the rewarded points after shooting attempts (especially for three pointers), this data per player alone is not sufficient to create a robust model for an arbitrary shooter.
2. To overcome this problem, we computed these values league wide and obtained a scaling factor between the minimum, median and maximum shooting performances (and by that the EP).
3. A minimum of five shots were set as a threshold to make the computation count. Under these number – according to the assumption that such an irregular shooter has in most cases a good reason for not shooting the ball from the particular position – we adjusted the results by pulling the value down to the average of all the shots that were taken by players having less than five attempts from the area. The adjustment was weighted according to the number of missing attempts to reach five. This way, we avoided larger skews in case of e.g., a player having only two made attempts and by that being a perfect shooter.
4. For any player, given their own median, minimum and maximum performances (in terms of EP) and defender distances from the area, we can interpolate and scale their median EP (by applying the league wide scaling factor on the range from their median to the minimum/maximum) to get an estimation of the EP in the situation given that particular defender distance.

Having these EP for all the available options, we compared them to that of the direct shot of the actual ball handler. Any option that produces a higher EP (after deducting 0.576%, which represents the turnover ratio in the passes that are detected as open) than the shot directly taken is an overlooked opportunity in our analysis – if the conditions described in the next paragraph are met.

Some of the areas are slightly overestimated (Arc 3 and Corner 3), while Mid-range shots are underestimated by the model according to the real-game data. This can have several reasons (e.g., the closest defender not being the responsible player for a Mid-range shooter – as those shots are more crowded generally) and to overcome its effect on the model, we computed the bias per area and accounted for it by:

- Computing the error proportions for the areas
- Comparing them pairwise between the areas
- Setting a threshold by these comparisons for converting the EP between the pairs
- Counting as overlooked opportunity only if the yielded EP after the pass is above the EP of the direct shot plus the computed threshold range.

Results

Model evaluation

Pass congestion

Assessing the success rates above and below the 0.5 turnover probability threshold (computed from the congestion scores), we found that the chance for a turnover was almost four times higher for passes above the threshold compared to those below. The details can be seen in Table 1. Because there is 0.576% chance for a turnover even among the passes under the threshold, we deducted this percentage from the expected points for all the potential extra pass possibilities in our analysis.

Note that we do make a distinction between general and standing receivers, as for the extra passes the latter case is more frequent and therefore more relevant.

	general			***standing receiver***		
	whole data set	**under threshold**	**over threshold**	**whole data set**	**under threshold**	**over threshold**
turnover %	1.295%	0.576%	2.271%	0.976%	0.485%	2.051%

Table 1. Percentage of turnovers under and over the threshold for being open according to the congestion scores

However, the purpose of this model is not recognizing turnovers among the attempted passes – the mere possibility of a turnover is already an excluding criterium for an extra pass (in our cases the passing player has already a decent shot opportunity; giving it up for a potential turnover would be highly unrecommendable). To assess, whether the congestion score is signaling which players are open for the pass and which are non-considerable, we compared the congestion scores of all the offensive players on the floor (without the ball) in the moment of the pass – calculated on the full data set (half season data). The comparison between the pass receiver (assumed to be open) and all the other teammates (assumed not to be open at least in most of the cases) can be seen in Table 2. The values confirm that there is good separation between pass-receiving players (who are open in most cases) and non-receiving players (we assume that the majority of them is not open; however, it is clear that in many cases multiple players are open and ready to receive the ball at the moment of the pass).

	non-receiving player	**receiving player**	**receiving player (standing)**
count	327,369	109,123	20,213
mean	0.690	0.340	0.288
std	0.416	0.279	0.231

Table 2. Comparison of pass receiving and non-receiving players in terms of pass congestion scores

Pass duration

After determining the type of the pass, we computed its duration given the distance using quantile regressions, which you can see on Figure 6. The quantile regression with the median (q=0.5; upper, red line on the left plot of Figure 6) has a relative weak pseudo R^2 score (0.124) because passes vary strongly in their characteristics. Therefore, we computed a range of possible results by setting two parameters for the quantile regression. According to our analysis of Expected Points outcomes, the setting with q=0.15 is a more accurate approximation for these situations, and by that, we set the lower limit of duration to the output of this setting (pseudo R^2=0.181; lower, dark red line on the left plot of Figure 6).

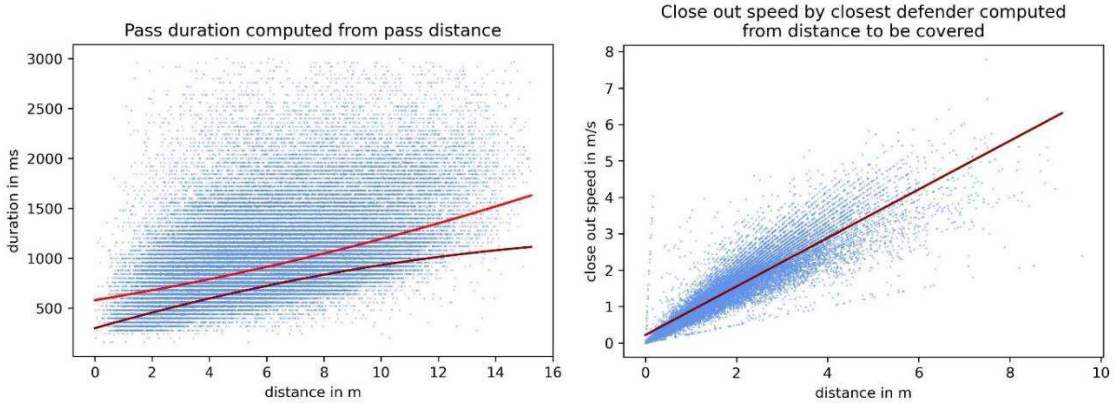


Figure 6. Left – Quantile regressions to compute pass durations from distances; Right – Linear regression to compute the close out speeds from distances to be covered by the defender

Distance covered by the close out

To find the distance possibly covered by the closest defender, we needed to multiply the already determined pass duration by the speed of this defender. We used a linear regression to create a relationship between the distance to be covered to reach the potential shooter and the speed, which you can see in Figure 6 (R^2=0.813).

Shooting model

Having determined the exact (possible closest) position of the defender, we used a shooting model to assign the EP to these situations. We modelled the shooting performance of all players per area given the distance of their closest defender. The evaluation of all the shots in the used data set can be seen in Figure 7, broken down to these areas.

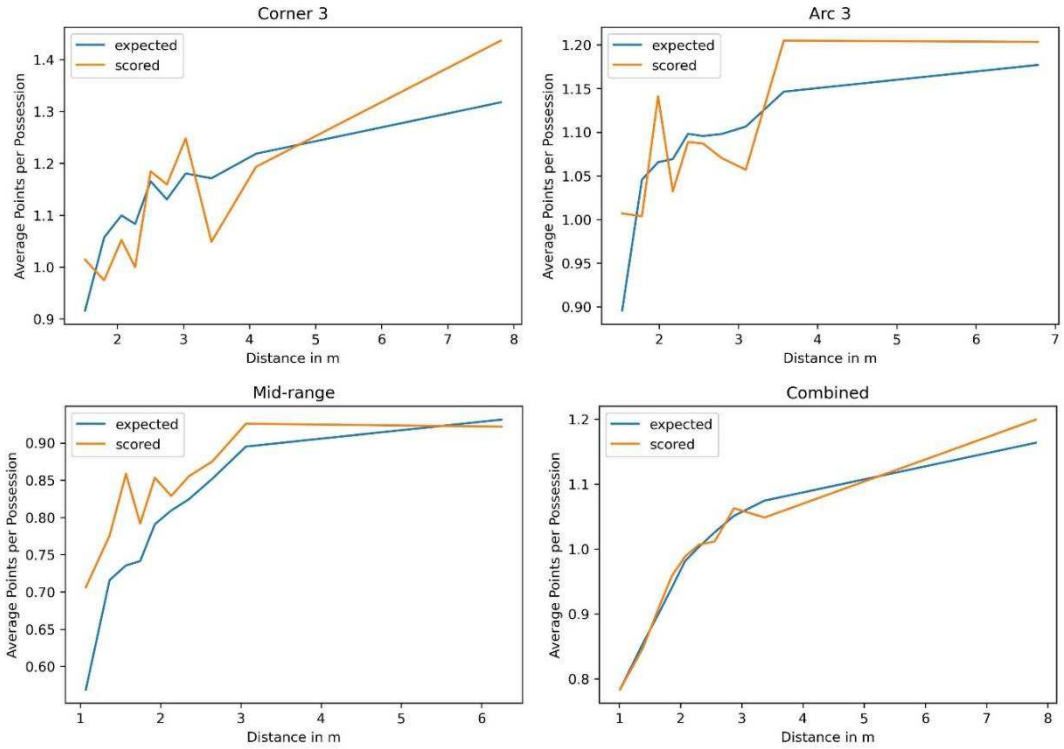


Figure 7. Comparison of actual scored and expected points of shots grouped per deciles of closest defender distance

To account for the systematic differences between the areas in terms of error in Expected Points (that can be seen in Figure 7), we calculated a correction factor based on the pairwise comparisons of the error proportions by averaging the results per area and computing a pairwise scaling factor according to these averages. The exact average results, which are the bases for this computation, can be found in Table 3.

	Expected Points	Scored Points
Mid-range	0.785	0.841
Arc 3	1.080	1.091
Corner 3	1.133	1.129

Table 3. Comparison of averages of actual scored and expected points of shots

The proportional differences of the error rates between the pairwise compared areas served as a tool to set the threshold for potential conversion errors. During the comparison of the EP of two players in the same situation, we used this computation to see whether a potential option is reliably more effective in terms of EP than the other.

Analysis of league patterns

General patterns

We looked for the league wide proportion of shooting and passing decisions (that lead to a shot) in situations where this decision happened no more than 0.5s after receiving the ball. Players pass the ball on in such situations only 7.53% of the times – much less than our results by the model in the analyzed situations (encompassing 15,479 assisted shooting events in half court offenses, with less than 0.5s between receiving the ball and shooting), which ranges between

19.98% and 34.06%.

Figure 8 provides further general insights after running the model on these shooting sequences. We can see that the most overlooked opportunities are behind the three-point arc (Figure 8 – left) – even if we break down to a comparison per degree (Figure 8 – middle). However, the list of the proportions of correct shooting decisions per area (Figure 8 – right) is led by the corner threes – that is no surprise, as teams put high emphasis on creating these shots. Important to note that the tendencies do not differ by using the different parameters for the ranges.

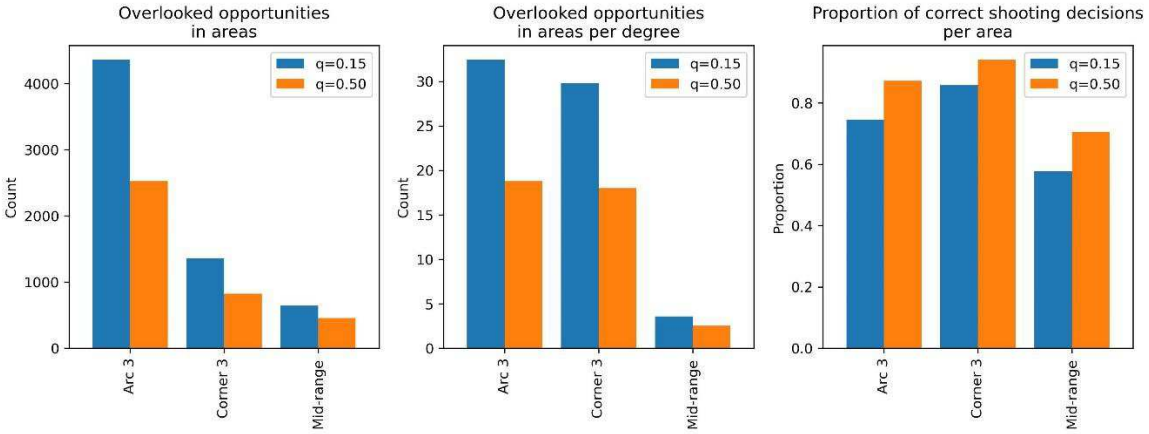


Figure 8. Left – Overlooked opportunities by the areas where the potential shooters were located; Middle – Overlooked opportunities per areas normalized by the degrees the area covers; Right – Proportion of correct shooting decisions by areas where the shooter was located.

Player evaluation

Figure 9 shows the top correct shooting decision makers according to the model – broken down to player level. The players are sorted by the average of the two ranges (q=0.15 and q=0.5). The list shows the top 12 players in the league that satisfy the requirement of having taken at least 100 shots in our data set.

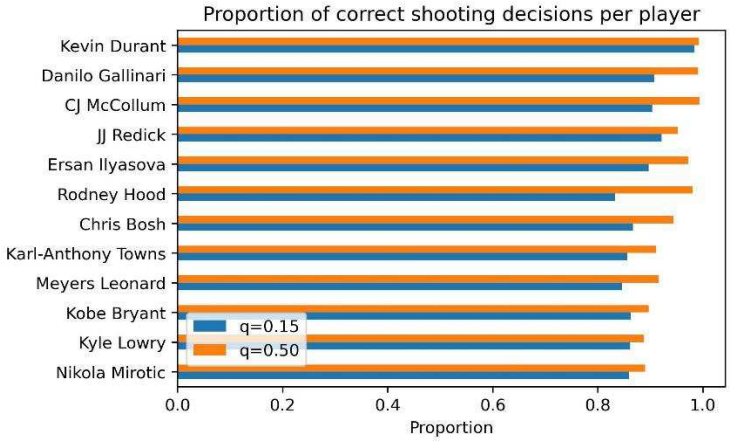


Figure 9. Proportion of correct shooting decisions broken down to players

The corner three

Zooming into the (left) corner area, we can see that most of the shooters who missed the extra pass opportunities were located at the wing or the high post area of the same side (Figure 10). This pattern of the majority of players standing at around 45 degrees away when falling short to make the extra pass is not unique for the corners.

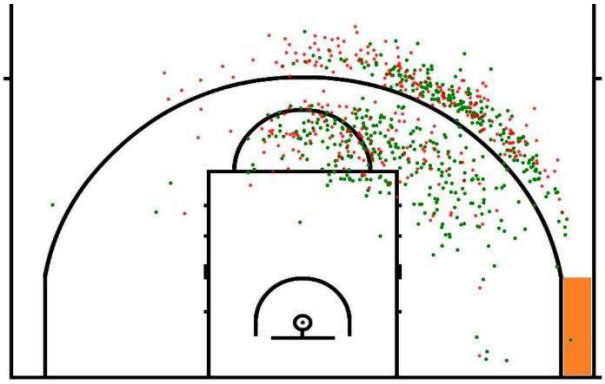


Figure 10. Shooter locations (green & red dots), when they miss the extra pass opportunities to the left corner (orange). Green dots represent situations detected by both parameter settings, red dots only by q=0.15. Note that for this plot, we accounted for the positions on the whole court – including close-ranged shots.

Discussion

Extra passes are elementary pillars of great teamwork: They signal trust, selflessness and team-first mentality among the players. However, deciding whether the extra pass really serves the team is tricky, as giving up a decent shooting opportunity – for which the team worked the whole possession long – can even hurt the performance if the timing is not proper. With our model, we aimed to analyze the characteristics of such actions to detect missed opportunities of these passes, where the final shot is actually expected to be a better opportunity given the context.

By using data from the one moment when the player receives the ball, we modeled the situation in which the player must make the quick decision: shoot or pass. As extra passes happen most frequently after attacking the basket and kicking the ball out to provide the (extra) passer already a decent shooting opportunity, the final shooter is many times set up and ready to catch and shoot already at this moment of decision. Because of this feature, the congestion score at the moment of the potential pass / shot is a telling metric, whether teammates are open for the extra pass.

Obviously, we do not know which defender is about to challenge a potential shot after a hypothetical pass − it can depend on defensive philosophies and tactical considerations. Out of this reason, we modeled the possible movement of the closest defender to the shooter at the moment of the pass – assuming that this defender is taking maximum effort to challenge the upcoming shot in case the extra pass is happening. By that, we avoid creating a model that is repeating the past and chose to simulate a worst-case scenario (from offensive standpoint) instead. This helps to ensure that the model does not give useless false positives where the situation dictates different priorities than in similar situations in the data set (i.e., few players are highly effective from the mid-range over a long run, but it might be of priority for a team to stop a particular shooter out of several reasons). However, because there is still reasonable uncertainty in the quality of the pass and the reaction of the defender, we created a range of results by providing a lower and an upper limit of passing durations and accordingly speeds. These parameters have a high impact on the model output, as they determine how much time the defense has for its response.

Having the circumstances of the potential shot is a very important step, but to translate them into Expected Points we also need to account for the skill level of the shooter. To create meaningful statistics for as many players as possible, we had to use all the catch-and-shoot data that we could find in the data set – meaning that a more accurate selection of situations would be also possible, if more than a half-season data is used. However, the model caught the patterns of shooting tendencies and performed well overall. Mid-range shots seem to be a bit

underestimated; but this error makes sense, as the output of Expected Points for the shooting model depends strongly on the distance of the closest defender. The Mid-range area is the most crowded one among the three, and many situations occur where the defenders do not line up (in terms of who single defenders are responsible for) according to how close they are to an offensive player. As an example, we can take short rolling to the high post after a pick. This action can create scenarios, where two or three defenders can qualify for being the closest one to the screener – in case of a pass to them, it is not sure that the priority of taking away a Mid-range shot – in most cases anyways with a low EP – is high enough for switching responsibilities and giving up shots in any other areas of the court. Our assumption for modelling the movement of the closest defender is however still including that this defender is taking maximal effort to challenge the shot because we cannot distinguish how much priority the defense has for challenging particular shots in general.

Running the model on the data set and looking for extra pass opportunities generated some interesting insights. Our intuition that many situations occur in the NBA, where players could play one more (extra) pass was confirmed, as the model signaled open teammates with great scoring perspectives in many situations. The fact that the most overlooked opportunities were found behind the three-point arc is somewhat logical (Figure 8 – left), as this area is not only huge but is positionally easy to miss recognizing. From these two factors mentioned, the size of the area could be accounted for, by creating the same evaluation per degree (Figure 8 – middle). Most notably, the arc-three stayed still the most overlooked area, meaning that teams are well equipped to use the advantages of the corner-threes by multiple-pass sequences (Supola et al., 2022). This notion is confirmed by the correct shooting decision per area plot (Figure 8 – right), which shows that corner-threes are taken in most cases correctly.

For basketball practitioners, the most interesting aspect of the model is probably the assessment broken down to player level. As we analyzed over 15,000 shooting actions, we can evaluate how many of them are labelled as correct by the model – meaning that there is no player that would be open and would have had a better shooting opportunity directly. This analysis can bring light to which players are taking shots that are the best options at that moment. In these terms, Kevin Durant was the most effective player according to our model – his result ranges between 98.46% and 99.24%. In our data set, he takes shots 93.14% of the time when receiving the ball and making a quick decision whether to shoot or pass to someone that got immediately into the shooting action (However, we should be careful to jump to the conclusion that Durant should have had taken more shots. Considerations as balancing the score between the players out of reasons such as maintaining a level of entropy can also factor in when the usage of a star shooter is that high). It demonstrates well that getting a good percentage of correct shooting decisions depends strongly on the shooting skill too – besides great vision and the willingness to play the extra pass. Kevin Durant is a high-volume shooter, while Russell Westbrook – his teammate at that time – took proportionally less shots (48.28%) but ended up further behind in the category of correct shooting decisions by the model. This shows the contextual characteristics of this metric: While Westbrook was giving passes more often that ended up in direct shots, he is not as effective as a shooter out of the catch as his teammate. By that, it is not only coming easier that a taken shot by him has lower Expected Points, but by being surrounded by players that are great (spot up) shooters, the model is more prone to signal that someone (i.e., Durant) could have had a better shooting opportunity. The diversity of player profiles that can contribute to be good in this type of shot selection is shown by the fact that our list has some sharp shooters, stretch fours, smart playmakers and even great mid-range shooters (Figure 9).

Besides the general analysis discussed above, the implementation of this model design can benefit basketball experts in the more practical field of scouting as well. Knowing the tendencies of the opponents is an important skill as much as evaluating the own players after the games.

Coaches can improve the tactical awareness of their teams by finding situations where their players frequently miss opportunities to create more ball movement and better shots.

Mastering the skill of playing the right pass at the right time is also in correlation with playing experience (Lorenzo et al., 2019; Sampaio, Godoy, & Feu, 2004) – investigating the correlation to good decision making in this regard by using this model would be an interesting topic for future work. Analyzing the passing skill of the ball handler from the technical aspect could also be an important detail, even though on youth level it seems to be uncorrelated to efficiency (Sachanidi et al., 2013). As an additional feature, the model could be extended to account for players being on fire (eventually considering the debated hot hand phenomena – see more in (Bocskocsky, Ezekowitz, & Stein, 2014)), or the fact that someone is spotting up in an area that corresponds to the optimal strategy for the team according to the actual score and the time left on the clock (Skinner & Goldman, 2015).

Stancin and Jovic (2018) showed the importance of passing and created a formula of the Effective Passing Ratio after statistically analyzing the importance of several box score and advanced metrics. Their formula has the number of secondary assists in its nominator as a summand. However, secondary assisted actions can strongly differ in the way they are formed: They can be the finishing part of a designed play as well as a spontaneous extra pass in response of the defensive rotation following a potential assist. A similar analysis – that also distinguishes between such types of actions – could reveal further insights on the question of why secondary assists bring a solid contribution to wins from a statistical perspective.

Also, as the effectivity of shot faking has already been shown (Meyer et al. 2022), the deceptive nature of extra passes could be investigated in more details. In such situations, there is often no need to even fake it, because the situation already implies the high probability of an upcoming shot. Comparing the effects of deceiving the defense by an actual fake and situations that are inherently deceptive – such as extra passes – seems to be a promising area of investigation of tactical elements.

Finally, an interesting question could be to think about the reasons why a particular player / team is missing out on extra pass situations. According to Quílez Maimón and Rojas Ruiz (2017), the reaction time of passing decreases significantly with uncertainty. Based on this, for coaches who find their team overlooking many of these extra pass opportunities, it would be practical to train looking for such openings a count earlier (maybe prior to receiving the ball) in order to lower the uncertainty of the potential passing station.

One of the main limitations of the analysis is that the movement of the players is not included. Therefore, detecting unconventional extra passes where the action relies more on the momentary movement is not possible. These actions might also violate the definition of already existing shooting opportunity of the potential receiver; however, it still makes the model less valid for flipping the question we investigated in this paper (proportion of correct shooting decisions) and limits the validity of figuring i.e., whether a player is overpassing.

The shooting model has also some limitations, as we needed to use all the catch and shoot data available. In the analyzed situations, the model has under- and overestimations for several areas, and we accounted for them with correction thresholds. However, these thresholds help only to make sure that the model does not create false positives for the overlooked opportunities; it does not confirm that the direct shot was surely the best decision for the cases where the EP of the two situations to be compared are close to each other (and within the conversion-error threshold).

Furthermore, some players have less than five shots from an area out of other reasons than being an under-average shooter. As we already mentioned, this limitation is easily avoided by using more data or can be adjusted with the help of expert opinions.

Conclusion

We modeled a highly relevant game situation for team play by using the momentary positions of the players and some statistics about the offensive players' shooting skills. We broke down the situation into its characteristic parts and created a modular system that can be tuned in every aspect in case the expert team has extra specifications. In this form, the model can determine whether a player made the right choice by taking a shot after receiving the ball or should have passed the ball to a particular teammate for a better direct opportunity. This information can be vital for coaching staffs when assessing the willingness for team contribution of a player, designing new options for a play set or looking for new aspects of practice situations to create more ball movement and better team chemistry.

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References

Bocskocsky, A., Ezekowitz, J., & Stein, C. (2014). The Hot Hand: A New Approach to an Old "Fallacy". *MIT Sloan Sports Analytics Conference*, 2014, February 28-March 1, Boston, Massachusetts. MIT.

Colás, Y., & Colas, S. (2012). What We Mean When We Say 'Play the Right Way': Strategic Fundamentals, Morality, and Race in the Culture of Basketball. The Journal of the Midwest Modern Language Association, 45(2), 109–125.

D'Amour, A., Cervone, D., Bornn, L., & Goldsberry, K. (2015). Move or Die: How Ball Movement Creates Open Shots in the NBA. MIT Sloan Sports Analytics Conference, 2015, February 27-28, Boston, Massachusetts. MIT.

García, J., Ibáñez, S. J., De Santos, R. M., Leite, N., & Sampaio, J. (2013). Identifying Basketball Performance Indicators in Regular Season and Playoff Games. Journal of Human Kinetics, 36, 161–168. https://doi.org/10.2478/hukin-2013-0016

Ibánez, S. J., Sampaio, J., Feu, S., Loernzo, A., Gómez, A. M., & Ortega, E. (2008). Basketball game-related statistics that discriminate between teams season-long success. European Journal of Sport Science, Volume 8, 2008(6), Pages 369-372.

Koenker, R., & Hallock, K. F. (2001). Quantile Regression. Journal of Economic Perspectives, 15(4), 143–156. https://doi.org/10.1257/jep.15.4.143

Lee, A. (2015). Assist Quality: Measuring the True Value of Basketball Assists. New England Symposium on Statistics in Sports, 2015, September 26, Cambridge, Massachusetts. Harvard University Science Center.

Lorenzo, J., Lorenzo, A., Conte, D., & Giménez, M. (2019). Long-Term Analysis of Elite Basketball Players' Game-Related Statistics Throughout Their Careers. Frontiers in Psychology, 10. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.00421

Marmarinos, C., Apostolidis, N., Kostopoulos, N., & Apostolidis, A. (2016). Efficacy of the "pick and roll" offense in top level European basketball teams. Journal of Human Kinetics, 51(1), 121–129. https://doi.org/10.1515/hukin-2015-0176

Martin, B. (n.d.). Stephen Curry, Warriors lead the NBA in secondary assists. NBA.com. Retrieved 12 July 2022, from https://www.nba.com/news/stephen-curry-warriors-lead-the-nba-in-secondary-assists

Melnick, M. J. (2001). Relationship between Team Assists and Win-Loss Record in the National Basketball Association. Perceptual and Motor Skills, 92(2), 595–602. https://doi.org/10.2466/pms.2001.92.2.595

Meyer, J., Fasold, F., Schul, K., Schön, T., & Klatt, S. (2022). Shot fakes as an indicator of successful offense in basketball. Human Movement Science, 82, 102920. https://doi.org/10.1016/j.humov.2021.102920

Johnson, N. (2015). BasketballData. Rertieved September 2019, from https://github.com/neilmj/BasketballData

Quílez Maimón, A., & Rojas Ruiz, F. J. (2017). Assessment of the Point of No Return in Choice Reaction Time under Uncertainty Conditions in Basketball Pass." SPORT TK: Revista Euroamericana de Ciencias del Deporte, 6 (Supl.) 2017. https://digitum.um.es/digitum/handle/10201/53203

Robertson, M. (2017). An Analysis of NBA Spatio-Temporal Data. Master's thesis, Department of Statistical Science in the Graduate School of Duke University; 2017.

Sachanidi, M., Apostolidis, N., Chatzicharistos, D., & Bolatoglou, T. (2013). Passing efficacy of young basketball players: Test or observation? International Journal of Performance Analysis in Sport, 13(2), 403–412. https://doi.org/10.1080/24748668.2013.11868657

Sampaio, J., Godoy, S. I., & Feu, S. (2004). Discriminative Power of Basketball Game-Related Statistics by Level of Competition and Sex. Perceptual and Motor Skills, 99(3_suppl), 1231–1238. https://doi.org/10.2466/pms.99.3f.1231-1238

Skinner, B., & Goldman, M. (2015). Optimal Strategy in Basketball. ArXiv:1512.05652 [Physics]. http://arxiv.org/abs/1512.05652

Stancin, I., & Jovic, A. (2018). Analyzing the influence of player tracking statistics on winning basketball teams. 2018 41st International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO), 1533–1538. https://doi.org/10.23919/MIPRO.2018.8400276

Stavropoulos, N. (2020). Relevant statistical observations in the basketball competitions of 2014 and 2019 Men's Basketball World Cups—ProQuest. Journal of Physical Education and Sport, 20(4), 1972–1983. https://doi.org/10.7752/jpes.2020.04267

Stephanos, D. K., Husari, G., Bennett, B. T., & Stephanos, E. (2021). Machine learning predictive analytics for player movement prediction in NBA: Applications, opportunities, and challenges. Proceedings of the 2021 ACM Southeast Conference, 2–8. https://doi.org/10.1145/3409334.3452064

Supola, B., Hoch, T., & Baca, A. (2022). The role of secondary assists in basketball – an analysis of its characteristics and effect on scoring. International Journal of Performance Analysis in Sport, 22(2), 261–276. https://doi.org/10.1080/24748668.2022.2039090

Terner, Z., & Franks, A. (2020). Modeling Player and Team Performance in Basketball. Annual Review of Statistics and Its Application, Vol. 8, 1–23.

Zillgitt, J. (n.d.). Spurs' Gregg Popovich passes Don Nelson as NBA's all-time winningest coach. USA TODAY. Retrieved 1 February 2023, from https://www.usatoday.com/story/sports/nba/spurs/2022/03/11/spurs-gregg-popovich-nba-all-time-record-coaching-wins/9447071002/