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Article

Understanding the movement of professional and high school soccer players

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SUMMARY

Data analytics plays an increasingly visible role in the sports industry. Professional soccer utilizes data analytics to gain competitive advantage. It is intuitive that basic metrics like speed and passing matter, but the difference they make in the ability to score a goal is an open question. In this project, we were interested in discovering the statistical evidence that differentiates goal-scoring from no-goal-scoring sequences. Using a trajectory data set from professional games, we hypothesized that goal and no-goal sequences would be statistically different. Indeed, we found evidence that faster, longer possessions with more passes were more successful. From the same data set, we also investigated Long Ball, an offensive strategy that pushes the ball to the target goal via a big kick. We hypothesized that Long Ball was effective for goal scoring but found evidence to the contrary. In addition, we were interested in how professional and student players move differently. Comparing a student trajectory data set against the professional data set, we hypothesized that the movement directions of the two groups would be different. Indeed, we found evidence that professional players tended to run where the ball is going whereas students moved towards the ball's current location more often than professionals. Throughout our study, we applied the 2-sample Kolmogorov–Smirnov test on the cumulative distribution function of each metric to calculate statistical differences between sequences. Our findings support the importance of basic skills in soccer, and this is useful for players at all levels. Additionally, by pinpointing a weakness in student movement, our findings could help students to move more like professional soccer players.

INTRODUCTION

Data-driven decision making is becoming indispensable for the sports industry. Sports analytics applies data analysis to evaluate different aspects of a sport such as player performance, game strategy, opponent statistics, drafting and trading, and more (1). The findings from these analyses are then used to make informed decisions and create a competitive edge on the playing field. These analyses have increasingly replaced the traditional decision making that is based on intuition, gut feelings, and past practices (2, 3). Leading academic institutions, such as the Massachusetts Institute of Technology (4) and Carnegie Mellon University (5), also recognize sports analytics as a serious research field. For example, MIT hosts the annual Sloan Sports Analytics Conference (4), a platform for sports executives, researchers, and students to exchange new discoveries in sports analytics. Professional soccer is one of the sports that utilizes data analytics to gain competitive advantage. One notable example was Germany's national soccer team, which created a custom database to analyze individual and team performance as well as strategies (6). Measured metrics such as average possession time, number of kicks, and movement speeds played a large role in Germany's 4th World Cup win in 2014 (7).

Earlier work has studied soccer movement using different types of data sources. STATS, a leading sports analytics company, uses cameras to collect player movement and has made a data set of 7500 possessions available to the public (8). STATS researchers analyzed this possession data set by using imitation and unsupervised learning to identify player positions and predict future movement (9). Instead of studying movement within a possession, Hobbs et al. analyzed transitions where possessions switch from one team to another (10). Other research teams have used GPS measurements in small-sided games to study collective variables such as team centroid position and player spacing to capture game dynamics (11, 12, 13). Using this method researchers observed from three games that the centroid of the attacking team overtakes that of the defending team before a goal. Additionally, some researchers track player movement in televised soccer games (14). However, it is hard to calculate player coordinates using this method due to changing camera angles.

In this project, we focused on two soccer trajectory data sets, one of possessions from professional games and one from high school games. We were interested in finding out whether there are differences between goal-scoring and non-goal-scoring possessions as well as between professional and student player movement. We hypothesized that we can uncover statistical differences for these comparisons from these trajectory data. In the first component, we discovered that goal possessions were longer, faster, started closer to the target goal, and contained more passes. We computed the average value for possession duration, speed, the starting location of the ball, and number of passes per possession. In addition, we examined the cumulative distributions of these metrics, which also captured the minimum, maximum, and median values. We used the 2-sample Kolmogorov–Smirnov (KS) test to further confirm the statistical differences between goal and no-goal distribution. In the second component, we observed that professional players tended to run where the ball was headed, but students ran to the ball's current location more often than the professionals. We again used the 2-sample KS test to illustrate the difference in the movement directions. We also hypothesized that Long Ball is effective for goal scoring but found evidence to the contrary.

RESULTS

Goal versus No-goal Possessions

One objective of this project was to quantify the difference that basic metrics such as speed and passing make in the ability to score a goal. We first compared goal and no-goal possessions using a data set from STATS (8). This data set consists of possessions from professional soccer games. Each possession, or a time period during which one team has the control of the ball, was represented as a time series of coordinate vectors of the players and the ball. Specifically, the coordinate vector at time *t*

$$\vec{V}(t) = [\, x_1(t), y_1(t), x_2(t), y_2(t), \ldots, x_{23}(t), y_{23}(t)]$$

had player *i* at location $(x_i(t), y_i(t))$ for $1 \leq i \leq 22$ and has the ball at $(x_{23}(t), y_{23}(t))$. Players 1 to 11 were on the defending team, and players 12 to 22 were on the attacking team, which possesses the ball. From the time series of coordinate vectors, we computed metrics including possession duration, player speed, ball speed, ball coordinates at the start of sequences, and number of passes (see Materials and Methods for details). We then tested the hypothesis that goal possessions and no-goal possessions had quantifiable difference. For each metric, we compared the means (**Table 1**) and cumulative distribution functions (CDFs) (**Figure 1**) of our metrics in goal and no-goal possessions. We performed a 2-sample Kolmogorov–Smirnov test (KS test) (15) to determine whether the CDF for the goal possession and that for the no-goal possession were from similar distributions and whether they could be considered statistically different. For p-values smaller than 0.05, two samples are considered statistically different.

We first studied how possession duration differs for goal and no-goal possessions. The average length of goal possessions was 21.4 seconds, whereas the average length of no-goal possessions is 17.5 seconds, almost 4 seconds shorter (**Table 1**). The CDFs of possession duration for goal and no-goal possessions highlighted clear differences between the two types of possessions (**Figure 1A**). Overall, the goal possessions was shifted to the right of the no-goal possessions, which means for every percentile, goal possessions lasted longer than no-goal possessions. A 2-sample KS Test on the goal and no-goal possession durations showed the two CDFs have statistically different distributions (*p*-value = 0.0007, KS-statistic = 0.2).

When comparing speeds, the average ball speed was

	Mean		2-sample KS Test	
	Goal	**No-Goal**	**p-value**	**KS-statistic**
Duration (s)	21.40	17.50	0.0007	0.2
Players speed (m/s)	2.54	2.37	0.04	0.13
Ball speed (m/s)	8.02	7.77	0.007	0.16
Ball x-coord at start (m)	-4.00	-14.30	0.009	0.16
Number of passes	7.20	6.10	0.01	0.15

Table 1: Comparison of possession duration, player speed, ball speed ball, ball position at start, number of passes between goal and no-goal possessions using mean and 2-sample Kolmogorov–Smirnov (KS) Test.

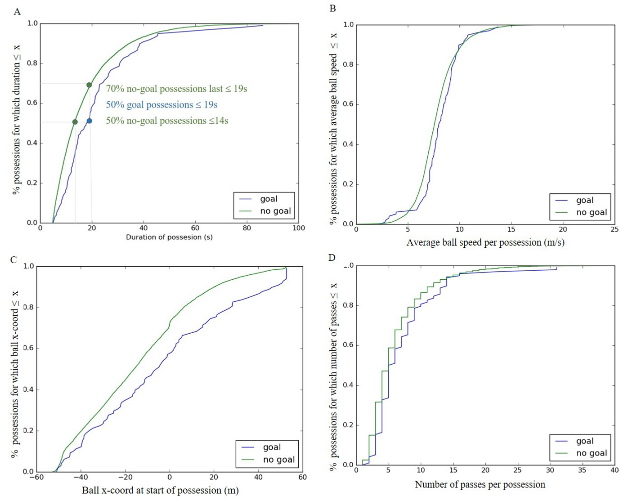

Figure 1: CDFs (cumulative distribution functions) for goal possessions vs no-goal possessions. A) Duration of a possession. B) Ball speed. C) Number of passes. D) x-coordinate of the ball at the start of the possession.

8.02 m/s for goal possessions and 7.77 m/s for no-goal possessions (**Table 1**). Again, the ball speed distribution in goal possessions was largely shifted to the right of the distribution for no-goal possessions (**Figure 1B**). Our 2-sample KS test indicated that the ball speed in goal possessions was significantly faster than that in no-goal possessions (*p*-value = 0.007, KS-statistic = 0.16). The same observation held for player speed: both the average (**Table 1**) and the CDF (data not shown) showed faster player speed in goal possessions than in no-goal possessions.

To study how distance to the target goal affects scoring, we examined the *x*-coordinate of the ball at the start of each possession relative to the center of the field. The data acquired from STATS positioned the target goal on the right. The target goal mouth was from (52.5, -3.66) to (52.5, 3.66) on a rectangular pitch with lower-left coordinate (-52.5, -34) and upper-right coordinate (52.5, 34). Therefore, the larger the *x*-coordinate, the closer the ball is to the target goal. For goal possessions, the ball started with an average *x*-coordinate of -4.0 (**Table 1**). For no-goal possessions, the starting x-coordinate of the ball was --14.3 (**Table 1**). Since the goal possession CDF was shifted to the right of the no-goal CDF (**Figure 1C**) and the p-value and KS-statistic were 0.009 and 0.16, respectively, we concluded that goal possessions start closer to the target goal than no-goal possessions, on average.

Finally, the average number of passes during goal possessions was 7.2 and the average number during no-goal possessions was 6.1 (**Table 1**). The goal possession CDF exhibited an identical rightward shift to previous parameters relative to no-goal possessions (**Figure 1D**), highlighting that more passes occurred during goal possessions than during no-goal possessions (*p*-value = 0.01, KS-statistic = 0.15).

We therefore observed that goal possessions were longer, faster, started closer to the target goal, and contained more passes. We note that for the CDF curves showing the possession duration (**Figure 1A**), speed (**Figure 1B**), and *x*-coordinate of the ball at start of possession (**Figure 1C**), the no-goal possession distribution curves are smoother than

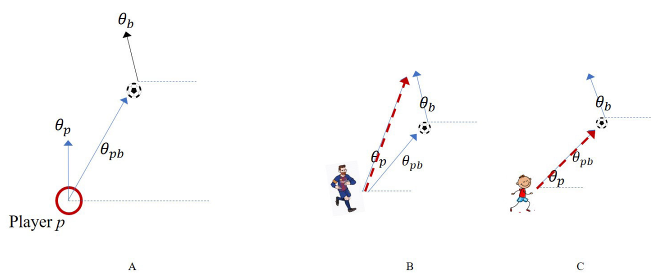

Figure 2: Movement direction. A) Player movement direction θ_p, ball movement direction θ_b, and player-to-ball direction θ_{pb}. B) Illustration of player running in the direction of the ball. C) Illustration of player running towards the ball.

the goal possession curves. This is because the STATS data set contained more no-goal possessions (7402 out of 7500 possessions) than goal possessions (98 out of 7500), which allows for a more continuous representation of the data. The CDF curves for the number of passes (**Figure 1D**) are step-like for both goal and no-goal possessions since the number of passes are represented by discrete integers.

Professional versus Student Movement

We explored how professional players move differently from student players. To do this, we created a student data set by videotaping high school games and then turning video frames into time series of coordinate vectors in the same format as the STATS data. In comparing movement direction of the players, we observed that professional players tended to match their own direction of movement more closely to the direction the ball was moving rather than to the line between themselves and the ball, but student players considered these two directions equally when determining their own trajectories.

Using the STATS data and the high school data, we tested the hypothesis that professional and student movement directions are different. We tracked three angles relating to each players' position at different time points (**Figure 2**). At time t and relative to a defined origin, we let $\Theta_b(t)$ be the direction of the ball's movement, be the movement direction of the player p, and $\Theta_{pb}(t)$ be the direction from the player p to the ball b. We illustrate the movement direction of the professional players (**Figure 3**), and then compare against the movement direction of the students (**Figure 4**). We first generated the distribution of angular distances $\Theta_p(t) - \Theta_b(t)$ for professional players over all players p and time t (**Figure 3A**). The mode of the distribution was approximately when $\Theta_p(t) = \Theta_b(t)$ with a strong, well-defined peak. In comparison, the angular distance $\Theta_p(t) - \Theta_{pb}(t)$ distribution for professional players was much flatter with a less definitive mode and a broader distribution outside $\Theta_p(t) = \Theta_{pb}(t)$ (**Figure 3B**). These two plots were significantly different from each other (p-value = 0.0001, KS-statistic = 0.14). Together, this indicated that professional players tended to run in the direction the ball is moving (measured by Θ_b) more often than run towards where the ball is (measured by Θ_{pb}). In contrast to professional players, the two angular distance distributions for student players were quite similar to each other (p-value = 0.12, KS-statistic = 0.03) (**Figure 4**). The similar peaks around $\Theta_p(t) = \Theta_b(t)$ (**Figure 4A**) and $\Theta_p(t) = \Theta_{pb}(t)$ (**Figure 4B**) indicated student player movement direction was equally influenced by where the ball was and where the ball was moving.

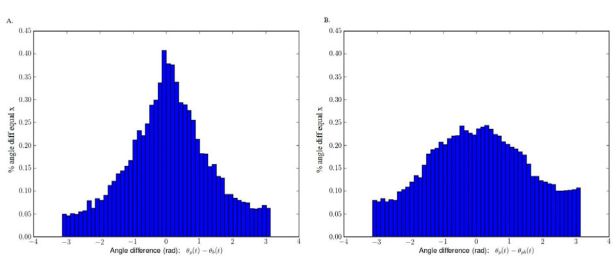

Figure 3: Distribution of angular distances for professional players. A) $\theta_p(t) - \theta_b(t)$. B) $\theta_p(t) - \theta_{pb}(t)$.

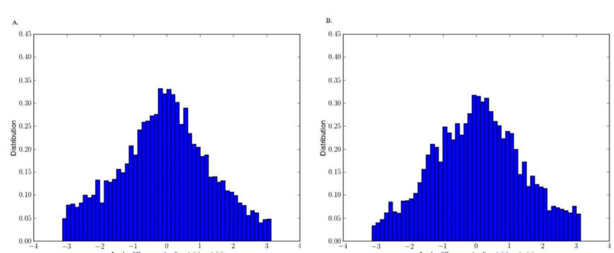

Figure 4: Distribution of angular distances for student players. A) $\theta_p(t) - \theta_b(t)$. B) $\theta_p(t) - \theta_{pb}(t)$.

Long Ball Tactic

Next, we investigated whether we can uncover evidence to support success rates of goal-scoring tactics. We focused on Long Ball, an offensive tactic that moves the ball a long distance upfield via one kick to an attacking player, with the ball generally bypassing the midfield. The merit of playing long ball is often debated (16). Though it is viewed as practical, the tactic is not considered as elegant as a sequence of short passes between players. When teams aim to score towards the end of a match, Long Ball is often the chosen strategy due to the lack of time for a gradual build-up.

Using the STATS dataset, we tested whether Long Ball was more prevalent in goal-scoring possessions. Evaluating the CDFs of the distance of the longest kick upfield for goal and no-goal possessions (**Figure 5**), we found that they overlap with each other and are not readily separable (p-value = 0.6, KS-statistic = 0.07), which suggested that these distributions were not statistically different. Therefore, the evidence does not support the hypothesis that Long Ball is effective for goal scoring.

DISCUSSION

In this project, we compared goal-scoring versus non-goal-scoring possessions and professional versus student player movement, and we found evidence to support the hypothesis that they are statistically different. We observed that goal possessions were longer, faster, started closer to the goal and contained more passes. We also observed that professional players tended to run where the ball was going whereas students moved towards the ball's current location more often than professionals.

The difference between goal and no-goal possessions supported the hypothesis that basic metrics such as speed and ball-control skills (reflected by possession duration and the number of passes) are important for goal scoring.

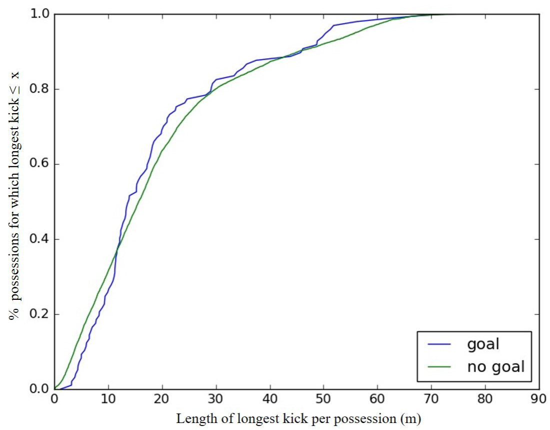

Figure 5: CDFs of longest kick for goal possessions vs no-goal possessions.

Although sports news articles report measurements such as average player speeds and possession time (7, 17), we are not aware of published work that quantifies the difference between goal and no-goal possessions.

Interestingly, we did not find evidence to support our hypothesis that Long Ball was effective in goal scorin, as the CDFs for the goal and no-goal possessions show little difference. This finding is consistent with the earlier evidence that goal-possessions have a higher number of passes and longer duration. The "Long Ball theory" was first proposed by Charles Reep in the 1950s in England (16). The theory coupled with the "three pass optimum" claim drew criticism (18). While there is no agreement on the effectiveness of Long Ball, the tactic continues to be used by teams betting on a last-minute goal.

Although our findings supported statistical differences in our evaluated parameters, there were several limitations in our studies. In our 46-dim coordinate vector shown above, we know that players 1 through 11 form the defending team, 12 through 22 form the attacking team, and that players 1 and 12 are goalies. However, we do not know in the STATS data which coordinates correspond to offenders, defenders or midfielders of each team. We therefore analyzed player movement collectively, not distinguishing players based on their positions. However, we hypothesize that movement speed, direction, and distance covered are different for offenders, defenders, and midfielders. This hypothesis could be easily verified if we had information associating coordinates with player positions.

Another consideration is that goal scoring often involves multiple possessions. The analysis of transitions where possessions switch between teams is another topic of soccer analytics. Hobbs et al. studied the importance of transition play, especially the connection between scoring and time taken to create a goal chance when a team transitions from defense to offense (10). A recent New York Times article (17) stated, "In recent years, the average time between winning the ball back and scoring by all teams has increased: from 10.58 seconds three years ago to 12.50 seconds last season. Teams are taking slightly more time in possession than previously." Unfortunately, we do not know if possessions from the STATS data set come in a sequence, or even whether they belong to the same game or were played by the same teams. If we had sequencing of possessions, we would be able to study the relationship between multiple possessions and goal and no-goal outcomes.

Additionally, we were unable to find any student trajectory data like the professional possession data from STATS. We therefore created the student trajectory data set from video clips of two high school games taken from an iPhone. One challenge in translating video frames to 46-dim coordinate vectors is tracking players so that, within the same possession, $(x_i(t),y_i(t))$ of the same subscript i is associated with the same player from one video frame to the next. While real-time object detection algorithms like You Only Look Once (YOLO) (19) aim for object tracking, they often make mistakes, including missing players or mixing players from frame to frame. Therefore, automatic player tracking still requires a lot of human intervention to ensure correctness. This made creating a high school data set a labor-intensive and time-consuming process. We also found it difficult to divide a sequence of moves into possessions as we could not always tell which team owned the ball. We therefore focused on student movement direction, which was independent of possessions. We marked player and ball coordinates on the video frames using OpenCV, an open-source computer vision library (20).

Although our student data set was much smaller than the professional set, we have started the first step in creating an expansive student repository. When player tracking can be automated, creating a large student set would become possible and many more studies could be conducted. For example, we could track the growth of a youth team over multiple years and see how their skills, e.g., speed and movement direction, improve. We could also compare teams across different leagues and see whether players from the top leagues indeed outperform those from the lower leagues.

Our analyses highlighted that goal-scoring possessions are longer, faster and have more passes, indicating that speed and ball control play a significant role in goal scoring. The fact that professionals run where the ball is going more often than the students gives supportive evidence that students are less efficient in their movement direction. This resonates with Wayne Gretzky's famous quote, "I skate to where the puck is going to be, not where it has been." The findings of this study can inspire players at all levels to improve. This project also highlights the limitation of the soccer trajectory data available to the public. The lack of player, position, team and game information within the STATS datasets prevents potentially interesting associations from being discovered. Additionally, the creation of an extensive student trajectory data set is something we believe can be useful for youth soccer, and we hope this project has helped to start this effort.

We hope our study inspires players at all levels to sharpen their basic skills. This study also quantified the difference in movement direction between professional and student players, which is a piece of evidence explaining why students are less effective. We also hope that our study pinpoints an aspect that students can improve to play more like professionals.

MATERIALS AND METHODS

The data set of 7500 possessions from professional games was provided by STATS (8), where each possession is represented as a time series of 46-dimensional coordinate vectors. We created the student trajectory data set from video clips of two high school games taken from an iPhone (Model 6S A11688). We focused on video clips that clearly captured the ball since the player movement direction analysis relied on the ball location. We manually marked the ball and the foot location of each player on the video frames, and OpenCV returned their coordinates (20). Within a time-series of coordinate vectors, we made sure that the same player was matched from one video frame to the next. We marked two video frames per second.

After we obtained player and ball coordinates on a video frame, the remaining task was to translate coordinates on the screen into coordinates on the field. The translation uses properties of vanishing points in projective geometry (21). Andrews, 2020, presents how to do the projection in further detail (22). To project screen coordinates to field coordinates, we needed some reference points whose coordinates were known both on the field and on the screen, which we called anchors. Since the games we recorded were played on an American football field, the endpoints of the 10-yard and 30-yard line served as four anchors. We chose their field coordinates to be (10,0), (30,0), (10,50), (30,50), and we knew their coordinates on the video screen from OpenCV. We first showed that if the four corners of any rectangle on the field serve as anchors, we can compute a unique projection. This was because a set of parallel lines on the field converged to a common vanishing point on the screen. A rectangle provided two sets of parallel lines and therefore defined two vanishing points, say *u* and *v*. The coordinates of *u* and *v* were computed from the screen coordinates of the anchors. For any point of interest *p* on the screen, the lines *pu* and *pv* when projected on the field must be parallel to the two sides of the reference rectangle. These provided enough constraints so that *p*'s projection on the field was unique. On the other hand, we also showed that if only three of the four corners of a rectangle served as anchors, there may not be a unique projection (22).

Once both data sets were in the format of 46-dim coordinate vectors, we developed Python 3.5 code for data processing, analysis and plotting. The Python SciPy library also had an implementation of the 2-sample KS-test.

To compare goal and no-goal possessions, we needed to compute possession duration, movement speed, the number of passes per possession and the x-coordinate of the ball at start. To compare professional and student movement, we needed to compute movement speed and direction.

The possession duration for the STATS data set is the number of records per possession times 10 because the records were taken every 0.1 seconds. The x-coordinate of the ball at start came directly from the data set. Movement speed and direction were extracted as follows.

The speed of a player *p* at time *t*, $s_p(t)$, was computed from *p*'s location $(x_p(t), y_p(t))$ at *t* and *p*'s location $(x_p(t+\delta), y_p(t+\delta))$ at $t+\delta$ where position vectors were recorded every δ seconds.

For STATS, δ = 0.1 s, and for the student data, δ = 0.5 s.

$$s_p(t) = \frac{1}{\delta}\sqrt{\left(x_p(t+\delta) - x_p(t)\right)^2 + \left(y_p(t+\delta) - y_p(t)\right)^2}$$

The speed for the ball at time *t* was computed identically.

For the number of passes per possession, we defined the closest attacker within a meter of the ball to be the owner of the ball (sometimes the ball had no owner). When the ball had a new owner, we marked that a pass had taken place.

The angles $\Theta_b(t)$, $\Theta_p(t)$ and $\Theta_{pb}(t)$ were computed as follows. Suppose player *p* is at location $(x_p(t), y_p(t))$ at time *t* and at $(x_p(t+\delta), y_p(t+\delta))$ at time $t+\delta$, then

$$\theta_p(t) = arctan2\,\frac{y_p(t+\delta) - y_p(t)}{x_p(t+\delta) - x_p(t)}$$

The *arctan*2 function from the Python numpy library is different from the usual *arctan* function. The *arctan* function has range $(-^{\pi}/_{2}, ^{\pi}/_{2})$, whereas the Python *arctan*2 function returns an angle in the range of $(-\pi, \pi]$ and chooses the right quadrant by the signs of $y_p(t+\delta) - y_p(t)$ and $x_p(t+\delta) - x_p(t)$. We used *arctan*2 since we need the angle range of 2π to specify a direction. The formula for $\Theta_b(t)$ was identical. The formula for $\Theta_{pb}(t)$ was

$$\theta_{pb}(t) = arctan2\,\frac{y_p(t) - y_b(t)}{x_p(t) - x_b(t)}$$

The angular distances $\Theta_p(t) - \Theta_b(t)$ and $\Theta_p(t) - \Theta_{pb}(t)$ are restricted to be in $(-\pi, \pi]$. If the angular distance was bigger than π or smaller than $-\pi$, the distance was adjusted by 2π.

Finally, to test the long ball hypothesis, we needed to compute the length of a pass. Since we already defined the beginning and the end of a pass, we knew the coordinates of the ball at the beginning and the end of a pass and therefore the length of the pass. The longest ball per possession is the longest pass.

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