# Expanding Plus-Minus for Visual and Statistical Analysis of NBA Box-Score Data

Robert Sisneros and Mark Van Moer

**Abstract**— In this work we present an augmentation of the plus-minus statistic as well as a new visual platform for exploring our derived values. Specifically, we apply the concept of measuring impact via differentials to all box score statistics and expand the focus of analysis from a player to a team. That is, on a per-game basis for a stat, we are concerned only with how many more or less than an opponent a team accumulates of that stat. We consider traditional plus-minus numbers at the team level as a measure of the quality of a win/loss for a team; this creates several interesting opportunities for evaluating the impacts of player accomplishments numerically at the team level. We will detail PluMP, the plus-minus plot, and provide illuminating examples found in 2012-2013 NBA box score data. Further, we will provide a representative example of more general analysis that follows directly from our paradigm.

**Index Terms**—Visualization, analytics, basketball, plus-minus, numerical, PluMP.

## 1 Introduction

There is a recent trend toward the use of "advanced statistics" for analyzing sports. The National Basketball Association represents a sport still in its fledgling phase of analytics. Many advanced calculations are per-minute or per-possession stats; this is a typical data normalization that provides the ability to make much more accurate comparisons among players or teams. Another simple but effective advanced stat is plus-minus. A player's plus-minus is calculated as the difference of his team's and the opposing team's points while he is on the floor. Conceptually, this is a direct measure of a player's contribution and is therefore typically the first-adopted by those transitioning to data analytics.

Another increasingly pervasive advanced stat is John Hollinger's player efficiency rating (PER). PER is a single-number measure of how many "good" things a player does minus the "bad" things a player does per unit of playing time. Moreover, a combination of team as well as league averages are used in calculations and adjustments made for a team's pace to not adversely affect those on slower-paced teams. PER is an excellent example of the difficulty in combining standard accumulated stats into a meaningful metric. One need only compare league MVPs with PER rankings to realize PER's potential as a powerful analytic measure.

However, as Hollinger himself mentions, PER is not meant to be the final word for NBA players and is known to undervalue defensive specialists or other players whose presence is valuable but unaccounted for in box-score statistics. There is also debate as to whether or not volume shooting is over-awarded. We believe the root of uneasiness (besides the sheer mass of the formula) to be in the leading term: $\frac{1}{MP}$. That is, all contributions are divided by a player's minutes played. It has been pointed out that this may tilt unfairly toward players with low playing time, though rankings are only provided for those with some minimum amount of minutes. As a measure of *efficiency* it is perfectly reasonable to do this. However, coaches, arguably the preeminent basketball minds, show which players are most *valuable* by playing them.

Actually measuring a player's value is a daunting task and one that is likely predicated on a debatable definition of value. Our assertion that value is both natural and intractable can be most readily seen in the NBA's annual awards. The majority of these awards, including the MVP (Most Valuable Player) award are voted on by media members. A quick internet search reveals the pundits' exhaustive debates over what value *should* mean. Is value: a player to win with now?, a player to build a franchise around?, the best player on the best team?, the player that does the most with the least? Yet somehow, when the league's MVP is announced, there are no surprises. All-star selections are made through a fan vote; *value* of popularity aside, all-star rosters are still filled with the right talent. Interestingly, the only player superlatives handed out by coaches are the all-defensive teams, to the very players for which typical advanced stats are not commendatory.

In this paper we start with simple box-score statistics and take a closer look at plus-minus. As a measure of contribution, we believe plus-minus to represent the only common NBA statistic that aligns with the most natural of assessments, *value*. However, there are several aspects that make plus-minus a difficult study:

- Unlike other advanced stats, plus-minus is not normalized, and maybe shouldn't be.
- There are external factors that intuition says may (drastically) affect plus-minus.
  - Does plus-minus reflect a player's contribution, or those of his teammates?
  - Does a talented sixth-man have an unfair advantage given that he plays against the opposing team's second unit?
  - How much does "trash time" skew plus-minus? (trash time: when the game is a rout, and any action on the court has little impact on the game's outcome)
- Even with complete understanding of these subtleties, there is no obvious way to quantify them with simple box-score data. That is, without in-depth per-minute, lineup-based game measurements.

We explore building on the fact that plus-minus somehow inherently incorporates both help and competition in its values, and look to extend to the team level. Whereas our initial direction was to view the league as a function of two teams to a win or loss, we realized plus-minus at the team level leads to a slightly different, and more easily managed paradigm. That is, a game is a function from two teams to a measure of team plus-minus ("winness"). This gives us a much better target for correlative analysis. Just as importantly, instead of analyzing and attempting to quantify exactly how plus-minus handles all the subtleties of competition, we simply leverage whatever it is with all other stats as well. Starting with box-score data, we calculate on a per game basis, the team plus-minus for all stats; all calculations and visualizations are based on different comparisons of these plus-minus statistics. For all results in this paper, NBA box-score data from the 2012-2013 season is used.

In the remainder of this paper, we investigate the state of the art in NBA and sports analytics in Section 2. In Section 3 we detail the plus-minus plot (PluMP) and give implementation details and usage

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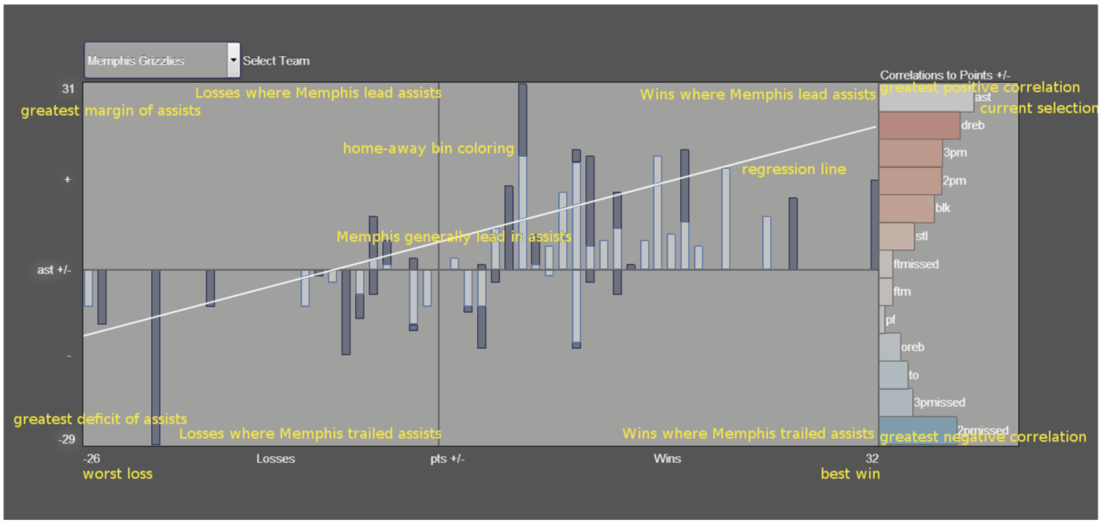



Fig. 1. An example PluMP, the assists PluMP for the Memphis Grizzlies. Various aspects of the plump are annotated in yellow.

scenarios. We then take the next logical statistical analysis steps based on our simple foundation in Section 4. We end with a discussion of results from our PluMP system and possible next steps in Section 5.

## 2 Related Works

Tufte [30] offers a historical and critical overview of charts, plots and visualization. Since sports statistics are often collected as scalar values, any of these standard plotting techniques may be suitable for use. However, it is unclear whether visualizations are leveraged to provide added benefit over a simple sortable table. In this section we will survey recent work in displaying and analyzing sports data.

### 2.1 Recent NBA Visual Analytics

We classify typical analyses of NBA data into two categories: those utilizing simple, box-score type statistics and those built around more extensive data measurements such as per-possesion data, lineup-based data, or even extensive data containing player positions, shot types, etc. NBA analytics utilizing game statistics without an inherent court geometry context tend toward displays in which communication is valued over interactive/exploratory analysis. This variety often uses traditional two-dimensional data presentations such as tables [16, 2, 14], histograms [16, 22, 17], scatter plots [10, 18, 25], bar charts [21, 5], stacked bar charts [17], line plots [9, 14, 8], and nodal graphs [1, 15, 3].

With recent developments, increased capabilities, and successes in the field of data analytics, there is motivation to collect larger amounts of more complex or complete data. A more recent strain of NBA analytics considers the physical court space. Such data has been contextualized as heat maps [17, 11, 16], player movement paths [16], 3D histograms [16], and backboard schematics [28, 27]. Their concrete spatial setting lends greater credence to their effectiveness. However, these visualizations often rely on access to proprietary data. Also, there remains a strong delineation between the analysis and display of this data. This new breed of plots, while typically very informative, maintains focus on simply finding the best way to display the data. We know of no published work directly concerned with increasing knowledge of underlying processes. As such, the future utility of using this type of visualization in estimating player value is uncertain.

There are also hybrid approaches spanning both classification categories. While still involving positionless data, it is possible to allow for three dimensional plotting, such as creating as surface plots [9]. Similar directions offer interesting possibilities, but so far available information regarding explicit validation of the utility of these methods is sparse. Finally, we see a conspicuous relative lack of certain plots common in the general statistical community, such as box plots. We see this as further evidence of separation of visualization and analysis.

### 2.2 Quantifying Team and Player Value

Analyses seeking to account for player value rather than ability have a long history in baseball analytics. Known metrics include the Total Player Rating [29], and Win Shares [13]. Another popular style of analysis revolves around direct comparisons of a specific player to the average, as in Fangraphs Wins Above Replacement [6], Baseball-Reference.com Wins Above Replacement [4], and Value Over Replacement Player [31].

Similar calculations are performed for football players. A rating for offensive unit value is Defense-adjusted Value Over Average. There are also single player value measurements, such as Defense-adjusted Yards Above Replacement [7]. Quarterbacks in particular pose both obvious benefits and complications for in-depth analysis. The NFL's Passer Rating and ESPN's QBR [19] distill large quantities of domain expertise into systems for quarterback ranking.

Hockey is credited with introducing Plus/Minus ratings, a single value indicating goals scored while a player is on ice. Shea [26] recently adapted the WAR value metric to NHL goalies with Wins Over Replacement Player [26]. The recurrence of similar cross-sport calculations imply the analysis of sports data may be more generally applicable than one's sport of choice and that guidance may be found within a number of communities.

Quantifying the value of an NBA team or player is a difficult task, but there is a foundation of work to reference. Indeed, basketball analysis has considered team value with both Offensive Rating and Defensive Rating [20]. Also, individual player value has been assessed with various types of Plus/Minus [24]; James' Win Shares have been adapted to basketball by Basketball-Reference.com; and Hollinger's player efficiency ratings [12]. Work by Oliver [20] contains a survey of various value stats.

We have found many advanced statistics to be variations of linear weighting of singular statistics that are averages or accumulations. Often, this leads to the notion of value being akin to "more is better." It is possible for this to be the optimal or even correct approach. This is particularly true for baseball offense, where a strong intuitive argument can be made that home runs are always the best kind of hit.

## 3 PluMP: The Plus-Minus Plot

Benefits of the basis of this work included an easy entry point as well as simple calculations for deriving necessary data. We found that current visualization tools lack the capacity for efficient analysis of this data. Flexibility in variable handling and display density were the key ingredients that we felt a useful tool should have. We developed the plus-minus plot (PluMP) to not only cycle through dependent variables, but to also swap out the independent variable. In addition, the derivation of season long plus-minus values from per game player cumulative stats is built into the system. This obviates the need for extensive data preprocessing before using the PluMP.

We also wanted to be able to bin home and away games and have the bins visually delineate home from away games. In effect, we are recreating both the functionality of a scatterplot and a histogram, while having to handle the fringe cases of both. Showing the relative magnitude of the season-long contribution of the various plus-minus categories was another objective, along with their respective regression lines. Finally, we wanted as much of this to live in a single interface as possible. This was probably the major impetus in deciding to implement a programming solution. Implementing with processing [23] and javascript allowed us to quickly prototype features and provided the necessary flexibility for iterating through design ideas. As a bonus, each prototype was already a web-enabled application.

### 3.1 Interface Tour

As an example of what the interface offers, consider Figure 1. This is an annotated view of the assist PluMP for the Memphis Grizzlies. First, each team and the league overall is available from a drop-down menu. The quadrant plot automatically scales to the range of the selected stat. In this case, horizontally we see that Memphis' greatest margin of victory was by 32 points, while their worst loss was by 26. Games with the same point margin are binned together, e.g., the assists for every game Memphis won by five points are binned together. The vertical range for the assists is then the highest and lowest assist totals for these bins. Note this should not be interpreted as in some particular game Memphis out-assisted an opponent by 31; but, rather there was a collection of wins of a particular margin wherein the accumulated assists came to 31. The bins are colored in proportion to home and away, which affords at a quick glance any potential home court vs. road game advantages. For consistency, away coloring within a bin is always placed further from the baseline. The coloring scheme uses either white or white with alternate home jersey color for home games and primary traveling jersey color for away games.

The plot is split into quadrants. The left hand quadrants are losses, the right, wins. Close games surround the vertical axis. The upper quadrants indicate a positive differential in the stat, the lower, a negative. For Memphis, we see immediately that in losses, they rarely led their opponents in assists, while in wins, they rarely trailed. Generally the location within the plot of where the axes cross reveals quadrant information at a glance. The horizontal location instantly conveys a team's record while the vertical location provides an overview of the team's plus-minus for a stat. For each team PluMP we also calculate a simple linear regression. This is the white line in Figure 1 and shows the trend of assists to points. The positive slope indicates a positive correlation, while the y-intercept indicates that Memphis generally led their opponents in assists. A greater slope, rising steeply from left-to-right, indicates a greater correlation between that particular statistic and wins. Conversely a steep, negative slope indicates a strong negative correlation to winning.

The right hand side of the plot contains a bar graph with the various statistics ordered from greatest positive correlation to greatest negative correlation. The relative strength is indicated in bar length and hue. Length mirrors the correlation magnitude. The colormap is a divergent blue-red scale where deeper blue indicates more negative and deep red more positive. Clicking a bar changes the PluMP to show that statistic's particular plot. Deselecting all statistics gives a game by game margin of victory plot, for an example see the Los Angeles Laker's season long plot, Figure 4(a).

## 4 Analyzing Team-Level Plus-Minus Data

In the realm of sports, where the focus of the vast majority of those involved is shared among love of the game, storied traditions, or the bottom line, a change in data collection or dissemination can have perceived negative effects on one or all of these. Therefore, the successful analysts are those who rely on a wealth of knowledge and experience when attempting to glean some of the many complex or subtle interactions among whatever data happens to be available. This is directly related to why so few advanced metrics are widely adopted; they tend toward being complex, unintuitive, and are often based on an expert's definition of what is "good."

Anything condensing the complexity of contribution into a single number is volatile at best, but such metrics find use. Using the PluMP, we are able to visually differentiate the values of box-score statistics both for a team and among teams. In the PluMP interface, we show for each box-score statistic, the direct correlation of its differential to point differential. We consider this an indication of fundamental problems with metrics of a league-wide scale. While we believe the general consensus is that the last thing the world needs is another convoluted process that ends in a single number for ranking players, we provide exactly this. Doing so allows for an easy comparison to the state of the art, but more importantly acts as a gut check for whether or not things "make sense."

### 4.1 Values of Box-Score Stats

Here we detail our method for the logical continuation of correlating box-score stats' differentials to those of points for generating a player-ranking metric. The following calculations are distinctive in that after a decision to deal in differentials, we leverage no domain knowledge. We make simplifying assumptions and logical leaps, but all are statistical/numerical, and hopefully serve to maximize simplicity. We consider this an initial exercise in differential metrics and therefore resulting only in rough heuristics.

One bar of the PluMP's right-side bar chart displays Pearson's correlation coefficient, $r$ for a single box-score stat. For this stat, say rebounding, it is a measure of whether out-rebounding an opponent is as an indicator of out-scoring that opponent. The square of a sample's correlation coefficient, $r^2$, is a quantity used in simple linear regression analysis and is known as the coefficient of determination. That is, if we calculate a simple linear regression with a set of points $y_i, x_i$ to find the line $y = \alpha + \beta x$, $r^2$ estimates the percent of $y$'s variance accounted for by the estimator $\alpha + \beta x$.

For the calculation of our metrics, we use the following stats (all as per game plus-minus): assists, blocks, defensive rebounds, free throws made, free throws missed, offensive rebounds, personal fouls, steals, three pointers made, three pointers missed, turnovers, two pointers made, two pointers missed. Each is treated as independent, and calculations are the same across all.

1. How well does an increase in stat $X$ over an opponent indicate an increase in points scored over that opponent, $Y$? Calculate the $\alpha$ and $\beta$ of the best fitting line.

2. With value $x_1 \in X$, generate the approximate points plus-minus, $\hat{y}_1$.

3. $r^2$ tells us that on average, we can expect $|\hat{y}_1 - \bar{y}| \leq r^2 \, |y - \bar{y}|$, or $|y - \hat{y}_1| \leq \left(1 - r^2\right) |y - \bar{y}|$. $\bar{y}$ is the expected value of $Y$.

4. On average, $|y - \hat{y}_1| \leq \left(1 - r^2\right) \sigma_y$, or $y$ is in the range: $\left[\hat{y}_1 - \left(1 - r^2\right)\sigma_y, \hat{y}_1 + \left(1 - r^2\right)\sigma_y\right]$. $\sigma_y$ is the standard deviation of $Y$. Note, but for $\hat{y}$, this range is of constant width, which we will denote as $2 * error$. If this entire range is negative or positive, we consider the likelihood of winning a game with a stat differential of $x_1$ to be 0 or 1, respectively.

5. Therefore, for $x_2 = x_1 + 1$, we consider the relative shift of the range for $\hat{y}_2$ to correspond to the increase/decrease in the likelihood of winning attributable to a $+1$ in the differential of that stat, or: $P(X) = \frac{\hat{y}_2 + error}{2 * error} - \frac{\hat{y}_1 + error}{2 * error}$

This quantity is more easily conceptualized if $\hat{y}_1 = 0$, then its upper bound is positive, and the lower bound is negative. This equation is then the measure of the percent of the range that changes from negative to positive. $P(X)$ is the foundation for our described metrics. We can now normalize $P(X)$ across all stats for a team by dividing by the average number of the stat a team accumulates per game. A stat with few occurrences is more statistically relevant than one of many, e.g.

Table 1. Top 30 players as ranked by increase in *chance* to win.

| | | |
|---|---|---|
| 1. Stephen Curry | 11. Nicolas Batum | 21. Marc Gasol |
| 2. Deron Williams | 12. Russell Westbrook | 22. Jrue Holiday |
| 3. Kevin Durant | 13. Monta Ellis | 23. Klay Thompson |
| 4. Goran Dragic | 14. Jameer Nelson | 24. Greivis Vasquez |
| 5. James Harden | 15. Paul Pierce | 25. Kemba Walker |
| 6. Brandon Jennings | 16. Joakim Noah | 26. Kyrie Irving |
| 7. Paul George | 17. Chris Paul | 27. Damian Lillard |
| 8. LeBron James | 18. Josh Smith | 28. Kyle Korver |
| 9. Dwight Howard | 19. Kyle Lowry | 29. Ryan Anderson |
| 10. Mike Conley | 20. Mario Chalmers | 30. Kobe Bryant |

Table 2. Comparison of ranking metrics.

| Awards | | | Average Rankings | | |
|---|---|---|---|---|---|
| Award | Recipients | Voters | ESPN | PER | WC |
| All-Star | 25 | Fans | 21.12 | 32.00 | 68.16 |
| Most Valuable Player | 1 | Media | 1 | 1 | 1 |
| Defensive Player of the Year | 1 | Media | 35 | 34 | 7 |
| Most Improved Player | 1 | Media | 27 | 87 | 8 |
| Sixth Man of the Year | 1 | Media | 53 | 67 | 19 |
| All-NBA First Team | 5 | Media | 5.20 | 4.20 | 9.40 |
| All-NBA Second Team | 5 | Media | 15.80 | 13.40 | 13.80 |
| All-NBA Third Team | 5 | Media | 14.00 | 36.00 | 20.80 |
| All-Defense First Team | 5 | Coaches | 56.33 | 56.00 | 32.83 |
| All-Defense Second Team | 5 | Coaches | 66.60 | 98.20 | 48.80 |
| | | | 27.09 | 37.89 | 43.64 |

steals vs. points. This provides direct, inherently weighted multipliers for a player's stats giving us insight as to how he contributes to his team's chance to win.

In Table 1 we display the top 30 players in the league as ranked by this measure. This list has some unsurprising results, and shares a good deal with a "name the top one or two players on each team" ranking. Indeed, 21 teams are represented in this table. This list is, however, lackluster as an actual player ranking for a few reasons: (i) these are the players contributing the stats that matter most to a team, but if a team is terrible, these may be the wrong stats; (ii) probabilities in our calculations may be outside of the range [0, 1] and it is unclear how to really interpret what an increase in probability from -10 to -9 is; (iii) the best player on a bad team is not necessarily and is unlikely to be "better" than several of the best players on the best teams. We continue to address these issues in the next section.

### 4.2 The Win-Contribution Metric

In Section 4.1 we outlined the beginning of our calculations toward developing a system for ranking players based values of statistics specific to single teams. We now extend the calculation to be weighted for illustrating not only which players are contributing valuable stats, but which are doing so when it matters most. First, and still for a single stat, we quantify "matters most."

1. Find $\hat{y}_{loss}, \hat{y}_{win}$ such that $\hat{y}_{loss} + error = 0, \hat{y}_{win} - error = 1$. These approximate point differentials represent for some box-score stat, the maximum value in which the entire range of possible differentials is still less than zero $\left(\hat{y}_{loss} = \frac{-error-\alpha}{\beta}\right)$ and the minimum values for which this range is greater than 1 $\left(\hat{y}_{win} = \frac{1+error-\alpha}{\beta}\right)$.

2. We sum a team's per game stat differential over all games played in the season (we will use 82, although Boston and Indiana only played 81) and clamp to the range $[\hat{y}_{loss} * 82, \hat{y}_{win} * 82]$. Referring to this sum as $S(X)$, we may now calculate the value of a season long differential for $X$ as $P(X) * (S(X) - \hat{y}_{loss} * 82)$. This represents the total value for that stat to the team, and can be negative.

3. To divide this among the players of the team, we simply assign each player the percentage of value for a stat exactly corresponding to his contributing percentage of the team-wide, season-long accumulation of that stat. A player's total number of blocks for the season divided by the team's total number, e.g. The win-contribution metric is the sum of all of a player's percentages of stats values.

Table 2 is the evaluation of the our wins-contribution metric. To do this, we compare player rankings among our WC metric, Hollinger's PER, and ESPN's rating. We take a diverse group of players universally accepted as the best in the league and consider a metric successful by ranking these players high. Our set of valuable players are those receiving various recognition through being voted to all-star teams, all-NBA teams, all-defensive teams, or major skill-based individual awards. There is a good deal of overlap among these categories, but we view this as further proof that the best players are chosen reliably. The table displays the number of players designated for each category, and what the average rank for each metric was for those players. Generally, we consider lower rankings to signify better metrics, but note that this is in no way indicative of what the metrics, particularly PER, were designed for; this is simply a convenient avenue for appraisal.

Upon reviewing all metrics' ratings, we can report them to be generally similar. There are ways in which the WC metric differs vastly from the other two. These differences highlight either the successes of or the issues with our metric. One discrepancy appears in the final average rankings in Table 2. Based on our own suggestion for metric measurement we stand dead last among our comparators, even to that not created for such a ranking. The higher average ranking for the WC metric comes directly from the extremely high, by comparison, average WC rank for all-stars.

For better or worse, our metric places a value on wins that suggests there is no such thing as a great player on a terrible team. We are not necessarily at odds with this philosophy but readily admit that there are not 379 players in the league more valuable than Lamarcus Aldridge, which is how the WC metric has him ranked. Of the 52 (not distinct) award winning players we used, there are exactly three on non playoff-bound teams, and have very low WC ratings: Lamarcus Aldridge, Kyrie Irving, and Jrue Holiday. It is therefore clear the WC metric is not a direct measure of value. However, these players ranked much higher with the metric used in Table 1 (Aldridge was $35^{th}$). There is certainly potential to combine these metrics, but any perceived possibilities were either completely arbitrary or against the foundation of not leveraging domain expertise; we therefore stick to investigating the WC metric as a stand alone player metric. Nonetheless, with those players treated as anomalies and removed from the calculations of averages for all three metrics: the ESPN rating increases from 27.09 to 27.77, PER decreases from 37.89 to 37.46, and WC decreases from 43.64 to 29.38.

There were other noteworthy cases of divergence among the metrics. WC's higher average for All-NBA first team was due to the ranking of Kobe Bryant at $29^{th}$ compared to ESPN's $3^{rd}$ and PER's $9^{th}$. Bryant's season ending injury was late enough to not affect his WC rating. Injuries present an area where normalization is important, as is discernible in our ranking of Rajon Rondo at $143^{rd}$ (we included him in this list since he was still voted in as an all-star). Regarding Bryant, we could point to the Lakers' low, by their standards, win percentage of .549, but Dwight Howard is ranked prominently at $12^{th}$ by WC, which was also higher than with either of the other metrics. There was also a significant disparity regarding our ranking of Brook Lopez. Last season marked his first all-star appearance as the only representative from Brooklyn, a team with plenty of wins to register a player in the top 10 in WC rankings. Yet our metrics do not have Lopez contributing the stats that matter most to Brooklyn's success (Deron Williams, Joe Johnson, Gerald Wallace, and Reggie Evans are all ranked higher).

Table 2 also suggests that the WC metric excels in the inclusion of the widest range of *types* of players into the upper ranks. This can be seen in our ranking of Paul George, recipient of the Most Improved award, but especially so for the Sixth Man of the Year, J.R. Smith. Another compelling result is that in addition to being ranked in the top 20 as a non starter, J.R. Smith was ranked only two spots higher than his primary competition for the award, Jamal Crawford.

Most importantly, the WC metric rewards defense. Our metric ranks defensive players considerably higher as is clear in all defensive categories in Table 2. Paul George's high WC ranking is likely representative of his inclusion on the All-Defensive Second Team rather than status as most improved. All-Defensive First Team member Tony Allen is widely considered a great perimeter defender and is a perfect example of the type of player that falls through the cracks when attempting to rank the players of the league. His win-contributions rank him $61^{st}$ versus $167^{th}$ and $197^{th}$ via his ESPN rating and PER, respectively. We merrily recognize the WC metric to scale well with the expertise of those deciding player superlatives.

## 5 Our Picks of Pertinent PluMPs

Now we turn our attention to how the PluMP enables us to provide a contextual narrative to certain aspects of the 2012-2013 season.

### 5.1 The Top Tier

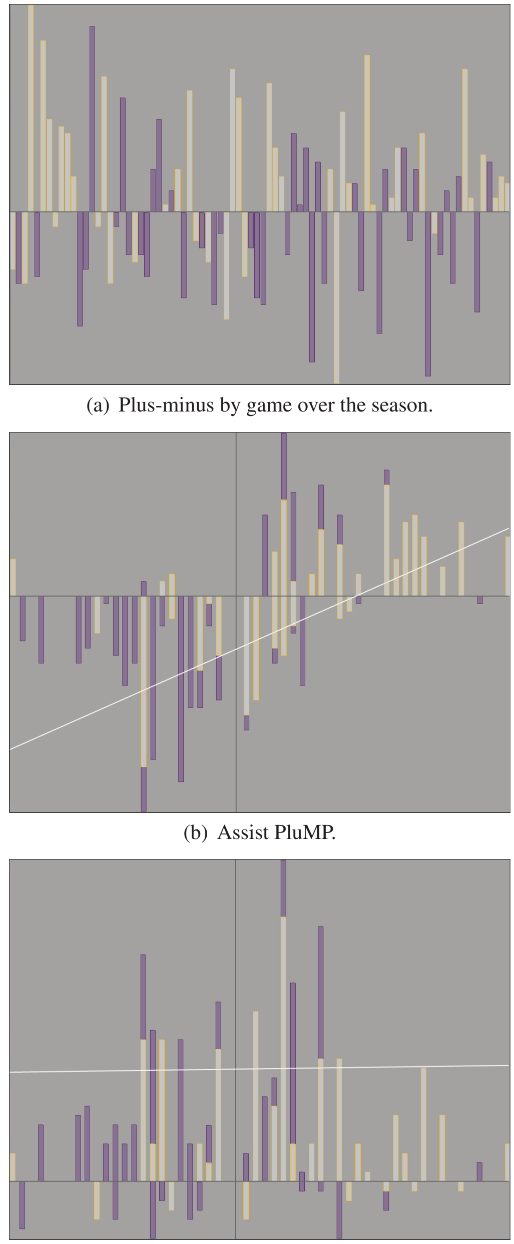
Consider the teams with the top three records in 2012-2013 in Figure 2: Miami (column one), Oklahoma City(column two), and San Antonio (column three). Their Stat Correlation to Wins bar charts are similar. This meshes with the intuition that winning teams do similar things well. In particular, each has their highest correspondence to victory associated with out-assisting their opponents. However, taking a closer look at the PluMP for assists (top row) indicates there may be a more interesting story. Both the Heat and the Thunder have graphs which indicate that if they have fewer assists than their opponents, they are very likely to lose and conversely, if they have more, they are likely to win.

This relation is less true for San Antonio. Assists are still the statistic with the highest correspondence to winning for the Spurs and they generally have more assists than their opponents, as indicated by the positive y-intercept of the regression line. Yet, assists are less indicative of a Spurs victory, as can be seen by the greater number of losses with plus-assists *and* wins with minus-assists. This suggests San Antonio is less dependent on their ball handlers and assist producers for victory. Notice also that for close wins or losses, i.e., the area close to the vertical division, San Antonio has more bins. This might signify that while a positive assist differential corresponds to a Spurs victory, it is not a death knell for the opponent. This opponent is likely better served by shifting focus from clamping down on assists in close games. San Antonio's blowout wins with large amounts of assists might be skewing the correspondence positively. A future analysis might focus on tighter margins of victory.

Another interesting line of investigation starts by comparing the three-pointers-made PluMPs (middle row of Figure 2). This statistic is second in correspondence to winning for Miami, fourth for Oklahoma City and third for San Antonio. Again observe that the Heat and Thunder have very few losses with a positive three pointer differential, while San Antonio, similarly to with assists, has played in more losses and had more close games where three pointers do not appear to play a decisive role over the course of the season. These charts could indicate that close games have a more random outcome for San Antonio and suggest that the end of game six of the 2012-2013 NBA Finals, while amazing, was not anomalous. These highlight one of the primary uses we see for PluMP, as a simple starting place for complex analyses.

### 5.2 Defense

One thing the top tier teams have in common is that they are among the most efficient teams in terms of both offense and defense. As a possible point of contrast, we look at two teams: the team with the highest offensive efficiency not in the top ten in defensive efficiency, the New York Knicks, and the team with the highest, and league leading, defensive efficiency not also among the best in offensive efficiency, the Indiana Pacers. Indeed, there are differences among the Correlation



(a) Plus-minus by game over the season.

(b) Assist PluMP.

(c) Free-throws-missed PluMP.

Fig. 4. PluMPs for pondering Lakers.

plots of these five teams, chiefly the prominent placement of defensive rebounds for both New York and Indiana in their correlation plots (Columns one and two of Figure 3).

Look to the same Figure to compare the defensive rebound PluMPs between the Knicks and Pacers. In Pacer wins, they almost never trail in defensive rebounds, while this does not hold for the Knicks. That jibes with the perception of these teams being defensively and offensively minded, respectively and also with the empirical output of the efficiency ratings. So far, this has not led to any new insights. Now, though, consider Charlotte, one of worst teams in the league in 2012-2013, and last in defensive efficiency. Interestingly, Charlotte's defensive rebound PluMP is almost exactly point symmetric to Indiana's. This might indicate that being out defensive rebounded was one of the major elements to Charlotte's woes. If this is the case, the strong positive correlation for the Knicks' defensive rebounding may actually be highlighting the stat in need of the most improvement.

None of this, though, helps explain how the Knicks are able to over-

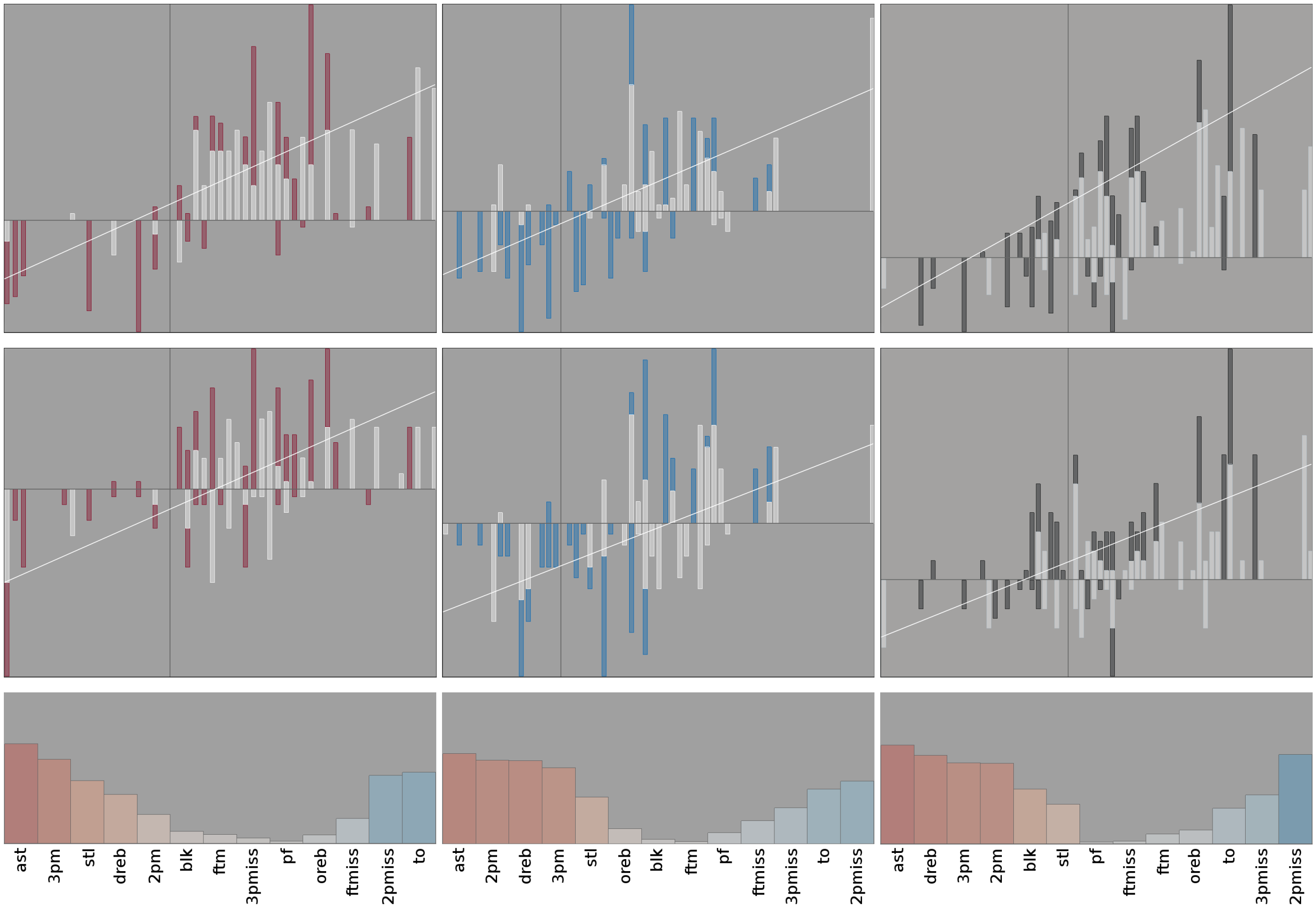



Fig. 2. A comparison of the top three teams in the league: or Heat PluMPs, Thunder PluMPs, and Spurs PluMPs. The first column is Miami's assists PluMP (top), three-pointers-made PluMP (middle), and Stat Correlations to Wins chart (bottom). Similar for OKC (second column) and San Antonio (last column).

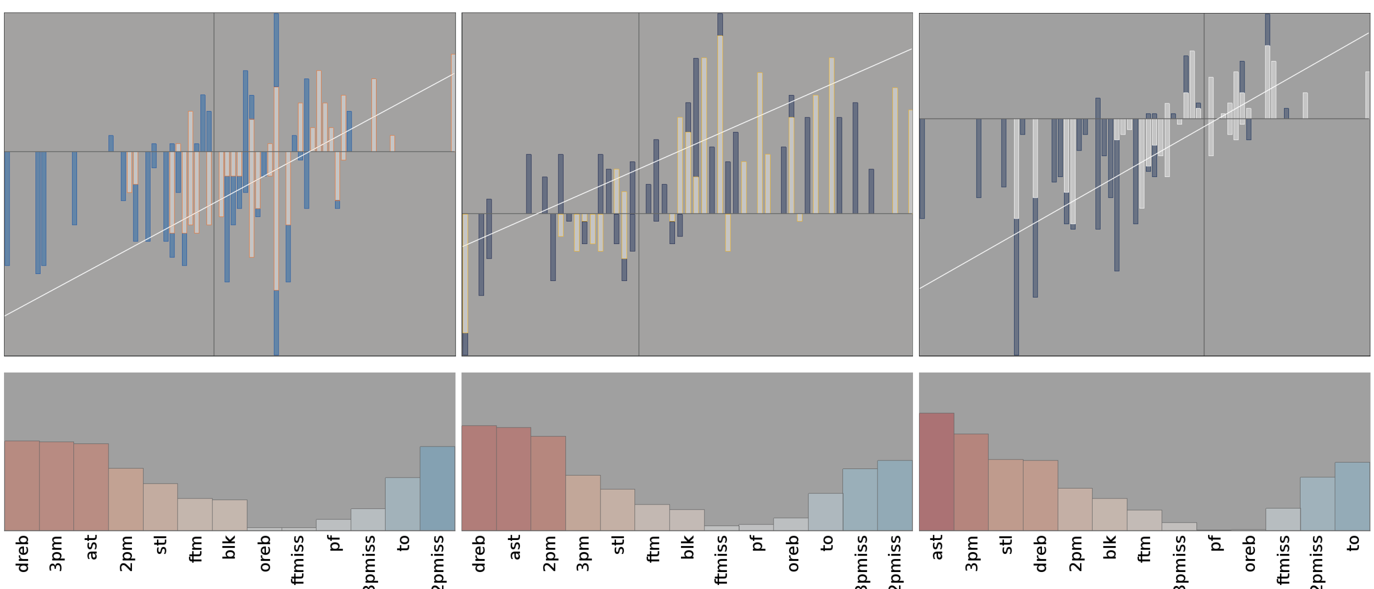



Fig. 3. New York's defensive rebounding PluMP and Correlations Plot in column one followed by Indiana's in column two and Charlotte's in column three.

come a negative differential in this stat. Our guess is that the Knicks are a so much so a "live by the three, die by the three" team that they were often able to overcome their defensive rebounding deficiencies.

### 5.3 The Lakers

The Lakers had a tumultuous season. There was a constant undercurrent of doubt as to their chances to even make it into the post season, which they just did. However, an already difficult first round series became insurmountable with the late season loss of Kobe Bryant to injury. Figure 4(a) shows the default overview PluMP for the Lakers, typical plus-minus for each game over time (x-axis). It is within this plot we can recall the 1-4 start leading to the first coaching change and see the solid play leading into the second coaching change. We can then witness it all punctuated by the random win-loss pattern in the plot that signifies the total lack of team cohesion in the up-and-down remainder of the season. The regression line is removed for overview plots, but were it there, it would show a negative correlation between point differential and time.

The Lakers' preparation 2012-2013 included the headline-grabbing acquisitions of Dwight Howard and Steve Nash during the offseason. While the headlines never stopped, enthusiasm and positivity eventually did. Luckily for us, there were memorable news worthy events related to box-score stats that we can now relive via PluMPs. First was the emergence of Kobe Bryant: point guard. Partway through the season, Bryant took over as facilitator to attempt to single-handedly get his team involved and back to their winning ways. The correlation line in the Lakers' assists PluMP. Figure 4(b), suggests he was right to this. However, the quite negative y-intercept shows the long term execution of this plan was lacking. Furthermore, the home/away coloring suggests that being down on the road is a guarantee of the return of "hero ball."

Another development in the Laker's season was the ability, and willingness for opposing teams to employ the Hurt-a-Howard technique of banking on missed free throws from Dwight Howard as a means to a win. Much was made of this strategy, as well as Howard's apparent poor response to it. Amidst continued headlines and even public pressure from teammates Howard continued to miss his free throws. Figure 4 is the Lakers missed-free-throw PluMP. This shows that the Lakers were overwhelmingly out-matched at the charity stripe all season, and that there was literally no correlation between this and their record.

## 6 Conclusion and Future Work

In this paper we presented two novel devices for analyzing NBA box-score data. Both are based on our simple generalization of the plus-minus statistic. Specifically, we extend plus-minus to the team level and consider differentials of all box-score stats rather than points alone. The two contributions of this work directly followed: (i) a specialized tool for visualizing the plus-minus of team statistics (PluMP), and (ii) a new metric for evaluating the win-contribution of a player based on statistics most relevant at the team level (WC). We believe the WC metric is an interesting first step in evaluating players whose presences are believed to be underrepresented in box-score data, and the PluMP to be a valuable tool for simple analyses/team comparisons. However, we do intend to investigate improving the PluMP, particularly how single plots are scaled, toward providing a tool more applicable for in-depth comparisons among teams.

This work presents several potential directions for future efforts. A natural first step is to analyze dependencies among box-score statistics. Accounting for dependencies would increase the mathematical robustness of our techniques and could lead to better results. Additionally, we believe the core concepts in this paper to be directly applicable to other sports and we have interest in exploring this. Finally, we would like to extend our analysis of NBA data to incorporate more complicated data. For instance, by tracking statistics for distinct sets of five-man units we can adjust calculations to better represent a player's true contribution.

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