# Predicting performance at the group-phase and knockout-phase of the 2015 Rugby World Cup.

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## Abstract

*Objectives:* The primary aim of this paper was to produce a model that predicts outcome in the group-phase of the 2015 Rugby World Cup and to determine the relevance and importance of performance indicators (PIs) that are significant in predicting outcome. A secondary aim investigated whether this model accurately predicted match outcome in the knockout-phase of the competition. *Methods:* Data was the PIs from the 40 group-phase games of the 2015 RWC. Given the binary outcome (win/lose), a random forest classification model was built using the data sets. The outcome of the knockout-phase was predicted using this model and accuracy of prediction of the model from the group-phase. *Results:* The model indicated that thirteen PIs were significant to predicting match outcome in the group-phase and provided accurate prediction of match outcome in the knockout-phase. These PIs were tackle-ratio, clean breaks, average carry, lineouts won, penalties conceded, missed tackles, lineouts won in the opposition 22, defenders beaten, metres carried, kicks from hand, lineout success, penalties in opposition 22m and scrums won. For the group-phase matches tackle ratio, clean breaks and average carry were accurate standalone predictors of match outcome and respectively predicted 75%, 70% and 73% of match outcomes. The model based on the group-phase predicted correctly 7 from

8 (87.5%) knockout-phase matches. In the knockout-phase clean breaks predicted 7 from 8 outcomes, whilst tackle ratio and average carry predicted 6 from 8 outcomes.

Keywords: Rugby World Cup, random forest, performance indicators, LIME.

## Introduction

The Rugby Union World Cup (RWC) is a quadrennial tournament with forty group-phase and eight knockout-phase matches. Factors influencing success in rugby union, as in other sports, are evaluated and quantified through performance indicators[1] (PIs). It is essential to understand the relationship between success and PIs as this information can be used to improve performance[2] with the most meaningful PIs differentiating successful and unsuccessful outcomes[1]. Previous rugby union investigations attempting to determine the PIs associated with success at a RWC have had varied conclusions[3–7]. Kicking from hand was a successful tactic at the 2011[3,6] and 2015[5] RWC. A team's average number of kicks predicted success in the 2011[6] competition knockout stages, whilst at the 2015 knockout stages winners kicked the ball more between the halfway and opposition 22 m line[5]. Scrutinising the details of kicking strategy during the group and knockout-phases of the 2011 RWC suggests scrum halves of winning teams kicked the ball more frequently and over a greater distance than those of losing teams[3]. Positional attacking and defensive qualities[3] were also related to success at the 2011 RWC in both the group and knockout-phases. Specifically, successful teams had scrum halves, front rows and inside backs that were more effective at the tackle area, but outside backs that missed more tackles attempts. The same study revealed that in attack, the outside and inside backs of winning teams were better ball carriers and the second and front rows of winning teams completed more offloads[3]. This study also demonstrated the second rows of winning teams made more line breaks, while those of losing teams made more pick and drives[3]. Research examining the knockout stages alone revealed that winning teams stole a greater percentage of opponents' throws[5]. In the knockout stages penalty statistics also varied; although there were no differences in the number of penalties winners and losers conceded in 2011, winners conceded a larger percentage of penalties between halfway and the opponent's 22 m line[6].

The nature of the RWC means that in the group-phase higher ranked teams face lower ranked teams, whereas in the knockout-phase teams are more evenly matched. This could lead to changes in strategy between the group and knockout-phases and hence differences in how PIs relate to outcomes. In rugby union, match-type and level of competition have previously been demonstrated as circumstantial variables when differentiating outcome. Indeed, the PIs that identified winning teams in closely contested Super 12 matches did not relate to match outcome in closely contested international matches[8]. This is corroborated by research on the 2007 RWC that demonstrated the number of rucks teams won in the group-phases of the competition was positively related to outcome, but in the knockout-phases the association was negative[7]. However, van Rooyen et al.[7] examined only a single PI and no research has examined how multiple PIs relate to success during the group-phases of the RWC and whether these PIs can also explain success in the knockout-phases.

In rugby, outcome depends on the ability and performance of both teams. Therefore, when considering associations between PIs and outcome, equal emphasis should be placed on data from each team[2], with failure to do so likely distorting any relationships present[1]. Processing PIs as a differential between opponents is known as descriptive conversion[9] with this procedure providing a better evaluation of a contest's outcome[9,10]. Descriptive conversion has been shown to alter the meaning and conclusions drawn from data in rugby union[10] previously.

This study has two aims. First, to produce a model that predicts performance in the group-phase of the 2015 RWC and determine the importance and relevance of PIs that are significant in predicting match outcome. Second, to determine how effectively the group-phase model applies to the knockout-phases.

## Methods

PIs from the 2015 Rugby World Cup were downloaded from the OPTA website (optaprorugby.com). The data consisted of 40 group-phase and 8 knockout-phase matches. All team PIs (n = 26) were utilised in the analysis; these PIs and their definitions are listed in Table 1. This project has been approved by the College of Engineering Research Ethics Committee, Swansea University (approval number: 2019-047).

For each match, descriptive conversion was undertaken by calculating the differences between teams for each PI investegated[10].

Collinearity was assessed as per Bennett et al[10], with collinearity being noted between defenders beaten and tackles missed. A separate analysis was run with tackles missed eliminated[11]; results indicated that collinearity had no effect on either predictive ability or causal inferences from the model. Indeed, multicollinearity has no effect on extrapolation of a fitted model to a new data set, provided predictor variables follow the same pattern of multicollinearity[12]. Taking this into account, the analysis was run with the full set of PIs.

*Insert Table 1 around here*

The 26 descriptively converted PIs were used as predictors for match outcome. To interpret relationships between PIs and match outcome a random forest classification model was developed, using data from the group-phase matches with randomForest[13] in the R[14] caret[15] package. This ensured viable utilisation of the model with the LIME (Local Interpretable Model-Agnostic Explanation) package[16,17] later in the analysis. Classification models predict categorical outcomes from predictor variables[18]. The RandomForest package uses ensembles of decision-making trees to classify data[19]. Decision trees repeatedly repartition data, with binary splits, to maximise subset homogeneity, and estimate the class or distribution of a response[20]. The aggregate tree approach of a random forest algorithm has improved performance compared to a single tree[19]. Random forests utilise bootstrapped data samples and random subsampling of predictors in each tree to improve prediction accuracy and prevent overfitting[19]. The mean decrease of accuracy (MDA)[19] was utilised to assess PI importance towards classification of match outcome in the group-phase. A negative MDA represents a decrease in importance, not the presence of inverse relationships[21]. The significance level ($p < 0.05$) of the MDA of each PI was calculated, using the rfPermute package[22], which permuted the response variable and produced a null distribution for each predictor MDA and a p-value of observed. Predictive accuracy of the model was recorded (overall accuracy of prediction and balance). The predictive ability of the model's performance on the knockout-phase matches was assessed with the F-measure. The F-measure produces a single numerical value to assess predictive performance using precision and recall[23,24]. Precision is defined as the proportion of predicted positives that are truly positive and recall as the number of true positives divided by the total number of true positives and false negatives[23]. A maximal F-measure of performance would be 1, a minimum 0[24]. For each PI found significant in predicting match outcome, a standalone value for its ability to predict match outcome was calculated, which was the percentage of matches won when that particular PI had a more advantageous relative value.

The model that predicted match outcome for group-phase matches was utilised alongside the LIME package[16] to predict and explain outcomes of matches from the knockout-phase using descriptively converted PIs. LIME is a novel technique that explains the predictions of classifiers in an understandable manner by learning an interpretable model locally around the prediction[25]. The basis of the explanation is that globally complex models are approximated well at a local-level through linear models[25], with 'explanation' meaning the presentation of textual or visual artifacts that enables qualitative understanding between the instance's components and the prediction the model has made[25]. To explain a prediction, LIME permutes the data-set to create replicated data with slight modifications. It then calculates similarity distance measures between this new information and the original. Outcomes for these data-sets are then computed with the original machine-learning model and features that best describe the model are selected. A simple local model is fitted to the permuted data sets, weighting each by its similarity to the original. The feature weights are extracted from the simple model and used to describe the prediction in question[17]. LIME predictions provide greater than 90% recall on classifiers and the explanations provided are accurate to the original model[25]. The explanations were presented as separate plots for each knockout-phase match classification (Figure 1). The plots examined 13 PIs (all significant PIs included in the explanations; Table 1) and their weighting towards match outcome. The X-axis represents the LIME algorithm's weighting of the PI as it related to match outcome. The greater the value assigned to the weighting the greater the influence the model suggests that the PI had on match outcome[25]. Negative values represent PIs that contradicted a winning outcome, whereas positive values represent PIs that supported a winning outcome. The prediction of the model can be confirmed by the summation of the feature weightings, in this study a positive sum meaning a winning outcome, negative a losing outcome[25].

**Results**

Using the group-phase data, the model was trained to an accuracy of 100% (95% CI 95-100%, $p<0.05$). From the knockout-phase, this model then correctly predicted 7 from 8 winning data sets and 7 from 8 losing data sets for an overall accuracy of 87.5% (95% CI 62-98%, $p<0.05$). The F-measure for the knockout-phase was 0.88. The magnitude of the MDA values for the 26 predictors ranged from 23.90 to -3.14 (Table 2) and the model determined that 13 predictors had distributions that varied significantly from the null ($p<0.05$). The ability of significant PIs to predict group-phase match outcome as a standalone predictor also varied across the PIs (Table 2).

Plots representing LIME's explanation of each knockout-phase match are presented in Figure 1; negative values are red and positive are green. The explainer graphs are plotted from the winning team's relative data. Therefore an overriding green colour means that the actual outcome agrees with the LIME explanation, a dominant red colouring means a disagreement between the actual match outcome and the LIME explanation. LIME correctly predicted seven from eight outcomes, the incorrect prediction being the match between Australia and Argentina (Figure 1, Plot F).

*Insert Table 2 around here*

**Discussion**

The primary aim of this study was to produce a model that predicted match outcome in the group-phase of the 2015 RWC and determine the importance and relevance of PIs deemed significant in predicting match outcome. The secondary aim was to investigate whether the model that predicts success in the group-phase of the competition could be successfully applied to the knockout-phase. The model produced from the group-phase matches predicted the outcomes with 100% accuracy. Identifying 13 PIs that predicted outcome far exceeds the number observed in the previous literature[3–7]. The potential reasons for this disparity are twofold and relate to the structure of the data used and the analytical method. First, previous research examining multiple PIs at RWCs[3–6] have not utilised descriptively converted data, meaning distortions in any relationships present[1] and inaccurate reflections of the sport's nature [9]. Indeed, descriptively converted data produces a more accurate model of match outcome and identifies a greater number of significant predictors in comparison to isolated data in rugby union[10]. Second, the analytical method has likely influenced findings, previous methodologies have used parametric statistical methods[3–6], but the complexity of the data and the possible non-linearity of relationships means these methods are sub-optimal[26]. This is further reinforced by rugby union's dynamic and chaotic nature[27]. The MDA values for "clean breaks" and "percentage tackles made" are very similar in magnitude. Taking into account the stochastic nature of a random forest[26], it would not be advisable to conclude which of these PIs has the greater importance in predicting match outcome, only that each was highly relevant in ensuring model accuracy in predicting match result. The importance of PIs that describe open field play is clear; the top three PIs predicting outcome describe the ability to prevent the opposition making metres in contact or the ability to beat opposition players. This supports previous findings where descriptively converted data has been used to describe match outcome[10]. The importance of the tackle area and the ability of a team to beat opposing defenders is verified by the fact that in 24 out of 25 (of a possible 40) group-phase matches where a team had both a more advantageous tackle ratio and a greater number of clean-breaks relative to the opposition, the match outcome was a win. It is unsurprising that in collision sports the team dominating the tackle and breaking opposition tackles are most likely to win matches. The number of scrums a team wins, number of lineouts won, field position of lineouts won (i.e. in the opposition 22) and percentage lineout success were all positively related to match outcome at the group-phase of the competition. The ability of a team to successfully win their own lineout ball has previously been shown to be a factor in knockout-phases of a RWC[5] though not in group-phases. This research confirms the importance of winning lineout ball but the MDA values indicate that set-piece ability is not as important as general open-field play in deciding match outcome. Villarejo[3] has previously demonstrated that tight five forwards of successful teams were superior in open-field play at the 2011 RWC. The research presented in the current paper was not able to ascertain whether superior open-field abilities of winning teams were a result of differences across the team or consist wholly of positional differences. The results of this paper indicate that in the group-phase, penalty count and location of conceded penalties are contributors to match outcome. Similarly in the knockout-phase of the 2011 RWC, winning teams conceded more penalties between the opposition 22 m and half-way lines[6]. Although this PI was not available for investigation in the current study, winning teams did win more penalties in the opposition 22. Further work is needed to investigate whether penalties won in the opposition's 22 reflect point scoring opportunities (kicks for goal) or whether, alongside lineouts in this area of the field, they provide insight into areas of the field successful teams have field position and possession.

*Insert Figure 1 around here*

The model produced on the group-phase has predicted, with a high degree of accuracy (87.5%), outcomes in the knockout-phase with only a single match being predicted incorrectly (Figure 1F). The LIME explainer plots allow examination of individual match to understand reasons behind each classification (Figure 1). The explainer plots in Figure 1 confirm the importance of open-field skills in the prediction of match outcome in the knockout-phase stages of the competition as well as the group-phase. Clean breaks predict 7 from 8 winning outcomes, with tackle ratio, average carry and number of kicks predicting 6 from 8 winning outcomes. Eventual champions New Zealand (Figure 1 B, E and H) were superior in every aspect of open field play in all knockout-phase matches. Figure 1F describes the semi-final contest between Australia and Argentina, the single match predicted incorrectly. LIME assessed the probability of a positive outcome for Australia at 46% and Argentina 54%. The explainer plots demonstrate that Australia had the greater number (+6 kicks) of kicks from hand. Prior research indicates kick number to be a strong predictor of match outcome in the RWC[5,6]. A kick value of +6 has also been found a strong indictor of match success in English Premiership rugby leading to the suggestion that kicking possession away is a successful tactic to gain field position and provide space for attack[10], and also to relieve pressure situations when penalties or turnovers become likely. The original model in the current study was built with group-phase data where the ability of teams is often not evenly matched and superior teams can play from weak positions without the need to kick, devaluing the importance of kicking in comparison to evenly matched competitions. It is therefore possible that the kicking of Australia produced success in this match and this was not weighted heavily enough in the model given that the group-phase data were used to develop/train the model. The order of the PIs in the graphs remains relatively consistent (Figure 1). The five PIs, which are most important in the group-phase, are always the most important in explaining knockout-phase matches, confirming the homogeneity of the PIs that are required for success in each stage of the tournament. It allows conjecture that the same abilities separate teams in close knockout-phase matches as separate those in unevenly contested group-phase matches, and that relative quantitative differences in these PIs are the differentiator rather than a change in PI.

This research compares the importance of multiple PIs across the group-phase and knockout-phase of a RWC, the first time this type of comparison has occurred. It demonstrates the importance of basic open play abilities in the competition and suggests they are just as relevant in the knockout-phase as in the group stages, indeed the winners of the competition are superior in every aspect of open play in the knockout-phase of the competition.

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Table 1. Isolated and descriptively converted PIs from a single game (South Africa V Argentina)

| | Isolated | | Descriptive conversion | |
|---|---|---|---|---|
| Team | South Africa | Argentina | South Africa | Argentina |
| Round | Knock out | Knock out | Knock out | Knock out |
| Outcome | Win | Lose | Win | Lose |
| Carries made | 96 | 184 | -88 | 88 |
| Metres made | 367 | 560 | -193 | 193 |
| Average carry | 3.82 | 3.04 | 0.78 | -0.78 |
| DefenderBeaten | 17 | 32 | -15 | 15 |
| Offloads | 6 | 15 | -9 | 9 |
| Passes | 134 | 245 | -111 | 111 |
| Tackles | 195 | 106 | 89 | -89 |
| Tackles missed | 32 | 17 | 15 | -15 |
| Ratio tackles made to tackles missed | 0.164 | 0.160 | 0.004 | -0.004 |
| Turnovers | 14 | 21 | -7 | 7 |
| Kicks from hand | 29 | 18 | 11 | -11 |
| Clean breaks | 8 | 7 | 1 | -1 |
| LO throws won on own ball | 15 | 13 | 2 | -2 |
| LO throws lost on own ball | 1 | 0 | 1 | -1 |
| LO Opp 22 | 3 | 1 | 2 | -2 |
| Percentage line out success | 93.8% | 100.0% | -6.3% | 6.3% |
| Scrums Won | 4 | 5 | -1 | 1 |
| Scrums Lost | 0 | 1 | -1 | 1 |
| Percentage scrums won | 100% | 83.3% | 16.7% | -16.7% |
| Rucks won | 67 | 141 | -74 | 74 |
| Rucks lost | 3 | 6 | -3 | 3 |
| Penalties conceded | 11 | 15 | -4 | 4 |
| Free kicks conceded | 1 | 0 | 1 | -1 |
| Scrums won opposition 22 | 0 | 1 | -1 | 1 |
| Penalties in opposition 22 | 2 | 2 | 0 | 0 |
| Yellow cards | 0 | 1 | -1 | 1 |

Table 2. Performance indicators (PIs) downloaded from OPTA website including operational definitions.

| Performance indicator | Definition |
|---|---|
| Carries made | A player touching the ball is deemed to make a carry if they have made an obvious attempt to engage the opposition |
| Offloads | The ball carrier passed the ball in the process of being tackled |
| Clean breaks | The ball carrier breaks the first line of defence. |
| Defenders beaten | A ball carrier has made a defending player miss a tackle through evasive running, physical dominance or with a chip kick |
| Metres made | Total metres carried past the gain line |
| Tackles | A player has halted the progress or dispossess an opponent in possession of the ball |
| Tackles missed | A player has failed to affect tackle when they were in a reasonable position to make the tackle |
| Ratio tackles made to tackles missed | Tackles missed divided by tackles |
| Turnovers | A player has made an error which leads to the opposition gaining possession of the ball, either in open play or in the form of a scrum/lineout |
| LO throws won on own ball | Own line out throws won |
| LO throws lost on own ball | Own line out throws lost either from opposition stealing the ball or from an offence at the lineout |
| LO throws won opposition 22 | Number of LO won on own throw in when in opposition 22 |
| Percentage line out success | LO won on own ball divided by total line out throws awarded to a team |
| Scrums won | Scrums won on own put in |
| Scrums lost | Scrums lost on own put in |
| Scrumss won opposition 22 | Number of scrum won on own put in in when in opposition 22 |
| Percentage scrums won | Scrums won on own put in divided by total scrums awarded to a team |
| Penalties in opposition 22 | Total penalties a team is awarded in the oppositions 22 |
| Penalties conceded | Penalties conceded by a team |
| Free kicks conceded | Free kicks conceded |
| Kicks from hand | Kicks made when the ball is in hand, excluding penalties and free kicks. |
| Average carry | Total metres carried past gain line divided by carries made |
| Passes | The ball carrier performs a pass |
| Rucks won | Rucks won when in possession |
| Rucks lost | Rucks lost in possession |
| Yellow cards | The team has had a player sin binned for a penalty offence |

Table 3. Mean decrease in accuracy (MDA) for the Random Forest model based on the group-phase data (* denotes significance p<0.05). Accuracy IP reflects the accuracy of the performance indicator (PI) as a standalone predictor of match outcome in the group-phase, calculated only for significant PIs.

| Performance indicator | MDA | Accuracy IP |
|---|---|---|
| Tackle ratio | 23.90 * | 75% |
| Clean breaks | 23.25 * | 70% |
| Average carry | 18.57 * | 73% |
| LO won | 18.42 * | 64% |
| Penalties conceded | 17.40 * | 67% |
| Missed tackles | 16.58 * | 70% |
| LO won opp 22 | 15.08 * | 65% |
| Defenders beaten | 15.07 * | 70% |
| Metres made | 12.45 * | 67% |
| Kicks from hand | 10.91 * | 54% |
| LO succcess | 10.02 * | 59% |
| Penalties in opp 22 | 8.07 * | 60% |
| Scrums won | 6.12 * | 60% |
| Pass | 5.29 | NA |
| Turnovers | 4.29 | NA |
| LO lost | 3.70 | NA |
| Carries | 3.40 | NA |
| Scrum Success | 2.87 | NA |
| Tackles | 1.59 | NA |
| Rucks won | 1.48 | NA |
| Rucks lost | 1.48 | NA |
| Scrums won opp 22 | 0.89 | NA |
| Offloads | 0.14 | NA |
| Scrums lost | -1.10 | NA |
| Yellow cards | -2.61 | NA |
| Free kicks | -3.14 | NA |

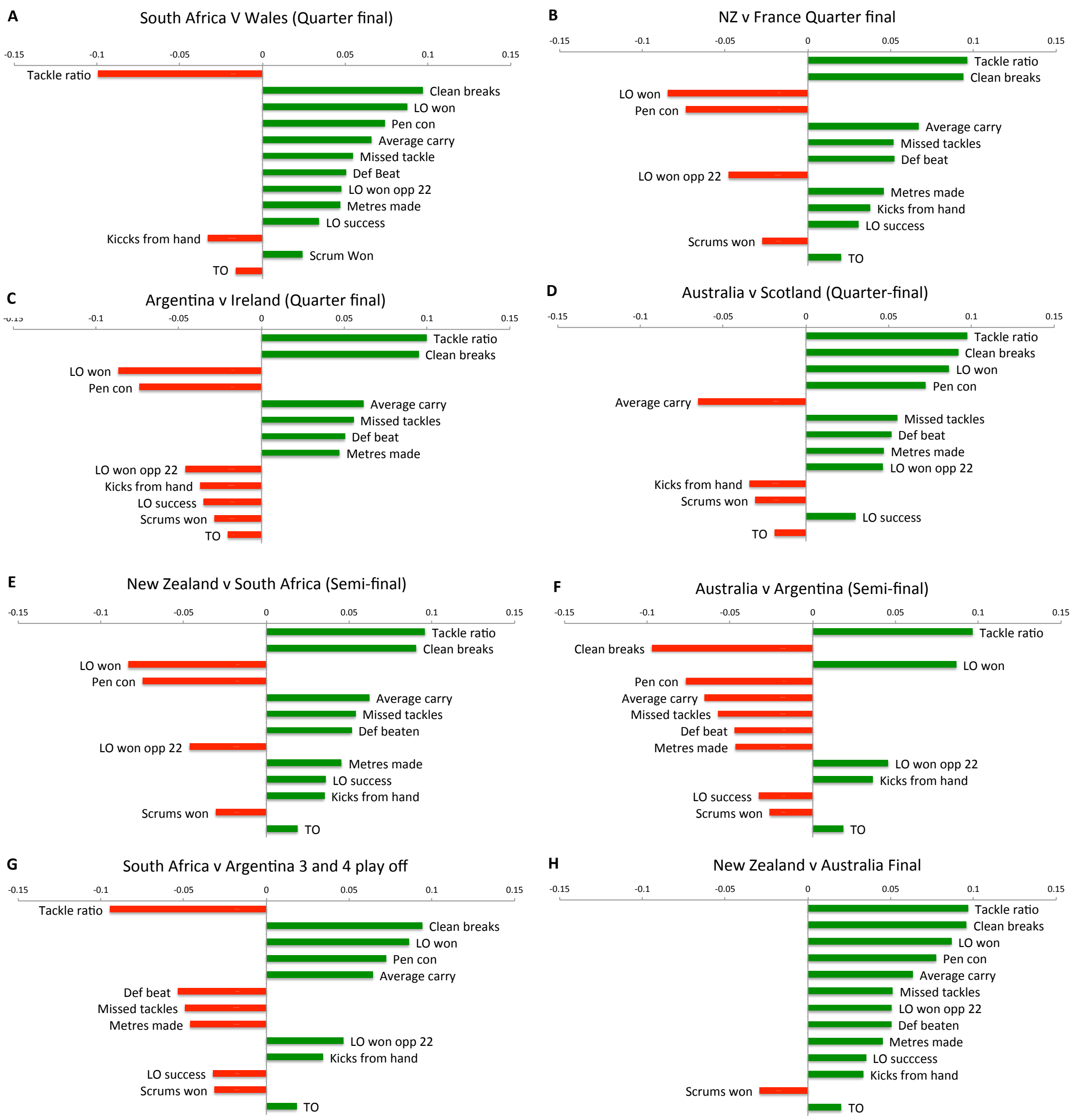


Figure 1. Graphical representation of the LIME algorithm's local explanation for the outcome of each knockout-phase match