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

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This project has been approved by the College of Engineering Research Ethics Committee, Swansea University (approval number: 2019-047).

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). Understanding the relationship between PIs and outcome is of pragmatic use to coaches and support staff in sport, providing valuable information that influences tactics and training[2]. The most meaningful PIs differentiating successful and unsuccessful outcomes[1]. Previous rugby union investigations attempting to determine the team PIs associated with success at a RWC are both scarce and have had varied conclusions[3–6]. Kicking from hand has been shown to be a successful tactic at both the 2011[5] and 2015[4] RWC. A team's average number of kicks predicted success in the 2011[5] competition knockout stages, whilst at the 2015 knockout stages winners kicked the ball more between the halfway and opposition 22 m line[4]. Set piece has been shown to be a predictor of match outcome at the knockout stages of the world cup with winning teams stealing a greater percentage of opponents' lineout throws[4]. Previous research has also demonstrated that, in the 2011 knockout stages, team discipline was a predictor of success; although there were no differences in the number of penalties conceded between winners and losers in 2011, winners conceded a larger percentage of penalties between halfway and the opponent's 22 m line[5].

In international rugby terms a unique feature 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 been previously 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[7]. 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[6]. However, van Rooyen et al.[6] 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[8] with this procedure providing a better evaluation of a contest's outcome[8,9]. Descriptive conversion has been shown to alter the meaning and conclusions drawn from data in rugby union[9] previously.

This study has two aims. First 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. This information is of practical use to coaching staff and teams, it informs them with regard to the areas where teams need to focus their tactical and technical training leading into a Rugby World Cup, previous research has demonstrated that in rugby union the PIs that predict match outcome retain stability between seasons[10,11]. The second aim is to determine how effectively the group-phase model applies to the knockout-phases, the pragmatic use of this data lies in its use to understand the need to (or not) change training and tactical focus in the transition period between the group and knockout phases of the competition, it seems from previous research there is a requirement to have varying tactics that are dependent upon both the competition[7] and the stage of the competition[6]. A unique focus of this research is that it will investigate the competition using descriptively converted datasets, rather than isolated datasets as used in previous research[3–6]. Descriptively converted datasets have previously been shown to provide more accurate and relevant information when predicting match outcomes in rugby union[10].

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[12], all PIs were employed in the analysis to ensure bias was avoided. There is currently no reliability data for OPTA rugby union analysis, however very good levels of reliability have been reported in OPTA analysis relating to professional soccer[13]. The rugby data is considered both accurate and representative of the game and is used as a source of information by a number of elite teams including the New Zealand Rugby Union, the Australian Rugby Union and the English Rugby Union[14]. For each match, descriptive conversion was undertaken by calculating the differences between teams for each PI investegated[9]. An example of a data set from OPTA and the descriptively converted values can be found in Table 1.

Insert Table 1 around here

Collinearity between predictors was investigated with the rfUtlities package[15] in R[16], utilising qr-matrix decomposition (threshold=0.05[17]). Collinearity was noted between defenders beaten and tackles missed. To further investigate this collinearity three separate analyses were run. For the first analysis the data set remained whole, i.e. with both collinear variables in situ. Two further analyses were undertaken each with a single collinear PI removed, that is in one analysis defenders beaten was removed and second with tackles missed removed. The results indicated that the collinearity had no effect on the predictive ability or the order of importance of the casual inferences of the random forest. There were small changes in the MDA values of predictors A focus of this research was to provide pragmatic, useful information for coaches and sports practitioners. Removal of either of these predictors would be tantamount to making the decision that it has no relevance to match outcome, the individuals utilising the data should make this decision. With this in mind, alongside the fact that removal of either collinear variable had no effect on prediction accuracy or the order of MDA values MDA of other variables, the decision was taken to continue with the initial, whole data for analysis.

Insert Table 2 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[20] in the R[16] caret[21] package. This ensured viable utilisation of the model with the LIME (Local Interpretable Model-Agnostic Explanation) package[22,23] later in the analysis. Classification models predict categorical outcomes from predictor variables[24]. The RandomForest package uses ensembles of decision-making trees to classify data[25]. Decision trees repeatedly repartition data, with binary splits, to maximise subset homogeneity, and estimate the class or distribution of a response[26]. The aggregate tree approach of a random forest algorithm has improved performance compared to a single tree[25]. Random forests utilise bootstrapped data samples and random subsampling of predictors in each tree to improve prediction accuracy and prevent overfitting[25]. The mean decrease of accuracy (MDA)[25] 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[27]. The significance level ($p < 0.05$) of the MDA of each PI was calculated, using the rfPermute package[28], which permuted the response variable and produced a null distribution for each predictor MDA and a p-value of observed. The classification accuracy was recorded as a percentage of the outcomes classified correctly, the sensitivity (in this case the ability to correctly identify winning outcomes) and specificity (the ability to correctly reject losing outcomes) of the algorithm were also calculated[29]. .

The model that predicted match outcome for group-phase matches was utilised alongside the LIME package[22] 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[30]. The basis of the explanation is that globally complex models are approximated well at a local-level through linear models[30], 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[30]. 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[23]. LIME predictions provide greater than 90% recall on classifiers and the explanations provided are accurate to the original model[30]. 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[30]. 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[30].

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%, $p<0.05$), sensitivity and specificity balanced at 87.5%. 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 3 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 were significant in predicting match outcome far exceeds the number observed in the previous literature[3–6]. The potential reasons for this disparity are twofold and relate to the structure of the data used and the analytical method. First, as previous research examining multiple PIs at RWCs[3–5] have not utilised descriptively converted data, meaning distortions in any relationships present[1] and inaccurate reflections of the sport's nature [8]. 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[9]. Second, the analytical method has likely influenced findings, previous methodologies have used parametric statistical methods[3–5,31], but the complexity of the data and the possible non-linearity of relationships means these methods are sub-optimal[32]. This is further reinforced by rugby union's dynamic and chaotic nature[33].

In terms of the importance of individual PIs in predicting match outcome in the group stages of the competition 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[32], 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[9]. 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[4] 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 when predicting match outcome. Villarejo[31] 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 unable to determine whether superior open-field skills of winning teams were due to the abilities of all players in the team or a result of players in specific positions.

The results of this paper indicate that in the group-phase, penalty count and location of conceded penalties are predictors of 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[5]. Although this PI was not available for investigation in the current study successful 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 random forest trained on the group stage data predicted all group stage outcomes correctly, this combined with the fact that only 40 match data cases were used in the analysis indicates that the model was over fitted[34]. An over fitted model will use individual nuances and unique properties in the data set to classify outcomes, this is a disadvantage when attempting to classify other data sets where these nuances and properties are not present[24]. Less complicated or more general models perform better on future data sets[34]. In this research study an over fitted model was advantageous, the ability to predict the knockout stages of the completion with a complicated model indicated that the two stages of the competition shared a large degree of common feature and properties. The model produced on the group-phase 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, as 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[4,5]. 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[9], 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.

Practical applications

Three main practical applications can be derived from this research. Firstly the research provides a useful analytical method for professional rugby teams to measure their performance and understand the major contributors to success and failure in individual matches. The use of the lime package allows for production of understandable diagrammatic representations of the tactical and technical performance in matches, these methods are not currently used in professional rugby union. It is worthwhile noting that these methodologies can be transferred to any sport where PIs are measured and recorded. The second practical application sits in the understanding that in elite rugby tournaments such as the RWC the technical and tactical elements that define performance in the group stages of the competition do not change when a team enters the knockout stages. The third practical application is that research such as this provides valuable information to coaches of tier 2 nations, who do not have the funding or personnel to provide in depth performance analysis. The information regarding the importance of PIs in predicting match outcome can be used to direct team tactical and technical training.

Limitations of the research

There are three major limitations to be considered with regard to this research. The first major limitation is related to the simplistic nature of the data. Rugby is complex sport, all PIs do not provide the same value in the context of match outcome[1,2,35]. It is highly probable that the area on the field where a notated action takes place, as well as the class of PI, effects its contribution to game outcome; this paper cannot consider these factors. A second limitation can be considered with regard to the associative nature of the relationships revealed by the research methodologies. In observational studies associative relationships cannot not be presumed to be causal, even when causality is present it is difficult to confirm the direction of causality, do teams win because they make more clean breaks more or have they made more clean breaks because they have won? Interpretation of results should be completed with care and used alongside expert opinion before being employed in an applied situation. The third limitation to consider is the historical nature of the nature; the game changes and the importance of PIs may change as the game evolves. There are two counters to this, the first being that previous research has demonstrated that in rugby union the PIs that predict match outcome retain stability between seasons[10,11], the second being that the methodology utilised in this research holds greater practicality than the relevance of the PIs in predicting match outcome.

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1. Hughes MD, Bartlett RM. The use of performance indicators in performance analysis. *J Sports Sci*. 2002;20(10):739-754.

2. McGarry T. Applied and theoretical perspectives of performance analysis in sport: Scientific issues and challenges. *Int J Perform Anal Sport*. 2009;9(1):128-140.
3. Hughes MT, Hughes MD, Williams J, James N, Vuckovic G, Locke D. Performance indicators in rugby union. *J Hum Sport Exerc*. 2012;7(2).
4. Hughes A, Barnes A, Churchill SM, Stone JA. Performance indicators that discriminate winning and losing in elite mens and womens Rugby Union. *Int J Perform Anal Sport*. 2017;0(0):1-11. doi:10.1080/24748668.2017.1366759
5. Bishop L, Barnes A. Performance indicators that discriminate winning and losing in the knockout stages of the 2011 Rugby World Cup. *Int J Perform Anal Sport*. 2013;13(1):149-159. doi:10.1080/24748668.2013.11868638
6. van Rooyen KM, Diedrick E, Noakes DT. Ruck Frequency as a predictor of success in the 2007 Rugby World Cup Tournament. *Int J Perform Anal Sport*. 2010;10(1):33-46.
7. Vaz L, Van Rooyen M, Sampaio J. Rugby game-related statistics that discriminate between winning and losing teams in IRB and Super twelve close games. *J Sports Sci Med*. 2010;9(1):51.
8. Ofoghi B, Zeleznikow J, MacMahon C, Raab M. Data mining in elite sports: a review and a framework. *Meas Phys Educ Exerc Sci*. 2013;17(3):171-186.
9. Bennett M, Bezodis N, Shearer DA, Locke D, Kilduff LP. Descriptive conversion of performance indicators in rugby union. *J Sci Med Sport*. 2019;22(3):330-334.
10. Bennett M, Bezodis N, Shearer DA, Locke D, Kilduff LP. Descriptive conversion of performance indicators in rugby union. *J Sci Med Sport*. 2018.
11. O'Donoghue P, Ball D, Eustace J, McFarlan B, Nisotaki M. Predictive models of the 2015 Rugby World Cup: accuracy and application. *Int J Comput Sci Sport*. 2016;15(1):37-58.
12. OPTA. Rugby Union Post Match Analysis Operationa Definitions. 2015.
13. Liu H, Hopkins W, Gómez AM, Molinuevo SJ. Inter-operator reliability of live football match statistics from OPTA Sportsdata. *Int J Perform Anal Sport*. 2013;13(3):803-821.
14. OPTA. OPTA Rugby Union. OPTA Rugby Union Staistics.
15. Evans JS, Murphy MA. rfutilities. R package version 1.0-0. 2014.
16. Team RC, others. R foundation for statistical computing. *Vienna, Austria*. 2013;3(0).
17. Austin G. The New S Language, A Programming Environment for Data Analysis and Graphics. 1990.
18. Woods CT, Sinclair W, Robertson S. Explaining match outcome and ladder position in the National Rugby League using team performance indicators. *J Sci Med Sport*. 2017.
19. Gujarati D, Porter D. Multicollinearity: What happens if the regressors are correlated. *Basic Econom*. 2003;363.
20. Breiman L, Cutler A, Liaw A, Wiener M. Package'randomForest'. *Softw available URL http//stat-www berkeley edu/users/breiman/RandomForests*. 2011.
21. Kuhn M. The caret package. *R Found Stat Comput Vienna, Austria URL https//cran r-project org/package= caret*. 2012.
22. Pederson TL. Package 'lime.' https://cran.r-project.org/web/packages/lime/lime.pdf. Published 2018. Accessed March 1, 2019.
23. Pederson TL, Benesty M. Understanding Lime. https://cran.r-project.org/web/packages/lime/vignettes/Understanding_lime.html. Published 2018. Accessed March 1, 2019.
24. Kabacoff RI. *R in Action*. manning; 2010.
25. Breiman L. Random forests. *Mach Learn*. 2001;45(1):5-32.
26. Jones Z, Linder F. Exploratory data analysis using random forests. In: *Prepared for the 73rd Annual MPSA Conference*. ; 2015.
27. Ng VW, Breiman L. Bivariate variable selection for classification problem. In: *Technical Report, Department of Statistics, University of California-Berkeley*. ; 2005.
28. Archer E. rfPermute: estimate permutation p-values for Random Forest importance metrics. *R Packag (Zenodo), Version*. 2016;2(1).
29. Phillips ND, Neth H, Woike JK, Gaissmaier W. FFTrees: A toolbox to create,

visualize, and evaluate fast-and-frugal decision trees. *Judgm Decis Mak*. 2017;12(4):344.
30. Ribeiro MT, Singh S, Guestrin C. Why should I trust you?: Explaining the predictions of any classifier. In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ; 2016:1135-1144.
31. Villarejo D, Palao J-M, Ortega E, Gomez-Ruano M-Á, Kraak W. Match-related statistics discriminating between playing positions during the men's 2011 Rugby World Cup. *Int J Perform Anal Sport*. 2015;15(1):97-111.
32. Strobl C, Malley J, Tutz G. An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychol Methods*. 2009;14(4):323.
33. Robertson S, Back N, Bartlett JD. Explaining match outcome in elite Australian Rules football using team performance indicators. *J Sports Sci*. 2016;34(7):637-644.
34. James G, Witten D, Hastie T, Tibshirani R. *An Introduction to Statistical Learning*. Vol 112. Springer; 2013.
35. Castellano J, Casamichana D, Lago C. The use of match statistics that discriminate between successful and unsuccessful soccer teams. *J Hum Kinet*. 2012;31:137-147.

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
Defender beaten	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 lineout success	93.8%	100%	-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/line out
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 line out won on own throw when in opposition 22
Percentage lineout success	Line out 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
Scrums won opposition 22	Number of scrums won on own put 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 opposition 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 the gainline divided by carries made
Passes	The ball carrier performs a pass
Rucks won	Rucks won when in possession
Rucks lost	Rucks lost when 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 success	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

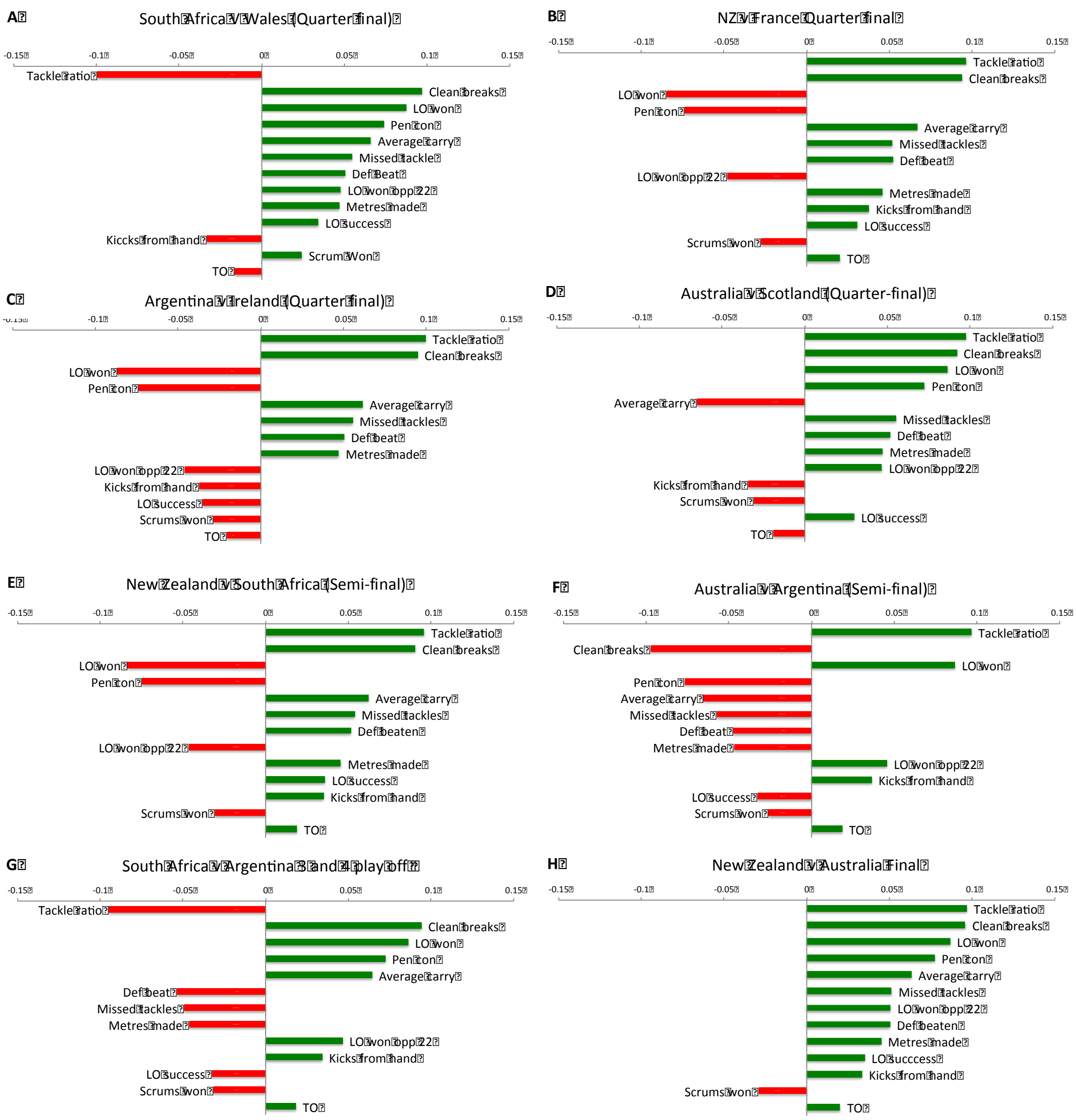

Figure 1. Graphical representation of the LIME algorithm's local explanation for the outcome of each knockout-phase match