Descriptive Conversion of Performance Indicators in Rugby Union

27   **Abstract**

28

29   *Objectives:* The primary aim of this study was to examine whether accuracy of rugby union

30   match prediction outcomes differed dependent on the method of data analysis (i.e., isolated

31   vs. descriptively converted or relative data). A secondary aim was to then use the most

32   appropriate method to investigate the performance indicators (PI's) most relevant to match

33   outcome.

34   *Methods:* Data was 16 PI's from 127 matches across the 2016-17 English Premiership rugby

35   season. Given the binary outcome (win/lose), a random forest classification model was built

36   using these data sets. Predictive ability of the models was further assessed by predicting

37   outcomes from data sets of 72 matches across the 2017-18 season.

38   *Results:* The relative data model attained a balanced prediction rate of 80% (95% CI – 75-

39   85%) for 2016-17 data, whereas the isolated data model only achieved 64% (95% CI – 58-

40   70%). In addition, the relative data model correctly predicted 76% (95% CI – 68-84%) of the

41   2017-18 data, compared with 70% (95% CI – 63-77%) for the isolated data model. From the

42   relative data model, 10 PI's had significant relationships with game outcome; kicks from

43   hand, clean breaks, average carry distance, penalties conceded when the opposition have the

44   ball, turnovers conceded, total metres carried, defenders beaten, ratio of tackles missed to

45   tackles made, total missed tackles, and turnovers won.

46   *Conclusions:* Outcomes of Premiership rugby matches are better predicted when relative data

47   sets are utilised. Basic open-field abilities based around an effective kicking game, ball

48   carrying abilities, and not conceding penalties when the opposition are in possession are the

49   most relevant predictors of success.

50

51   Keywords: Team sport, random forest, performance indicators, partial dependence plots

Introduction

Success in sport can be assessed and quantified with performance indicators (PIs)[1]. Understanding PI's that relate to success in sport is important for coaches to improve future technical, tactical and physiological performance[2]. Whilst the most meaningful PI's should differentiate between successful and unsuccessful outcomes[1], no consensus can currently be drawn in rugby union regarding PI's associated with success [3–9].

Based on the available literature, the frequency of ball kicking differentiates success in both domestic and international rugby union matches[4,7,8]. Winning teams kick the ball more and kick away greater proportions of possession. Match winners also have lower error[4,9] and turnover[8,9] rates compared to losers. In addition, winners have an effective defensive game, with a superior success rate at the tackle[8] and make more tackles overall[4]. Attacking actions, such as higher distance of average carry[8] and making more clean breaks in the opposition's defensive line[3,7,8], are also associated with successful performances. Together with open field actions, set piece performance is important, with winners securing more opposition lineouts[9] and a greater effectiveness at the scrum[7]. However, some research has failed to uncover significant differences in PI's between successful and less successful teams. For example, at the 2011 World Cup competition, multiple indicators were examined and no differences were established that explained tournament ranking[5].

It is unlikely that the complex, dynamic and interactive games such as rugby union can be represented by simple analysis or frequency data[5]. The conflict in current literature with respect to PI's and match outcome is best represented by Vaz et al[4]. They reported significant predictors of match outcome in the Super Rugby competition, but the same PI's did not differentiate between winners and losers in an International competition. The authors

77 suggested international level differences between winners and losers do not exist or are

78 masked by variations in playing styles that underpin match outcome.

79

80 A significant limitation of the above research is the failure to acknowledge that, in rugby

81 union, outcome depends on ability and performance of both teams. Therefore, when

82 considering associations between PI's and competition results equal emphasis should be

83 placed on data from each team[2]. Failure to do so will likely distort any relationships present[1].

84 Processing sports data to consider PI's as a differential between opponents is suggested as a

85 better descriptor of a sport's nature[10] and a contest's outcome. In analysing sports data, this

86 type of data processing method has been termed "descriptive conversion" but has not been

87 applied in the literature concerning rugby union. Only isolated data has been considered,

88 'isolated' referring to the PI's of each participating team considered discretely and not

89 relative to the opposition.

90

91 The primary aim of this study was to examine whether accuracy of match prediction

92 outcomes differed dependent on the method of data analysis (i.e., isolated vs descriptively

93 converted data). A secondary aim was to use the most appropriate method to identify the

94 most relevant PI's for successful outcomes in rugby union and specify how this information

95 can have practical relevance to sports practitioners.

96

97 **Methods**

98 PI's for the 2016-17 English Premiership Rugby Union regular season and the first 12 rounds

99 of the 2017-18 season were downloaded from the OPTA website (optaprorugby.com). The

100 2016-17 season data consisted of 22 rounds of 6 matches (132 matches total, 12 teams). As

101 the study assessed the impact of PI's on a binomial outcome (win/loss), matches that finished

102   with a draw (n = 5) were excluded from analysis. The full set of team PI's for each match

103   were utilised in the analysis. These PI's were "carries made", "clean breaks", "offloads",

104   "total number of defenders beaten", "total number of metres ball was carried", "tackles

105   made", "tackles missed", "ratio tackles missed to tackles made", "turnovers a team won",

106   "turnovers a team conceded", "lineout throws won on own ball", "lineout throws lost on own

107   ball", "the number of kicks from hand", "penalties conceded offence" (with the ball),

108   "penalties conceded defence" (without the ball) and "the average distance for each ball

109   carry".

110

111   The PI's of a single team, from one match, were considered isolated data. For example, if

112   team A carried 450 m in total during the game and team B 300 m, the assigned isolated data

113   values would be 450 m for team A and 300 m for team B. From each game, descriptive

114   conversion was also undertaken by calculating the differences between teams and this data

115   set was termed the relative data set. From the previous example the relative data values

116   would be +150 m for team A and -150 m for team B.

117

118   Collinearity between predictors, in both data sets, was investigated using the rfUtlities

119   package[11]. No collinearity was noted between predictors in the isolated data set. Collinearity

120   was noted between defenders beaten and tackles missed in the relative data set. A separate

121   analysis was run for the relative data set, with these predictors eliminated. The results

122   indicated that the collinearity had no effect on the predictive ability or the casual inferences

123   from the random. forest. With this in mind the decision was made to run the analysis with the

124   original "intact' data set.

125

126

127   PI's from each data set (relative and isolated) were used as predictors for match outcomes

128   (win/lose). To interpret relationships between PI's and match outcome a random forest

129   classification model was developed, using 2016-17 season data, with the randomForest[12]

130   package in R[13]. A classification model predicts categorical outcome from a set of predictor

131   variables[14]. The randomForest package uses ensembles of decision making trees to categorise

132   data[15]. A decision tree repeatedly repartitions data, with binary splits, to maximise subset

133   homogeneity, and estimates the class or distribution of a response[16]. The aggregate tree

134   approach of a random forest algorithm, has improved performance when compared to a

135   single tree[15]. Random forests also utilise bootstrapped data samples and random subsampling

136   of predictors in each tree to improve prediction accuracy and prevent overfitting[15]. The mean

137   decrease of accuracy (MDA)[15] and mean of the distribution of minimal depth[17] of each PI

138   were utilised to assess the importance of each predictor towards classification of game

139   outcome and Pearson's correlation coefficients used to assess agreement between PI MDA

140   and mean of distribution of minimal depth in each model[18]. A negative MDA value

141   represents a decrease in importance and not the presence of an inverse relationship[19]. The

142   significance level ($p < 0.05$) of the MDA of each PI was calculated, using the rfPermute

143   package[20], the rfPermute package permutes the response variable and produces a null

144   distribution for each predictor MDA and a p value of observed.

145

146   Partial dependency plots were produced for each significant predictor in the model defined as

147   most appropriate by the primary statistical analysis. Partial dependency plots are useful to

148   summarise the relationships between predictor and outcome relationships[21] and are based on

149   permeated data sets that calculate the relationship between outcome and particular predictor

150   changes, accounting for averaged associations of all other predictors on outcome[16].

151

152   Data from the first 12 rounds of the 2017-18 (i.e. the subsequent season) English Premiership

153   competition was then used to test the predictive relevance (i.e. overall accuracy of prediction

154   and balance) of both the isolated and relative models. Balance ensured models were equally

155   adept at picking winning or losing data sets and not having bias of success to either[22].

156   Statistical significance of predictive accuracy for each model was recorded, as were z-scores

157   for McNemar's test[23], which was performed against the comparison of predictive ability of

158   each model. McNemar's test produces a z-score which when above 1.64 is indicative of a

159   confidence level of 95% that one model has better performance than another.

160

161   **Results**

162   The randomForest model based on the isolated data set from the 2016-17 season classified 85

163   from 127 losses (67%) and 78 from 127 wins (61%), giving an overall accuracy of 64% (95%

164   CI 58-70%, p<0.05). The randomForest model based on the relative data set predicted 102 of

165   127 losses (80%) and 101 of 127 wins (80%), with an overall accuracy of 80% (95% CI 75-

166   85%, p<0.05). The McNemar's value of 57.7 (p<0.05) confirmed that the relative model

167   outperformed the isolated model.

168

169   When assessing the predictive ability of the isolated data model against the first 12-rounds of

170   the 2017-18 season, 58 from 72 (81%) losses and 43 from 72 (60%) wins were correctly

171   classified, giving an overall accuracy of 70% (95% CI 63-77%, p<0.05). Assessment of the

172   model based on relative data resulted in correct predictions for 54 of 72 wins (75%) and 55 of

173   72 losses (76%). This equated to an overall accuracy of 76% (95% CI 68-84%, p<0.05).

174   McNemar's z score (31.1, p<0.05) again confirmed the superior performance of the relative

175   data model.

176

177   Data with respect to each individual predictor variable's MDA is summarised in Table 1 and

178   Table 2 for the models based on the isolated and relative data sets, respectively. The isolated

179   data set model contained eight predictors whose distribution varied significantly from the

180   null. The relative data set model included ten predictors whose distribution varied

181   significantly from the null. The magnitude of significant MDA values ranged from 13.8 to -

182   1.8 in the isolated data model and 51.6 to -4.6 in the relative data model. Mean values for

183   minimum depth value for predictors in the isolated set varied from 2.53 for the strongest

184   predictor to 4.4 for the weakest. In the relative set these values were between 1.81 and 4.44.

185   A strong, negative correlation existed between MDA values of predictor importance and

186   mean minimum depth distribution within both models, the coefficient for the relative data

187   model being significantly higher[18] (r^2=-0.63 isolated data predictors ($p<0.05$), r^2=-0.91

188   relative data predictors ($p<0.05$).

189

190   ****Table 1 ****

191

192   ****Table 2 *****

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195   Partial dependence plots for the top four predictors (based on MDA) were produced for the

196   relative data model (Figure 1a-d). Plots demonstrate positive associations between match

197   outcome and numbers of relative kicks from hand, relative clean breaks and relative average

198   carry. A negative relationship is present with penalties conceded in defence (when the

199   opposition are in possession). Plots also reveals upper limits are present for each PI, beyond

200   which no increase in the probability of a positive match outcome was noted.

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8

202   ****Figure 1 ******

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205   **Discussion**

206   The primary aim of this study was to investigate for the first time whether a relative (a data

207   set that has undergone descriptive conversion) or an isolated data set best predicted outcomes

208   of rugby union matches. Results indicated relative data was more effective at predicting

209   match outcome compared to isolated data. The model based on the relative data set

210   outperformed the isolated data model in terms of overall accuracy and, as per previous

211   research[24,25], the balance of prediction was poorer from the isolated model. Isolated data sets

212   are a less accurate reflection of the association between PI's and match outcome[1,10]. If data

213   used to produce classification models is not an entirely accurate reflection of competition

214   results, a bias will be present in the predictive outcomes. The reduced accuracy and balance

215   of the isolated model in this study may help explain the conflict in previous research that

216   have used isolated data sets[4–7].

217

218   Stability of the ranking of predictors produced from random forests is key to their

219   interpretation[26]. The stochastic nature of a random forest is a result of the bagging,

220   randomisation and permutation of the data set that is intrinsic to the methodology used in the

221   process[27]. Variable importance measures with small magnitudes of difference are more likely

222   to have their rankings influenced by the processes that are central to the methodology. The

223   MDA values of the models are presented in Tables 1 and 2. The PI's ranked first and fourth

224   (for example) from the relative data model have larger magnitudes of differences between

225   them than the first and forth ranked PI's from the isolated data model. This denotes greater

226   stability to deviations in ranking from the inherent modelling process and likely perturbations

227   in future data. The larger magnitude of the MDA vales for the model based on the relative

228   data set also signify greater overall importance and relevance of the data's ability to predict

229   match outcomes[28], bringing into question the use of isolated PI's in rugby union. This

230   conclusion is supported by the mean minimum depth distribution for a variable (Table 1),

231   confirming the primacy of the relative data model. Pearson's correlation coefficients between

232   mean minimum depths of each predictor and its MDA value confirmed a greater level of

233   agreement within the relative model.

234

235   A secondary aim was to specify how our information can have practical application to sports

236   practitioners. Partial dependence plots are a novel method to examine a multitude of

237   relationships[29] but have not been utilised extensively in a sports performance setting to

238   interpret statistical information for practical use. They provide a useful summary of the

239   relationships between predictor variables and the predicted probability of match outcome[21].

240   The partial dependence plots indicate there are upper limits for predictor levels, beyond

241   which no advantages are inferred towards game outcome (but not necessarily points

242   difference). These upper limits (and their associated lower limits) offer objective outcome

243   measures for teams to base game plans on and assess where training time is spent to win

244   more matches.

245

246   The top four predictors from the relative data model were represented in the partial

247   dependence plots (Figure 1a-d) and show that increases in average carry, clean breaks made

248   and kicks made are related to improved likelihood of positive match outcomes. Conversely

249   increased penalties, whilst the opposition have the ball, make a negative outcome more

250   likely. Of note, penalties conceded when the opposition have the ball had a significant

251   relationship with match outcome but penalties conceded when in possession of the ball did

252 not. Possibly, this relationship is not solely a reflection of the penalties given away but a

253 vestige of possession levels of teams; a high number of penalties conceded when the

254 opposition have the ball may merely be a function of increased quantity of possession of the

255 opposition. A further investigation needs to be undertaken that directly examines the

256 relationships between penalties conceded when the opposition possess the ball, team

257 possession, and game outcome. Whilst it is problematic to make presumptions without these

258 objective data, the relationship between match outcome and penalties is such that teams need

259 to focus on defensive strategies that are within the laws of the game. Similar conclusions can

260 be inferred between the relationship of game outcome and number of kicks from hand, with

261 relative kicks being an expression of relative possession levels. Data was not available for the

262 original 2016-17 season model to investigate further but, for the 2017-18 season, the number

263 of possessions a team attained in a match was positively related with the number of kicks

264 from hand (r^2=-0.42 ($p<0.05$)). Possession statistics therefore explain only 42% of the

265 variance between kicks made in matches, the remainder provided by team attributes including

266 match tactics and strategy. It can therefore be conjectured that kicking has an impact on game

267 outcome outside of revealing a team's possession levels. In rugby union, kicking away

268 possession might be advantageous when teams have exhausted other options and are under

269 pressure of turning the ball over or being penalised in an unfavourable position. Equally,

270 kicking the ball away before a team is under pressure may be advantageous, and the

271 relationship between kicking and success could simply reflect the advantages inferred

272 through good tactical kicking strategy. Previous research suggests a positive relationship

273 between possession kicked and success in both international[7] and domestic[4] rugby. Ortega[7]

274 discusses how successful teams kick more frequently, but not the proportion of possession

275 kicked. Vaz[4] however suggests that successful teams kick a greater amount of their

276 possession away allowing teams to gain territory more effectively than a carrying game. This

277 suggestion being equally applicable to the relationship between penalties in defence and

278 match outcome.

279

280 The MDAs for clean breaks made and average carry verify the positive impact of teams

281 having a strong ball carrying game. Indeed, research indicates clean breaks differentiated

282 between successful and unsuccessful teams in both domestic[3] and international[7] competitions.

283 This research demonstrates that average carry appears a more important predictor than the

284 total metres carried. Successful teams should have strategies and players who carry greater

285 average distance, compared to the opposition. Also, teams who prevent the opposition from

286 carrying ball past the gainline will have a positive impact on their relative average carry. This

287 confers the importance of robust defence as well as attacking ability and is supported by

288 MDA values for missed tackles and ratio of tackles missed to tackles made being significant

289 predictors of match outcome. Indeed, tackle completion has previously been shown to be an

290 important PI in determining success[7,8]. Within the current study, tackle completion only

291 reached significance as a predictor of match outcome in the relative model. In rugby league,

292 regression of tackle technique is associated with fatigue, the greatest reductions in technique

293 occurring in the players with lowest aerobic fitness levels[30]. The same relationship may exist

294 in rugby union, indicating aerobic fitness offers an advantage toward success. No work has

295 demonstrated a link between aerobic fitness and match outcome in rugby union.

296

297 It seems feasible that successful and unsuccessful teams differ in ability to identify tactical

298 processes. Average distance per carry is a more accurate predictor of outcome than overall

299 metres carried. This, combined with the observation that successful teams kick away more

300 ball compared to losing teams may indicate the ability of successful teams to identify when

301 effective carries can be made or otherwise to kick ball tactically. Tactically superior teams

302 may also use the kicking game to open up attacking options as well as a pressure relieving

303 method. A successful kicking game means opposition teams invest greater resource in

304 covering the backfield, resulting in a weakened defensive line and opportunities for effective

305 ball carries. Similar can be said around the tackle area, the ability to select when there is a

306 good chance of a turnover will mean the defensive line stays intact and gives the opposition

307 less opportunity to find space. It also has the added advantage of decreasing the number of

308 defensive penalties conceded in these situations.

309

310 This work offers insight into rugby union not reported in the literature to date. It advances

311 evidence that relative data surpasses isolated data in explaining game outcome, therefore

312 being more relevant to analysts and coaches trying to influence behaviours of players and

313 teams[2]. For instance, in previous studies success at the lineout has been demonstrated to be a

314 predictor of success[7,9]. In this study lineouts won and lost were significant indicators in the

315 isolated data set, but not when considered as a relative data set. This is an appropriate

316 example of predictor and outcome relationships distortion when isolated data sets are used[1].

317 It is plausible the equivocality of current literature respective to predictors of performance in

318 rugby union is in part due to the exclusive use of isolated measures of PI's. Future research

319 should investigate physical and technical strategies to improve ball carrying quality, whilst an

320 in-depth exploration of kicking and its impact on game outcome would also provide valuable,

321 practical information.

322

323 **Conclusions**

324 This study demonstrates the effectiveness of utilising data that has undergone descriptive

325 conversion in predicting match outcomes. It also demonstrates game outcomes are more

326 closely related to open field abilities and basic skills such as ball carrying, kicking and

327 tackling ability than they are to set pieces and, despite the apparent complexity of the game,

328 success can be explained by a small number of basic components.

329

330 **Practical applications**

331 • The use of relative data sets rather than isolated data sets, when evaluating match

332 performance

333 • Devising game strategies to maximise average carry and tackles at or over the gainline.

334 • Having a focus on defensive strategies that minimise the likelihood of conceding

335 penalties. This would include areas of the game where high numbers of penalties are

336 conceded in matches, for example when defending driving line-outs.

337 • Using partial dependency plots to set objective team performance markers.

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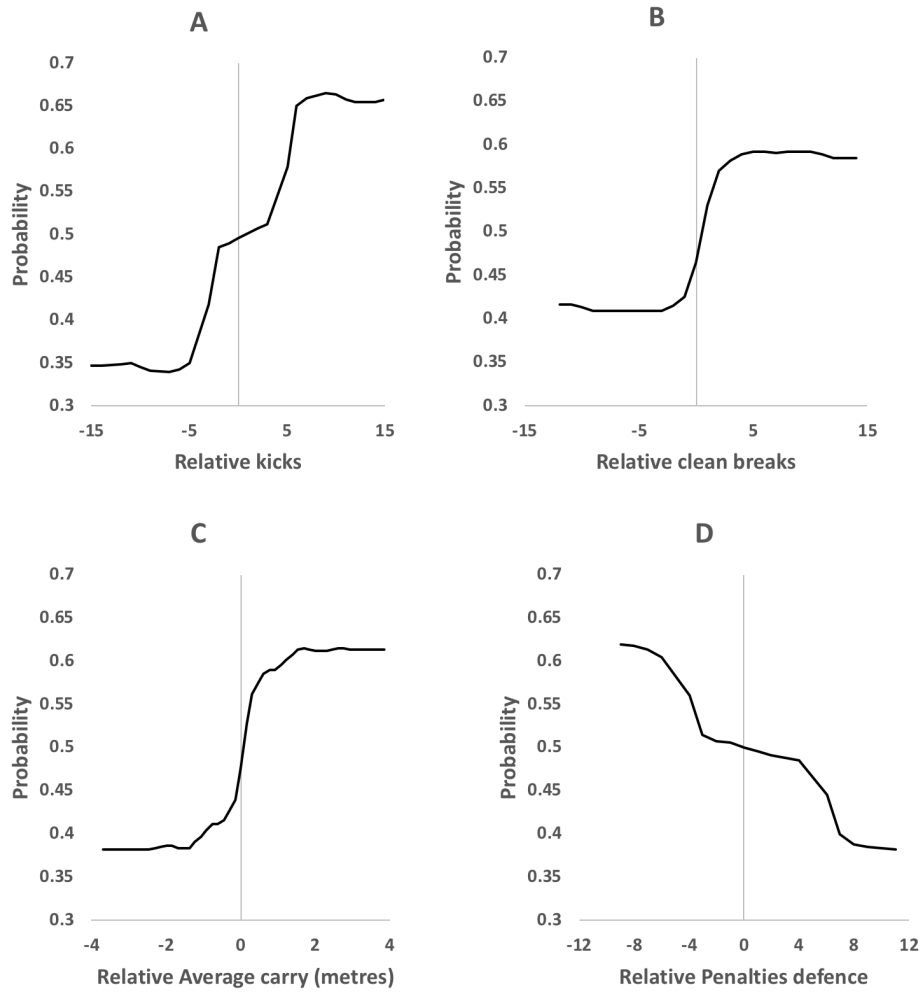415

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430 **Figure 1**. Partial dependence plots for Random forest model based on the relative data set.

431 The plots show the effect of relative kicks (Panel A), relative clean breaks (Panel B), relative

432 average carry (Panel C) and relative penalties in defence (Panel D) on the classification of

433 match outcome.

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443   **Table 1**. Mean decrease in accuracy, associated p values and mean value of minimum depth

444   distribution for the Random Forest model, based on the isolated set.

Performance indicator	MDA	p value	Mean min depth
Average carry	13.8	0.0198	2.53
Turnovers conceded	13.4	0.0099	2.98
Clean breaks	11.0	0.0198	3.19
Total metres carried	10.7	0.0297	2.9
Missed tackles	9.8	0.0297	3.29
Tackles made/missed	8.7	0.0594	2.65
Kicks from hand	8.7	0.0495	3.10
Own LO won	8.5	0.0396	3.90
Own LO lost	6.7	0.0495	3.85
Defenders beaten	6.6	0.0693	3.46
Carries	4.1	0.1386	3.87
Penalties defence	2.4	0.2178	3.52
Tackles made	0.6	0.3663	3.62
Penalties offence	-0.3	0.4275	4.4
Turnovers won	-0.6	0.5050	3.9
Offloads	-1.8	0.6535	3.95

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461 **Table 2**. Mean decrease in accuracy, associated p values and mean value of minimum depth

462 distribution for the Random Forest model, based on the relative set.

Performance indicator	MDA	p value	Mean min depth
Kicks from hand	51.6	0.0099	1.81
Clean breaks	34.3	0.0099	2.31
Average carry	34.2	0.0099	2.17
Penalties defence	23.9	0.0099	2.62
Turnovers conceded	20.9	0.0099	2.79
Total metres carried	16.9	0.0099	2.88
Defenders beaten	12.3	0.0099	3.54
Tackle made: missed	12.2	0.0099	3.19
Missed tackles	12.0	0.0099	3.67
Turnovers won	6.2	0.0495	3.31
Carries	5.4	0.1800	3.89
Own LO won	3.5	0.2574	3.58
Offloads	1.8	0.2574	3.68
Tackles made	1.4	0.2673	3.93
Own LO lost	-0.1	0.4653	3.94
Penalties defence	-4.6	0.9505	4.44

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