VICTORIA UNIVERSITY
M E L B O U R N E   A U S T R A L I A

A method to assess the influence of individual player performance distribution on match outcome in team sports

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1   # A method to assess the influence of individual player
2   # performance distribution on match outcome in team
3   # sports

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1 **Abstract**

2 This study developed a method to determine whether the distribution of individual player

3 performances can be modelled to explain match outcome in team sports, using Australian

4 Rules football as an example. Player-recorded values (converted to a percentage of team

5 total) in 11 commonly-reported performance indicators were obtained for all regular season

6 matches played during the 2014 Australian Football League season, with team totals also

7 recorded. Multiple features relating to heuristically determined percentiles for each

8 performance indicator were then extracted for each team and match, along with the outcome

9 (Win/Loss). A generalised estimating equations model comprising eight key features was

10 developed, explaining match outcome at a median accuracy of 63.9% accuracy under 10-

11 fold cross validation. Lower 75th, 90th and 95th percentile values for team goals and higher

12 25th and 50th percentile values for disposals were linked with winning. Lower 95th and higher

13 25th percentile values for Inside 50's and Marks respectively were also important

14 contributors. These results provide evidence supporting team strategies which aim to obtain

15 an even spread of goal scorers in Australian Rules football. The method developed in this

16 investigation could be used to quantify the importance of individual contributions to overall

17 team performance in team sports.

18

19 **Keywords:** performance analysis, coaching, strategy, Australian Rules football

1   **Introduction**

2   In sport, the term 'performance indicator' is used to refer to an action variable that defines

3   an aspect of a successful performance (Hughes & Bartlett, 2002). This definition has been

4   used broadly to extend to anthropometric, physiological and skill-related variables (Reilly,

5   2001; Robertson, Burnett, Newton & Knight, 2012). In the team sport notational analysis

6   literature, discrete performance indicators (i.e., passes completed, shots on goal) have

7   specifically been used to develop models explaining competition outcome in football

8   (Castellano, Casamichana & Lago, 2012), basketball (Gomez, Lorenzo, Barakat, Ortega &

9   Palao, 2008) and rugby (Vaz, Van Rooyen & Sampaio, 2010). This information can then

10   potentially be used to make inferences about which characteristics of competition are

11   typically most important to achieving success.

12   However, such approaches have also experienced some criticism in the literature.

13   Specifically, it has been proposed that they neglect to consider the spatiotemporal

14   components of sporting competitions, such as the location and sequences of possession

15   between multiple players (Cervone, D'Amour, Bornn & Goldsberry, 2014) and the dynamic,

16   interdependent relationships that exist within a team (Clemente, Martins, Couceiro, Mendes

17   & Figueiredo, 2014). Consequently, an increase in research relating to assessing player and

18   ball movement patterns as they pertain to team performance has gained popularity of late

19   (Cervone *et al.,* 2014; Clemente *et al.,* 2014; Passos, Davids, Araujo, Paz, Minguéns &

20   Mendez, 2011). Additionally, investigations into quantifying the contribution of individual

21   players within a team context have also emerged (Duch, Waitzman & Amaral, 2010;

22   Tavana, Azizi, Azizi & Behzadian, 2013).

23   As in many professional team sports, the collection and reporting of performance

24   indicators is commonplace by the 18 teams participating in the elite-level Australian

25   Football League (AFL) competition. Australian Rules football is played on an oval field

26   with two opposing teams consisting of 22 players each (18 on the field + 4 interchange).

1   Scoring is achieved by kicking the ball between the two large goal posts located at either end

2   of this field. In the AFL, discrete performance indicators are typically obtained via a

3   commercial sports statistics company (Champion Data Pty Ltd, Melbourne, Australia),

4   which uses a mixture of live and retrospective video coding in order to produce data for both

5   professional clubs and media sources. Investigations into how these performance indicators

6   associate with match outcome, defined as either 'Win/Loss' (Robertson, Back & Bartlett,

7   2015; Stewart, Mitchell & Stavros, 2007) or score differential (Stewart, Mitchell & Stavros,

8   2007) have been previously undertaken. In these studies, higher team totals relative to the

9   opposition for kicks, Inside 50's and goal conversion were shown to be particularly

10   influential on the match result.

11   Recent improvements in the reporting combined with the technologies used to

12   capture such information (i.e., wearable athlete devices) has seen a concurrent increase in

13   both the number and complexity of performance indicators reported in the AFL. Attempts to

14   quantify the individual's contribution to the team in the AFL have also been noted in both

15   the media (i.e., the AFL player ranking system) and the peer-reviewed literature (Heasman,

16   Berry, Dawson & Stewart, 2008; Sargent & Bedford, 2013). In addition to understanding the

17   value of an individual to the team, these approaches may also allow for the evaluation of

18   player selections for a given match.

19   However, it is evident that each team sport contains a unique set of constraints

20   which limit the contribution of an individual player to the overall success of their team

21   (Vilar, Araujo, Davids & Travassos, 2012). These constraints can be conceptualised as

22   relating to the individual, task or environment and differ for each sporting competition

23   (Newell, 1986). Examples include the position played (Bourbousson, Deschamps &

24   Travassos, 2014), the physical and technical abilities of an individual (Kempton, Sirotic,

25   Cameron & Coutts, 2014) and their designated role within the team (Buszard, Farrow &

26   Kemp, 2013). In Australian Rules football specifically, given the percentage of match time

27   typically spent by a defender in their own half of the field it may be unreasonable to expect

1   this individual to create as many scoring opportunities as a forward player. In contrast, a

2   defender may be expected to produce a higher contribution to the team total for tackles than

3   a forward, due to their defined role within the team.

4   Despite these generally accepted perceptions, a quantitative method of

5   understanding how the distribution of individual player contributions within a team relates to

6   achieving a successful match outcome has not been reported in the literature to date. In

7   basketball for example, it could be hypothesised whether it is preferable for a single player

8   to record a high percentage of a team's points scored in a game, or whether a more even

9   spread of contributors is desirable? Obtaining this type of information for performance

10   indicators having previously been shown as important to match outcome in a sport would

11   have clear practical benefits. Notably, such findings could be used to inform team selection

12   (i.e., optimisation of team structure), improve the validity of player scouting and list/roster

13   management as well as increased sophistication of existing performance analysis.

14   This study developed a method to assess the influence of the distribution of

15   individual player contributions in team sport on match outcome. The aim of this study was

16   to provide an application of this method using AFL performance indicator data obtained

17   from all 18 teams during the 2014 regular season.

18

19   **Methods**

20   *Data collection and analysis*

21   Performance indicator data from all 198 games played during the 2014 AFL regular season

22   was obtained from www.afl.com.au/stats. Specifically, a total of 13 discrete performance

23   indicators were selected for extraction based on their reporting in previous literature

24   (Robertson, Back & Bartlett, 2015; Stewart *et al.,* 2007; Tangalos, Robertson, Spittle &

1   Gastin, 2015; Young & Prior, 2007), with definitions of each presented in Table I. The study

2   was approved by the relevant human research ethics advisory group.

3   ****INSERT TABLE I ABOUT HERE****

4   Following this, raw (absolute) individual player ($n = 22$) values for each performance

5   indicator ($n = 13$) were extracted for all AFL teams ($n = 18$). This process was undertaken

6   for all 22 games each team played during the 2014 regular season ($n = 396$), with the match

7   outcome (Win/Loss) also obtained. One draw occurred during the 2014 season; this match

8   was removed from the analyses. As all 22 player contributions for each team were included

9   in the dataset, the sample consisted of players injured during the course of a match, along

10   with a single substitute (a player who typically only participates in one quarter of a match).

11   *Coding reliability and validity*

12   As performance indicator data is provided to the AFL by a commercial provider (Champion

13   Data Pty Ltd, Melbourne, Australia), the reliability and validity of such information is not

14   publicly available. In order to determine the inter-rater reliability of the extracted data, a

15   sample of all matches from a single round during the 2014 AFL season were selected for

16   assessment. This process consisted of the lead author observationally coding each of the nine

17   matches for all 13 performance indicators whilst blinded to the original AFL values. The

18   coding was undertaken using a specially constructed output window in Sportscode (version

19   10.3, Sportstec Pty Ltd, Warriewood, Australia). Three time-synchronised video files for

20   each match (side, behind the goals and broadcast view) were used to undertake the coding,

21   with all vision provided by a single AFL club. Totals of each performance indicator for all

22   teams were then obtained and recorded for comparison with the AFL data. Kappa statistics

23   were not able to be determined due to the research team being blinded to the original coding

24   results from Champion Data. This meant that a direct comparison between raters may not

25   have always resulted in the identical number of observations (i.e., a kick may be missed

26   altogether by a coder, rather than misclassified as in typical scenarios where kappa or

1   weighted kappa may be applied). Thus, using team totals ($n = 18$) for each performance

2   indicator ($n = 13$), two-way mixed single measure intra-class correlation coefficients (ICC

3   3,1) were used to determine the agreement between AFL and author-coded values. To

4   determine the validity of the author's coding, root mean square error (RMSE) values were

5   obtained for each performance indicator in order to provide an absolute error estimate (using

6   the AFL data as the criterion measure).

7   *Data conversion and feature extraction*

8   For modelling purposes, each of the 22 player's contribution to the team total was converted

9   to its relative format, by transforming this value to a percentage of their team total for a

10   given match. For example, if a team recorded a total of 200 kicks in a match and a player

11   contributed 13 to this total, then this player's relative contribution to the team was calculated

12   as 6.5%. This descriptive conversion process of data from an absolute to relative format

13   (Ofoghi, Zeleznikow, MacMahon & Raab, 2013) allowed for multiple matches to be

14   included in the modelling process, as different team totals for each performance indicator

15   were anticipated for each game.

16   By descriptively converting data for all 22 players in a match, multiple features

17   could then be extracted to provide a representative profile of each performance indicator for

18   a given team. For instance, consider 'kicks' as the performance indicator of interest and the

19   total number of kicks recorded in a game be M between m players. Let m_i be the number of

20   kicks recorded by ith ($i=1,2,…m$) player. Define the weight of the ith player w_i as

21   [m_i/M]. The profile of the team for kicks can then be quantified by m dimensional

22   vector $w=(w_{(1)},w_{(2)},..,w_{(m)})$. From vector w we can extract the features of the kick profile for

23   the team by obtaining percentiles at levels being set at (0.05, 0.10, 0.25, 0.50, 0.75, 0.90,

24   0.95) respectively. The levels of the percentiles chosen for use in the study were selected

25   heuristically. Therefore, the 11 features extracted for each performance indicator consisted

26   of the minimum, maximum, mean, standard deviation as well as each of the abovementioned

1 seven percentile levels. This meant that 143 features in total (11 features x 13 performance

2 indicator) were extracted for each game played by each team. All features were then

3 propagated forward for modelling, subject to validity screening. Following this, the ordered

4 weight vector was then constructed for each performance indicator and match, with the

5 corresponding features extracted for subsequent modelling. The complete information

6 extracted in this manner was then collated along with match outcome (Win/Loss) and team

7 identity.

8 *Statistical Analysis*

9 The method of generalized estimating equations (GEE) (Halekoh, Hojsgaard & Yan, 2006)

10 was employed to construct a model explaining match outcome as a function of the feature

11 set for the performance indicators. For the analysis, the family was set as binomial with an

12 exchangeable correlation structure. Considered as an extension of the generalised linear

13 model, GEE has recently shown increased use in sporting contexts (see van Ark *et al.,* 2015;

14 Robertson, Burnett & Gupta, 2014; Young *et al.,* 2015 for examples). It is particularly useful

15 in situations where longitudinal data are being considered, as many similar modelling

16 techniques do not take into account the correlations between repeated measures on the same

17 participants or group (Zeger, Liang & Albert, 1988; Ziegler & Vens, 2010). Further, GEE

18 has been shown to show higher classification accuracy in comparison to methods such as

19 logistic regression in such instances (Önder, 2015). In this study, the GEE method was used

20 to explain the relationship between the match outcome and the corresponding feature set,

21 whilst adjusting for the dependence of the 18 teams.

22 For the validity screening of predictors, only those features showing significantly

23 different (P <0.05) means for match outcome (via ANOVA and not exhibiting a multi-

24 collinearity problem (r = <0.80 with another feature) were included in the model. The

25 parsimonious model was selected using the backward search method. The match outcome of

26 win was set at predicted probability level of 0.7, due to overall classification performance

1 being higher comparative to iterations using alternate levels (i.e., 0.5 = 56.3% and 0.6 =

2 58.1%). The proposed model was then evaluated by computing the overall accuracy for

3 match outcome via 10 fold cross-validation for a random selection of 33% of the data.

4 Analyses were undertaken using R (version 3.0.1, R Core Team, Australia) using the

5 *Geepack* package (Yan, Højsgaard, & Halekoh, 2012).

6

7 **Results**

8 The reliability assessment revealed very high agreement between the author's and Champion

9 Data's coding (ICC range = 0.947 to 1.000) for all performance indicators used in the study

10 (Table II). Validity results showed low absolute error for the author's coding with respect to

11 the Champion Data values (RMSE range = 0.0 to 4.5) Consequently, AFL reported values

12 were used in all subsequent analyses.

13 **** INSERT TABLE II ABOUT HERE****

14 The validity screening resulted in the removal of 107 of the 143 features initially extracted,

15 leaving 36 for inclusion in the modelling process. This feature set was further reduced to

16 eight features based on each providing a significant ($P <0.05$) contribution to the GEE

17 model.

18 ****INSERT TABLE III ABOUT HERE****

19 Table III provides an overview of the contribution of the eight features to the model,

20 based on their model estimate, standard error and corresponding Wald statistic. The three

21 features providing strongest contributions to the model all related to the performance

22 indicator Goals, with lower P_{75}, P_{90} and P_{95} values all most strongly linked with a winning

23 team outcome. Lower P_{90} for Behinds and P_{95} values for Inside 50's were also positive

24 contributors to the model. In contrast, higher P_{25} and P_{50} values for Disposals and P_{25} for

1   Marks were related with winning (Table III). Overall classification accuracy of the model

2   (median ± SD) was reported at 63.9 ± 4.2% for the 10 fold cross-validation.

3   **** INSERT FIGURE 1 HERE ****

4   The individual influence of each feature on match outcome is presented in the

5   Tornado plot shown in Figure 1. Each bar in the graph indicates the influence of the feature

6   value when keeping all other variables constant (at their mean level) in the GEE model. The

7   bars in blue represents the win probability for the lowest realised value of the feature for

8   2014, while the red bar relates to the win probability for highest realised value of the feature

9   in the sample. Using $Goals.P_{75}$ as an example, it can be seen that the probability of win is

10   reduced from 83.84% to 18.94% as relative goal contributions to the team total decrease

11   from the highest observed value to the lowest. Considering that the outcome of win is set at

12   a probability level of 0.7 (or 70%), this example illustrates that lower P_{75} team values are

13   preferable in order to maximise the probability of winning. In contrast, Figure 1 shows that

14   for the feature Disposals.P25, the probability of win is improved from 5.99% to 72.64% as

15   team relative disposal contributions increase from the lowest observed value to the highest.

16   **** INSERT FIGURE 2 ABOUT HERE ****

17   Figure 2 presents an example of the vector *w* for a win and loss scenario, in this

18   instance for the performance indicator Goals. Figure 2a depicts the raw mean distribution of

19   goals for each player in the 2014 AFL season, prior to conversion to a relative format. The *y*

20   axis relates to the mean goals contribution per match, whilst the 22 players are represented

21   on the *x* axis ordered by magnitude of their contribution. Unsurprisingly, winning teams

22   displayed higher mean values for goals for all 22 players in the season. Specifically, Figure

23   2a shows that the leading individual player for winning teams contributed almost four goals

24   per game to the team, whereas this value was less than three for losing sides. The figure also

25   shows that a greater number of players typically contributed to the number of goals kicked

26   for winning sides. Specifically, Figure 2b reveals the same data shown in Figure 2a, having

1   been converted to relative values for each player (i.e., percentage contribution to team total).

2   As is shown in the area curve, higher relative contributions to the team goal total is noted for

3   the top six players for losing teams. This reflects the findings from the GEE model showing

4   that lower P_{75}, P_{95} and P_{90} values are advantageous. In contrast, the tail of the Win curve is

5   larger comparatively to that of the Loss, showing the importance of having greater

6   contributions to team goals from multiple players. Specifically, it can be noted that during

7   the 2014 season winning teams recorded up to 13 goal scorers, whereas this value was rarely

8   higher than 10 for losing sides (Figure 2b).

9   **** INSERT FIGURE 3 ABOUT HERE ****

10 Figure 3 shows an example of the strongest feature of the model, Goals.P75, with respect to

11 its mean value for each of the 18 AFL teams in both wins and losses. The sides have been

12 ranked from left to right based on their final ladder position at the end of the regular season.

13 With the exception of one team (Melbourne) Goals. P75 values were typically lower in

14 losses compared to wins, further emphasising the generalisability of this particular feature's

15 influence.

16

17 **Discussion**

18 This study aimed to develop a method of quantifying relative contributions from each of the

19 22 players on an AFL team, with respect to the influence on winning a match. To achieve

20 this aim, each player's individual contribution was measured using 13 commonly-reported

21 performance indicators, with the data then converted to a relative format and expressed as a

22 percentage of the team total. Multiple features were then extracted from each performance

23 indicator in this relative format, in order to represent the distributions across the 22 players

24 in a team.

1   Results showed that only eight of the 143 extracted features contributed

2   meaningfully to a model capable of explaining match outcome in the AFL. In particular,

3   features relating to Goals and Disposals were prominent, with both providing multiple

4   estimates to the model in the negative and positive direction respectively. Based on these

5   estimates, it is apparent that players capable of playing both midfield and forward roles

6   respectively should be considered by coaches when undertaking team selection. Specifically,

7   the proposed model suggests that a comparatively more even contribution of individual goal

8   scorers is beneficial to team success, whilst higher median (P_{50}) player disposal

9   contributions are desirable. Given the three strongest features included in the model all

10   related to the performance indicator Goals, it can be surmised that AFL sides should look to

11   select a team capable of producing multiple goal kickers. In Australian Rules football

12   typically six forwards will compete on the ground at any given time, along with same

13   number of midfielders and defenders (18 in total). However, these results illustrate the

14   importance of players other than forwards contributing to team goal scoring, particularly for

15   winning sides.

16   This paper also provides a new insight into the manner in which performance

17   indicator distributions across a team can be understood in order to maximise the likelihood

18   of winning. Practically, team scouts, recruiting staff and list managers may use such

19   information in order to identify potential deficiencies within their playing roster.

20   Specifically, the findings relating to goal distribution potentially point to a need for the

21   development of empirical position-specific models for Australian football, which have been

22   previously considered as important to define in sport (Reilly, 2001). Specifically, it may be

23   pertinent for list managers and coaches to compare the relative contributions from different

24   positional groups based on match outcome or when competing against different opponents.

25   This could then allow these staff to make more informed decisions relating to the type of

26   player which should be recruited to their particular club, potentially maximising

27   considerable time and financial investment in the process. It may also further inform the

1   structure of team training, to focus on player and ball movement patterns which facilitate

2   achieving these player contribution distributions. Based on the findings from this study

3   specifically, it is clear that sides should look to practice situations which readily facilitate

4   opportunities for a wide range of players to contribute to team scoring.

5   It should be noted that the GEE model proposed in this paper represents a

6   population-averaged approach to addressing the question of explaining team sport match

7   outcome. Although recent work has used the GEE method successfully for various purposes

8   in both team and individual sports (van Ark *et al.,* 2015; Robertson, Gupta, Kremer &

9   Burnett, 2014; Young *et al.,* 2015), the overall model performance in the present study could

10   be considered as only fair. Specifically, just under two thirds of matches from the 2014 AFL

11   were correctly classified. However, considering that the model takes into account only the

12   differences in player performance distribution for winning and losing matches and not the

13   magnitude (i.e., raw values), the results are nonetheless encouraging. Consequently, the

14   methodology proposed could be implemented in a variety of team sports, particularly those

15   with a similar number of players competing as in Australian football (i.e., rugby or football).

16   A limitation relating to this study was the lack of inter- and intra-rater reliability as

17   well as validity data available for each of the performance indicators used. However, results

18   from the comparison with our own analysis of a subset of data revealed generally high

19   agreement for each performance indicator along with corresponding low RMSE values. The

20   process undertaken by the commercial provider used by the AFL involves numerous human

21   statistical coders working on multiple matches in a given week. Whilst previous research has

22   also reported the validity of this data as high (O'Shaughnessy, 2006), unfortunately the inter-

23   and intra-rater reliability of this information is not available. It is also possible that the

24   addition of more sophisticated performance indicators currently used by AFL clubs (i.e.,

25   metres gained) or those from other domains (i.e., physical performance) may have improved

26   the accuracy of the GEE model. Further studies could look to include the team distribution

27   of high intensity running or the total distance covered by players. It may also be of interest

1   to determine the success of this analysis approach in sports which include fewer players on

2   the field at any one time.

3   Future work may look to undertake investigation into the external validity of this

4   model by evaluating its performance on new data obtained over subsequent seasons.

5   Specifically, it may be of interest to determine whether similar player contribution

6   distributions have been associated with winning in previous years. Obtaining such

7   information would serve to further elucidate any longitudinal changes in the game (see

8   Norton, Craig & Olds, 1999 for previous work in this area). For instance, it would be

9   beneficial to determine whether previous successful sides were more or less reliant on

10   forwards providing the majority of scoring, or midfielders providing the majority of

11   disposals. Further, the use of an alternative dependent variable in the modelling (i.e., score

12   margin) may also yield different results and presents another future avenue for investigation.

13   The use of machine learning analysis approaches may represent an alternative option to GEE

14   in being able to identify multiple player performance distribution profiles for different

15   teams. However, it is important to recognise that such analysis techniques do not adjust their

16   output based on the level of correlation between multiple same-team performances which

17   would likely be present in a sample typical of that used here. Nonetheless, these types of

18   analyses may hold value in identifying non-linearity in the performance behaviour both

19   between and within different teams and thus may have future applicability.

20

21   **Conclusions**

22   The findings of this study represent a novel approach to understanding the relative

23   contributions of individual players in team sports with respect to match outcome. By

24   extracting features relating to performance indicators in sport, a more thorough

25   understanding of how different players contribute to a team's success can be achieved. The

26   accuracy of the model proposed in this study could potentially be further improved in future

1   through the addition of data from previous AFL seasons, along with the inclusion of more

2   sophisticated team performance indicators. Future work should focus on the application and

3   refinement of this model to other team sports.

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1   Figure 1. Tornado plot displaying predicted probabilities of match outcome for each of the

2   eight key performance indicator features in isolation when all others are held constant. The

3   blue bars represent the probability of 'Win' when the feature is at the lowest level whereas

4   the red bars represent the highest level

5

6   Figure 2. Mean (± SD) player contribution to team match totals for the performance

7   indicator 'Goals' for games played during the 2014 AFL regular season. Figure 2a displays

8   the contribution in absolute terms (raw), whilst Figure 2b displays the contributions as a

9   percentage of the team total (relative)

10

11   Figure 3. Goals.P75 values for each of the 18 AFL teams represented by wins and losses in

12   the 2014 regular season. Teams are ranked from left to right based on final ladder position at

13   the end of the regular season