Transferring an Analytical Technique from Ecology to the Sport Sciences

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Abstract

Background: Learning transfer is defined as an individual's capability to apply prior learnt perceptual, motor or conceptual skills to a novel task or performance environment. In the sport sciences, learning transfers have been investigated from an athlete-specific perspective. However, sport scientists should also consider the benefits of cross-disciplinary learning to aid critical thinking and metacognitive skill gained through the interaction with similar quantitative scientific disciplines.

Objective: Using team sports performance analysis as an example, this study aimed to demonstrate the utility of a common analytical technique in ecology to the sports sciences; namely, non-metric multidimensional scaling.

Methods: To achieve this aim, three novel research examples using this technique are presented, each of which enables the analysis and visualisation of athlete (organism), team (aggregation of organisms) and competition (ecosystem) behaviours.

Results: The first example reveals the technical behaviours of Australian Football League Brownlow medallists from the 2001 to 2016 seasons. The second example delineates dissimilarity in higher and lower ranked National Rugby League teams within the 2016 season. Lastly, the third example shows the evolution of game-play in the basketball tournaments between the 2004 to 2016 Olympic Games.

Conclusions: In addition to the novel findings of each example, the collective results demonstrate that by embracing cross-disciplinary learning and drawing upon an analytical technique common to ecology, novel solutions to pertinent research questions within sports performance analysis could be addressed in a practically meaningful way. Cross-disciplinary learning may subsequently assist sport scientists in the analysis and visualisation of multivariate datasets.

Key points

- The graphical outputs of non-metric multidimensional scaling (nMDS) enable the recognition of non-linear behavioural patterns at the athlete (example one), team (example two) and competition (example three) levels.
- Accordingly, cross-disciplinary learning may assist sport scientists with the resolution of practically meaningful questions in performance analysis.
- Sport scientists in other sub-disciplines are encouraged to 'think outside the box' when analysing and visualising data.

Key words: Transfer of learning; cross-disciplinary learning; sports performance analysis; data visualisation

1. Introduction

An integral component of learning concerns an individual's capability to transfer its production from one performance context to another [1]. This concept, referred to as a transfer of learning [2], typically extends to motor, perceptual or conceptual tasks or variables. It suggests that tasks expressing a similar production, outcome or performance environment may afford greater transference (i.e., a positive transfer of learning) [3, 4]. The principle of learning transfer has been examined in and across a range of scientific disciplines, such as educational science [5], health and medical science [6], rehabilitation science [7], and sport science [8]. With a focus on the sport sciences, there has been a large quantity of work examining motor and perceptual learning transfers between sports or performance environments [9-12]. In each of these studies, athletes have been the target population, with their capability to transfer a prior learnt skill to a relatively novel sport being the outcome of interest.

However, learning transfers can also be encouraged from the sport scientist's perspective, in addition to the athletes they interact with. Cross-disciplinary learning is likely to extend sport scientists critical thinking and metacognitive skill through novel perspectives generated by the interaction with similar quantitative sciences [13]. For example, Duarte et al. [14] discussed how sporting teams could be viewed as 'superorganisms', in a similar fashion to how ecologists view aggregated organisms, such as flocks of birds, given that athletes are likely to base movement decisions on environmental information extracted from opponent (predator) and teammate (organism aggregate) relative positioning. Considering players and sporting teams in such a nuanced way can provide novel insights into collective behaviours and patterns in play [14]. However, extracting meaning from these often large, longitudinal and multivariate datasets can represent an analytical challenge. Further, linear statistical approaches, which are popular in the sport sciences, may not adequately reveal non-linear behavioural patterns [15]. Thus, examination of this data may require alternative or 'outside of the box' approaches adopted from other disciplines. One potential discipline of relevance to sport scientists is ecology, which often seeks to delineate non-linear behavioural patterns across an organism type, an aggregation of organisms or an ecosystem [15, 16]. This analytical cross-disciplinary learning transfer from ecology to the sport sciences may enable the emergence of novel, data visualisation techniques, while simultaneously increasing the sophistication of research questions regarding athlete and team behaviour. Ultimately, this may provide sports coaches or sporting administrators with greater objectivity to support the decisional processes they commonly encounter.

One particular analytical and visualisation approach commonplace in ecology for the study of organism behaviour is non-metric multidimensional scaling (nMDS) [17]. Fundamentally, nMDS is an indirect gradient analysis, producing an ordination based on a dissimilarity matrix [17]. This matrix is ascertained via isotopic regression, which is a type of non-parametric regression that iteratively searches for a least squares fit based on ranks of the dissimilarities [17, 18]. Accordingly, this is a ranked-based approach, where original distance data is substituted with ranks. The output of this isotopic regression provides a measure of 'stress', which decreases as the rank-order agreement between dissimilarities improves; lower 'stress' values (i.e., closer to '0') represent a closer fit [19]. In contrast to other ordination techniques, nMDS makes few assumptions about the data properties. For example, a principal component analysis (PCA) assumes linear relationships between variables within datasets, whereas nMDS does not, enabling its utility in multivariate datasets that contain diverse data properties [17]. Further, while other ordination techniques attempt to maximise the variance between objects in an ordination, nMDS represents, as closely as possible, the pairwise dissimilarity between objects [18, 19]. Subsequently, the graphical output of nMDS provides a map that spatially illustrates the relationships and patterns between samples in a reduced two- or three-dimensional space [18] (Figure 1). Transferred to team sports performance analysis, performance indicators (e.g. behaviours) may be coded as the samples within a multivariate dataset, with the dissimilarity of these samples being analysed between players in a team or group (e.g. organisms in an aggregate), teams in a competition (e.g. aggregates in an ecosystem) or competitions over time (e.g. ecosystem dynamics).

****** INSERT FIGURE 1 ABOUT HERE ******

Using team sports performance analysis as the sub-discipline, this study aims to demonstrate the applicability of nMDS to sport science. To achieve this aim, three original research examples will be independently presented. Each example was chosen to reflect player (organism), team (aggregation of organisms) and competition (ecosystem) behaviours, complementing the 'superorganism' perspectives offered by Duarte et al. [14].

2. Methodology

The datasets used in each proceeding example originate from commercially accessible sources, with institutional ethics declaration being acquired prior to data extraction. Despite nuanced methodologies being described in each proceeding example, all analyses were performed using the 'vegan' package via the *metaMDS* function in *R*, which is a commonly used package for nMDS in ecology [19]. Further, the *R* code used in each example is presented as Supplementary Material.

3. Results

Example 1 – Player Behaviour: *Revealing technical skill behaviour in Brownlow Medal winning Australian Football League players from the 2001 to 2016 seasons*

Introduction: Australian football (AF) is a team invasion sport that requires physical, technical and perceptual skills [20-22]. At the elite level, the Australian Football League (AFL), game-play is contested between two teams of 22 players, who field no more than 18 players at a time. Following the conclusion of each 23-week 'home and away' game, the umpires award three votes to the player from either team whom they perceive exemplified the 'best and fairest' on the ground. To assist with this 'voting' process, the umpires are provided with a range of player technical skill involvements immediately following each game. At the conclusion of the season, the player who accrues the greatest number of votes is then awarded the Brownlow Medal; or more colloquially, the competition's 'best and fairest' player. Understanding the technical characteristics of these winners would be of scientific and practical interest by offering insight into the evolution of the performance of the best players in the AFL. This example aims to reveal the technical skill characteristics of Brownlow medallists between the 2001 to 2016 AFL seasons using nMDS.

Methodology: Brownlow medallists from the 2001 to 2016 seasons were identified (n=19), with three separate winners awarded in the 2003 season and two separate winners in the 2012 season. Fifteen individual performance indicators were extracted for each player within the analysed period from a commercial source (http://www.afl.com.au/stats). Using the individual performance indicators, a dissimilarity matrix was built with the Bray-Curtis measure and plotted in two dimensions. The ordination surfaces were fitted using generalised additive models that employed an isotopic smoother via thin-plate regression splines [18]. Further, 'arrows' were used to denote the progression of profiles across the ordination surface using the *geom_point*, *geom_segment*, and *geom_path* functions in the 'ggplot2' package [23].

Results: The dissimilarity matrix solution was reached after 20 iterations (stress = 0.15, rmse = 1.4×10^{-4}, maximum residual = 4.8×10^{-4}). The ordination plot of the matrix showed a high seasonal dissimilarity (Figure 2). Notably, the profile of the 2001 winner was markedly dissimilar to the 2002 winner. Further, despite two of the three winners in the 2003 season possessing similar ordination positions, the third winner for that season possessed a relatively dissimilar position (Figure 2). Following the 2003 season, the player profiles then 'zigzagged' across the ordination surface, displaying large season-to-season dissimilarity. Relative to the seasonal positioning of each player, the largest ranked dissimilarity was observed between the profiles of the 2014 and 2015 winners.

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

Conclusions: Using nMDS, the results of this example showed high dissimilarity in the technical skill characteristics of AFL Brownlow medallists between the 2001 to 2016 seasons; enabling three main conclusions to be drawn. Firstly, the objective multivariate qualities that umpires deemed worthy of votes may have seasonally changed. Secondly, the objective player profiles reflective of a dominant performance may be continually evolving. Thirdly, changing rule interpretations throughout the analysed period may have influenced how players obtained ball possession or interacted with their opponents, potentially impacting on an umpires' perceptions of 'best and fairest' play.

Example 2 – Team Behaviour: *Revealing dissimilarity in higher and lower ranked teams within the 2016 National Rugby League season*

Introduction: Rugby league (RL) is a team invasion sport characterised by a diverse set of multidimensional performance qualities [24]. The elite competition in Australia and New Zealand is the National Rugby League (NRL), which currently consists of 16 teams who compete in a 26-week 'premiership' season. Within this season, teams are awarded two points for a win, with the accumulation of these points being used to rank teams on a ladder (16 being the lowest rank and one being the highest rank). The eight highest ranked teams at the conclusion of the premiership season then compete in a finals series for the opportunity to compete in the NRL grand final. Resolving the technical dissimilarity of team's ranked high or low on the ladder may assist coaches with the design of game-plans for prospective seasons. Additionally, objective insights into opponent dissimilarity would likely assist with team selection strategies by enabling coaches to select rostered players to generate a (mis)match between an opponent's characteristics. Using nMDS, this example aims to delineate the dissimilarity of teams ranked high or low on the ladder at the conclusion of the 2016 NRL premiership season.

Methodology: Fifteen team performance indicators were extracted from a commercial source (http://www.nrl.com/stats) for each of the 16 NRL teams following the 2016 season. Teams were *apriori* classified into quartiles based upon their ladder ranking; these being the top four (1-4), upper middle four (5-8), lower middle four (9-12) and bottom four (13-16). Using the team performance indicators, a dissimilarity matrix was built with the Bray-Curtis measure and plotted in two dimensions. The ordination surfaces were fitted using generalised additive models employing an isotopic smoother via thin-plate regression splines [18]. Accordingly, teams were labelled and colour coded relative to their ladder position on the ordination using the *geom_label* and *geom_segment* functions, while their progression across the ordination surface was illustrated using the *geom_path* function [23].

Results: The dissimilarity matrix solution was reached after 20 runs (stress = 0.07, rmse = 3.6 x 10^{-6}, maximum residual = 1.1 x 10^{-5}). The ordination plot shows a similarity in the positioning of teams relative to their quartile (Figure 3). However, despite placing in quartile three, the West Tigers displayed a profile that expressed relative similarity to the teams ranked in quartile two. Certain team profiles appeared more similar than others, with the Raiders and Cowboys showing similarity relative to the other top four teams, while the Sea Eagles and Eels (who are located below the Sea Eagles on Figure 3) possessed an almost identical positioning on the ordination surface.

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

Conclusions: A high dissimilarity was observed between NRL teams grouped in different quartiles following the 2016 season. Specifically, teams in quartile one were located at the bottom left of the ordination surface, while teams in quartile four located the top right of the ordination surface. This indicates that the top four teams generated unique profiles relative to their lower performing opponents in the 2016 season. Further, the positioning of certain teams on the ordination surface revealed similar profiles, which suggests similar game-plans and/or player types.

Example 3 – Competition Behaviour: *The evolution of game-play in an Olympic basketball tournament from 2004 to 2016*

Introduction: Basketball is team court sport consisting of physical, technical and perceptual components [26, 27]. Arguably the most recognised international basketball tournament is within the summer Olympic Games. For males, it was first introduced at the summer Olympics in 1936, with participating countries currently competing against one another in two separate pools consisting of six teams. At the conclusion of this round robin ‘group stage’, the four highest placed teams in each pool then compete in knockout quarterfinal, semi-final and ‘gold medal’ games. Understanding how game-play in this tournament has evolved would be of interest to performance analysts and coaches, as it would likely assist with the continued design of ‘contemporary’ game-plans. Accordingly, this example examines the evolution of game-play in male Olympic basketball tournaments from 2004 to 2016.

Methodology: Twelve team performance indicators were collected from a commercially accessible source (http://www.eurobasket.com/Olympic-Games/basketball.asp) for each male team participating in 2004, 2008, 2012 and 2016 summer Olympic Games. This resulted in 48 teams across the four Olympic Games. Using the team performance indicators, a dissimilarity matrix was built with the Bray-Curtis measure and plotted in two dimensions, with ordination surfaces being fit via generalised additive models employing an isotopic smoother via thin-plate regression splines [18]. Additionally, convex hulls were overlayed on the ordination surface to cluster each Olympic Games using the *geom_polygon* function [23], while teams were plotted on the ordination surface using the *geom_point* function [23].

Results: The dissimilarity matrix solution was reached after 20 runs (stress = 0.21, rmse = 1.4×10^{-4} maximum residual = 7.6×10^{-4}). Despite the 2004 and 2008 tournaments showing dissimilarity noted by the spread of teams on the boundary of the convex hulls, team similarity progressively increases over the 12 years. Specifically, team profiles are moving toward the top right corner of the ordination surface (Figure 4). Relative to the 2004, 2008 and 2012 tournaments, the 2016 tournament displayed the greatest similarity in the profiles of competing teams, shown by their grouping within the purple convex hull (i.e., smaller surface area) (Figure 4).

****** INSERT FIGURE 4 ABOUT HERE ******

Conclusions: There was a distinctive progression in the positioning of team profiles on the ordination surface from the 2004 tournament to the 2016 tournament. The 2016 season shows the highest relative similarity based on the size of the convex hull, with teams clustering in the top right corner of the ordination surface. This indicates that game-play in the Olympics has become more homogenised, with teams expressing similar profiles. It could be speculated that the dominance shown by certain countries in this tournament may therefore be reducing, with the team standards equalising as coaches become more strategically equipped to match the profiles of more dominant countries. Beyond the confines of basketball, this example shows the power of nMDS to reveal the evolution of competition dynamics both between teams and across multiple seasons.

4. Discussion

Using an analytical technique common to ecology, this study aimed to demonstrate the utility of nMDS in team sport performance analysis. To achieve this aim, three original research examples were presented, each orienting player (organism), team (aggregation of organisms) and competition (ecosystem) behaviours. Despite each example yielding idiosyncratic findings, the collective results demonstrate the capability of nMDS to simultaneously analyse and visualise non-linear behaviours extracted from multivariate datasets. Accordingly, each example displays how coaches and competition administrators can obtain decisional support through the interpretation of multivariate data signatures uncovered by nMDS, rather than generating inferences based upon univariate model sets [25]. While it is known that sport scientists already engage in cross-disciplinary learning (for an example, see Pion et al. [28]), this work offers a comprehensive basis for how they may wish to continually draw upon analyses or theories ingrained in other quantitative sciences to assist with the resolution of questions in their respective sub-discipline of sport science.

As briefly discussed in each example, the graphical output of nMDS is likely to be compelling for coaches or sports administrators in numerous ways. Firstly, although example one shows the dissimilarity between AFL Brownlow medallists, the methodology could be extended to inform team selection strategies by highlighting the level of (dis)similarity between players on a roster or between players in a competition. This information, would be critical when attempting to replicate certain player 'types' or when selecting players that generate a (mis)match to an opponent in an effort to generate a competitive advantage. However, given the dyadic requirements of team sports, it would be beneficial for coaches or analysts to consider player-to-player interactions when using nMDS as a basis for team selection. The second example may assist coaches with the establishment of team profiles that explicitly express (dis)similarity to an opposition, enabling them to establish both unique and innovative multivariate profiles or to match the profile of a more dominant opponent. Lastly, the third example could be used to show how environmental changes (such as rule changes) alter the dynamics of team profiles at the competition level. Knowledge of this information is likely to offer sports administrators with an objective basis to assist with decisions orienting how game-play may progress in prospective seasons.

This study offers a unique perspective of the transferability of analytical methods between scientific disciplines. Indeed, it is possible that more common analyses within the sport sciences may have offered similar results by observing magnitudinal changes between individual performance indicators across players, teams or competitions. However, linear and univariate approaches are limited in what information they can extract from multivariate datasets [25]. As shown, nMDS enables the analysis and visualisation of data in multiple dimensions simultaneously, which is important within sports performance analysis when addressing questions that orient how collective player, team or competition behaviours (dimension one) change over time (dimension two) [25]. Further, and perhaps practically most important for coaches and competition administrators, the graphical outputs of nMDS enable the interpretation of object interactions, such as the similarity between players in a team, teams in a competition or competitions over time [25].

Beyond team sports performance analysis and the three examples presented here, the authors perceive that nMDS could yield implications for other areas of sport science. For example, it is common for strength and conditioning specialists to record multiple metrics when quantifying training load [29]. The data properties of these metrics are often diverse, with practitioners typically integrating continuous measures of external load such as distances run above certain velocity thresholds with categorical measures of internal load such as perceived exertion [29]. Accordingly, given that nMDS is a rank-based approach, makes few assumptions about underlying data properties and does not assume linear relationships between variables within a dataset [17], strength and conditioning practitioners could use this ordination technique to simultaneously analyse and visualise multivariate training load datasets to delineate relationships between athletes at different levels of experience (e.g. 1st year compared to +5 year athletes) or phases of a season(s). Concomitantly, it is common for talent identifiers to integrate both objective and subjective measures to inform decisions surrounding player recruitment [30]. Given the likely diverse properties of such data, nMDS may assist talent recruiters with the recognition of youngsters who express similar multivariate qualities to elite senior (rostered) athletes. Specifically, the positioning of youngsters on an ordination surface relative to their elite senior counterparts may enable the identification of similar player 'types', which would be pertinent information when attempting to compensate weaknesses on a playing roster. However, despite the promising utility of this analysis for the sports sciences, it does possess limitations that warrant resolution. Primarily, it does not enable coaches to gain insights from qualitative skill qualities that would likely be of value when basing decisions around factors such as player recruitment or team selection. Accordingly, while this analysis is likely to offer quantitative support, coaches may wish to consider its use complementary to qualitative sources to optimise its decisional support.

Analytical cross-disciplinary learning transfers have been discussed elsewhere [13]. Notably, Cutler et al. [31] demonstrated the utility of the random forest algorithm (a machine learning technique used in computational sciences) for classification and prediction in ecology. Additionally, Huang et al. [32] transferred analytical knowledge from computational science to economics by using support vector machines to forecast stock market variations. Coupled, these studies demonstrate the benefit of cross-disciplinary learning to address pertinent research questions within their respective fields. Thus, while nMDS was the analytical technique discussed here, a concomitant outcome of this work is to encourage sport scientists to 'think outside the box' when analysing data. By doing so, it is conceivable that sport scientists can approach research questions with novel and informative analyses, providing coaches with greater objective support.

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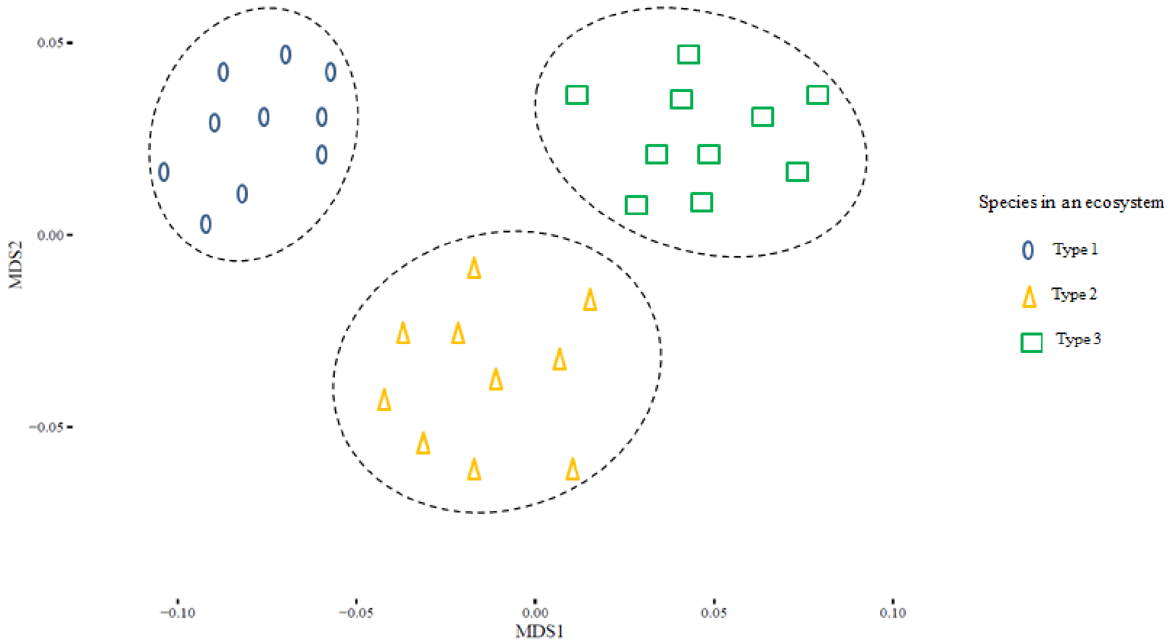
Figure 1. An example of an ordination plot using nMDS of a dissimilarity matrix calculated from organism behaviour in an ecosystem

Figure 2. The ordination plot using nMDS of a dissimilarity matrix calculated from individual performance indicators of Brownlow medallists from 2001 to 2016

Figure 3. An ordination plot using nMDS of a dissimilarity matrix calculated from team performance indicators of each NRL team in the 2016 season

Figure 4. An ordination plot using nMDS of a dissimilarity matrix calculated from team performance indicators for each country participating in the 2004, 2008, 2012 and 2016 male Olympic basketball tournaments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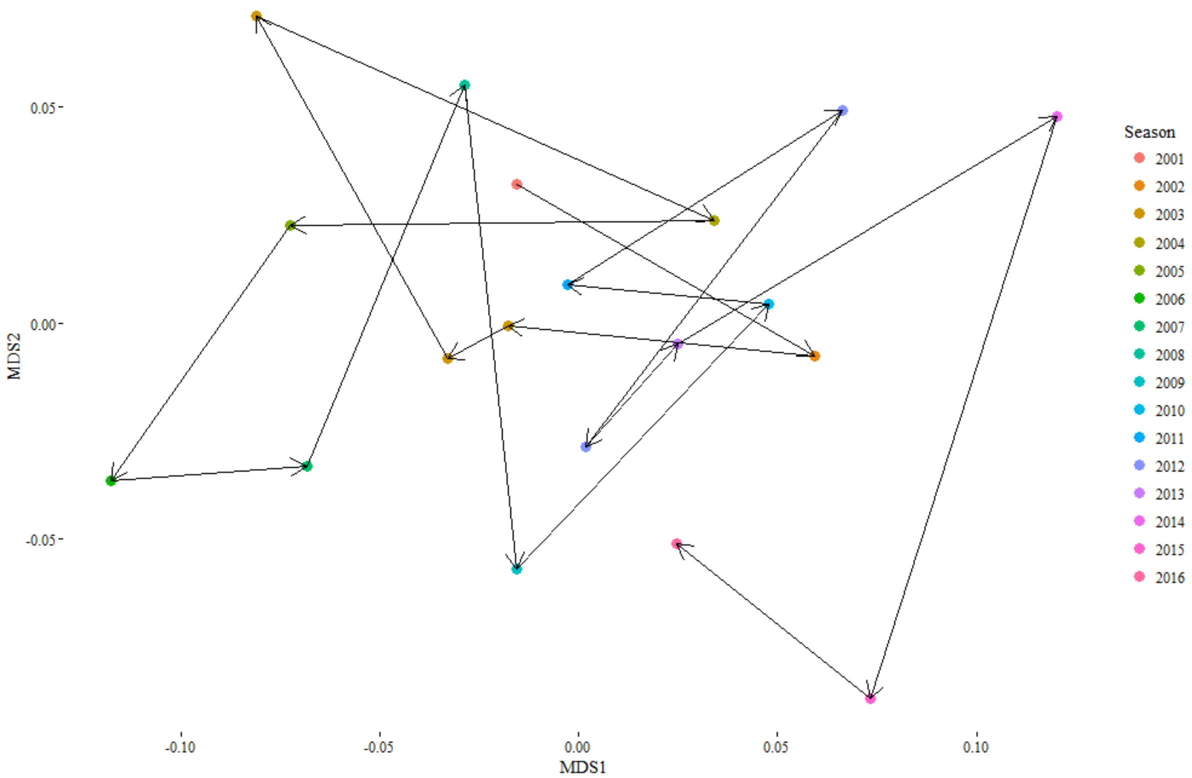
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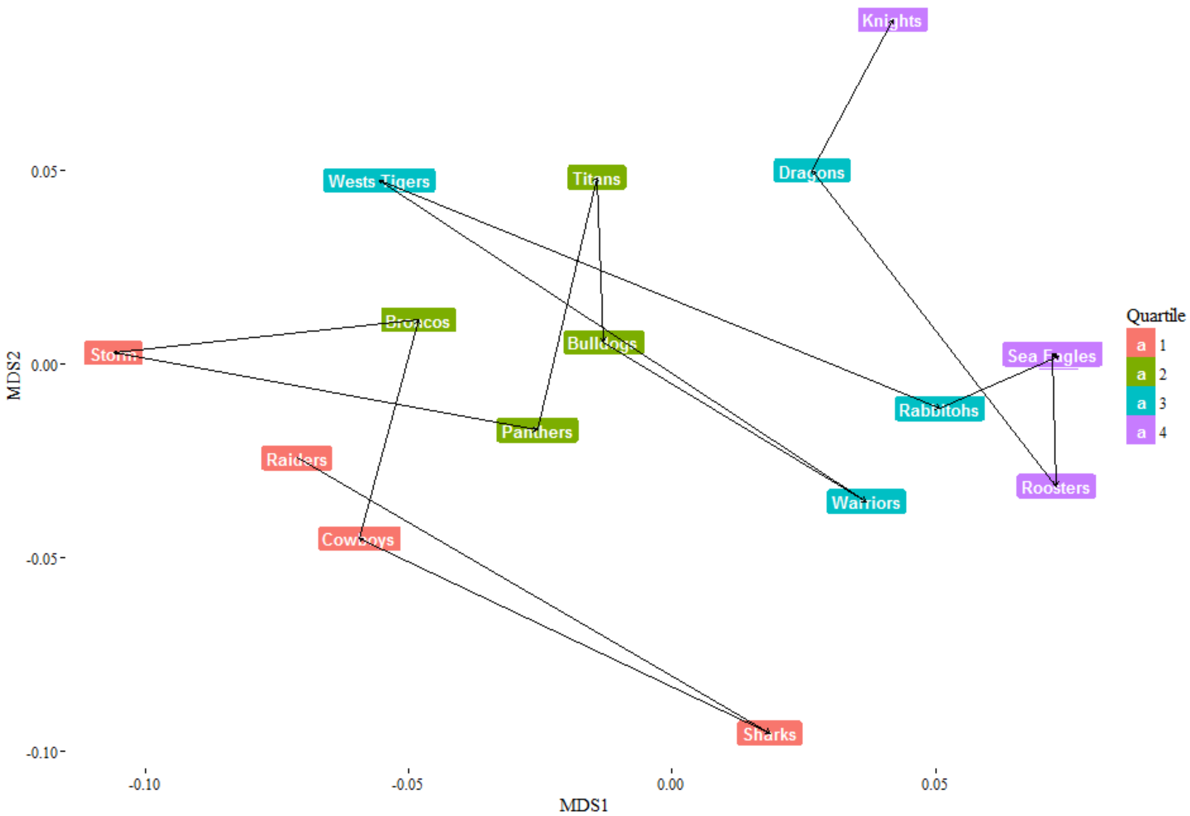
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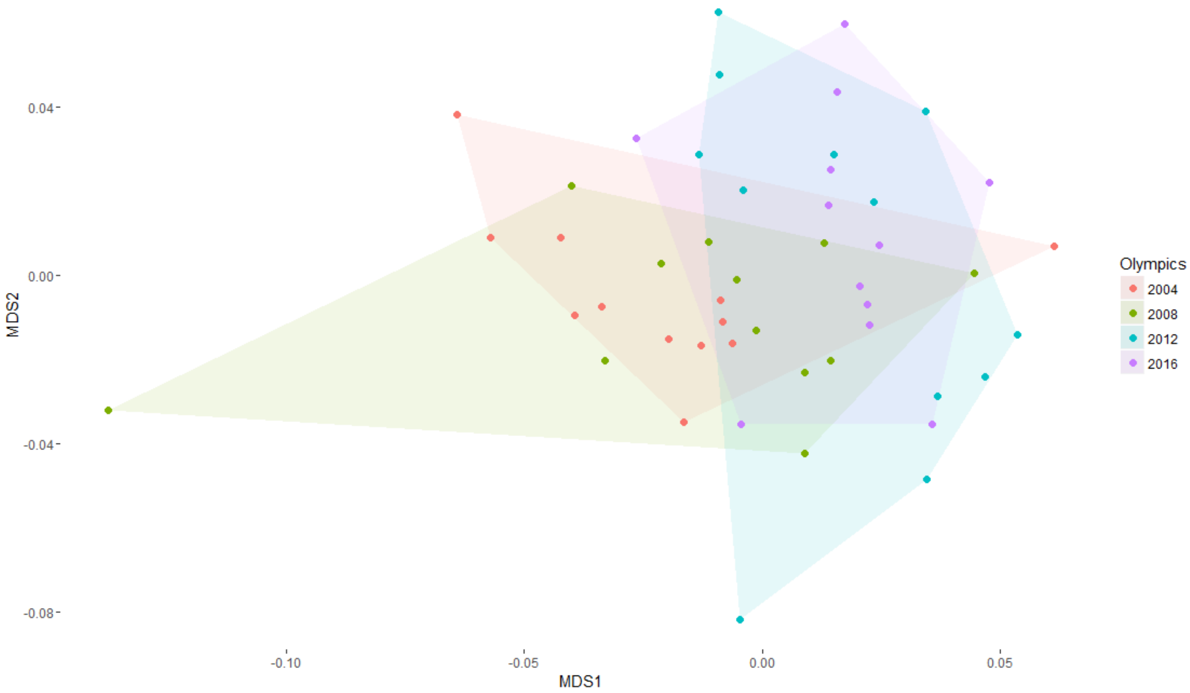

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