PROVIDING AUTOMATED DECISION SUPPORT FOR ELITE ATHLETES

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Abstract
The Victorian Institute of Sport routinely collects vast amounts of data. To utilise the use of this data and develop decision support systems to help improve elite athletes’ performances, we describe how knowledge discovery from databases, feature subset selection and recommender systems can be gainfully employed.

1. Introduction
Each year, a vast amount of competition, psychological and physiological data is collected about elite athletes. However, these data are rarely appropriately analysed to provide advice for coaches and athletes decision-making. To better utilise the available data and knowledge, we are developing decision support systems that analyse the information and provide useful advice with regard to advanced training and performance.

Once decision models of success in individual sports have been developed, we are developing data mining techniques for finding the smallest feature set having the most beneficial impact on performance and constructing recommender systems, tailored for individual athletes.

Following testing against design specifications and user acceptance, a generic framework for the construction of decision support systems to support elite sports performance will be developed.

To construct such a framework we are using
a) Decision models – we are developing decision models for defining and understanding success in specific sporting domains;
b) Knowledge Discovery from Databases – given a model of successful athletic performance, we can attempt to learn the patterns that led to the attainment of excellence and which variables can lead to negative repercussions, such as loss or injury. For example, what strategies are most significant for successful performance and which variables can be used to predict the development of injuries during training or competition;
c) Feature subset selection - finding the smallest feature set having the most beneficial impact on performance;
d) **Developing recommender systems** - once we have evaluated and agreed upon the results of the learning used in b) and c), we can then build systems to advise upon training, performance and strategies. These systems are being tailored for individual athletes, and use data and knowledge to enhance training, reduce injuries and improve performance. When completed, they will be tested against design specifications and emphasize user acceptance.

Our goal is to use the vast amount of physiological and competition data available to us to integrate these approaches, where possible. We recognise both the importance and the difficulty of providing semi-automated psychological advice and hence do not address this task in the current project.

### 2. Modeling Sports Performance

The German Research Center for Peak Performance Cologne at German Sport University Cologne annually tests about 600 young and national level athletes on about 3000 variables\(^1\). So they have an electronic internet based data-set that also can be visually/textual printed for different athletes and coaches. Currently, a one-page information sheet is selected in a profile-manner for individual athletes and compared to some means of talent groups to see if specific athletes are far above/beyond the mean. There are also already decision meetings implemented between the diagnostic centre, coaches and other people. However, currently, they do not have an electronic decision support system: instead all the information is shown to the coach without any help or comparisons. Our goal in this project is to meet this need by providing both the Victorian Institute of Sport and the German Research Center for Peak Performance Cologne with electronic decision support.

Johnson (2006) provides an introduction to the theoretical, practical, and methodological advantages of applying cognitive models to sports decisions. The use of sequential sampling models, in particular, is motivated by their correspondence with the dynamic, variable processes that characterize decision-making in sports. He offers a brief yet detailed description of these process models, and encourages their use in research on decision-making in sports. Although the formulation focuses primarily on deliberation among a set of options, incorporating other critical task components (e.g. option generation, learning) is contemplated. A criticism of Johnson’s modelling is that it may not be appropriate in application to athlete option choice which is time-constrained {limiting the ability to generate options, for example, see also Zsambok and Klein (1997)}. The use of the cognitive models of (Johnson 2006) will prove highly useful for developing process models. Recent mathematical modelling of choices can be used as a framework to set up choice rules for talents description (Johnson and Raab, submitted), talent prediction and a decision tool for coaching decisions as individuals or groups (Farrow & Raab, 2008).

#### 2.1. Decision Analysis and Sport:

There are numerous approaches for developing decision analysis techniques for the sporting domain. A well known use of statistics in baseball is sabermatics - a statistically-based approach for developing and applying objective knowledge to baseball. James (2004) coined the term “Sabermetrics” which stems from the group SABR (Society for American Baseball Research). Lewis (2003) in his book Moneyball details how Oakland Athletics general manager Billy Beane and his staff used statistical

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analysis to design a low-budget team that could compete with teams in bigger markets with larger payrolls. He did this by isolating the important factors in winning baseball games. Under Beane’s leadership, the A’s managed to reach the playoffs for four consecutive years. Over that period their salary cost per victory was less than half of the next highest spending team and less than a quarter of teams like the New York Yankees. Whilst the Yankees are relatively successful, this success has occurred at a great price. Gröschner and Raab (2005) have used a theoretical approach that is called simple heuristics (e.g. less information can lead to better decisions) and compared them to Bayesian strategies\(^2\). For instance, according to the take-the-best heuristic, when making a judgment based on multiple criteria, the criteria are tried one at a time according to their cue validity, and a decision is made based on the first criterion which discriminates between the alternatives (Gigerenzer and Goldstein 1996). Decision support systems and algorithms that use regression or Bayes, versus simple heuristics are natural comparison candidates for further testing the benefits of decision support systems. Given our experience in modelling sporting comparisons, we wish to develop support systems based on the Decision Field theory (see Raab & Johnson, (2004)), T-ECHO (Explanatory Coherence for Harmonic Optimization) computational approach on choices (Johnson & Raab, submitted), simple heuristics versus regression and Bayesian networks. (Gröschner & Raab, 2005) and compare these to the artificial intelligent approaches such as neural networks, optimization procedures and KDD (see below). For a variety of sports chosen by the Victorian Institute of Sport (beginning with swimming, but including cycling, rowing, track and field and golf) we will develop criteria to define ‘success’ Depending on the individual athlete, this might mean winning a gold medal, winning any medal, reaching the final or semi-finals, or achieving a personal best. Different success criteria will also be developed for athletes at different stages of their careers. Strategy and risk is also a component of performance in sport. In many human endeavours such as business, government, law and medicine, decision-makers wish to minimise risk. Hence, they do not attempt to find optimal solutions to problems (Zeleznikow 2002). Unique to sport, however, it is generally the participant’s goal to achieve an optimal result\(^3\), where often the margin for losing may matter less than the loss itself, hence strategic risk-taking in both training and performance is standard. Contrary to optimizing strategies are satisfying strategies as described above in form of simple heuristics or rules of thumb or thresholds in a decision field theory that allows coping with limited time, limited resources and limited capacity of humans making fast and frugal decisions.

2.2 KDD and Sport:

According to Frawley et al (1991) knowledge discovery from databases (KDD) is the 'non trivial extraction of implicit, previously unknown and potentially useful information from data'. Data mining is a problem-solving methodology that finds a

\(^2\) Bayesian methods provide formalism for reasoning about partial beliefs under conditions of uncertainty. In this formalism, propositions are given numerical values, signifying the degree of belief accorded to them. Bayes’ theorem is an important result in probability theory, which deals with conditional probability.

\(^3\) In the 1960s, the great American (Green Bay Packers) football coach Vince Lombardi is quoted as saying “Winning isn’t everything, it is the only thing”. However, the quote is first attributed to UCLA Bruins football coach Henry Russell (“Red”) Sanders, who in 1950, at a California Polytechnical University at San Luis Obispo physical education workshop developed the notion (Rosenbaum 1950).
logical or mathematical description, eventually of a complex nature, of patterns and regularities in a set of data (Fayyad et al 1996).

Recent reviews of expertise in sport have indicated that many coaching practices are based on “anecdotal evidence and historical precedence” developed from “intuition, tradition and emulation” (Williams and Ericsson, 2005), rather than from empirical research. This highlights the need for empirical evidence to rationalize evaluation and skill testing practices in order to guide training, selection and decision making practices with regard to maximizing performance.

The KDD process begins with the analysis of data stored in a database or data warehouse and ends with the production of new knowledge. Fayyad et al (1996) describe knowledge discovery as a process with five distinct stages:

a) Data selection;  
b) Data pre-processing;  
c) Data transformation;  
d) Data mining and  
e) Evaluation/Deployment.

Fayyad et al (1996) claim that data mining techniques derive from four different sources:

1) artificial intelligence;  
2) database theory;  
3) inferential statistics, and  
4) mathematical programming.

Artificial intelligence research has contributed data mining techniques such as neural networks, rule induction and association rules. Linear logistic and multiple regression in addition to algorithms such as K-means and K-medians have been developed by statisticians. Mathematical programming has contributed techniques such as the min-max method from optimisation theory.

Recent developments in KDD, data mining and statistics have allowed analysts to develop significant models of how decisions are made. In sport, competition and physiological data is precise, each team and individual has their own capabilities and needs. It is desirable to provide athletes with specific realistic training regimes and performance targets.

Whilst Knowledge Discovery has been used in individual sports (for example the Advanced Scout system for basketball in USA, described in Bhandari et al (1997)), there is no generally accepted framework for using KDD in sport. In this project we shall examine the use of artificial intelligence, inferential statistics and mathematical programming in modeling elite sports performance.

Bhandari et al. (1997) claim that the Advanced Scout software seeks out and discovers interesting patterns in game data. They argue that with this information, a coach can assess the effectiveness of certain coaching decisions and formulate game strategies for subsequent games.

Smith et al. (2007) used a form of data mining, Bayesian classifiers, to predict Cy Young Award winners (best pitchers) in American baseball. The model was compared against two statistical models designed to perform the same task (James (2004) and
Sparks and Abrahamson (2005). Over the years from 1967 through 2006, the accuracy of the Bayesian classifier was similar to that of the other two models. When all three models were used with starting pitchers, accuracy was greater than 80%.

Performance evaluation falls under the domain of skill acquisition, sports biomechanics, and sports physiology. Typical applications have included structuring training sessions (Shea and Morgan, 1979) and monitoring training loads (Halson and Leukendrup 2004), examining technique and coordination patterns, developing instructional material, and managing administrative tasks.

Owusu (2007) claims there is enormous potential for Artificial Intelligence technologies to make a significant contribution in the analysis phase. Indeed AI technologies have been applied to performance evaluation in recent years, though their applicability has been limited for a variety of reasons. The main factor has been a lack of characterisation of the domain of performance evaluation. Owusu (2007) reviews selected research and applications of computational models and Artificial Intelligence technologies in particular in performance evaluation of sporting feats for individual based events.

Liao (2008) performed a tactics analysis on female swimmers in the 800m freestyle race using speed coefficient theory. Chen et al (2007) use cluster analysis to identify elite swimmers’ race patterns. They claim that the identification of elite swimmers’ race patterns is of fundamental importance for coaches in training promising elite swimmers. To address this problem, a system of cluster analysis for studying group structures on the basis of elite swimmers’ race results and various available race components, such as lengths, speeds and times, is described that uses standard statistical algorithms to arrange elite swimmers according to similarity of tactics in their race patterns.

Puterman and Wittman (2009) used statistical methods to categorise PGA tour players’ careers. They used K-means cluster analysis and multinomial mixture models to categorize professional golfer performance for the period between 1980 and 2006. Correlation patterns between other measures suggested that career performance was well described by the proportion of years a player finished in specific meaningful money list categories such as the Top 10 or outside the Top 125. Using both clustering methods, they found that players divide into five natural and interpretable groupings, one being a small ‘Elite’ group and four others which the authors refer to as ‘Distinguished,’ ‘Established,’ ‘Journeymen’ and ‘Grinders.’ They used analysis of variance to compare groups on the basis of other career performance measures including consistency, streakiness, longevity, and others as well as to investigate differences in the clusters produced by the two methods. This methodology extends to any sport or endeavour in which performance is measured in terms of end of year rankings or money lists.

3. Decision Support Techniques for Enhancing Elite Sports Performance

3.1. The Victoria Institute of Sport

The Victorian Institute of Sport (http://www.vis.org.au/about.asp) was established in 1990, by the Victorian Government, to assist the development of Victoria’s best athletes. The VIS is a non-residential institute, which utilises Melbourne’s sporting facilities, to allow high performance athletes to live and train in Melbourne. VIS programs are conducted in partnership with State Sporting Organisations. Over 400 athletes from a wide range of sports participate in VIS programs. Both able-bodied
athletes and athletes with a disability have scholarships. Support Services include advanced and specialised coaching, sport science and sports medicine services, career and education advice, and training and competition support are provided to VIS athletes.

The VIS provides scholarship holders with the best possible integration of the key athlete services of sports medicine, sport science, sports psychology, physical preparation, physiotherapy, nutrition, massage, athlete career and education advice, and an information resource centre. VIS Sport Science has achieved a total focus on improving performance through the integration of internal and external scientists and consultants into VIS programs. The key discipline areas of VIS Sport Science are Physiology, Biomechanics, Psychology, Human Perception and Performance, Sports Engineering and Computer Science. VIS Sport Science has a diverse staff with qualifications and experience in the traditional areas of sport science and new areas such as aerospace engineering, industrial design and computer hardware and software design. This has led to a large array of in-house skills to draw upon and the emergence of some exciting projects within VIS Sport Science.

In its goal to provide enhanced sports science advice to its coaches and athletes, VIS is keen to enhance the computer supported analysis and advice it offers. It has a huge repository of data: such as split-times and event times in races, currents in ocean swimming, blood analysis, VO2 max, BMI, body fat, time taken underwater in swimming turns and numerous golf data inputted to the TRACKMAN system.

VIS approached Professor Zeleznikow in the hope that his research group could help analyse and interpret their vast data repositories with the goal of developing decision support systems to enhance elite sports performance. Examples of questions they would like answered include:

a) How can biomechanics and the TRACKMAN system be best used to enhance how golfers should best use swing, angle and trajectory to improve their performances?

b) What are the key variables to examine whether an amateur golfer should turn professional?

c) How can we best provide feedback and training and race plans for coaches and athletes?

d) In analysis swimming performances, what variables are important (heart rate, stroke rate, break out time, distance turn time, physiological data, blood analysis, hydration)?

e) In triathlons, what sort of 10 km times should athletes be completing? And where should they be positioned at the end of the swim leg?

To meet VIS needs, we are conducting research on feature selection and recommender systems.

3.2. Feature Selection

Feature selection or relevance analysis attempts to identify features that contribute to the knowledge discovery task (Stranieri & Zeleznikow 2005). Feature subset selection aims at finding the smallest feature set having the most beneficial impact on machine learning algorithms, i.e. its prime goal is to identify a subset of features to focus on. By removing the most irrelevant and redundant features from the data, feature selection
helps improve the performance of learning models by speeding up the learning process and improving model interpretability.

Skabar et al. (1997) used genetic algorithms to determine which features Australian Family Court judges consider the most important in deciding the distribution of marital property. Stranieri et al (1994) had previously used 94 variables in their neural network model that examined marital property distribution. Skabar et al. (1997) however, were able to make more accurate predictions using only 16 variables.

Our research is using feature selection techniques to help decide what competition and physiological factors (e.g. PH, hydration, heart rate, split-times and event times in races, currents in ocean swimming, blood analysis, VO2 max, BMI, body fat, time taken underwater in swimming turns) are important in predicting future results and improving training. By using feature selection algorithms, we expect to maximise training techniques by focusing upon the small number of vital factors that significantly help and/or hinder success.

3.3. Recommender Systems

Maes et al. (1999) claim that recommender systems provide advice to users about items they might wish to purchase or examine. Typically, a recommender system compares the user's profile to some reference characteristics, and seeks to predict the 'rating' that a user would give to an item they had not yet considered. Bridge et al. (2005) describe case-based recommender systems, and further, define a framework in which such systems can be understood.

Whilst recommender systems have been heavily used in providing tourism advice (Ricci et al 2002), they have not been used in providing advice for athletes. However, we argue that they can prove very valuable in providing training and performance advice. Developing specific training schedules for each individual athlete based on this greater analysis of the data will enable the VIS and associated sport scientists to enhance athlete performance and minimize injury. Moreover, the publication of our results on the use of KDD, feature selection and recommender systems will enhance global training and performance.

We can also use Information Technology to support Decision Making during an event. Many decisions need to be made by athletes and coaches during an event in progress. For example, an athlete in a high jump or pole vault has decisions to determine at what height on the bar should the athlete enter or resume in the competition. It is common for athletes to raise the height of the bar, rather than clearing it at a lower height. If successful then the athlete gains a significant advantage over the other competitors by requiring fewer jumps and less effort. However, if unsuccessful then the athlete runs the risk of finishing in a lower position than if they attempted to jump at the lower height, or even worse, being eliminated. These decisions are usually subjectively based and do not involve the use of information technology.

Bedford et al. (2009) developed methods to determine how much risk a badminton player should be taking on serve during a match in progress, where coaching intervention and the use of computers are allowed. Pollard et al. (2008) developed methods to determine how much risk a tennis player should be taking on serve during a match in progress, where coaching intervention may or may not be allowed. In the latter case, the model incorporated players viewing real-time statistics from the scoreboard.

We are developing quantitative models to assist athletes during an event in progress on the height of the bar in high jump or pole vault; the level of difficulty in gymnastics,
diving or aerial skiing; the amount of weight in weightlifting; and the club selection in golf. The analyses for all these sports depend on the scoreboard, i.e., the current positioning of the athlete relative to the other competitors at a particular time in the event. With the use of coaching intervention and computer technology, the decision making process around strategy could help improve performance.

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References


