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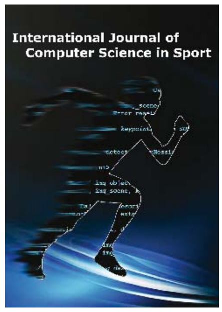

Decision Support System for Mitigating Athletic Injuries

Peterson, K.D., Evans, L.C.

Sports Science Department, University of Iowa, Iowa City, IA USA

Abstract

The purpose of the present study was to demonstrate an inductive approach for dynamically modelling sport-related injuries with a probabilistic graphical model. Dynamic Bayesian Network (DBN), a well-known machine learning method, was employed to illustrate how sport practitioners could utilize a simulatory environment to augment the training management process. 23 University of Iowa female student-athletes (from 3 undisclosed teams) were regularly monitored with common athlete monitoring technologies, throughout the 2016 competitive season, as a part of their routine health and well-being surveillance. The presented work investigated the ability of these technologies to model injury occurrences in a dynamic, temporal dimension. To verify validity, DBN model accuracy was compared with the performance of its static counterpart. After 3 rounds of 5-fold cross-validation, resultant DBN mean accuracy surpassed naïve baseline threshold whereas static Bayesian network did not achieve baseline accuracy. Conclusive DBN suggested subjectively-reported stress two days prior, subjective internal perceived exertions one day prior, direct current potential and sympathetic tone the day of, as the most impactful towards injury manifestation.

KEYWORDS: PROBABILISTIC GRAPHICAL MODEL; TEMPORAL REASONING; SPORT EPIDEMIOLOGY; ETIOLOGY

Introduction

Injuries within collegiate athletics are of great significance, not only to the athletes themselves, but to the team and ultimately the institution. Beyond protecting the health and well-being of student-athletes, injuries that result in lost time alter team structure, reduce cohesion, and impair performance (Gabbett, 2016). Sport medicine professionals are classically responsible for 'predicting' when athletes may become more susceptible to injury in hopes to abate these unfortunate events. Despite the vast devotion to musculoskeletal injury mitigation however, conventional investigations into the etiology of sports injuries have struggled to push agendas with non-dynamic, frequentist methodology (Meeuwisse, 1994; Quatman, Quatman, & Hewett, 2009). Such analyses are restricted by the inherent assumptions, which ultimately attenuate interpretations, and thus predictability, of such events. Alternatively, forecasting events that occur within high-dimensional, dynamic systems warrants the utility of modern sophisticated modeling and requires robust computational power. Therefore, if sports medicine professionals wish to curtail injury occurrences in such complex nonlinear organisms, then the predictive models employed must appreciate both the erratic internal milieu as well as the multifarious external mediators.

Consequently, there has been a recent challenge towards the profession, calling for a shift in modeling strategies to reflect the dynamic nature of sport-related injuries (Cook, 2016). Generally, there are two antagonistic views concerning the epistemology of causality: deductive versus inductive – and sport epidemiology has classically peered through the deductive lens (Quatman, Quatman, & Hewett 2009). Rather than deducing predictions from set hypotheses and comparing how well the predictions accord with what actually happened, an inductive approach starts by gleaning observations, discerns a pattern (usually algorithmically), and subsequently infers how the parameters relate to the phenomena being captured (Williamson, 2005, 118-129). To a large extent, the field of machine learning is fundamentally inductive by promoting the formation and integration of high-dimensional interactions (Biermann, 1987). Complex system-based thinking for instance, which involves a high degree of conditional independencies where the timing of such relationships are important, have traditionally turned to various machine learning approaches, such as network-based models, when attempting to answer such complicated questions (Nicholson, Holmes, Lindon, & Wilson, 2004).

At its core, a simulatory network is a simplified abstract of the real world, which generates predictions of systemic behaviors under different conditions (Friedman, 2004). Network-based approaches are certainly not new to other domains solving complex, dynamic problems, such as bioinformatics (Zou & Conzen, 2005), health-care (Lucas, van der Gaag, & Abu-Hanna, 2004), even econometrics (Gemela, 2001). An attractive feature of simulatory networks is the ability for agents to test theoretical interventions in lieu of discovering associative observations from finite datasets (Galea, Riddle, & Kaplan, 2010). Although this ideological influence seems to have a delayed entry into sport epidemiology, support for this type of higher-level modelling to ameliorate sport practitioners' decision-making process is undoubtedly gaining headway (Bittencourt et al., 2016).

The previous dogmatic conjecture that high external training load is the culprit of non-contact injury occurrences has recently been debunked. Sport epidemiology literature is repeatedly revealing strong evidence that the mismanagement of training load is rather a key contributor towards non-contact injurious events (Blanch & Gabbett, 2015; Gabbett, 2016; Drew & Finch, 2016; Hulin, Gabbett, Lawson, Captui, & Sampson, 2015). Specifically, inappropriate fluctuations in external training loads are likely responsible for non-contact, soft-tissue injuries and hence are viewed as mitigable in the sports medicine community (Gabbett, 2010).

This idea of appropriately prescribing training loads based upon an athletes' physiological (and psychological) readiness has certainly prompted the vast array of athlete monitoring technologies in recent years.

In general, the goal of athlete monitoring is to capture how athletes are coping with imposed stressors to potentially express untoward fatigue trends, and thus, allow practitioners to instigate appropriate interventions in hopes to combat maladaptation (Soligard 2016). However, relying on parameters in isolation to detect when athletes are entering a maladaptive state has yet to be validated. Rather, shifting from risk factor identification to complex pattern recognition has been called upon (Bittencourt et al., 2016). For instance, conjoining internal and external training loads, in addition to corroborating athletes' subjective with objective responses, can ultimately create a so-called 'web of determinants' (Phillippe & Mansi, 1998) to elicit insight regarding the readiness of a particular athlete (Halson, 2014). This type of comprehensive approach can be advantageous for practitioners when attempting to determine if athletes are adapting in the intended direction. Furthermore, practitioners planning the chronological sequence of training could theoretically simulate prospective athlete responses to multivariate interventions (which may not necessarily reside in the original dataset) and subsequently compare the predictions to counterfactual outcomes, perhaps replacing conventional periodization models.

Although this obligatory shift in methodology is well-accepted, there is a paucity of documented exploration of complex, simulatory applications towards sport injury etiology (Soligard et al., 2016). Therefore, in response to the aforementioned challenge, the purpose of this treatise is to explicitly demonstrate an inductive approach for dynamically modelling sport-related injurious events via probabilistic graphical models. The type of probabilistic graphical model implemented is called a Dynamic Bayesian Network (DBN), which was chosen due to its well-established framework for temporal uncertainty management (Larranaga & Moral, 2011). To preserve practicality for practitioners, the network entails variables commonly captured when monitoring athlete readiness in collegiate and professional settings. A secondary purpose is to illustrate how practitioners could utilize DBNs to stochastically simulate how an athlete may acutely adapt in response to training. Such simulatory environment could greatly augment the training management process by allowing practitioners to play out the potential effects of various loading patterns prior to administration.

Background

Serving under the umbrella of artificial intelligence, Bayesian Networks present a marriage between probability and graphical theory. This conjugation allows for interpretable and flexible representations of probabilistic relationships and, perhaps more importantly, has the ability to withstand omnidirectional interactions that are commonly encountered in dynamical systems (Coffey, 1998). The product of a Bayesian Network is a directed acyclic graph in which each node (discrete random variable) is annotated with quantitative probability information and is connected by arcs, representing direct dependencies between variables (Korb & Nicholson, 2011, 1-28). The absence of an arc between variables indicates a lack of dependency between respective variables. When discussing network construction, it is common to apply a family metaphor, that is, a node is described as a parent of a child when there is a directional arc from the former node to the latter node (Korb & Nicholson, 2011, 29-54). The resultant network topology specifies, in graphical terms, the dependencies and conditional independencies amongst variables in a multivariate context (Fuster-Parra et al., 2014).

It is imperative to note the Bayesian interpretation of probability is first, mental rather than physical, and secondly, is symbolic of an agent's rational degree of belief (Williamson, 2005, 4-13). To clarify, when evidence is provided for a random variable, the degree of belief is updated to 1.0 (100% probability), which is termed instantiation (Korb & Nicholson, 2011, 29-54). When a random variable is instantiated, the degree of belief descends to the respective child, which subsequently updates the child's degree of belief. Within a fully-connected network, instantiating a variable simultaneously updates all other nodes throughout the network allowing immediate visual and computational interpretation of omnidirectional inference. This mechanistic chain of events is a summary by which inference is interpreted, and thus predicted, which is called belief propagation (Pearl, 1988, 143-238).

Formally, a Bayesian Network represents a set of random variables $X_i = \{X_1, \ldots, X_n\}$ as a product of conditional probabilities (Russell & Norvig 2003, 492-536). Intuitively, an arc between variables within a constructed network signifies that the parents of X_i ($Pa(X_i)$) have a direct influence on X_i, denoted as $P(X_i \mid Pa(X_i))$ (Russell & Norvig 2003, 492-536). The resulting product is of the form

$$P(X_i, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid Pa(X_i)) \tag{1}$$

called the chain rule for Bayesian Networks (Koller & Friedman, 2009, 43-102). Another useful concept is the Markov Blanket of X_i in a given network, which constitutes X_i's parents, X_i's children, and the parents of X_i's children (Russell & Norvig, 2003, 492-536). Let V denote a set of random variables, P be their probability distribution, and $X_i \in V$. A Markov Blanket (MB) of X_i is thus the set of variables conditionally independent (I) of all other nodes in the network given its MB (Neapolitan, 2004):

$$I_P(X_i, V - (MB \cup \{X_i\}) \mid MB). \tag{2}$$

Qualitatively, the Markov Blanket entails the smallest set of variables carrying information about X_i that cannot be obtained from any other variable (Korb & Nicholson, 2011, 29-54).

Our focus thus far has been describing probabilistic reasoning in the context of static worlds, in which random variables possess a single fixed value. However, when a question includes a temporal component, like the adaptive state of an athlete for example, the underlying distribution of a random variable changes over time. To capture this dynamic feature requires the utility of Dynamic Bayesian Networks, which model the stochastic evolution of a random variable over time (Friedman, Murphy, & Russell, 1998). For the most part, the underlying principles of DBNs do not deviate far from the aforementioned constructs. However, a key difference is their ability to predict distributions over different trajectories of time (Koller & Friedman, 2009, 199-246). Temporal trajectories are thus assigned to random variables $X_i^{(t)}$ at respective time points t. The ability for DBNs to infer probabilities in the correct chronological sequence is dependent upon what is called the first-order Markov process, which ensures the current state of a random variable is only dependent on the previous state and not on any earlier states (Russell & Norvig 2003, 537-583). In other words, this prevents inference from propagating backwards in time. Using the chain rule notation from Equation 1, the corresponding distribution is in direction consistent with time by the Markovian system (Koller & Friedman, 2009, 199-246)

$$P\left(X^{(0)}, \ldots, X^{(T)}\right) = \prod_{t=0}^{T-1} P(X^{(t+1)} \mid X^{(t)}). \tag{3}$$

This temporal element is valuable for sport practitioners when trying to simulate how athletes are coping to demands over time. For instance, if an athlete endures a very high external training load, this will in turn affect how the athlete internally responds to external stimuli the subsequent day. This biological process, inherently driven by time, can be accounted for with DBNs.

There are two disparate tactics when learning Bayesian network structures, constraint-based versus score-based (Koller & Friedman, 2009, 783-804). Constraint-based learning traditionally approach network construction according to the conditional independencies found amongst the data, whereas score-based learning evaluate the goodness of fit of a candidate network with respect to the data (Koller & Friedman, 2009, 783-804). Score-based learning thus relies on heuristic search techniques to solve the optimization problem of formalizing a network to best fit the training dataset. Let D be a dataset and B be a Bayesian network, the score of a network is the sum of scores for the individual nodes:

$$Score(B \mid D) = \sum_{i=1}^{n} Score(X_i \mid Pa(X_i), D). \quad (4)$$

The scoring function explored in the present manuscript is called Minimum Description Length (MDL), which is coded to minimize the global entropy (uncertainty) of the resulting topology given the data (Lam, & Bacchus, 1994).

Methodology

Data and Variables

De-identified injury data were retrieved from the University of Iowa Sports Injury Management Systems (FlanTech, Inc., Iowa City, IA, USA) HIPAA-compliant database. In order to homogenize classification scheme, each of the following criteria were to be adhered to before an injury instance was entered into dataset:, 1) soft-tissue, non-contact, 2) of lower extremity, 3) occurred within practice or competition, and 4) resulted in time loss. For an injury to properly fit the network criteria, the student-athlete must have been previously monitored from each of the mediums described below as a part of their routine health and well-being surveillance. A total of 28 injury occurrences from 23 female student-athletes (from 3 undisclosed teams during their 2016 seasons) fit the aforementioned criteria. Supplementary Document provides a brief glossary of all-encompassing parameters.

External Training Load

External training load has been defined as the amount of work performed by an athlete, independent of internal characteristics, that can be quantified externally (Halson, 2014). As a means to quantify gross human motion attained within a session, triaxial accelerometers were worn by student-athletes for every practice and competition. Monitors were secured in a compression garment located posteriorly at the upper thoracic region amid session, and data was subsequently processed post-session. Player Load™, recorded by Catapult Optimeye S5 monitors (Catapult Sports, Melbourne, Australia), has been measured as a reliable and reproducible metric in the quantification of cumulative motion in both indoor and outdoor sports (Barrett, Midgley, & Lovell, 2014). Expressed in arbitrary units (a.u.), accumulative triaxial (anteroposterior, mediolateral, and vertical) g-force alterations produced by the athlete, summate to create a resultant vector magnitude, thus representing the external training load endured within a session (Boyd, Ball, & Aughey, 2011). IMA™ (Inertial Movement Analysis) expressed at count data (ct), aggregates triaxial accelerometer and triaxial gyroscope data to form a non-gravity vector to detect and quantify the frequency of sport specific micro-movements (Holme, 2015). An IMA™ is detected by the application of polynomial smoothing curves between the start and end point of identified accelerative events. The magnitudes of such events are subsequently calculated by summing the accelerations under the polynomial curves, measured in terms of delta-velocity (a unit of impulse; m/s^{-1}) (Holme, 2015). In addition to total summation, IMA™ units were dissected into each respective plane to analyze the directional distribution of high-intensity movements (right-left, acceleration-deceleration, and vertical jumps). All aforementioned external training loads were summed per calendar day if the student-athlete performed more than one session in a given day (e.g., morning practice prior to evening competition, etc).

While monitoring absolute external training load is imperative for comprehending imposed stimuli, absolute measures fail to account for the rate of load application. To overcome this limitation, a well-accepted notion called 'acute:chronic workload ratio' was formulated to address relative external load changes over time (Soligard et al., 2016). Therefore, acute:chronic (A:C) workload ratios were calculated for Player Load™ to account for relative rates of external load application. Individual Player Load™ A:C workload ratios were computed using an exponentially weighted moving average (EWMA) strategy (Williams, West, Cross, & Stokes, 2017). Let t denote current time step, L be individual's absolute external training load, N_a be acute decay constant (7 days) and N_c be chronic decay constant (28 days):

$$A{:}C\ Ratio_t = \frac{\left(L_t - \frac{2}{(N_a+1)}\right) + \left(1 - \frac{2}{(N_a+1)} \times EWMA_{t-1}\right)}{\left(L_t - \frac{2}{(N_c+1)}\right) + \left(1 - \frac{2}{(N_c+1)} \times EWMA_{t-1}\right)}. \qquad (5)$$

Internal Training Load

Internal load has been described as the relative physiological and/or psychological stress imposed onto an athlete's biological system, which can be obtained both objectively and subjectively (Halson, 2014). Objectively speaking, heart rate variability (HRV) is a common athlete monitoring tool to provide indication of global physiological readiness (Halson, 2014). Beat-to-beat variability of the heart is reflective of autonomic balance, which sport practitioners exploit in an effort to delineate an organism's adaptive capabilities (Buchheit, 2014). Omegawave (Omegawave Oy, Espoo, Finland) technology allows comprehensive analysis of heart rate variability through a number of linear and nonlinear techniques. Additionally, direct current (DC) biopotentials, measured via vertex-thenar method, provide a global indication of central nervous system (CNS) readiness by estimating the level of active wakefulness (Ilyukhina, 2011). To ensure reliable HRV measurements, student-athletes performed assessments antemeridian in a rested state while lying supine in a room with minimal light and distraction.

On the other hand, subjective internal load is captured to represent both the perceived physiological stress and daily psychological stress experienced by the student-athletes. Regarding physiological outputs, Rating of Perceived Exertion (RPE) is a common, valid method for assessing an athlete's perceived internal load from a given training session (Foster, 1998). Within 30 minutes post-session, student-athletes provide a self-reported score from 1-10 (1 = very easy; 10 = very difficult) regarding the difficulty of the session to the sport medicine professional, who subsequently multiples the athlete's RPE by the session duration in minutes. In addition to session RPE, individual RPE A:C workload ratios were calculated using Equation 5.

Lastly, as a strategy for coaches to capture insight regarding life demands of student-athletes, daily subjective wellness questionnaires are submitted by the athletes upon rising every morning. The employed questionnaire was a modified Hooper-Mackinnon survey due to its speed and practicality (Hooper, Mackinnon, Howard, Gordon, & Bachman, 1995). Student-athletes answer 5 questions, each on a 1-5 scale (1 = very bad; 5 = very good): Sleep Quality, Sleep Duration, Fatigue, Stress, and Nutrition. All aforementioned internal training loads were recorded once per day regardless of the number of training sessions performed by the student-athlete.

Network Construction and Evaluation

BayesiaLab software (Bayesia S.A.S., Changé, France) version 7.0 was used for Bayesian network construction. Due to the hybrid of both discrete and continuous random variables entailed, all continuous variables were discretized into 3 bins to avoid the inherently infinite number of possible conditional probabilities. The number of bins was selected for two reasons: 1) for an intuitive ‘low’, ‘medium’, ‘high’ ordinal interpretation, and 2) to minimize the overall quantity of conditional probabilities while still allowing the discovery of non-monotonic relationships. A supervised discretization procedure was executed via the R^2-GenOpt algorithm, a proprietary BayesiaLab genetic algorithm which performs a metaheuristic search to maximize the R^2 between the discretized variable and its corresponding continuous variable (Conrady & Jouffe, 2015). The target variable ‘Injury’ was structured to represent a discrete binary variable. The binary descriptor denotes whether a particular student-athlete suffered an injury, or not, on any given calendar day. The resultant discretized variables were then temporalized into 7 time steps (i.e., each node was unfolded into 7 preceding calendar days). The number of time steps was chosen to maintain practicality for practitioners to project acute adaptations within a given training week.

With a fully unconnected network, ‘Injury’ was set as the target node to enable supervised learning. BayesiaLab’s proprietary Markov Blanket supervised learning algorithm was executed to discover a generative model to characterize which set of nodes directly affects the target node. Subsequently, the Tabu unsupervised metaheuristic search algorithm was applied to construct a network around the pre-established Markov Blanket while simultaneously minimizing the global MDL score function. Tabu search was chosen for its stability for score-based searches; once a locally optimum network is found, Tabu search performs additional iterations to ensure no other local optimum is found (Glover, 1986; Jouffe & Munteanu, 2001).

Upon completion of search algorithm, conclusive network’s accuracy was assessed via 3 rounds of 5-fold cross validation. To verify validity, DBN model accuracy was compared with the performance of its static counterpart, which was also assessed with same cross validation procedures. Model classification accuracy was calculated from conventional confusion matrix tabulation of the sum of correct classifications divided by total classifications: (TP+TN) / (TP+TN+FP+FN). Additionally, mean lift index was calculated for each model to provide context of true positive prediction rates (Tufféry, 2011). DBN and static Bayesian network’s accuracy results were tested against naïve baseline algorithm (prior distribution = 96.53%) to provide context of improvement over baseline accuracy.

In order to be judged statistically significant, t-statistic was calculated from respective accuracy measurements against naïve baseline accuracy threshold. With 14 degrees of freedom, alpha set to 0.05, $t_{crit} = 1.76$, which t-statistic would need to surpass in order to be judged significant.

To express the functional relationship of the target’s Markov Blanket, prior and posterior probabilities were independently calculated from each random variable’s discretized state. Normalized continuous probability distributions were also calculated to supplement the Markov Blanket influence analysis. Mutual information, along with geodesic distance, was computed between the target node and each random variable to analyze variable importance among the conclusive network's independent nodes. Mutual information was normalized between 1 (most important) and 0 (least important) for ease of interpretation. To compare reasoning patterns, genetic optimization algorithms were performed to produce node instantiation scenarios for the illustration of temporal belief propagation in a positive and negative manner. To elicit the most ideal condition, optimization objective was set to discover node states to minimize the posterior belief of 'Injury', whereas worst-case scenario was set to discover node states to maximize the posterior belief of 'Injury'.

Results and Discussion

The resultant network in Figure 1 illustrates the inductively discovered variables and their relative relation towards injury in a temporal orientation. Although each variable was temporalized into 7 time steps, the tabu search only resulted with time steps *t*-3 to *t* in terminal topology. The vast accuracy improvement compared to the static counterpart emphasizes the necessity of adding a temporal component when modeling adaptive behavior. DBN surely was able to learn, in part, an underlying mechanism towards injury manifestation considering statistically significant accuracy achievement, denoted in Table 2. Conversely, static Bayesian network was unable to reach naïve baseline accuracy. Although the present DBM may be seen as a pilot study, the predictive accuracy is promising for future work in formulating decision support systems for sport injury etiology. Fortunately, the respective relationships discovered possess physiologically relevance and will be addressed below.

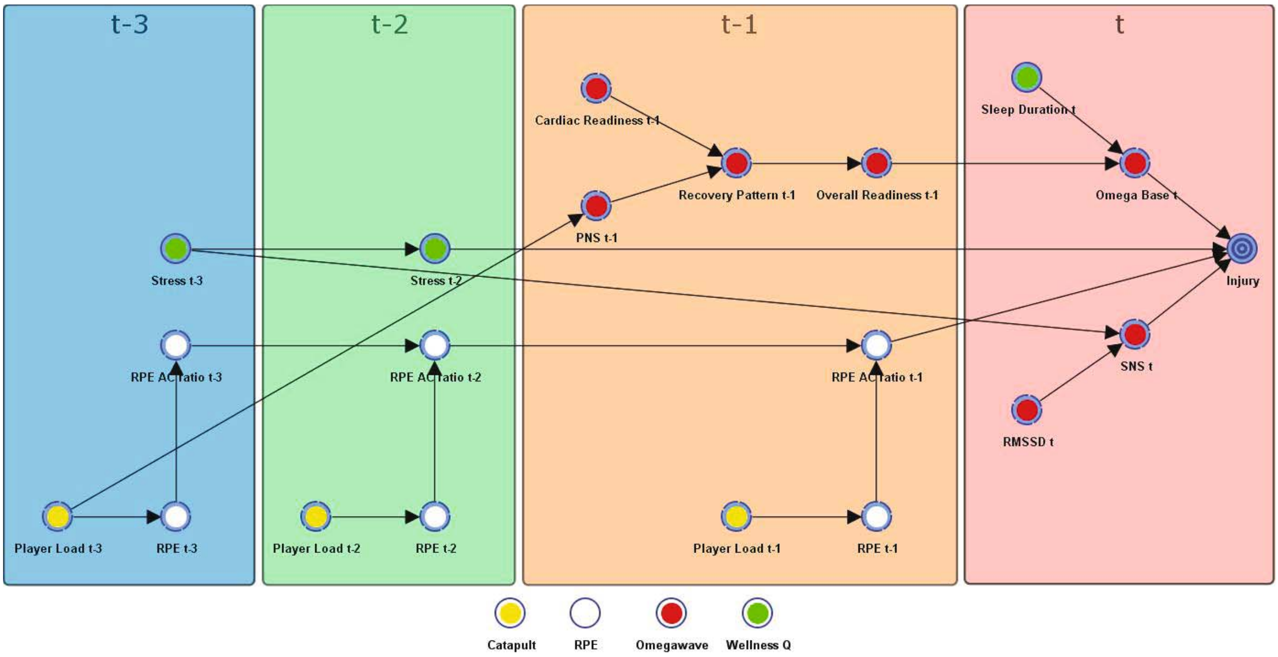

Figure 1. Conclusive network topology illustrating relative relation towards injury in temporal orientation. RPE = Rate of Perceived Exertion, PNS = Parasympathetic Activity, SNS = Sympathetic Activity, RMSSD = Root Mean Sum of Differences of Successive Intervals.

To begin, Figure 2 depicts the functional relationship of the target's Markov Blanket. Starting in the top left, the functional relationship of Omega Base t suggests a positive parabolic relationship towards injury. That is, when an athlete records lower values (≤ 12mV) or higher values (≥ 30mV) increases the belief of an injury occurrence that same day (referring to the heightened posterior distribution in Figure 2). However, when an athlete records between 12 – 30mV the belief of injury is attenuated, suggesting this optimal range provides a protective mechanism towards injury. To the author's knowledge there is no study directed at the independent association between DC potential and injury, however, it may be theorized that the association between sleep duration and DC potential activity in the present model may partially explain central fatigue, which negatively impacts an individual's motor control and biomechanics, such as speed or reaction time (Mah, 2011), and movement accuracy (Reyner, 2013), and ACL risk (Zebis, 2010). Since direct current potential has been suggested for the study of cortico-subcortical organization of the cerebral systems (Ilyukhina, 2011; Ilyukhina, 2013) underlying functional states may also substantiate why Sleep Duration t is a parent of Omega Base t in the present model.

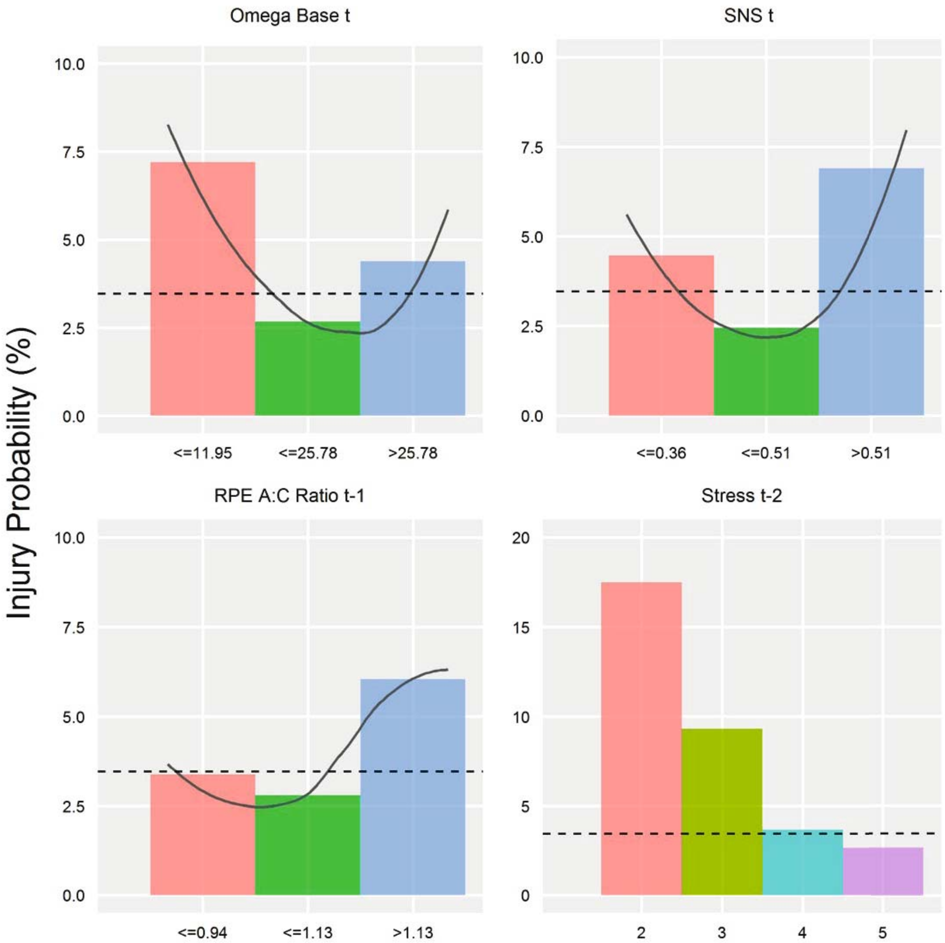

Figure 2. Markov Blanket functional relationships: horizontal dashed line represent prior belief of an injury occurrence without providing node evidence (3.47 %). Vertical bars represent posterior probability of injury when nodes are instantiated to the respective discretized state. Solid lines represent estimated effect from the normalized continuous distributions. The absence of a solid line, as for Sleep Duration *t*, indicates an innately discrete variable.

SNS *t* and 'Injury' (top right Figure 2) also has limited evidence for its relationship. However, there has been previous speculation that increased sympathetic activity increases pro-inflammatory cytokines, which may negatively impact tissue tolerance (Gisselman, 2016).

Additionally, increased sympathetic activity has been associated with muscle fatigue or contractures (Vilamitjana, 2014), which may also justify the topological proximity of SNS *t* to 'Injury'.

Transitioning to bottom left of Figure 2, RPE A:C *t*-1 and ‘Injury’, also appears to follow prior literature, suggesting the rate of external load application is more pertinent to soft-tissue injury than absolute loads attained (Blanch & Gabbett, 2015; Drew & Finch, 2016). Emergent acute:chronic workload ratio and injury research has repeatedly revealed that high chronic external workloads may not necessarily be the culprit, rather how loads are accumulated over time is a more powerful predictor (Gabbett, 2016; Hulin, Gabbett, Lawson, Captui, & Sampson, 2015). Regarding Dye (2001, 2005) tissue homeostasis model, large acute stimuli may stress the tissue beyond its adaptive ability, perhaps substantiating the sigmoidal relationship in the present model.

Table 1. Normalized mutual information and geodesic distance between individual variable and target node.

Monitoring Variable	Normalized Mutual Information	Geodesic Distance
Stress *t*-2 *	1.00	1
Omega Base *t* *	0.72	1
SNS *t* *	0.59	1
RPE AC Ratio *t*-1 *	0.50	1
Stress *t*-3	0.23	2
RMSSD *t*	0.23	2
RPE AC Ratio *t*-2	0.20	2
Sleep Duration *t*	0.18	2
RPE AC Ratio *t*-3	0.15	3
Overall Readiness *t*-1	0.14	2
Recovery Pattern *t*-1	0.07	3
Cardiac Readiness *t*-1	0.06	4
RPE *t*-1	0.06	2
RPE *t*-2	0.05	3
RPE *t*-3	0.05	4
Player Load *t*-1	0.04	3
Player Load *t*-2	0.02	4
Player Load *t*-3	0.00	5

* Denotes Markov Blanket.

Table 1 reports, in numerical order, the normalized mutual information between each variable and ‘Injury’. Mutual information represents the extent to which knowledge of the random variable reduces the uncertainty about the target, generating a quantitative measure of the strength of dependency between X and Y (Koller & Friedman, 2009, 783-848). Taking into account the inverse relationship between mutual information and corresponding geodesic distance can give an indication of the mechanism of topological construction; nodes with stronger dependence tend to be proximate to ‘Injury’. With this, it is imperative to note how influential Stress *t*-2 is compared to all other network variables, which is also apparent in Figure 2. A theorized mechanism for why subjectively-reported psychological stress has such a potent effect towards injury belief in our network may be through the somatic adjustments that can occur when high levels of stress are perceived, such as increased distractibility or perhaps peripheral narrowing (Williams, Tonymon, & Anderson, 1991; Rodgers & Landers, 2005), along with increased muscular tension, fatigue, and reduced coordination (Laux, Krumm, Diers, & Flor, 2015). Previous literature suggests evidence of daily hassles experienced by athletes rapidly changes injury risk (Ivarsson & Johnson, 2010) and that chronic hassles may generate a so-called ‘snowball effect’ by heightening their vulnerability to consider minor stressors as stressful events (Ivarsson, Johnson, & Poglog 2013). The three- and two-day latency period between reported stress and ‘Injury’ discovered by our network perhaps suggests practitioners may have time to intervene by modifying external training load prescription for athletes who appear unfocused or uneasy as a consequence of perceived stress. Timpka et al (2015) has also demonstrated the importance of integrating psychological with physiological parameters, and that indicators of maladaptive coping behaviors may allude to an athlete’s ability to accept and respond to prescribed loads, and thus, negatively affect risk of injury.

Table 2. Resultant network performance indices (mean ± SD). t-statistic calculated from one-sample t-test against naïve baseline accuracy ($t_{crit} = 1.76$).

Model	Lift Index	Accuracy	t-statistic
Dynamic Bayesian Network	4.37 ± 0.14	97.56 ± 2.01	1.98*
Static Bayesian Network	3.89 ± 0.26	83.87 ± 7.87	-6.23

* Denotes statistical significance.

The arc between PlayerLoad t-3 and Recovery Status t-1 is imperative to mention as this relationship has been previously documented (Hautala, 2000) (Buchheit, 2009). Hautala et al. (2001) found that athletes undergoing prolonged maximal exercise bouts appear to suppress parasympathetic outflow for many hours, and suggested that amid recovery, there may be an occurrence of accentuated parasympathetic rebound on the second day. This phenomena may be explained by exercise induced plasma volume expansion (Buchheit, 2009). This may help elucidate why absolute external load is a parent to parasympathetic activity two days later in the present model.

To introduce the simulatory environment of such methodology, Figure 3 provides prior discretized distributions of all parameters, indicating belief for each node state before evidence supplied. Prior beliefs were naively considered as the initial distributions found in dataset.

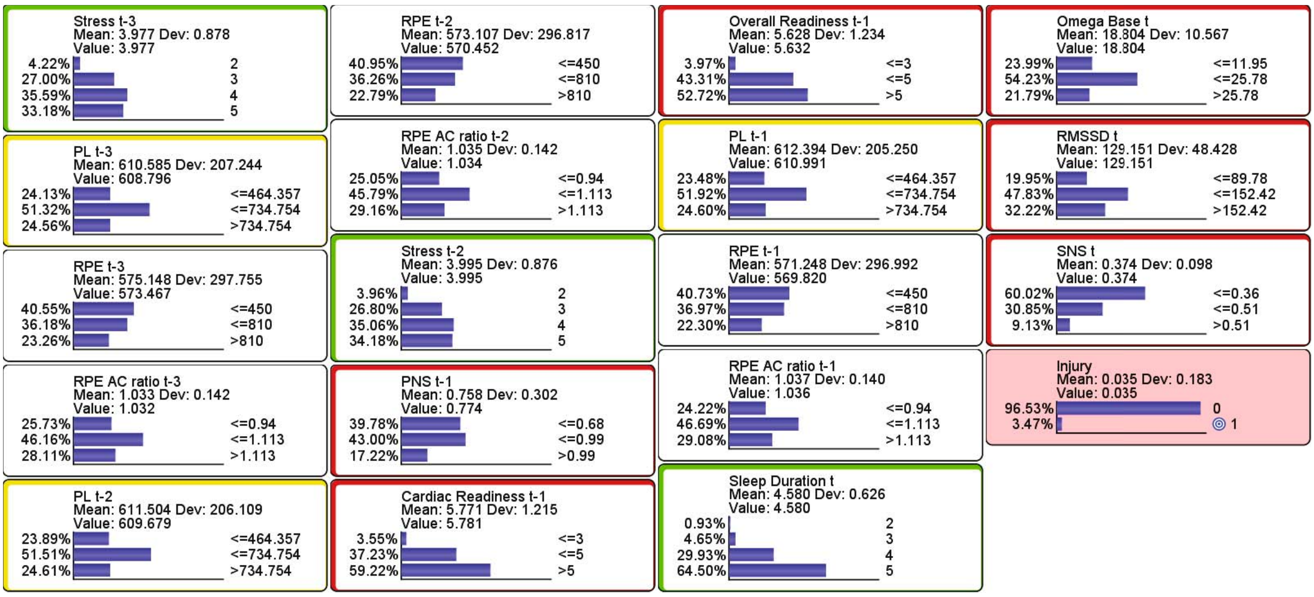

Figure 3.Prior discretized distributions of all network variables. In chronological order from top left (t-3) to bottom right (t) toward injury manifestation.

Target optimization scenarios were then employed to demonstrate the evolution of 'Injury' belief in a negative (undesired) and positive (ideal) manner, respectively (Table 3). When optimization algorithm was set to maximize belief of 'Injury', resultant instantiation scenario increased prior 'Injury' belief from 3.47% to a posterior belief of 50.00%, whereas minimization algorithm discovered a scenario that decreased to 0.04% posterior belief.

The vast difference between the two instantiation scenarios is the aftermath of manipulating the conditional probabilities to maximize (or minimize) the joint probability distribution, which can also be theoretically interpreted from a physiological perspective.

Table 3. Node instantiation scenarios from optimization algorithm. Posterior distribution of Injury is given for each simulation scenario. Table sorted in descending chronological order.

Monitoring Variable	Maximization	Minimization
Player Load *t*-3	857.20	619.68
RPE *t*-3	907.84	663.51
RPE AC *t*-3	1.14	1.09
Stress *t*-3	3.00	5.00
Player Load *t*-2	603.44	559.23
RPE *t*-2	638.58	600.15
RPE AC *t*-2	1.19	1.03
Stress *t*-2	2.00	5.00
Player Load *t*-1	631.94	307.80
Recovery Pattern *t*-1	0.35	0.15
RPE *t*-1	667.06	285.18
RPE AC *t*-1	1.20	0.98
PNS *t*-1	0.60	0.29
Cardiac Readiness *t*-1	4.00	7.00
Overall Readiness *t*-1	4.00	7.00
RMSSD *t*	78.41	112.68
SNS *t*	0.13	0.46
Sleep Duration *t*	3.00	5.00
Omega Base *t*	5.46	18.81
Injury (%)	50.00	0.04

Beginning with t-3 variables in the maximization state, if an athlete were to experience an increased external workload (Player Load), and subjectively experience a demanding session (RPE) in contrast to the minimization scenario, all while undergoing increased subjective stress prior to participation of activity, may lead to an unfavorable psycho-physiological cost. If such psycho-physiological state were to continue on subsequent days would cumulatively heighten the belief of injury occurrence. Whereas if workloads, both objectively and subjectively, were to be significantly different (*t*-3, *t*-1), with physiological indicators in more favorable states, may be suggestive that an athlete under these conditions may be coping favorably, which is reflected in such negligible injury belief in minimization scenario. While present scenarios were found mathematically, in practice, practitioners would be able to manually instantiate nodes to stochastically explore how different training interventions influence Injury belief before implementation.

Limitations

It is recognized that increasing dimensionality may improve the accuracy of future models, as the current network is, albeit practical, still oversimplified. Incorporating more internal parameters such has hydration, endocrine function, biomechanical characteristics, and genetic factors, or extrinsic parameters such as weather, playing surface or competition calendar schedule may augment accuracy in forthcoming models.

Current sample size is also a limitation to consider. Lengthening the longitudinal analysis, or collaborating to create a multi-center approach, would be wise strategies to grow sample size in order to fully validate such approach.

Conclusions

The present study examined the utility of Dynamic Bayesian Networks to aid sport practitioners in athlete injury mitigation efforts. Resultant network presented predictive accuracy above naïve baseline threshold while also illustrating physiological relevance amongst network topology. Subjectively-reported stress two days prior, subjective acute:chronic internal perceived exertions one day prior, direct current potential and sympathetic tone the day of injurious event, were suggested as the most impactful monitoring metrics towards injury manifestation. It is therefore recommended for practitioners in the field to consider employing an inductive approach to better comprehend time-course adaptations of their athletes and perhaps improve the decision-making process by reducing confirmation bias from human generated beliefs.

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Appendix

Table 1. Glossary of all-encompassing monitoring parameters prior to inductive learning.

Category	Name	Scale	Units	Interpretation
Objective Internal	Adaptation Reserve	O	scale (1-7)	Reflects how long cardiac system can express adaptability.
	Aerobic Index	I	N/A	Reflects state of aerobic metabolic pathways.
	Anaerobic Index	I	N/A	Reflects state of anaerobic metabolic pathways.
	Cardiac Readiness *	O	scale (1-7)	Comprehensive indicator of cardiac readiness.
	Direct Current Potential (Omega Base) *	C	mV	Present activation of frontal brain system. Reflects active wakefulness.
	Fatigue Index	O	scale (1-7)	Reflects temporary state of cardiac system.
	Heart Rate at Anaerobic Threshold	I	bpm	Overall indicator of endurance level.
	High Frequency	C	ms^2	Power in high frequency range. Reflects parasympathetic activity.
	High Frequency Normalized Units	C	N/A	High frequency power in normalized units.
	Low Frequency	C	ms^2	Power in low frequency range. Reflects parasympathetic activity.
	Low Frequency Normalized Units	C	N/A	Low frequency power in normalized units.
	Low Frequency / High Frequency Ratio	R	N/A	Reflect sympathetic-parasympathetic balance.
	Metabolic Grade	O	scale (1-7)	Comprehensive indicator of metabolic system coordination.
	Metabolic Reactive Index	C	N/A	Estimate of overall coordination of metabolic systems.
	Overall Readiness *	O	scale (1-7)	Comprehensive indicator of global readiness.
	Parasympathetic Activity (PNS) *	C	sec	Indicator of current level of parasympathetic nervous system regulation.
	Recovery Pattern *	C	sec	Indicator of parasympathetic activity.
	Root Mean Sum of Differences of Successive Intervals (RMSSD) *	C	ms	Square root of sum of difference of sequential cardio intervals. Reflects autonomic activity.
	Share of Aperiodic Influences	C	sec	Reflects level of random activity that influences heart rhythm.
	Standard Deviation of Aspirate Waves	C	N/A	Reflects level of automatization of heart rhythm regulation.
	Standard Deviation of Normal-to-Normal Intervals	C	ms	Reflects autonomic regulation from full array of cardio intervals.
	Standard Deviation of Successive Differences	C	ms	Standard deviation of differences between adjacent intervals.

	Stress Index	O	scale (1-7)	Level of tension in cardiac system.
	Sympathetic Activity (SNS) *	C	%	Indicator of current level of sympathetic nervous system regulation.
	Tension Index	C	N/A	Reflects level of centralization of heart rhythm regulation.
	Total Power	C	ms^2	Variance of all intervals to reflect level of regulatory system.
Subjective Internal	Sleep Duration *	O	scale (1-5)	Subjectively reported sleep duration.
	Sleep Quality	O	scale (1-5)	Subjectively reported sleep quality.
	Fatigue	O	scale (1-5)	Subjectively reported fatigue.
	Stress *	O	scale (1-5)	Subjectively reported stress level.
	Nutrition	O	scale (1-5)	Subjectively nutrition quality from day before.
Objective External	Player Load™ *	C	a.u.	Cumulative motion attained during session measures via triaxal accelerometer.
	IMA™ Jump	C	ct	Inertial Movement Analysis. Frequency of high intensive jumps.
	IMA™ Right	C	ct	Inertial Movement Analysis. Frequency of high intensive right change of direction cuts.
	IMA™ Left	C	ct	Inertial Movement Analysis. Frequency of high intensive left change of direction cuts.
	IMA™ Acceleration	C	ct	Inertial Movement Analysis. Frequency of high intensive acceleration efforts.
	IMA™ Deceleration	C	ct	Inertial Movement Analysis. Frequency of high intensive deceleration efforts.
	IMA™ Total	C	ct	Inertial Movement Analysis. Summation of all directions.
	Player Load™ Acute:Chronic	R	N/A	Refer to equation 5.
	IMA™ Total Acute:Chronic	R	N/A	Refer to equation 5.
Subjective External	RPE *	C	N/A	Subjectively reported score of session intensity (1-10) multiplied by the session duration in minutes.
	RPE Acute:Chronic *	R	N/A	Refer to equation 5.

C = continuous; I= interval; O = ordinal; R = ratio. * Denotes chosen variable from Markov Blanket and Tabu search algorithms.