MANAGING RESILIENCE WITH A WEB OF KNOWLEDGE (WeKnow) TO SENSE AND SHAPE COLLECTIVE STRESS SITUATIONS

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Abstract

We posit that our our models of systems resilience persistently demonstrate incomplete and fragmented knowledge bacause we fail to fully perceive the complexity of our systems and the collective stress situations (CSS) that perturb it. We argue for a framework to build a web of knowledge, or WeKnow, that embodies complexity absorption (integrated view of the laws of requite variety, knowledge, and complexity) and integrates data-centric, specialized and perceptual intelligence. WeKnow is aimed to provide a more holistic understanding of system structure, interaction behaviors, context, temporal and perceptual boundaries, emerging irregularities or inaccuracies, as well as proven or plausible alternative system resilience strategies. Ultimately, WeKnow is aimed to provide the capability to sense and shape impending, emerging, or ensuing CSS.

1 MOTIVATION

Despite the significant advances in science and technology, human and economic losses due to disasters, terrorist attacks, pandemics, social upheavals, and humanitarian crises remain significant. These situations, which can be referred to as *collective stress situations* (CSS), occur when due to internal or external shocks the system critically fails to provide the expected conditions of life to its components [Gillespie, 1988]. We believe that losses remain significant because we have yet to fully perceive the complexity of our systems and the CSS that perturb it. Their nature are indeed complex - nonlinear, spanning multiple simultaneous temporal and spatial scales, and with large interrelations and interdependencies among parts. Their evolving nature can affect physical, ecological, economic, and social dimensions simultaneously [Carpenter at al., 2009].

Our failure to fully perceive their complexity is because we tend to wrap our minds around the computable even though we are fully cognizant of the non-computable aspects of complex problems [Carpenter et al., 2009; Fowler & Fischer, 2010]. Another reason is that we heavily rely on the narrow, segregated, domain-dependent, and incomplete views of dominant experts rather than solving complex problems by engaging diverse perceptions [Carpenter et al., 2009]. Furthermore, we get intimidated in finding the critical links that mesh our human, environmental, social and technological systems into a cohesive and coherent whole. As a result, our models of systems resilience persistently demonstrate partial and fragmented knowledge.

Our proposed solution is a *web of knowledge*, or *WeKnow*, that embodies complexity absorption to account for the noncomputables and uncertainties associated with complexity. WeKnow is an integration of heterogeneous intelligence aimed to provide a more holistic understanding of system structure, interaction behaviors, context, temporal and perceptual boundaries, emerging irregularities or inaccuracies, as well as proven or plausible alternative system resilience strategies. Ultimately, WeKnow is aimed to provide the capability to sense and shape impending, emerging, on-going, or ensuing CSS. Sensing is the prelude to shaping that involves prediction, situation analysis and awareness, anticipation, as well as providing actionable information [Robertson & Olson, 2013]. Shaping is influencing and changing the course of CSS and the way the system responds adaptively.

2 LAWS OF REQUISITES AND THE THEORY OF COMPLEXITY ABSORPTION

Carpenter et al. [2009] suggest that to account for uncertainties, we must consider a wide variety of sources of knowledge, stimulate a diversity of models, and manage for the emergence of new syntheses that reorganize fragmentary knowledge. We further precise this by embodying in WeKNow three essential laws of requisites:

a. *Law of Requisite Variety*. By having diverse response and action mechanisms available to the system, the system is able to compensate a larger variety of perturbations [Ashby, 1958]. Richardson and Cilliers [2001] explained that the need for multiple approaches is to achieve a relative goodness of fit, i.e., since knowledge can only be partial and fragmented, pluralism offers a venue to obtain the best possible elucidation of phenomena present in a given set of circumstances.

b. *Law of Requisite Knowledge*. Managing a perturbation is not only dependent on a requisite variety of actions in the system, the system must also know which action to select, and how, in response to the perturbation present [Heylighen, 1992]. Otherwise, the system would have to try out actions blindly and therefore compromise its survival.

c. *Law of Requisite Complexity*. The complexity of the system must be commensurate to the complexity of the environment in which it is embedded in order to function effectively [Boisot, 2003]. Casti [2012] theorizes that a system collapses due to the widening complexity gap between itself and its environment. To achieve requisite complexity requires complex adaptive systems capability of knowledge capture, creation and refinement [Gilpin & Murphy, 2008].

From the above, we can see that the laws are connected in that the first is incorporated in the second and the third incorporates both of the previous. We can also view this integration in terms of the theory of complexity absorption as explained by Gilpin & Murphy [2008]: In the multiplicity of options and diverse representations, albeit possibly conflicting, there is the ability to adapt and self-organize, as novel knowledge is obtained, or generated in order to modify an existing goal or adopt a new goal. Achieving complexity absorption (an integration of the three laws) leads to overcoming the partial and fragmented knowledge problem.

3 WeKnow FRAMEWORK

We now elucidate our framework for constructing WeKNow that embodies complexity absorption. Our framework involves multiple levels and dimensions that start with acquiring heterogeneous data from multiple sources that need to be fused and translated into the knowledge that will characterize a complex system capable of sensing and shaping CSS. We start with *how* knowledge is formed, and then *what* knowledge is derived and concluded from evidence using automated reasoning (i.e., inferred), and *to what* end.

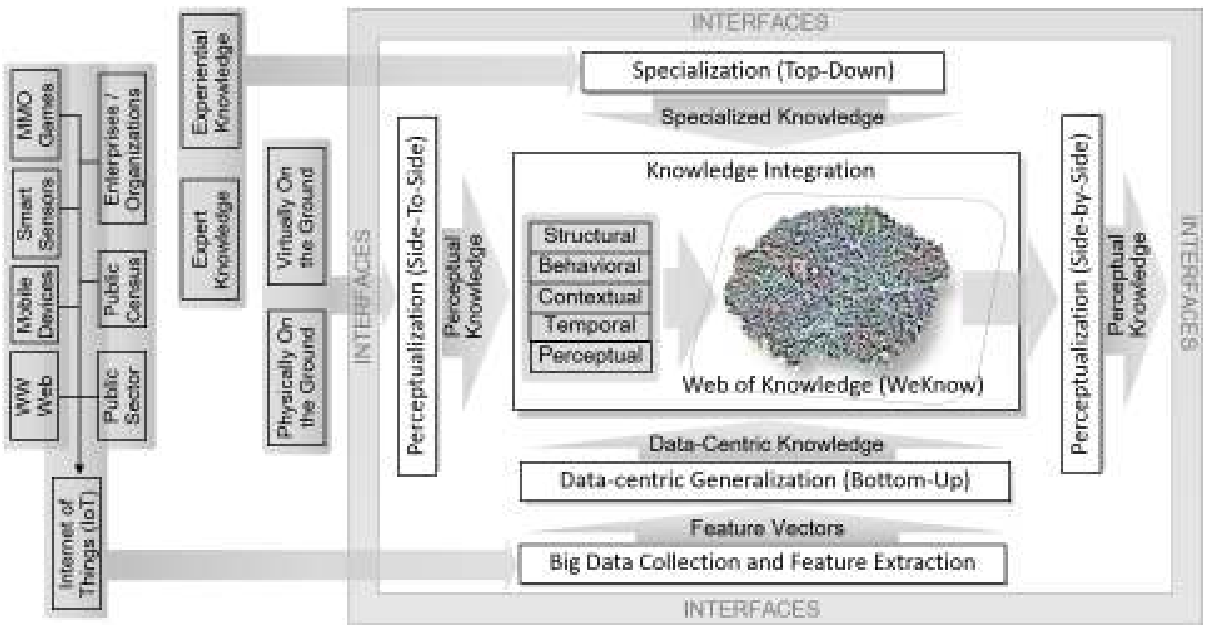

Figure 1. *WeKNow framework*

3.1 WeKnow HOW?

We are surrounded by information of incomprehensible and unimaginable amount. Information related to humans, enterprises, environments, and technologies, and their interactions are often reported from a multiplicity of sources, each varying in representation, granularity, objective and scope. Our human mind can only take in, let alone piece together, a portion of these vast amount of information usually on a need-to-know basis. However, with our advanced technological systems, we can do significantly much more, i.e., even to derive previously unknown meaningful information (knowledge) from raw data. Our framework espouses a socio-technical complex system with a three-pronged approach to deriving knowledge. Although numerous frameworks have the first aspect [Mitchell, 2012][Hall & Jordan, 2010][Mitchell, 2010][Liggins et al., 2009][Roy, 2001], they do not include the other two aspects of our framework.

3.1.1 Data-centric Generalization – A bottom-up approach

This universe is ever expanding as millions of data points are created every second form various sources. The Web is an open world and quintessential platform for us to share and receive information of various kinds. Our mobile devices have powerful sensing and computing capabilities that allow us to log our daily activities, do web searches and online transactions, and interact on social media platforms and micro-blogging sites, among others. Ubiquitous and interacting ambient sensors [Bohn et al., 2005; Poslad, 2009] can gather large volumes of human (e.g., mass movements, traffic patterns) and environmental (e.g., climate and weather changes, changing landscapes and their topographies, light and CO_2 emissions) data. There are massively multiplayer online games (MMOGs) that have become unprecedented tools to create theories and models of individual and group social and behavioral dynamics [Shim et al., 2011]. There are data that the public sector produces, which include geographical information, statistics, environmental data, power and energy grids, health and education, water and sanitation, and transport. There are the systematically acquired and recorded census data about households and the services (e.g., health and medical, education, water, grabage/waste disposal, electricity, evacuation, and daily living-related programs) made avaible to them. Enterprises (corporations, small businesses, non-profit institutions, government bodies, and possibly all kinds of organizations) may collect billions of real-time data points about products, resources, services, and their stakeholders, which can be insightful on collective perceptions and behaviours and resource and service utilizations. And lastly, there is the Internet of Things (IoT) that extends internet connectivity beyond desktop and mobile computers to a diverse range of devices that communicate and interact with the external environment - all via the Internet.

Data acquired from various sources tend to be heterogeneous in terms of their spatial and temporal aspects, data collection modalities, structure type (structured, semi-structured or unstructured), data type (hard physical data vs. soft data), and in sensor outputs with different resolutions and sampling rates. This data-centric approach should therefore consist of techniques and algorithms to preprocess the data to prepare them for the subsequent processes. The result of preprocessing will be a single concatenated feature vector that represents the set of features of the entities of interest (EoI), which can be objects or events that are endogenous or exogenous to the system. This is certainly a non-trivial task. If the varied data are commensurate, then raw signal data can be easily combined (e.g., using Kalman filtering). Otherwise, extracting a common feature vector may involve further data transformation, such as filtering out noises and outliers, data alignment (remove any positional or sensing geometry and timing effects from the various data), common referencing (obtain a common spatio-temporal reference), and data association (determine which object is associated to which event) [Roy, 2001]. Metadata may also be generated to describe the heterogeneous data [Hall & Jordan, 2010].

After the EoI vector is extracted, general models of the EoI should then be constructed. This is basically the kind of problem being addressed by data mining, machine learning, artificial intelligence, pattern recognition, time-series analyses, and many other methods.

3.1.2 Specialization – A top-down approach

Carpenter et al. [2009] suggest that the tendency to ignore the noncomputable aspects can be countered by considering a wide range of perspectives and encouraging transparency with regard to conflicting viewpoints. Our society puts more value in the dominant models, i.e., the ones we consider best practices because they are prescribed by experts, albeit there are evidences where the perceptions of “non-experts” (only because they lack formal education) but experience-filled individuals led to breakthroughs. Carpenter et al. [2009], for example, noted several cases: crucial information provided by village hunters and loggers prompted new approaches that saved the giant jumping rat in Madagascar from their sudden demise, and opinions and knowledge of indigenous fishermen saved endangered bumphead parrotfish.

Complex problems may have many solutions which may differ in the required execution to obtain the quality of the desired outcome [Carpenter et al., 2009]. Hence, a diverse team of experienced individuals is more suited than a team of expert solvers [Page, 2007]. Knowledge engineering approaches can be used to build and maintain knowledge-based systems that capture relevant contributions based on expertise and experience.

3.1.3 Perceptualization – A side-to-side approach

We use the term *perception* to refer to the process in which we *actively* and *purposefully* acquire, organize, and interpret the sensory information we receive in order to make sense of our environment and situation, as well as achieve environmental cognition, i.e., we structured our thinking on environmental circumstances and conditions (citations in [Legaspi et al., 2014]). The knowledge that are obtained in this approach are from individuals who are (*i*) *physically* on the ground, i.e., directly experiencing CSS, such as the members of the affected community, local government, law enforcers, first responders, and disaster managers, and (*ii*) *virtually* on it, i.e., are not in the affected area but have a good view of the CSS over the internet and in social media.

Here, social computing platforms, natural language processing, knowledge and ontology engineering, pattern recognition, and visualization can be used to gather, preprocess and organize the data, and infer perceptual knowledge that can function as feedback for situation analysis, awareness, and validation. However, at the other side of the framework, WeKnow's perceptual knowledge, i.e., information as perceived by WeKNow after it has integrated all knowledge, should be sent to the same individuals as actionable information for decision-making and response (hence, side-to-side). Here, the cognitive affordances of visual models can support the second perceptualization process. i.e., visualization can explicitly show the unified diverse knowledge in WeKnow.

3.1.4 Knowledge Integration and Incremental Learning

Once knowledge is inferred from these varied sources, the next step is to weave together these knowledge. *Knowledge integration* will involve inferring knowledge relationships among hugely varying domains into a coherent structure, while revealing hidden assumptions and reconciling areas of conflicts, inconsistencies, and uncertainties. It should describe how domain-specific concepts are interrelated for transdisciplinary problem and solution formulation. It must be able to synthesize micro-level, individualized and domain-dependent knowledge to contextual systemic knowledge. This task is difficult and remains to be an open research area.

Knowledge integration involves weaving the diverse knowledge into coherent networks, hence, a *web of knowledge*. Paperin et al. [2011] provide an excellent survey of previous works that demonstrated how complex systems are isomorphic to networks and how many complex properties emerge from network structure rather than from individual constituents. Representing the integrated knowledge into coherent networks can be accomplished by using network and dynamic graphs theories and models.

The specialized knowledge-based systems and the stored or incoming perceptual knowledge can be used to guide the data-centric generalization process as background knowledge (e.g., labels of objects and events for supervised and semi-supervised machine learning), feedback, and for validation. At the same time, any data-centric knowledge that was not accommodated in the other two can be used to correct or fine-tune their knowledge. Each can aid the others in pinpointing and correcting or clarifying malicious, erroneous, or conflicting information. Hence, the components of this tripartite knowledge elicitation can co-evolve together with increasing predictive isomorphism [McKelvey, 1999]. The inclusion of knowledge from diverse sources should not lead to vague generalities, but rather to become effective in completing our fragmented knowledge. Finally, new facts should be continuously derived and incoming evidence should be used to improve current knowledge repositories. Hence, WeKnow will be *learned incrementally*. The WeKNow framework, with its synergistic integration of knowledge, may enable an *emergent level of increasing intelligence* in the midst of complexity.

To conclude this subsection, the WeKnow framework therefore achieves *complexity absorption* [Gilpin & Murphy, 2009]: more than it integrates and preserves varied technologies for triangulating for the truth, it continuously tracks incoming and on-going information as well as evolving circumstances and conditions, and aids the system to better self-organize as it generates new information, infers new knowledge, adapts with new functions, and transforms to new goals. The objective of the framework is to unmask the heightened uncertainty created by the multiple sources of knowledge in order to be resilient in a complex world.

3.2 WeKnow WHAT?

We need to identify the properties that can be used to describe the complexity of the system, the CSS, and their interaction. We believe that the Five Aspects Taxonomy [Rhodes & Ross, 2009] ensures a good coverage of the essential aspects of the complexity we need to be knowledgeable of. The taxonomy is conceived for the engineering of socio-technical systems that exhibit complexities in multiple levels (components, subsystems, systems, and linked systems of systems) and dimensions (aspects).

The five aspects include: (a) s*tructural* - elaborate hierarchical/layered network arrangement of the components of the system, demonstrating couplings, interrelationships and interdependencies in multiple scales; (b) *behavioral* - variances in system responses to different stimuli; (c) *contextual* - environmental circumstances in which the system exists; (d) *temporal* - various system properties, dimensions and needs may change over time together with the dynamic environment in which it exists; and (e) *perceptual* - stakeholder perceptions of the system and its environment, which may change with context shifts and cognitive constraints and biases.

3.3 WeKnow TO WHAT END?

Given that WeKNow contains the connected and evolving knowledge derived from various sources about system and CSS structure, behaviour and context, and how they are perceived, to be changing over time, what then can we use the knowledge for? Again, for sensing and shaping of the EoI, which are most certainly the system failure and CSS that can threaten the existence of the system and its components.

Sensing can be achieved in a number of ways. By mining WeKnow, descriptive analysis can explain what has already happened and why it happened - after the fact or in real-time, and predictive analysis can forecast possible future outcomes across various scenarios or situations [Ernst & Young, 2014]. Second, after mining WeKNow for structures, behaviors, contexts and perceptions that are considered normal, routinary and expected, anomaly detection techniques can then be used to detect what is out of the normal, which can include proxy indicators or digital smoke signals of upcoming changes [Robertson & Olson, 2013]. Furthermore, while it is possible that conflicting information are received due to cognitive biases, perceptual errors, or communication differences, with various information coming from multiple angles, however, it is possible to perform multi-dimensional corrections and validations that can eliminate the false positives. Finally, there is potential for *unsaid analytics*, a term we introduce here to refer to inferring knowledge that was not explicitly stated because it depicts intuition, common sense, wisdom, and culture-based assumptions - those that are hard to quantify and measure but have proved essential to identifying anomalies and vulnerabilities.

The primary focus, however, is still is to provide actionable strategies that will convert sensing to shaping to avoid the worst consequences of CSS. Shaping via WeKnow can be achieved by prescriptive analysis to identify which decision and response will lead to the optimal or most effective result against a specific set of objectives and constraints [Ernst & Young, 2014]. Second, with knowledge about system interrelations and interdependencies, it is possible to implement creative chaos, i.e., to provoke sufficient perturbation to navigate the system into the portal of change. It is more efficient and effective to create situations that can force latent problems to surface than design the system to not fail, which, paradoxically, only makes it less resilient. By intriducing chaos into the system, not only do we make the system adaptive to failures, but we also let opportunities for innovation to surface since chaos would break tight couplings only to give way to new and previously unknown effective connections. Incidentally, the Five Aspect Taxonomy is claimed to be a basic frame to comprehend facets of innovation strategeis and communicate emeging technologies [Rhodes and Ross, 2009]. Third, we can use WeKnow to infer a lever point [Holland, 2005], i.e., the critical place within the system where applying a little change can make a big difference and a small shift a big change, and at that point the behaviour of the complex system changes fundamentally. We can also infer theories of system boundary, openness and modularity and their trade-offs [Carpenter et al., 2012]. Modularity can help contain ensuing CSS by compartmentalizing. However, too much compartmentalization can prevent aid from moving in and out of the system from various sources. Also, too much openness can casue harmful shocks to be transmitted or cascaded. Lastly, WeKnow can be used to provide real-time mapping of the events and feedback loops occurring during CSS. The ability to monitor the behaviours of human, environmental, social and technological systems in real time during CSS make it possible to understand where models, plans and policies are failing and to make adaptations.

3 CONCLUSION

On a complex systems point of view, we argued that the fundamental difficulty in managing resilience is the complexity that characterizes our system and the collective stress situations that result from perturbations. On an engineering point of view, we argued for managing resilience with an integrated knowledge of this complexity, which is automatically inferred from gathered, extracted, and structured heterogeneous intelligence about the nature and contextual interaction behaviours of our systems. With state-of-the-art technologies this integrated knowledge may learn incrementally and autocomplete itself. On a resilience point of view, we argue that with a holistic understanding of systems behaviour we can experience a paradigm shift in the way we view their vulnerability or resilience, hence, proactive. By sensing and shaping CSS, our systems become more adaptive. With this greater capacity to sense and shape, the system can better meet head-on the so-called unknown unknowns or uncertain uncertainties.

REFERENCES

Ashby,R.W.(1956). *An Introduction to Cybernetics*. London: Methuen.

Bohn, J., Coroamă, V., Langheinrich, M., Mattern, F. & Rohs, M. (2005). Social, economic, and ethical implications of ambient intelligence and ubiquitous computing. In W. Weber, J.M. Rabaey, and E. Aarts (Eds.), *Ambient Intelligence* (pp. 5-29). Springer Berlin Heidelberg.

Boisot, M. (2003). Is there a complexity beyond the reach of strategy? In E. Mitleton-Kelly (Ed.), *Complex Systems and Evolutionary Perspectives on Organisations: The Application of Complexity Theory to Organisations* (pp. 185–202). New York: Pergamon Press.

Carpenter, S. R., Folke, C. , Scheffer, M. & Westley, F. (2009). Resilience: Accounting for the noncomputable. *Ecology and Society* 14(1):13.

Carpenter, S.R., Arrow, K.J., Barrett, S. et al. (2012). General resilience to cope with extreme events. *Sustainability 4*, pp. 3248-3259.

Casti, J. (2012). *X-Events: The Collapse of Everything*. New, York, NY: HarperCollins Publishers.

Ernst & Young (2014). Big Data: Changing the way businesses compete and operate. *http://www.ey.com/Publication/vwLUAssets/EY_-_Big_data:_changing_the_way_businesses_operate/$FILE/EY-Insights-on-GRC-Big-data.pdf*, accessed on 04-05-2015.

Fowler, T. B. & Fischer, M. J., Eds. (2010). Rare events: Can we model the unforeseen? *Sigma 10(1)*, pp. 30-35.

Gillespie, D.F. (1988). Barton's theory of collective stress is a classic and worth testing. *International Journal of Mass Emergencies and Disaster 6(3)*, pp. 345-361.

Gilpin, D.R. & Murphy, P.J. (2008). *Crisis Management in a Complex World*. Oxford University Press, 2008.

Hall, D.L. & Jordan, J.M. (2010). *Human-Centered Information Fusion*. Norwood, MA: ARTECH House.

Heylighen, F. (1992). Principles of Systems and Cybernetics: An evolutionary perspective. In R. Trappl (Ed.) *Cybernetics and System '92* (pp. 3-10). World Science.

Holland, J.H. (2005). Studying complex adaptive systems. *Journal of Systems Science and Complexity 19(1)*, pp. 1-8.

Legaspi, R., Maruyama, H., Nararatwong, R. & Okada, H. (2014). Perception-based resilience: Accounting for the impact of human perception on resilience thinking. In *Proc. 2014 IEEE Fourth International Conference on Big Data and Cloud Computing* (pp. 547-554).

Liggins, M.E., Hall, D.L. & Llinas, J. (2009). *Handbook of Multisensor Data Fusion – Theory and Practice, Second Edition*. Boca Raton, FL: CRC Press, Taylor & Francis Group.

McKelvey, B. (1999) Self-Organization, complexity, catastrophe, and microstate models at the edge of chaos. In Honor of Donald T. Campbell, J.A.C. Baum and B. McKelvey, (Eds.), *Variations in Organization Science* (pp. 279-307). Thousand Oaks, Calif: SAGE Publications.

Mitchell, H.B. (2010). *Multi-Sensor Data Fusion*. Springer-Verlag: Berlin Heidelberg.

Mitchell, H.B. (2012). *Data Fusion: Concepts and Ideas*. Springer-Verlag: Berlin Heidelberg.

Page, S. E. (2007). *The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies*. Princeton, NJ: Princeton University Press.

Paperin, G., Green, D.G. & Sadedin, S. (2011). Dual-phase evolution in complex adaptive systems. *Journal of The Royal Society Interface 8(58)*, pp. 609-629.

Poslad, S. (2009). *Ubiquitous Computing: Smart Devices, Environments and Interactions*. Wiley.

Rhodes, D.H. & Ross, A.M. (2010). Shaping socio-technical system innovation strategies using a Five Aspects Taxonomy. *http://seari.mit.edu/documents/preprints/RHODES_EUSEC10.pdf*, accessed on 04-05-2015.

Richardson, K.A. & Cilliers, P. (2001). What is complexity science? A view from different directions. *Emergence 3(1)*, pp. 5–22.

Robertson, A. & Olson, S. (2013). *Sensing and shaping emerging conflicts: Report of a Workshop by the National Academy of Engineering and United States Institute of Peace Roundtable on Technology, Science, and Peacebulding*. The National Academies Press.

Roy, J. (2001). From data fusion to situation analysis. In *Proc. 5th International Conference on Information Fusion*.

Shim, K.J., Pathak, N., Ahmad, M.A., DeLong, C., Borbora, Z., Mahapatra, A. & Srivastava, J. (2011). Analyzing human behaviour from multiplayer online game logs: A knowledge discovery approach. In H. Chen & Y. Zhang (Eds), *Trends and Discoveries 26(01),* pp. 85-89.