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Collective intelligence: analysis and modelling

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Abstract

Purpose – The purpose of this paper is to focus on the underpinning dynamics that explain collective intelligence.

Design/methodology/approach – Collective intelligence can be understood as the capacity of a collective system to evolve toward higher order complexity through networks of individual capacities. The authors observed two collective systems as examples of the dynamic processes of complex networks – the wiki course PeSO at the Universidad de Los Andes, Bogotá, Colombia, and an agent-based model inspired by wiki systems.

Findings – The results of the wiki course PeSO and the model are contrasted with a random network baseline model. Both the wiki course and the model show dynamics of accumulation, in which statistical properties of non-equilibrium networks appear.

Research limitations/implications – The work is based on network science. The authors analyzed data from two kinds of networks: the wiki course PeSO and an agent-based model. Limitations due to the number of computations and complexity appeared when there was a high order of magnitude of agents.

Practical implications – Better understanding can allow for the measurement and design of systems based on collective intelligence.

Originality/value – The results show how collective intelligence emerges from cumulative dynamics.

Keywords Artificial intelligence, Knowledge management, Self-organization, Social networks, Complexity

Paper type Research paper

1. Introduction

The production of knowledge in contemporary societies has experienced a phase of transition away from individualism toward collectivism. The science of past centuries, for instance, was characterized by eponymy (Merton, 1968), a situation that brought about some famous first author disputes: Newton vs Leibnitz on differential equations or Darwin vs Wallace on evolutionary theory. In these cases, discussions about and between first authors were frequent and open. Today, acknowledgement of the individual scientist is not so important; for instance, the paper entitled "A precision measurement of the mass of the top quark" from 2004 has more than three hundred authors, who collectively form the DØ Collaboration (Abazov *et al.*, 2004).

The aim of this paper is to understand new forms of knowledge production. The internet has allowed for new forms of social interaction and organization. In the new socio-technical system, ideas flow and interchanges grow over time in a way that

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has not been seen before. Along with this expansion have come questions about plagiarism and other forms of misconduct (although we do not develop on this topic here). Furthermore, collective behavior on the internet has given rise to projects such as Wikipedia, a collectively developed encyclopedia that is the most comprehensive to date, and crowdsourcing, where many ideas from many participants are organized together to solve complex problems. Such examples show how alternative forms of organization around knowledge production may appear in the context of new socio-technical possibilities.

In this paper, we study collective intelligence through two complementary approaches. On the one hand, we analyze the structural properties of networks from the wiki system of the course PeSO at the Universidad de Los Andes, Bogotá, Colombia. On the other hand, a mathematical model of collective intelligence based on wiki systems is proposed. This work is based on networks, specifically equilibrium and non-equilibrium networks (Dorogovtsev and Mendes, 2013).

The results show similar behavior for both the model and the PeSO wiki. The model reproduces the curves of clustering coefficient and average path length over time in a similar way to small world networks. The empirical networks (the model and the PeSO wiki) are compared with a random baseline. The results are consistent, revealing small world network properties as a model for studying collective intelligence. Thus, the measurement of collective intelligence can be based on the differences between a random process and self-organized criticality (Barrat *et al.*, 2008, Tang and Bak, 1988; Chialvo, 2004; Sornette, 2006; Dorogovtsev and Mendes, 2013).

This document is organized into four sections. The first section presents our motivation for measuring and proposing a theoretical framework for collective intelligence. The second section describes the empirical analysis and the proposed model. The third section shows the results. The final section presents the discussion and future work.

2. Toward the measurement of collective intelligence

2.1 Collective intelligence and the theoretical framework

2.1.1 Complex systems. Intelligence is hard to define in a rigorous way, but it is related to the perception, adaptation and even modification of an environment, for the purpose of survival and reproduction (Dawkins, 1986). Systems that are completely organized and where nothing changes (or that only follow deterministic rules) are rigid; they cannot adapt to differing or complex environments. On the other hand, systems that are completely random have, by definition, no memory, thus the system cannot learn from similar past situations and react appropriately. In an intermediate point are systems that can adapt better to extreme events (Langton, 1990) and can generate self-organized structures. (Kauffman, 2000) says that the complexity of the universe is due to the fact that it is not ergodic, i.e. all possible configurations have not been explored. Complexity comes from non-equilibrium systems and irreversible processes that change dynamic states (Prigogine, 1980, 1997). This means that the maximum disorder of one system is related to non-equilibrium thermodynamics; similarly, equilibrium networks are related to random processes, and self-organized criticality process are related to non-equilibrium networks. Thus we observe and measure the network change between a random process and self-organized criticality (Tang and Bak, 1988; Chialvo, 2004; Sornette, 2006; Barrat *et al.*, 2008; Dorogovtsev and Mendes, 2013).

Classical random networks (Erdős and Rényi, 1959) are constructed with connections between randomly selected pairs of vertices. By contrast, small world networks are characterized as being highly clustered, with small path lengths (Watts and Strogatz, 1998). For the networks in our study, we computed clustering coefficient and average path length. Both have behaviors that are totally different in equilibrium networks (random networks) and non-equilibrium networks (Dorogovtsev and Mendes, 2013). We assume that the mechanisms underpinning the networks of wiki systems are not random, but are rather mechanisms that self-regulate collective production. Thus collective intelligence emerges intrinsically as a process of self-organization, where the self-organization is distributed among members of the group and each one is part of the emerging organization (Heylighen, 2013).

2.1.2 Collective intelligence. We assume that many people are nowadays interconnected via the internet, and that the resulting interactions and networks allow for the development of projects of collective intelligence. In fact, around the world there are 2.8e109 internet connected people producing information, outcomes and knowledge, such as Linux (operating system), Wikipedia (open encyclopedia), Open Government (in the US), crowdfunding (funding networks) and crowdsourcing (networks to solve complex problems based on knowledge).

Teamwork is understood as a group of individuals collaborating or competing with each other, but where the emergence of intelligence is not inherent (Alag, 2011). In the age of the internet, people and computers have become connected in order for collective intelligence to develop, with the possibility of gaining some benefit from participation (Georgi and Jung, 2011). Thus, collective intelligence can be understood as the capacity of a group of people to collaborate in order to achieve goals in a complex context (Heylighen, 2013). Existing literature on models to describe collective intelligence is presented in Table I.

Author	Characteristics
Malone *et al.* (Malone *et al.*, 2010)	What: create – decide Who: crowd – hierarchy Why: financial reward – intrinsic motivation – recognition of achievements How: collection – contest – collaboration
Bonabeau (Bonabeau, 2009)	Approaches: outreach – additive aggregation – self-organization Decision process: decentralized vs distributed – diversity vs expertise Engagement: cash rewards – recognition – desire to transfer knowledge or share experiences
Lykourentzou *et al.* (Lykourentzou *et al.*, 2010)	Attributes: sets of actions, system state, the objectives of participants Functions: user action function – future system state function – objective function Factors of influence: critical mass of the system – participants' motivation (monetary compensation – intrinsic motivation – social recognition)
Georgi and Jung (Georgi and Jung, 2011)	Objective of a task Size of a contribution Form of input of the process Form of output of the process Stakeholders
Miller (Miller, 2010)	Distribution of tasks Dialog without imposition Consensus No top-down control

Table I.
Models of collective intelligence

Collective intelligence can be seen as the capacity of a community to evolve toward higher order complexity thought, problem solving and integration through collaboration and innovation (Pór, 1995). In addition, intelligence is distributed within a network, where each interaction continually aggregates value. It is coordinated in real time, developed through the effective mobilization and reciprocity of competencies (Lévy, 1994).

In this sense, we propose a definition of collective intelligence based on which it is possible to compute measurements and modeling. Thus collective intelligence is defined – more or less successfully – as the capacity of a collective system to evolve toward higher order complexity through networks of individual capacities. The complexity of the network structure (an equilibrium or non-equilibrium network) can be observed and measured over time.

2.2 Research proposal

We observed the collective production of knowledge over time by building up a co-authorship network through the Wiki-ITRB (http://wiki.uniandes.edu.co/PESO/tiki-index.php). The Wiki-ITRB is one activity in the course "Organizational System Thinking" or PeSO (its Spanish acronym), offered at the Universidad de Los Andes, Bogotá, Colombia. The activity was developed between 2011 and 2012.

The purpose of the Wiki-ITRB is to collectively write ITRB (Informe Técnico de Revisión Bibliográfica – Technical Reports of Literature Reviews) documents. ITRB documents propose one question for a given topic, and students then include arguments, author positions and opinions about the proposed question. The activity aims to encourage students only to acquire the competencies to write argumentative documents. Based on the theory of collective intelligence, we designed a collaborative document schema via a wiki platform. Students participated in the writing and modification of several documents, with references, arguments, corrections, etc. Each student could promote, eliminate and/or edit a text or document. Finally, each student decided to be the author of a subset of documents, which she or he edited and evaluated.

Participation of students in the Wiki-ITRB is stored up over time. This allows for the building up of a network from the aggregation of connected authors via co-authored documents. We constructed a dynamic network through the extraction of subnets of documents over time. We were therefore able to evaluate the dynamics of structural network properties.

3. Empirical analysis and modeling

In this paper, we study the network of co-authored Wiki-ITRB pages based on clustering coefficient and average path length. At the same time, the proposed agent-based model was studied using the same measurements. Wiki systems were therefore studied based on independent structural features. Random graphs, built according to the Erdős-Rényi model, exhibit a small average shortest path length (typically varying as the logarithm of the number of nodes) along with a small clustering coefficient. Small world models have a small average shortest path length, but at the same time a clustering coefficient significantly higher than expected for a random model.

We propose an agent-based model to understand collective intelligence in a socio-technical system. This is a model organized by a non-linear combination of agents (Wolfram, 2002; Flake, 1998). Thus we propose that collective behavior can be modeled as non-linear relations among editors. In this paper, we focus on the study of non-equilibrium networks and their structural properties as a measurement of collective intelligence, as explained above.

3.1 Agent-based modeling

The aim of the agent-based model is to understand the evolution of wiki systems in order to gain a better understanding of collective intelligence. The agents are people and documents, where people have an agent edition capacity that indicates how many documents they can edit (not the number of modifications they are able to do in a single document). Documents have a probability of being selected, and in terms of the accumulation of total edits, this affects (in a similar way to votes) their probability of being selected in the next iteration of the model.

The parameters analyzed are the number of agents, agent edition capacity and simulation time (represented as steps in the execution of the model). For each parameter, one network of co-author editions was constructed and measurements of clustering coefficient and average path length obtained.

Our study of collective intelligence was made through the accumulation of editions for each document and its influence on the documents' probability of being selected and taken into account for future edition by an agent. Thus the evolution of a network of co-author editions on the basis of previous editions is presented. The model's reinforcement loops perform in a similar way to other complex systems, such as brains, ant colonies, etc. (Wolfram, 2002; Flake, 1998).

3.1.1 Assumptions

- Agent edition capacity is a natural value and all agents have the same capacity; for instance, when agent edition capacity = 2, this means that one agent can edit two documents.
- Each agent edits documents according to the agent's edition capacity; the greater the edition capacity, the more documents can be edited.
- The agent selected at each step is chosen in a uniformly random way.
- The edition of documents positively affects their probability of selection in the future, similar to votes. Therefore, documents with more editions are more likely to be edited again in the next round.

3.1.2 Description of the model. The model produces a network of agents or a co-author editions network, where an edge connects two agents who have made editions to the same document. The network is constructed as follows:

```
total-editions = 0
for i = 1 to t
 iteration
link all agents that edited the same document
```

Pseudocode for one iteration:

```
agent = choose one random agent
for i = 1 to k
 document = choose one document based on probability
```

```
  add agent to documents list of editors
  increment by 1 editions in document
  increment by 1 total editions
 for each document in documents
  probability=(editions+1)/(total-editions+total-docs)
```

k = agent edition capacity and t = simulation time

The documents' probabilities are updated as follows: at the beginning of the simulation, every document has the same probability, 1 per total number of documents. After each iteration, as can be seen in the pseudocode, the probability of one document is calculated taking into account the edition made to it and the total editions made in the system.

3.1.3 Experimental design. The probability of connection between two agents, given a determined number of agents, depends on the simulation time and the agent edition capacity. We observed the structural properties of the co-author editions network according to three assigned parameters: total agents, time simulation and agent edition capacity.

Each parameter was evaluated as follows: total agents between 10e1 and 10e3. For each number of agents, the time simulation was evaluated from two times to ten times the number of agents. Agent edition capacity was evaluated from one to ten. Each simulation was run 80 times, thus the measurements presented below correspond to the average over 80 simulations.

Experiments were performed in NetLogo 5.0.5 (Wilensky, 1999), with an implemented extension to export the resulting graph to graph6 format (https://github.com/erikasv/NetLogo-graph6). The analysis was performed in Mathematica 9 (Wolfram Research Inc., 2012).

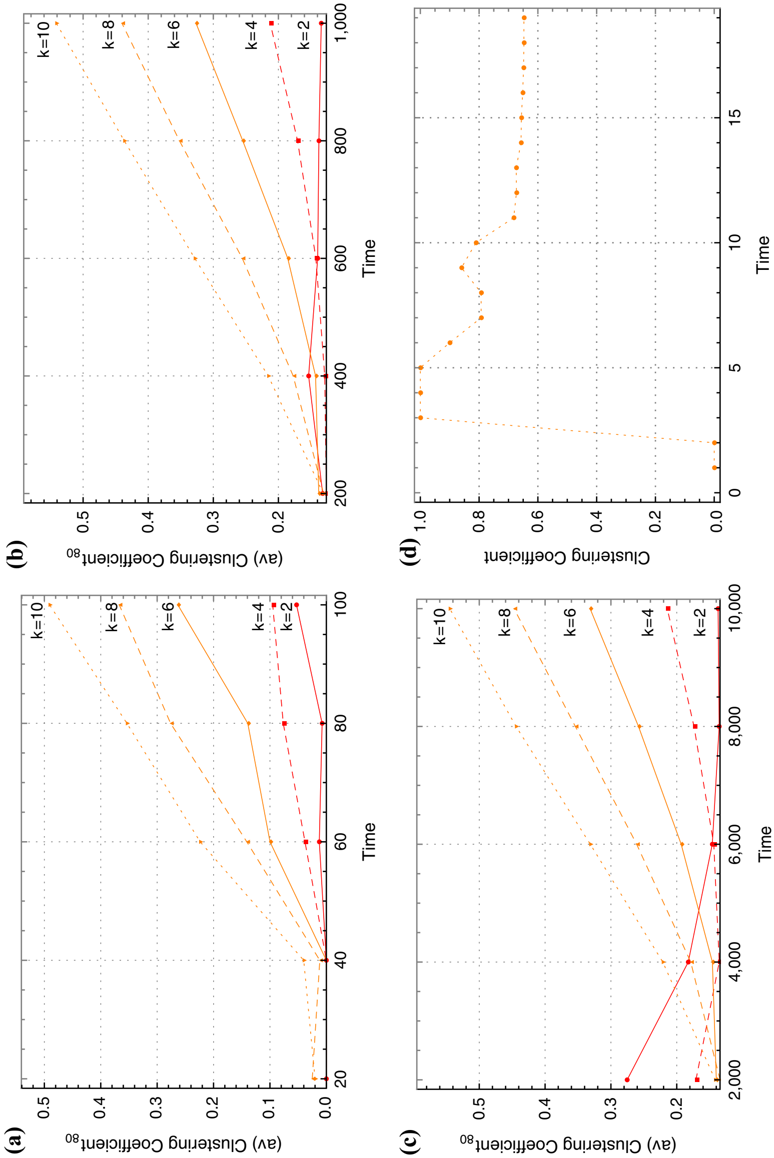
4. Results

Aside from the produced results, the model was developed as a framework to study networks constructed from interaction rules at a micro level. It allows for the study of collective intelligence based on a network science approach.

Figure 1 shows the clustering coefficient for each number of agents and the Wiki-ITRB. In Figure 1(a)-(c), the results show how the curve of the average clustering coefficient evolved over 80 simulations. Figure 1(d) shows the dynamic of higher values of clustering coefficient for the Wiki-ITRB. The clustering coefficient in both wiki systems (the model and Wiki-ITRB) demonstrates the same behavior and is consistent with the clustering coefficient in small world networks.

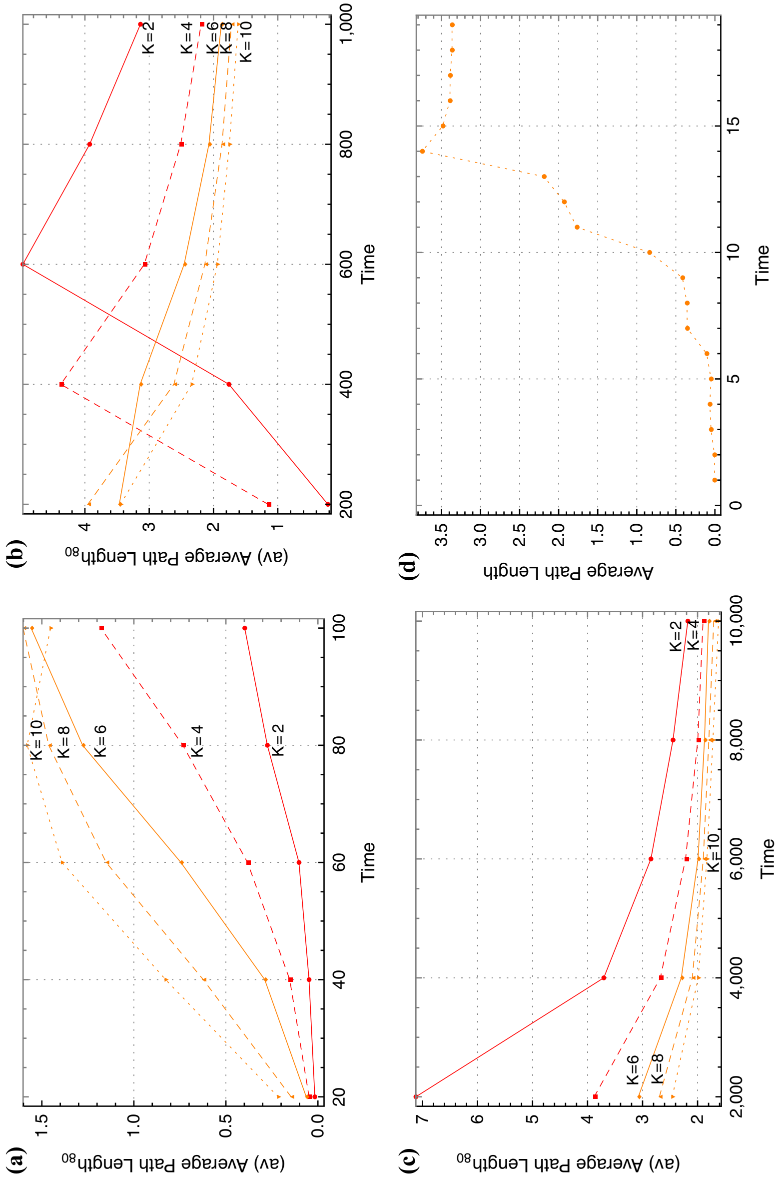
Figure 1 shows that when both time (t) and edition capacity (k) increase, the clustering coefficient also increases. Regardless of the number of agents, all graphics resulting from the model are very similar to the one of the Wiki-ITRB. While k increases, there is monotonic growth over time; however, this behavior is not present for low values of k. Thus, when $k \geqslant 3$ and $t \geqslant 5$ times the total number of agents, behavior is expected to be consistent.

Figure 2 shows the average path length (apl) for each number of agents and the Wiki-ITRB. In Figure 2(a)-(c), the results show how the curve of the average apl over 80 simulations evolved for the model, and Figure 2(d) shows the same for the Wiki-ITRB. The apl in wiki systems demonstrates the same behavior. The results shown in Figures 1 and 2 are consistent with Ingawale *et al.* (2009).



Notes: Figures (a), (b) and (c) correspond to model executions with 10e1, 102 and 10e3 agents respectively, and figure (d) corresponds to the Wiki-ITRB. along the *x*-axis are time units, while the *y*-axis shows the clustering coefficient. Figures (a), (b) and (c) show the clustering coefficient of the resulting network after running the model. Each line in the graphic corresponds to one value of agent edition capacity (k)

Figure 1.
Values of the clustering coefficient through time units



Notes: In this figure, apl is represented along the *y*-axis. Contrary to the clustering coefficient, the apl decreases when t and k increase, which is consistent with the behavior of small world networks

Figure 2.
Values for average path length through time units in model executions with 10e1 (a), 10e2 (b), c) 10e3 agents and d) correspond to the Wiki-ITRB

Figure 3 shows the evaluation of each document in the Wiki-ITRB, and demonstrates how the documents with more editions or more co-authors receive a better evaluation (scale 1-5). These results suggest that individual edition capacity and time are relevant for the acquisition of emergent properties such as those of small world networks, where group composition is self-organized. At the same time, the accumulation of a number of editions has an effect on the qualifications of documents. In sum, it suggests that collective intelligence is related to the accumulation dynamics of editions; thus with better documents there are more editions and more agents working collectively on a specific set of documents. This self-organizes the evolution of co-editor networks, and the structural properties of small world networks appear.

5. Discussion and future work

The question of how to design teaching methodologies to develop collective thinking is an open one in the educational context (Miller, 2010; Malone *et al.*, 2010). Better understanding of the underpinning dynamics of collective intelligence will thus allow for its better measurement and design. In this sense, we present a tension between traditional education and collective intelligence, in which the combining of individual pieces and collective working (collective intelligence) contrast with the notion of one person as the final expert (traditional school) (Ilon, 2012). With collective intelligence, each person holds a piece of necessary information and has the skills to solve complex problems. Thus while formal schools teach each student individually, collective intelligence builds global learning systems, content and networks (Ilon, 2012).

With collective intelligence, the learning of knowledge is distributed; in other words, it is not located in one person/place. Knowledge is represented by a network of connections, in which each connection can be the experiences of interactions with a knowing community. The student is an empowered learner who thinks and interacts in new ways. The design of teaching methodologies changes for learning based on conversation and interaction, on sharing, creation and participation; the learning is embedded in meaningful activities such as games, workflows (Yang and Yuen, 2009) or wiki systems.

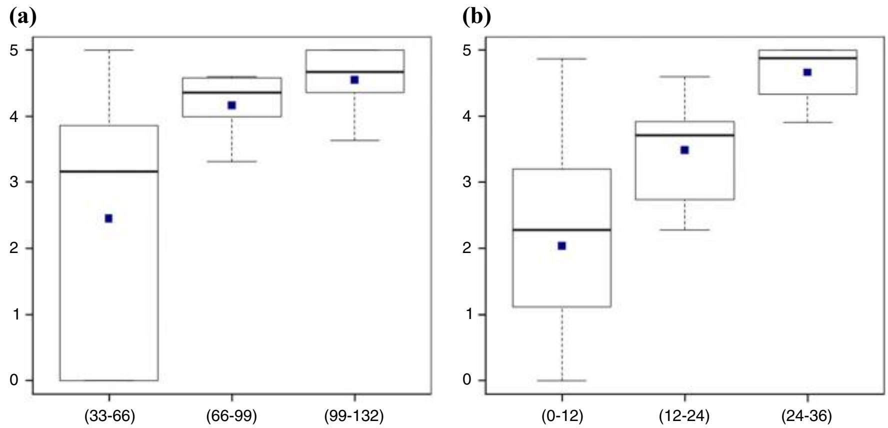


Figure 3.
Values of evaluation (scale 1-5)

Notes: (a) Average evaluation and standard deviation of evaluation documents by bins of number of editions; (b) shows the average evaluation and standard deviation of evaluation documents by bins of number of co-authors of wiki pages

Literature shows other characteristics of modelling systems based on collective intelligence, which are presented in Table I. Furthermore, we propose the design of teaching methodologies based on self-organization mechanisms, where accumulation dynamics can be taken into account to design activities based on collective intelligence.

Here, the technology Web 2.0 was used, and the wiki systems allowed us to build up the socio-technical system. Furthermore, the network of interaction between students and professors drove the collective production of knowledge surrounding the ITRBs. Collective behavior was modeled as non-linear relations among editors. Furthermore, the cumulative editions carried out reflected the quality of documents, which can be explained by the network structure. Thus the small world structure represents the highest clustering or number of connected groups (in which each group represents students and professors working on specialized topics) and lower than average path length that shows the highest connectivity between groups. In this sense, the interactions within the knowledge community were efficient in the built network (Wiki-ITRB).

Two collective systems were observed in terms of a dynamic process in complex networks – the wiki course PeSO and an agent-based model based on wiki systems. The results from both the course and the model were contrasted with a random network baseline model. Both the course and the model show dynamics of accumulation, in which statistical properties of non-equilibrium networks appear. The proposed model reproduces the behavior observed in the PeSO course; this behavior is also described for small world networks (Watts and Strogatz, 1998).

We show how the process of accumulation of editions and votes per page can be seen as a self-organized system. Thus the results presented here demonstrate how collective intelligence emerges from cumulative dynamics. We understand wiki systems as resulting from a cumulative process, whereby the accumulation of editions goes toward the development of wiki pages. Thus, the more editions there are, the better the wiki page (more visible, more votes and/or more edited); furthermore, the more editions a wiki page receives, the more editions it is likely to receive in the future. This reinforcement cycle of the wiki system transforms a random network into a small world network of co-authors or co-editors. The results show that the wiki documents that students edited more had more co-editors and better evaluations (scale 0-5). This suggests that collective intelligence is related to the accumulation dynamics of editions; thus with better documents there are more editions and more agents working on them.

We consider that the evaluation and development of strategies for teaching methodologies of collective intelligence in education remains an open question. Thus we intend to fit the current model and explore new models in order to better understand the design of socio-technical systems based on collective intelligence.

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References

Abazov, V.M., Abbott, B., Abdesselam, A., Abolins, M., Abramov, V. and Acharya, B.S. (2004), "A precision measurement of the mass of the top quark", *Nature*, Vol. 429 No. 6992, pp. 638-642.

Alag, S. (2011), "Understanding collective intelligence", in Altmann, J., Baumöl, U. and Krämer, B. (Eds), *Advances in Collective Intelligence*, Springer, Berlin, pp. 5-22.

Barrat, A., Barthelemy, M. and Vespignani, A. (2008), *Dynamical Processes on Complex Networks*, Cambridge University Press, Cambridge.

Bonabeau, E. (2009), "Decisions 2.0: the power of collective intelligence", *MIT Sloan Managment Review*, Vol. 50 No. 2, pp. 45-52.

Chialvo, D.R. (2004), "Critical brain networks", *Physica A: Statistical Mechanics and its Applications*, Vol. 340 No. 4, pp. 756-765.

Dawkins, R. (1986), *The Blind Watchmaker*, Norton, New York, NY.

Dorogovtsev, S.N. and Mendes, J.F. (2013), *Evolution of Networks: From Biological Nets to The Internet and WWW*, Oxford University Press, New York, NY.

Erdős, P. and Rényi, A. (1959), "On random graphs I", *Publicationes Mathematicae Debrecen*, Vol. 6, pp. 290-297.

Flake, G.W. (1998), *The Computational Beauty of Nature: Computer Explorations Of Fractals, Chaos, Complex Systems, And Adaptation*, MIT Press, Cambridge.

Georgi, S. and Jung, R. (2011), "Collective intelligence model: how to describe collective intelligence", in Altmann, J., Baumöl, U. and Krämer, B. (Eds), *Advances in Collective Intellogence*, Springer, Berlin, pp. 53-64.

Heylighen, F. (2013), *Self-organization in Communicating Groups: the Emergence of Coordination, Shared References and Collective Intelligence*, Springer, Berlin, Springer Berlin Heidelberg, Berlin.

Ilon, L. (2012), "How collectibe intelligence redefines education", in Altmann, J., Baumöl, U. and Krämer, B. (Eds), *Advances in Collective Intelligence*, Vol. 133, Springer, Berlin, pp. 91-102.

Ingawale, M., Dutta, A., Roy, R. and Seetharaman, P. (2009), "The small worlds of Wikipedia: implications for growth, quality and sustainability of collaborative knowledge networks", *Proceedings of the 15th Americas Conference on Information Systems*, Vol. 1 No. 1, pp. 439.

Kauffman, S.A. (2000), *Investigations*, Oxford University Press, New York, NY.

Langton, C.G. (1990), "Computation at the edge of chaos: phase transitions and emergent computation", *Physica D: Nonlinear Phenomena*, Vol. 42 No. 1, pp. 12-37.

Lévy, P. (1994), *L'intelligence Collective: Pour Une Anthropologie Du Cyberspace*, La Découverte, Paris.

Lykourentzou, I., Papadaki, K., Vergados, D., Polemi, D. and Loumos, V. (2010), "CorpWiki: a self-regulating wiki to promote corporate collective intelligence through expert peer matching", *Information Sciences*, Vol. 180 No. 1, pp. 18-38.

Malone, T.W., Laubacher, R. and Dellarocas, C. (2010), "The collective intelligence genome", *MIT Sloan Management Review*, Vol. 51 No. 3, pp. 21-31.

Merton, R.K. (1968), "The Matthew effect in science", *Science*, Vol. 159 No. 3810, pp. 56-63.

Miller, P. (2010), *The Smart Swarm: How Understanding Flocks, Schools, and Colonies can Make Us Better at Communicating, Decision Making, and Getting Things Done*, Avery Publishing Group, Wayne, NJ.

Pór, G. (1995), "The quest for collective intelligence", in Gozdz, K. (Ed.), *Community Building: Renewing Spirit and Learning in Business*, New Leaders Press, San Francisco, CA, pp. 271-280.

Prigogine, I. (1980), *From Being to Becoming: Time and Complexity in the Physical Sciences*, W.H. Freeman & Co, New York, NY.

Prigogine, I. (1997), *The End of Certainty*, The Free Press, New York, NY.

Sornette, D. (2006), *Critical Phenomena in Natural Sciences: Chaos, Fractals, Selforganization and Disorder: Concepts and Tools*, Springer Science & Business, Berlin.

Tang, C and Bak, P. (1988), "Critical exponents and scaling relations for self-organized critical phenomena", *Physical Review Letters*, Vol. 60 No. 23, pp. 2347-2350.

Watts, D.J. and Strogatz, S.H. (1998), "Collective dynamics of'small-world'networks", *Nature*, Vol. 393 No. 6684, pp. 409-410.

Wilensky, U. (1999), *Center for Connected Learning and Computer-Based Modeling*, Northwestern University, Evanston, IL, NetLogo, available at: http://ccl.northwestern.edu/netlogo

Wolfram Research Inc. (2012), *Mathematica*, 90th ed., Wolfram Research Inc, Champaign, IL.

Wolfram, S. (2002), *A New Kind of Science*, Wolfram Media, Champaign, IL.

Yang, H.H. and Yuen, S.C. (2009), *Collective Intelligence and E-learning 2.0: Implications of Web-Based Communities and Networking*, IGI Global, Hershey, PA.

Further reading

Gell-Mann, M. (1994), *The Quark and The Jaguar: Adventures in the Simple and the Complex*, W.H. Freeman and Company, New York, NY.

Surowiecki, J. (2004), *The Wisdom of Crowds*, Anchor, New York, NY.

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