Prediction Markets as a Vital Part of Collective Intelligence

Rafał Palak
Department of Information Systems
Wrocław University of Science and Technology
Wrocław, Poland
Rafal.Palak@pwr.edu.pl

Ngoc Thanh Nguyen
Department of Information Systems
Wrocław University of Science and Technology
Wrocław, Poland
Ngoc-Thanh.Nguyen@pwr.edu.pl

***Abstract*— Nowadays, collective intelligence becomes more and more popular. Despite its high usability, many aspects of collective intelligence stay unexplored. Many companies have recognized the potential of collective intelligence and have begun using it. Prediction markets are the real life implementation of collective intelligence. The fact that prediction markets outperform experts makes it a great tool for predicting the future. In this paper, we try to answer important questions that have to be asked before the creation of a prediction market e. g. "What factors influence the prediction market error and how could this be minimized?". This paper treats the problems more broadly. Therefore, the areas of collective intelligence that have a strong influence on prediction markets are also included in the problem analysis.**

***Keywords*— collective intelligence, prediction markets, crowdsourcing, collective intelligence factors**

I. Introduction

Many definitions of collective intelligence exist nowadays. In [27] authors define collective intelligence as "*the capacity of human collectives to engage in intellectual cooperation in order to create, innovate and invent*." In [34] authors treat collective intelligence as a phenomenon where "*groups of individuals acting collectively in ways that seem intelligent*." A group of individuals in the literature usually is called a collective if they realize a common task. Authors of work [32] state that "*a collective decision capability [that is] at least as good as or better than any single member of the group*." This means that collective intelligence should not achieve results worse than the worst result of the group members. This fact is a major advantage of collective intelligence because whichever method would be used collective intelligence has the boundary that cannot be passed.

Nowadays intelligent people are very important in our society. Our society often listens to opinions of intelligent individuals, therefore interviews with such known people as Bill Gates, Elon Musk, Mark Zuckerberg, etc. are so popular. Journalists especially like to ask them about the unknown future. Their opinions are usually cited around the world, sometimes even with the same confidence as facts. Theirs opinion is particularly important when it comes to predicting unknown events and results of risky decisions. Great knowledge and high intelligence possessed by them are not guarantee infallibility, they make mistakes. Some mistakes could be costly for companies, therefore the most important is to minimize risk.

Research shows that group of normal people could forecast events with more accuracy than one expert. The more accurate forecast could be priceless for many companies, therefore nowadays so many companies use collective intelligence.

It is important to realize that determining collective knowledge is one of the most important processes. The state of collective knowledge is considered a consensus of the members' states of knowledge. [21] The choice of consensus is usually understood as "a general agreement in situations when parties have not agreed on some matters." [38] Sometimes it is not an easy task to determine collective knowledge, therefore the properly chosen consensus function is so important for the properly functioning collective intelligence.

Collective intelligence has been known for many centuries. Aristotle first described it in Politics (350 BC) [6]. About fifty years later, in the Period of Warring States (around 300 BC) in China Lord of Menchang invited three thousand guests in order to tap into advice and expertise from a diverse group. [33] About two thousand years later in Plymouth, during the annual West of English Fat Stock and Poultry Exhibition in 1906, a contest was announced, in which 800 people participated. The participants' task was to forecast the weight of a fat ox. The crowd did surprisingly well because the average guess (1197) was unbelievably close to the real weight (1198) [16]. Despite an existence of thousands of years, collective intelligence has never been formally studied in the field of organizational behavior and leadership [33]. Nowadays, many researchers try to fill this gap, but still a lot of things have not been formalized yet.

Collective decision making is seen as a perfect tool to solve complex problems [19]. Therefore, collective intelligence is used in many companies, especially its real life implementation is the prediction market. Prediction market [1] was defined as "virtual markets created to aggregate crowds' opinions and operate in a way similar to stock markets.". Prediction market helps many companies in categorizing, evaluating, and sharing knowledge, making predictions and solving problems. Widespread usage could be considered as a proof of its

978-1-5090-5795-5/17/$31.00 ©2017 IEEE

effectiveness [8]. Beside popularity of prediction markets, there are still many unanswered questions. One question that has to be answered is: "What factors influence the prediction market error and how could this error be minimized?". It is important to minimize prediction error in order to obtain the highest quality of prediction. High quality of prediction allows making better decisions because decisions will be made based on better knowledge. Another question that has to be answered is: "Could computer participants improve the quality of prediction?". Computer participants are much cheaper than normal people, and besides, it is much easier to create prediction with computer participants than with normal people.

The remaining part of this paper is organized as follows: the next section describes the division of collective intelligence. Section 3 presents crowdsourcing (prediction markets belong to that part of collective intelligence). Section 4 includes pieces of information about prediction markets. The last section includes some conclusions.

II. Collective Intelligence

As described above, collective intelligence has been known for a long time. Therefore, many methods of collective intelligence were created. A large number of approaches required to define its classification. In [3] the authors distinguished: human computation, crowdsourcing, social computing as part of collective intelligence (Fig. 1.). Authors include data mining as part of collective intelligence because it has some connections to collective intelligence.

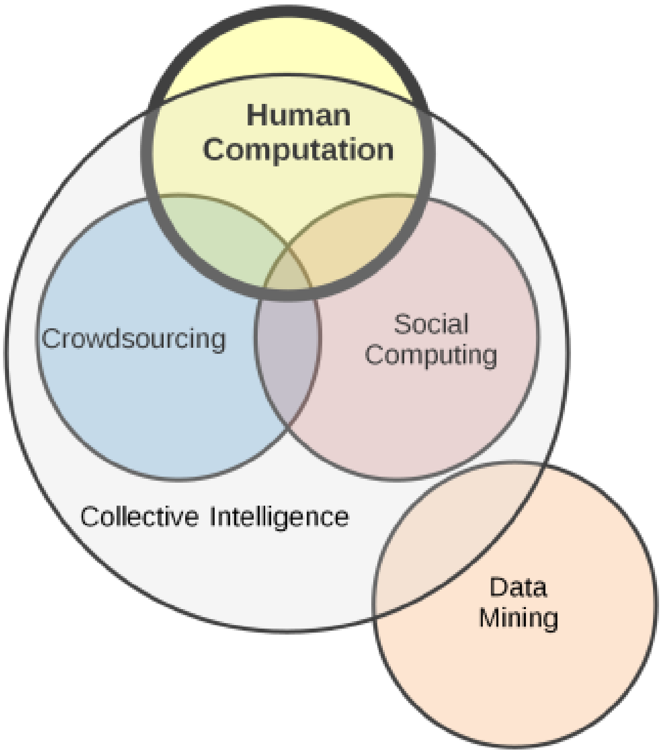

Fig. 1. Collective intelligence [3]

Human computation is defined as "*...the idea of using human effort to perform tasks that computers cannot yet perform, usually in an enjoyable manner*" [13]. In [3] authors empathies that human computation could include tasks, in which human participation is directed by the computational system or process, and the problem solved by humans fits the general paradigm of computation. Human computation could not be involved in projects, where the initiative and flow of activity are directed primarily by the participants' inspiration, but human computation could be involved in a project, where a predetermined plan is designed to solve a computational problem. [3]

Another subfield of collective intelligence is crowdsourcing. Crowdsourcing is defined as "*the act of taking a job traditionally performed by a designated agent (usually an employee) and outsourcing it to an undefined, generally large group of people in the form of an open call.*" [15]. Crowdsourcing replaces human with a group of people. The intersection of crowdsourcing with human computation in Fig. 1. "*represents applications that could reasonably be considered as replacements for either traditional human roles or computer roles*" [3]. Prediction markets are part of crowdsourcing.

Social computing is another element of collective intelligence, it is defined as "*... the interplay between persons' social behaviors and their interactions with computing technologies*" [11] Authors in [3] emphasize that the key distinction between human computation and social computing is the fact that social computing makes the human interaction easy, that is mediated by technology, whereas people in human computation are directed by human computation systems. [3]

Data mining could be considered as part of collective intelligence because data mining algorithms usually extract patterns from human-created data. In [3] authors give Google PageRank as a major example of this statement. PageRank is based on a structure of hyperlinks between pages that define page importance. Authors justify that by linking the pages by humans that were not caused by the system.

III. Crowdsourcing

As it was described by Surowiecki in his book [16], crowds could outperform experts in many cases. Conducted experiments support the hypothesis that a general collective intelligence factor exists in groups [5]. In his work, he shows many examples where crowds perform some tasks unbelievably well. In [10] authors showed that experts could outperform small crowds but could still be outperformed by large collectives. Authors give an example of game show "*Who wants to be a millionaire*" to support this thesis, where the crowd gives the right answer in 91% of situations, but experts are only right in 65% of the time. In [10] an experiment was conducted where the crowd was asked to forecast temperature one week into the future. The crowd performed this task unexpectedly well (crowd forecast 29,89 degrees' vs. 29 degrees actual). In other countless works authors focus on the crowd's ability to forecast the future with phenomenal accuracy but many times it is omitted that the collective knowledge could be greater than the sum of knowledge of its members of a collective, e.g., one member knows that: A>B and other member knows that: B>C, they both known: A>B, B>C and A>C. Countless works in this field positively affect prediction markets. Prediction markets are part of crowdsourcing and many times research done in crowdsourcing gave major contribution for the prediction market working properly, therefore in this part of the paper, the most important research in crowdsourcing will be described.

One of the most important advantages of collective intelligence is the boundary of the lowest possible quality of knowledge. In literature, it is well known that quality of collective knowledge could not be worse than the worst knowledge quality of collective member. Authors in [36] have proven it mathematically that the distance of collective knowledge state to real knowledge will always be higher or equal to the average distance from knowledge states of collective to real knowledge state (if collective is not homogeneous, collective knowledge state is better than the average distance from knowledge states of collective to real knowledge state). This is important for the study of collective intelligence because it moves on the boundary of collective knowledge quality. Collective knowledge is always better than the worst knowledge state of its member.

Properly functioning prediction market gives better results for some collectives than others. In many works, researchers have tried to discover factors responsible for that. In [16] author identified three requirements for the emergence of collective wisdom: diversity, decentralization of opinion and independence. Despite a large number of publications and various points of view on this subject, most of the researchers are confirming this theory. Compliance with these principles should increase the quality of collective knowledge.

Authors in [5] conducted an experiment to discover factors that allow groups to behave in an intelligent manner. The authors stated that group IQ is "*not strongly correlated with the average or maximum individual intelligence of group members but is correlated with the average social sensitivity of group members, the equality in the distribution of conversational turn-taking, and the proportion of females in the group.*" [5]. Authors in [7] emphasized that beside many citations of this article, there are not many publications, which tried to replicate this results. In [7] in an experiment replicated from [5] showed strong ladings on individual IQ (rather than weak), beside that the conducted experiment did not show any correlations between group IQ and number of females in the group, also social sensitivity failed to emerge as a significant predictor of group-IQ [7].

In [10] authors distinguish two ways to improve collective knowledge: by reducing individual error (increase individual expertise) and by increasing group diversity. Diversity and expertise will not matter if individuals are unfamiliar with the task, thus being unable to apply their information and knowledge. [16] The experiment conducted in [19] supports this thesis. This opinion is also presented by Page [31], in his work he distinguishes four kinds of diversity:

- diversity of perspectives – kind of diversity representing situations and problems
- diversity of interpretations - kind of diversity categorizing or portioning perspectives
- diversity of heuristics - kind of diversity representing situations and problems
- diversity of predictive models - kind of diversity inferring cause and effect

Page also formalized the range of diversity in a prediction diversity that reflects how far the individuals are from an average participant from a group.

In [23] author tried to measure the diversity of a crowd and call it "inconsistency." Inconsistency in this work represents the coherence and density levels of collective knowledge states. The author defined five functions for measuring the degree of inconsistency of a collective.

In [10] authors distinguish the raising group diversity as one of the methods to improve collective knowledge quality. Many works try to formally prove the positive influence of inconsistency degree on the quality of collective knowledge. In [36] authors propose a mathematical model and they proved that collective with a higher inconsistency degree has better quality of knowledge than collective with a lower inconsistency degree. The experiment conducted in [37] confirms that theoretical results are true.

Authors in [37] check how adding and removing members of a collective affect collective knowledge quality. In the conducted experiment two cases were tested: when inconsistency increases and decreases. They concluded that collective knowledge increase results from the inconsistency degree of a collective. At first sight, the results could be unintuitive because higher inconsistency always means a consensus which is harder to achieve, but evidence delivered by research is unequivocal. Results of experiments allow us to conclude that a high inconsistency degree positively affects the collective knowledge (collective knowledge increase).

In [35] simulations conducted by authors show that adding members to a collective, such that causes the decrease in the inconsistency degree of a collective is not helpful in improving the quality of collective knowledge. Despite that, it is helpful to make quality of knowledge stable.

As it was shown, diversity positively affects the quality of collective knowledge, but at the same time, the higher diversity always means that a consensus is harder to make. A consensus is one of the most important elements for collective intelligence because it is significant in determining collective knowledge. Consensus of all knowledge States represents the knowledge state of crowd. Therefore, it is so important for proper functioning collective intelligence. The author in [24] and [23] defined ten postulates that should be met by consensus function:

- Reliability - each nonempty profile should have at least one consensus
- Unanimity – for homogeneous profile (in homogeneous profile all elements are the same) exists only one consensus: it is the element belonging to this profile
- Simplification - consensus of a profile should also be a consensus of any of its multiples

- Quasi-unanimity – "*if an element x is not a consensus of the profile X, then it should be a consensus of a new profile X' containing X and n elements x for some n*" [23]
- Consistency - if some element x is a consensus for the profile X, and if x is added to the profile X, x should still be a consensus for the new profile
- Condorcet consistency - "*if two disjoint subsets of voters V and V would choose the same alternative using (social choice function) f, then their union should also choose this alternative using f*" [23]
- General consistency – "*common consensus of two profiles should also be a consensus of their sum, and a consensus of the sum of two profiles should be a consensus of at least one of them*" [23]
- Proportion - difference between consensus and its elements is greater for a bigger profile
- 1-Optimality - requires the sum of the distances between a consensus and elements of the profile to be minimal
- 2-Optimality – it is similar to requires 1-Optimality but in this case the sum of the squared distances between a consensus and the profile elements to be minimal

All postulates are easy to understand and comply with the intuition. Postulates should be used for every consensus function because postulates formally represent everything that should be required from a consensus function. Fulfillment of these postulates guarantees the good consensus function.

The author in [23], [22] distinguishes a term of susceptibility to consensus, this allows us to answer the question: "*Is the consensus sensible and may it be accepted as the solution of the conflict?*" [23]. The author's statement: if an average distance from a consensus to the elements of collective knowledge is lower or equal to an average distance in collective knowledge, then consensus could be accepted. This definition has a simple intuition: if opinions are sufficiently densely concentrated around the consensus, then consensus could be accepted as solution of the problem.

Accurate predictions require the assimilation of knowledge from previous experiences with specific information relevant to the context [12]. Besides, the crowd that participated in prediction markets should fulfill all requirements (diversity, decentralization of opinion and independence [16]), crowd members should also be familiar with the subject. This is important to prediction market accuracy because for people unfamiliar with the subject of the task it will be harder than for people familiar with the subject. This intuition seems to be confirmed by research. In [9] authors conducted a field study and simulations. They show a great impact on task complexity on collective performance. It was suggested that involvement of a higher number of people to get involved in more complex tasks allows to accumulate more knowledge than they would have while working on their own. This opinion was confirmed in [36], authors based on mathematical models created by themselves proved that is true. Similar results are achieved in [33], where collective accuracy falls dramatically for the difficult task. Authors noticed that when collectives are familiar with the task, their judgment models are highly consistent and accurate [33].

In [2] authors analyzed noise traders and their influence on the quality of prediction markets. Noise traders are defined as "*participants that trade for non-informational reasons and divert asset prices from efficient values*" [2]. Authors based on theirs research concluded that prediction markets without noise traders have a better performance. Authors emphasized that inviting large numbers of traders may lead to a degree of uninformed traders, which may distort prices.

IV. Prediction Markets

A. *FACTORS INFLUENCING THE PREDICTION MARKET ERROR*

Prediction market is one of the most popular examples of collective intelligence usage. In [25] authors define an idealized prediction market where "*traders are motivated by profits to buy or sell shares of contracts about future events. If and when they obtain relevant information they act quickly in market. Knowledge is continuously updated and aggregated, making prices generally good estimates of chances of future events*" [25]. Prediction markets are wildly used in many organizations, e.g., Google, HP and Intel collect sales forecast from its employees [8], Siemens aggregated employees' opinions on whether projects will be delayed [14], the Defense Advanced Research Projects Agency (DARPA) used prediction markets to improve strategic intelligence decisions [26]. Prediction market may be the answer to a problem with launching new products – only one of every five products is successful [33]. Companies are frequently unable to capitalize on successes of new product blockbuster because of poor demand forecast. In [33] authors show that methods used nowadays to resolve this problem have many problems, prediction markets seem to be the answer to this problem. They distinguish five principals of prediction markets [33]:

- Incentive - Prediction markets must provide strong incentives for a good use of market information. They should neither reward status nor dominance, which are common in organizations.
- Indicator - Prediction markets employ a clear information indicator. In particular, price is used to convey aggregation information to all participants
- Improvement - Prediction markets encourage individuals to improve their knowledge
- Independence - Prediction markets benefit from independent information sources
- Crowd - Prediction markets work best in a large crowd

These authors show that prediction markets motivate people to share information clearly and freely through the price discovery process. They encourage participants to learn from each other, and they pool from a large group of diverse individuals. Authors emphasize that as long a prediction market is active, it always contains the most current wisdom of the crowd.

Despite the fact that authors in most cases agree with each other that a large number of people has a positive influence on the quality of prediction by prediction markets. Authors have different opinions on why large numbers of people have positive influence on the collective knowledge quality, for example: in [33] authors prove this is grounded on the statistical principle of the Law of Large Number, but in [10] authors emphasize that collective intelligence is not the manifestation of Law of Large numbers. Both authors agree on the fact that beside the crowd size, other factors are equally important. In [2] authors analyze two theories:

- "*large markets offer higher returns to informed trading, and therefore more information is acquired, traded upon, and incorporated into prices*."
- "*information is by its nature distributed across the population, and not held by just a few individuals, and therefore prices in a broader market will harness the wisdom of these crowds and prove to be more accurate.*"

Authors point out that the answer is not overwhelmingly clear, but the results of the experiment support the first theory slightly more, in which a larger crowd rises the returns to informed trading.

In [29] authors proposed a decentralized prediction market. Nowadays, decentralized prediction markets are gaining on popularity. It should be noticed that a traditional prediction market is centralized, in the sense that there exists a trusted center that creates markets, oversees transactions, and closes the market appropriately. The main difference between centralized prediction markets is the way to close a prediction market, decentralized prediction markets are closed by consensus, unlike in centralized prediction market where a decision is made by the center. One of the advantages of a decentralized prediction market is that it may remove requirements for a highly trusted center necessary for the functioning of a prediction market. Authors in [28], [17], [20] point out that a decentralized prediction market removes a very important requirement: a highly trusted center, but a decentralized prediction market also allows each arbiter to directly influence the outcome of the market, in much the same way that agents may deliberately manipulate an event due to their stake in the market; this is known as outcome manipulation.

While organizing prediction market participants are its most important element. In [30] authors emphasize that people should be properly reworded to avoid: producing herding effects, reducing information available to the group and suppressing collective intelligence. Research on prediction markets suggests that prediction markets may systematically underweight a large pool of informational factors that are limited by predictive power individually, but which can contribute powerfully to aggregate predictions if agents can be persuaded to pay attention to them. Authors tested three reward systems. The most effective system is the system called "minority reward," where agents are rewarded for an accurate prediction when fewer than half of the other agents also vote accurately. Minority rewards will produce near-perfect accuracy for any problem size as long as the population of agents remains large relative to the number of factors. [30] Authors suggest that rewards should be primarily oriented towards those who made successful predictions in the face of majority opposition from their peers, i.e. towards those who tell us something we do not already know.

B. *COMPUTER PARTICIPANTS AND THEIR INFLUENCE ON THE QUALITY OF PREDICTION MARKETS*

It is important to realize that participants in prediction markets could not be only humans. In [39] authors state that combining human and machine predictions sometimes give better results. Authors, in order confirm that, compare three deferent types of predictions: groups of humans, groups of artificial-neural-network agents, and 'hybrid' groups of humans and agents. Authors emphasize that combining human and machine predictions is not always better, but in some situations it is true that they are better. In [39] authors used a hybrid approach, where humans and artificial intelligence agents are participants, that approach provides better trade-off between sensitivity and specificity than the approach, where participants are only humans or the approach, where participants are only artificial intelligence agents.

In [39] despite groups with artificial-neural-network agents have not achieved the best result, they sometimes achieve better results than humans. That may suggest that artificial intelligence could perform better than humans, but there are not many publications where authors use prediction markets with artificial intelligence agents. This situation could be caused by the lack of understanding of the whole decision-making process by humans. Although, in many works, computer participants achieve results similar to humans. Paper [18] could be a great example of using only computer participants as participants in prediction market. They use it to combine predictions from machine classifiers. In [4] authors try to prove a thesis that humans are supernal to machine learning model in forecasting sports events. The experiment conducted by authors has not provided enough evidence supporting this thesis, results achieved by humans were not statically greater than in the machine learning model. That fact may result in more research in this field with computer participants in the near future.

V. CONCLUSIONS

Collective intelligence has been known for many centuries, but studies on it have just started formalizing it. Nowadays, prediction markets are one of the most popular implementations of collective intelligence, but despite the popularity, this area still needs more research. In literature, many authors tried to explain collective intelligence phenomena. Many of them distinguished factors that influence quality of decision made by collective intelligence. They sometimes have different opinion in that matter but most of them agree that crowd size and independence of participants have strong influence on collective intelligence prediction error. The size of the prediction market is a great example of that, in literature all authors agree that bigger crowds usually give more accurate predictions, but it is still required to understand why large crowd produces more accurate results. Currently, the available results try to answer this question, but none of these works provide a clear answer. Despite its popularity, its many elements remain unknown.

Authors of publications do not often use artificial intelligence agents for prediction markets. Examples were described by researchers rarely exceed performance of a human. Possible cause of that fact is that there is not enough understanding of how collective intelligence works. As the result of constant improvement of the knowledge about collective intelligence, the accuracy of predictions given by artificial intelligence agents used in prediction markets will increase correspondingly. Collective intelligence will grow more dynamically in the future due to wide range of applications [40], [41].

REFERENCES

[1] A. Bassamboo, R. Cui, and A. Moreno, "The wisdom of crowds in operations: Forecasting using prediction markets." Available at SSRN: https://ssrn.com/abstract=2679663 2015.

[2] A. Brown, and F. Yang, "The Wisdom of Large and Small Crowds: Evidence from Repeated Natural Experiments in Sports Betting." Available at SSRN: https://ssrn.com/abstract=2898762 2017.

[3] A. J. Quinn, and B. B. Bederson, "Human computation: a survey and taxonomy of a growing field." In Proceedings of the SIGCHI conference on human factors in computing systems, pp. 1403-1412. ACM, 2011.

[4] A. Pretorius, and D. A. Parry, "Human Decision Making and Artificial Intelligence: A Comparison in the Domain of Sports Prediction." In Proceedings of the Annual Conference of the South African Institute of Computer Scientists and Information Technologists, p. 32. ACM, 2016.

[5] A. W. Woolley, C. F. Chabris, A. Pentland, N. Hashmi, and T. W. Malone. "Evidence for a collective intelligence factor in the performance of human groups." science 330, no. 6004: 686-688, 2010.

[6] Aristotle, "Politics", Vol. III, (B. Jowett, Trans.) 350 B. C. E

[7] B. Green, "Testing and quantifying collective intelligence." In Proceedings of the 25th Annual International Conference on Computer Science and Software Engineering 2015.

[8] C. R. Plott, and K. Y. Chen, "Information aggregation mechanisms: Concept, design and implementation for a sales forecasting problem." Social Sceince working paper No. 113 2002.

[9] C. Wagner, and A. Suh, "The wisdom of crowds: impact of collective size and expertise transfer on collective performance." In 2014 47th Hawaii International Conference on System Sciences, pp. 594-603. IEEE, 2014.

[10] C. Wagner, and T. Vinaimont, "Evaluating the wisdom of crowds." Proceedings of Issues in Information Systems 11, no. 1: 724-732, 2010.

[11] D. C. Dryer, C. Eisbach, and W. S. Ark, "At what cost pervasive? A social computing view of mobile computing systems." IBM Systems Journal 38, no. 4: 652-676, 1999

[12] D. Kahneman, and A. Tversky. "On the psychology of prediction." Psychological review 80, no. 4: 237-251, 1973

[13] E. Law, & L. von Ahn, "Input-agreement: a new mechanism for collecting data using human computation games." Proc. CHI, 1197-1206. 2009

[14] G. Ortner, "Forecasting markets - An industrial application." Working paper, Department of Managerial Economics and Industrial Organization, University of Technology, Vienna, Austria. 1997

[15] J. Howe, "Crowdsourcing: A Definition" http://crowdsourcing.typepad.com (15.03.2017)

[16] J. Surowiecki, "The wisdom of crowds." Anchor, 2005.

[17] J. E. Berg, and T. A. Rietz. "The Iowa electronic markets: Stylized facts and open issues." Information Markets: A New Way of Making Decisions: 142-169. 2006

[18] J. Perols, K. Chari, and M. Agrawal. "Information market-based decision fusion." Management Science 55, no. 5: 827-842, 2009

[19] K. A. McHugh, F. J. Yammarino, S. D. Dionne, A. Serban, H. Sayama, and S. Chatterjee. "Collective decision making, leadership, and collective intelligence: Tests with agent-based simulations and a Field study." The Leadership Quarterly 27, no. 2: 218-241. 2016

[20] M. Chakraborty, and S. Das. "Trading on a rigged game: Outcome manipulation in prediction markets." In Proceedings of the 25th International Joint Conference on Artificial Intelligence (IJCAI). 2016

[21] N. T. Nguyen "Processing inconsistency of knowledge in determining knowledge of a collective." Cybernetics and Systems: An International Journal 40, no. 8: 670-688, 2009

[22] N.M. Udin et al. "Semantic Similarity Measures for Enhancing Information Retrieval in Folksonomies". Expert Systems with Applications 40(5), 1645–1653.

[23] N. T. Nguyen, "Advanced methods for inconsistent knowledge management." Springer London, 2008.

[24] N. T. Nguyen, "Using distance functions to solve representation choice problems." Fundamenta Informaticae 48: 295-314, 2001.

[25] P. Atanasov, P. Rescober, E. Stone, S. A. Swift, E. Servan-Schreiber, P. Tetlock, L. Ungar, and B. Mellers. "Distilling the wisdom of crowds: Prediction markets vs. prediction polls." Management Science 63, 691 – 706, 2016.

[26] P. F. Yeh, "Using prediction markets to enhance US intelligence capabilities." Studies in Intelligence 50, no. 4: 137-149. 2006

[27] P. Lévy, "From social computing to reflexive collective intelligence: The IEML research program." Information Sciences 180, no. 1: 71-94. 2010

[28] P. Shi, V. Conitzer, and M. Guo. "Prediction mechanisms that do not incentivize undesirable actions." In International Workshop on Internet and Network Economics, pp. 89-100. Springer Berlin Heidelberg, 2009.

[29] R. Freeman, S. Lahaie, and D. M. Pennock. "Crowdsourced Outcome Determination in Prediction Markets." arXiv preprint arXiv:1612.04885 2016.

[30] R. P. Mann, and D. Helbing. "Minorities report: optimal incentives for collective intelligence." arXiv preprint arXiv:1611.03899 2016.

[31] S. E. Page, "The difference: How the power of diversity creates better groups, firms, schools, and societies." Princeton University Press, 2008.

[32] S. R. Hiltz, and M. Turoff, "The network nation: Human communication via computer." MIT Press, 1993.

[33] T. H. Ho, and K. Y. Chen, "New product blockbusters: The magic and science of prediction markets." California Management Review 50, no. 1: 144-158, 2007

[34] T. W. Malone, and M. S. Bernstein. "Handbook of collective intelligence." MIT Press, 2015.

[35] V. D. Nguyen, N. T. Nguyen, "An influence analysis of the inconsistency degree on the quality of collective knowledge for objective case." In Asian Conference on Intelligent Information and Database Systems, pp. 23-32. Springer Berlin Heidelberg, 2016

[36] V. D. Nguyen, N. T. Nguyen, & H. B. Truong, "A Preliminary Analysis of the Influence of the Inconsistency Degree on the Quality of Collective Knowledge." Cybernetics and Systems, 47(1-2), 69-87, 2016.

[37] V. D. Nguyen, N. T. Nguyen, "Some Novel Results of Collective Knowledge Increase Analysis Using Euclidean Space." In International Conference on Artificial Intelligence and Soft Computing, pp. 352-363. Springer International Publishing, 2016.

[38] W. H. E. Day, "Consensus methods as tools for data analysis." In 1. Conference of the International Federation of Classification Societies, pp. 317-324. 1987.

[39] Y. Nagar, T. Malone. "Making business predictions by combining human and machine intelligence in prediction markets." Presentation from the 32nd International Conference on Information Systems. Association for Information Systems, Shanghai, 2011.

[40] T.H. Duong, M.Q. Tran, T.P.T. Nguyen. "Collaborative Vietnamese WordNet building using consensus quality". Vietnam Journal of Computer Science 4 (2), 85-96, 2017.

[41] J. Contreras-Castillo, S. Zeadally, J.A.G. Ibáñez. "A seven-layered model architecture for Internet of Vehicles". Journal of Information and Telecommunication 1(1), 4-22, 2017.