How to cite this paper:

Sayed Nafiz Haider, Su-Cheng Haw, & Fang-Fang Chua. (2017). Group-in-the-loop: architecture for harnessing and creating collective intelligence in Zulikha, J. & N. H. Zakaria (Eds.), Proceedings of the 6th International Conference on Computing & Informatics (pp 511-516). Sintok: School of Computing.

GROUP-IN-THE-LOOP: ARCHITECTURE FOR HARNESSING AND CREATING COLLECTIVE INTELLIGENCE

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ABSTRACT. As pervasive computing is becoming more pervasive and new ways to collaborate are emerging, humans and algorithms are co-creating "Collective intelligence". Moreover, human can deliver at points where automatic machine learning algorithms fail. In the light of this context, the need for new tools and techniques is becoming apparent to harness the collective intelligence more effectively. In this paper, we investigate different approaches to utilize the collective intelligence in computer aided collaborative works. We reviewed recent works on the human-in-the-loop approach to artificial intelligence and proposed an architecture that uses scaled up version of human-in-the-loop approach, "Group-in-the-loop".

Keywords: Human-in-the-loop, collective intelligence, recommender system, group-in-the-loop, collaborative work

INTRODUCTION

As technologies to collaborate advance and becomes more accessible, the opportunity for the collective intelligence (CI) to evolve increases and so does the importance of harnessing this intelligence. CI is linked to the capacity to solve problems as a group, instead of individual. It is an emergent property of the synergies between: 1) information-knowledge-data; 2) software and hardware; and 3) experts (personnel with knowledge and recognized authorities) (Glenn et al., 2009).

There are different approaches to exploit CI. For example, Malone et al. (2009) identified the genes to classify the building blocks of CI systems. They defined a gene as a particular answer to two pairs of related questions associated with a single task in the CI system. The objective of these questions is to know the staffing, incentives, goals and process or structure of a task.

On the other hand, Human Centered Design (HCD) methodology is used to create new solutions involving products, services, environments, organizations, and modes of interaction for the world (HCD toolkit, 2009). IDEO, an international design firm published this methodology as HCD toolkit. The HCD toolkit is accepted across the globe and has a big online community of users. In this paper, we will refer to this community as "Design community".

HCD helps the team hear the needs of constituents in new ways, create innovative solutions to meet these needs, and deliver solutions with financial sustainability in mind. One of the key features of HCD is it encourages the stakeholders to get involved throughout the design process (HCD toolkit, 2009).

The context of our work is CI generated from the HCD process, a design process performed by a group of designers and stakeholders. Better decision support tools are required to harness this CI. Table 1 depicts the mapped genome of CI for HCD. This mapping process confirms that mechanisms for producing CI exists in the HCD process and therefore, exists the opportunities to harness this intelligence. In this paper, we have identified the potential to use crowd-workers' or design community's knowledge in the design process, identified the limitation in the state of the art and proposed an architecture to harness the CI.

Table 1. Mapping the CI Genome for HCD.

	What		Who	Why	How
Products or services out of HCD toolkit	Create	New services or products	Stakeholders & designers	Money, Love, glory	Collaboration
	Decide	On methods and solutions throughout the process	designers	Money, Love, glory	Group decision

RELATED WORKS

The contributions of this paper are built upon prior works on harnessing CI in computer aided collaborative work, crowd powered recommender system (RS) and human in the loop generative machine learning approach.

In the context of computer aided collaborative work to harness CI, Klein (2011) introduced a large scale argumentation system that reduces redundancy and encourages clarity. The author argued that social media technologies pose some flaws for creating polarization, disorganized content, quantity rather than depth and so on, when applied to complex, controversial problems. In this approach, the community members made their contributions in the posts, where by each post represent a single unique issue, idea, or argument (pro or con of the idea or argument). Another example of collaborative work is OpenIDEO. OpenIDEO is an open innovation platform to enable people across the world to collaborate to tackle global issues (OpenIDEO, 2010).

In the current context, participants usually go through the following process in Figure 1. None of the above two platforms use any decision support tool where human and artificial intelligent system learn from each other and improve their ability to guide a design team over time.

Flores et al. (2015) introduced a software framework for inventive problem solving. The framework proposed to implement the techniques from CI research field in combination of the systematic method provided by the TRIZ (Russian acronym for "The Theory of Inventive Problem Solving") theory. Their intention was to improve the method and tools by the TRIZ, with collective contributions. The authors used the TRIZ along with case based reasoning (CBR).

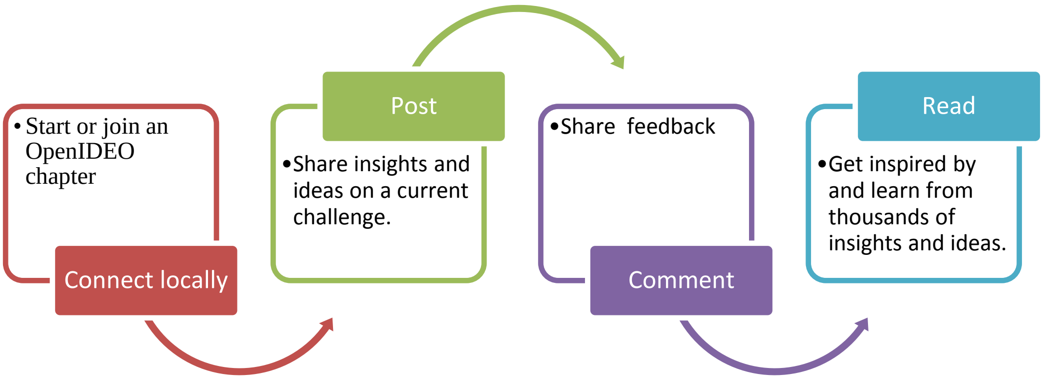

Figure 1. Participation Process in OpenIDEO (Official Website of OpenIDEO , 2010).

In the context of crowd-sourced based approaches for RS, Felfernig et al. (2014) provided engineering techniques that allow persons without technical expertise in the development of constraint-based recommenders to easily develop their own recommenders on the basis of micro-contributions. The RS, named as RecTurk asked simple questions (in the form of micro-tasks) and then (from the given answers) derived a recommendation knowledge base. The advantage of this approach was Knowledge engineering task became simplified with the help of completed micro-tasks by the contributing users.

Chang et al. (2016) explored different workflows for incorporating people in the recommendation process. From their study, it was shown that crowdsourcing approach produced more novel and diverse recommendations as compared to collaborative filtering algorithms.

Automatic machine learning approaches greatly benefit from the presence of big data, in rule based environments. However, there can be situations when automatic approaches may deliver unsatisfactory result in the absence of adequate contextual informaiton, e.g., in natural language translation/ curation (Holzinger et al., 2016). In such instances, “human-in-the-loop” approach could help in solving computationally hard problems by reducing the exponential search space through heuristics. Holzinger et al.(2016) applied Ant Colony Optimization framework on Travelling Salesman Problem. Louis Rosenberg (2016) took a human-in-the-loop approach to A.I. The author introduced UNU, an online platform that enabled networked users to assemble in real-time swarms and tackle problems as an Artificial Swarm Intelligence (ASI).

PROPOSED ARCHITECTURE

In our proposed architecture, we propose to use a modified version of human-in-the-loop approach in the RS. We expect human to form a group and propose to use their recommendation along with the machine generated recommendations. We have named this scaled up version of human-in-the-loop approach as “Group-in-the-loop”.

Overview of the general architecture is shown in Figure 2, while overview of the pure algorithmic approach is shown Figure 3. The functionalities of the architecture can be divided into three parts: (i) Pre-processing of the case studies, (2) Recommendation from case studies using pure algorithmic approach, and (iii) Combining human recommendations and learning preferences.

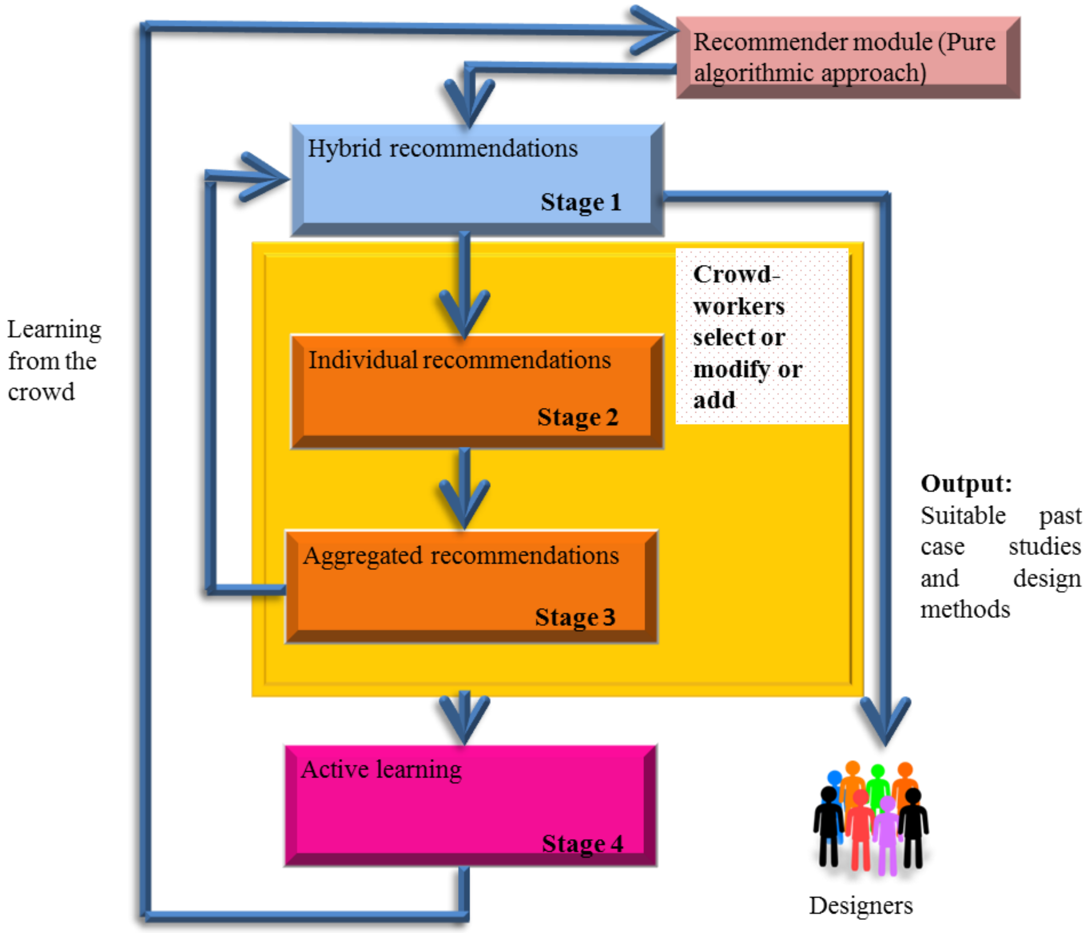

Figure 2. Proposed Top Level Architecture.

Pre-processing of the case studies

Case studies which are in unstructured text format need to be converted into ontology. This forms the case base for our proposed architecture. With the help of suitable natural language processing, ontology creation and word to concept mapping tools, we plan to create and populate the ontology suitable for reasoning.

Recommendation from case studies using pure algorithmic approach

Figure 3 highlights the function of this module. Initially the group will enter description of the working case or project. The case description will go through the pre-processing step described in this paper and will be converted in the form of ontology. After the Case similarity measurement, further filtering can be done by the designers for some specific contexts. As a result, the recommendation will be contextualized.

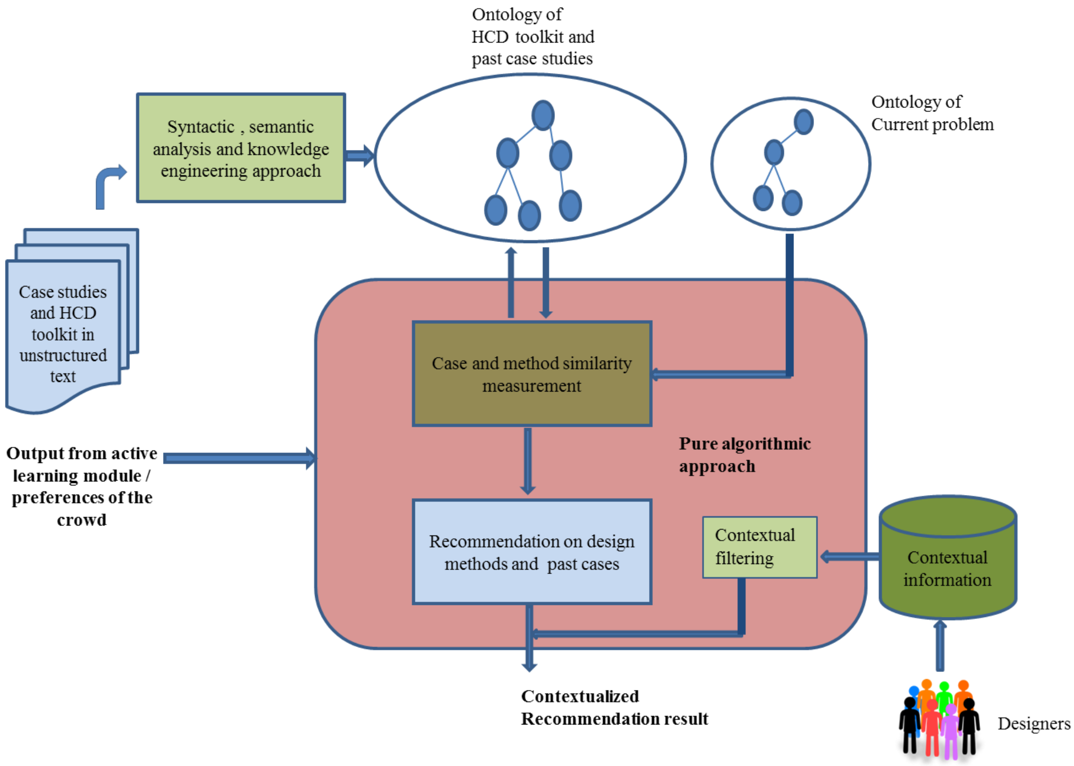

Figure 3. Pure Algorithmic Approach.

Combining human recommendations and learning preferences

In this stage we apply the proposed group in the loop approach and involve crowd-workers and/or design community to provide recommendations. Recommender module from Figure 3 can also learn the preferences of the group through active learning module (Figure 2).

In summary, there are four key stages in the overall recommendation process:

Stage 1. Aggregated recommendations from crowd-workers and/or members of design community and recommendations (from past case studies) are combined to produce recommendations. Crowd-workers can be provided a controlled environment to mimic decision making process in a group.

Stage 2. In this stage, crowd-workers/ design community can get inspirations from the hybrid recommendations (combining human generated recommendations and pure algorithmic approaches) and can select or modify or provide new recommendations.

Stage 3. The individual recommendations are aggregated and provided as input to the hybrid recommender module.

Stage 4. The active learning module learns the preferences of the members of the design community and the output goes to the Recommender module that generates recommendations from past case studies using pure algorithmic approach (Figure 3).

CONCLUSION AND FUTURE WORK

This paper investigates how CI was harnessed and generated in computer aided collaborative work across different domains and contexts. Through this process, we have identified opportunities for a recommender system in exploiting CI and proposed an architecture for a hybrid recommender system that can take group generated text content, crowd-workers' and design community's input into account while generating recommendations .

Considering crowd-workers' or design community's recommendation into the loop can let the RS learn about group's, consisting of crowd-workers' or members of design community, preference. We plan to implement and experiment on the proposed architecture to identify a suitable way to aggregate human generated and machine generated recommendations.

ACKNOWLEDGMENTS

This work was partially supported under Graduate Research Assistants scheme, an internal funding from Multimedia University.

REFERENCES

Chang, S., Harper, F. M., He, L., & Terveen, L. G. (2016, March). CrowdLens: Experimenting with Crowd-Powered Recommendation and Explanation. In Tenth International AAAI Conference on Web and Social Media.

Felfernig, A., Haas, S., Ninaus, G., Schwarz, M., Ulz, T., Stettinger, M. & Reiterer, S. (2014). *Recturk: Constraint-based recommendation based on human computation*. In RecSys 2014 CrowdRec Workshop (pp. 1-6).

Glenn, Jerome C. Collective Intelligence (2009) – One of the Next Big Things, Futura 4/2009, Finnish Society for Futures Studies, Helsinki, Finland.

Holzinger, A., Plass, M., Holzinger, K., Crişan, G. C., Pintea, C. M., & Palade, V. (2016, August). Towards interactive machine learning (iml): Applying ant colony algorithms to solve the traveling salesman problem with the human-in-the-loop approach. In International Conference on Availability, Reliability, and Security (pp. 81-95). Springer International Publishing.

Human-Centered Design Toolkit. *A step-by-step guide to the elements of human-centered design*, (2009). Retrieved from http://www.ideo.org/, (last accessed on 2 January, 2014).

Klein, M. (2011). *How to harvest collective wisdom on complex problems: An introduction to the mit deliberatorium*. Center for Collective Intelligence working paper.

Lopez Flores, R., Belaud, J. P., Le Lann, J. M., & Negny, S. (2015). Using the Collective Intelligence for inventive problem solving. *Expert Systems with Applications: An International* Journal, 42(23), 9340-9352.

Malone, T. W., Laubacher, R., & Dellarocas, C. (2009). Harnessing crowds: Mapping the genome of collective intelligence.

OpenIDEO: A platform to harness collaboration for social good (2010). Retrieved from (https://www.ideo.com/post/a-platform-to-harness-collaboration-for-social-good, last accessed 25 October, 2016).

Officail website of OpenIDEO. Retrieved from http://openideo.com/ (last accessed 24 October, 2016).

Rosenberg, L. (2016). Artificial Swarm Intelligence, a Human-in-the-loop approach to AI. Thirtieth AAAI Conference on Artificial Intelligence.