Guest Editors' Introduction

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“With intelligence augmentation, the ultimate goal is not building machines that think like humans, but designing machines that help humans think better” (Akkiraju, 2016; Guszczka, Lewis, & Evans-Greenwood, 2017).

Technology companies nowadays, including IBM and Deloitte, have turned their attention to what they call *cognitive collaboration* or *augmented intelligence*, which basically refers to collaboration between human and machine through the means of cognitive computing tools (Guszczka, Lewis, & Evans-Greenwood, 2017; Pagnier, 2016). Advancements in this area are impressive, and have achieved remarkable results, but deeper examination reveals a rather simple level of collaboration between humans and computers. We are still far away from the kind of advanced collaborative problem solving by human and machine that would be needed to push the limits of problem solving as we know it (Marfil, Escolano, & Bandera, 2009). To harness the combined (computing and cognitive) power of both machine and human, it is essential to understand the power and limitations of both machines and humans. The computational power of machines is typically framed in terms of computational complexity. To better understand the power of the human cognitive system, one approach is to familiarize ourselves with and classify the families of cognitive functions that the human cognitive system is capable of leveraging. This can help us better understand the limits of the human cognitive system so that we can better support it with techniques such as machine learning. In this way the weaknesses and inherent limitations of one system can be better supported by the other.

In this special issue, we approach the need to better understand the computational power and limits of human cognition by examining the role that internal representations play in human problem solving. Representation of problem input impacts problem-solving performance in a number of different domains, both in terms of external representation (Marfil et al., 2009) and internal representation (Newell & Simon, 1972). While internal representation impacts performance, as seen in expert chess playing, it is of interest to better understand what determines, for example, which internal representation(s) are used on a given problem, and what limits which internal representations are available to different kinds of problem solvers or for different kinds of problems.

We investigate this topic from different angles, including the computational complexity perspective of the roles of internal representation, mechanisms for trying to identify plausible internal representations, and, in light of goal modification, the identification of features that help problem solvers tackle visual problems.

REFERENCES

- Akkiraju, R. (2016, August 23). How humans and machines can collaborate to solve problems and communicate compassionately. *Venturebeat.com*. <https://venturebeat.com/2016/08/23/how-humans-and-machines-can-collaborate-to-solve-problems-and-communicate-compassionately/>
- Guszczka, J., Lewis, H., & Evans-Greenwood, P. (2017, January). Cognitive collaboration: Why humans and computers think better together. *Deloitte Insights*. <https://dupress.deloitte.com/dup-us-en/deloitte-review/issue-20/augmented-intelligence-human-computer-collaboration.html>
- Marfil, R., Escolano, F., & Bandera, A. (2009). Graph-based representations in pattern recognition and computational intelligence. *International Work-Conference on Artificial Neural Networks*, 399–406.
- Newell, A., & Simon, H. A. (1972). *Human problem solving* (1st ed.). Englewood Cliffs, NJ: Prentice-Hall.
- Pagnier, M. (2016, June 11). The rise of cognitive collaboration. *LinkedIn SlideShare*. <https://www.slideshare.net/soccnx/cognitive-collaboration>