Design implications for Designing with a Collaborative AI

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Abstract

This paper presents requirements for interacting with collaborative designing systems. Using the agent-model interaction from the mixed-initiative interaction framework as a model, an ideal interaction scenario in a design context is described and implications for designing collaborative systems are presented. Previous work on machine learning and artificial intelligence in interaction design has already looked at recognition of designers' intent and combinatorial problem-solving in design. However, this overview should trigger new discussions about the design of creative systems from a human-centered perspective and the need to include designers within the process.

Can systems become collaborative partners in a design process? I would like to reformulate this questions and ask: What does a systems has to know in order to communicate and collaborate with a designer in a creative context? This formulation allows a practical view on the underlying problem, which I will unfold in this paper.

In the following I will first elaborate on the need and definition of collaborative design, which is followed by an ideal scenario illustrating how a collaborative designing system (CDS) interaction could look like. In the last part, I will explain the requirements for the creation of a CDS from an interaction design perspective.

Collaborative Design

Designing is a creative approach to problem-solving. Creative thinking and approaches build the fundament of design and the design process. Definitions of creativity are numerous, however in this work the version of Sarkar et al.'s comprehensive work on 160 definitions of creativity is used. They conclude that 'Creativity occurs through a process by which an agent uses its ability to generate ideas, solutions or products that are novel and valuable.' (Sarkar and Chakrabarti 2008). This is not only in line with recent research on creativity as an incremental process (Sawyer and others 2014), but also illustrates the connection to the design process, which consists of identifying the needs and requirements of the user, generating ideas for potential solutions and evaluate them to satisfy the users needs (Preece, Rogers, and Sharp 2015). The uncertain, exploratory nature of designing, where neither the final goal, nor the complete design

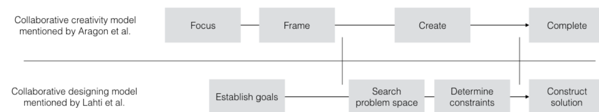

Figure 1: Collaborative design models

space is specified beforehand and potential solutions are created and rejected iteratively (Allen, Guinn, and Horvtz 1999) makes designing to a complex problem-solving task.

Creative collaboration plays an increasingly important role in solving such complex interface problems (Lahti, Seitamaa-Hakkarainen, and Hakkarainen 2004). The combination of different skills in a design team allows an extensions of the solution space and increases the amount of resources, cognitive and creative, available to find an optimal solution. By that, it allows to overcome uncertainty through discussion and interactive evaluation of consequences and limitations.

In order to illustrate collaborative design, two different models with different focuses on the same process are presented. The first model from Aragon et al. (Aragon and Williams 2011) focuses on the creative process of collaborative designing, while the second one, mentioned by Lathi et al. (Lahti, Seitamaa-Hakkarainen, and Hakkarainen 2004), draws from a more practical understanding of collaborative design. The combination of both will be used for the later described scenario of a CDS. For clarification, an overview is presented in Figure 1.

The first model introduces four key phases of collaborative creativity which are *focus, frame, create and complete*. Within the *focus* phase the group's rationale is explored and discovered, which is followed by the *framing* phase, in which the group forms trust and common understanding within a given context to enable an effective and efficient collaboration. These more preparing phases are then followed by the *creation* phase, where "ideas [are] generated by individuals, then shared and built upon by the group members from the perspective of their particular knowledge bases, adding aspects of information and data that may not have been apparent to the idea's originator" (Aragon and Williams 2011). In the final *completion* phase ideas converge to final structured ideas, which is evaluated and approve by the client.

The model mentioned by Lahti et al. describes collaborative design also as a four step process of actively communicating and working together. (Lahti, Seitamaa-Hakkarainen, and Hakkarainen 2004) The aim is to jointly *establish design goals*, *search through design problem space*, *determine design constraints*, and *construct design solutions* with a common goal in mind. *Establish design goals* describes in this model the problem-clarification phase (Cross and Cross 1995). The *search through design problem spaces* describes the exchange of different views on the design problem. In the phase all participants build on, neglect or reinterpret previous ideas in order to interactively explore the solution space. The fit of the created solutions is evaluated based on earlier identified requirements in the *determine design constraints* phase (Lahti, Seitamaa-Hakkarainen, and Hakkarainen 2004). These two steps are iterated until the groups decides for certain potential solutions and *construct design solutions*.

In line with the Mixed-Initiative Interaction (MII) framework, a CDS would be a member of the design team that shares the same goals and collaborates with the designer. In order to fulfill these requirements the system has to constantly update its understanding of the task, in a similar manner as the designers understanding of the goal specifies during the design process. I see promising potential for such a system, due to the ability of systems to holistically gather and evaluate (design) information of relevance and offering alternatives according to them. However, a natural interaction in a creative context requires new interaction concepts that go beyond already known concepts (Hook 2000) and ask for more involvement of designers in the creation process of such systems.

Scenario: Designing with Collaborative AI

Borrowing the concept of legitimate peripheral participation for the context of design, we can look at a system as a newcomer to a project and the designer as an experienced mentor. Over time the system observes and learns the practices of a designer as the designer would learn new approaches from the system until both reach the state of equal mentorship and discover their legitimate participation role within this process. In the following I will describe how such collaboration could look like by combining the above explained models of creative collaboration based on the MII idea of changing initiating and supporting roles within a collaboration.

Focus phase / Establishing goals Assuming a designer gets the job to create a new landing page for a company and approaches this task together with a CDS. First, the goal of the project, as discussed with the client, has to be communicated. This includes the discussion about facts, like target groups, but also soft factors like the aimed impression of the page. This part is rather an instruction process with feedback questions for clarification than an active discussion. As there are common feature dimensions of project information, the system could trigger further relevant questions, while illustrating the current understanding of the projects through lists and examples. This feedback from the system allows the designer to recognizes miss understandings or unclear areas.

Frame phase / Establishing goals Aragon describes the 'framing' phase as the time of building trust in the understanding of the underlying project aims, which is crucial for a successful collaboration. The designer discusses the stated requirements with the systems and first ideas, similar projects or inferred information and are suggested by the system and discussed. Based on the designers feedback, the system adapts its understanding and presents it to the designer by continuing the discussion. This helps foremost the system to create a better understanding and to become a more equal participator in the collaboration, but also allows the designer to sharpen its understanding of the project.

Create phase/ Searching the problem space After a common understanding of the task is established, the designer starts to look for inspiration from other related projects, like competitors, or other sources that provoke impressions the designer aims for in the current project as well as reflecting on established ideas from previous own projects. The systems suggests examples for inspiration, allowing the designer to save, compare or elaborate on certain inspirations as well as rejecting them. As part of this ideation, new ideas for the current web page are created. The CDS offers a representation of ideas that allow the designer to navigate easier in the solution space by recovering previous ideas or having the ideas evaluated for certain requirements at retrieval.

Create phase/ Determine Constraints Every design has to be evaluated for constraints it might be causing e.g. it increases task efficiency, but the usability for elderly users decreases. Instead of user testing potential solutions, the system simulates and predicts user behavior from different perspectives and presents the supported requirements as well as constraints fro each design. This helps to reduce the number of tests and improves the efficiency of the decision process.

Complete / Construct solutions When both agree on a number of possible solutions, the design of high fidelity prototypes starts. The system highlights aesthetic, usability, readability etc. opinions on the current designed solution and compares them with the designers opinions. It further suggests own design ideas and argues for them based on the given requirements. Together with the designer a suitable interface solutions for final user tests is chosen or combined based on preferred features. The system supports the designer to create such hybrids by suggesting preferred interaction concepts, structures etc. from the discussions.

After the project the system analyzes the reasons for the rejected solutions and learns from it. In a later project with similar requirements, it will inform the designer about this analysis and both decide how relevant they are in the new context. This helps the system to discover its legitimate participation role within the process of designing and leads to a more equal impact on the following projects. The system also adapts its interaction with the designer in phrasing ideas or presenting alternatives, as the designer learns how to explain certain thought chains to the system. This is a natural development within teams and improves their efficiency and solution quality over time as it would by interacting with a designing system.

Implications to the design of Collaborative AI

The presented scenario reflects a negotiated mixed initiative collaboration defined within the MII framework (Allen, Guinn, and Horvtz 1999), which includes the active initiation of dialog and reasoning on a equal stand. Due to the complexity of the task, the system is required to sustain a model of the task and the world around it. The agent-based

models that plan, execute and monitor acting and receiving interactions/information have to be dynamically updated to preserve the currently best known model to be able to act upon it. (Allen et al. 2001)
To design artificial intelligence that collaborates with designers on equal standing, one should consider the need for following requirements from an interaction perspective. For clarification I distinguish task model and world model related requirements.

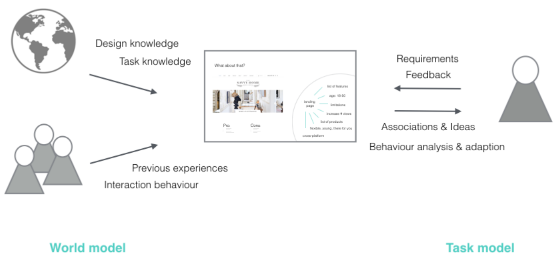

Figure 2: Requirements for designing creative systems

Task model related requirements

Requirements should include information like type of web page, target group, but also soft factors like aimed impression of the web page or brand management. Having a conclusive understanding of the given task helps the system to communicate and act in a goal oriented way. Expressing this knowledge to the designer does not only increases the trust in the system, but also increases the system's predictable, which is crucial for the usability of the system (Shneiderman 1989).

Associations/Bisociation relates to examples with similar design needs within the same or other contexts. While association are often related to find connections within a domain, Koestler introduced the term bisociation as associations or connections of ideas beyond the current domain (Koestler 1964). This would allow systems to create suggestions for current issues that go beyond the replication of previous ideas or obvious links in a human perceived (transformational) creative way (Boden 1998).

Interaction preferences of the current designer are an essential feature of collaborative interaction. In line with the behavior adaption among group members in a creative collaboration (see Aragon's 'framing' phase), the agents task model should as well consider preferences of the current designer. These preferences include the way of communicating, e.g. to visual or abstract descriptions, preferred approaches of ideation or prototyping as well as general preference of design styles, e.g. straight lines or figurative. This knowledge enables the system to adapt the way of organizing and expressing the communication with the designer.

World model related requirements

Task domain knowledge includes features and challenges that are specific in the current design domain. Information about these challenges could be retrieved for example from behavior data or analysis of support/complain tickets. In the above described landing page example such a challenge would be the diverse target group such designs often address. A diverse target group, e.g. in age, implies certain design constraints due to the different cognitive abilities to orientate on web pages of different age groups. These information can be discussed in the focus phase as well as highlighted by the system during the create phase. Cognitive workload models could even be used in the final evaluation phase. With every project this knowledge increases and helps the system and the designer to consider more possible challenges early on.

Design domain knowledge includes general descriptions of design relevant approaches, concepts and tools - also considered as general design knowledge. It includes an understanding of the design process, concepts like ideation, wireframing, prototyping, testing as well as more applied knowledge like interaction concepts for different devices or visualization techniques. It further includes knowledge about current design trends in graphics, technologies and interaction concepts. Those can be retrieved from dedicated design web pages and analyzed by their difference to the already known understanding. The design domain knowledge allows the system to actively create, suggest and evaluate potential solutions for a given design problem in a designer like manner. An increasing amount of research is done within this domain, e.g. interactive wireframing tools that suggest design alternatives (Todi, Weir, and Oulasvirta 2016).

Previous experiences knowledge is related to learning from previous projects. It includes the connection of successful applied ideation approaches, interaction concepts, color schemes, structures etc. combined with requirements and tasks. Those could be considered as preferred actions in similar occurring contexts and be used as inspiration for new projects. At the same time systems should learn from earlier rejected ideas. This equals the human understanding of experience and allows systems to react faster with appropriate suggestions, especially in the focus, frame and creation phase of the design process. As for the human designer, this knowledge will not necessary lead to the optimal solution, but allows a faster exploration of possibilities. While research on detecting similar designs solutions to a given design (Kumar et al. 2013) and interactive machine learning, e.g. (Amershi, Fogarty, and Weld 2012), present first solutions towards this requirement, however, a holistic solution is still missing.

Human interaction behavior refers to the general understanding of human communication and argumentation. Effective communication between the designer and the system is crucial for every step of the process. We can identify three dimensions of human interaction behavior, which are 'what','when' and 'how' to communicate with another participant (Allen, Guinn, and Horvtz 1999). While the above described requirements focused mainly on the 'what' to communicate, the 'when' requires certain decision from the system, explained within the MII framework. A system has to decide when to engage with the designer for more information, when to act proactive and when to pass on the control in a collaborative manner. The MII and Intent recognition research community showed relevant advance in the last decades on creating more natural interaction between human and systems, e.g. (Perugini and Buck 2016). Those advances are mostly in semi-structured dialog, which covers a large part of the above described scenario.

However, unstructured dialog like in the creation phase require further research in this field.

While the approaches of the MII framework answer to 'what' and 'when' to interact with a designer, the last open question of 'how' to communicate in a collaborative interaction is still not presented. How to communicate includes: how can a system or human communicate intents allowing others to follow thought chains or how can a system communicate reasoning behind a design decision. This is crucial to build trust and enable the designer to navigate efficient in the design space together with the system. Even though the awareness of self-expressiveness of machine learning and artificial intelligence algorithms increased over the last years, e.g. automatic justification of predictions (Lei, Barzilay, and Jaakkola 2016) and intentions to visualize reasoning behind inference (Lieberman and Henke 2015), more research on system expressiveness is still missing. I personally see a huge potential in including design and computer visualization researchers in artificial intelligence projects. This would allow to create concepts of interaction and visualization, which would be integrated in the core structure of the system with the aim to help users to understand the them.

Conclusion

To make AI acceptable and adopted in creative pursuits, it is critical to strive away from the goal of automating creative efforts. Instead, we need more support for collaboration between designers and intelligent machines. The above mentioned requirements should open up discussions on how to develop creative machines. It also presents a lack of research related to expression strategies for intelligent systems. This is why I argue for stronger involvement of interaction designer in the whole process of developing creative systems. Their knowledge about expressing information in uncertain, exploratory environments and ability to envision human understanding could lead to new kind of intelligent algorithms and systems.

In the poster I will present, I will present my vision of how interfaces could communicate in every stage of the above described scenario with a designer. I will as well give a short overview of the here described requirements of designing creative systems.

About the Author

I am a PhD student in the field of Human-Computer Interaction with the User Interface Group at Aalto University in Finland, focusing on interactive design optimization. My research applies computational sciences, HCI, and design to the problem of principles of collaborative design, even though my background is mainly in HCI. My work ranges from understanding the impact of inspiration and human perception on design, to computationally generate design alternatives in collaborative systems with a designer.

In my previous projects I implemented a perceptual grouping algorithm based on Gestalt Law principles. It allowed computers to detect relations between elements from a human perceptual perspective. Assuming a semantic connection among together perceived elements, I am currently working on a restructuring algorithm of existing web layouts based on those connections. The aim is to create new designs that are able to inspire designers by offering similarly aesthetic and useful interface.

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