Mixed Initiative Generative AI Interfaces: An Analytic Framework for Generative AI Applications

Michael Muller, Justin D. Weisz, and Werner Geyer
IBM Research AI
Cambridge MA 02142 USA
{michael_muller, jweisz, werner.geyer} @us.ibm.com

Abstract

Recent advances in deep generative models have enabled a broad range of use cases, from drug design to music synthesis. Many of these applications will require a collaborative effort between humans who steer the generative process, and generative models to reach the desired outputs. However, our expressive power to describe interactions with these models has not kept pace. We review frameworks for *mixed initiative user interfaces* (Horvitz 1999) and *mixed initiative creative interfaces* (Deterding et al. 2017) and identify gaps due to new capabilities produced by deep generative models. We present a new framework, Mixed Initiative Generative AI Interfaces (MIGAI), that describes human-AI interaction patterns in the generative space.

Introduction

Shneiderman recently challenged researchers in HCI and AI to reconsider our models of human and AI agents in interaction (Shneiderman 2020). Emphasizing human needs and abilities, he criticized what he called "one-dimensional models" in which humans and AI systems engage in an implicit *competition* for influence or initiative (e.g., (Brooks 2017; Parasuraman, Sheridan, and Wickens 2000)). Shneiderman offered an alternative two-dimensional analytic space in which humans and computers appear as independent factors. Shneiderman's approach removes the requirement of an inverse (i.e., competitive) relationship.

However, we assert that this refined framing of human-AI interactions does not yet provide analytic concepts to describe the highly-collaborative and equitable nature of generative AI applications such as collaborative writing (Wolf et al. 2019), drawing (Bau et al. 2020), package design (Quanz et al. 2020), fashion design (Zhao and Ma 2018), and game design (Liapis, Smith, and Shaker 2016).

In this abstract, we pursue the theme of human-AI *collaboration* as a refinement on Shneiderman's vision, although we base our work on a different stream of thought in the research literature. Horvitz considered a series of principles for *mixed-initiative* user interfaces (Horvitz 1999). Some of these principles implied a competitive relationship between human and computer, but other principles were more about common purposes and the combination of strengths. Biles similarly offered four patterns for human-computer creative interaction, including one pattern that explicitly called for collaborative work by human and computer (Biles 2002).

This collaborative theme was emphasized in a CHI 2017 workshop on *mixed-initiative creative interfaces* (MICIs), that highlighted ways in which humans and computers (including AI systems) could build upon each others' actions and contributions (Deterding et al. 2017). Spoto created a website of project profiles from the workshop and introduced a model and graphical notation to describe the collaborative actions of human and computer partners in a co-creative process (Spoto 2017). Significantly, her model proposed that each action could be performed by either human or computer, although the strengths of each party might influence the choice of which activities are performed by which partner.

Mixed Initiative Generative AI Interfaces

We extended Spoto's framework for collaborations that involve deeper co-creative projects. Recent innovations in deep generative AI applications have opened new creative and co-creative opportunities (Elgammal et al. 2017; Goodfellow et al. 2014), extending the potential power of the projects in the MICI workshop and framework (Deterding et al. 2017; Spoto 2017).

Spoto's framework used a two-dimensional analytic space of two actors (human and computer) and seven actions. In our Mixed Initiative Generative AI Interfaces extension (MIGAI), we include 11 actions that can be performed by either human or computer, plus one additional "meta-action" that consolidates data and knowledge over longer timeframes. In the following list, we use an asterisk to indicate the new MIGAI actions we have added beyond Spoto's original MICI framework:

- **Learn***. *AI systems* construct an internal representation of the data. *Humans* familiarize themselves with the domain and work practices in that domain.
- **Ideate**. Create high-level concept(s) that guide or shape the production of a fully-realized artifact.
- **Constrain**. Set limitations on the desired artifact.
- **Produce**. Create one or more artifact(s).
- **Suggest**. Create a set of options to be chosen by the other agent.

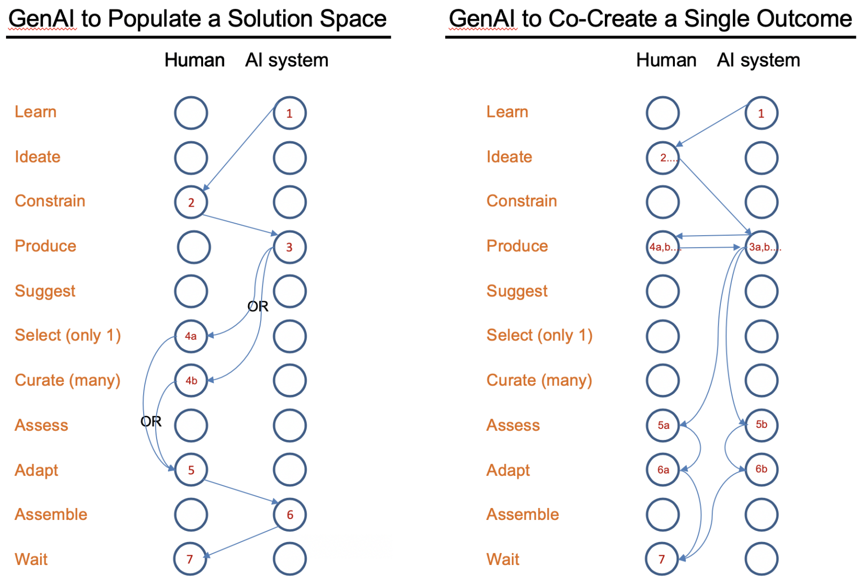

Figure 1: Comparison of two generic Generative AI (GenAI) application patterns using the Mixed Initiative Generative AI Interfaces (MIGAIs) framework. **Left side:** AI system learns a domain of scientific practice. Human provides constraints; AI system produces potential solutions, which the human inspects and edits as need. AI system constructs (assembles) solution from those pieceparts. The human tests the solution offline (e.g., for molecular discovery, the human might synthesize a molecule specification in a wet lab). **Right side:** AI system learns a language+style domain. Human and AI system take turns adding to a shared text. Human evaluates and edits through human stylistic discernment; AI system evaluates by applying spelling, grammar, and usage rules. Human publishes the outcome.

- **Select**. Choose one satisfying artifact.
- **Curate***. Select or structure a subset of artifacts from a collection.
- **Assess**. Provide an explicit evaluation of the artifact.
- **Adapt**. Adjust or edit an existing artifact or artifact specification.
- **Assemble***. Combine artifacts, or parts of artifacts, into a cohesive whole.
- **Wait***. One party must wait while the other party engages in a non-interactive process separate from the collaboration (e.g., a long-duration computation or testing of physical materials).
- **IterativeLoop***. Optionally, results may be fed back to the **Learn** step either as an addition to the AI system's data set, or as part of the human's personal learning.[1]

We have applied this notation to a diverse set of generative AI applications, including our own in-house projects. Two contrasting exemplar patterns are shown in Figure 1.

- A generative algorithm is used to *populate a space with multiple candidate solutions*. This pattern has been used to explore diverse novel artistic images (Elgammal et al. 2017), to create a portfolio of packaging options (Quanz et al. 2020), and for generating fashion concepts (Zhao and Ma 2018).

[1]E.g., through processes of reflective practice (Schön 1992) or reflective design (Dalsgaard and Halskov 2012).

- A generative algorithm is used to *create a single outcome* in a tightly-coupled human-AI interaction process. This pattern has been used to co-author text (Wolf et al. 2019), to collaboratively modify (Bau et al. 2020), to repair (Weber et al. 2020) painted images, and to co-create levels in a gaming environment (Liapis, Smith, and Shaker 2016).

Goals

In this workshop, we look forward to learning from others' projects with two specific aims:

1. We wish to validate the comprehensiveness of the additional actions we have defined for generative AI applications, and identify any other actions that may currently be missing.
2. We wish to determine whether there are additional generic exemplar interaction patterns with generative AI systems, beyond those described above.

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