Human and Machine Creativity

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Humans are inherently creative. Decorating a Christmas tree, making up a story for why you were late, mixing left-over food to create a new dish, or transforming your old jeans into a handbag are all examples of human creativity.

Specifically, these are instances of personal or little-c creativity (Richards 1990)—the day-to-day creativity of individuals. Note that this is different from Big-C creativity (Simonton 1994; Kaufman and Beghetto 2009) which refers to break-through creations and discoveries, for example, the Mona Lisa by Leonardo DaVinci, or the heliocentric theory by Nicolaus Copernicus. These contributions are (1) hard to study since they leap into the unknown, and (2) hard to evaluate since they involve recognition by the masses. On the other hand, little-c creativity is often a natural response to constraints and can be studied under well-defined and tractable experimental settings.

I am interested in the computational mechanisms underlying human little-c creativity, including the *processes* of producing creative products, and the characteristics of the *products* themselves. Creativity is commonly studied by means of divergent and convergent thinking tests. My focus is on divergent thinking, the act of generating many novel and useful responses to a problem. Popular divergent thinking tasks include the Alternate Uses Task in the verbal domain, and the Creative Foraging Task (Hart et al. 2017) in the visual domain. While works have extensively studied the creative products and processes arising from divergent thinking tasks *descriptively*, there are only few that *computationally* model them. Computational models are beneficial to the community by providing a better framework for defining, quantifying, and comparing creative aptitudes. Recently, a review by Lloyed-Cox (2023) argues for the need and benefit of computational modeling in neurocognitive creativity research. My aim is to contribute towards this goal to help advance the understanding of human creativity.

A second parallel interest of mine is to compare and contrast creative performance of humans and machines. With the dawn of foundation models, AI aptitudes, including creativity are crossing the level of an average human. This on the one hand begs the question of if and how humans and machines differ, but on the other hand encourages us to think how can we actively collaborate with such systems to become better. My aim is to contribute towards this goal to help advance the understanding of AI creativity, and human-AI co-creativity.

Here I outline some ongoing and completed projects that are a first step in achieving my aims in understanding human and machine creativity.

1. Towards a Computation Model of Creative Thinking: This is currently ongoing work trying to propose a model of creative thinking in the Alternate Uses Task, with the aim to extent it across modalities. During divergent thinking, people produce responses spanning various classes. Hart *et al.* (2017) found producers displaying phases of local itinerancy (exploitation) and global (exploration) itinerancy, *i.e.*, producing many outputs of one class before producing outputs of another. This process has a few characteristics. First, explore phases are slower with more meandering paths than exploit phases which are quicker with more direct paths. Second, people need not exploit the whole class before transitioning to another. Third, people might get stuck in chains of thought. Fourth, some people are quick to discover and quick to drop classes (flexible), while some others are slow to discover and slow to drop classes (persistent). These features can be modelled in various ways. For example, Area-restricted Search or Levy-walk formulations can be used to model the movement across space (Rhodes and Turvey 2007; Dorfman, Hills, and Scharf 2022; Hills, Kalff, and Wiener 2013). Further, a multi-arm bandit setup with each arm representing a class could also fit the problem description (Lévy-Garboua et al. 2024). I am presently working on identifying a suitable model description and running simulations to approximate human response trajectories in the Alternate Uses Task.

2. Characterising the creative process in humans and large language models (LLMs): This is recently completed work trying to delineate the human and LLM creative process in the Alternate Uses Task (Nath, Dayan, and Stevenson 2024). Research on LLM creativity has focused solely on products, with little attention on the creative process. In line with the features mentioned above, we provided an automated method to characterise how humans and LLMs explore semantic spaces on the Alternate Uses Task, and contrast with behaviour in a Verbal Fluency Task. We use sentence embeddings to identify response categories and compute semantic similarities, which we use to generate jump profiles. Our results corroborate earlier work in humans reporting both persistent (deep search in few semantic spaces) and flexible (broad search across multiple semantic spaces) pathways to creativity, where both pathways lead to similar creativity scores. We found LLMs to be biased towards either persistent or flexible paths, that varied across tasks. Though LLMs as a population match human profiles, their relationship with creativity is different, where the more flexible models score higher on creativity.

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