Digital Systems for Humans Graduate School

2024-2025 PhD Subject Proposition

Proposition de Sujet de Thèse 2024-2025

Modeling and Estimation of Creative Strategies in Problem Solving (CreaStra)

Modélisation et Estimation des Stratégies Créatives dans la Résolution de Problèmes (CreaStra)

Doctoral School: Doctoral School in Societies, Humanities, Arts and Literature (ED SHAL)

Thesis supervisor: Margarida Romero and Patricia Reynaud-Bouret

Host laboratory: Laboratoire d'Innovation et Numérique pour l'Education (LINE), INSPE Liégeard, 43 Avenue Stephen Liégeard, 06100 Nice

Subject description: Creativity [1] is considered an important skill for the current and future society [2]. It enables us to find solutions to problems that do not have clearly defined solutions and that we have never encountered before [3]. In the field of mathematics education, creativity is considered an essential element [4], and it plays a fundamental role in the PISA tests, where France has recently dropped to 23rd place in the OECD rankings. However, the study of human creativity has mainly been developed in tasks where the individual is asked to produce a large variety of words, for instance [5]. These tests follow the tradition of psychometric measures in the field of psychology and struggle to capture the dynamics of the creative process itself [6]. Therefore, we want to draw on recent advances in the design of creative problem-solving tasks and in the modeling and estimation of individual learning strategies to create new "creative" stochastic models based on machine learning algorithms. These models will then allow us to evaluate different individual creative strategies.

Creative problem solving (CPS) is a dynamic process that engages the participant in a situation where they have to create a solution using the knowledge and tools at their disposal [7]. CPS tasks encourage the exploration of different strategies to approach the solution(s) through divergent thinking approaches, as well as the evaluation of these strategies through convergent thinking processes [8]. When activities are instrumented by educational robots, it is possible to observe divergent processes through the robot configurations created by the participant [9]. By fostering both divergent and convergent thinking, CPS activities create conditions for the emergence of both individual and collaborative creative processes [10]. These CPS tasks can be seen as a form of learning from an algorithmic perspective. In traditional learning, through a series of attempts, errors, and successes, individuals gradually converge towards a certain way of solving a type of problem. This is what happens in the classroom, for example, when learning addition. From a machine learning point of view, this type of incremental learning can be well modeled by bandit or reinforcement learning algorithms, which provide a gain or loss based on the chosen actions until finding the right action. It is then possible to fit these algorithms on an individual's learning data to understand which type of algorithm, and therefore which strategy, is closest to the individual in a learning situation [11, 12]. This type of estimation can help characterize certain behaviors, such as the different actions taken by smokers and non-smokers when faced with a bandit problem [13].

In a CPS, as the creative problem-solving process unfolds, the number of possible actions becomes so large that each individual will discover new actions to take (divergence) and then sort through these possible actions to find relevant sequences of actions (convergence). If the "sorting" phase closely resembles the classical learning phase, the main issue is to model the creation/discovery of actions or sequences of elementary actions. To our knowledge, there is no mathematical model of this type. However, we can mention two inspiring models: in [14], the model creates new categories to organize objects; in [15, 16], hierarchical reinforcement algorithms divide problems into subproblems to solve.

Therefore, we want to combine the knowledge of Mr. Romero in CPS design and P. Reynaud-Bouret in estimation of learning strategies to co-build models of creative strategies. This by modeling and estimating the creative strategies in problem solving. To do so, we want to implement reinforcement learning algorithms, such as bandit algorithms, and propose a way of adapting these algorithms to the creation of novel ideas. This work relies on an important basis on cognitive science and analysis of problem-solving experiment but also on an vast mathematical knowledge of estimation and modeling through the use of reinforcement learning and stochastic tools

Supervision:

- Margarida Romero, Full professor, Laboratoire d'Innovation et Numérique pour l'Education, Université Côte d'Azur, Nice

- Patricia Reynaud-Bouret, Research Director CNRS, Laboratoire Mathématiques & Interactions J.A. Dieudonné, Université Côte d'Azur, Nice

Candidate profile**:**

The candidate:

- must be a graduate student with a solid foundation in cognitive science, with a particular emphasis on problem-solving strategies.
- must have a strong background in machine learning, statistics, modeling, and estimation.
- proficiency in programming is essential, with demonstrated expertise in both R and Python. The candidate should be capable of developing and implementing algorithms and statistical models using these languages.
- high level of proficiency in written and spoken English is required, enabling effective communication and collaboration within a diverse academic environment.

References:

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