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Discovering the preference hypervolume: an interactive model for real world computational co-creativity

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Discovering the Preference Hypervolume

an Interactive Model for Real World

Computational Co-creativity

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Abstract

In this thesis, the ideas of Guilford about divergent thinking, Jung on intuition and Sartre on reflection by others are combined to create a Hegelian creative process. It is posed that the central object of preference discovery is a co-creative process in which the Other can be represented by a machine, as is often done in the computational creativity community. This thesis explores efficient methods to enhance introverted intuition using extraverted intuition's communication lines.

Possible implementations of such processes are presented using novel algorithms that perform divergent search to feed the users' intuition with many examples of high quality solutions, allowing them to take influence interactively. In this process, the machine feeds and reflects upon human intuition, combining both what is possible and preferred. The machine model and the divergent optimization algorithms are the motor behind this co-creative process, in which machine and users co-create and interactively choose branches of an ad hoc hierarchical decomposition of the solution space.

The proposed co-creative process consists of several elements, which are treated in this thesis in the following order: a formal model for interactive co-creative processes, evolutionary divergent search, diversity and similarity, data-driven methods to discover diversity, limitations of artificial creative agents, matters of efficiency in behavioral and morphological modeling, visualization, a connection to prototype theory, and methods to allow users to influence artificial creative agents.

We tend to portray human creativity as having few boundaries. It might seem folly for a computer scientist to venture into such a domain where we have biases about human capabilities and are not capable of quantifying results in an objective manner without involving the human we aim to partially replace. This dissertation

is an effort to connect the field of computer science with the fields of philosophy, psychology, and biology, to enhance, not replace human creativity.

The ethical, social and political consequences of replacing humans by algorithms are part of a wider debate about how we organize society in the light of artificial intelligence's deep impact. But instead of replacing the human, this thesis explicitly chooses to embrace human-computer interaction in creative design, putting the human back into the loop of algorithmic design in generative AI and optimization.

Replicators [...] should be thought of as having extended phenotypic effects, consisting of all its effects on the world at large, not just its effects on the individual body in which it happens to be sitting.

(Dawkins 1982)

There is a power and utility to regarding the gene as the unit of selection, but equally there is value to seeing the organism as the unit of niche construction.

(Laland 2004)

Can There Ever Be Too Many Options?

(Scheibehenne 2010)

No one can tell what the painting of tomorrow will be like; one cannot judge a painting until it is done.

(Sartre and Elkaïm-Sartre 1946)

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List of Symbols

k	number of nearest neighbors
\mathcal{X}	population matrix with one member per row
\mathcal{A}	phenotypic archive used as a niching method by quality diversity algorithm
\mathcal{D}	phenotypic feature coordinate matrix with one member per row
$\mathcal{N}(\mathbf{m}, \sigma)$	Gaussian random variable with mean m and variance σ^2
A	area
l	circumference length
P	point symmetry
$d\mathbf{R}$	radial deviation of polygon key point
$\mathcal{D}\theta$	angular deviation of polygon key point
$L(x, \hat{x})$	evidence lower bound between predicted output x and ground truth \hat{x}
$C(\cdot, \cdot)$	binary cross-entropy between two entrees
$K(\cdot, \cdot)$	Kullback-Leibler divergence between two distributions
β	regularization factor scalar in Kullback-Leibler divergence
γ	annealing factor in Kullback-Leibler divergence
μ	learning rate for optimization algorithms
p	significance value
κ	parameter that controls exploration and exploitation in upper confidence bound acquisition function within Bayesian optimization context

$d()$	pointer to function that returns phenotypic descriptors (features) of a solution in a divergent optimization context
$f()$	pointer to function that evaluates a solution in optimization
\mathbf{M}_f	surrogate model that predicts fitness
\mathbf{M}_d	surrogate model that predicts phenotypic descriptors
u_{max}	maximum air velocity in a flow field
E	enstrophy: a turbulence metric of a flow field
t	point in time
Re	Reynolds number of a flow field
\mathbf{s}	input vector of a neural network
\mathbf{o}	output vector of a neural network
p_{c_L}	lift penalty used in objective function
p_A	area penalty used in objective function
\mathcal{H}	decision hypersurface based on members of QD archive
\mathcal{T}	projection of archive members into similarity space
$\hat{\mathcal{T}}$	projection model
δ	distance measure
\mathcal{S}	selected solutions
$\bar{\mathcal{S}}$	deselected solutions
\mathcal{P}	binary selection partition
\mathcal{M}	user decision hypersurface model
E_s	symmetry error
$p(x)$	constraint penalty of a candidate solution x , selected by a user
