

# The importance of applying computational creativity to scientific and mathematical domains

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## Abstract

The *Proceedings of the International Conference on Computational Creativity* will be compiled from electronic manuscripts submitted by the authors. This paper provides brief style instructions that will facilitate a high-quality, consistent proceedings.

## 1 Introduction

In the 2017 study of application domains in computational creativity (CC) ?, Loughran and ONeill found that, of 16 categories, papers on Maths, Science and Logic accounted for only 3% of the 353 papers on CC across 12 years. They argue that “tackling scientific, logical or realistic issues could help bring the reputation of CC away from a purely aesthetic domain towards developing solutions for real world problems.” *Ibid. p7* , and that “It is imperative that the field remains balanced as it grows and that we remember to reflect on all areas of growth.” *Ibid. p7* . We further their arguments in this paper – arguing both that it is imperative for the CC community to apply their work to scientific and mathematical domains, and that this would be mutually beneficial for the domains in question. We propose a research programme for doing so, using examples from mathematics and geology throughout.

## 2 Why should CC researchers apply their work to scientific domains?

### 2.1 A possible saturation point for generative CC in the arts

Despite the best efforts of the organising committees and community, CC has always attracted significantly more interest from researchers in artistic domains than scientific and mathematical domains. We could hypothesise why this is the case: (i) researchers in other domains are doing creativity-related work, but use other terminology, or have other venues for publication and engagement; and/or (ii) other, practical, priorities in scientific domains have led to a focus on techniques such as search, data-mining and automated deduction. Since these generate results of interest to domain experts, the more difficult, fluid and tenuous concept of creativity may be seen as unnecessary, risky or simply not a priority. This may particularly be the case given the various “AI winters” in the twentieth century (the second of which ended in 1993, just six years before the first workshop on CC), and the need for AI to “prove itself”.

CC has long been seen as more than “mere generation”<sup>1</sup>, with many other aspects of the creative act modelled, in particular aesthetic judgements, but also (more controversially) the importance of framing information and meta-level processes which can generate, for instance, the means by which an artefact is generated. The importance of such other aspects is reflected in CC evaluation models, such as the FACE model [ref] and SPECS [ref]. Nevertheless, generation is a crucial part of CC and in particular, artefact-driven CC. Recent developments in other areas of AI – principally machine learning (ML) – have led to astonishingly rapid progress in generative processes. The annual Conference on Neural Information Processing Systems (one of the largest conferences in AI) has held an annual workshop on Constructive Machine Learning since 2016 [check], which already dwarfs the CC conferences in size [specifics?] and has led to impressive generative results in both the arts and sciences, including [faces], painting, music, poetry, gaming, drug design, and gene design [refs for all] – usually in collaboration with domain experts.

Our concern is that the sheer size and combined resources of the ML community may render generative work in CC untenable. Furthermore, the arts domains *may* reach a saturation point for CC: as the novelty and backstory of computer-generated

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<sup>1</sup>The slogan at the 2012 ICCA conference was “scoffing at mere generation for more than a decade.” - although this has been challenged, for instance by Ventura [] and Cook and Colton[]

art grows old, society may question whether and why we want more computer-produced artistic artefacts. In order to keep the field alive, we propose that we need to both (a) focus on other aspects of creativity [see our framing paper]; and (b) find other application domains (as argued in this paper).

## **2.2 Aspects common to both arts and sciences**

The idea that the arts and the sciences are significantly different in CC terms requires close scrutiny. Certainly, at least some aspects of (some) sciences are very close to the arts domains, providing “low hanging fruit” to CC researchers. In this section we give some examples of aspects which are common to both arts and sciences.

## **2.3 Visual thinking in the sciences**

Visual art may be closer to geology than poetry.

Geological interpretations are a chain of interlinked events that occurred to form the rocks we observe. There are different types of events and different orderings and timings but effectively geology is a discretization of time, lumping the long continuum of processes and changes into key events that form the features we see. Differences of opinion can be, perhaps, differences in the events ordering and nature. Small differences in the story early on can have major influences on the overall outcomes.

Interpretations of seismic images and geological landscapes, based upon observation and background knowledge, are used to analyse the subsurface geology as well as the geological setting and history of the area of interest, both of which are vital tools for many exploration and oil extraction decisions. The issue that arises is the uncertainty caused by human bias during the process of the interpretation. Most importantly, it is really hard for one geologist to generate lots of ideas as cognitive biases lead to anchoring in a limited range of ideas/concepts and interpretations based on recency and prior knowledge (Bond 2007).

## **2.4 Subjectivity and the role of interpretation in the sciences**

According to Bond et.al (Bond 2007), geoscientists and geologists interpret seismic images and geological outcrops relying upon previous experience while applying

a set of certain geological concepts as explained with the case study later in this paper. They performed an experiment providing a single synthetic seismic image (Figure 1) to 412 geoscientists with different training and experience to record the variability in the interpretations and to quantify the conceptual bias, which may lead to conceptual uncertainty.

There are many factors that contribute to the human bias in interpretation with some of them being: a) expertise in a specific tectonic setting, b) experience in the relevant field, c) type of training, d) interpretational techniques and also influence of broader contextual information and background knowledge a geoscientist or geologist use in their interpretation (Bond 2007). Bond et.al observed that multiple interpretations of the single synthetic seismic image, as shown in Figure 1b, saying “Observations of participants’ interpretations suggest that they used a range of prior knowledge to undertake the interpretation exercise.” (Bond 2007). Quantifying the conceptual uncertainty is crucial in resource explorations as well as on other multiple areas of geoscience and geology. Conceptual uncertainty could thus be a major risk factor for various sciences that are heavily involved with decision making being based on the interpretation of limited information datasets.

## **2.5 Beauty as an aesthetic in the sciences**

What is the value of a discovery?

[maybe something on coincidences here]

aesthetics (spectrums): peers like it (cf Hume, publishable, ...)

truth (perhaps as a likelihood) beauty understandability predictive power applicability?

breadth of task

importance/influence (to field/collective knowledge)

## **3 Differences between the arts and sciences**

Differences between the arts and sciences provide opportunities for new developments in CC (trigger for progress, eg in methodology/evaluation)

## 4 Why should researchers in scientific domains work with the CC community?

1. ML is being increasingly used in science. [evidence] AI techniques can help to overcome human limitations, eg memory, brute search, cognitive biases (such as anchoring)
2. **But**, ML is limited and can be wrong: “crisis in science”. replicability, understandability, explanation, predictability, [does FACE reflect the scientific method? what is the scientific method now? what are values in science?]. CC can help with these aspects.

Thus, we argue that *(i)* science is a useful application domain for AI researchers to develop their techniques, *and (ii)* AI is a useful tool for scientists to employ in their research.

[cf pitching - AI-as-collaborator]

## 5 AI and CC approaches

### 5.1 Domain and task

AI techniques tend to be domain-independent but task-specific

CC techniques tend to be domain-specific but task-independent

### 5.2 The provenience and role of data in AI

Where does the data come from, and what purpose does it play? In data-mining, we’re given the data.

In evolutionary art we’re not given data but rather it is generated during the process. This is then used to produce artworks. The data itself (for instance, pixel placement) is not of interest in itself.

### **5.3 Generative and analytic approaches**

## **6 Science as an evolving enterprise**

What we mean by science and what we want science to be has changed since AI started to become a valuable tool.

## **7 FACE applied to science**

including in collaborative, mixed initiative settings.

how to study whether FACE is a good model to use here. we can show it in action but more work would be needed to show that it's a good model to use.

can we show FACE in both geology and maths?

## **8 Evaluation**

all measures developed as domain-independent methods

“Turing-style” distinguish tests (but see our paper here)

Anna's - ask domain expert

Ritchie's artefact-based criteria

FACE

Stuff with DanW?

We may need to develop further evaluation criteria. - applying to science domains could be a trigger for further development in methodology

## **9 Case study I: Mathematics**

To many people *Automated reasoning* is synonymous with *Automated theorem proving*. This shows the focus on proof in this area.

## **9.1 State of the art**

Review of what sort of work is going on in CC and sciences, even if not published in this conference, by this community.

Note differences in terminology between these fields and CC. discovery v creation

Automated Reasoning, ATP, ATF, the last generation paper, ones with ursula, etc.

Lenat, ...

## **9.2 Within reach**

### **9.2.1 Context**

EK47

### **9.2.2 Peer review**

ABC conjecture

Hume

### **9.2.3 Different conceptual schemes**

nunez (and wheelbarrow stuff)

log/linear

## **9.3 Big challenges**

## **10 Case study II: Geology**

Automated Scientific Discovery.

Geology and other sciences.

Progol...

Recent EPSRC call for Automated Scientific Discovery. What was their criteria?  
what were/weren't they looking for? [Simon]

## **10.1 State of the art**

## **10.2 Within reach**

### **10.2.1 Interpretation**

### **10.2.2 ..**

### **10.2.3 ..**

## **10.3 Big challenges**

how it would work in maths/geology. what would it take to have a mixed initiative  
collaborator?

# **11 Research Programme**

Here's how to do it.

A series of concrete recommendations for people.

1. How to collaborate: Team up with a domain expert. problem of where to publish/how to fund.
2. Mixed Initiative:
3. wide view of what the subject comprises
4. How to evaluate: cf Anna, Graeme, FACE

# **12 Conclusion**

Wrap up