From Computational Creativity Metrics to the Principal Components of Human Creativity

Conference Paper · November 2014


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Abstract. Within the field of Computational Creativity, significant effort has been devoted towards identifying variegating aspects of the creative process and constructing appropriate metrics for determining the degree that an artefact exhibits creativity with respect to these aspects. However, in the effort to determine if an artefact is creative by human standards, it is also important to examine the perception of creativity by humans and to which extend this perception can be formalized and applied on the evaluation of creative works. In this paper, we investigate how the human perception for creativity exhibited in text artefacts can be correlated by the usage of appropriate formulations of computational creativity metrics. To this end, we propose a model for transitioning from traditional metrics to a space that adheres to the principal components of human creativity and reflects the way that human approach the assessment of the creative process.
Keywords: Computational Creativity; Creativity Measurement; Creativity in Texts; Cognitive Models.

1 Introduction

Human creativity is a multifaceted, vague concept, combining undisclosed or paradoxical characteristics. As a general notion, creativity adheres to the ability to move beyond traditional and established patterns and associations, by transforming them to new ideas and concepts or using them in innovative, unprecedented contexts and settings [1]. In general, the creativity of a person can be divided qualitatively by taking into account its origin in psychometric or cognitive aspects of their thinking process [2].On the other hand, machines can mimic human creativity, or provide the necessary stimuli for encouraging and promoting the production of creative ideas and artefacts, it is not straightforward to assess the exhibited creativity by using automated techniques. Rather, most efforts have been focused on analyzing creativity on different aspects and producing different metrics, based on the nature of the examined artefacts.

In the present work, we propose text-based metrics for the core aspects of creativity as the latter are determined in the relevant literature and examine their conformance with the human perception of what constitutes a creative artefact. We proceed to identify the deviations between these two perspectives (computational metrics and human judgment) and propose a model for transforming the automatic measures to a space that more accurately reflects the human opinion.

2 Understanding the Human Perception of Creativity

2.1 Metrics for Computational Creativity over Textual Content

The association of creativity metrics with quantifiable results derived from the textual data is the critical step for automating the evaluation process. The formalization of creativity metrics for textual content is a complex task, and the related work is focuses on very specific characteristics of the examined content in order to model creativity.
Zhu et al. [1] propose a machine-learning approach based on features derived from computer science and psychology perspectives. Other works focus on concrete linguistic and morphological characteristics of the text, e.g. analogies [3].
In our previous work [4], we presented a formulization of a set of Computational Creativity Metrics for Novelty, Surprise, Rarity, and Recreational Effort, over textual artefacts. In this paper, we extend this work in order to correlate these Computational Creativity Metrics with the perception of creativity by humans.

2.2 Correlation of Computational Creativity Metrics with the Human Perception of Creativity

In order to assess the adherence of the proposed metric formulization with the human perception for creativity, we organized and conducted an experimental session based on storytelling activities. For the execution of the experiment, we employed forty (40) human participants, split in ten (10) teams of four (4) members each. All teams were asked to construct a story, on a specified premise, the survival of a village's habitants under a ravaging snow storm. The stories were created incrementally, with twenty (20) fragments produced for each story.
Following the completion of the stories, the teams were organized in two groups, each consisting of five teams. Without any interaction between the groups, each team was called to rate the stories of the remaining four teams belonging to their group, using a rank-based 4-star scale (i.e. the best story received 4 stars, the second-best story received 3 stars etc.). In this way, we obtained a ranked list of the five stories in each group. The goal of our experiment was to determine if, using the ranked lists of one of the test groups and a formalized representation of the computational creativity metrics, we can identify their correlation and examine if the distribution of values for the metrics follow the pattern of human judgment. To this end, we define a constrained optimization problem over functions of the aforementioned metrics, which is described below.

2.3 Extracting a Model for the Human Perception of Creativity.

Each artefact (story) S_n is characterized (via the execution of the computational creativity metrics presented in the previous section) by a set of 4 independent properties $g^{S_n} = ({g_1}^{S_n}, {g_2}^{S_n}, {g_3}^{S_n}, {g_4}^{S_n})$ where g_1 stands for "Novelty", g_2 for "Surprise", g_3 for "Rarity" and g_4 for "Recreational Effort". We define as partial creativity function (PCF) related to artefact property g_k a function that indicates how important is a specific value of the property g_k when calculating the creativity of an artefact S_n. This function is defined by the following formula:

$$PCF_{g_k}({g_k}^{S_n}) = w_{g_k} * \left(\frac{c_{g_k} * \left(1 - d_{g_k}\right)}{e^{\left(a_{g_k} * {g_k}^{S_n} + b_{g_k} \right)^2}} + \frac{d_{g_k}}{2} \right), \quad (1)$$

where ${g_k}^{S_n} \in [0,2]$ is the value of property g_k for the artefact S_n, and $0 \le a_{g_k} \le 5$, $-4 \le b_{g_k} \le 4$, $0 \le c_{g_k} \le 1$, $0 \le d_{g_k} \le 2$ are parameters that define the form of the partial creativity function, whereas $0 \le w_{g_k} \le 1$ represents the weight of property g_k in the calculation of the overall creativity. The calculation of the above parameters for all g_k properties lead to the calculation of the complete creativity function (CCF), as the aggregation of the partial creativity functions, as follows: $CCF(g^{S_n}) = \frac{1}{4} * \sum_{k=1}^{4} PCF_{g_k}({g_k}^{S_n})$

If CCF_{S_1} is the complete creativity of an artefact S_1 and CCF_{S_2} is the complete creativity of an artefact S_2, then the following properties generally hold for the complete creativity function:

$$CCF_{S_1} > CCF_{S_1} \Leftrightarrow (S_1)P(S_2),$$

$$CCF_{S_1} = CCF_{S_1} \Leftrightarrow (S_1)I(S_2),$$

where P is a strict preference relation and I is an indifference relation, as perceived by humans when evaluating the creativity of these artefacts.

Given a preference ranking of a reference set of artefacts, we define the creativity differences $\Delta = \left(\Delta_1, \Delta_2, \dots, \Delta_{q-1}\right)$, where q is the number of artefacts in the reference set and $\Delta_i = CCF_{S_i} - CCF_{S_{i+1}} \ge 0$ is the creativity difference between two subsequent artefacts in the ranked set.

We then define an error parameter E for each creativity difference:

$$\Delta_i = CCF_{S_i} - CCF_{S_{i+1}} + E_i \ge 0.$$

We can then solve the following constrained optimisation problem:

$$Minimise \sum_{i=1}^{q-1} (E_i)^2 \text{ s.t. } \begin{cases} \Delta_i \ge 0, if\ (S_i)P(S_{i+1}) \\ \Delta_i = 0, if\ (S_i)I(S_{i+1}) \end{cases}$$

This optimisation problem leads to the calculation of the partial creativity function parameters (a, b, c, d and w) for each property g_k.

Regarding the impact of the various metrics in the computation of the overall creativity, we observed that Novelty is generally considered a particularly positive attribute creativity-wise for the stories, its partial creativity (PC) increasing as its value increases. In contrast, the remaining metrics reached their maximum partial creativity at a certain value, after which their partial creativity started to decrease, indicating that e.g. recreational effort greater than a certain point is not perceived as a direct indication of creativity. Hence, the obtained results indicate that, while the proposed computational creativity metrics are correlated with the perception of humans for creativity, this correlation is not direct for all metrics. The following section discusses on the implications of these observations and details our approach for using the proposed metrics towards building a dimensional plane that more accurately reflects the human perspective for creativity.

3 Transferring Computational Creativity Metrics to the Human Perspective

As stated, the four computational creativity metrics discussed, provide a good estimation for the respective creativity aspects exhibited by textual artefacts. However, in the process of using such metrics to approach the human notion for creativity, the derived results indicated some deviations between this formalization and the way humans think. In broad terms, we observe the following two characteristics that should be taken into account when trying to model the human perspective:

- Humans prefer to think *monotonically*, perceiving the value of a metric / dimension as analogous to the “quality” of the examined artefact in that dimension;
- Humans prefer to think *orthogonally*, perceiving each of the features as a dimension independent from the rest.

The first step towards identifying the adherence of our metrics with the human perspective is to examine the orthogonality of the proposed metrics formulation. To this end, we ran an experiment for calculating the four basic computational creativity metrics on two datasets derived from distinct and distant domains, and determined whether the four metrics are orthogonal.

The first dataset comprised transcriptions of European Parliament Proceedings [5]. Given the described formulation of computational creativity metrics, we consider as a “story” the proceedings of a distinct Parliament session and as a fragment the speech of an individual MP within the examined session. The second dataset was derived from a literary work, Stories from Northern Myths, by E.K. Baker, available via the Project Gutenberg collection. In this case, the story is a book chapter and the story fragment is a paragraph within the chapter. In total, we examined 50 distinct parliament sessions from the Europarl dataset and 40 chapters from the storybook.

Based on the obtained results, we calculated the correlation between the four computational creativity metrics. Table 1 (left) provides the correlation values between the four metrics. It is evident that the computational creativity metrics by themselves are not orthogonal. Hence, in order to better approximate the human perception for creativity, we propose the following abstraction for modelling the examined aspects of creativity to a space more closely resembling human thinking:

	N.	S.	R.	R.E.	Type	I.	At.	
N.	1.000	0.134	0.123	-0.407	Formal Verbal Transcripts	1.0000	2.986E-07	**I.**
S.	0.134	1.000	0.265	-0.432				
R.	0.123	0.265	1.000	-0.335		2.986E-07	1.0000	**At.**
R.E.	-0.407	-0.432	-0.335	1.000				
N.	1.000	-0.642	0.104	-0.108	Literary Work	1.0000	1.436E-07	**I.**
S.	-0.642	1.000	0.074	-0.025				
R.	0.104	0.074	1.000	-0.039		1.436E-07	1.0000	**At.**
R.E	-0.108	-0.025	-0.039	1.00000				

Table 1. Correlation of Computational Metrics (left) and Creativity Dimensions (right)

-*Innovation*, that is, the tendency to produce ideas and artefacts that are disassociated with the other elements on a given context.

-*Atypicality*, that is, the tendency to deviate from the norm without actually breaking through.

Innovation, by its nature, is a perspective which closely associated with the Novelty computational metric. To this end, the magnitude of Innovation for a textual artefact is equal with its value for the novelty metric. On the other hand, we consider Atypicality as a combination of the Surprise, Rarity and Recreational Effort metrics, each bearing a different weight towards determining Atypicality. These two axes also provide a rough conceptualization of the two major qualitative aspects of creative work: whether the said work is *visionary*, i.e. it provides a groundbreaking approach on a given field; and whether it is *constructive*, i.e. it uses in a novel way established techniques and ideas in order to produce a high-quality artefact.

As indicated by the experiment described in Section 2.2, Innovation has an analogous and close to monotonic association with the human judgment for creativity. Therefore, and in order to satisfy our second requirement (orthogonality), we consider Innovation as the strictly defined dimension of our space and seek for the formulation of Atypicality that results to a dimension orthogonal to Innovation.

More specifically, let Atypicality of a text t be the normalized weighted sum of its Surprise, Rarity, and Recreational Effort:

$$A(t) = \frac{w_s Sur(t) + w_r Rar(t) + w_e Eff(t)}{w_s + w_r + w_e}, \text{ with the weights } w_s, w_r, w_e \in [-1,1].$$

We aim to find the weight values that constitute Atypicality orthogonal to Innovation, i.e. those weight values for which *Correl(Innovation, Atypicality)* = 0. We thus define the following optimization problem:

$Minimise \sum_{i=1}^{n} (\; Correl(Innovation_i, \; Atypicality_i) \;)^2$ s.t. $w_s, w_r, w_e \in [-1,1]$,

where *n* is the number of the combined datasets.

Although the search space of the optimization problem above is highly non-linear, solving this problem is straightforward. The optimum weight values in our case are:

$$(w_s, w_r, w_e) = (0.13951, 0.10154, 0.06905)$$

Table 1 (right) presents the correlations between innovation and atypicality in the two datasets for the found optimum weight values. The resulting model defines two orthogonal axes, Innovation and Atypicality, which define the space for measuring and characterizing the observed creativity, as an Euclidean vector, the length of which indicates the quantitative aspect of the creativity exhibited by the artefact, while its direction indicates the tendency for either Innovation (visionary creativity) or Atypicality (constructive creativity). Using this model for the evaluation of the storyset of the initial experiment, and taking into account the vector length for each story, we obtained the same ranking as the one produced by the human evaluation. This is a strong indication that the proposed model accurately reflects human judgement, while also pertaining to core principles of the human perception of creativity.

4 Conclusions

Understanding the elements of the Creative Process, is a challenging research issue, which combines research results from several research fields, like neuroscience, psychology and philosophy. Within the field of Computational Creativity, there have been significant results for the identification of various aspects of the creative process and the construction of appropriate metrics for these aspects. However, in the effort to determine if an artefact is creative by human standards, it is also important to examine the perception of creativity by humans and to which extend this perception can be formalized and applied on the evaluation of creative works.

The work described in the present manuscript showcases our findings towards transitioning from computational creativity metrics associating specific attributes of text artefacts with creativity aspects to a creativity calculation model that better reflects the human perception of creativity.

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