# Creativity Profiling Server: Modelling the Principal Components of Human Creativity over Texts

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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, the formalization of a person's creativity (i.e. a creativity user profile) as a derivative of such creations is not straightforward, as it requires a transition to a space reflecting the core principles of creativity as perceived by humans. This becomes a necessity in domains where personalization goes beyond timely and personalized knowledge provision, targeting the encouragement and fostering of creative thinking. Thus, it becomes essential to develop methodologies for modelling creativity to support personalization based on creativity aspects / characteristics of users. The paper proposes a user modelling framework for formulating creativity user profiles based on an individual's creations, by transitioning from traditional computational creativity metrics to a space that adheres to the principal components of human creativity. Furthermore, the paper presents the Creativity Profiling Server (CPS), a system implementing the aforementioned user modelling framework for computing and maintaining creativity profiles and showcases the results of experiments over storytelling educational activities.

**Keywords:** Human Creativity Modelling, Creativity Profiling, Computational Creativity

## 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]. The usage of computational methods for producing creative artefacts, as well as, unveiling the essence of human creativity and using computers understanding it, is the subject of extensive debate [2]. Along with such philosophical approaches, research results from neuroscience should also be considered in the process of revealing/ understanding the human creative process. In general, the creativity of a person can be expressed qualitatively by taking into account its origin in psychometric or cognitive aspects of their thinking process [3]. An example of the former is the work of [4], who examine how the human mind perceives complex auditory stimuli e.g. music. In this case, they look at the brains of improvising musicians and study what parts of the brain are involved in the kind of deep creativity that happens when a musician is really in the groove. Their research has deep implications for the understanding of creativity of all kinds. In any case, while 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.

Hence, the core assumption for building a user's creativity profile, is that his/her creativity is showcased by his/her creations, named Creativity Exhibits. These exhibits can follow different modalities, corresponding to the aforementioned reasoning patterns, e.g. texts, diagrams/pictures, actions etc.

The calculation of a creativity profile, constitutes the process of (a) measuring the creativity expressed by given creativity artifacts; (b) associating these measurements with dimensions of human creativity corresponding to the given dimension.

For achieving (a), we employ creativity metrics derived from computational creativity and formulate them in accordance to the characteristics of the examined exhibits. A number of different creativity metrics are proposed from the literature on computational creativity.

More specifically, Novelty reflects the deviation from existing knowledge/ experience and can be measured as a difference metric between what is already known and the given piece of content. Novelty is a generally accepted dimension of creativity within the area of computational creativity and an essential candidate for measuring elements of creativity within the human-created content when interacting with the machine. It has been used as a heuristic for driving the generation of novel artefacts in exploratory creativity [3] known as novelty search, an approach to open-ended evolution in artificial life [5]. Surprise is another essential characteristic which may be represented as the deviation from the expected [6]. The higher the deviation the higher the perceived surprise. Surprise offers a temporal dimension to unexpectedness [7]. Likewise, impressive artefacts readily exhibit (ease of recognition) significant design effort and may be described via two heuristics, Rarity (rare combination of properties) and Recreational Effort (difficult to achieve) [8]. These four metrics will be used to construct the creativity profile of a human user, as expressed by the artefacts that this user has been constructed alone or as a participating member of a group of users. In the case of Textual Exhibits, examples of such artefacts include a written story, a dialogue and any other textual creation.

In our previous work [9] we presented the formulization of the Computational Creativity Metrics for Novelty, Surprise, Rarity and Recreational Effort over textual artefacts. In the present work, we use these text-based metrics for the core aspects of creativity 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. In this way, the constructed human creativity profiles can be used for providing personalized material / content that is suitable for a specific user or addresses his/her limitations regarding creativity.

The rest of the paper is structured as follows. We examine the correlation of the proposed metrics with the human perception of creativity. Afterwards, we build on these observations to propose a transition model from computational metrics to a two-dimensional orthogonal space which aims to closely reflect the way human beings perceive creativity. We present the experiments for assessing the effectiveness of the proposed model towards this goal, describe the architecture and functionality of the Creativity Profiling Server, a system that incorporates the proposed model and report on the experiments for a preliminary evaluation of the system. Finally, we summarize the present research and report on our next steps.

# 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.

## 2.1 Extracting a Model for the Human Perception of Creativity

Each artefact (story) $S_n$ is characterized (via the application of the computational creativity metrics presented in the previous section) [9] 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:

$PCF_{g_k}({g_k}^{S_n}) = w_{g_k} * \left( \frac{c_{g_k} * \left(1 - d_{g_k}\right)}{e^{\left( a_{g_k} * {g_k}^{S_n} + b_{g_k} \right)^2}} + \frac{d_{g_k}}{2} \right)$, where ${g_k}^{S_n} \in [0,2]$is the value of property $g_k$ for the artefact $S_n$, and $0 \leq a_{g_k} \leq 5$, $-4 \leq b_{g_k} \leq 4$, $0 \leq c_{g_k} \leq 1$, $0 \leq d_{g_k} \leq 2$ are parameters that define the form of the partial creativity function, whereas $0 \leq w_{g_k} \leq 1$ 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:

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

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

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 $\Delta_i = CCF_{S_i} - CCF_{S_{i+1}} \geq 0$ is the creativity difference between two subsequent artefacts in the ranked set.

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

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

We can then solve the following constrained optimization problem:

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

This optimization problem leads to the calculation of the partial creativity function parameters for each property $g_k$.Based on these values and the human assessment of the story rankings, the results of the constrained optimization problem defined in the previous section resolves in the calculation of the partial creativity parameters (a, b, c, d and w). 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 (see Figure 1). 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 (see Figure 1).

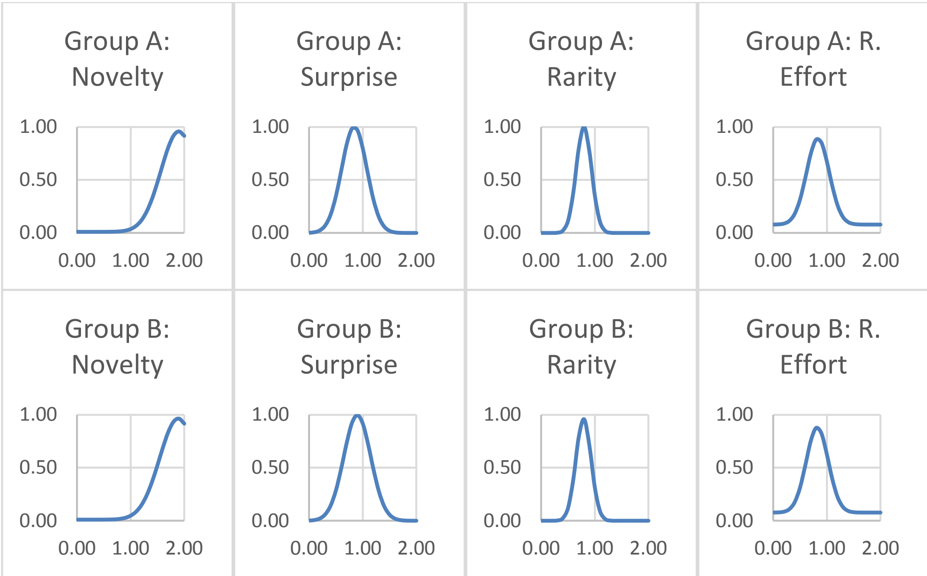


**Fig. 1.** PCs of Computational Creativity Metrics wrt their value (Group A & B respectively)

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, each textual artefact can be described by 4 computational creativity metrics, namely, Novelty, Surprise, Rarity and Recreational Effort. Following the formulation of the creativity metrics, therefore, the next hypothesis that was examined was the reduction of the dimensional space for representing creativity as expressed through creative artefacts, in an orthogonal space. In order to effectively conceptualize human creativity, orthogonality is a particularly desirable attribute of the conceptualization space to be used, since it allows the examination of independent variables when trying to analyse and influence / encourage certain creativity aspects. Hence, the first step towards identifying the adherence of the computational creativity 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 [10]. Given the formulation of computational creativity metrics described in [9], 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.

**Table 1.** Computational Metrics Correlation: Formal Verbal Transcriptions

| | Novelty | Surprise | Rarity | R. Effort |
|---|---|---|---|---|
| Novelty | 1.00000 | 0.13393 | 0.12329 | -0.40681 |
| Surprise | 0.13393 | 1.00000 | 0.26453 | -0.43151 |
| Rarity | 0.12329 | 0.26453 | 1.00000 | -0.33499 |
| R. Effort | -0.40681 | -0.43151 | -0.33499 | 1.00000 |

**Table 2.** Computational Metrics Correlation: Literary Work

| | Novelty | Surprise | Rarity | R. Effort |
|---|---|---|---|---|
| Novelty | 1.00000 | -0.64243 | 0.10392 | -0.10762 |
| Surprise | -0.64243 | 1.00000 | 0.07376 | -0.02538 |
| Rarity | 0.10392 | 0.07376 | 1.00000 | -0.03882 |
| R. Effort | -0.10762 | -0.02538 | -0.03882 | 1.00000 |

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. Tables 1 and 2 provide the correlation values between the four metrics. It is evident that the computational creativity metrics by themselves are not orthogonal. 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:

*Novelty* is the perspective to be held as the one dimension of the dimensional space, as the conducted showed that it has a monotonic incremental relation with the perception of humans on what is creative. Further more, it is a generally accepted dimension of creativity. [11]

*Atypicality*, that is, the tendency to deviate from the norm without actually breaking through. In other words, to what extend (without necessarily being novel) the artefact differs from the ordinary (thus being surprising, rare and difficult to construct)

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 stated, Novelty has an analogous and close to monotonic association with the human judgment for creativity. Therefore, and in order to satisfy our requirement of orthogonality, we consider Novelty as the strictly defined dimension of our space and seek for the formulation of Atypicality that results to a dimension orthogonal to Novelty.

More specifically, let Atypicality of a text $t$ be the normalized weighted sum of its Surprise, Rarity, and Recreational Effort: $A(t) = \frac{w_s Sur(t) + w_r Rar(t) + w_e Eff(t)}{w_s + w_r + w_e}$, with $w_s, w_r, w_e \in [-1,1]$ . We aim to find the weight values that constitute Atypicality orthogonal to Novelty, i.e. those weight values for which Correl(Novelty, Atypicality)= 0. We thus define the following optimization problem:

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

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 resulting model defines two orthogonal axes, Novelty 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 Novelty (visionary creativity) or Atypicality (constructive creativity). The following tables present the novelty and atypicality in the two datasets, as well as, the correlation between these two dimensions for the found optimum weight values.

**Table 3.** Correlation of Creativity Dimensions: Formal Verbal Transcription

| | Novelty | Atypicality |
|---|---|---|
| Novelty | 1.00000 | 2.986E-07 |
| Atypicality | 2.986E-07 | 1.00000 |

**Table 4.**Correlation of Creativity Dimensions: Literary Work

| | Novelty | Atypicality |
|---|---|---|
| Novelty | 1.00000 | 1.436E-07 |
| Atypicality | 1.436E-07 | 1.00000 |

# 4 The Creativity Profiling Server

The Creativity Profiling Server (CPS) allows the storage, maintenance and update of creativity profiles of users using creativity exhibits that are produced from applications of the outside world. CPS provides a simple and straightforward API in order to expose its functionalities and to facilitate the communication with the outside world. Through the CPS API, the example application can submit creativity exhibits and receive the corresponding creativity measurements, create group of users and finally receive the creativity profile of a user. The aforementioned functionalities and the internal structure of CPS are depicted in Figure 2.

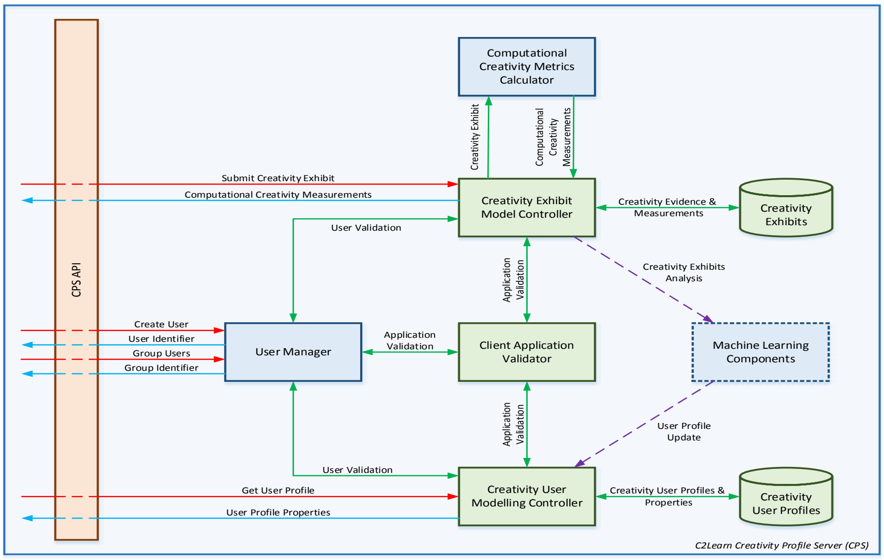


**Fig. 2.** CPS Architecture

The distinct modules incorporated in the CPS Architecture are the following:

- Client Application Validator: The module is responsible for ensuring that a client request is originated from an application registered to CPS.
- User Manager: This module is responsible for ensuring that client requests contain a valid user profile ID. Also User Manager is responsible for creating and destroying groups by joining and disjoining user profile properties respectively
- Creativity Exhibit Model Controller: This module is responsible for storing, maintaining and updating the creativity exhibits delivered by applications and also forward the creativity exhibits to the Computational Creativity Metrics Calculator: This module is responsible for calculating all the metrics of a creativity exhibit regarding of its type.
- Creativity User Modelling Controller: This module is responsible for storing, maintaining and updating the Profile Properties of each User Profile in CPS. Also this module delivers to client applications the properties of particular user profiles.
- Machine Learning Components: This module is responsible for calculating the value of the Creativity Profile Properties of a given user.

In a typical situation an application creates a user through the CPS API. The CPS API send the request to the User Management. Afterward User Management verifies through the Application Validation module that the application is registered to CPS. Since the application is validated User Management creates a unique user profile id and sends it to the application. Since a user profile is created then the application can submit creativity exhibits of this user. More specifically the application submits the creativity exhibit to the CPS API along with type of the creativity exhibit and the timestamp the creativity exhibit was created. After submission the API sends the creativity exhibit and its type to the Creativity Exhibit Model Controller module. After validating the user and the application through the User Management and the Application Validator respectively, the module sends the creativity exhibit to the Computational Creativity Metrics Calculator module. The Computational Creativity Metrics Calculator returns back the measurements of the creativity exhibit. Afterwards, the Creativity Exhibit Model Controller module stores the creativity exhibit along with the measurements to the CPS database. Finally, the Creativity Exhibit Model Controller invokes the Machine Learning Components. Machine Learning Components take as input the creativity exhibit and calculate the values of the profile properties of the user. Afterwards the newly calculated values are send to the Creativity User Modelling Controller module, which stores the values to the CPS database.

Once a user creativity profile is created, then the application can request through the CPS API the User Profile Properties and also the Model which describes the profile. After sending the request to the API, the request is redirected to the Creativity User Modelling Controller module. This module, after validating the user and the application through the User Management and the Application Validator respectively, retrieves from the CPS database the properties for the corresponding user and send them back to the application.

## 5 Incorporation of the model in CPS

Following the definition of the model, we combine within CPS the Surprise, Rarity and Recreational Effort metrics in order to form another metric, which we call Atypicality and is orthogonal to Novelty. Atypicality is calculated as a weighted average of Surprise, Rarity and Recreational Effort, as follows: $AT_i = \frac{w_S * S_i + w_R * R_i + w_E * E_i}{w_S + w_R + w_E}$, where: i refers to an artifact, Si , Ri ,Ei and ATi to Surprise, Rarity, Recreational Effort and Atypicality metrics respectively for the given artifact i, and wS,wR and wE are positive weights assigned to Surprise, Rarity and Effort respectively, in order to calculate the Atypicality metric in a way as much uncorrelated (and thus, orthogonal) with Novelty as possible. A user's Creativity Profile, thus, consists of a two-dimensional vector expressing two types of user's creativity. The Visionary Creativity, which is measured by the Novelty metric, and the Constructive Creativity, which is measured by the Atypicality metric. CPS gathers all Creativity Exhibits (artefacts) that are produced by its users within external applications. In discrete time intervals, which we call Time Window, CPS calculates and/or updates the Creativity Profile of each user. The calculation of the creativity profiles for the users of the CPS is a repeated (once per Time Window) two-phase process, and is explained below:

Phase A: *Calculation of optimum Computational Creativity Metric Weights for the Application Domain*

We aim to find/ update the weight values [wS,wR,wE] of Surprise, Rarity and Recreational Effort that constitute Atypicality orthogonal to Novelty, i.e. those weight values for which Correl(N, AT) = 0. The optimum vector [wS,wR,wE] will be used in

Phase B for the calculation of the users' Creativity Profiles for the new CPS Time Window.

We thus define the following non-linear optimization problem:

$$Min.\ Correl(N, AT)^2,\ st.\ w_S, w_R, w_E \geq 0\ ,\ w_S + w_R + w_E \neq 0$$

Each time where a new CPS Time Window starts, we solve the above minimization problem for all the artefacts of the application domain (all the creativity exhibits collected for all CPS users and for all CPS Time Windows so far). It is evident that in each execution of this process there is a strong probability of discovering a new vector [wS,wR,wE] that makes Atypicality (AT) more orthogonal to Novelty (N). In order to reduce the sensitivity of the system to this continuous change, we update the vector [wS,wR,wE] to be used in Phase B with the new vector retrieved by solving the optimization problem defined in Eq. 1 only when the improvement (minimization) in Correl(N, AT)2 exceeds 5%.

Phase B: *Construct/update of Users' Creativity Profiles*

A user's creativity profile is determined by the creativity exhibits produced by the user alone or as a member of a group. Groups are treated by CPS as a user, meaning that CPS will construct a creativity profile also for each group. In this case, the creativity profile is constructed/ updated based on the creativity exhibits of the group during the last (just finished) time window. In the case of simple users (not groups) their creativity profile is constructed/ updated based on all the creativity exhibits they constructed (either alone or as a group member). The first step for computing the creativity profiles is to transform the space (N,S,E,R) to the space (N, AT) and compute the average of N and AT measures for the creativity exhibits for a given user and for the time window that just finished, as follows:

*B1. Calculate Average Novelty and Atypicality of Creativity Exhibits*

In the general case, let a user U which participates in groups UG. In the case of computing the creativity profile of a group, we have only the user U, which represents the group. Such a user cannot be part of other groups. Let $E_T \equiv [\overline{Novelty}, \overline{Atypicality}]$ of a user U, calculated for the creativity exhibits in the time window T, after the transformation of the space (N,S,E,R) to the space (N, AT) using the optimal weight vector [wS,wR,wE] (calculated in Phase A). Let also $G_T \equiv [\overline{Novelty}, \overline{Atypicality}]$ of a user U, calculated for the creativity exhibits of UG in the time window T, after the transformation of the space (N,S,E,R) to the space (N, AT) using the optimal weight vector [wS,wR,wE] (calculated in Phase A).

The overall Average Novelty and Atypicality (PT) of all creativity exhibits for user U is calculated as a fusion of ET and GT, relying on the analogy of the user's and the groups' achievements. If the user's creativity (ET) surpasses the creativity exhibited within his/her participation in groups (GT), then only ET is considered. Otherwise, a part of the difference between groups' creativity and user's creativity is also considered, as follows:

$$P_T = \begin{cases} E_T & E_T \geq G_T \\ E_T + k * (G_T - E_T) & E_T < G_T \end{cases},\ \text{with}\ k = \frac{1}{2} + \frac{1}{2} * tanh(2 * [(G_T - E_T) - 1])$$

*B2. Calculate Visionary and Constructive Creativity of User*

Though all exhibits must be taken into account, the recent ones are considered more important, as they depict the exact current status of the user's creativity whereas past exhibits play a less vital role. To give our model an essence of decay through time, we use this formula: $C_T = \frac{P_T}{D} + \frac{D-1}{D} * C_{T-1}$, where: $C_T$ is the vector describing the Creativity of the user (or group) at the time window T, and $C_{T-1}$ at the time window T-1 respectively $C_T \equiv [Visionary\ Creativity, Constructive\ Creativity]$ and D, a proportional constant of decaying analogous to the timespan.

## 6 Preliminary CPS Evaluation

In order to obtain a preliminary assessment for the effectiveness of the proposed approach, we conducted a two-phase experiment in order to determine (a) the degree to which the selected computational creativity metrics conform to the opinion of experts regarding the creativity exhibited in a textual artefact and (b) the degree to which the proposed model for human creativity reflects the opinion of such experts.

For the purposes of the experiment, we employed twenty students who were asked to produce five stories each under pre-defined topics. For the first stage of the experiment, we sampled the stories produced during the aforementioned story writing session, randomly selecting two stories by each student, and asked five experts to rank them with respect to their creativity, as the latter is perceived by each of these experts. We then compared the ranking results with the ranking derived from the results produced by the CPS. For the second stage of the experiment, we picked the complete set of stories (i.e. five stories) for five of the users and asked from the same five experts to rank these users with respect to their creativity, using as evidence the produced stories. We then compared the expert ranking to the one produced by the CPS.

In order to evaluate the similarity between the rankings of the experts and the rankings of the CPS, for the textual exhibits' and the users' ranks, we employed a metric based on Kendall's Tau, defined by the following equation: $Success = \frac{1}{2} + \frac{N_{concordant} - N_{discordant}}{n(n-1)}$, where $N_{concordant}$ stands for the concordant pairs of ranked exhibits or users, $N_{discordant}$ stands for the discordant pairs when comparing the ordering of the experts and the CPS and $n$ is the number of the examined exhibits or the users. We calculated this metric for the series of textual exhibits rankings and the series of participating users rankings. The following table presents the summary statistics of the two Success metric series we had as an outcome.

**Table 5.** Correlation Coefficient between Expert and CPS rankings

| | Textual Exhibits | Users |
|---|---|---|
| Min Success | 0.58 | 0.56 |
| Average Success | 0.74 | 0.71 |
| Max Success | 0.89 | 0.88 |

# 7 Conclusions & Future Work

The work described in the present paper 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. Furthermore, the present manuscript provides a summary of the architectural design and functionality of the Creativity Profiling Server (CPS).

Towards the continuation of our research, we aim to examine the effectiveness of the model in more complex experiments, examining textual exhibits from different domains and modalities (prose, poetry, speech) in order to obtain a more general reflection of the human perception of creativity. Observation over more open-ended experiments will likely lead to further refinements and extensions of the proposed human creativity model.

# 8 References


1. Zhu, X., Xu , Z., Khot, T.: How creative is your writing? a linguistic creativity measure from computer science and cognitive psychology perspectives. In *Proceedings of the Workshop on Computational Approaches to Linguistic Creativity*, Association for Computational Linguistics, pp. 87--93, (2009).
2. Lubart, T.:How can computers be partners in the creative process: classification and commentary on the special issue. In *International Journal of Human-Computer Studies,* vol. 63, pp. 365--369, (2005).
3. Boden, M.: The Creative Mind, 2nd Edition. London: Routledge, (2004).
4. Limb, C. J., Braun, A. R.:Neural substrates of spontaneous musical performance: An fMRI study of jazz improvisation. In *PLoS One,* vol. 3, (2008).
5. Lehman, J., Stanley, K. O.:Exploiting Open-Endedness to Solve Problems Through the Search for Novelty. In *ALIFE*, pp. 329--336, (2008).
6. Macedo, L., Reisenzein, R., & Cardoso, A.: Modeling forms of surprise in artificial agents: Empirical and theoretical study of surprise functions. In *Proceedings of the 26th annual conference of the cognitive science society*, NJ: Erlbaum, pp. 873--878, (2004) .
7. Maher, M. L., Brady, K., Fisher, D. H.:Computational models of surprise in evaluating creative design. In *Proceedings of the Fourth International Conference on Computational Creativity*, (2013).
8. Lehman, J., Stanley, K. O.:Beyond Open-endedness: Quantifying Impressiveness. In *Artificial Life*, pp. 75--82, (2012).
9. Karampiperis, P., Koukourikos, A., Panagopoulos, G.:From Computational Creativity Metrics to the Principal Components of Human Creativity. In *Proc. of the 9th International Conference on Knowledge, Information and Creativity Support Systems*, Limassol, Cyprus, (2014).
10. Koehn, P.:Europarl: A parallel corpus for statistical machine translation. In *MT summit*, pp. 79--86, (2005).
11. G. Ritchie.:Some empirical criteria for attributing creativity to a computer program. In *Minds and Machines,* vol. 17, pp. 67--99, (2007).
12. Kövecses, Z.:A new look at metaphorical creativity in cognitive linguistics. In *Cognitive Linguistics,* vol. 21, pp. 663--697, (2010).
13. Veale, T.:An analogy-oriented type hierarchy for linguistic creativity. In *Knowledge-Based Systems,* vol. 19, pp. 471--479, (2006).

14. Lehrer, A.:Brendalicious. Lexical creativity, texts and contexts. Amsterdam, John Benjamin, , pp. 115-136, (2007).
15. Chiru, C. G.:Creativity Detection in Texts. In ICIW 2013, The Eighth International Conference on Internet and Web Applications and Services, (2013).