Fostering creativity in learning
through digital games

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Creative Emotional Reasoning Computational Tools Fostering Co-Creativity in Learning Processes

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EMOTIVE REASONING & EMOTION DETECTION COMPUTATIONAL TOOLS

C²LEARN PROJECT DELIVERABLE NO. D3.3 (FINAL)

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EXECUTIVE SUMMARY

C^2Learn at a glance

C^2Learn (www.c2learn.eu) is a three-year research project supported by the European Commission through the Seventh Framework Programme (FP7), in the theme of Information and Communications Technologies (ICT) and particularly in the area of Technology-Enhanced Learning (TEL) (FP7 grant agreement no 318480). The project started on 1st November 2012 with the aim to shed new light on, and propose and test concrete ways in which our current understanding of creativity in education and creative thinking, on the one hand, and technology-enhanced learning tools and digital games, on the other hand, can be fruitfully combined to provide young learners and their teachers with innovative opportunities for creative learning. The project designs an innovative digital gaming and social networking environment incorporating diverse computational tools, the use of which can foster co-creativity in learning processes in the context of both formal and informal educational settings. The C^2Learn environment is envisioned as an open-world 'sandbox' (non-linear) virtual space enabling learners to freely explore ideas, concepts, and the shared knowledge available on the semantic web and the communities that they are part of. This innovation is co-designed, implemented and tested in systematic interaction and exchange with stakeholders following participatory design and participative evaluation principles. This happens in and around school communities covering a learner age spectrum from 10 to 18+ years.

About this document

Deliverable D3.3 reports on the design and implementation of the Emotive Reasoning Computational Tools that are used within creative activities designed in C2Learn, in order to investigate the link of emotions and Lateral Thinking, as it is described by the C2Learn theory for creativity. The document provides information on the different types of computational tools, indicates their origins to the underlying reasoning theories, and presents details on the experimental design for training and deploying the components.

Finally, the document describes the design and implementation of House of Emotions, a gamified demonstrator showcasing the functionality of the relevant Emotive Reasoning Computational Tools.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF TERMS AND ABBREVIATIONS

Term/Abbreviation	Definition
CER	Creative Emotional Reasoning
LT	Lateral Thinking
LTC^2	C^{2}Learn's Lateral Thinking
DLT	Diagrammatic Lateral Thinking

1. INTRODUCTION

C2Learn's Lateral Thinking (LTC^2) theory is built on Lateral Thinking and Brainstorming Techniques. The term Lateral Thinking (LT) is invented in 1967 by Edward De Bono [1]. As he elucidates:

"The brain as a self-organizing information system forms asymmetric patterns. In such systems there is a mathematical need for moving across patterns. The tools and processes of lateral thinking are designed to achieve such 'lateral' movement. The tools are based on an understanding of self-organizing information systems."

"In any self-organizing system there is a need to escape from a local optimum in order to move towards a more global optimum. The techniques of lateral thinking, such as provocation, are designed to help that change."

In deliverable D2.1 (Creative Emotional Reasoning), three kinds of LT are suggested: Semantic, Diagrammatic, and Emotive. In the context of the present deliverable, we elaborate on the Computational Tools related to the last of these kinds of LT, i.e. Emotive Lateral Thinking.

1.1 THEORETICAL BACKGROUND

The following subsection provides a brief analysis of the elements and techniques of Emotive Lateral Thinking, with respect to the process of identifying the type of computational tools needed to support them within a digital environment. For further details on the techniques, cf. deliverable D2.1.2, Creative Emotional Reasoning.

1.1.1 BASIC EMOTIVE REASONING PROCESSES

Emotive Lateral Thinking distinguishes between two levels of emotive lateral judgement, that is, the ascribing of emotive value in a given disruption element:

– *First-order Emotive Lateral Judgement*: This type of Emotive Lateral Judgement is associated with the emotive impact of entities on a human actor. It, therefore, allows the identification of analogies between entities, in terms of their emotive impact, i.e. their *emotive value*.
– *Second-order Emotive Lateral Judgement*: This second level at which emotive techniques operate deals with the alteration of the established rules for solving a problem, while being aware of the emotive response from other observers (the public, examiners, etc.).

Towards fostering emotive lateral judgement, C2Learn offers tools and services that estimate the emotive response of humans to creative artefacts. These tools, consequently, can be used in different contexts in order to push humans to assess the emotive impact of an item or concept (first-order) or act according to the expected emotive impact that their actions will have to others (second-order).

The following section presents the C2Learn tools that realize emotion detection, describing the training process and the flow of the training sessions and the usage of the resulting classification modules.

2. EMOTIVE REASONING COMPUTATIONAL TOOLS SUITE

The C2Learn Emotive Reasoning Computational Tools Suite is designed to analyse different characteristics and behaviours in order to detect the emotive response of human actors associated with an artefact. The suite comprises tools for detecting the emotive response of humans when creating and when accessing or viewing textual and pictorial artefacts.

2.1 EMOTION DETECTION OVER TEXTUAL ARTEFACTS

The core premise of the tool is that the emotive response of humans to a textual artefact is related to specific features of the text in hand, which are not known beforehand. This section presents the experimental setup for training a component that identifies the emotions linked to a text, based on the latter's characteristics.

2.1.1 TRAINING DATASET

Obtaining a ground truth for the relation between textual artefacts and the emotions they evoke is a difficult, demanding and time-consuming task. It can involve the provision of questionnaires both designed and evaluated by psychology experts, the tracking of brain activity using specialized devices, the real-time inspection of user activity by experts, etc. Since these processes are outside the scope of C2Learn in terms of context and temporal resources, NCSR-D conducted the team of the Jacobs University department of Psychology that participated in the successful CyberEmotions[1] project, which offered a dataset associating emotions with online discussions.

The dataset used is a subset of 20 discussion forum threads, selected by four psychologists from various websites. As describe in the relevant publication [3], each thread includes 10 posts, forming a conversation between the forum members about various subjects (depending on the forum) and it is pre classified by the experts as negative, positive or neutral in respect of valence. Valence in psychology, when addressing emotions, is perceived as the intrinsic allurement or disinterest, for positive and negative valence respectively. The psychologists chose the forums in such a way to ensure the discussions cover the most possible range of emotional valence. The list of the forum topics and their links can be found in the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/T-AFFC.2012.26. The following table shows some statistics for the whole set of discussions.

# of discussions	*20*
# of tokens	*15035*
Unique tokens	*1966*
Avg. tokens per discussion	*751.75*

2.1.2 MACHINE LEARNING FRAMEWORK FOR ESTIMATING EMOTIVE RESPONSE

As text is generally a complex expression medium, with underlying characteristics and semantics, it is difficult to establish a set of features that completely model a manuscript with respect to its valence. The latest advances of deep learning techniques have led to extremely promising results in similarly complex tasks like computer vision [4] and model-free affect recognition [5]. Furthermore, deep architectures have been successfully applied to dissimilar spatio-temporal datasets assisted by a pre-training [6] phase which can be interpreted as a method to find good initial configurations that facilitate supervised learning. This phase has allowed efficient training of large hierarchical models – referred to as deep architectures – which otherwise yield poor results [7].

The process for training a deep neural network that is able to estimate the valence of a given text is depicted in the following figure.

[1] http://www.cyberemotions.eu/

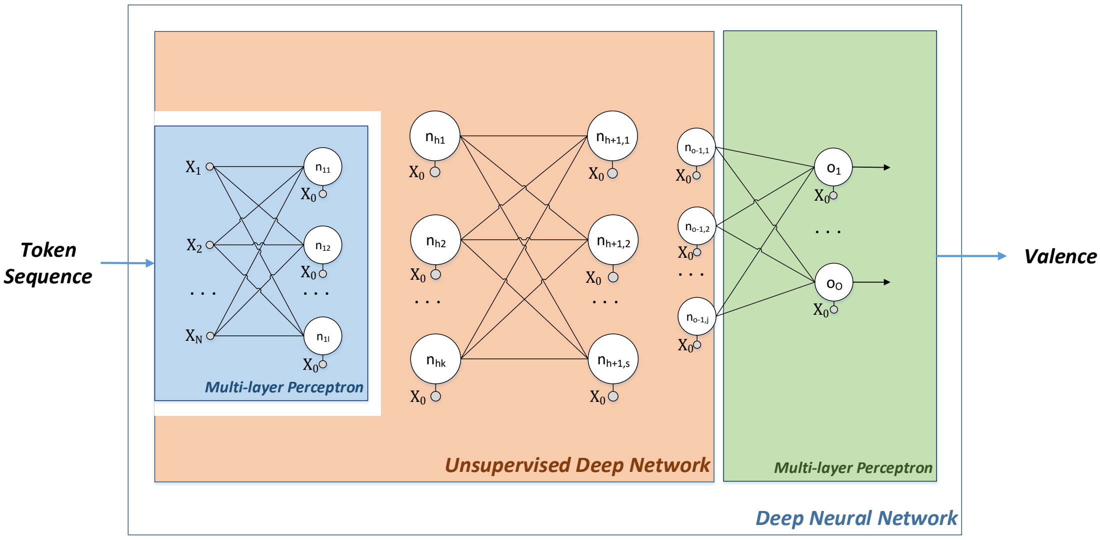

Figure 1: Deep Neural Network Architecture for Associating Character Vectors to Valence

The process is initiated with the training of a shallow neural network, which operates on the character vectors of the distinct stems existing in the raw text and aims to learn a finite set of text features defined beforehand. These features are the following:

Sentiment: Taking a classic sentiment analysis approach, we calculated the sentiment of the whole conversation's text as negative, neutral or positive based on the existence of sentimental weighted words in it. The source of these words was a SentiWordNet v3.0. Sentiment analysis has been shown to have correlations with the overall valence of the examined text [8], thus it is an important feature for training an automatic emotion detection system.

Transitional Sentiment: To extract the oscillations of the sentiment between the posts, we introduce the notion of transitional sentiment. First we compute the sentiment of each post in the discussion, in similar fashion as in the first feature, then we derive the percentage of times the discussion goes from one type of sentiment to another, divided by the total number of posts minus one (the number of transitions). This process concludes in a percentage number for each of the possible transitions, namely positive to negative, positive to neutral, neutral to negative, neutral to positive, negative to positive and negative to neutral. This feature captures the dynamics of the dialogue and its emotional escalation, a dimension of crucial importance in revealing the writers' and readers' emotional situation when they participated in that discussion.

As the aforementioned features operate on the word (stem) level, the input for the neural network would have an extremely high dimensionality, which can lead to the construction of overly large structure and the deterioration of performance. To avoid this, we apply two measures for reducing the dimensionality of the problem. First, stop words are removed from the initial text and are not taken into account in the remaining process. Second, consecutive sentences that are of low semantic distance are purged, holding only the first one for the remaining analysis steps. Semantic distance offers a temporal dimension to unexpectedness. Its notion represents the deviation from the expected and is defined as the difference of semantic coherence between the consecutive fragments of the text. The PSD of each thread was measured from the overall unified text of all the posts included in the thread, using the distinct sentences as fragments.

$$PSD(Sn) = \frac{\sum_{i=2}^{|F|} |D(F_i) - D(F_{i-1})|}{|F| - 1}$$

Where F is the set of sentences in the unified text. The function D is defined as the semantic coherence of a sentence:

$$D(F) = \frac{\sum_{i,j=1}^{|T_n|} sem(T_{ni}, T_{nj}), i \neq j}{|T_n|}$$

Where T_n is the set of the dominant terms in the sentence, in terms of TF-IDF , with volume $|T_n|$ analogous to 1/3 of the overall terms in the sentence. The terms are all filtered by a stop & offensive word removal process, and undergo stemming to ensure that two words with the same notion will not be considered distinct by the algorithm, but will count as the same semantic object. The function sem serves as the semantic difference between two terms, which is analogous to $0.75 * WordNet\ Distance + 0.25 * Levenshtein\ Distance$.

The trained network is incorporated in the deep neural network as the initialization of the deep learning component of the machine learning framework, essentially acting as an auto-encoder, i.e. a non-linear generalization of PCA used for pre-training deep architectures [9]. The unsupervised deep network layer is responsible for expanding the feature set handled by the neural network and results in an extended feature set associated with the overall problem at hand (associating text and valence). The final layer of the overall deep neural network is trained under supervision over the valence values provided by the training dataset.

2.1.3 GET EMOTIVE STATE FROM TEXT SERVICE

The trained module is used as the basis of a service for identifying the emotive response of humans to a given text. The service accepts as input the said text, and responds with the valence estimated by the machine learning component described in the previous subsection.

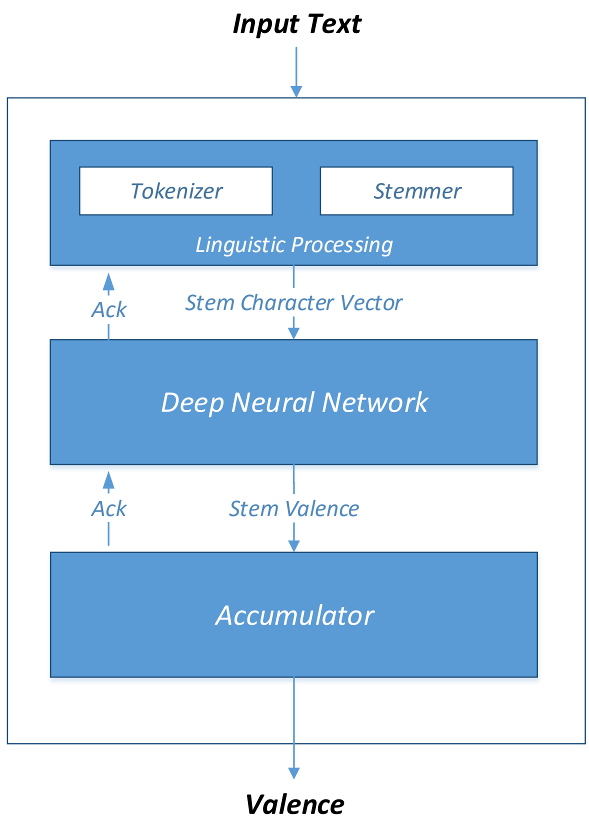

Figure 2: Workflow of the Text-Valence Association Service

2.2 ASSOCIATION OF EMOTIVE STATE WITH COLOUR

Visual stimuli are one of the most important factors that determine the emotive state and emotive response of humans. In particular, colour-emotion association is well documented and the subject of extensive research[2] [10]. In the context of C2Learn, the association of colours with emotions defined by Naz Kaya [11] was combined with the definition of the six basic emotions by Ekman and Friesen [12] in order to implement a service that associates any colour with a specific emotion.

Colour	Basic Emotion
Red	Anger
Orange	Shame
Yellow	Fear
Green	Greed
Blue	Confusion
Purple	Power

Table 1: Association of Colours and Emotions

The service accepts as input the RGB code for a colour. It then computes the Euclidean distance of the code from the RGB codes of the basic colours and return the emotion that corresponds to the basic colour closest to the input.

3. DISTRIBUTION OF EMOTIVE REASONING TOOLS SUITE

The source code for all the tools included in the Emotive Reasoning Tools suite has been made available under the GPL v3.0 License. The source code, along with requirements and usage instructions is available via GitHub, at the following link:

https://github.com/CRU-NCSRD/Emotive-Reasoning-Tools

4. EMOTIONS AND CREATIVITY

The aforementioned methodologies focused on the estimation of the emotions during the usage of an artefact (reading a text, seeing a pictorial representation). Another interesting aspect that is worth examining is the connection between emotions and creativity when creating an artefact. An initial investigation was carried out, using the deep neural network architecture described in section 2 of this document and the implementation of the computational creativity metrics described in deliverable D3.4, User Profiling and Behaviour Detection. As stated in the latter, an artefact is associated with four metrics with respect to the creativity exhibited through it: Novelty, Surprise, Rarity and Recreational Effort. The last two are combined to form the Impressiveness metric (equal to their average).

The connection between each of these metrics with the valence of the artefact as calculated by the deep neural network is tested by calculating the correlation of the vectors corresponding to each metric with the valence vector for the artefact.

We carried out the aforementioned investigation on two distinct datasets. The first dataset comprised transcriptions of European Parliament Proceedings [13]. 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.

[2] http://www.colorsystem.com/?lang=en

In total, we examined 50 distinct parliament sessions from the Europarl dataset and 40 chapters from the storybook.

Table 2 summarizes the acquired values for the four computational creativity metrics and valence for a 5-item sample of the aforementioned datasets.

		Computational Creativity Metrics				Valence
	Doc No.	Novelty	Surprise	Rarity	R. Effort	
Formal Verbal Transcriptions	1	0.05090	0.15521	0.16667	0.77820	0.245101
	2	0.11686	0.84821	0.25000	0.01014	0.64311
	3	0.04792	0.21635	0.14394	0.56020	0.214945
	4	0.07355	0.13729	0.05000	0.50697	0.12754
	5	0.01267	0.12373	0.25000	0.19011	-0.31651
Literary Work	1	0.05138	0.10716	2.00000	1.78925	0.21583
	2	0.05097	0.10142	0.26667	1.68172	0.66235
	3	0.03030	0.16625	0.26667	1.60000	-0.26402
	4	0.06409	0.08024	2.00000	1.41075	0.37431
	5	0.04940	0.14300	2.00000	1.69892	-0.14274

Table 2. Computational Creativity Metrics Values for Europarl and Storybook datasets

The following table summarizes the average correlation values between the three computational creativity metrics (Novelty, Surprise, and Impressiveness) and the valence for the two datasets.

	Novelty	Surprise	Impressiveness= $\frac{1}{2}$(Rarity+R.Effort)
Formal Verbal Transcriptions	0.38	0.12	0.04
Literary Work	0.31	0.51	0.01

Table 3: Correlation between Valence and Computational Creativity Metrics

As shown in the table, the correlation with Novelty is approximately constant on the two datasets. On the other hand, there is a strong discrepancy in the case of Surprise. Finally, Impressiveness seems to have a very weak correlation with the valence of the examined test.

5. EMOTIVE REASONING TOOLS IN GAMIFIED DEMONSTRATORS

This section presents House of Emotions, a gamified demonstrator built for showcasing the functionality of the services included in the ERT Suite.

5.1 HOUSE OF EMOTIONS GAME PLAY

House of Emotions is a multiplayer game, supporting sessions of two to five players. It takes place in a haunted house, at 23:30. The players have 30 minutes to turn on all the lights until the house ghost appears. This is achieved by carrying out different missions assigned to each player. The missions fall under the following categories:

a) Dramatization of an Emotion: The player is presented with an emotion and he / she is called to make a facial expression that reflects the particular emotive state. He / She captures this expression using the tablet’s camera. The rest of the players are called to guess the emotion dramatized by the initial player. Thus, the players are drawn to use Second-order Emotive Lateral Judgements in order to appropriately dramatize the emotion in ways that can be correctly interpreted by the other players.

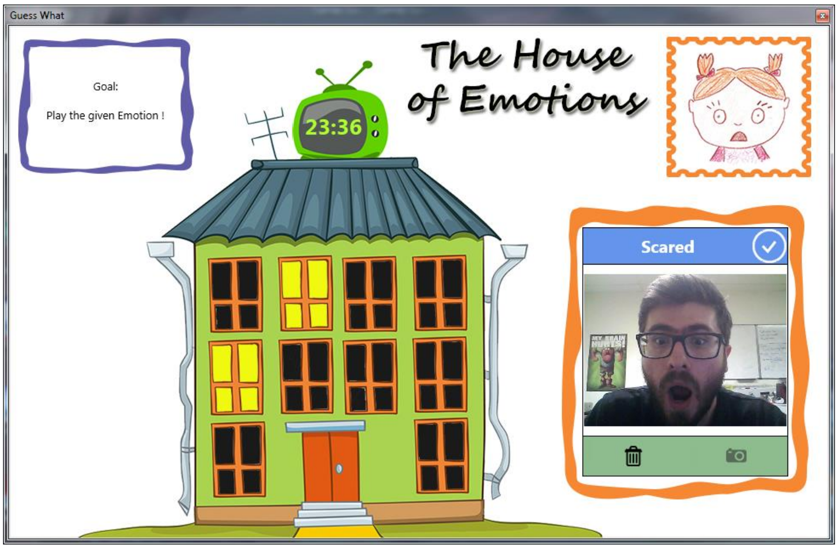

Figure 3: Dramatization of an Emotion

b) Pictorial representation of an Emotion: A player tries to produce a drawing the represents an emotion assigned by the Wizard. The rest of the players are called to correctly guess the emotion represented by the drawing.

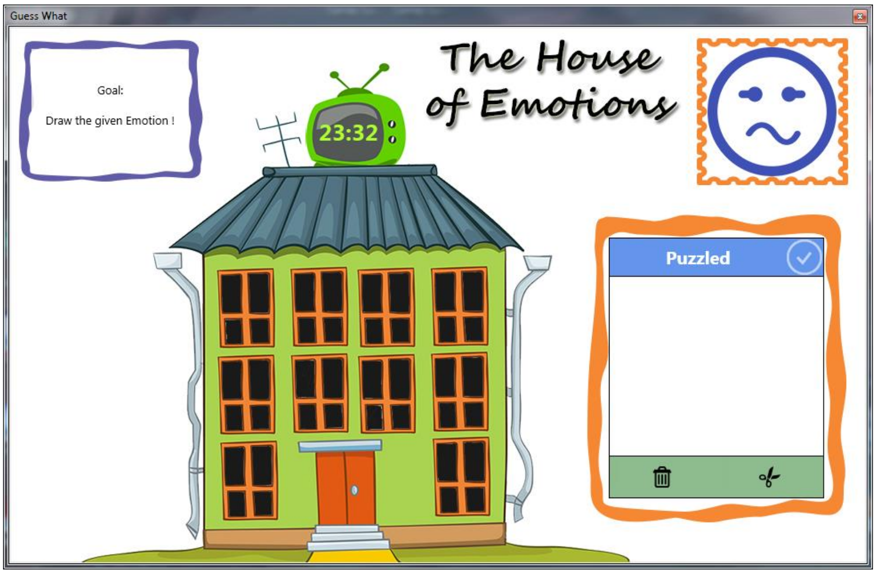

Figure 4: Pictorial Representation of an Emotion

c) Evoke a sentiment through text: The player is asked to write a short story evoking positive or negative sentiments. As he/she writes the story, the game evaluates the evoked sentiment and provides feedback on the player's progress towards the set goal.

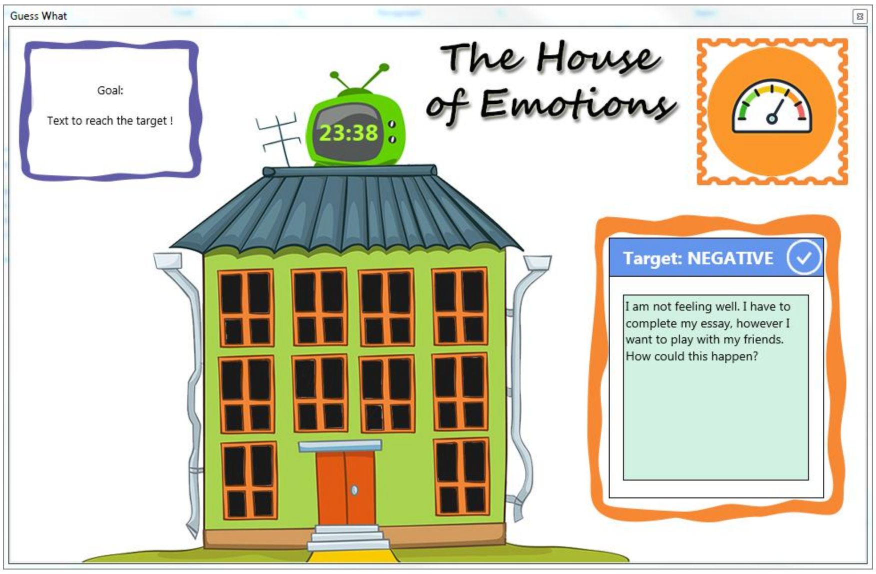

Figure 5: Evoke a sentiment through text

d) Associate an emotion with a colour: The player is assigned an emotion by the Wizard and is asked to select the colour most closely associated with the specific emotion.

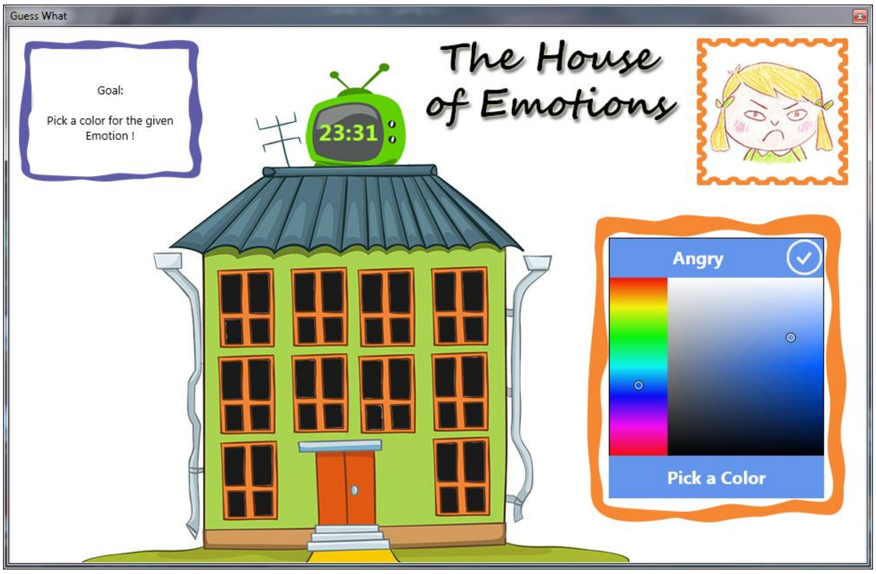

Figure 6: Associate an emotion with a colour

Beside the mission assigned by the Wizard, random events influence the players' progress, either positively (the Wizards turns on a light himself) or negatively (a disaster like fire, lightning or a wind gust turns off a light).

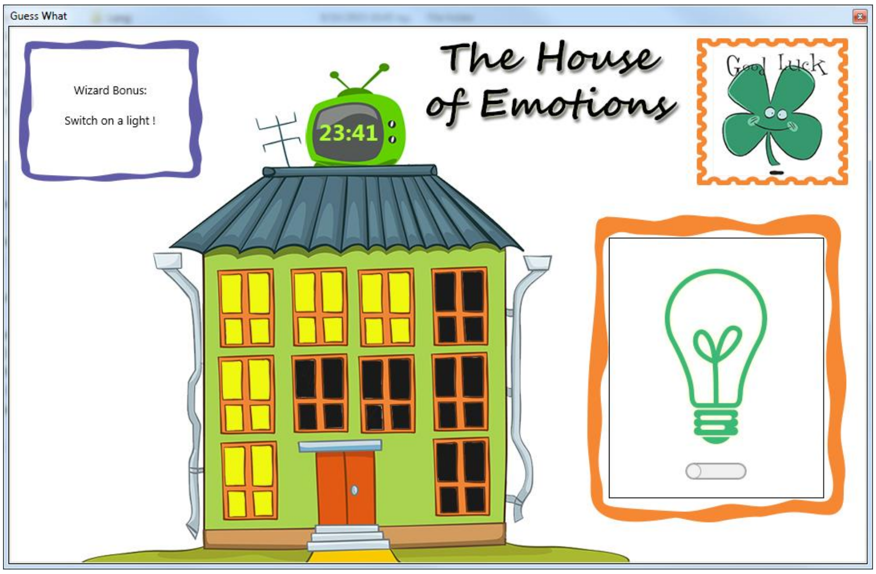

Figure 7: Light turned on by Wizard (Game Event)

5.2 HOUSE OF EMOTIONS USAGE OF EMOTIVE REASONING TOOLS

The two services comprising the Emotive Reasoning Tools suite are used in House of Emotions as part of the missions assigned during gameplay. More specifically, the challenge of evoking a sentiment via text uses the service for estimating emotive response to a text in order to assess the player's progress towards the established goal of the mission (i.e. result to a text fragment that carries positive or negative valence).

5.3 HOUSE OF EMOTIONS DISTRIBUTION

House of Emotions is available as an Android application. It is available for all Android devices running Android 4.2 or newer and having a screen size of at least 7". The Google Play Store link for the app is:

https://play.google.com/store/apps/details?id=com.cru.HouseOfEmotions

Furthermore, House of Emotions is available as a Win32 desktop application. The installer for the application can be found at the following link:

https://dl.dropboxusercontent.com/u/2915261/Creative%20Games%20Suite/HEInstaller.exe

For desktop PCs running Windows 10, the Creative Games Suite application is available via the Windows Store. The application provides access to the installers of all the gamified demonstrators (cf. also deliverables D3.1 and D3.2), including House of Emotions.

Figure 8: Creative Games Suite

6. DEMONSTRATION / DISSEMINATION ACTIONS

House of Emotions was used in various dissemination events, where the usage of the Emotive Reasoning Tools was showcased and the principles underlying the training process were presented.

6.1 NCSR-D SUMMER SCHOOL 2015

During the Annual Summer School organized by NCSR-D, two C2Learn actions have taken place:

- A talk around creativity, where the basic principles and concepts of human creativity are discussed. The presentation, titled Usage of Brain-Computer Interfaces on Modeling and Measuring Human Creativity, showcased computational creativity techniques that can be used for constructing the appropriate stimuli towards encouraging creative thinking, as well as, measuring different parameters related to it. The presentation focused on the incorporation of such techniques in digital games and the description of the methodologies for measuring the impact of these games on the creativity expressed by the players, using Brain-Computer Interfacing devices.
- A laboratory session, where the participating students were familiarized with machine learning techniques and were asked to carry out a machine learning training session using data from C2Learn activities.

6.2 EDUCATIONAL ACTIVITY (ONGOING)

NCSR-D organizes and runs weekly demonstrations of technological innovations for visiting primary and secondary schools. The CRU laboratory participates in the demonstrations, organizing brief gaming sessions using the games of the Creative Games Suite, including House of Emotions.

Until the finalization date for the deliverable (30/10/2015), twelve (12) schools represented by forty-five students each have attended the relevant workshops (540 students in total). The activity will be taking place until the end of May 2016, when it is expected that forty-four schools (approximately 2000 students) in total will have attended.

7. CONCLUSIONS

The present document describes the algorithmic design and the development of the C^{2}Learn Emotive Reasoning Computational Tools Suite, which aims to foster the Emotive Lateral Thinking techniques as defined by the theory, within C2Learn gaming environments.

Furthermore, the document describes the initial experimental investigation carried out in order to examine the connection between emotions and creativity via the computation of the correlation between the valence of a textual artefact and its scores on four computational creativity metrics. As the experiments showed, there is a relatively constant and substantial correlation between valence and novelty, which is a finding worthy of further research and analysis.

Finally, the report describes House of Emotions, a gamified demonstrator incorporating the Emotive Reasoning Tools suite, and showcases the exploitation of the relevant tools in a well-defined game design. Nevertheless, the exact usage of the C2Learn Emotive Reasoning Computational tools is dependent on the Game Design of each individual game and, thus, can be used from different games in different gaming platforms.

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