# Computational Creativity

**A**
**Seminar Report**

*by*

**Aakanksha N S**
**B130203CS**

Department of Computer Science and Engineering
National Institute of Technology, Calicut

Monsoon-2015

National Institute of Technology, Calicut
Department of Computer Science and Engineering

*Certified that this Seminar Report entitled*

**Computational Creativity**

*is a bonafide record of the Seminar presented by*

**Aakanksha N S**
**B130203CS**

*in partial fulfillment of*
*the requirements for the award of the degree of*
Bachelor in Technology
*in*
*Computer Science and Engineering*

---

**TA Sumesh**
*(Group Seminar Coordinator)*
*Department of Computer Science and Engineering*

**Acknowledgment**

This seminar is of immense value for any student as this experience gives one an opportunity to gain needed expertise in professional presentation as well as all the related work that goes in the preparation for the same. I have learnt a lot during the preparation for this seminar and I am quite confident that this would help a lot in my professional development as well as improve my public speaking abilities.

I would like to thank my group coordinator, TA Sumesh for giving me this opportunity of presenting a seminar on a topic of my choice and gaining deeper insight into the topic in this process. I would also like to thank my family and friends who served as a source of inspiration and helped me throughout the preparation.

**Abstract**

One of the most striking features that differentiates computers from human beings is the ability to think and the degree of creativity and innovation which is displayed by us in our behaviour. Human-level intelligence not only implies creativity on the grand scale, but mostly in daily activities like understanding intentions, emotions, behaviour and invention of new words. Even though there is still poor understanding of this subject, computational models may be used to implement speculative ideas about brain processes involved in creative thinking.

This seminar aims at covering certain prominent fields which have seen progress in the field of computational creativity such as:

1) Art: Humans have mastered the skill to create unique visual experiences through composing a complex interplay between the style and content of an image in fine art, especially painting. However,in other key areas of visual perception such as face and object recognition near-human performance was recently demonstrated by a class of biologically inspired vision models called Deep Neural Networks. We shall discuss two different approaches towards generating art using computers.

2) Inventing novel interesting names: A model of creative processes behind invention of novel words related to description of products and services will be discussed.

3) Music : Computational creativity in the music domain has focused both on the generation of musical scores for use by human musicians, and on the generation of music for performance by computers.

# Contents

# 1 INTRODUCTION

From the beginning of the modern computing era, possibilities of machine intelligence with reference to creative arts have been questioned by notable experts. Logical-mathematical and linguistic forms of intelligence are measured in IQ tests, but artistic, spatial, musical and bodily-kinesthetic intelligences are of a different kind. Interpersonal behaviour, including emotional intelligence, is also quite different and does not necessarily have correlation with other types of intelligence. One can exhibit creative, intelligent behaviour in all these areas [4]. As a society, we humans take pride in our creativity: creative people and their contributions to progression of culture are given great value. Creative behaviour in people draws on a full set of intelligent abilities, so simulating such behaviour computationally poses a serious technical challenge for Artificial Intelligence research. However, neuroscientific and psychological literature argues strongly that creativity is a product of ordinary cognitive processes and as such should be amenable to computational modeling.

Computational creativity is an interesting and challenging discipline that is located at the intersection of the fields of artificial intelligence, philosophy, cognitive psychology and the arts. It aims to model, stimulate or replicate creativity in a computer, to achieve one of several ends:

- to construct a computer or program capable of human-level creativity
- to get a better understanding of human creativity and formulate an algorithmic perspective on human creative behaviour
- to design programs to enhance human creativity without necessarily being creative themselves

Creativity is manifested in various areas, including invention of new ideas and concepts or production of objects of music and art. The degree of creativity involved in different activities is largely dependent on the cultural context at a given point of time. There has been significant research and development relating to artificial creativity in many areas. Langley, Bradshaw, Simon and Zytkow proposed heuristic search-based AI models for modeling creative processes that led to historical scientific discoveries [10]. Application to astronomy, elementary particle physics, chemistry, superconductivity and biology, [11] [10] [9] generated some interesting models too.

# 2 NEUROCOGNITIVE APPROACH TO CREATIVE AND INTUITIVE COMPUTING

Human brains are the only highly intelligent devices that can solve all kinds of complex problems. The "g-factor" used to measure intelligence has high correlation with working memory capacity, discrimination and choice reaction times, perceptual speed, the structure of event-related potentials (ERP), cerebral glucose metabolic rate, and nerve conduction velocity during cognitive activity [8]. Brains of intelligent and creative people probably differ in the density of synaptic connections, contributing to the richer structure of associations, and more complex waveforms of the ERP potentials. The structure of these potentials is dependent on the neural connections density and speed of neural signal transmission. Incoming stimuli are transformed into visual and auditory streams basic quantized elements, such as phonemes or edges with high contrast by Sensory systems. Larger patterns are formed from these elementary building blocks, building discrete representations for shapes and words, and at the working memory level of whole scenes and complex abstract objects[4].

Computational Problems requiring creativity are difficult to solve because neural circuits representing object variables and features that characterize the problem have only weak connections, and there is very small probability of forming appropriate sequence of cortical activities. The preparatory period - reading and learning about the problem - introduces all relevant information, activating corresponding neural circuits in the language areas of the dominant temporal lobe, and recruiting other circuits in the auditory,visual, motor and somatosensory used in extended representations .

Results of theoretical and experimental research lead to the following conclusion: neural processes are involved in creativity that are realized in the space of neural activities reflecting relations in some domain, with two essential components: 1) distributed chaotic (fluctuating) neural activity constrained by the strength of associations between subnetworks coding different concepts or words, responsible for imagination, and 2) filtering of results that are interesting, amplifying certain associations, discovering partial solutions that may be useful in view of the goals set. Filtering is based on forming associations, priming expectations, arousing emotions, and in case of linguistic competence on semantic and phonological density around words that are spontaneously created [4].

# 3 COMPUTATIONAL CREATIVITY AND ART

Genetic algorithm can serve as a very useful means to create art products. There is also an artificial system that creates artistic images of high perceptual quality that is based on a Deep Neural Network. Neural representations are used by the system to separate and recombine style and content of arbitrary images, providing a neural algorithm to create artistic images. However, it is very difficult to define the proper criteria for the fitness evaluation of art products. Furthermore, defining quantitative metrics based on qualitative criteria, is still a very challenging research area.

## 3.1 Generating Art Tile Patterns using Genetic Algorithm

The tile industry is one of the oldest industries and needs new methodology to improve its traditional policy and increase its performance and efficiency. Designing new up-to-date tiles is one of the most challenging issues that needs a considerable amount of time, expertise in designing, and is usually a very expensive process. Hence, an algorithm to do the same using computers has been proposed by Mostafa and Seyed in [7]. We shall discuss this algorithm in detail:

A very simple genetic algorithm has been proposed for generating art tile patterns, in which only one chromosome is taken as the initial population, reproduction and mutation is used to generate offspring, and the best offspring in iterations is selected. This is done using the following steps:

1. Representation:

   Only a quarter of the whole tile pattern is taken as a chromosome since most art tile patterns are symmetric. Figure 1 shows a tile and B is a segment that we use as a chromosome. It is sufficient to mirror

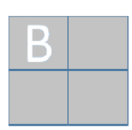



Figure 1: A quarter of the tile is considered as a chromosome. [7].

this basic element (B) horizontally for the right section, vertically for bottom section, and both for the last section, to construct a whole tile from this chromosome (Basic Element). Figure 2 shows how this is done.

Figure 2: Construction the whole tile from a chromosome. [7].

2. Initial Population:

   The population size is assumed to be 1 initially and the first population values are uniformly selected in the range of 0 to 255. Fig.3 shows an initial population sample.

Figure 3: Sample of initial population. [7].

3. Replication and Mutation:

   To generate offspring (child) 100 replications from the parent are created and the only evolutionary operator used is mutation. Here three different mutations are randomly used:

   1- Swapping the value of two random points

   2- Copying the value of a random point to another random point

   3- Assigning a random value to a random point

4. Fitness Evaluation:

   All the 100 children and the only parent can be candidates to be alive for the next generation. Given below is the cost function used to evaluate each candidate , where D means differential, H stands for the histogram and L is a constant value. The first term counts the differential of the value of every point with the next neighbor point in rows. The second term counts the differential of the value of every point with the next neighbor point in columns. The last term calculates the difference of image histogram from desired equalized histogram.

$$Cost\ function = \sum_{ij} D(p_{i,j}, p_{i+1,j}) + \sum_{ij} D(p_{i,j}, p_{i,j+1}) + \sum_{graylevels} D(H(img), H(equalized)$$ [7]

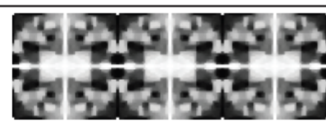
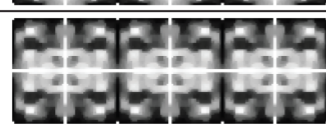
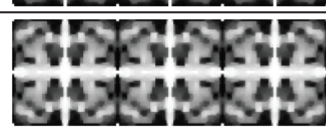
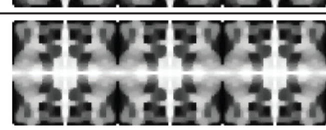
5. Selection:

   To select a candidate to be alive for the next generation,the algorithm simply ranks the candidates according to the mentioned cost function. A candidate with minimum cost function is selected and the others are removed.

6. Termination Conditions:

   Experimentally, 15000 iterations was determined as the termination condition.

The table below shows results of several runs of the algorithm:

| Row No. | Basic Element | In Each Row Three Tiles Is Repeated for Better Showing The Results. |
|---|---|---|
| 1 |  |  |
| 2 |  |  |
| 3 |  |  |
| 4 |  |  |

[7]

## 3.2 Art using Convolutional Neural Networks [5]

Convolutional Neural Networks are the most powerful of Deep Neural Networks in image processing tasks. They consist of layers of small computational units that process visual information hierarchically in a feed-forward manner. Each layer of units extracts a certain feature from the input image. It can be understood as a collection of image filters. Thus, the output of a given layer consists of what are called feature maps: differently filtered versions of the image given as input.

A representation of the image that makes information about the object increasingly explicit along the processing hierarchy is developed when Convolutional Neural Networks are trained on object recognition [6]. Therefore, along the processing hierarchy of the network, transformations of the input image into representations that increasingly focus on and care about the actual content of the image compared to its detailed pixel values takes place. The high-level content in terms of objects and their arrangement in the input image is captured by higher layers in the network, but they do not constrain the exact pixel values of the reconstruction and this is known as feature representation.

To obtain the style representation of an input image, we use a feature space designed originally to capture information about texture. This feature space is built on top of the filter responses in each layer of the network. It consists of the correlations between the different filter responses over the spatial extent of the feature maps. By considering the feature correlations of several layers, we obtain a stationary, multi-scale representation of the input image, capturing its texture information and not the global arrangement.

In Figure 4, at each processing stage in the CNN, A given input image is represented as a set of filtered images. While the number of different filters increases along the processing hierarchy, the size of the filtered images is reduced by some downsampling mechanism leading to a decrease in the total number of units per layer of the network. **Content Reconstructions**:The information at different processing stages can be visualised in the CNN by reconstructing the input image from only knowing the network's responses in a particular layer. We reconstruct the input image from from layers 'conv1 1' (a), 'conv2 1' (b), 'conv3 1' (c), 'conv4 1' (d) and 'conv5 1' (e) of the original image. We find that reconstruction from lower layers is almost perfect (a,b,c). In higher layers of the network, even though detailed pixel information is lost, the high-level content of the image is preserved (d,e). **Style**

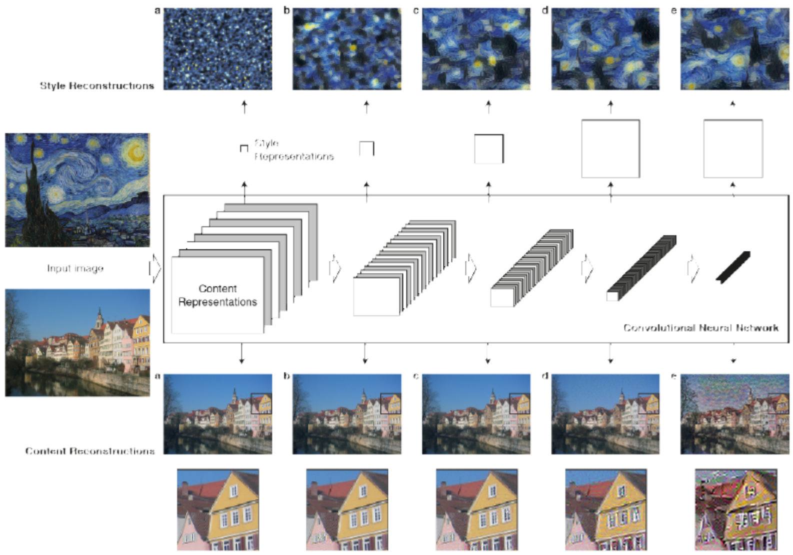



Figure 4: Convolutional Neural Network (CNN).[5]

**Reconstructions**: On top of the original CNN representations we built a new feature space that captures the style of an input image. The style representation computes correlations between the different features in different layers of the CNN. We reconstruct the style of the input image from style representations built on different subsets of CNN layers ( 'conv1 1' (a), 'conv1 1' and 'conv2 1' (b), 'conv1 1', 'conv2 1' and 'conv3 1' (c), 'conv1 1', 'conv2 1', 'conv3 1' and 'conv4 1' (d), 'conv1 1', 'conv2 1', 'conv3 1', 'conv4 1' and 'conv5 1' (e)). This creates images that match the style of a given image on an increasing scale while discarding information of the global arrangement of the scene [5].

Of course, image content and style cannot be completely disentangled but they have been separated to a large extent using CNN. Figure 5 shows how style and content from different sources can be mixed to achieve a completely new artwork. In the figure, Images that combine the content of a photograph with the style of several famous artworks are shown. The images were created by finding an image that matches the content representation of the photograph and the style representation of the artwork simultaneously. The original photograph depicting the Neckarfront in Tubingen, Germany, is shown in A. The painting used for providing the style for the respective generated image is shown in the bottom left corner of each panel.

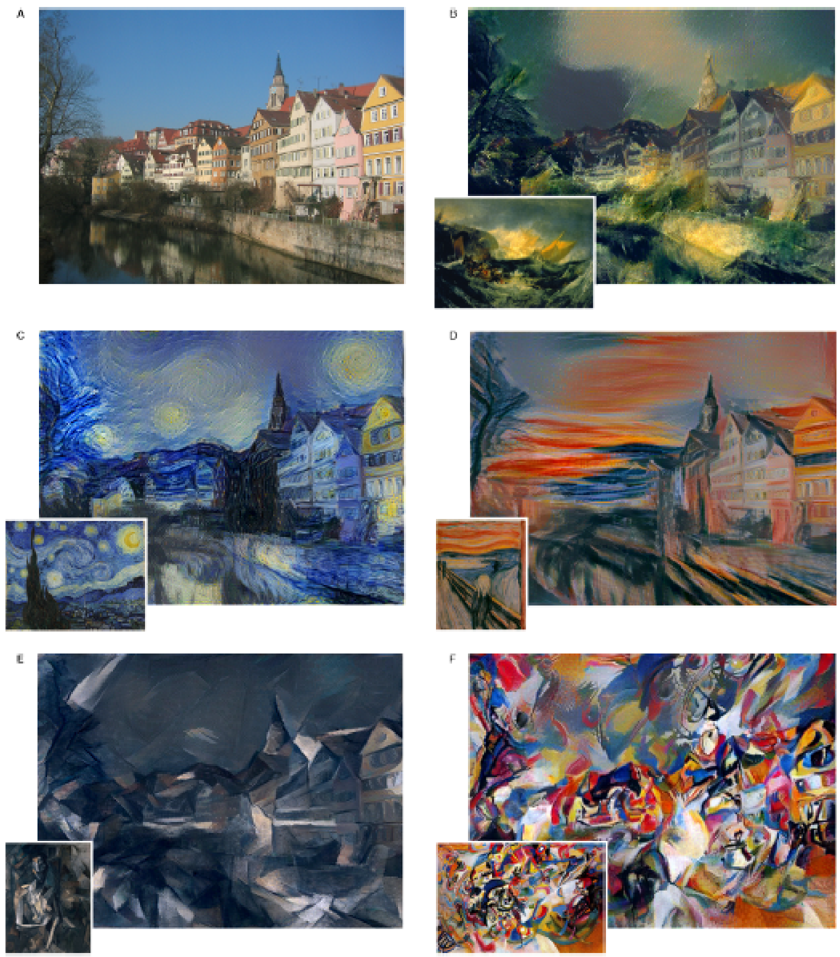



Figure 5: Images that combine the content of a photograph with the style of several well-known artworks.[5]

# 4 USING COMPUTATIONAL CREATIVITY TO GENERATE NOVEL INTERESTING NAMES

The problem to be solved here is: given a description of some object (product, organization, service, internet site,invention) create a new name that can be easily remembered and that reflects some qualities strongly associated with the object itself. The proposed algorithm discussed here takes as input, a short description or a set of words related to the topic, and optionally the number of iterations for searching related words in the database. The extended set of words is then used to obtain from dictionaries all inflections, derivations, irregular forms of verbs, etc. The result of this process is a set of priming words W that represents immediate associations potentially arising in the brain of an intelligent person. For example, the input word 'sing' is transformed into 'sing, song, music' and so on. The result set of words is considered as priming set. It should be matched to the set of all words, representing the background knowledge of the linguistic system. Here is an outline of the algorithm: The number of occurrences of every possible word w belonging to W in a large corpus is counted. Next, each word is split into n-grams, and those are put in the matrix - the n-gram determines the position within the matrix, while its occurrence count determines the value of the matrix element. The way this value is calculated depends on the settings of the program: it could be raw counts, binary values (0 for absent, 1 for present), probabilities and so on. When done, values in entire matrix are recomputed - depending on settings, it can be a normalization of the matrix, or just a row, or clipping the values to given range (typically 0-1), etc. This ends the procedure of calculating first matrix representing general knowledge of statistical relations in a given language. The priming set is now used to build the second matrix, representing active subpart of the general knowledge. After the estimation of likelihood that some n-grams are more probable than another are calculated for both sets of words - those taken from the dictionary and those from the priming set - the two matrices are added (alternatively maximum values maybe selected for each cell). This is based on assumption that priming increases probability of well-established associations in an additive way. The most active n-grams form the final matrix are combined to create new words [12]. These steps are presented in the diagram below.

The newly created word should pass several filters like: the rank of the word should not be too low, it should not closely resemble any other word in the dictionary (one can also check that it is not a substring of some other word or potentially offending words), and it should be associated with the priming words through overlapping n-grams. Novel words satisfying these conditions are added to the result set, and when this set grows too large words with lowest ranks are removed.

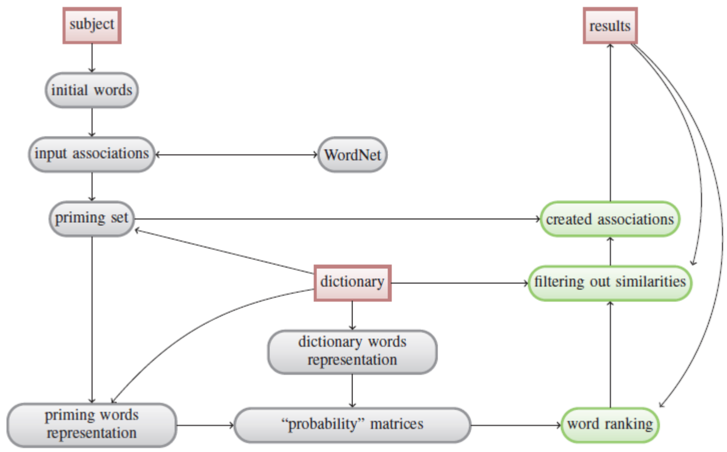



Figure 6: Workflow of the data, input and output are marked with red rectangles, processing steps - with ovals [12].

Many words have been generated using this algorithm. For example: *bookist, boomation, bookstion, cablects, cablected, cablector,collead, dataction, datamation, datnews, datmation, easnews,educatics, electroad, explobal, goinmation, gonewsy, infordata,inforld, inforlds, inforion, infornews, infortion, infonews, inforvel,infravel, lighbooks, newsion, newstion, papnews, travelation,travelnews, wentnews*[12]

# 5 MUSIC AND OTHER FIELDS

## 5.1 Music

The domain of generation of music using computers has included classical music and jazz. Perhaps the most notable work is by David Cope[2], who has written a software system called "Experiments in Musical Intelligence" (or "EMI" [3]) that has capability of analyzing and generalizing from existing music by a human composer to generate new musical compositions of the same style. EMI's output is convincing enough to persuade human listeners that its music is human-generated to a high level of competence.

### 5.2 Joke Generation

Humour is an especially tricky process, and the most successful joke-generation systems to date have focussed mostly on pun-generation, as exemplified by the work of Kim Binsted and Graeme Ritchie [1]. This work includes the JAPE system, which can generate a wide range of puns that are consistently evaluated as novel and humorous by young children.

### 5.3 Other fields

Apart from these, creativity using computers has been successfully used in storytelling activities, metaphor and simile generation, poetry and numerous other fields.

## 6 CONCLUSION

Computational Creativity is an interesting and emerging field of computer science. Even though there is still a long way to go before computer creativity levels can match those of humans, there have been tremendous advancements towards achieving this goal in the past decade. There is active research going on in numerous fields so as to incorporate artificial creativity and intelligence into them.

One day, we will expect the Internet to provide new ideas and new artefacts on demand, just like we expect it right now to provide old ideas and old artefacts. We will go online for: a new and relevant, joke for a speech; a new and exciting recipe for a party; or a beautiful new painting for a present. We cannot expect the world's creative people alone to supply artefacts for such a huge demand, so autonomously creative software will be required. The research undertaken in Computational Creativity projects will be pivotal in bringing about this technological and cultural revolution.

# References

[1] Kim Binsted, Helen Pain, and Graeme Ritchie. Children's evaluation of computer-generated punning riddles. *Pragmatics & Cognition*, 5(2):305–354, 1997.

[2] David Cope. *Computer models of musical creativity.* MIT Press Cambridge, 2005.

[3] David Cope and Melanie J Mayer. *Experiments in musical intelligence*, volume 12. AR editions Madison, WI, 1996.

[4] W. Duch. Computational creativity. In *The 2006 IEEE International Joint Conference on Neural Network Proceedings*, pages 435–442, 2006.

[5] Leon A Gatys, Alexander S Ecker, and Matthias Bethge. A neural algorithm of artistic style. *arXiv preprint arXiv:1508.06576*, 2015.

[6] Leon A Gatys, Alexander S Ecker, and Matthias Bethge. Texture synthesis and the controlled generation of natural stimuli using convolutional neural networks. *arXiv preprint arXiv:1505.07376*, 12, 2015.

[7] M. Heidarpour and S. M. Hoseini. Generating art tile patterns using genetic algorithm. In *Fuzzy and Intelligent Systems (CFIS), 2015 4th Iranian Joint Congress on*, pages 1–4, Sept 2015.

[8] Arthur Robert Jensen. The g factor: The science of mental ability. 1998.

[9] Sakir Kocabas and Pat Langley. An integrated framework for extended discovery in particle physics. In *International Conference on Discovery Science*, pages 182–195. Springer, 2001.

[10] Pat Langley. *Scientific discovery: Computational explorations of the creative processes.* MIT press, 1987.

[11] Pat Langley and Randolph Jones. A computational model of scientific insight. *The nature of creativity: Contemporary psychological perspectives*, 177:201, 1988.

[12] Maciej Pilichowski, Wlodzislaw Duch, et al. Braingene: Computational creativity algorithm that invents novel interesting names. In *CIHLI*, pages 92–99, 2013.