Resumen

Abstract

Dedicatoria

Dedico este trabajo a mi esposa Iliana Durón Landero por el apoyo incondicional que brindaste durante todo el proceso.

“Sabemos muy poco, y sin embargo es sorprendente que sepamos tanto, y es todavía mas sorprendente que tan poco conocimiento nos de tanto poder.” – Bertrand Russell

“Después de todo,cualquier tipo de conocimiento implica auto-conocimiento”– Bruce Lee

“El conocimiento descansa no solo sobre la verdad sino también sobre el error.”– Carl Jung

“El conocimiento depende del tiempo, mientras que el saber no. El conocimiento es una fuente de acumulacin, de conclusin, mientras que el saber es un continuo movimiento.”– Bruce Lee

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Chapter 1

Introduction

It is a reality that the World Wide Web in recent years, is growing exponentially, which means the presence of millions of users on Web sites, Web applications, Web systems, etc. [1]. There is a wide variety of Web systems, where we have different users interacting with them. These users have different goals when using these Web systems. For example to serching in Google [55] for a particular topic, make a reservation for a room in a luxury resort, check their bank account or simply checking their Facebook account status [14].This variation of users represents a complex diversity as individuals []. This diversity lies in the fact that users have different skills, interests, preferences, knowlage defferent ways of thinking and learning.For this reason users most to interact with the information presented by existing Web systems.

When we intend to customize any element in Web system, it is necessary to some personal information about the user. This information is a collection of needs, characteristics, tastes, preferences among others. This information allows designers to build a representation of knowledge about the users. This is what is known as user modeling (UM).

In order to understand specific users a user model must be constructed, this can be simple as a profile where the basic knowledge recorded. Or it can be as complex as complete representation of it's characteristics, needs, interests and preferences. In order to understand specific users. The main goal of user modeling is to represent aspects of the real world of the user's in an autonomous way.

On the other hand, interactive evolutionary computation (IEC) is a branch of evolutionary computation where users become a part of the evolutionary process by replacing the fitness function; evaluating individuals of a population based on their personal preferences[13]. These evaluations are subjective according to the user point of view based on their perceptions, interests and desires.

Normally such systems require users to evaluate large amounts of individuals actively, causing them to lose interest in participating by the fatigue that is generated[13]. Nowadays some of these systems are migrating to Web technologies looking for volunteer users to collaborate in the evaluation for distribute the load and lower the fatigue. Having Web- based interactive evolutionary systems opens the possibility of linking to social networks platforms in order to involve a larger number of users to assist in the evaluation of individuals produced by these systems.

This research presents a user-cetered framework that involves several techniques such as graph-based user modeling, fuzzy logic and human-interaction in the context of a Web-based interactive evolutionary computation. The purpose of this research is to increase voluntary participation of the users using the proposed framework.

1.1 Outline

- **Chapter 2**, describes an in-depth study of current and related works, presenting a general overview of Interactive evolutionary computation and their evolution in the pass and recent years, also user model approaches and finally gamification paradigm. This study includes Interactive evolutionary computations methods and techniques to understand how they work, as well as their problems of these systems. On the other hand this study also includes user modeling methods in order to understand how to create and apply them for certain necessities. Finally we discussed a gammification usability paradigm to understand how it work and subsequently apply this for the necessities of this work.

- **Chapter 3**, describes the fundamental concepts that form the basis of the proposed user-cetered framework.

- **Chapter 4**, presents a user-centered framework for interactivity Web-based applications, this proposed framework involves different paradigms in order to increase user participation. This chapter also includes the overall explanation of how the functionality the proposed framework works.

- **Chapter 5**, the case study is presented along with the explanation of the experimentation for this work. The experiments were realized using several versions of the same application in order to see which of them have most user participation.

- **Chapter 6**, The results of the case study are presented. This chapter includes all the data obtained from the experiments, these data are presented to see which of the versions meets the best performance regarding the increase of participation of users.

- **Chapter 7**, finally the conclusions and future work of this research are exposed.

At the end, this thesis includes appendices that describe detailed technical aspects about installation EvoDrawings application on heruku The rules of the fuzzy inference system are presented in

Chapter 2

State of the art and background

This chapter describes an in-depth review of current and related works, presenting a general overview of Interactive evolutionary computation and their evolution in the pass and recent years, also user model approaches, In the same way some works were review that contain the fuzzy logic concept and finally gamification paradigm is also review.

2.1 Interactive Evolutionary Computation.

This technology is branch of evolutionary computation. Based on subjective human evaluation. Basically, this technique requires that the objective function is replaced by a person (user) [12]. Takagi defines it as "A optimization technology that uses

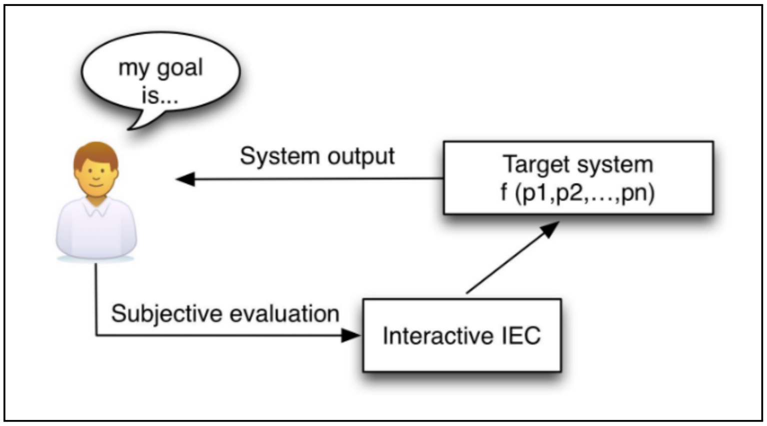

Figure 2.1: General Interactive Evolutionary Computation system based on subjective evaluation.

human evaluation in the optimization system instead of a human evaluation model. Simply stated, the interactive EC is an EC whose fitness function is replaced by a human. In figure 2.1 we show a general IEC system.

In this general IEC system we note that the user replaced the fitness function at the moment he or she interacts with the system. Logically the user needs a goal to know what is the evaluation he or she needs to perform. Finally the users receive an output and the process and start over again.

These techniques have been used in several areas of application, in particular:

- Music and sound.
- Digital Art.
- Design and editing documents

- Processing acoustic signals.
- Industrial design.
- Data mining and acquire knowledge.
- Face recognition.
- Robotics and control.

Below are some of the most outstanding works in the interactive evolutionary computing area, which are the following:

Dawkins's research was the pioneer of a significant addition to the 1990s IEC algorithms research works[16].

There is two key research approach about his field:

- **Creative Approach:** The Artificial Life (AL) was the base of creative approach. AL uses complex algorithms for biological life models emulation. To perform this task, it is needed to include some of the different techniques starting from right image treatment. Good graphic creation as well as a great music and quality sounds, [66], [68], [16], [21], [79]and [80].
- **Humanized technology approach:** The concept of humanized technology approach comes from the approach that is focused on the IEC algorithms interface, this is the research of interaction between humans and computer

systems. The main goal of this was to reduce the user's fatigue and to promote the inputs and outputs of algorithms to improve the efficiency of them. IEC has made his own way in practical fields such as engineering, education,etc., [57], [81], [72], [60], [58] and [71].

Computer graphics (CG) The Biomorph of Dawkins was the first IEC research, from this research comes to many motivated works mostly about the Selfish Gene, come of these works are: [52], [42].

In Dawkins work, a conventional recursive algorithm was used as a baseline maintaining the main target of trees with an L-system (Lindenmayer). This same L-system was the base for another experiment to create 2-D CG forms insects from a system called Blind Watchmaker who used L-system angles from L-system output intuitively selected; the creation was called biomorphs. These creations reach his target with the multiple selections of the users based on their preferences; all these selections acted like a natural adaptation filter.

We can find plenty of applications and works for fractal generation and [67], [4] and [5], [40], or [2],[61][Raynal 1999] and [41], for rendering in tridimensional, [75],[11], [15][Das 1994] and [73], for generation of virtual creatures, [64], or aerodynamic surface design (wings), [50], [49] and [][NGuyen 1997].

We can discover more than one additional way to use this research in the artistic field with several applications of IEC who are used for cartoon face construction and

Figure 2.2: Panspermia.

animations matters, like Mutator [76] and [77] or [6].

The genetic programming (GP) applications offers a category called Interactive Genetic Programming (IGP) with many examples of successful application in tridimensional artwork for artistic animations or construction using mathematical equations as CAVE [15], [56] and [21], [66], [67] and [46]. As this work consequence, Panspermia or Primordial Dance was created that are presented in figure 2.2 and figure 2.3.

The artistic field is only the first step of a great IEC implementation; it is important to mention another relevant projects called Galapagos, [69], and SBART, [79]. The IEC application Galapagos Project is the exhibit in Tokio Multimedia

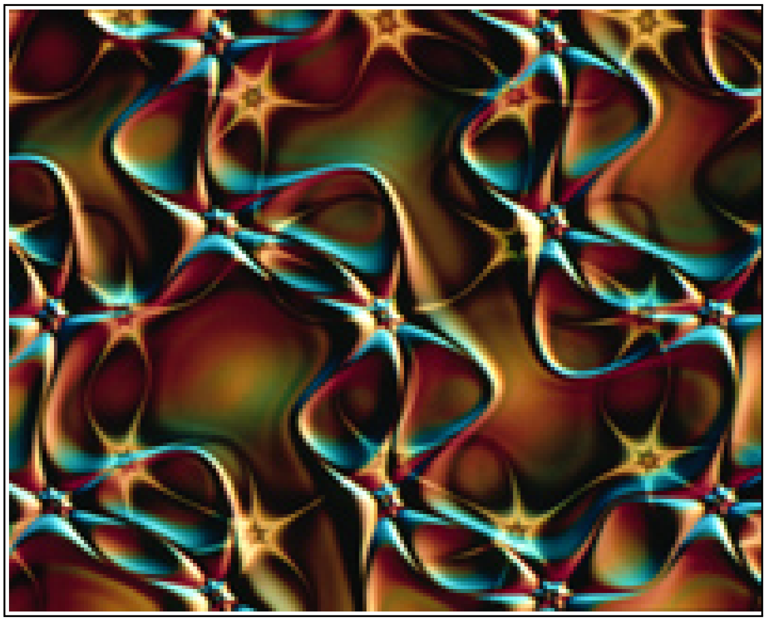

Figure 2.3: Primordial Dance.

Museum, (NTT Intercommunication Center) and this project originates engaging images to all visitors based on L-systems as we can see in figure 2.4 and figure 2.5.

There are created after one selection, to get a good solution through multiple repetitions. This action is performed with Genetic Programming (GP), after the calculation of each pixel value using trees of equations combining logarithm, maximum,

Figure 2.4: Galapagos: Tokio Multimedia Museum.

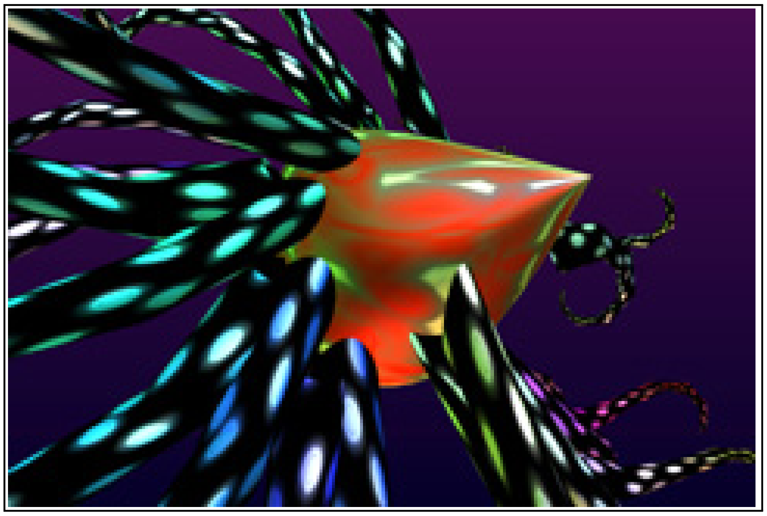

Figure 2.5: Galapagos' output sample.

and minimum, sine, root, cosine, exponential arithmetic operators. AnimationLab is found as an outstanding work who offer figures that can run or walk working with the user to receive more opportunities to be picked. A particular characteristic of all of the figures is that the figures extremities Mentioning open source works, we can find SBART as an IGP [79] tool to create graphics. SBART allow to users to evaluate 20 two-dimensional images, subsequently twenty new image has direction and angles as we can see in figure 2.6.

There are many examples for this field application as [44], [81], or [82], [38] and [39]. One of the Interactive Evolutionary Programming (IEP) artistic application was created by [2], as a fractal generation where the system allows the evolution of animations for the ones who were selected from the user, the application initially show only 10 animations to rate.

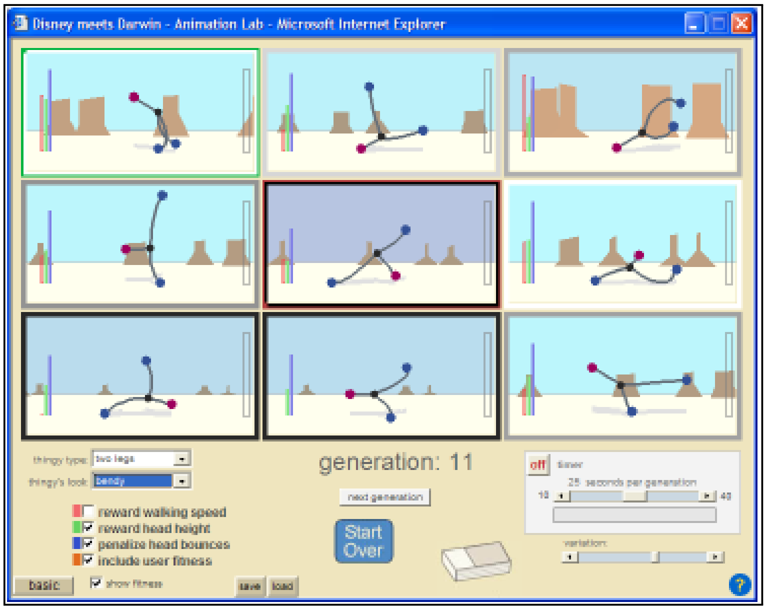

Figure 2.6: Animation Lab.

It is important to know how IEC was implemented in music generation, with several applications in this field. We will start mentioning the pioneer application GENJAM, [7], [8] or [9] and [10]. Some other attractive works are Sonomorph, [47] and [48], or SBEAT, [80], [30], [54], [78] and [23]. It is possible to hear a part of the music songs of these previously mentioned works broadcasted in the radio station WDYN. (100.1, New York, USA, WEBPage:http://www.wdyn.net/).

The IEC algorithms are the base for the functionality of the music generation systems, a visual representation of this is given in the below figure 2.7:

In 1998, a new input method for human operators of an interactive genetic algorithm to reduce the psychological weight is proposed. This method uses a discrete

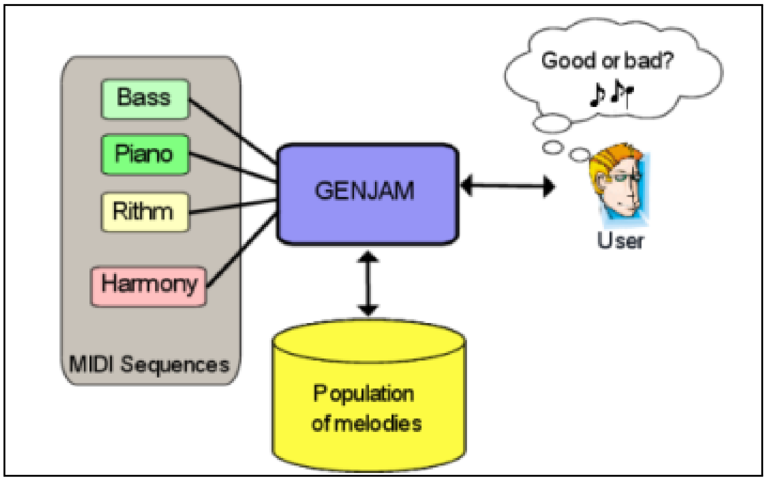

Figure 2.7: GENJAM squeme.

fitness values to reduce the psychological stress involved in the input procedure. They perform simulations to investigate the influence of the resulting quantization noise from the use of discrete values of fitness in convergence. Showing that the quantization noise does not significantly worsen in the convergence. In this method they evaluated using two subjective tests involving the task of drawing faces.

The subjective test results shows that this method significantly reduce the level of psychological stress of human interactive genetic algorithms operators [53]. Another approach, proposed to used novel method evaluation. Where the user only evaluates a satisfactory or unsatisfactory individual. These approach consider the level of sensibility of the different users to their perception of the beautiful and the ugly, and fitness is automatically calculated based on user evaluations and time. They also propose effective strategies for comparing different individuals of the same generation in uncertain fitness conditions of an individual. Where they obtains the probability of an individual dominance by use of the probability of the interval domain, and translate to a fuzzy number in a range based on -cut set [25]. They determine the dominant individual in tournament selection with size being two on base given by the probability of a particular domain. This approach was applied to an interactive evolutionary system for fashion design. In figure 1 we can see different user interfaces they used. Based on this approach, another work was de-rived. Where the approach adopt a fuzzy number described with a Gaussian membership function to express an individual's fitness. In order to compare the different individuals, they generated a fitness interval based on a cut set, and obtain the probability of interactive genetic algorithms with individual's fuzzy fitness. The contributions in this approach can improve the performance of existing income generating activities in alleviating user fatigue and finding optimal solutions to an optimization problem, so it is beneficial for solving complicated problems with implicit or fuzzy indices [26] we can see the user interface in figure 2.8.

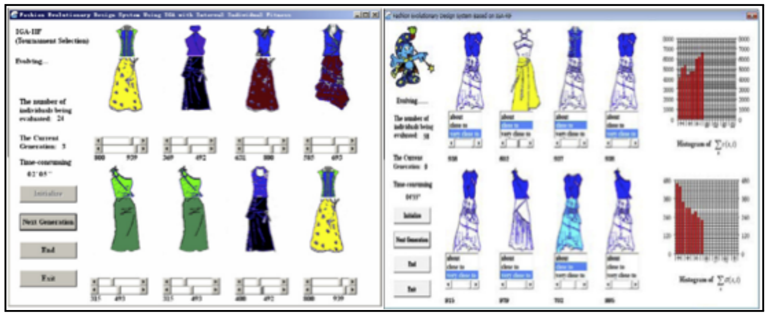

Figure 2.8: Different user interfaces interactive evolutionary system for fashion design.

2.1.1 Web-Based IEC aplications .

Picbreeder.

Picbreeder is a Web-based application that allows users to evolve images in a collaborative way maintaining a large catalog of user-created content allowing users collaboration by searching through extensive design spaces [65]. Picbreeder provides to users of all experience levels to enjoy all the creative contributions produced by other users. In this way users experience a new form of recreation called creative social recreation through collaborative exploration. In this sense these systems helps their users to find interesting images through tagging, browsing and searching as figure 2.9 show.

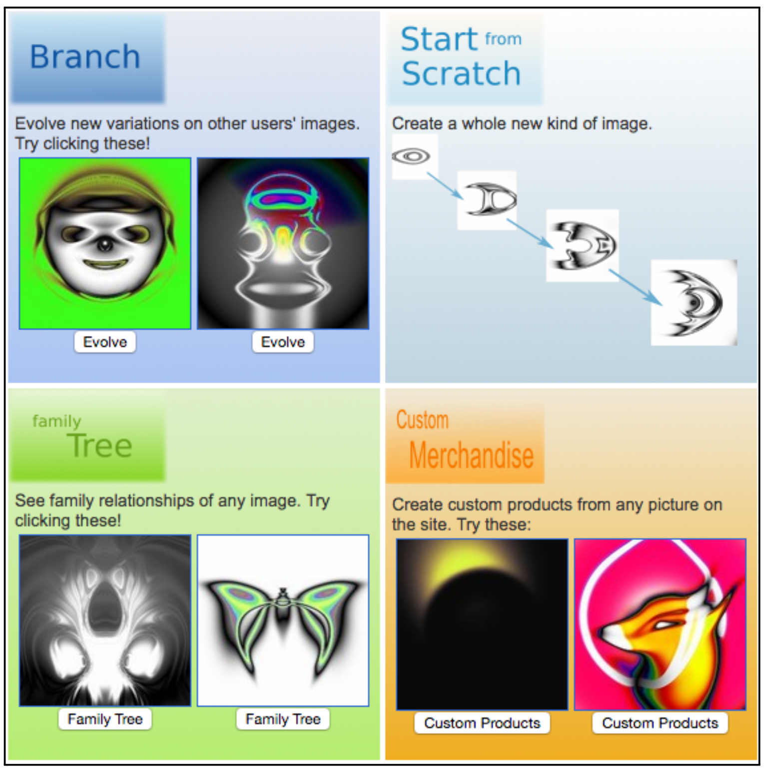

Figure 2.9: Picbreeder User Selection.

Figure 2.10: Alien objects from EndLessForms.

EndlessForms.

EndlessForms is a Web application that Explore object designs by choosing those the users like. These selected objects become the parents of the next generation of objects [13]. EndLessForms proposes a new way to evolve 3D objects inspired by biological morphologies using generative encoding. One of the experiments proposed in this paper was to use interactive evolutionary systems to determine the potential for generating complex and interesting 3D objects. They chose the interactive evolution, because that allows openended exploration of the design space of objects that can produce by their method. Additionally, the interactive evolution avoids the greedy nature of evolution by objectives, which potentially allows to access more interesting objects [13]. In figure 2.10 we can see some of this objects.

EvoSpace-Interactive

EvoSpace-Interactive is an open source framework focused on Web environments for collaborative interactive evolutionary applications. This framework defines three main components for each application, which are:

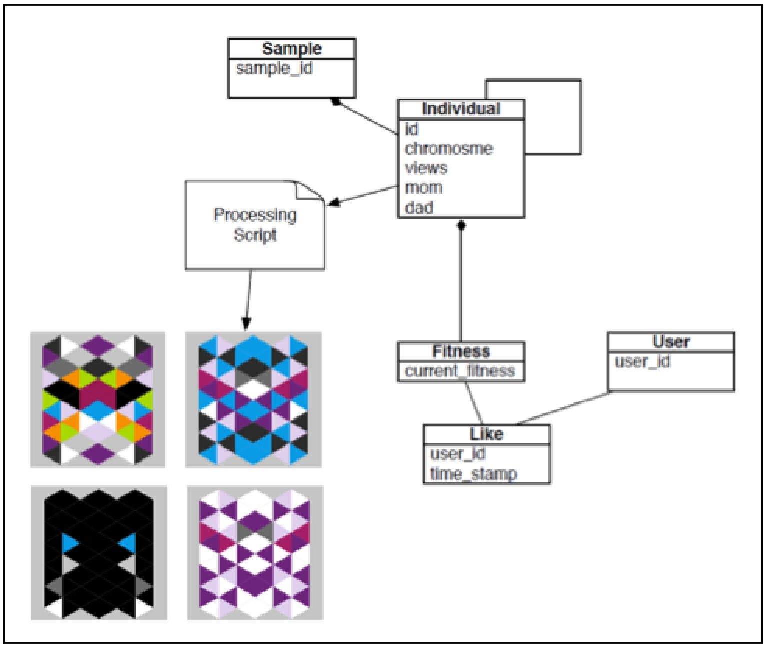

Figure 2.11: Individual Representation.

- Individual.
- Processing Script.
- Worker Script.

The individual is represented internally as a data dictionary stored in Redis [16] database management system; the individual contains main attributes as id, chromosome, mom, dad, and views. This attributes represents the key information of the individual as the individual offspring, the number of times that the individual has been selected, etcetera, as we can see in figure 2.11 [3].

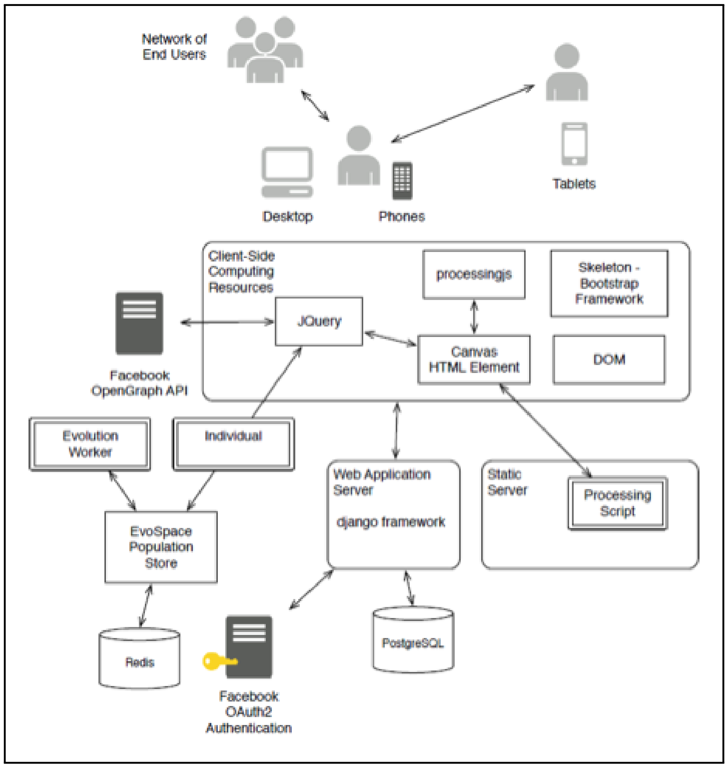

Figure 2.12: EvoSpace-Interactive Framework.

As we can observe on figure 5.1, this work uses database management systems to implement collaborative interactive evolutionary applications. One of the reasons that this framework is using Redis[15] is because it provides a hash- based implementation of sets and queues, which are natural data structures for the EvoSpace model. On the other hand this framework uses a relational database to save basic information about the user extracted from the social platform (Facebook) through open graph API and OAuth2 authentication.

2.2 User Modeling

User modeling can be represented as the technique of building a model of the user to personalize a system. The user model is commonly created as the user is working with the system. An example is an educational application that teaches students an individual skill: given the rules and knowledge in the user model, the difficulty level of the exercises in the form is altered as the user progresses. Formally definition of user modeling according to McTear [45] : " user modeling is the process of gathering information about the users of a computer system and of using the information to provide services or information adapted to the specific requirements of individual users (or groups of users)". The purpose of the user model is to have a module containing the operations that are needed to personalize the system, and the user profile, which includes the personal data of the user [](Mohamad et al., 2013). System personalization over user modeling is related to the research field of adaptive systems; this subject is beyond the scope of this research work. Focus on the human user, user modeling is a very cross-disciplinary research topic, comprehending the domains of artificial intelligence, computer science, and social science. Ideas have been coopted from an extensive range of subdomains, such as humancomputer interaction, elearning, information science, social computing, machine learning, data mining, cognitive science, and so on [34] [35]. There is interest in user modeling from both a scientific and commercial perspective [62].

2.2.1 Application Domains for user modeling

Amount Research and implementation exist in this domain in which personalization and user modeling plays an important role. This section presents several works of these domains. To understand this topic, the different objects are divided into three general categories:

- supporting a user during a task.
- giving a user a specific personalized experience.
- training and educating a user.

The categories especially differ in the kind of user data that is used. For each domain, the general purpose of the domain and the more accurate purpose of the user model are discussed.

2.2.2 User models for providing task support

Task support systems are f systems that help a user during a task by either supporting the user perform the task or by completely taking over this task [12](Nurmi et al., 2007). For instance, an application that automatically categorizes the incoming emails of the user. The goal of the user model in these requests is to promote the efficiency of interactions with the user, to simplify these interactions and to make complex systems more usable [62][24]. To perform this personalization, data is collected through observations of the user. This information is related to the users goals and needs, but especially to the task that the user currently is accomplished, like the users task knowledge and background. Much research has been done in this domain, but because many separate research projects are focusing on an exact task or subject [](Sannes, 2011), it is hard to make generalizations or to establish one delimited investigation topic. Commonly discussed research subjects are Decision Support Systems, Adaptive Hypermedia, and Adaptive Ubiquitous Systems, each having his or her own specific domain and way of personalization.

2.2.3 Decision support systems

Decision support systems are systems that support a user with making a decision in a complex, professional environment [] (Nurmi et al., 2007). For example, a system used at a pharmacy for automatically checking valid combinations of medicine. The method can be used to help the pharmacist in prescribing the right combinations and to give information for making a decision when a problem occurs. The purpose of the user model in decision support systems is to present the user with the right and appropriate information, giving different feedback or applying various decision steps according to the characteristics of the user.The data that is used is often associated with the users task and background knowledge. The adaptation takes place by adapting the amount and the content of the feedback provided by the system.

Decision support systems are traditionally ruled or logic-based systems, in which all the relevant information is represented in a knowledge base. This means that the content of the user model itself is also highly dependent on the way the rules and knowledge are represented.

2.2.4 Adaptive Hypermedia

Adaptive hypermedia system is a system that grant users to browse freely information network, structured by nodes and links, to retrieve items of information [17]. For instance an internet website application. The goal of the user model is to make the interface and structure of the system dynamic. This enables the application to adapt to the user and to make it easier for the user to search for and retrieve relevant information. The data used in the user model is related to the users abilities, knowledge, and goals in the application. The adaptation happens by adjusting the structure and the presentation style to the expected needs of the user. For example, by enhancing web search: promoting pages that might better correspond to the users characteristics, on the other hand by giving navigation support, through highlighting certain components of a page [63].

2.2.5 User models for providing a personal experience.

User models for providing the user with a personal experience have the goal to improve the user experience while using the system. This kind of user modeling is especially focused on more commercial fields, such as e-commerce, marketing, and computer games, and became popular with the rise of the Internet. The information that is used by the user in this main domain is mostly focused on the information that defines the user, such as the users preferences and interests. Since this data is regularly delicate, privacy is a big issue [74]. While in other domains the privacy of the user data is also important, in this area it is even a greater topic of discussion because the incentive of the application developers is frequently contradictory to the incentive of the actual user, considering gaining and sharing the users personal information. For instance, user profiles are often shared among diverse components of the same application, or even with different applications [12] [33], which presents additional weaknesses and possible undesirable information sharing. Ensuring personal data is not open to all people, in addition to defining strict privacy policies, is thus essential in these user models. Some investigation in this domain are.

2.2.6 Recommender Systems and User Adaptive Computer Games.

Recommender systems are concerned with presenting the user with relevant information and suggestions. They are commonly used on the Internet, for example on websites such as Facebook, to provide the user with personalized news, targeted advertisements and possibly new friends [12]. The purpose of the user model is to give the system with information that is assumed to be important for the user. The information that is stored for this goal is associated with the preferences of the user to certain objects, like products, music or people. To benefit a classification of these objects, the interaction history of the user is stored, or the user is explicitly asked to rate certain objects. The content of the system is eventually adjusted by showing the recently inferred objects. In these senses, objects can be inferred by looking at the attributes of the objects in the user profile, or by looking at the objects in other user profiles that are related to the user [35] [34]. As a result of the predominantly commercial target of these systems, the adaptations often take place in a very invasive way, to make sure the user notices the change. Most recommender systems are based on the Internet, which means that some typical technical difficulties are associated with these kinds of user models. First, the user profile is often only stored while the users visit, which means that fast and efficient adaption is important. Recommender systems usually become more precise when the user spends more time with the system. Second, the systems architecture is usually client-server, where the client side gathers user information and sends it to the server, where the actual process takes place.

2.2.7 User Adaptive Computer Games.

User Adaptive computer games are games that focus on increasing the perceived value by providing a strongly individualized experience (Brisson, 2012). For example is a firstperson shooter that adapts the performance of the enemy according to the shooting accuracy of the player.

The fundamental idea of the user model is to identify or classify the user, so the appropriate adjustment is made in the computer game. The information that is used addresses the preferences and progress of the user, such as the users current difficulty level or even the employed strategy. This data is usually obtained through the interactions of the user with the game, and therefor first should be translated and formalized before it can be used to interpret conclusions on a higher level. The adaptation that takes place in the game concerns changing the content and role of the game, such as the game difficulty, the behavior of nonplayer characters or even the background music [3].

Because of the emphasis on the user, user adaptive computer games have relatively a lot of processing power available for personalization. In this sense the user adaptive computer games domain is a very interesting research domain.

2.2.8 Adaptive Educational Games.

Adaptive Educational Games (AEGs) are complicated educational games that combine ideas from several investigations areas, to increase the students learning experience [59]. These are especially based on serious games: computer games with an educational approach, where things are taught to students by using a playful idea [36] [32]. For instance an AEG is a training application for fire fighters, letting the fire fighters train their skills and knowledge in a safe on a virtual environment.

The objective of the user model in an AEGs is to optimize the learning process and outcome. The user information is considered with the advance and knowledge of the student, but also with the students mental and cognitive characteristics. The gained data can be used to adjust the content, presentation, and system behavior to the students need, for example, by adjusting the content, tone, or amount of presented feedback. Adaptive computer games have a lot of processing power available for personalization, making a complex and interesting domain for user modeling.

2.2.9 Methods for user modeling.

In the user modeling topic, researchers have proposed more general design methods and frameworks to guide the developers in the process of user modeling. These general methods are useful in research projects, where the knowledge can be reused to adjust the user model to the systems characteristics. Also in commercial applications, these general methods have proven to be useful [12] , because they make it easier and more feasible to implement personalization into a system. In early work, the process of user modeling was mostly based on the intuition and experience of the developer or researcher. In recent work, the techniques of user modeling were essentially based on the intuition and expertise of the developer or researcher. As the user modeling research field evolved, there has been put much effort in creating a general way for designing and constructing a user model, by basing decisions on more empirical grounds and by defining methods applicable to the whole field [35] [22].

Frameworks, methodologies, and architectures have been developed, defining the strict process, restrictions and choices on how to design and build a user model. In the early days of user modeling, the focus was put on developing one method applicable to the user modeling field as a whole. However, user modeling is a very cross-disciplinary research subject. Therefore, throughout the decades, the user modeling area of research has been influenced by the important research topics and trends of their time. For example, when information technologies became a major subject in the early nineties, user modeling methods were also mostly focused on the application of stereotypes, knowledge bases, and logic to define a user model. With the rise of the Internet, the objectives of the user modeling field change to Web-oriented applications and all the specific problems that arise with this. Thus this connection, also the general user modeling methods that were developed, were focused on the popular research domains of their time [34]. The main approaches to user modeling did not change, but the specific fillingin of the user model, such as which technology to apply, did change. In this sense development of user modeling as a whole, most researchers eventually agreed that one method to solve all problems is not possible [45] [35]. Instead, a broad range of generic user modeling methods has been developed [24]; each of which supports only a few of the very different manifestations of personalization.

2.3 Gamification.

A definition given by Huotari [31] is Gamification is the process by which concepts are brought to the real world task associated with real people. Also gamification handle game design elements which are commonly known as non-game context in the presud to enhance user engagement, organizational productivity, flow, learning, evaluations, among others.

Games and game technologies increase exponentially the traditional boundaries of their medium, as evidenced by the growth of serious and pervasive games as an industry and research field. The most recent phenomenon in this path is gamification, paradigm for the use of video game elements (rather than full- fledged games) to improve user experience and user engagement in non-game services and applications [20].

2.3.1 Techniques.

Techniques in this context seek to persuade users to use their natural desire to compete, learn and socialize in given non-game context application [19][28]. Some works in the beginning used rewards for users as players to perform desired tasks in a certain application or involving users to compete with each other . For instance some sort of rewards include points [70], achievement badges or levels [27], the filling of a progress bar [51], or providing the user with virtual currency. By Making the rewards for tasks achievements visible to other players or providing leader boards are ways of encouraging players to compete [29]. Because the problematic consequences of competition, which can result in negative conduct, low cooperation and collaboration, or disadvantaging certain player demographics such as women [37], best-practice gamification designs try to refrain from using this element.

Another techniques to gamification is to make existing tasks feel more like games [18]. Some techniques used in this approach include adding meaningful choice, onboarding with a tutorial, increasing challenge, and adding narrative [43].

Chapter 3

Proposed user-centered framework

The fundamental goal of this research is to develop a user-centered framework for interactive evolutionary computation (IEC) in order to increase users participation and also to minimize the amount of evaluations needed for the evolutionary process in given Web-based IEC application.

In this chapter an explanation of the proposed framework is described. The different techniques used, such as user modeling, fuzzy logic, and human- interaction.

This framework is presented in figure 3.1. Each of the entities of this framework will be explained in detail in following sections.

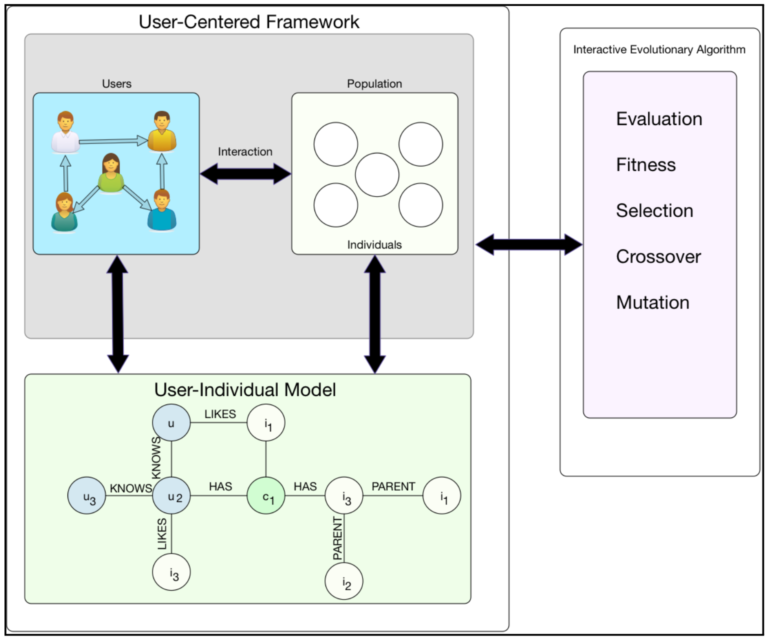

Figure 3.1: User-Centerd Framework.

3.1 Users

Users are a central part of this proposed framework as it aims to study their behavior when interacting with individuals within interactive evolutionary algorithms and other tasks that may exist within IEC systems. Thus users in this proposal are entities interacting with an evolutionary computation that has the fundamental purpose of evaluating individuals of a population replacing the fitness function according to their preferences and mood, among others []. This form of evaluate individual is given a subjectively way.

On the other hand in order to capture the attention of users and possibly increase their participation, currently there exist some basic actions that users can perform

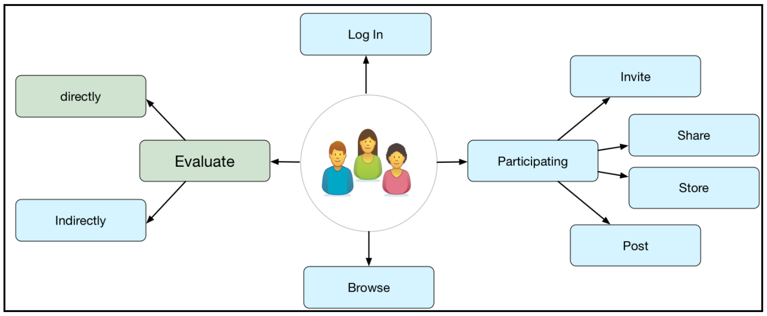

Figure 3.2: Users actions on interactive evolutionary systems.

in a given system, going from to be able to access a system through login mechanism, once the user has logged-in in to the system the users can interact with different actions, for example the inviting action is when users can be invited through social networks or maybe of person to person. Another example is the sharing action, that can occur when users want to share something of their interest through their social networks. In this sense the action of posting is when users want to put something on their wall who want others to know through their social networks. Likewise the storing action occurs when users want to retain permanently information that are of their interest. Finally the browsing action occurs when users are exploring content for their needs. All these actions go beyond only evaluating individuals.

In order to start the task of evaluating individuals is necessary that users access the system through a login mechanism. This mechanism consists of providing a username and a password in order to grant access to the system. All users accessing in this way they are considered active users within an IEC system.

For the evaluating action is proposed that users evaluate individuals indirectly, this means users can evaluate accepting indirect recommendations of friends that are currently active in the system. These recommendations can be store individuals in the system of users who know each other.

Also the browsing action is proposed within IEC systems, this means that users can explore information that other active users in the system are generating.

Finally activity participation is proposed. This can be divided into four different actions as fallows:

- The Inviting action occurs when a user invites another to the system through social networks or from person to person.
- The sharing action occurs when users share their individual creations with others active user in the system.
- The posting action occurs when published what they are doing within the system.
- The storing action occurs when users keep individuals in a collection, the collections concept will be discussed later in this chapter.

All the mention above is shown in figure 3.2

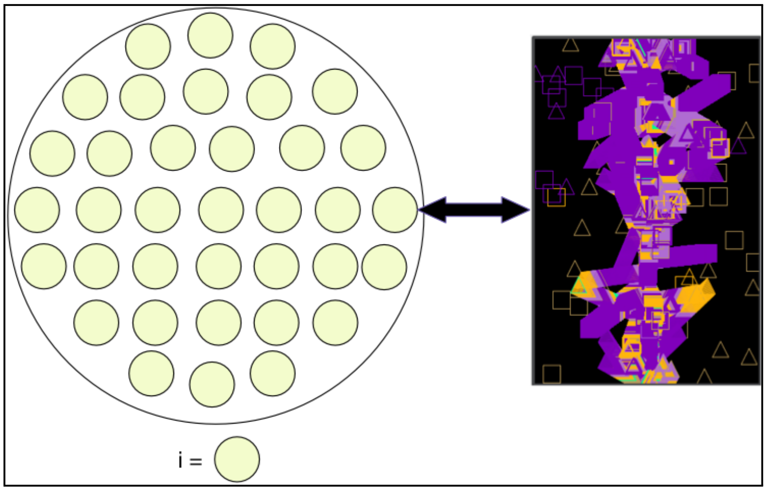

Figure 3.3: Individual representation.

3.2 Individual

Individuals are entities that form the population for the evolutionary algorithm. In particular for this work individuals are animated digital paintings, every individual in the population is defined by a chromosome []. This chromosome defines the behavior of the individual, so that it consists of a vector of real numbers of fifteen genes, where each gen define a particular behavior in painting. This individuals combined each other to generated new individual in the population following the genetic operators such as selection, crossover and mutation[]. An example of a individual in this case it is illustrated in figure **??**

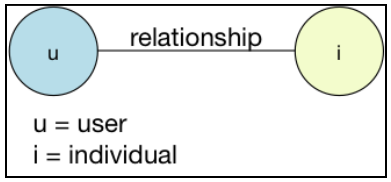

Figure 3.4: User-Individual.

3.3 User Model

Now that both users an individuals have been defined we can model the users behavior have with respect to individuals in a graph-based user model.

The reason for using a graph to model the user-individual is because it could can express in a simple way the behavior of this two entities having the necessary information to represent the knowledge, for example a vertex user and individual vertex connected through a edge that represents the relationship. this relationship can be the semantic between these two entities as figure 3.4 show. Each of these vertices contain properties as well as the edges, these properties will be explained as fallows.

In this proposed graph-based user-individual model the vertices are represented by set of nodes of USERS, INDIVIDUALS and COLLECTIONS. The edges are define by a set of relationships as LIKES, KNOWS, PARENT, HAS that represents the relationships between the vertices as seen in figure 3.4.

Already explained that represent USERS and INDIVIDUALS, now an explanation is given of what concerns for the concept of COLLECTIONS.

In this proposal a collection is defined as a container where users can store selected individuals laid within the collection. A collection is created when the user wants to store permanently individuals within the IEC system.

Now for the edges in this proposal are explained as follows:

- The LIKES edge represents a preference relationship that a user has with respect to an individual.
- Now the PARENT edge represents an ancestor of the individual, in other words where the individual comes from.
- Likewise the HAS edge represents that users have a collection where can contain individuals.
- Finally the KNOWS edge represents a relationship of friendship between users.

In figure 3.5 illustrated the above mentioned, about nodes and edges.

In each vertex is necessary to store knowledge about the users, individuals and also for the collections, this is what is known as property.

It is worth to mention that all vertices have a property called element_type among others. This property is used to identify which type of vertex is, for example if vertex corresponds to a user then this property label the vertex as a person. Likewise if the vertex corresponds to an individual this property label it as an individual and

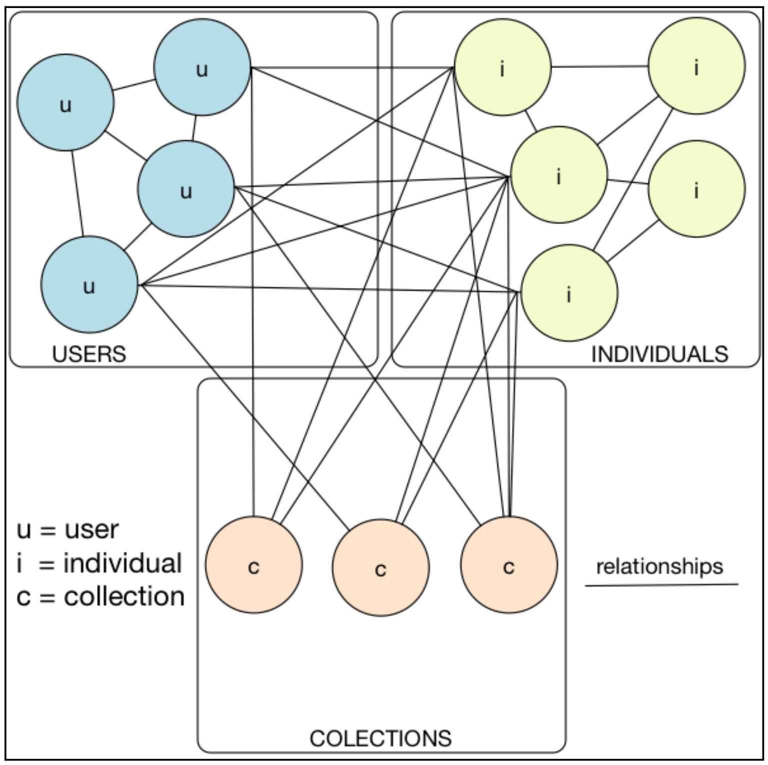

Figure 3.5: Nodes And Edges Representation.

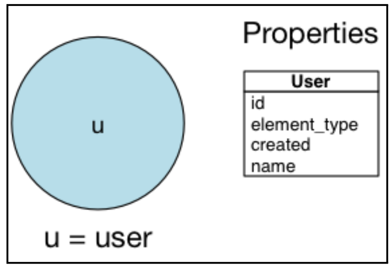

Figure 3.6: User Properties.

is the same for any vertex we want to add to the model. This property also has the purpose of being able to do operations on the graph according to the vertex type.

The properties for the vertex u are the following:

- id.
- created.
- name.
- element_type.

The id property defines that the vertex u has a unique identifier in the set of vertices, which means that there will not be duplicate vertices. The property created defines the creation date of the vertex u. The property name defines the name of the vertex u. The property element_type defines the element type that will be the vertex u.

In figure 3.6 the vertex u properties are shown.

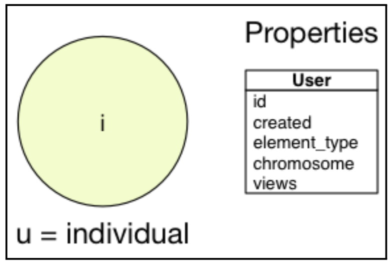

Figure 3.7: Individual Properties.

The properties for the vertex i are the following:

- id.
- created.
- element_type.
- chromosome.
- views.

The id property defines that the vertex i has a unique identifier in the set of vertices, which means that there will not be duplicate vertices. The chromosome property defines the chromosome of the individual representing the vertex i. which as defined above in this section. The property views defines the amount that users have seen this vertex i The property element_type defines the element type that will be the vertex i. The property created defines the creation date of the vertex i.

In figure 3.7 the vertex i properties are shown.

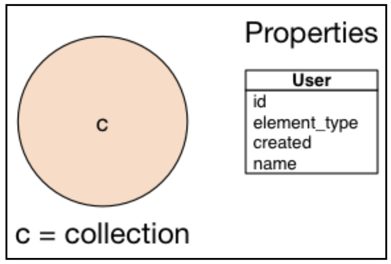

Figure 3.8: Collection Properties.

The properties for the vertex c are the following:

- id.
- element_type.
- created.
- name.

The id property defines that the vertex c has a unique identifier in the set of vertices, which means that there will not be duplicate vertices. The property element_type defines the element type that will be the vertex c. The property name defines the name of the vertex c. The property created defines the creation date of the vertex c.

In figure 3.8 the vertex c properties are shown.

In the same way that the vertices have properties also the edges, these properties are defined as follows.

The LIKES edge has the following properties:

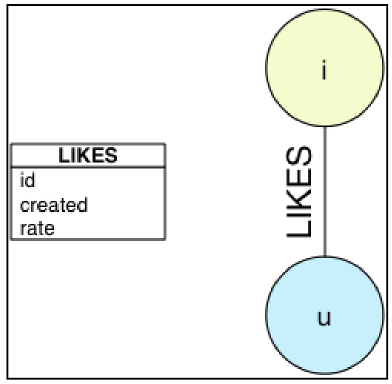

Figure 3.9: LIKES edge Properties.

- id.
- created.
- rate.

The id property defines that the LIKES edge has a unique identifier in the set of edges, which means that there will not be duplicate edges. The property created defines the date of creation of the this edge. The property rate defines the rate that the users give to the individual store in this edge.

In figure 3.9 the edge LIKES properties and the relationships with the vertices u and i are shown.

The KNOWS edge has the following properties.

- id.
- created.

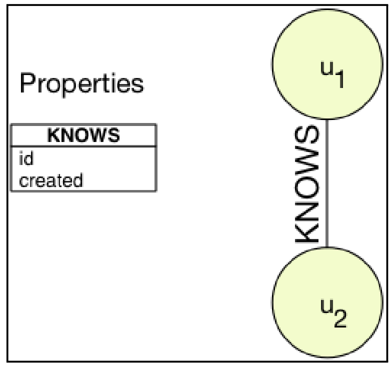

Figure 3.10: KNOWS edge Properties.

The id property defines that the edge KNOWS has a unique identifier in the set of edges, which means that there will not be duplicate edges. The property created defines the date of creation of the edge.

In figure 3.10 the edge KNOWS properties and the relationships between vertex u are shown.

The PARENT edge has the following properties, and represent the parents of a new individual.

- id.
- created.

The id property defines that the edge PARENT has a unique identifier in the set of edges, which means that there will not be duplicate edges. The property created defines the date of creation of the edge.

In figure 3.11 the edge PARENT properties and the relationship between vertex

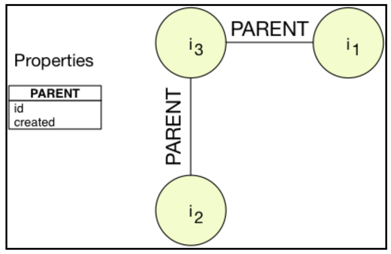

Figure 3.11: PARENT edge Properties.

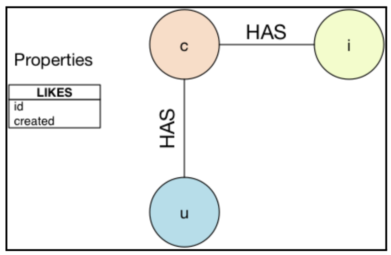

Figure 3.12: HAS edge Properties.

i are shown.

The edge HAS has the following properties, and represent the parents of a new individual.

- id.
- created.

The id property defines that the edge HAS has a unique identifier in the set of edges, which means that there will not be duplicate edges. The property created defines the date of creation of the edge.

In figure 3.12 the edge HAS properties and the relationship between vertices u, i and c are shown.

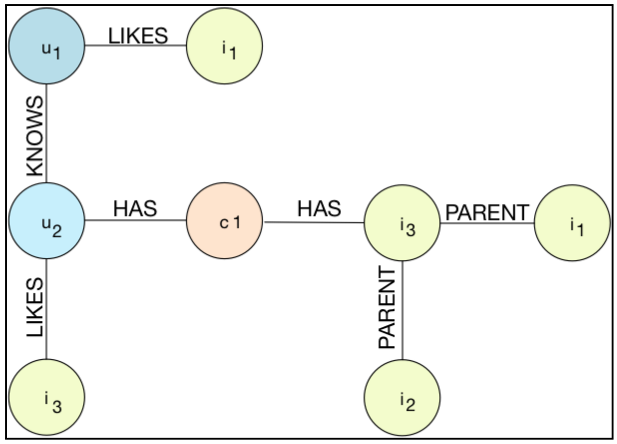

Figure 3.13: Graph-based user-individual model.

$$V = \{[u_1, u_2, u_3, ..., u_n], [i_1, i_2, i_3, ..., i_n], [c_1, c_2, c_3, ..., c_n]\},$$

$$E = \{[l_1, l_2, l_3, .., l_n], [p_1, p_2, p_3, ..., p_n], [h_1, h_2, h_3, ..., h_n], [k_1, k_2, k_3, ..., k_n]\}$$

Already defined the vertices and edges a graph-based user-individual model is proposed where vertices users are related to the vertices individuals, likewise the vertices individuals are related to themselves when evolution exist between them. In that sense the vertices users and individuals are related to the vertices collections as a vertex user can be related to a vertex collections and a vertex collections collections is related to n individuals vertex. In Figure 3.13 shows an example of the graph-based user-individual model.

Chapter 4

Fitness Estination

This chapter explains the proposed strategy to calculate the fitness of the individual in a web-based interactive evolutionary computation applications using fuzzy logic. Before showing our strategy, it is necessary to explain how the individual evaluation is made in the EvoDrawing application. The figure 4.1 shows the user interface where the user interacts with the application. The main goal of this in-teraction is the individuals evaluation, the first action of the user, in order to evaluate, is to login through a social platform account in this particular case Facebook[13], in order to have different futures as a collection creation, store individual in a collection, already explaind in the previus chapter. The evaluation takes place through a fivestar rate selection by the user; this rate represents the degree of user preference for an individual. The application keeps the record of every user activity using the

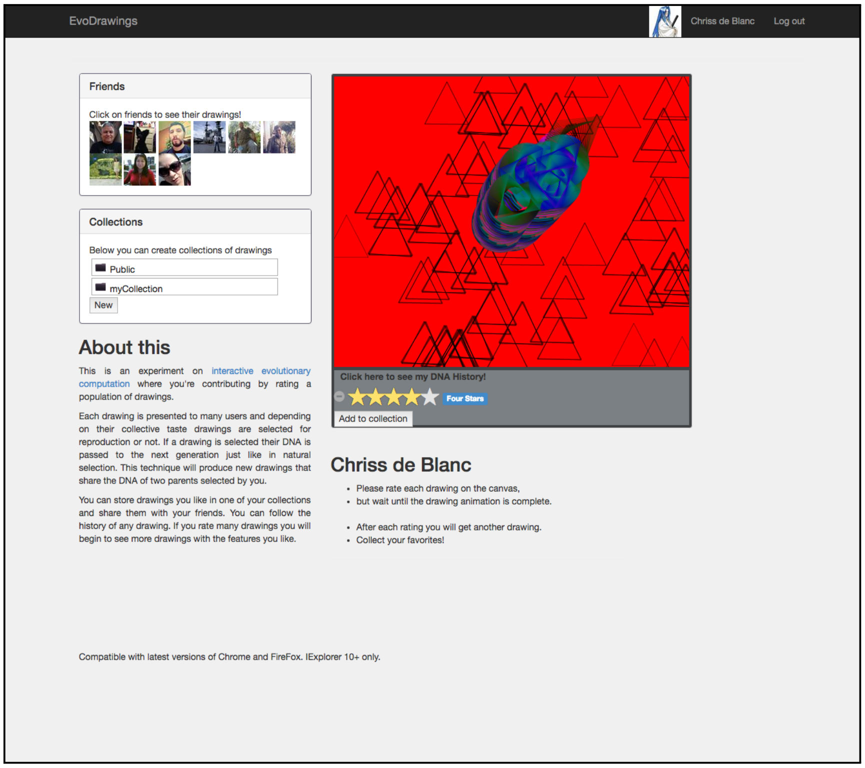

Figure 4.1: User interface ED01.

activities stream standard [14]. In these particular case the activities represents the user experience.

In this research we propose the using of fuzzy logic[10] in order to obtain a difuzzify value to be used to calculate the individual fitness trough a fitness function expression. It is used by modeling a fuzzy Mamdani type inference system [5] [6] as figure 4.2 shown. This model was designed empirically. The model consists of two input variables, which are the preference and the experience of the user as well as an output that we called fuzzy rate. The first one has 3 linguistic variables, which

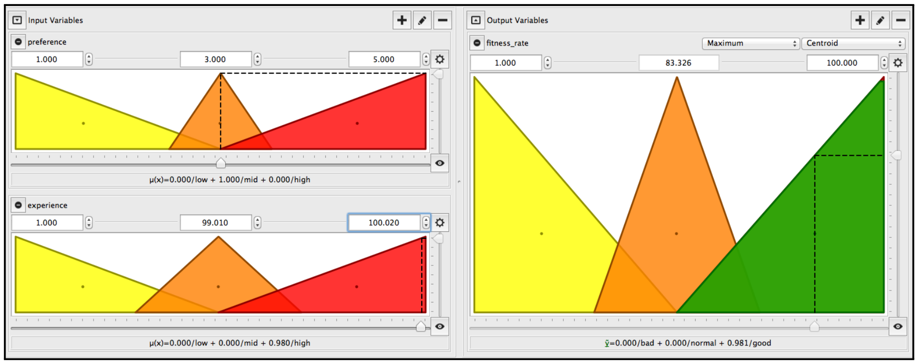

Figure 4.2: Fuzzy System Mamdani Type.

are low, medium and high, representing the preference with triangular membership functions over a range of 1 to 5. The second one also has three linguistic variables, which are low, medium and high representing the experience with triangular membership functions over a range of 1 to 100. Finally we have the output consisting of three linguistic variables bad, normal and good represent-ing the fuzzy rate with triangular membership functions in a range of 1-100.

Below we show the rules IF-THEN of the fuzzy system:

1. *If* ***preference*** *is low and* ***experience*** *is low then* ***fuzzy_rate*** *is bad.*
2. *If* ***preference*** *is mid and* ***experience*** *is low then* ***fuzzy_rate*** *is bad.*
3. *If* ***preference*** *is high and* ***experience*** *is low then* ***fuzzy_rate*** *is normal.*
4. *If* ***preference*** *is low and* ***experience*** *is mid then* ***fuzzy_rate*** *is bad.*
5. *If* ***preference*** *is mid and* ***experience*** *is mid then* ***fuzzy_rate*** *is normal.*

6. *If **preference** is high and **experience** is mid then **fuzzy_rate** is good.*

7. *If **preference** is low and **experience** is high then **fuzzy_rate** is normal.*

8. *If **preference** is mid and **experience** is high then **fuzzy_rate** is good.*

9. *If **preference** is high and **experience** is high then **fuzzy_rate** is good.*

These rules will give us a fuzzy rate value result, this is the value need it to be defuzzify by the centroide method in order to be used in our fitness expression, given by equatio4.1. This expression is responsible to represent the individual fitness.

$$fitness = \frac{\sum_{i=0}^{n} x_i + f(y_i)}{\sum_{i=0}^{n} f(y_i)} \tag{4.1}$$

Where n represents the number of users that have given an evaluation of the individual, x is the rate of preference for the individual given by the user, y is a function that calls the fuzzy system in order to have the fuzzy rate. This function needs x and the user experience level. The user experience level is given by the total activities that user have at the moment. In each activity we assign the score, for example if the user log in (join) to the application we assign 5 points, if the user evaluates (likes) an individual we give 3 points, etc; in figure 5 shows the flow for assigning fitness to the individual.

Chapter 5

Case study

5.1 Motivation and objectives

Our motivation begins from knowing if a user modeling in combination with techniques of usability and fuzzy logic increase the participation of users in a given interactive evolutionary system. It is well know that one of the main problems in these systems is fatigue, who is the cause of the decrease of user's participation [].

Our approach goes with the sense of increasing the participation of the users within these systems, providing to them very simple tasks to execute in order to capture their attention as well as to know their behavior.

Since we have described that the main approach is to increase the participation of users, in order to measure these results and to be able to demonstrate a real increase in the participation of these users, it was necessary to build a study case where an evolutionary art application is involved within an interactive evolutionary system which we call EvoDrawings. This application was modified in order to obtain three versions of this one, which were labeled with the names ED01, ED02, ED03. The objective is to extract data from each of the different versions and then quantify and compare which of these had the best result in the participation of the users.

5.2 EvoDrawings

EvoDrawings is based on the EvoSpace-i [] framework and consequently uses the same architecture which is presented in figure 5.1. In this architecture we have the individual block which contains different information, including the chromosome that represents the digital painting. Technically the individual is an associative arrangement (dictionary) where an abstract collection of keys and values is stored with a one-to-one association. Where keys represent a specific property in each object and the values are different types of data, such as lists, tuples, numbers, strings and dictionaries.

The individual has the following fields, shown in figure 5.2. The field is represented by a single string for each object. The chromosome field represented by a string, which for EvoDrawing represents an array of 15 numerical characters which

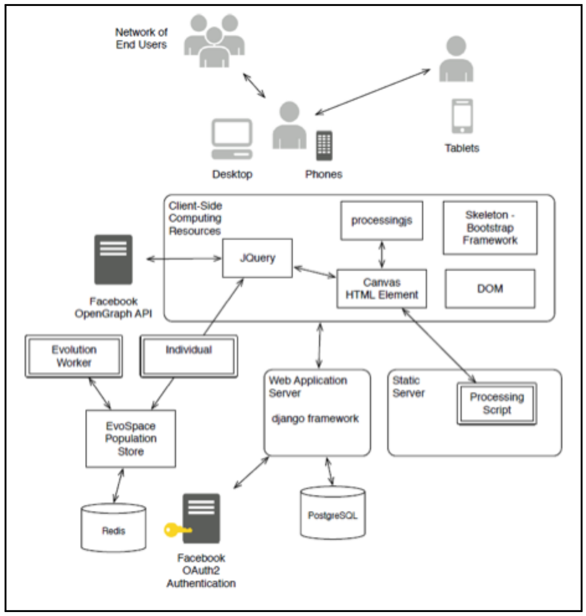

Figure 5.1: EvoSpace-i framework.

define the behavior of the digital drawing ... The fitness field is defined by a dictionary, this field contains the information of users evaluations as well as the creation date as a timestamp. The field called views is determined by a string and represent the number of times they have seen the individual. The keys called mom and dad define where the individual comes from. The GeneticOperator field is a string that specifies the genetic operator produced.

5.2.1 Processing Script

It is necessary to explain how the animation that the users visualize works. EvoSpace-i uses processing script in order to do the rendering of the individuals which contain

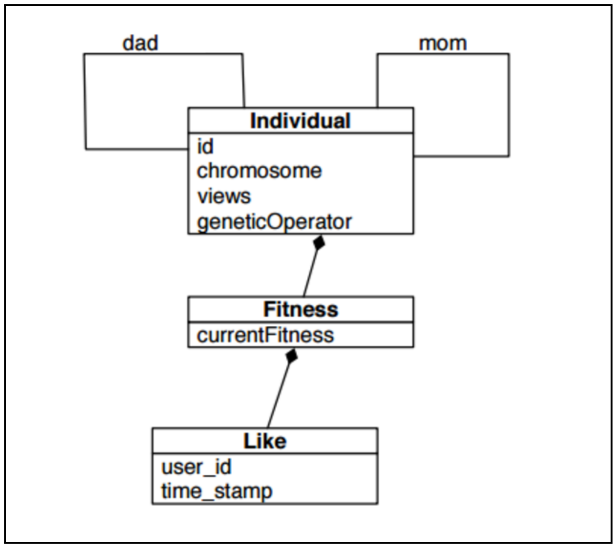

Figure 5.2: Chromosome representation.

the behavior of the figures. This application can run in browsers that are compatible with HTML 5, this is due to the use of a javascript library called processingscriptjs that is in charge of communicating with the base script and thus perform the render on HTML 5 canvas in The EvoDrawings application.

5.2.2 Fitness

The fitness assignment for each individual is given by the evaluations of the users. EvoDrawings has positive reviews when users give their rating as a star rating. We can see this rate of stars on the figure x of the interface that EvoDrawings uses in all its variations. This rate ranges from 1 star to 5 stars, which defines the user's liking for the digital drawing presented by EvoDrawings. When users evaluate a sample of individuals, some of these will not receive any evaluation. The view property, it increases by 1 when it is viewed. Internally, a fitness calculation is used defined by the following equation:

$$fitness = \frac{\sum_{i=0}^{n} x_i + 1}{\sum_{i=0}^{n} v_i + 1} \tag{5.1}$$

i represents the individual's. x is the range that individuals received when evaluated by users. v are the views that users have viewed individuals.

The above is used in version ED01. For the next two versions we use a different defined fitness based on the behavior that users perform within EvoDrawings, such as assigned tasks, the logging action in order to start evaluating individuals, individuals evaluation, creating collections for later store individuals and finally view the public individuals of friends who are participating in the application.

For ED02 we use a fuzzy inference system consisting of two inputs and one output. Entries are defined by preference and experience. The preference is the range of stars from 1 to 5 and are the evaluations that users give to the presented digital drawing, and are represented with triangular membership functions called high, medium and low. In the same way the input experience is defined by the tasks performed and it has the range of 1 to 100, each task receives points until reaching a threshold of 100 points where the user is considered as an expert within the application. This input is also represented by triangular membership functions called high, medium, low. Finally we have the output called fuzzy_rate in a range of 1 to 100, defined by triangular membership functions called bad, normal, good. This fuzzy system consists of 9 if-then rules:

1. *If **preference** is low and **experience** is low then **fuzzy_rate** is bad.*
2. *If **preference** is mid and **experience** is low then **fuzzy_rate** is bad.*
3. *If **preference** is high and **experience** is low then **fuzzy_rate** is normal.*
4. *If **preference** is low and **experience** is mid then **fuzzy_rate** is bad.*
5. *If **preference** is mid and **experience** is mid then **fuzzy_rate** is normal.*
6. *If **preference** is high and **experience** is mid then **fuzzy_rate** is good.*
7. *If **preference** is low and **experience** is high then **fuzzy_rate** is normal.*
8. *If **preference** is mid and **experience** is high then **fuzzy_rate** is good.*
9. *If **preference** is high and **experience** is high then **fuzzy_rate** is good.*

The fitness function is given by the following equation:

$$fitness = \frac{\sum_{i=0}^{n} x_i + f(y_i)}{\sum_{i=0}^{n} f(y_i)} \tag{5.2}$$

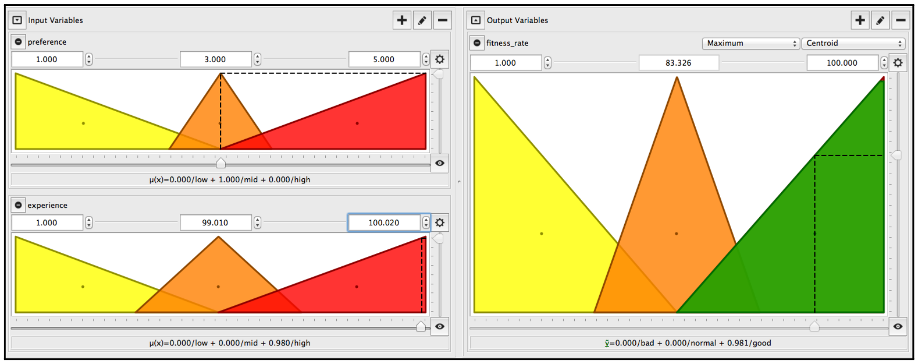

Figure 5.3: Chromosome representation.

i represents the individual's. x is the range that users gave to individuals.. $f(y_i)$ represents a fuzzy function composed of a fuzzy inference system and is represented by the equation 5.3.

$$y = fr(x, e) \tag{5.3}$$

fr represents the fuzzy rate. x it remains the range that users give according to their preferences to individuals. e is the experience that is defined by the activity that the user is doing within the application. The fuzzy inference system of it is a Mamdani type composed of two inputs that are x, e and a fuzzy rate output as shown in figure 5.3.

For ED03 the fitness function is given by the same equation as ED02 the difference relies in the inputs of the fuzzy function, for this case a new input is added with the name of ranking. This new input is the given by the cardinality of the

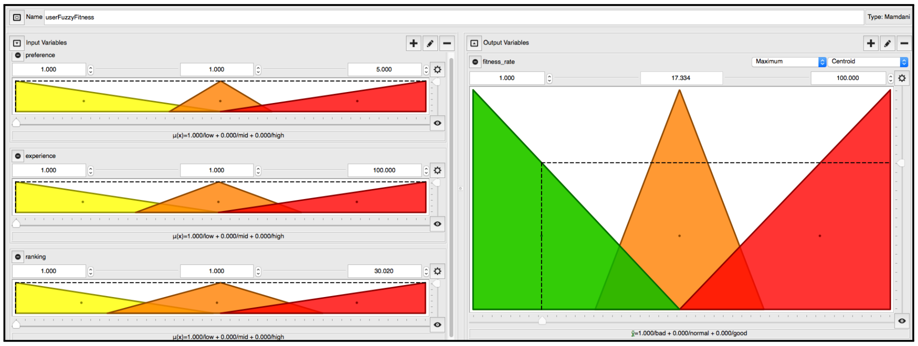

Figure 5.4: Fuzzy inference system for ED03.

graph of the user model for each user. here is the fuzzy function for ED03.

$$y = fr(x, e, r) \tag{5.4}$$

fr represents the fuzzy rate. x it remains the range that users give according to their preferences to individuals. e is the experience that is defined by the activity that the user is doing within the application. r is the ranking the user within the graph model. The fuzzy inference system it is a Mamdani type composed of three inputs that are x, e, r and a fuzzy rate output as shown in figure 5.4.

5.2.3 Configurations.

Previously we mentioned that EvoDrawings is an application of evolutionary art within an evolutionary system with the aim of being able to prove the increase of the participation of the users. To prove this hypothesis within this thesis, 3 different versions of EvoDrawing were designed. The EvoDrawing versions and the results of the experiments were compared to each other. All experiments and comparisons were performed on equal data, parameters and users.

For ED03 the initial configuration of our evolutionary algorithm in this version is the following:

1. **We have an initial population of 80 individuals.**
2. **An evolution parameter is 8 evaluations.**
3. **A mutation parameter of**
4. **With random selection between competition.**
5. **One horizontal genetic crossing Operator.**
6. **The fitness is given by the equation 5.1.**

For the interface in this version there is an easy-to-use Web interface for users to evaluate individuals. In figure 5.5 shows the navigation bar that have the functionality for the application access, it should be mentioned that this application only works with the social platform Facebook. Once logged in with a Facebook account an avatar appears in the navigation bar as well as the functionality to exit the application through a logout. Also within this interface exists the visual element 'Friends' where all the friends that are participating in the application appear, this element also has the functionality to be able to see the public collections that the friends have. Continuing with the explanation of the interface we have the 'Collections' panel which shows a list of collections that the users created and saved, as well as the functionality of being able to create new collections. Within this we have an 'About this' section where users are explained in which they are participating in a general way. Now to evaluate individuals the users have a visual canvas element that shows the behavior of the individual subject to evaluation (animation) and at the bottom is given the ability to evaluate the individual with a range of stars where one star means the user did not like it very much and five stars mean the user like it too much. Now at the bottom of the star range we have a button that provides the functionality of being able to add this individual to a collection that we have already created previously. At the top of the star rank is a league with the legend that says 'Click here to see my DNA History' this takes us to a detail about the individual that is about to be evaluated and thus to be able to observe the detail of the individual shows in image 5.6.

This detail presents important information about the individual's DNA history, such as the number of evaluations he has received in the form of likes, the number of views as well as the ancestry, his genetic crossing operator, the numerical representation of his Chromosome and its identifier within the population.

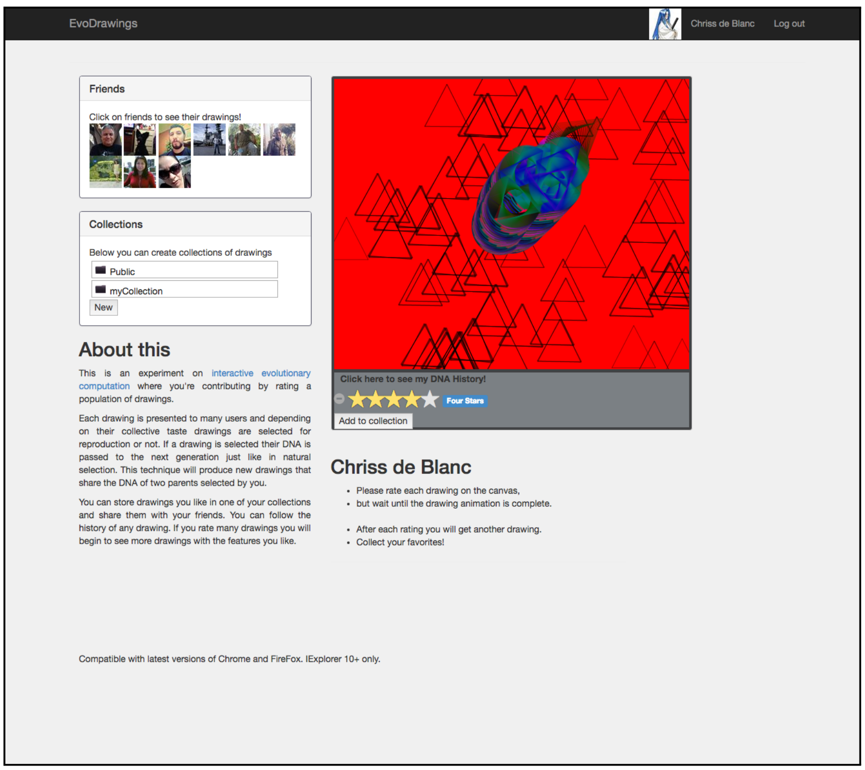

Figure 5.5: User interface ED01.

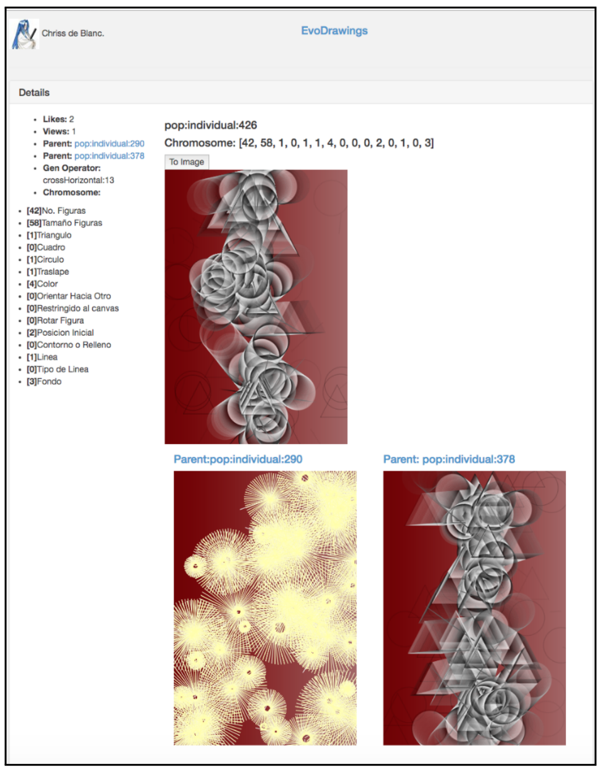

Figure 5.6: DNA history.

For ED02 there is an initial configuration of the interactive evolution algorithm as follows:

1. **We have an initial population of 80 individuals.**

2. **An evolution parameter is 8 evaluations.**

3. **A mutation parameter of**

4. **With random selection between competition.**

5. **One horizontal genetic crossing Operator.**

6. **The fitness is given by the equation 5.2.**

The user interface of this version is the same as the previous version. The difference between versions lies in how the inference is made internally.

For ED03 there is an initial configuration of the interactive evolution algorithm as follows:

1. **We have an initial population of 80 individuals.**

2. **An evolution parameter is 8 evaluations.**

3. **A mutation parameter of**

4. **With random selection between competition.**

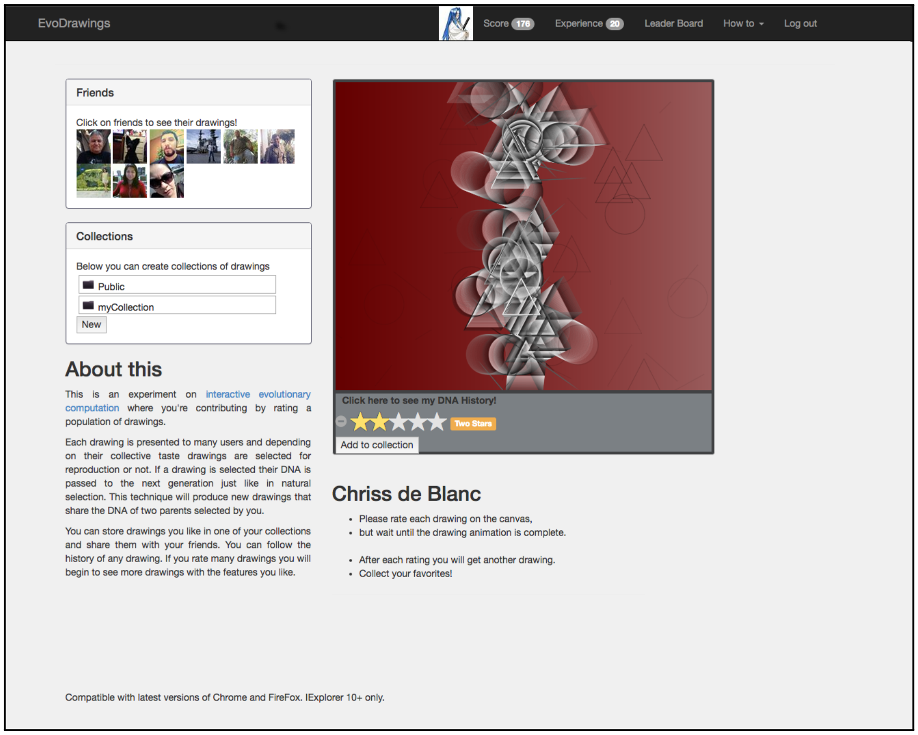

Figure 5.7: ED03 Web interface.

5. **One horizontal genetic crossing Operator.**

6. **The fitness is given by the equation 5.2.**

This version has a new intput on the fuzzy fuctionality named ranking and this value is given by the cardinality of the graph by each user within the graph- based user model. Also the fuzzy inferance system has a 27 if-then rules which can visualise in apandix b. The second difference is the usability elements where the gamification paradigm is apply. Figure 5.7 shows this usability elements that are the score level, the eperience level and also the leader board element.

Leader Board

#	User	Score	Experience
1	Frank Arce	2305	30
2	Ivan Hernandez	1664	29
3	Carlos Gaska	1074	27
4	Data Back	818	26
5	Elizabeth Hidalgo	803	26
6	Elid Bernabe Rubio Cota	705	25
7	Iliana DI	312	22
8	Mario García Valdez	256	21
9	Daniela Sanchez	231	21
10	Chriss de Blanc	171	20

Figure 5.8: Leader board at ED03.

This elements in the navigation bar is for users to visualise their scores inside ED03 application. Likewise the level of experience that is acquiring through its participations. This version also has an option to see the table of leaders within the application as shows in figure 5.8. This table shows the 10 best users and the number of entries that have been made so far.

5.2.4 Promote.

Each of the experiments was promoted through social networks particularly on Facebook and Twitter platforms through a short URL as well as an ad to motivate users

Table 5.1: Short URL for promoting the applicatins.

Long URL	Short URL
evodrawings01.herokuapp.com	goo.gl/J8TCe1
evodrawings02.herokuapp.com	goo.gl/jqjNy5
evodrawings03.herokuapp.com	goo.gl/J8TCe1

to press the link (short URL). This is in order to find participants on a voluntary basis. This short URL can be seen in table 5.1.

5.2.5 Heroku dynos and ad-ons server configurations.

It is necessary to be mentioned that each of the experiments was implemented under the cloud service (Heroku), in the following figure 5.2 can visualize its characteristics by each of the experiments.

The initial purpose of the experiments is to design specific applications and interfaces to enable users to participate voluntarily within the different applications. Each experiment allowed the task of collecting data that will later be analyzed to determine which of these versions had the largest number of user participations. To verify the initial hypothesis, 3 case studies were implemented with slight differences in the configuration characteristics of each application, which allowed to decide through the results obtained which of the case studies verify the hypothesis of this investigation. The results obtained are presented in the next chapter.

Table 5.2: characteristics of resources and services in cloud Heroku.

Service and resources	ED01	ED02	ED03
Heroku Free	✓	✓	✓
Deploy from Git	✓	✓	✓
Automated patching	✓	✓	✓
Self healing apps	✓	✓	✓
Undefined logs	✓	✓	✓
Number of process types	2	2	2
Always on Sleep after 30 mins of inactivity, otherwise always on depending on you remaining mostly free dynes hours	✓	✓	✓
Custom domains	✓	✓	✓
RAM 512	✓	✓	✓
Dedicated	x	x	x
Heroku Postgres ::DB Hobby Dev	✓	✓	✓
GrapheneDB Chalk	✓	x	✓
Redis To Go Nano	✓	x	✓
GrapheneDB Sandstone	x	x	✓
Redis To Go Mini	x	x	✓

Chapter 6

Results

This chapter presents the results obtained from the study case discussed in the previous chapter.

6.1 EvoDrawing01

The experiment EvoDrawing01 generated a graph user-model with the following data that is shown in table 6.1

These data is the total of nodes as well as relationships. Also in table 6.2 is the

Table 6.1: Data generated in graph-based user modeling.

	Data
Nodes	595
Relationships	2220

Table 6.2: Total number of volunteers active users.

	Users
Total	53

Table 6.3: Number of known among users.

User name	Number of known users
Chriss de Blanc	7
Alejandro Salcido	4
Jonathan Amezcua Aguiluz	1
Daniela Sanchez	1
Jennifer Llamas	1
Iliana Dl	1
Xochilt Ramirez Garcia	1
Manuel Elizondo	1
Julian Torres	1
Data Back	1
Frank Arce	1
Gustavo Vargas	1

total of volunteer active users.

In order to observe which users have better social interconnectivity within the experiments it was decided to make a relation of number known users that the users have. This relation is shown in table 6.3

Likewise in table 6.3 interconnectivity having a particular user with other users is shown. The degree of relationship of users is associated with the number of friends known within the application. This means that we have the degree of influence

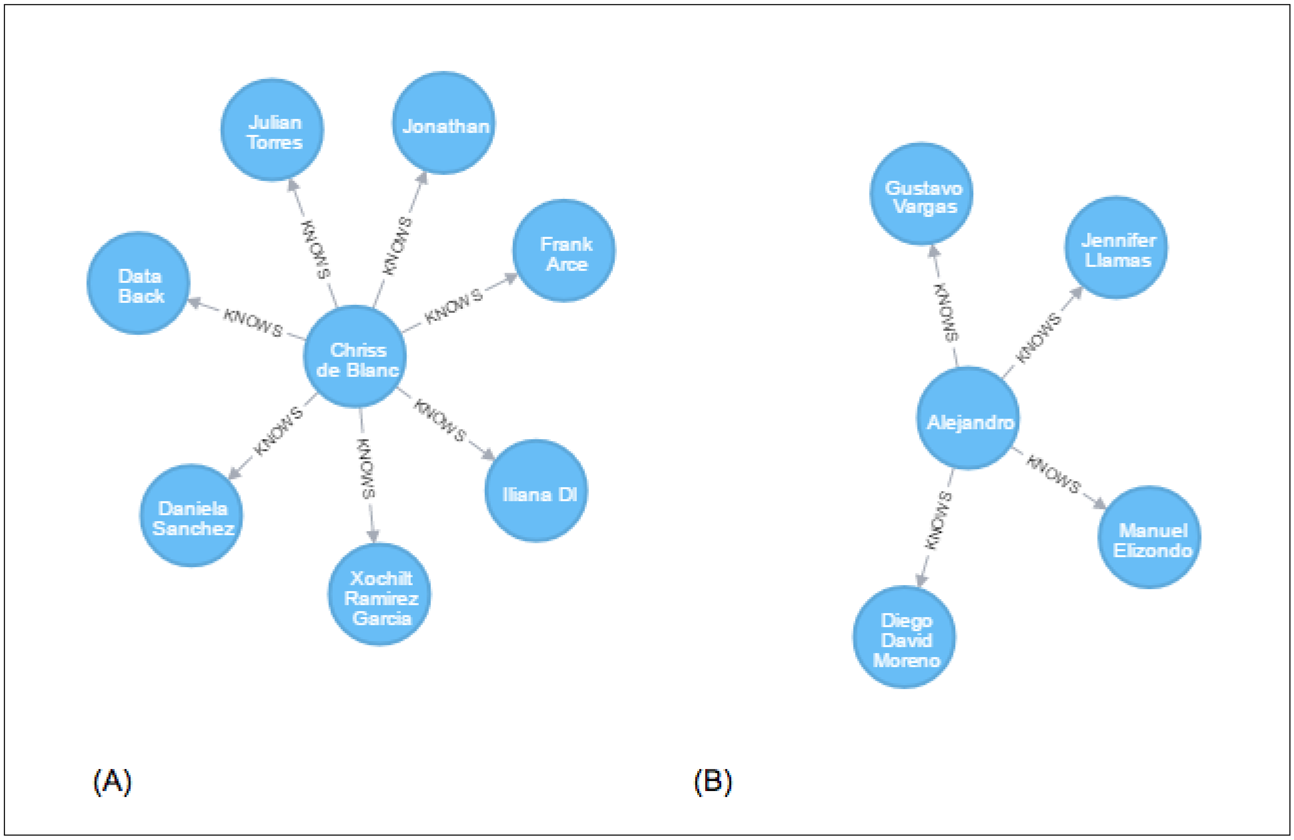

Figure 6.1: Graph users with greater interconnectivity.

among participants. For example "Chriss Blanc" user has a degree of relatedness 7 as shown in figure 6.1 indicating that this particular user can have more influence on the decisions of others. Moreover the user "Alejandro Salcido" has the second highest degree of relationship to other users as shown in figure 6.1.

In figure 6.1 shows users more connected in the graph. This may represent the degree of impact of a user and the possible influence that may have on the decisions of other users. For example, if the user with the greatest impact is affected in any

Table 6.4: Total number of individuals generated.

	Individuals
Total	500

decision likely other users may be affected in some way.

Table 6.4 presents the total number of individuals generated within the graph.

Table 6.5 contains a sample of 30/500 individuals were generated in the experiment. Where we present the unique identifier of the individual, its chromosome, as well as the number of views, likes available to the individual. This results are useful to observe individuals have been better evaluated by users.

Table 6.6 shows the results of the level of user participation in the experiment. These were obtained by counting the vicinity of nearest nodes from the base node in this case each user node.

In figure 6.2 we present a visual representation of user participation this experiment where the y-axis represents the level of participation and the x axis represents the number of users who participated in this experiment.

6.2 EvoDrawing02

In the experiment EvoDrawings02 the following data were generated and is presented in table 6.7.

Table 6.5: Sample of 30 individuals evaluated from.

id	Chromosome	Views	Likes
pop:individual:107	[125, 30, 0, 1, 0, 0, 3, 0, 1, 0, 0, 0, 0, 2, 1]	20	20
pop:individual:133	[143, 15, 1, 1, 0, 1, 3, 0, 1, 0, 2, 0, 0, 1, 1]	15	15
pop:individual:109	[125, 30, 1, 1, 0, 0, 3, 0, 1, 0, 0, 0, 0, 0, 1]	15	15
pop:individual:37	[87, 64, 1, 1, 1, 1, 4, 0, 1, 0, 0, 0, 1, 2, 3]	14	14
pop:individual:36	[95, 71, 0, 1, 1, 0, 3, 1, 0, 0, 0, 1, 1, 1, 2]	14	14
pop:individual:215	[138, 29, 1, 1, 0, 1, 3, 0, 1, 1, 1, 0, 0, 1, 1]	13	13
pop:individual:228	[42, 58, 0, 0, 1, 1, 4, 0, 0, 0, 2, 0, 0, 0, 3]	12	12
pop:individual:48	[51, 73, 0, 0, 0, 0, 2, 0, 0, 1, 3, 0, 1, 0, 3]	12	12
pop:individual:39	[60, 12, 1, 1, 1, 1, 4, 1, 1, 1, 0, 1, 0, 1, 1]	12	12
pop:individual:94	[49, 71, 0, 0, 1, 0, 4, 1, 0, 0, 1, 1, 1, 0, 2]	11	11
pop:individual:194	[87, 64, 0, 1, 1, 1, 1, 3, 0, 0, 0, 0, 1, 2, 3]	11	11
pop:individual:75	[97, 66, 0, 0, 1, 1, 3, 0, 1, 0, 3, 0, 1, 0, 1]	11	11
pop:individual:105	[125, 30, 0, 1, 0, 0, 3, 0, 1, 0, 0, 1, 0, 0, 1]	11	11
pop:individual:306	[87, 64, 1, 1, 1, 1, 4, 1, 1, 1, 1, 0, 1, 2, 3]	13	10
pop:individual:326	[138, 29, 1, 1, 0, 1, 3, 0, 1, 1, 1, 0, 0, 0, 0]	10	10
pop:individual:82	[81, 8, 1, 0, 0, 1, 4, 1, 1, 1, 2, 0, 0, 2, 1]	10	10
pop:individual:252	[125, 30, 0, 1, 0, 0, 3, 0, 1, 1, 3, 0, 1, 0, 3]	10	10
pop:individual:280	[53, 63, 1, 1, 0, 1, 3, 0, 1, 1, 0, 0, 0, 2, 1]	9	9
pop:individual:178	[53, 63, 1, 1, 0, 1, 3, 0, 1, 1, 0, 0, 0, 2, 1]	9	9
pop:individual:108	[42, 58, 0, 0, 1, 1, 3, 0, 1, 0, 1, 1, 0, 0, 1]	10	9
pop:individual:231	[125, 30, 0, 1, 0, 0, 3, 0, 1, 1, 3, 0, 1, 0, 3]	0	9
pop:individual:147	[122, 38, 1, 0, 0, 0, 0, 3, 0, 1, 0, 0, 0, 0, 0]	9	9
pop:individual:181	[143, 15, 1, 1, 0, 1, 3, 0, 1, 0, 0, 0, 0, 0, 1]	9	9

Table 6.6: Level of user participation.

User name	Participation
Ana Laura Lopez	116
Mario Garca Valdez	100
Chriss de Blanc	93
Xochilt Ramirez Garcia	85
Carlos David Gallardo Prez	73
Ulises Reus	70
Aaron Gutierrez Urbina	58
Cesar Lpez	49
Hector Beltran Medrano	48
Luis Alfonso Felix Garcia	45
Data Back	39
Amaury Hernandez Aguila	32
Osmar Herrera Duran	31
Jorman Gtz	29
Alexis Campos Lopez	29
Melissa Muoz Montes	28
David Gallegos	23
Jose Carlos	21
Toms Perrn	21
Manuel Elizondo	20

Table 6.7: Data generated in graph-based user modeling.

	Data
Nodes	648
Relationships	2596

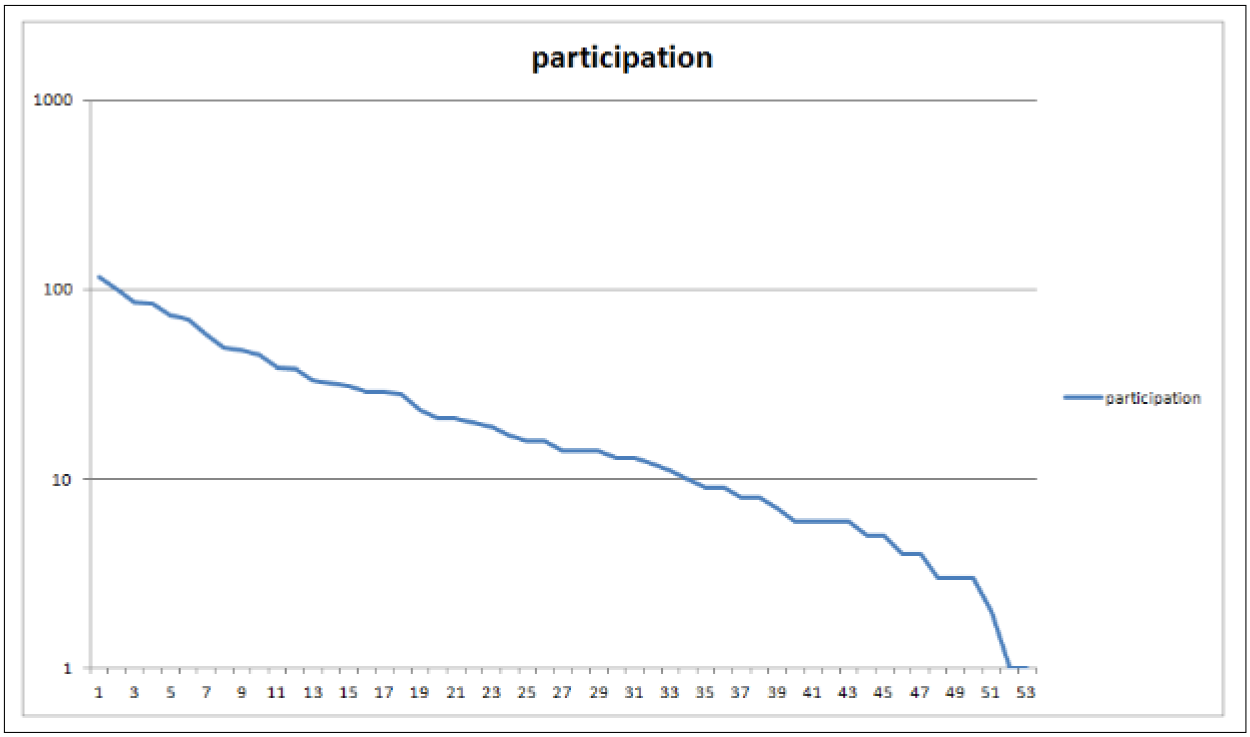

Figure 6.2: Visual representation of user participation in EvoDrawing01.

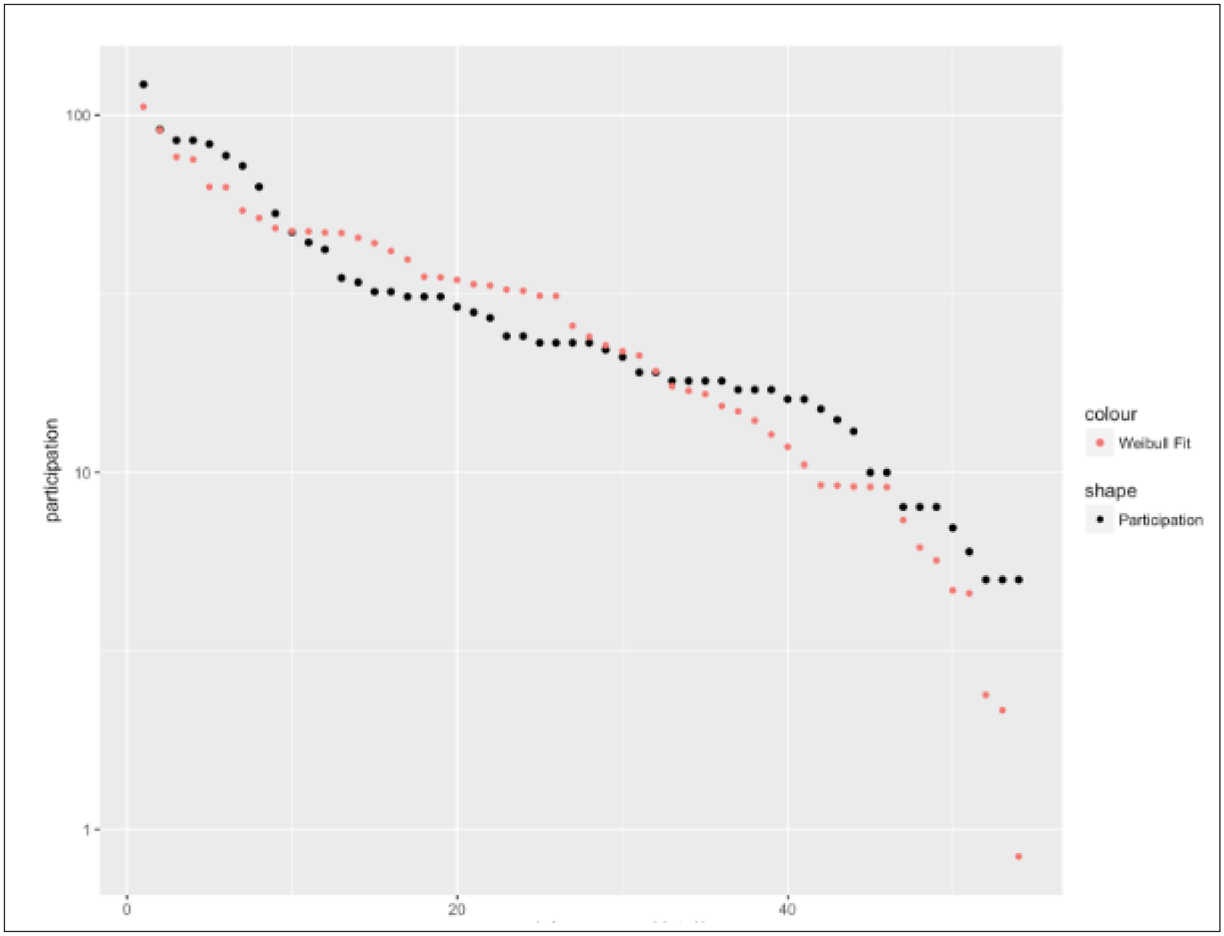

Figure 6.3: Weibull fit data representation.

Table 6.8: Total number of volunteers active users.

	Users
Total	54

Table 6.9: A sample of the top 10 users interconnected users.

User name	Number of known users
Rogelio UR	10
Barbara Sandoval	9
Evelyn Macedo	8
Chriss de Blanc	8
Cesar Rojas	8
Jasiel Calzada	8
Tonyy Maldonado	7
Silvano Peraza	7
Hector Beltran Medrano	6
Juan Ferman Lopez	6

These data are generated total of nodes as well as relationships. Also in table 6.8 is the total of volunteer active users is presented.

The total number of users who participate voluntarily shown in the table x.

Like the previous experiment which wanted to observe users had better social interconnectivity within this experiment, it was decided to see this relationship that correspond to the number of known users. This relationship is presented in table 6.8 where the top 10 user with social interconnectivity are shown.

In figure 6.4 shows users more interconnectivity in the graph. This may represent

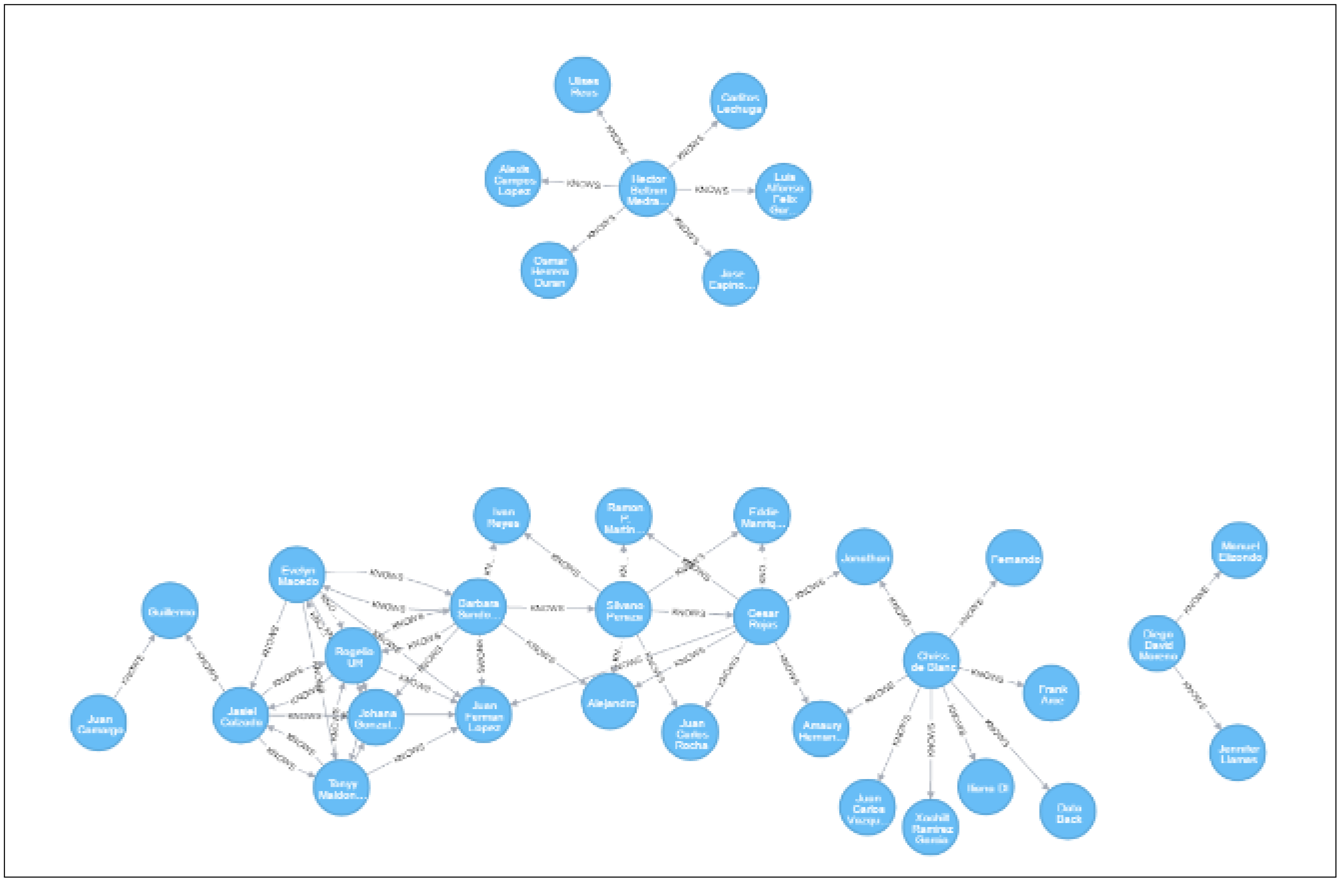

Figure 6.4: Sample of the top 30 individuals evaluated from a total of 556.

the degree of impact of a user and the possible influence that may have on the decisions of other users. For example, if the user with the greatest impact is affected in any decision likely other users may be affected in some way. Particularly in this experiment the degree of social interconnectivity among users is becoming more complex as compared to the previous experiment.

Table 6.10 contains a sample of individuals 30/556 generated in the experiment.This table shows the unique identifier of the individual, its chromosome, as

Table 6.10: Sample of 30 individuals evaluated from.

id	Chromosome	Views	Likes
pop:individual:55	[63, 58, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 0, 0, 3]	18	18
pop:individual:329	[98, 37, 0, 1, 1, 0, 4, 0, 0, 1, 0, 0, 0, 0, 2]	17	17
pop:individual:304	[63, 58, 0, 1, 1, 1, 4, 0, 0, 0, 3, 0, 0, 2, 2]	16	16
pop:individual:202	[107, 79, 1, 0, 1, 1, 3, 0, 0, 1, 3, 0, 1, 1]	15	15
pop:individual:58	[150, 79, 1, 0, 1, 1, 3, 0, 0, 1, 3, 0, 1, 1, 1]	14	14
pop:individual:310	[63, 58, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 1, 2, 2]	13	13
pop:individual:67	[65, 51, 1, 1, 0, 0, 3, 1, 0, 0, 3, 1, 0, 2, 3]	12	12
pop:individual:48	[51, 73, 0, 0, 0, 0, 2, 0, 0, 1, 3, 0, 1, 0, 3]	12	12
pop:individual:179	[98, 37, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 0, 0, 3]	12	12
pop:individual:114	[63, 58, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 0, 0, 2]	12	12
pop:individual:123	[124, 42, 0, 1, 1, 1, 4, 1, 0, 1, 1, 0, 0, 2, 1]	12	12
pop:individual:344	[97, 66, 0, 0, 1, 1, 3, 0, 1, 0, 3, 0, 1, 0, 1]	11	11
pop:individual:105	[63, 58, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 0, 0, 2]	11	11
pop:individual:435	[98, 37, 0, 1, 1, 0, 1, 1, 4, 1, 0, 0, 0, 0, 2]	11	11
pop:individual:140	[150, 79, 1, 0, 1, 1, 3, 1, 1, 0, 1, 1, 1, 2, 3]	11	11
pop:individual:216	[124, 42, 0, 1, 0, 0, 3, 0, 0, 1, 1, 0, 0, 1, 1]	11	11
pop:individual:290	[150, 79, 1, 0, 1, 1, 3, 0, 0, 1, 3, 0, 1, 0, 1]	10	10
pop:individual:255	[150, 79, 1, 0, 1, 1, 3, 1, 1, 1, 0, 0, 1, 2, 2]	10	10
pop:individual:14	[89, 66, 0, 0, 1, 1, 3, 0, 0, 0, 2, 0, 0, 2, 1]	10	10
pop:individual:366	[128, 66, 0, 1, 1, 4, 1, 0, 1, 0, 0, 0, 1, 2, 2]	10	10
pop:individual:215	[54, 72, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 0, 0, 2]	9	9
pop:individual:411	[113, 58, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 1, 2, 2]	9	9
pop:individual:254	[113, 58, 0, 1, 1, 4, 1, 0, 4, 1, 1, 0, 0, 3]	11	9

Table 6.11: Level of user participation.

User name	Participation
1122212314475816	122
1107674982600275	91
10207544086753085	86
1128990193799346	85
1067084180030552	83
985591718197586	77
969507913124553	72
10207004677610003	63
1223229694371825	53
10153904046011462	47
1032494570125948	44
995610090523549	42
975038365907627	35
10207487295119454	34
1041989022528624	32
471974623003503	32
1275844349097672	31
978744228875903	31
10205734318020434	31
10209454397419860	29

well as the number of views, likes available to the individual.This results are useful to observe individuals have been better evaluated by users.

In table 6.11 shows the results of the level of user participation in the experiment.These were obtained by counting the vicinity of nearest nodes from the base node in this case each user node.

In figure 6.5 we present a visual representation of user participation of this experiment where the y-axis represents the level of participation and the x axis represents the number of users who participated in this experiment.

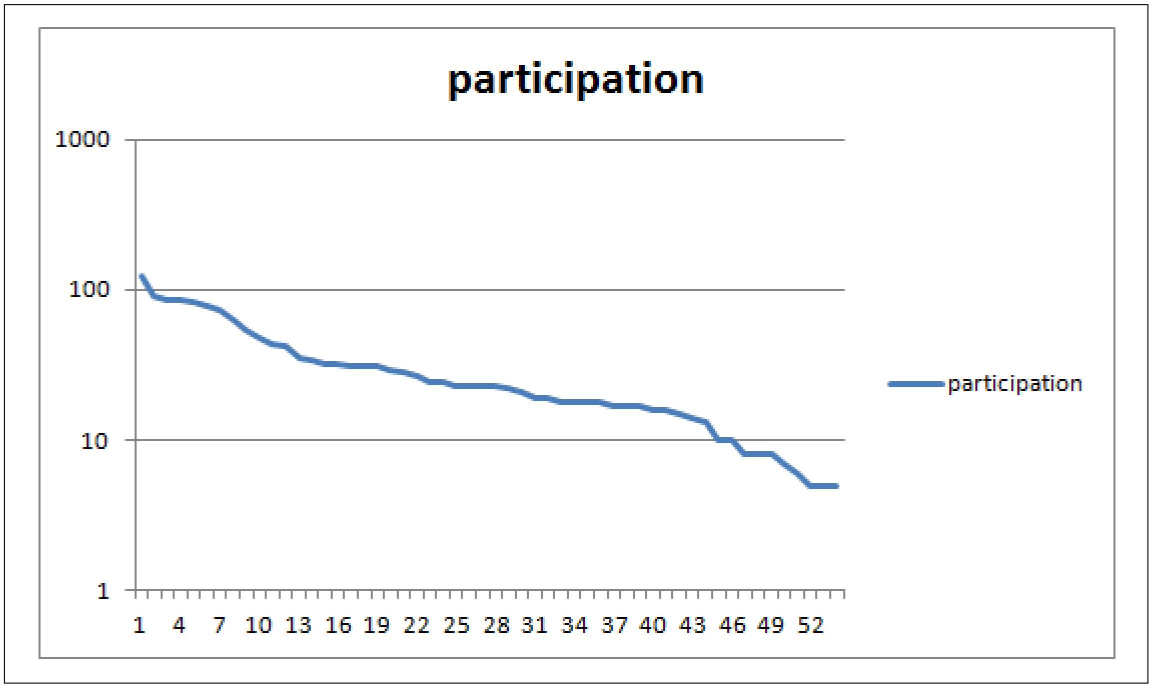

Figure 6.5: Visual representation of user participation in EvoDrawing01.

Table 6.12: Data generated in graph-based user modeling.

	Data
Nodes	3746
Relationships	17207

6.3 EvoDrawing03

In the experiment EvoDrawings03 the following data were generated presented in Table x.

The total number of users who participate voluntarily shown in table x.

In the same way as the previous experiment which wanted to observe users had better social interconnectivity within this experiment, it was decided a known ratio

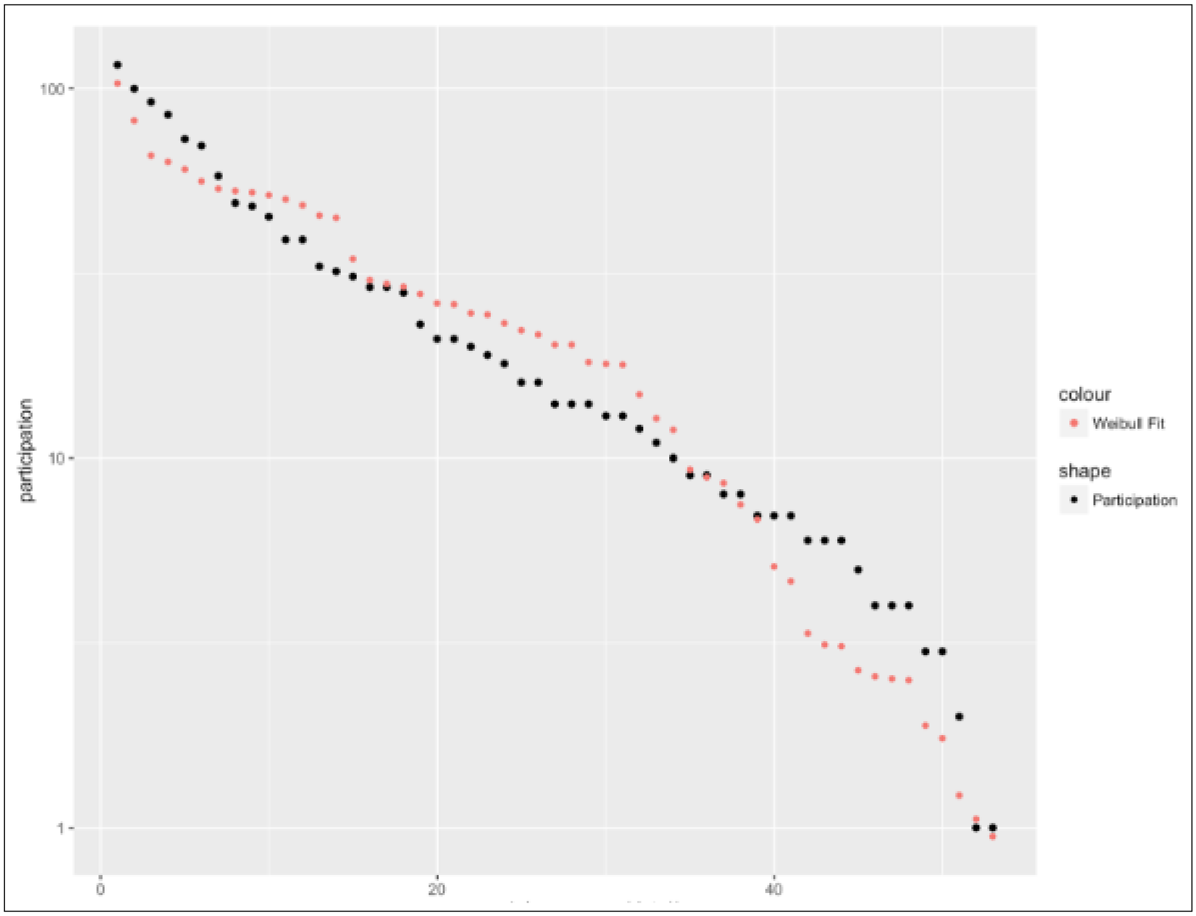

Figure 6.6: Weibull fit data representation.

Table 6.13: Total number of volunteers active users.

	Users
Total	68

Table 6.14: A sample of the top 10 users level influence on users.

User name	Number of known users
David Astorga Viramontes	23
Evelyn Macedo	18
Reyes Zuniga	17
Barbara Sandoval	16
Chriss de Blanc	15
Luis Alfonso Felix Garcia	15
Paulina NG	15
Marco Antonio Fuentes Alvarez	15
Jasiel Calzada	14
Hector Beltran Medrano	13

of the number of users that have. This relationship is presented in Table 6.14 13 where we show the 10 users with better social interconnectivity.

In figure 6.7 shows users more connected in the graph. This may represent the degree of impact of a user and the possible influence that may have on the decisions of other users. For example, if the user with the greatest impact is affected in any decision likely other users may be affected in some way. Particularly in this experiment the social graph interconnectivity among users is becoming more complex as compared to the previous experiment as we can observe that more closely resembles a social network.

In table 6.18 shows the total number of individuals evaluated by users in this

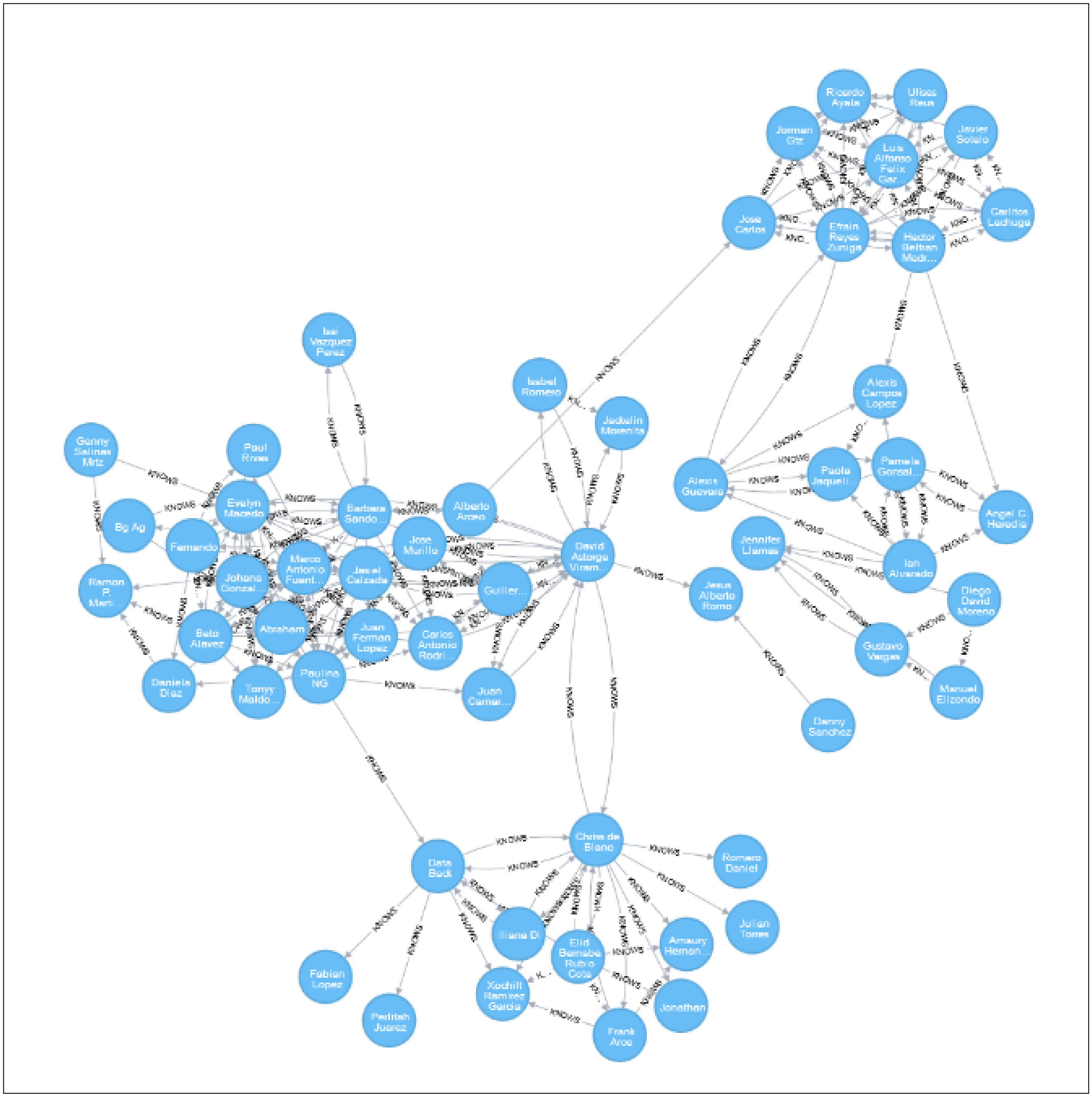

Figure 6.7: Social interconnectivity in graph-based user meodel.

Table 6.15: Total number of individuals.

	Individuals
Total	3594

experiment.

Table 6.18 contains a sample of individuals 30/556 generated in the experiment. In this its unique identifier of the individual, its chromosome, as well as the number of views, likes available to the individual presents. This results which are useful to observe individuals have been better evaluated by users.

In Figure 3 we present a visual representation of user participation of this experiment where the y-axis represents the level of participation and the x axis represents the number of users who participated in this experiment.

6.4 Comparison between experiments.

In chart 6.10 shows a comparative graph of the results obtained in the three phases of the study case, each of the lines on the graph represents one of the versions of EvoDrawing in relation to the number of units of users that were obtained are presented in different experiments. For instance the blue line represents EvoDrawing01 experiment, the red line represents EvoDrawing02 and finally the green line represets EvoDrawing03.

Table 6.16: Sample of 30 individuals evaluated from.

id	Chromosome	Views	Likes
pop:individual:3570	[113, 44, 0, 1, 0, 0, 1, 0, 1, 0, 3, 1, 1, 0, 1]	48	48
pop:individual:3544	[150, 44, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0]	32	26
pop:individual:210	[63, 58, 0, 1, 1, 1, 4, 0, 0, 0, 3, 0, 0, 2, 2]	16	16
pop:individual:202	[113, 5, 0, 1, 1, 0, 4, 0, 1, 1, 2, 1, 0, 2, 2]	22	22
pop:individual:58	[61, 70, 0, 0, 1, 0, 1, 0, 0, 0, 2, 0, 1, 0, 3]	23	21
pop:individual:858	[113, 1, 1, 1, 1, 0, 1, 1, 1, 3, 0, 1, 1, 0]	21	21
pop:individual:17	[113, 69, 0, 1, 1, 1, 3, 0, 1, 1, 0, 0, 1, 0, 3]	23	21
pop:individual:3636	[118, 44, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0]	22	21
pop:individual:33	[129, 79, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1]	20	20
pop:individual:74	[150, 50, 1, 1, 1, 1, 1, 1, 0, 1, 3, 1, 0, 1, 3]	21	19
pop:individual:65	[94, 62, 1, 0, 0, 0, 2, 0, 1, 0, 3, 0, 1, 2, 2]	20	19
pop:individual:50	[50, 70, 0, 1, 1, 1, 3, 1, 1, 1, 1, 1, 1, 1, 3]	19	19
pop:individual:52	[131, 63, 1, 1, 1, 0, 4, 0, 1, 1, 0, 0, 1, 0, 3]	20	19
pop:individual:2449	[113, 44, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 2]	18	18
pop:individual:44	[117, 54, 0, 0, 0, 0, 2, 0, 1, 1, 3, 1, 0, 2, 3]	19	18
pop:individual:113	[77, 21, 1, 0, 1, 0, 4, 0, 1, 0, 0, 1, 0, 3]	17	17
pop:individual:84	[102, 69, 1, 0, 1, 0, 3, 0, 0, 0, 0, 0, 1, 0, 3]	17	17
pop:individual:95	[68, 43, 0, 1, 0, 1, 3, 1, 0, 0, 3, 0, 0, 1, 2]	19	16
pop:individual:22	[137, 20, 0, 0, 0, 0, 0, 1, 0, 0, 3, 0, 1, 1, 1]	17	16
pop:individual:71	[79, 5, 0, 0, 1, 1, 2, 1, 0, 1, 0, 1, 1, 1, 3]	16	16
pop:individual:42	[112, 35, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 2]	9	9
pop:individual:411	[113, 58, 0, 1, 1, 1, 4, 0, 0, 1, 0, 0, 1, 2, 2]	16	15
pop:individual:59	[93, 23, 0, 0, 0, 1, 4, 0, 0, 0, 1, 0, 1, 2, 1]	17	15

Table 6.17: Level of user participation.

User name	Participation
1157401414272355	2035
1001585659925992	1828
1244770712203948	1722
990632971026794	552
987920194610578	456
10207675081608741	300
966757780068615	267
1228561717171956	258
985416538190778	203
1123938694291507	202
10207552420841432	200
1124138344283213	169
220415891643957	161
534039336778842	112
10153940958696462	93
10205543461172072	87
1281817738500333	81
10153866481615259	74
943775989063530	73
10205664691039169	71

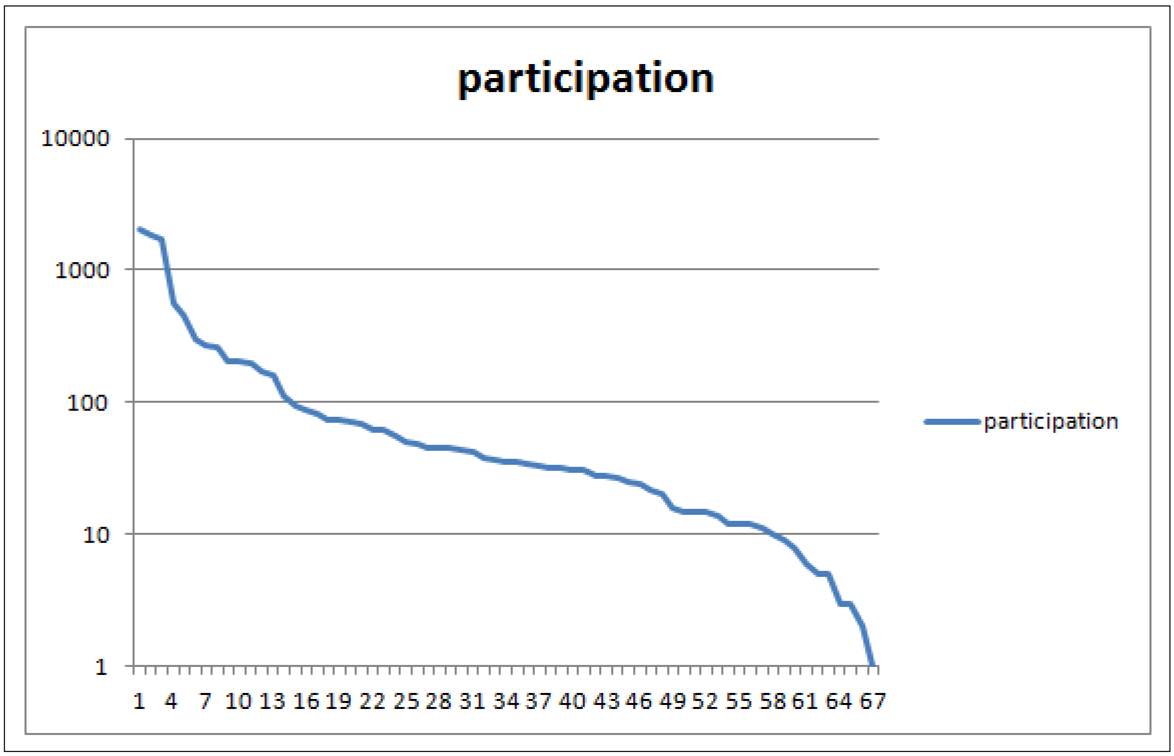

Figure 6.8: Visual representation of user participation in EvoDrawing01.

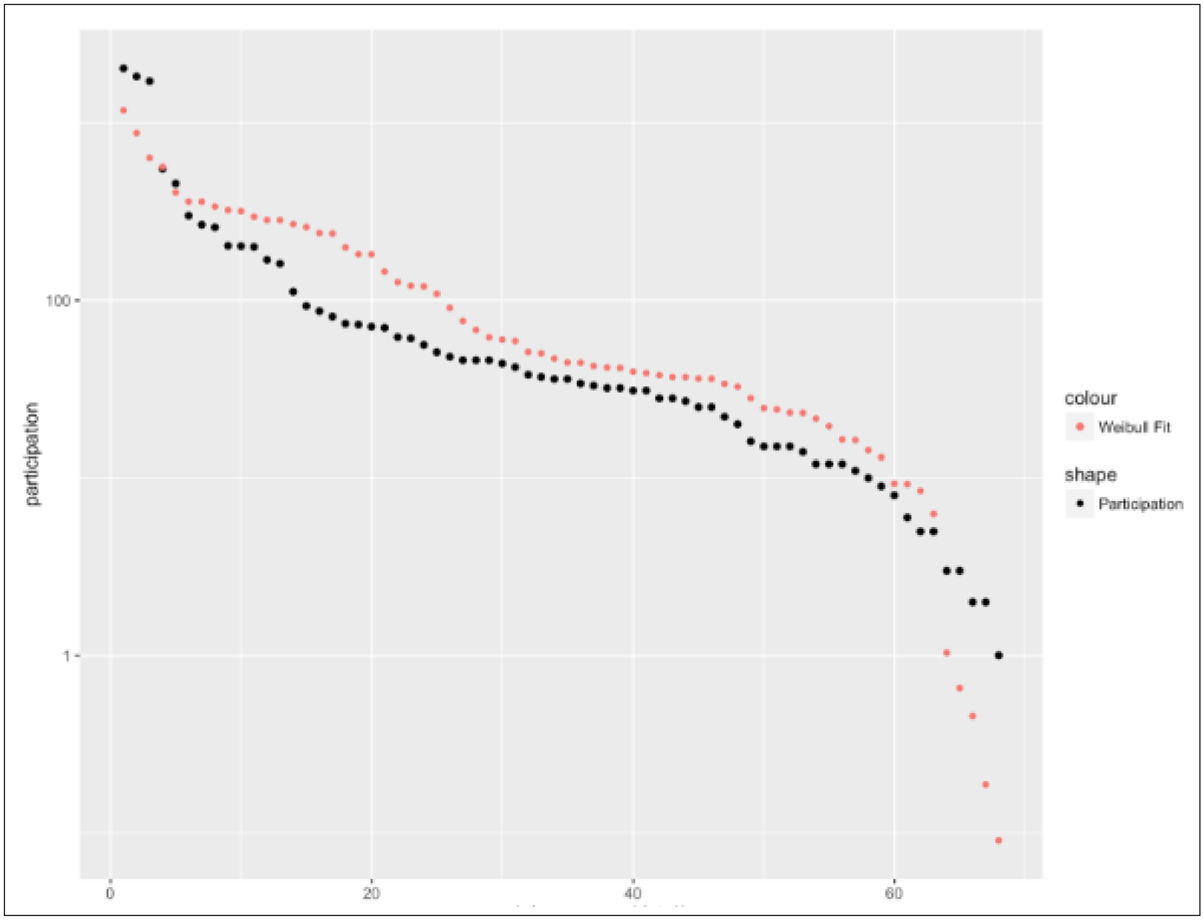

Figure 6.9: Weibull fit data representation.

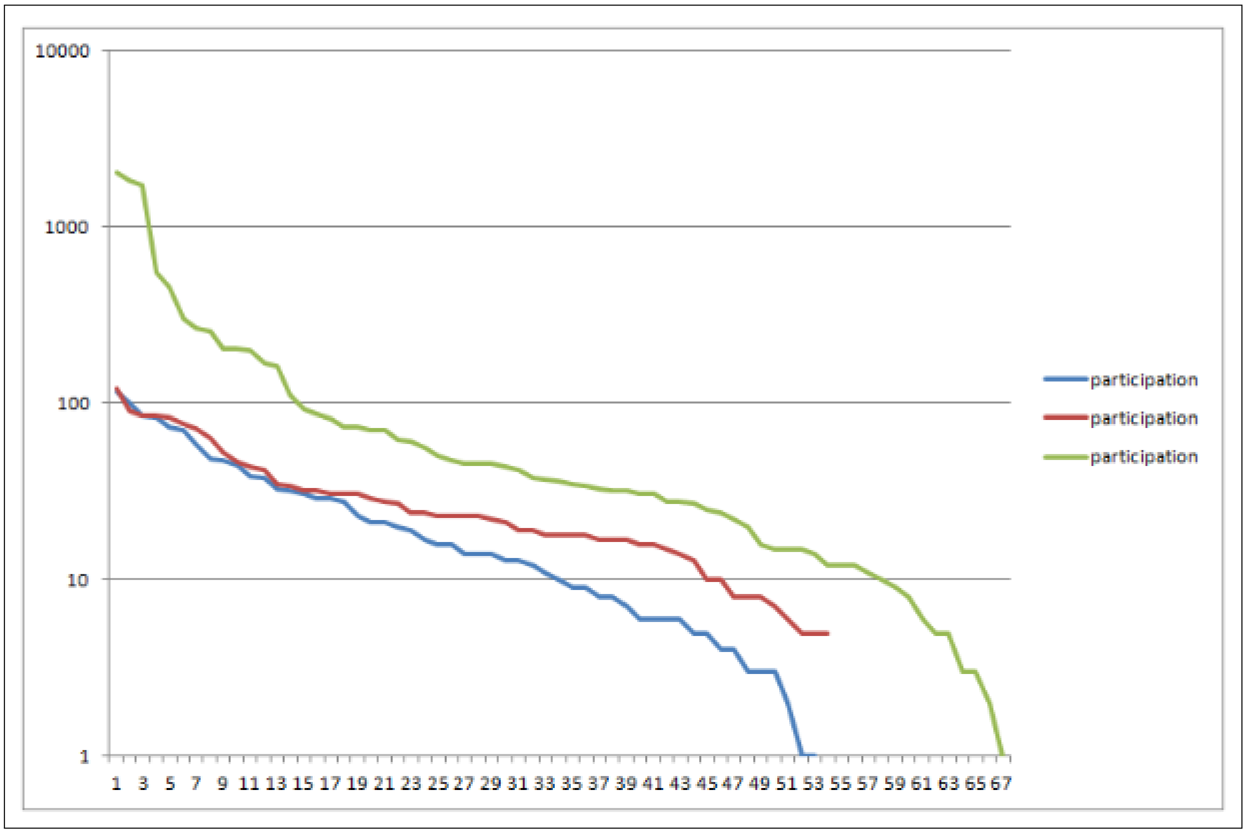

Figure 6.10: Graphical representation of user participation in the different experiments.

Table x the results of each experiment are described from column 1 to column 3 represents the number of shares of each user in each experiment respectively. The last three columns represent the difference of participations between experiments. In the figure and table x x an important phenomenon is observed, the difference between the participations of users in the first and second experiment is not wide, even in some users perceive that the first experiment got more shares.The important observable phenomenon is the difference between the shares of the top users of third experiment with respect to the first and second experiment, it is a very noticeable difference. The difference is attributed to the implementation of a model of "Gamification" adapted at the interface of the third experiment. It is presumed that this model encourages users to participate more in the interfaces due to the competitive nature among users.

Table 6.18: Difference between the top 30 user participations of the different experiments.

EvoDrawings01	EvoDrawings02	EvoDrawings03	Difference between ED02 and ED01	Difference between ED03 and ED01	Difference between ED03 and ED02
116	122	2035	6	1919	1913
100	91	1828	-9	1728	1737
93	86	1722	-7	1629	1636
85	85	552	0	467	467
73	83	267	10	383	373
70	77	258	7	230	223
58	72	203	14	209	195
49	63	202	14	209	195
48	53	200	5	155	150
45	47	169	3	157	155
39	44	161	2	161	156
39	42	112	2	130	127
33	35	93	1	128	126
32	34	87	3	80	78
31	32	81	2	62	61
29	31	74	3	58	55
29	31	73	8	52	50
28	31	71	8	46	43
23	29	70	7	50	42
21	28	62	7	50	42
21	28	70	7	49	42
20	27	62	7	42	35
19	24	61	5	42	37
18	24	56	6	38	32
16	23	51	7	35	28
16	23	48	7	32	25
14	23	46	9	32	23
14	22	46	9	32	23
14	22	46	8	32	24
13	21	44	8	31	23

Chapter 7

Conclusions and future work

7.1 Conclusions

Using a user model in Web-based interactive evolutionary computation overall with the different approaches such as fuzzy logic and gamification it demonstrated in experiment EvoDrawing03 that the users increase their participation with respect to other versions (EvoDrawing01, EvoDrawin02).

In this sense the results have shown a phenomenon in the users which is competitiveness. This phenomenon occurs naturally because as human beings is our nature to be competitive regardless of the topic or activity that we assign [Reference]. This gave support to users return to evaluate more individuals within the experiment EvoDrawings03 and consequently the participation increase exponentially.

In this research work also found that the way individuals was presented to be evaluated and how to evaluate them helped the user to take their evaluations so easy and quick. This means that users evaluated on average 40 or more individuals in an iteration, reducing the risk of demotivation assessment and therefore lose interest in participation. However, it was concluded that the biggest problem of interactive evolutionary computing systems remains on user fatigue.

The fatigue can be generated by many factors, such as how to evaluate individuals, the subject of the application, how to present the individuals, the objective within the application, expertise by users, and more. The resulting method of this research helps motivate users on the issue of participation in interactive evolutionary computing applications.

7.2 Future work

Competitiveness is among users regardless of the level of expertise they have. Still psychological test would be necessary to see the level of fatigue that users acquire in systems of this context. These psychological tests are beyond the scope of this thesis since the main objective of the research was about measuring the participation of users through a graph-based user modeling, which finally answers the hypothesis of this research. However this research allows adaptation and implementation of other techniques and research that enrich this work with multidisciplinary teams to determine that this method and other methods can reduce the user's fatigue in the context of Web-based interactive evolutionary systems.

Another way to attract and increase users participations is to work with techniques of intelligent interfaces and natural interfaces in order to the user's evaluate more naturally, thus creating more natural and intelligent way to evaluate individuals, with which the user may feel more comfortable in evaluating individuals. For instance gesture-based interfaces, visual interfaces using sensors (cameras, Kinnect) to detect the time or emotion felt by the user when presented with an individual who needs to be evaluated.

The combination of these techniques generates more robust methods in competitiveness among users using this type of interfaces, for example implement rewards medals type or representative plates when the user reaches a certain level of participation it increases the interest to continue participating and improving the level of expertise within the systems, as well as to share their achievements in their social networks. In this sense we believed that no matter the topic of interactive evolutionary computation systems users will participate collaboratively having fun without knowing in depth is participating.

Publications

1. *Restaurant Recommendations based on a Domain Model and Fuzzy Rules. Xochilt Ramírez-García, Mario García-Valdéz. International Seminar on Computational Intelligence. Tijuana Institute of Technology. Tijuana Mexico. (2012).*

2. *Post-filtering for a Context-Aware Recommender System. Xochilt Ramírez-García, Mario García-Valdéz. Recent Advances on Hybrid Approaches for Designing Intelligent Systems . Springer International Publishing Switzerland. (2013).*

3. *Recomendaciones contextuales basadas en el enfoque de post-filtrado. Xochilt Ramírez-García, Mario García-Valdéz. Modelado computacional de Habilidades Linguisticas y Visuales. Vol.74. Research in Computer Sciences, IPN. 2014.*

4. *Context-aware Recommender System Based in Pre-filtering Approach and Fuzzy*

Rules. Xochilt Ramírez-García, Mario García-Valdéz. Recent Advances on Hybrid Approaches for Designing Intelligent Systems . Springer International Publishing Switzerland. (2014).

5. *Context-Aware Recommender System Using Collaborative Filtering, Content-Based Algorithm and Fuzzy Rules. Xochilt Ramírez-García, Mario García-Valdéz, 2016.*

6. *A Hybrid Context-aware Recommender System for Restaurants. Xochilt Ramírez-García, Mario García-Valdéz, 2016.*

Appendix A

EvoDrawing deploy instructions

Appendix B

Fuzzy inference system IF-THEN rules for ED03

1. *If **preference** is low and **experience** is low and **ranking** is low then **fuzzy-rate** is bad.*

2. *If **preference** is low and **experience** is low and **ranking** is mid then **fuzzy-rate** is bad.*

3. *If **preference** is low and **experience** is low and **ranking** is high then **fuzzy-rate** is bad.*

4. *If **preference** is low and **experience** is mid and **ranking** is low then **fuzzy-rate** is bad.*

5. *If* ***preference*** *is low and* ***experience*** *is mid and* ***ranking*** *is mid then* ***fuzzy-rate*** *is bad.*

6. *If* ***preference*** *is low and* ***experience*** *is mid and* ***ranking*** *is high then* ***fuzzy-rate*** *is normal.*

7. *If* ***preference*** *is low and* ***experience*** *is high and* ***ranking*** *is low then* ***fuzzy-rate*** *is normal.*

8. *If* ***preference*** *is low and* ***experience*** *is high and* ***ranking*** *is mid then* ***fuzzy-rate*** *is normal.*

9. *If* ***preference*** *is low and* ***experience*** *is high and* ***ranking*** *is high then* ***fuzzy-rate*** *is normal.*

10. *If* ***preference*** *is mid and* ***experience*** *is low and* ***ranking*** *is low then* ***fuzzy-rate*** *is bad.*

11. *If* ***preference*** *is mid and* ***experience*** *is low and* ***ranking*** *is mid then* ***fuzzy-rate*** *is normal.*

12. *If* ***preference*** *is mid and* ***experience*** *is low and* ***ranking*** *is high then* ***fuzzy-rate*** *is normal.*

13. *If* ***preference*** *is mid and* ***experience*** *is mid and* ***ranking*** *is low then* ***fuzzy-rate*** *is normal.*

14. *If **preference** is mid and **experience** is mid and **ranking** is mid then **fuzzy-rate** is normal.*

15. *If **preference** is mid and **experience** is mid and **ranking** is high then **fuzzy-rate** is normal.*

16. *If **preference** is mid and **experience** is high and **ranking** is low then **fuzzy-rate** is normal.*

17. *If **preference** is mid and **experience** is high and **ranking** is mid then **fuzzy-rate** is normal.*

18. *If **preference** is mid and **experience** is high and **ranking** is high then **fuzzy-rate** is normal.*

19. *If **preference** is high and **experience** is low and **ranking** is low then **fuzzy-rate** is normal.*

20. *If **preference** is high and **experience** is low and **ranking** is mid then **fuzzy-rate** is normal.*

21. *If **preference** is high and **experience** is low and **ranking** is high then **fuzzy-rate** is good.*

22. *If **preference** is high and **experience** is mid and **ranking** is low then **fuzzy-rate** is normal.*

23. *If* ***preference*** *is high and* ***experience*** *is mid and* ***ranking*** *is mid then* ***fuzzy-rate*** *is normal.*

24. *If* ***preference*** *is high and* ***experience*** *is mid and* ***ranking*** *is high then* ***fuzzy-rate*** *is good.*

25. *If* ***preference*** *is high and* ***experience*** *is high and* ***ranking*** *is low then* ***fuzzy-rate*** *is good.*

26. *If* ***preference*** *is high and* ***experience*** *is high and* ***ranking*** *is mid then* ***fuzzy-rate*** *is good.*

27. *If* ***preference*** *is high and* ***experience*** *is high and* ***ranking*** *is high then* ***fuzzy-rate*** *is good.*

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