

# Recommendation of Videogames with Fuzzy Logic

Hugo Calderon-Vilca  
 Universidad Peruana de Ciencias  
 Aplicadas, Universidad Nacional  
 Mayor de San Marcos  
 Lima, Perú  
 pcsihcal@upc.edu.pe

Nilton Mercado Chavez  
 Universidad Peruana de Ciencias  
 Aplicadas  
 Lima, Perú

José María Rojas Guimarey  
 Universidad Peruana de Ciencias  
 Aplicadas  
 Lima, Perú

**Summary**— A videogame as software and as a product presents a great variety of characteristics: gender, theme, platform, target audience, among others. In recent years, the number of videogames developed has grown notably thanks to the industry, as users have a large catalog available, who often may be curious to play another videogame that has not been presented in an advertising medium. In present investigation we propose a videogame recommendation architecture and a recommendation system using Fuzzy Logic, in the construction we have designed 16 rules with fuzzy sets. A database of approximately 55,000 games and of its 16 attributes of which 5 were used for the recommendation system was used: 4 attributes (Critic Score, User Score, Global\_Sales, Year) to establish membership functions with the 16 rules of recommendation formed based on the opinion of experts in the field of videogame analysis and 1 attribute (Age) to develop the content filter according to age applying an ethics model in Artificial intelligence. The results of our computational experiments with the proposed architecture reached an accuracy percentage of 80,0%.

## I. INTRODUCTION

Currently, artificial intelligence allows solving problems in different fields such as medicine, education [41], [42], [43], [44], [45], likewise, video games require artificial intelligence algorithms to recommend to users.

In a given field, a recommendation system is an intelligent agent that provides users with a list of suggestions based on the user's profile, the features expressed in the user's profile allow exploring other patterns that relate to the user's interest, to relate and calculate those relationships there are many algorithms and techniques such as collaborative filtering [46], first order logic, fuzzy logic and probabilities that allow you to build the inference engine of an intelligent system.

The videogames market benefits greatly from the recommendation models and architectures, thanks to these models they can offer new games to their users more personally, the production of new videogames also grows exponentially, to insert these new varieties to the market is necessary to calculate directly the target audience, minimizing losses.

According to research, several models have been proposed to recommend videogames; in fact, these models are improvable or have problems. In [1], a recommendation model based on a collaborative filtering technique is used, which recommends videogames based on similarity of tastes with other users so that they largely depend on the rating of the user community. In [2], the model they propose is based on the content filtering technique, unlike the previous one, it uses exclusively the elements of the game to generate new recommendations, which can generate that very similar games are always recommended and not allowed to expand the user's

horizons. In contrast, in [7] they present a recommendation system based on a combination of evaluation criteria.

In [3], the proposed system learns from different cases, a person can play a game that is not compatible with his personality and thus update the content that will be used for future recommendations. Similarly, in [5] they used machine learning techniques, extracting user experience information. they used the development process and the testers as feedback. In [6], the behavior as a player and as a buyer is evaluated with a model similar to [5], focused on Extremely Randomized Trees (ERTs) and Deep Neural Networks (DNNs), they propose the recommendation of videogames.

In contrast to the previous models, in [4] several of the above criteria are applied and at the same time they perform a ranking system using the Bayesian networks technique, in which the information of each user is evaluated (primary criteria in [1], [2] and [7]), then the products (videogames) are categorized based on their individual information and relationships with users (evaluation similar to [3], [5] and [6]), concluded that the characteristics when combined with traditional matrix factorization techniques, they can lead to the generation and recommendation of highly effective bundles.

Carrying out an analysis of the previous proposals where they use different filters and models in the videogame recommendation, it was observed that they do not fit precisely the profile of the player user, because the moment of choosing their videogame depends on the emotion in a certain time, also the age is an important factor because it clearly differentiates the taste of games between an adult and a child.

Ethics in artificial intelligence raises the moral behavior of intelligent machines. As discussed in [13] about Autonomous Ethical (Ro) bots, on the other hand, intelligent systems such as bots, robots and autonomous assistants who make permanent decisions.

In this investigation we present a videogame recommendation architecture using fuzzy logic with an Artificial intelligence ethical filter module, additionally we propose an application that allow us to recommend videogames to users based on the characteristics (Critic Score, User Score, Global\_Sales, Year).

The videogame recommendation system collects from the user attributes of interest related to the videogame Critic Score, User Score, Global\_Sales, Year, which you can change or regulate at ease to asses and receive the recommendation of the system. This will allow a list of resulting videogames to be obtained that responds to the qualities that the user values most. To apply the necessary rules that guarantee the optimal functioning of the expert system with fuzzy logic, the rules imposed by the "Entertainment Software Rating Board" were

used, which is an American system in charge of classifying the content of videogames.

The rest of the document is structured as follows: Section II provides the State of Art, in which relevant research on the recommendation of videogames is reviewed. Section III describes the contribution of this investigation. Section IV details the design and implementation of the recommendation system. In Section V, the results obtained are validated and discussed by contrasting with other proposals. Finally, Section VI presents the conclusions and future work

## II. STATE OF THE ART

In [1], the authors propose a recommendation system based on a collaborative filtering technique to suggest videogames to users who request it, with the aim of modelling the behavior of a person who knows the user's interests, such as, friends and/or family, that such groups of people would be the most appropriate to recommend attractive items for the consumer. Collaborative filtering was used for the individual rating of the members of the player community and the rating of the games of a particular user in order to be able to recommend new videogames. So that the result of the proposed system results in videogames that match the preferences of the users, they used a history of the individual user ratings and thus recommend only games that users with similar tastes most value. After evaluating the results of their proposal, the researchers obtained that of the 25 cases in which videogames were recommended to certain users, 21 were correctly predicted.

Unlike [1] in [2] they propose a recommendation based on the similar judgment of other users, a recommendation model that adopts filtering based on content as opposed to collaborative filtering, which requires that all games have previous qualifications to be able to find relationships between the tastes of a user community, the filtering based on the context extracts relevant characteristics, in this case from a videogame to detect similarities. In [2] the researchers used the videogame FightingICE, which is generated procedurally, to extract and then compare various data of interest in video format. The experiment was carried out with 13 users, who played the clips of the game to evaluate according to their criteria how similar they were among the options. As a result, the resulting similarity between a couple of games coincided with its content and human perception.

In [3], they propose a videogame recommendation system that associates the user's profile with game genres, in order to suggest a personalized list of titles. The main audience that writers focus on is for the elderly and the disabled, so that they can perform mental and/or physical exercises and thus lead a fuller life. The proposed model used a list of disabilities recognized by the World Health Organization (WHO), which was indexed to a list of games, with the aim that a title is compatible with a certain disability. In addition, the algorithm used takes into account the user's personality since they created a correlation between people with a specific personality and their taste for a certain genre of videogames. The system is able to learn in case a person plays a game that is not compatible with his or her personality, and then can relate that personality to the genre of the game and the user experience. After evaluating the results of their proposal, the authors obtained that their model has an accuracy of 80%, which tends to improve the more extensive the database is.

In [4], the authors propose a package videogame recommendation system (bundles) using the Bayesian Personalized Ranking (BPR) method with a greedy algorithm.

They implement 3 basic notations: a set of users, a set of items (videogames) and a set of packages (bundles), where it must be fulfilled that every bundle must contain at least one item of the set and that through the entire ranking every user must have recommended at least two videogames, that is, at least one bundle of two items and that every user must have included two variations of a custom bundle. Two trainings data are used, the first one is BPR for items consisting of a set of triplets (u, ip, in) where u is the user; ip, a purchased item; and in, an item not purchased. The second one is BPR for bundles where it also uses a similar triplet, but instead of item the criterion is bundles, the problem they encountered with this type of algorithm is that there is a high risk of "saturation" in which they would suggest the same bundles, since negative values (unbought items and bundles) inhibit the generation of more personalized sales packages, so they used a sample algorithm to match the distribution and negative probability equal to the positive. This concludes in the greedy algorithm that for each iteration creates new bundles following a random initial one, combining bundles and high probability items, then compares which of the two has greater compatibility with the user and runs the algorithm again until there is a convergence.

In [5], an algorithm that recommends mobile videogames based on the information obtained from user interaction with the game is proposed. Similarly, information is collected during its development phase, from programmers and their testers. The result is, after finishing the videogame, a notification sent to the user with a list of recommended videogames. Multi-Agent Recommendation System (MARS) is the implemented system that uses the user experience as relevant data. Evaluate and normalize the player's ability to recommend similar videogames in difficulty, design and from the same developer or similar.

In [6] the authors propose a program that recommends videogames to users based on their experience and behavior with their products, that is time of play, duration in which the videogame ends, frequency of activity. The algorithm model is a mix between Extremely Randomized Trees (ERTs) and Deep Neural Networks (DNNs), where the computational efficiency of ERTs is used and tree branching offers a greater variation of options to recommend, from DNNs its nonlinear dynamic learning is taken advantage of to adapt to customer behavior (input as a vector), this proposal is interesting because the purchase predictions are given with a time variable (t) that serves to estimate the probability of buying a videogame per recommended player (isInNextPurchaseDate and isNextPurchase) and if the action was performed in a considerable time (isWithinWindow). The results prove that the ERT model improves the probability of finding the best item *isOnNextPurchaseDat* from 44 to 47%; one from 34% to 37% in *isNextPurchase*; and from 69% to 71% in *isWithinWindow*.

In [7], the authors propose a videogame recommendation system using implicit feedback in Top-L analysis and two models, one based on factors to eliminate empty values and the other oriented towards the proximity of users. An archetype analysis technique that decomposes matrices into archetypes (extreme entities) and stochastic vector coefficients is used to represent each data point as a combination of the archetypes found. The first model is simply based on recommending videogames that are more compatible with the unique factors of each player matrix. Instead, the second model calculates the distance or difference between player matrices and is recommended based on player factors and history sharing. The results verify that the greater number of videogames entered by the user, the recall is closer to 100%, the AFF parameterization

being  $k=50$  with approximately 97.5% with 30 initial titles and AANeP  $N=10$  with 95% with 30 initial titles.

In [8], the researchers propose a Word2Vec algorithm (concatenation of words to vectors) that by Deep Neural Network method recommends movies. They used the metadata of the movies recorded in a dataset, such as director, actors, year of production, cost, among others. After finding films similar to the conclusion made by the metadata, they generated a prediction of user view time in order to filter. Finally, through a classification, the films with the highest scores for the recommendation are shown in a list. The interesting thing about this proposal is the concatenation of a human language and the metadata of the films, which could simulate a reasoning criterion. The results show an improvement of 0.165 compared to the *item2vec algorithm*, concluding in successful learning using metadata.

In [9], the authors propose the development of the PeGRec application (Custom Games Recommender) to recommend board games to users. Unlike Amazon and Barnes & Noble, both great exponents in the area of table game sales, which recommend these products to their users based on consumer purchasing patterns and collaborative filtering, and therefore do not focus on the characteristics of the game to adapt the specific preferences of the user, the proposal of the researchers makes the suggestions based on the qualities of the product, such as popularity, number of players, analysis of opinions on the reviews of the games, time of game, complexity and category. The application asks users for information on board games that it has, which will be used to find candidate games, which are very similar to the previously mentioned characteristics of the base games. After evaluating their results, they obtained that the recommendations made by PeGRec are much more personalized and precise regarding the real interests of the user than those provided by Amazon and Barnes & Noble.

In [10], the researchers propose an algorithm that provides video recommendations to users of the online YouTube video platform through the use of Deep neural Networks. The factors used by the system to provide recommendations are scalability, the ability to distinguish relevance between new and old videos, and the use of metadata through user behavior (history and actions when watching a video), the algorithm uses two neural networks: the first one performs Candidate Generation, it is in charge of filtering millions of videos to hundreds of videos using criteria of the user's history and its behavior. The second Neural Network makes ranking with the user data, managing to filter the videos provided with the previous Neural Network, they also added a list of videos that were current trend, also added more features about other users who share similarities (likes, demographics, behavior). According to the researchers, they analyzed the problem of recommending current videos to the public, they saw that among other evaluation and ranking methods (scoring criteria) the training data had current videos as not recommended due to their low number of visits. Therefore, an "age" factor was added that allowed the algorithm to relate the upload time of a video with the popularity of the time-dependent video, with which the probability of suggesting more current videos was higher. The results prove that time-weighted loss is reduced up to 34.6% using all filters.

In [11], the researchers propose a reference system that uses genetic algorithms, with the aim of finding from past choices, tastes and evaluations, they try to show future choices that may be of interest to the user. To make more personalized

recommendations, they face internet service problems, because in their proposal they try to ensure that the content they offer to their users is delivered quickly and correctly and show only that information that is of interest to their audience and thus produce personal recommendations instead of just recommending generic content. For the specific case addressed by the researchers, the recommendations revolve around books, so they developed a virtual library. The proposed model initially selects a population of books with attributes (name of the book, writer, Publisher, categories, sub categories, serial number and label) similar to the books you have read and subsequently evaluated with genetic algorithms until you get twelve books of which, on average, 4.6 are of real interest to users.

In [12], they present the development of a probabilistic *Menu-Offering-Bundle* (MOB) generative model to capture the offer and the bundling or grouping of developers' projects. The objective of the system is to exceed the expectations of the design of prizes or bonuses offered by the bundles. They conclude that the more rewards that are offered by bundle and the degree of these grow on scales (*reward* tiers) the more likely their acquisition and success in the market will be. Humble Bundle, a digital platform that offers multimedia material (e-books, videogames, software, among others), uses this method or similar strategy to be able to sell videogames to the client, in addition, the items offered in the bundles are categorized according to their value or purchasing potential, that is a commercial videogame can be offered successfully in a high tier to get the attention of the customer and make him or her buy videogames from the lower tiers, simulating a recommendation of similar products. This strategy is recommended for the expert system that would recommend videogames, because they managed to offer a list of suggested videogames and the better known a videogame is, it is an important reference point for the generation of options.

In [13], they consider (*robots*) as algorithms created by humans and that inherently they must be implemented an ethical dimension through ethical rules or principles. They briefly explain the level of autonomy that a (*robot*) can have: low (human input needed), partial (supervised human input) and total (generates alternatives). Based on this, immutable ethical laws, computation of consequences by utility or a learning system would be implemented as an ethical integration approach depending on the level of autonomy of the algorithm. The proposed model (Decision Making Model) consists of two main fields: Planning Analysis assesses whether any action to be carried out requires an ethical evaluation and Ethical Guidance analyzes the possible alternatives through ethical rules and training data and defines a solution. The authors conclude that there should not be a black box that blocks the transparency of the algorithm's decision and analysis method as autonomous as it may be, so its use and applications must be monitored by experts in the field to be developed and users.

### III. ARCHITECTURE AND RULES DESIGN

In our contribution we design an architecture of a videogame recommendation system using fuzzy logic based on Critic Score, User Score, Global Sales and Year, which are characteristics of a particular videogame of a user, in order to present a list of videogame titles that resemble your user tastes. Also, in the proposal we designed a tool or application that was developed in the R language, using libraries: FuzzyR [47] to be able to use functions related to fuzzy logic and Shiny to implement an attractive graphical user interface.

### A. Input Data

A data set was obtained from the Kaggle page [16], from which data from various research areas can be downloaded. The data set used was provided by the user Abdulshaheed Alqunber, who made web scrapping to obtain data from the VGChartz site, which is an important exponent regarding the content of the information on videogames, in that content it houses a database of games in constant expansion, of which there are characteristics that were of interest in the present investigation. The selected data set contains a list of approximately 55,000 games, of which relevant information is stored in 16 columns or features; however, not all columns are of interest for this work, therefore we consider 4 characteristics: Critic Score, User Score, Global\_Sales and Year, we add an Age characteristic in the proposal as a filter based on the model proposed in [13], in Table I we describe these characteristics as input data.

TABLE I. INPUT DATA

Attribute	Description
Critic Score	Rating of the game according to critics (maximum value 10)
User Score	Rating of the game according to critics (maximum value 10)
Global_Sales	Total worldwide sales (in millions)
Year	Year of launch of the game.
Age	User age.

### B. Data Processing and Standardization

Before using the input data in our model that uses fuzzy logic, it is necessary to normalize, since some rows have no data in certain columns, to fill in those fields that present NA data (not available) the following steps have been performed: in the case of quantitative variables, the average found on the basis of those rows was assigned, the qualitative variables they will be assigned as the default value "Unknown". The purpose of treating the data set is to allow those rows that have an absence of data to also be considered when recommending the videogame collection and avoid corrupting the results.

After completing the data set, it was necessary to validate which rows or instances should be considered in our model, in order to minimize the problems inherent to the different units of each column and their different dispersions, it has been adjusted to the scale of these rows at the same interval, for practical purposes the [0,1] interval has been considered. In the equation the function used for the normalization of the data set can be seen:

$$f(X) = \frac{X - \text{Min}}{\text{Max} - \text{Min}} \quad (1)$$

In equation (1) the value of X represents the input value of the function, while Min and Max represent the minimum and maximum value respectively of a given column. The result of (1) is the normalized value for each variable in the data set.

### C. Fuzzy sets and membership functions

a). *Critic Score*: LevelUp is a site of best video game reviews[17], in this work LevelUp has been used as an attribute, its rating system used, which specializes in covering various news related to the area of videogames, specially to rate these to recommend them or not to its users, the fuzzy set that we devised for the *Critic Score* variable has the range for

qualification of [0,10], as far as the membership function is the probability that is measured in the range [0, 1].

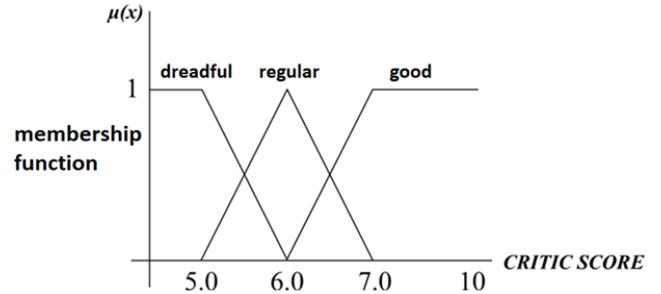


Fig. 1. Critic Score fuzzy set and its membership function

As can be seen in Fig. 1, the score of the variable "CRITIC SCORE" that critics use to rate games is contained between the number 1 and 10, in this investigation those games that are below the rating 5 are considered as "bad", rates between 5 to 7 are considered "regular" and those grades greater than 7 are considered "good". The triangular membership function that allowed to represent this variable was used.

b). *User Score*: For this variable, 3DJuegos was used as a reference [18], its rating system similar to LevelUp, specializes in covering various news related to the area of videogames, especially to rate these to recommend them or not to their users. The difference with LevelUp, is that 3DJuegos is characterized by giving greater emphasis to the opinion of users, which is why it has been considered in this investigation to model the fuzzy User Score set.

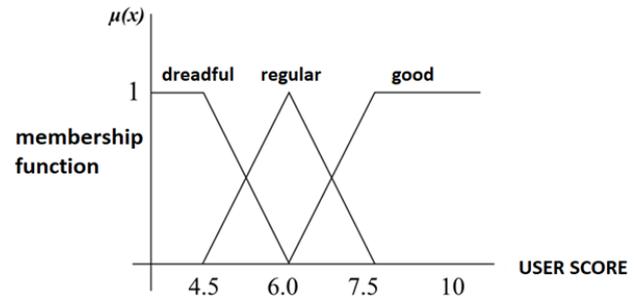


Fig. 2. Fuzzy User Score set and its membership function

As can be seen in Fig. 2, the variable "USER SCORE" are scores that users use to rate the games are contained between the number 1 and 10, in this work we have considered those games below the rating 4.5 as "bad", rates between 4.5 and 7.5 are considered "regular" and those rates greater than 7.5 are "good". The triangular membership function was used to represent this fuzzy set.

c). *Global Sales*: This variable was collected from the videogame database of the VGChartz website [19], which contains the total sales of an extensive list of videogames. After comparing a list of commercial failures and great successes, it was modeled with the Gaussian membership function.

As can be seen in Fig. 3, videogame sales are contained between the minimum amount of sales of the data set and their respective maximum normalized between [0,1], being those videogames that have sales below 0.8 considered as low and those over 0.8 were considered high. The Gaussian membership function was used, unlike the previous variables,

the sales variable covers a much more interval, this type of representation works best with those variables that can take small decimal values, since it allows a margin of tolerance around the value that is taken as more representative.

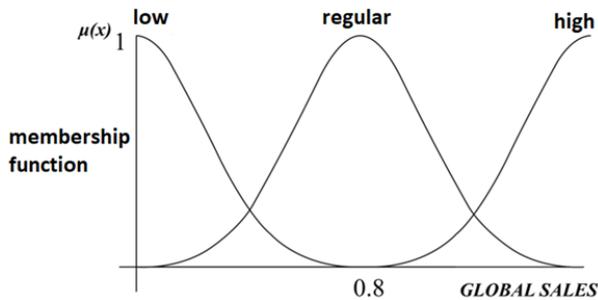


Fig. 3. The Global Sales fuzzy set and its membership function

c). *Year*: Year of launch of the game, this variable was collected from the IGN website [20], which specializes in covering various news related to the area of videogames, especially topics of further investigation. In one of the notes provided by this means, retro videogames are defined, those that belong to generations that differ in a great period of time with the current generation of videogames, in those that belong to the fourth generation, mainly formed by the consoles Super Nintendo Entertainment System and Sega Genesis, and backwards.

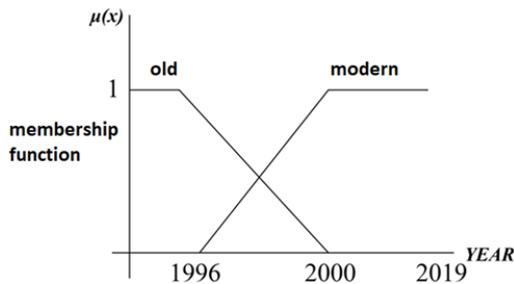


Fig. 4. Year fuzzy set and its membership function

As can be seen in Fig. 4, and according to the IGN note, videogames are considered old if they are at most up to the fourth generation of videogames, being that the last videogame released for that period was in the year 2000, in the same way, the beginning of the fifth generation, being already part of modern videogames, occurred in 1996 until current 2019 games, for this variable the trapezoidal membership function was used.

D. Design of inference rules

The degree of complexity of the rules varied according to the criterion of importance with which each attribute is considered in Table I and its possible values in their respective membership functions. In our proposal we have estimated that the *User Critic* has the highest interest judgment, because we consider its respective as the most independent of the others, in addition to the fact that the same user dictates their opinions, as regards *Critic Score* variable it is a company’s perspective media and not directly from the user, critics make judgments; the *Global Sales* variable represents how well the game was sold or how popular the activity of the product is; and the variable *Year* mainly represents the time or year that

the videogame has been inserted into the market, it also represents the accessibility to the game, sales and acquisition platforms, consoles, repositories, stores, among others.

The rules proposed in Table II were categorized using the four variables, if a videogame is recommended or not recommended, it is a result applying at least two variables. For this rating pages or ranking of videogames with mixed participation were used, that is, with the perspective of the workers of said platform and users [17], [21] and [22]. Likewise, information and opinions were used by content creators such as [23] and [24], who offer an analysis of videogame title performance, sales analysis and whether these games are recommended or not.

The decision mechanism starts from the segmentation between *User Score* and *Critic Score*, in this case for rule 1 in case in both fields they present a *Malo* rating the title will not be recommended, since it is considered as a bad title that does not satisfy the perspectives of a videogame or the average audience, for example the video game *E.T. The Extra Terrestrial* [25] and [26] in 1982 with huge sales for its time and considered one of the worst games ever.

For rule 9, when the *Critic Score* is *Regular*, taking into account the example of *No Man’s Sky* [27] in 2016 with huge sales and a poorly polarized criticism between the average and the players, but generally negative, in these cases we impose on the “not recommended” rule regardless of the other attribute.

To implement rules 12 and 13 it has been considered that if the *Critic User* variable is *Good* and if the videogame is *Old* in the *Year* variable, then the title will be recommended, as well as in *Chrono Cross* [29], but in case it is *Modern* in the *Year* variable will not be recommended, it is worth noting that many new or modern videogames lack user feedback to be recommended, as is the case of *Assassin’s Creed Odyssey* [29] in 2018.

Rule 16, if both *User Score* and *Critic Score* have a rating of *Good* then the game is recommended, since it is considered outstanding and good regardless of its time or sales, such as the case of *Super Mario 64* [30] or *The Last Story* [31].

Rule 8 that considers only two attributes is when the *User Score* qualifies as *Good* and *Global Sale* has a *Low* or *High* result in these cases it is recommended, many videogames despite their low initial popularity are high quality videogames as well as the game *Super Meat Boy* [33], also the popularity of these games is based on their quality and user preference, rather than the good result of an advertising strategy like the classic *Pokémon Red*. [34] or *Minecraft* [35].

Rules 2, 4, 5, 7, 10 and 14 that contain three attributes for the evaluation of recommendation are a combination of *Critic Score* attributes with the three *User Score* attributes with *Regular* and *Year* with *Old*. When the videogame has *Bad* or *Regular* as an analysis in *Critic Score*, the videogame will not be recommended, since they are considered outdated, that is they are videogames that have lower quality compared to the present time as *Dragon Ball Final Bout* [36] or *Bubsy II* [37]. On the other hand, when the analysis is *Good Critic Score* and *Year* is *Old* it will be recommended as in the case of *Earthbound* [38] because of its initial publicity in North America it obtained regular reviews from users but acclaimed by the average. The second combination of attributes is with *Global Sales* is *High* along with *Year* and *User Score* is not recommended because it symbolizes a negative impact of

videogame advertising on players, which is sought to rule out, such as *FIFA* o *Call of Duty sagas*; on the other hand, if *Global Sales* is *Regular*, it is recommended.

Lastly, rules 3, 11 and 15 are with the combination of the four attributes that are entered. What is sought is to simulate how the media and other expert critics recommend videogames that have a *Regular User Score* rating, with *Low* in *Global Sales* and *Modern* regarding their *Year* of publication. In these cases, they are not very popular videogames despite the ease of acquisition nowadays. An example of a videogame not recommended would be *Mario Party 10* [39] of 2015, which had regular reviews and low sales. On the other hand, *Fluidity* [40] would be recommended, because despite its low sales, expert criticism is very positive.

TABLE II. RULES DESIGN

Nº	Critic Score	User Score	Global Sales	Year	Result
1	Bad	Bad	-	-	Not Recommended
2	Bad	Regular	-	Old	Not Recommended
3	Bad	Regular	Low	Modern	Not Recommended
4	-	Regular	Regular	Modern	Recommended
5	-	Regular	High	Modern	Not Recommended
6	-	Good	Low	-	Recommended
7	-	Good	Regular	Old	Recommended
8	-	Good	High	-	Recommended
9	Regular	Bad	-	-	Not Recommended
10	Regular	Regular	-	Old	Not Recommended
11	Regular	Regular	Low	Modern	Not Recommended
12	Good	-	-	Old	Recommended
13	Good	-	-	Modern	Not Recommended
14	Good	Regular	-	Old	Recommended
15	Good	Regular	Low	Modern	Recommended
16	Good	Good	-	-	Recommended

E. Proposed Architecture

Fuzzy logic allows us to introduce a degree of ambiguity in the ways of qualifying, which is useful for representing human reasoning in machines, generally inaccurate terms are used that do not fit with classical logic. That is why, to simulate a recommendation expressed by a human being, we have designed an architecture that makes use of user input data to recommend videogames with a probability of recommendation. Fig. 5 illustrates the steps involved in obtaining the final list of recommendations, the fundamental objective of the approach proposed is the design of an architecture that shows the user a list of videogames with a probability of recommendation similar to that requested by him or her. In this proposal we add a filter based on the age of the user in order to avoid recommending videogames for adults to children, this filter is based on the model of ethical decision making by intelligent agents proposed in [13]. In

summary, the proposal is an approach that contains several components: apply fuzzy logic rules to the input data to obtain a recommendation probability, calculate the videogame data set with a probability similar to that requested and apply a filter according to the age of the user, with the aim of keeping in mind the ethical aspect in the model.

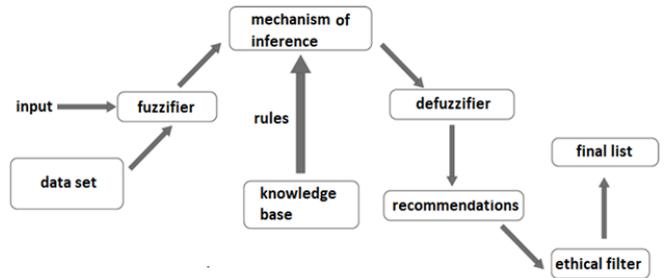


Fig. 5: General architecture of the proposal.

The objective is to find the list of videogames that resemble the probability of recommendation found according to the input data. When starting the application for the first time, the probability of recommendation of all the elements of the data set is found, so that they do not have to be calculated every time the user enters new parameters to obtain recommendations, for which the rules obtained from the knowledge base. Next, we proceed to explain in detail the proposed architecture.

1) *Fuzzy Inference Mechanism*: The input data provided by the user are fuzzy sets subject to the inference rules seen in Table II, the purpose is to calculate the probability of recommendation, for this the user provides the values that he or she considers necessary on a videogame at a certain moment he or she is playing, the rules are applied in fuzzy logic to obtain videogames that have a degree of recommendation probability similar to what you have valued.

2) *Ethical Filtering*: After obtaining the list of videogames with a probability of recommendation similar to what the user is looking for, a filter is applied in relation to the player’s age. The filter was applied according to the model proposed by [13], the filtering criteria is based on the criteria offered by the “Entertainment Software Rating Board” institution, which assigns each videogame a category based on the content of this, the usefulness of using the categories offered by that agency allows avoiding videogames that differ with social norms, which helps the proposal maintain an ethical approach. For example, videogames of category “M” could not be recommended to children, since they contain material recommended for people over 17, such as violence, blood, sexual issues or insults.

F. Output Data

The output data is composed of a list of videogames with a percentage of recommendation similar to that requested by the user, this list of videogames is an output matrix, its description is detailed in Table III.

TABLE III. OUTPUT DATA

Attribute	Description
Name	Name of the videogame.
Genre	Genre of the videogame.
ESRB_Rating	Classification of the videogame according to the ESRB.
Platform	Platform in which the videogame was published.
Publisher	Videogame publishing company.
Developer	Videogame developer company.
Critic_Score	Rating of the game according to critics (maximum value 10).
User_Score	Rating of the game according to users (maximum value 10).
Total_Shipped	Total copies sold of the game.
Global_Sales	Total worldwide sales (in millions).
NA_Sales	Sales in North America (in millions).
PAL_Sales	Sales in Europe (in millions).
JP_Sales	Sales in Japan (in millions).
Other_Sales	Sales in the rest of the world (in millions).
Year	Year of launch of the game.
Recommendation	Percentage of videogame recommendation.

G. Defuzzification

As a final result it is expected to obtain a probabilistic numerical value, on the other hand, the result of applying the rules of the fuzzy sets whose output is not interpretable for the context, so it is necessary to convert the fuzzy set resulting from adding all the rules to an exact value. That is why, to transform the range of output values obtained from applying all the previously described rules to a value that can be easily interpreted by people, we have applied the Mandani defuzzification method, the model calculates the centroid of the area bellow the curve obtained in the diffuse inference mechanism, for which it is based on the following equation:

$$y = \frac{\sum_i b_i f u(i)}{\sum_i f u(i)} \tag{2}$$

In equation (2), the value of y represents the defuzzified value, which is found by multiplying the range of values obtained by the fuzzy inference by its respective index and dividing it by the same range, this defuzzified value is the probability of recommendation, the closer to 1 means that it is highly recommended otherwise if it approaches 0 means very little recommended.

IV. APPLICATION DESIGN

In the present investigation we additionally propose a videogame recommendation system, it is intended to be deployed in web browsers, so it was decided to implement it in the R language with the FuzzyR library, for the application of the rules and Shiny [48], which allows deploying interactive solutions on the platform to which it is aimed.

A. Implementation

For the construction of the algorithm that composes the videogame recommendation system, the following steps were followed:

- Preprocessing and standardization were applied to the set of data selected using the methods described in section III.

- The fuzzy inference mechanism was constructed from the fuzzy sets described in section III.
- The 16 built rules were applied to the fuzzy inference mechanism.
- A function that applies the fuzzy inference model to the set of videogames chosen was implemented. This step is performed only once at the beginning, in order to have the results saved and avoid having to recalculate each time the user starts a new request.
- The Mamdani method [49] was applied to defuzzify the fuzzy set obtained after applying the inference and thus obtain the percentage of recommendation of each videogame in the list.
- Two other data sets were created applying the ethical filter, concluding in: 1. Complete set of videogames; 2. Set of videogames suitable for minors; and 3. Set of videogames suitable for children.
- A function was implemented that allows to list videogames with an associated probability that similar videogames of the user that is pointing, a filter function of titles that do not correspond to the age introduced by the user, with the objective of maintaining ethical principles and avoiding expose minors to material with content not suitable for them.

B. Graphic Interface

We designed a simple interface for data entry and to show the results is directly accessible by running the application from R.

In the initial tab, the input data that the user must enter to make their query is shown on the left, which can be altered through a scroll bar Fig. 6.



Fig. 6. Graphical data input interface

At the far right, the fuzzy sets applied are presented, clicking on the links shows the results of each one, in this case the fuzzy Critic Score set with the triangular membership function Fig. 7.

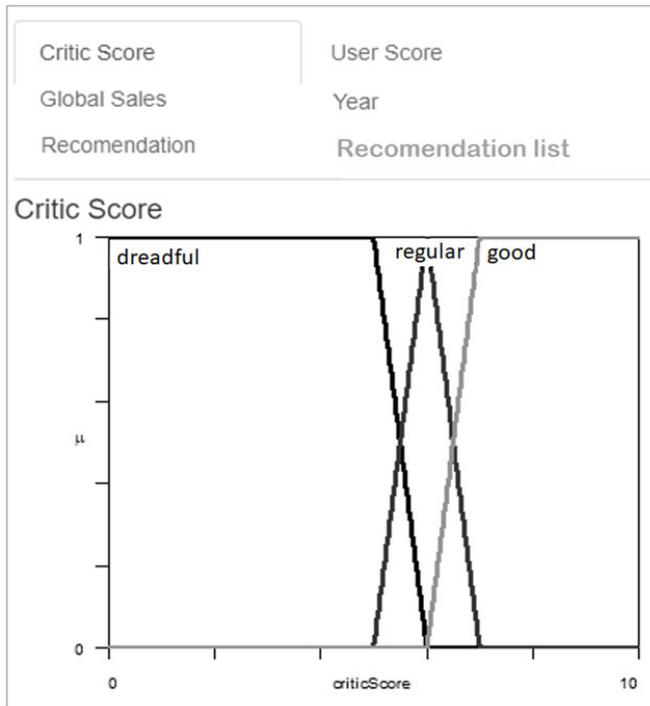


Fig. 7. Fuzzy Critic Score sets implemented

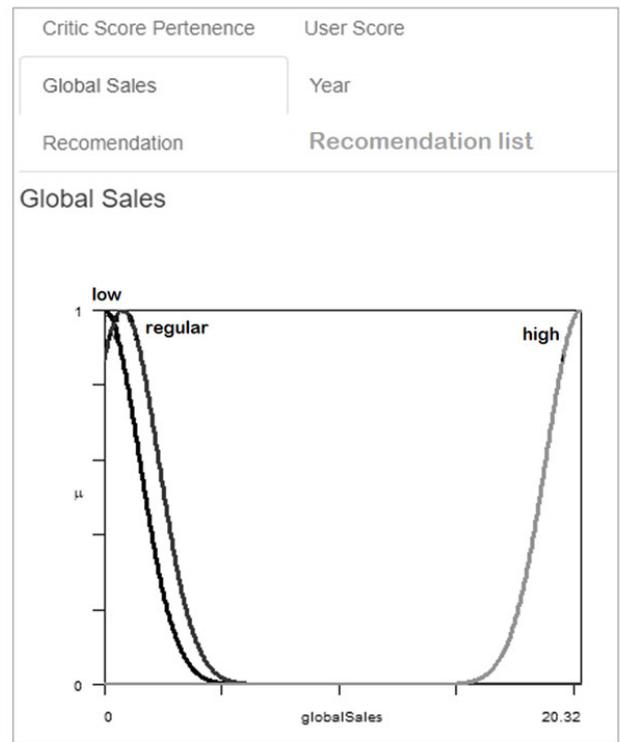


Fig 9. Fuzzy Global Sales sets implemented

Similarly, for the Global Sales variable, the gaussian membership function has been applied, Fig. 9.

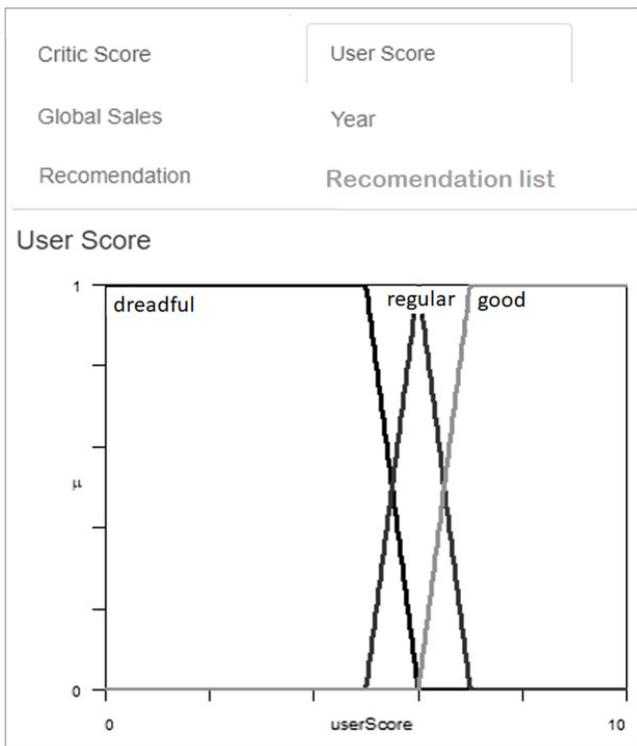


Fig. 8. Fuzzy User Score sets implemented

Fig. 8 shows the result of the application of the User Score fuzzy set applied with the triangular membership function.

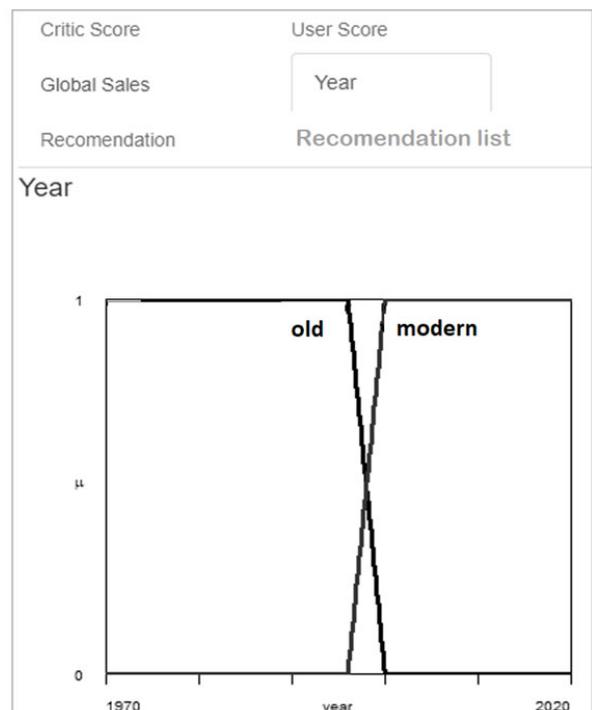


Fig. 10. Fuzzy Year sets implemented

The Year attribute was applied with the triangular membership function, to show its range between old and modern, Fig 10.

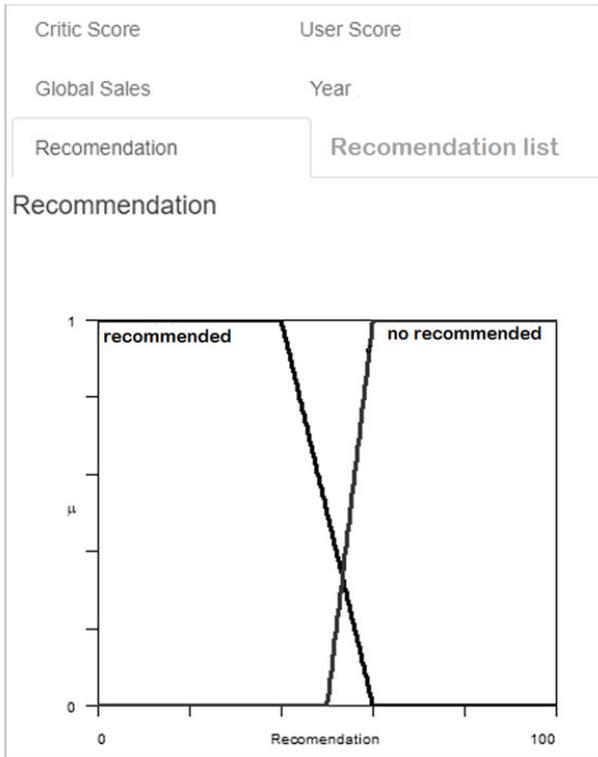


Fig. 11: Fuzzy Recommendation sets (model output)

After applying the membership functions with each fuzzy set, a previous list of recommended videogames is obtained for the data provided by a user.

Rank	Name	Genre	ESRB_Rating	Platform	evaluation
542	Saints Row 2	Action	M	X360	75.59
544	The Sims: Vacation	Simulation	T	PC	75.59
545	Call of Duty: Ghosts	Shooter	M	XOne	75.59
546	Heavy Rain	Adventure	M	PS3	75.6
547	LEGO Batman: The Videogame	Adventure	E10	DS	75.6
548	Borderlands 2	Shooter	RP	X360	75.6
549	Kung Fu Panda	Platform	E10	X360	75.6

Fig. 12. Recommended videogames list

Finally, the age filter was applied based on the ethical principle, showing a list of recommended videogames

according to age, to meet this objective a tab of recommendations is presented that allows users to consult the videogame list Fig. 8, we clarify that those videogames that do not comply with the content intended for the user's age were not taken into account.

V. RESULTS AND DISCUSSION

A. Results

We have tested the expert system with 100 users who made 5 queries each, the total of 1000 queries with different input values in each attempt, in order to be recommended a list of videogames. After conducting the experimentation stage, they were asked for their opinion regarding the titles that had been recommended, the results were as follows:

- Of the total of 1000 queries made, 80% had at least one videogame of interest to the user or one that he had already played and could validate the recommendation (80% success rate).
- 90.0% of users consulted considered that the use of the score of other users was an important criterion, since the specialized media score is usually influenced and does not reflect the actual valuation of the titles, so it must be supported by other factors.
- 20% of queries made by users were not useful for users because they did not like the recommendation list, concluding that the list of titles shown by the application was of considerable length and the characteristics of the videogames it contained did not present considerable variability (Critic Score, User Score or Global Sales).

B. Discussion

In the research [11], the model proposed by the researchers shows recommendations with a success rate of 84% (4% higher than this proposal), because they use prior information on the interests of users to generate recommendations with a higher degree of recommendation, in our case we use fuzzy logic and show that this type of recommendations can be made with another technique.

In [2], the model they proposed was based on the content filtering technique, which uses exclusively the elements of the game to generate new recommendations, which can generate that very similar games are always recommended, and the user's horizons are not allowed to expand. Instead, this proposal uses a broad data set, with which you can make recommendations with a greater degree of variability, because using fuzzy sets includes the ambiguity factor.

In [3] and [5], the researchers used algorithms that are characterized by working with much larger databases and/or constantly increasing or learning user behavior, which improves their ability to recommend. In our work we use 55,000 games as a knowledge base, as for the technique we use Fuzzy Logic, of many attribute we determine the most important ones, in this regard, four variables were necessary to implement our model, in the validation we show an accuracy of 80% similar to [3] where the same accuracy was obtained. In [5] they present a list like our proposal, its algorithms stand out in scalability and level of competition from the perspective of product sales, we emphasize that the recommendation can also be made with fuzzy logic techniques.

In [11], the authors propose a model that uses genetic algorithms to find future book recommendations, we similarly recommend videogames using fuzzy logic based on attributes that make up fuzzy sets.

In the investigations [1], [2], [3] and [5] different proposals make videogame recommendations with different techniques each investigation without considering the ethical model, we in this investigation add a filter based on the ethical model [13] which presents the videogame list according to the age of the player, guaranteeing that an older videogame could not be recommended for a minor.

#### CONCLUSIONS AND FUTURE WORK

With the four attributes of videogames, a fuzzy set has been designed with each attribute, these attributes are the elements of our model.

We present a videogame recommendation system architecture, for the inference engine 16 rules are designed to calculate the recommendation, using the Mamdani model it has been defuzzified to show the associated probability in the recommendation.

Finally, we present an application, videogame recommendation system tool implemented in R.

As future work, it is possible to achieve a higher success rate by combining the proposed model with other methodologies such as content filtering or collaborative filtering, in order to generate a hybrid model that previously uses the data of interest of players and others with similar tastes, without neglecting the ethical issue presented by the current proposal regarding the recommendation of videogames with content suitable according to age.

#### VII. REFERENCES

- [1] S. Muhammad, T. Shahzad, Z. Sattar, R. Khan, M. Majid, "A Game Recommender System Using Collaborative Filtering (GAMBIT)", 14th International Bhurban Conference on Applied Sciences & Technology (IBCAST) 332, 2017
- [2] K. Mori, S. Ito, T. Harada, R. Thawonmas, K. Kim, "Feature Extraction of Gameplays for Similarity Calculation in Gameplay Recommendation", IEEE 10th International Workshop on Computational Intelligence and Applications November 11-12, 2017
- [3] L. Catalá, V. Julián, J. Gómez, "A CBR-Based Game Recommender for Rehabilitation Videogames in Social Networks", Intelligent Data Engineering and Automated Learning – IDEAL 2014 pp 370-377, 2014
- [4] A. Pathak, K. Gupta, and J. McAuley, "Generating and Personalizing Bundle Recommendations on Steam", 40<sup>th</sup> International ACM SIGIR Conference on Research and Development in Information Retrieval – SIGIR '17, pp. 1073-1076, 2017
- [5] P. Skocir, L. Marusic, M. Marusic, and A. Petric, "The MARS - A Multi-Agent Recommendation System for Games on Mobile Phones", Lecture Notes in Computer Science, pp. 104-113, 2012
- [6] P. Bertens, A. Guitart, P. Chen, and A. Periañez, "A Machine-Learning Item Recommendation System for Video Games", IEEE Conference on Computational Intelligence and Games (CIG), 2018.
- [7] R. Sifa, C. Bauckhage, and A. Drachen, "Archetypal Game Recommender Systems", 2014.
- [8] Y. Yoon, and J. Lee, "Movie Recommendation Using Metadata Based Word2Vec Algorithm", 2018 International Conference on Platform Technology and Service (PlatCon), 2018
- [9] Y. Ng, I. Seaman, "Personalized Table-Top Game Recommendations", IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI), 2017
- [10] P. Covington, J. Adams, and E. Sargin, "Deep Neural Networks for Youtube Recommendations" Mountain View, CA, 2016.
- [11] C. Aygün, O. Yıldız, "Development Of Content Based Book Recommendation System Using Genetic Algorithm", 24th Signal Processing and Communication Application Conference (SIU), 2016
- [12] Y. Lin, P. Yin, and W. Lee, "Modeling Menu Bundle Designs of Crowdfunding Projects", Conference on Information and Knowledge - CIKM'17, pp. 1079-1088, 2017
- [13] F. Alairi, and A. Vellino, "A Decision Making Model for Ethical (Ro)bots", 2017 IEEE International Symposium on Robotics and Intelligent Sensors, pp. 203 – 207, 2017
- [14] N. Farhana, S. Mariyam, S. Yuhani, "Deep Learning and Its Applications: A Review", Postgraduate Annual Research on Informatics Seminar, 2016
- [15] N. Manzoor, M. Kirmani, "Emotion Analysis: A Survey", International Conference on Computer, Communications and Electronics (Comptelix)", 2017
- [16] Kaggle: Video Games Sales 2019 <https://www.kaggle.com/ashaheedq/video-games-sales-2019> January 11, 2019
- [17] LevelUp: Reviews de Videojuegos <https://www.levelup.com/reviews> January 11, 2019
- [18] 3DJuegos: Análisis de Videojuegos <https://www.3djuegos.com/index.php?zona=top100> / January 11, 2019
- [19] VGChartz: Base de Datos de Videojuegos <http://www.vgchartz.com/> January 11, 2019
- [20] IGN: Definiendo lo Retro <https://es.ign.com/retro/99289/feature/definiendo-lo-retro> y <https://es.ign.com/article/review> January 11, 2019
- [21] Metacritic/games: Review de Videojuegos <https://www.metacritic.com/game> , January 11, 2019
- [22] IGN/games: Review de Videojuegos <https://www.ign.com/reviews/games> January 11, 2019
- [23] YongYea, periodista y crítico de videojuegos y películas [https://www.youtube.com/channel/UCT6iAerLNE-0J1S\\_E97UAuQ](https://www.youtube.com/channel/UCT6iAerLNE-0J1S_E97UAuQ) January 11, 2019
- [24] Cleanprincegaming, creador de videos-essay sobre videojuegos: <https://www.youtube.com/channel/UCXj7EFAEM6PtQLjh0wfsSA> January 11, 2019
- [25] Gamespot, E.T.: The Extra Terrestrial – Reviews <https://www.gamespot.com/e-t-the-extra-terrestrial/reviews/> January 11, 2019
- [26] Harris John, Review Roundup: Was E.T. Really the "Worst Game Ever"? , The Video Game History Foundation, <https://gamehistory.org/et-atari-reviews-worst-game-ever/> January 11, 2019
- [27] Metacritic, No Man's Sky PS4 version reviews <https://www.metacritic.com/game/playstation-4/no-mans-sky> January 11, 2019
- [28] IGN, Chrono Cross <https://www.ign.com/articles/2000/08/16/chrono-cross> January 11, 2019
- [29] Metacritic, Assassin's Creed Odyssey PC version reviews <https://www.metacritic.com/game/pc/assassins-creed-odyssey> January 11, 2019
- [30] Metacritic, Super Mario 64 reviews <https://www.metacritic.com/game/nintendo-64/super-mario-64> January 11, 2019
- [31] Metacritic, The Last Story reviews <https://www.metacritic.com/game/wii/the-last-story> January 11, 2019
- [32] Metacritic, Super Meat Boy PC version reviews <https://www.metacritic.com/game/pc/super-meat-boy> January 11, 2019
- [33] Metacritic, Battlefield V PC version reviews <https://www.metacritic.com/game/pc/battlefield-v> January 11, 2019
- [34] IGN, Pokemon Red review <https://www.ign.com/articles/1999/06/24/pokemon-red> January 11, 2019
- [35] Metacritic, Minecraft PC version reviews, <https://www.metacritic.com/game/pc/minecraft> January 11, 2019
- [36] Gamespot, Dragon Ball Final Bout review <https://www.gamespot.com/reviews/dragon-ball-final-bout-review/1900-2547221/> January 11, 2019
- [37] Gamespot, Bubsy II review <https://www.gamespot.com/bubsy-ii/reviews/> January 11, 2019

- [38] IGN, Earthbound review  
<https://www.ign.com/articles/2013/07/24/earthbound-review>  
January 11, 2019
- [39] Metacritic, Mario Party 10 reviews  
<https://www.metacritic.com/game/wii-u/mario-party-10> January 11, 2019
- [40] Metacritic, Fluidity reviews  
<https://www.metacritic.com/game/wii/fluidity> January 11, 2019.
- [41] Julca-Mejía, W., H. D. Calderon-Vilca, and F. C. Cárdenas-Mariño. "Evaluation of Source Code in ACM ICPC Style Programming and Training Competitions.", 2018.
- [42] H. D. Calderon-Vilca, K. E. C. Callupe, R. J. I. Aliaga, J. B. Cuba and F. C. Mariño-Cárdenas, "Early Cardiac Disease Detection Using Neural Networks," 2019 7th International Engineering, Sciences and Technology Conference (IESTEC), Panama, 2019, pp. 562-567.
- [43] M. A. Silva-Fuentes, H. D. Calderon-Vilca, E. F. Calderon-Vilca and F. C. Cárdenas-Mariño, "Semantic Search System using Word Embeddings for query expansion," 2019 IEEE PES Innovative Smart Grid Technologies Conference - Latin America (ISGT Latin America), Gramado, Brazil, 2019, pp. 1-6
- [44] H. D. Calderon-Vilca, E. G. Ocrospoma-Callupe, F. C. Cárdenas-Mariño and E. F. Calderon-Vilca, "Architecture and mobile application with augmented reality, visualizing videos and 3d objects in museums," 2019 IEEE CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON), Valparaiso, Chile, 2019, pp. 1-5.
- [45] C. E. Serquen-Llallire, H. D. Calderon-Vilca and F. C. Cardenas-Mariño, "Comparison of two Algorithms for Routing Questions and Answers, Applied to Group of Students Software Engineering," 2018 IEEE Latin American Conference on Computational Intelligence (LA-CCI), Guadalajara, Mexico, 2018, pp. 1-6.
- [46] Vijay Kotu, Bala Deshpande, "Chapter 11 - Recommendation Engines", data Science (Second Edition), 2019, Pages 343-394, 2019.
- [47] Chao Chen, Jon Garibaldi, Tajul Razak, "Package FuzzyR - Fuzzy Logic Toolkit for R", <https://cran.r-project.org/web/packages/FuzzyR/FuzzyR.pdf>, 2019
- [48] Winston Chang, Joe Cheng, JJ Allaire y otros, "Package shiny - Web Application Framework for R", <https://cran.r-project.org/web/packages/shiny/shiny.pdf>, 2020.
- [49] Segismundo S. Izquierdo and Luis R. Izquierdo, "Mamdani Fuzzy Systems for Modelling and Simulation: A Critical Assessment", Journal of Artificial Societies and Social Simulation 21(3) 2, 2018.