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Intelligent Recommender System for online clothing optimization of casual clothing: An approach from the Competitive Imperialist Algorithm

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***Abstract*: The future state of the companies that offer online services is of great importance for the professionals of the stock market. According to the efficient theory of the market, it is impossible to adequately predict suitable suggestions to the clients considering the historical reference data. A precise prediction offers companies greater credibility, as well as an increase in their sales. The present research demonstrates the resolution of a problem based on the modeling of the online shopping process, selecting the garments that best suit a specific profile. The objective of this research is based on obtaining a recommendation model that allows customizing clothing shopping suggestions online. For this, the Competitive Imperialist Algorithm (ICA) is implemented, analyzing 300 in-stances of garments from a Database provided by the University of Hong Kong. As a result, specific purchase profiles are obtained using our bioinspired algorithm verified through Case-Based Reasoning (CBR), where in this process we will be able to solve the new problems based on the solutions of previous problems to improve the shopping experience in line of users, allowing the adaptation of multiple dynamic environments.**

***Keywords*:** Imperialist competitive algorithm, Evolutionary algorithms, Intelligent Recommender system, Case-based reasoning**.**

I. Introduction

To achieve an accurate prediction of possible recommendations to the client, the identification of effective characteristics is crucial. In other words, the representative characteristics of the factors play a key role in the effectiveness of the prediction [1]. Recommendation systems are used to recommend, for example, to people who have made a certain purchase, what other products might interest them. Nowadays, it is used by almost all online sales companies, such as Amazon [2], [3]. Not only are products recommended to be purchased, other things can be recommended, such as videos that can help you (Youtube), movies that you like (Netflix), music that you feel like listening (Pandora), people who can be your friends (Facebook), etc. There are many types of recommendation models. The simplest recommendation model is that of recommending what is most popular (Recommendation Model based on Popularity). If we have a database with songs that 200,000 people have heard. [2], [3] A popularity-based recommender will recommend the same thing to anyone: the most listened to song among all 200,000 people have heard. Therefore, it is a non-personalized model. A slightly more advanced step will be precisely to achieve some personalization of the recommendation. A model based on characteristics that are known by users and products, such as: historical purchases, time of day when purchases were made, product characteristics, among others. [4]-[6] It works as a classification model. The problem with these recommenders is the possible lack of data from both the users and the products. The third type of recommenders is based on collaborative filters. These models consider what other people bought who also bought the product that a user has bought. The logic behind it can be summarized with a matrix that is created for each product, the Co-occurrence Matrix, which il-lustrates what other product the users who bought the product purchased. [5]. They are divided into Recommendation Models based on Normalized or Weighted Cooccurrence. The technique of trading traditionally referred to the presentation and rotation of products in the store. Currently, e-commerce is booming, most stores have a website where customers can buy the same products that are in the store or even some that are sold only online. It is very important to direct the customer to the product and facilitate

the purchase action. Be able to offer the customer the product they want, thus guaranteeing sales. Through this project it is proposed to be able to customize the offer of products to the customer during the process of buying clothes online. This is a benefit that can only be achieved in a virtual environment and that few companies are taking advantage of. Personalization can be based on various factors from the consumer's preferred brands to the time of day or the day of the week in which they usually make purchases. The present research focuses on solving part of these situations -among them the concept of retail- that is to say the control of stock, by providing a model that allows improving the set of purchases made online considering that there is a lot of information that is You get, but little analysis of what you are buying, also offer a selection of products that suits your preferences, as well as get that selection change dynamically according to the tastes of customers. No similar applications have been found in the literature. It is intended to work with catalogs of online stores, totally free of cost and easy to access, mainly of the Zara brand, with the aim of forming the database system to perform the consultations and tests of the algorithm.

II. Competitive Imperialist Algorithm

The domain of bio-inspired computing is gradually gaining momentum in modern times. As society moves towards a digital age, there has been an explosion in the amount of data generated. This explosion of data makes it increasingly difficult to extract information, as well as collecting knowledge through standard algorithms, due to the growing complexity of the analysis [5]. Finding the best solution becomes increasingly difficult to identify, it is not impossible due to the large and dynamic scope of the solutions and the complexity of the calculations. The optimal solution for a NP-hard problem is a point in n-dimensional hyperspace and the identification of the solution is computationally very expensive or even not feasible. Therefore, smart approaches are needed to identify appropriate work solutions [6]. Within metaheuristics, bio-inspired algorithms are gradually gaining prominence as they are intelligent, can learn and adapt as biological organisms. These algorithms are drawing the attention of the scientific community due to the increasing complexity of the problems, to a growing range of potential solutions in multidimensional hyperplanes, to the dynamic nature of the problems and constraints and incomplete, probabilistic and imperfect changes in the information decisions. However, the rapid developments in this domain is increasingly difficult to track due to the different algorithms introduced.

Evolutionary optimization methods, inspired by natural processes, have shown good performance in solving complex optimization problems. Evidence of this is the genetic algorithms (inspired by the biological evolution of the human species and others), the optimization of ant colonies (based on the effort of the ants to find the optimal path in the search for the source of food) and particle swarm optimization (reference to the behavior of particles in nature), are widely used to solve problems of optimization of engineering [7]-[10]. The imperialist competitive algorithm (ICA) is a new evolutionary method of optimization inspired by imperialist competition. It starts with an initial population like other evolutionary algorithms denominated in the country, which are colonized or imperialist [11]-[15]. Imperialist competition is the main part of the proposed algorithm and allows the colonies to converge to the global minimum of the cost function. This method is a new global search strategy, socio-politically motivated, which has recently been introduced to address different optimization tasks [16]-[18]. Table 1 shows the parameters with which the ICA works, as well as its corresponding description.

Parameters	**Description**
Np	The number of countries is determined by the total population.
Nimp	The number of imperialists would be 10-13% of the number of countries.
Ncol	The number of colonies is determined by the subtraction between the number of countries and the number of imperialists.
Decades	Number of iterations.
Revolution rate (pr)	It randomly modifies the possession value of a country and allows reaching areas of the search space that were not covered by the countries of the current population. A large value reinforces exploration, while a small value encourages exploration
Beta (β)	Assimilation coefficient. A small value determines a short explanation, while a large one results in a long scan
Gama (γ)	Coefficient of assimilation of the angle.
Zeta (ζ)	Association coefficient. Associated with the power of the colonies of the empire. For a large value the colonies bring more power to the empire, while for a small value the imperialist provides more power.
DampRatio	Maximum probability of cushioning a fault.
Percentage	Size of the search space, which allows the process of joining two empires.

Table 1. Description of the ICA parameters.

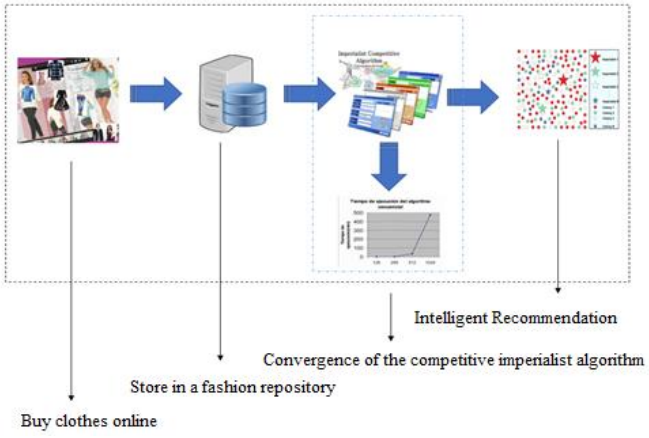


Figure 1. Methodology proposed.

The information referring to 300 garment instances characterized by the variables identified in table 2 is stored in the database (database.sqlite).

Price
Buying criteria
Quality product
Multi-options
Trends
Trust
Resistance
Adaptation
Color
Shape
Type of clothing
Characterization

Table 2. Characteristic variables of the garments.

Then the queries are made to the database, based on data related to search criteria such as texture, color, shape, style among others. In order to identify the values needed to operate the algorithm. The ICA reviews all the instances and considering the value entered, proposes a recommendation[19], [20].

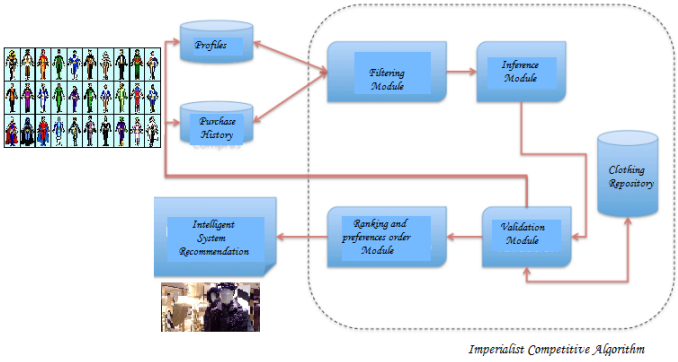


Figure 2. Intelligent recommendation process proposed.

III. Multiple matches

A range of eleventh evaluations is made according to different combinations of colors and costumes of more than 50 performances in different scenarios. The bidding process for the final selection of the closet for each issuance will begin when different characteristics are analyzed. In the interests of proportional development, all garments must be represented, as far as possible and depend on the interest generated in each. The time to evaluate and contract each offer of garments will be very important, especially at the beginning of the series. Preference will be given to issues with more socio-cultural similarities. To compete 87 outfits will be selected. Each number accepted and will be proposed to participate in exactly eleventh of these evaluations. The themes will evaluate your preference for tournaments, once the final list of multiple matches is evaluated and the algorithm evaluates them. The algorithm reserves the right to assign garments to be evaluated according to the needs of its commercial dresser and the garments for each commercial dresser, as well as to assign the list of garments before the cycle begins. Each evaluation will have up to 300 items combining on a program of seventeen evaluations with their respective executions. With the aim of harmonization by the algorithm, it will be programmed to meet the comparison program of different similarities using a multiple concordance analysis round and based on the gender assigned to a theme, as in figure 2. Qualifying garments for the selection in a commercial display will be chosen taking into account the following priority:

A. Matches

For the first cycle of similarity, all clothes in the store and similarity matches will be invited to participate in different comparisons, trying to determine the two items more like a person. Given the organization of each of the garments that coincide in each round in the algorithm, all these garments will be asked to commit their participation in the evaluation of each series[21]-[22]. In case any of these garments stops participating in the series, the algorithm can designate a garment to replace and this garment must be classified in the upper part of the reposition of the warehouse, taking into account this situation as relevant, mainly when the warehouse is limited.

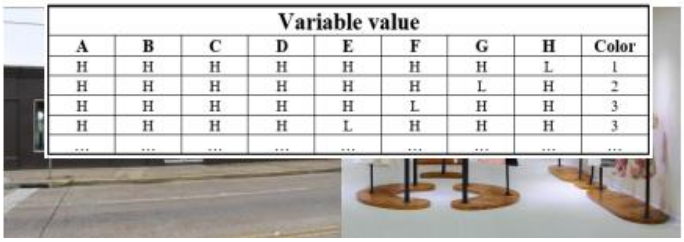
B. Classification

Based on an average calculation to two decimals, the qualification list in the series of comparisons before the beginning of the cycle, twenty qualifiers will be selected (excluding the seven garments to be compared the coincidences). If the garment has the same average grade, the number of similarities evaluated (grading period) will be used to determine the classification. To ensure participation in the future, a minimum of 25 commissions on the four qualification lists is recommended, including the start value of the qualification list. Given the brief explanation of its evaluation and notification in the first edition of complete evaluations, the use of a narrative guide is proposed for it. If any clothing does not agree to play in the series of multiple matches, then the selection process will be adopted using the average score plus the number of games played in the qualification period until the number of qualifiers required for the match is completed.

IV. Experimentation

In order to organize the most efficient arrangement of garments in a dressing table, we develop an atmosphere capable of storing the data of each one of those representing these garments, in order to distribute in an optimal way each of the garments. evaluated. One of the most interesting features observed in this experiment was the diversity of the cultural patterns established by each garment with respect to its symbolic capital. The structured scenarios associated with the agents cannot be reproduced in general, since they represent only a few times given in the space and time of the different garments. These represent a unique and innovative form of adaptive behavior that solves a computational problem that does not attempt to group the garment only with a factor associated with its external appearance (attributes of each attire), trying to solve a computational problem that involves a complex change between the existing representations [21]-[22]. The configurations generated can be related to the knowledge of the behavior of a potential

client with respect to an optimization problem (to culturally select similar clothes, without being of the same type). The main experiment was to detail each of the garments of a collection, with 500 agents and a condition of 50 times, which allowed us to generate the best selection of each type of garment and its possible location in a commercial dresser. It was obtained after comparing the different cultural and social similarities of each dress and evaluating each of them with the multiple coincidences model. The research allowed to classify each of the garments belonging to each type, with different clothing for garments with cultural identity only, which allows to identify changes in time with respect to other garments. Figure 3 shows the final sideboard (exterior-interior) constructed according to up to eight different attributes, respectively (see Figure 3a).



Variable value								
A	B	C	D	E	F	G	H	Color
H	H	H	H	H	H	H	L	1
H	H	H	H	H	H	L	H	2
H	H	H	H	H	L	H	H	3
H	H	H	H	L	H	H	H	3
...	...	...	...	...	...	...	...	...

(a)

(b)

Figure. 3. Final sideboard (interior-exterior) built according to up to eight different attributes: (a) based on the Competitive Imperialist Algorithm (Multiagent System) [23]-[26], and its representation in real mannequins

The design of the experiment consists of an orthogonal matrix test, with the interactions between the variables: emotional control, fighting ability, intelligence, agility, strength, resistance, social leadership and speed. These variables are studied in a range of color (1 to 64). The orthogonal arrangement is LN (2 ** 8), in other words, 8 factors in N executions, N is defined by the combination of the possible values of the 8 variables and the possible color range (See Figure 5). According to the results obtained for the lodging time in the transport, it must be done to accommodate the download time in the following sign. Based on the results obtained in the experiment, the average similarity between the garments was found to be 4.0625; This means that you must have to improve in the management of the use of the combination of colors and standard according to the climate. Other factors that would affect the use of accessories such as: bracelets, necklaces, pins and charms, an implementation to solve this problem is the use of fashion visualization. As you can see to maintain this type of materials it is necessary to use direct and indirect merchandise. The indirect merchandise secures the floor, gives resistance to the lateral and longitudinal movement of the clothes.

While the direct ties anchored to the mannequins in the chest of drawers. To carry out this process, it is necessary to have the correct dimensions and the distance of the street and the height of these, cables or cadences, taking into account the material of these mannequins, as is shown in Figure 3b.

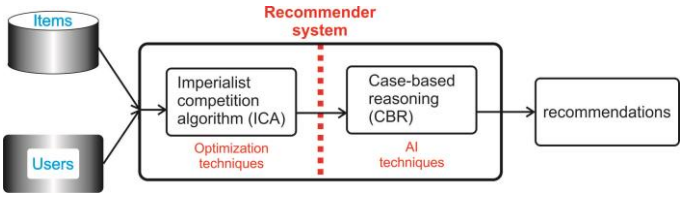


Figure 4. Schematic of basic operation of a recommender system.

In addition to the proposed experiment, the incorporation of a case representation in CBR [27] shown in Figure 4, where the familiar knowledge representation forms of AI are used to represent the experience contained in the cases for reasoning based on clothing, can be used due to the multiple combinations of clothes, accessories and other features of clothing. As a result, it is more logical to introduce case recovery methods after examining the representation methods to link them together. A case is a contextualized knowledge that represents an experience that teaches a fundamental lesson to achieve the objectives of the reasoner[27], [28]; and is characterized by:

- A case represents a specific knowledge linked to a context, in this case the combination of clothes and accessories. These knowledges are recorded at the operational level[30], [31].
- Cases can come in many different shapes and sizes, covering large or small-time segments, associating solutions with problems, results with situations, or both [32], [33].
- A case records experiences that are different from what is expected. However, not all differences are important to register. Cases worthy of being recorded as cases teach a useful lesson [34], [35].
- Useful lessons are those that have the potential to help a reasoner achieve a goal or set of goals more easily in the future or that warn about the possibility of a failure or point to an unforeseen problem [36]-[40].

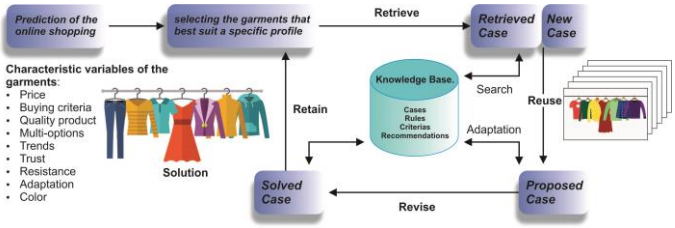


Figure 5. Scheme of CBR adapted to prediction of the online shopping

The proposed CBR shown in Figure 6, serves to make the prediction suitable for a problem based on the modeling of the online shopping process, selecting the garments that best suit a specific profile. In function of the result of the previous experiment, the system is fed so that this improves the suggestion of the prediction and has more alternatives for which the companies make better decisions. So, to detonate marketing and distribution processes more appropriate to customer profiles. The presentation of CBR follows below:

- Representation case. The representation of the cases is based on the disposition of the garments in a dressing table. as already commented, the wide range of combinations that exist between these garments and their accessories, coupled with the diversity of cultural patterns established by each garment with respect to its symbolic capital; it makes sure that the base of cases has enough and different data.
- Case of indexation. It is necessary that the application uses indexes in each case to easily choose the most appropriate one. For this scenario, the detail of the order and the capacity restrictions were used to classify the cases of disposition of the garments and their optimal combination.
- Case recovered. To recover a case, use the nearest neighbor method, compare the indices of the new case with others, that is, take the characteristics of the restrictions of the cases of disposition of the garments and their optimal combination. Once the possible cases are taken, the response vectors of similar cases are compared with the current case and take the most similar ones.
- Reuse and adaptation of the case. Once the most appropriate or similar cases have been obtained, the criteria and recommendations of the same are analyzed. In accordance with these criteria, the actual recommendations will be assigned to the current case.
- Case of revision and retention. The new case is analyzed and, according to the recommendations, it is decided if it will be stored in the base case. If it is different from another, then it is stored, otherwise it is discarded.

The recommendations given by the system satisfactorily covers the prediction for the purchasing system. Therefore, the decision in this commitment is considered tactical in line with the reasoning with respect to the variables and characteristics of the systems.

The information infrastructure improves the flow and visibility of the information of the features chosen by the users. This is evident, and the system will store the recommendations issued for future situations that set the trend of users. Better information on fashion trends simplifies the forecasting process, leading to greater accuracy in forecasting. Receiving timely information on trends and demands also allows a company to make flexible decisions.

The problems of recommendation are complex and varied as they require a high knowledge of the tastes and preferences of the user to provide recommendations that are satisfactory. They are also considered of great interest both in the scientific and applied aspects. Therefore, the development of efficient and adaptable recommendation techniques in different application domains is the goal of many research projects. No matter how many technologies are applied to a recommender system, the important thing is that it complies with the main objective, which will always be: guiding the user towards the resource that best suits their preference or need [19], [41]-[46] .

V. Conclusions and future research.

Through the use of the ICA the understanding is improved to obtain the change of the "best paradigm", because the communities of agents are properly classified based on an approach to the relation maintained by their attributes, this allowed to understand that the concept of " fashion based on symbolic capital "exists based on the determination of the acceptance function by the rest of the clothes to the proposed place for the rest of them. ICA offers a powerful alternative to the problems of optimization and redistribution of the clustering technique. For this reason, this technique offers a com-prehensible picture of the cultural phenomenon represented. This technique allows to include the possibility of generating experimental knowledge created by the community of agents for a new application domain. The analysis of the level and degree of cognitive knowledge of each community is an aspect that we wish to evaluate for future research. The answer may lie between the similitude that exists in the communication between two different cultures and how they are perceived. On the other hand, understanding the true similarities that different societies have based on the characteristics that make them cluster contributors and allows them to maintain their own identity, shows that the small variations go beyond the phenotypic characteristics and are mainly associated to tastes and similar characteristics developed over time. A new Artificial Intelligence can be careful to analyze at retail these complexities that each society maintains, without forgetting that they still need us methods to understand the original and characteristics of each society. An innovative proposal is to use case-based reasoning to determine the effect of associated symbolic capital and the use of a particular team through the construction of a model or user profile that can be obtained implicitly or explicitly through content filtering, demographic, collaborative or hybrid, the latter combines one of the two filters mentioned above to make recommendations and even combine with some artificial intelligence technique such as fuzzy logic, evolutionary computation or deep learning.

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