Gender violence's models and discrimination-aware data mining*

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Abstract. The violence against women, bases in the inequity of opportunities in every social stratum. According to national surveys, women and girls are considered a vulnerable population due to the inequalities in access to essential services such as education, economic independence and technology. Currently, governments show interest to address this problem and provide parity of opportunities to contribute to the development of society. Therefore, several social studies analysed the situation of women and their impact on welfare indicators regarding the development of the population, in this context, some techniques propose solutions through Data Mining to measure and recognise possible discrimination and violence. The thesis work intends to develop data mining models to identified discrimination mainly towards women and girls, taking into account the environmental factors such as individual, community, social and institutions.

Keywords: Discrimination aware · association rules · Spatial-Data Mining · Gender violence.

1 Introduction

The World Health Organisation defines gender violence as behaviour towards a person, which caused physical, psychological or sexual harm. Around the world, one out of every three women over 15 years old, is a victim of physical or verbal aggression [10]. Gender Violence is considered a global problem, categorised as a hate crime according to the legislation of some countries [8] and as part of a series of consequences related to social stability.

The relationship between discrimination and violence has been defined by [18], since the feeling of disagreement, whether by the oppressor or the relegated group, often generates a violent response.

However, most of social studies seek global differences rather than analysed gender attribute in isolation, also gender discrimination can appear in specific contexts, because of this, registries from discrimination facts are scares and comes from different references, complicating the analysis.

In contrast, the use of social networks and digital devices (mobile phones, banking transactions, etc.), leave a trace which records the behaviour of people

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[11], making possible to describe the context of interaction, through an automated data collection in higher volume of data.

For instance, the notion of ubiquity shows inequity can be compare on the level of mobility in men and women. It is not possible to affirm that the role of a housewife is rooted in a particular geographic space, but through studies of trajectories, we can see the distances that women travel with respect to men are considerably smaller [21] or like shopping habits [19], where women with regard to men register higher expenses in supermarkets and grocery stores.

This context leads us to pose the following question: ¿How to measure gender discrimination in society through digital records?.

This article is organised as follow: The state of the art gathers research antecedents from social sciences and data sciences, to identify phenomena and factors related to violence; the proposal and approximations regarding the state of the art, the methodology to validate the hypothesis; so far, the results show information about environmental factors and finally the discussion about the difficulties that this research face it.

2 State-of-the-art

Our research lines has two main groups, the social sciences and the data sciences. In this context, International Institutions are interest to address this problem on detail. They develop indicators about environment factors, which might arise the persistence of violence in emerging societies or not. [5, 6]. These studies describes a large gap for access to basic services of housing, health, food and education [3].

Another view, mention that lifestyle have an influence of men who report having perpetrated physical violence towards their couple throughout his life [14]. For instance, multi-variant analysis of community factors, also found that men who were witness of family violence from father to mother, are more likely to engage in gender violence, reinforcing the theory of the transmission of intergenerational violence [20]. In an attempt to predict gender gaps in children, they included the participation of parents and their perspective of gender roles, finding that parents with gender role paradigms, will have children with the same stereotypes [4].

They concluded, that it is necessary to understand how inequity affects the development of societies, the difficulties to face these problems and the factors predisposing to disparity [16].

Although most of these studies propose indicators to face inequity [7], they are not in agreement with each other, due to a variety of variables, which is valid and does not turn out to be a problem in itself. However, they are not addressing the interaction of these factors nor the influence on discrimination, that might give emphasises a particular element to establish priorities. The proposal refers to this problem, to incorporated data mining techniques to improve the granularity of the rules that support decision making process.

In contrast, Data Mining techniques allow a variate of task (managing data, measuring and predicting social phenomena), as long as it relies on information of the real context (variable and labels) to build models.
The measures to determine discrimination, in general, have not been fully developed by the data sciences, although, the Discrimination-Awareness Data mining (DADM) [23] address this issue becoming into an ever-increasing field, discovering discrimination hidden in a volume of historical records for decision making, recognising direct discrimination [1] and indirect [2] according to social context.

As indirect discrimination is not explicit in electronic digital records, to infer direct discrimination it is necessary to know the external and individual factors of the study sample (sex, race, pregnancy status, age, ethnicity, religion, state civil). Thus, some research papers [2, 21] find a relationship of inequity between social factors such as illiteracy, child malnutrition, access to contraceptives, and external factors (climate, geography, etc.), in geographic spaces. Methodological works proposed another measures of discrimination [9, 12, 15, 23], considering the social and individual factors, concerning the causes of direct segregation towards people. Some variations of the data transformation process, suggests using the evenly distributed information to improve the representativeness of all the groups in the datasets [22].

3 Proposed Approach

The thesis work proposes two goals within the framework of state-of-the-art: First, to develop models to measure discrimination based on digital records. The guiding is the DADM, to build classification rules that recognise direct and indirect discrimination, as long as there will two elements: the class that defines a discriminating rules and the context to validate the elements of the rule are discriminant, as shown in Figure 1 [9]. where it is necessary know the background to unveil discrimination.

Because discrimination records are scare, we include historical information from two different periods and various geographical spaces. According state-of-art, the rules generated from databases with a known class type, provide enough information to classified the rules into potentially discriminant (PD) and non-discriminating(PND). However, is not the case of our data, so it is necessary to develop new strategies to determine the class. These rules are relationships and will add quality to the results like as co-occurrences, which means that it is likely they would be related to social context. The second goal, refers to the validation of the models carried out in the first stage through socio-demographic context. However, it would be necessary to demonstrate that these variables are sufficient or in any case, to experiment and applying engineering features.

[1] Direct discrimination: explicit, impose barriers between a group. Ex. Ethnicity: indigenous, History: Good Credit: Poor

[2] Indirect discrimination: not explicit, but impose barriers between a group (conscious or unconscious). Ex. Provenance: Rural, History: Good Credit: Bad; if it is known that the rural population has a high percentage of indigenous people.

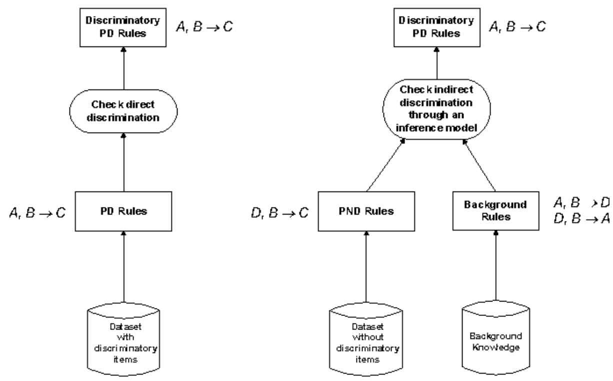

Fig. 1. Modeling the process of direct (left) and indirect(right) discrimination analysis by Dino Pedreschi, Salvatore Ruggieri, Franco TuriniPublished 2008 in KDD

4 Methodology

The KDD (Knowledge discovery databases) process of extracting patterns from databases is composed of four stages [13]. The process begins obtaining the data and ends with the validation of the results (patterns). These stages will serve as the guiding thread for the realisation of the research project.

- Construction of the database: heterogeneous dataset about discrimination cases and environmental factors. Datesets used for this research has different origins and have four sources:
  - ENDES: The Demographic and Family Health Survey in Peru, with structured records of socio-demographic reality (health, education, sexuality and domestic violence in 2016 and 2017).
  - Census to the police stations: Structured data about the crimes registered in 2016 and 2017.
  - Banking transactions: structured data of the register of banking transactions (expenses and purchases) in customers in Peru (2016 to 2017).
  - News about violence against women: a repository of unstructured news data in Peru, concern to gender crimes in 2016 and 2017.

  As shown in the information above, it is possible to identify the characteristics of the environment through the data collected for this investigation.
- Pre-data processing: to select the attributes or events related to gender discrimination, it is necessary organised the data in order to be easy to describe and interpret, through data cleaning techniques and feature engineering (extrapolation, prediction of classes, operation between fields) to preserve the integrity of the information.
- Pattern extraction: the attributes selected in the previous stage are transformed to be used as input and output in a pattern extraction algorithm.
- Restitution, visualisation and validation of patterns: Results would be compare with real context, it is essential at this stage to combine data mining methods with visualisation methods.

5 Results

The first approach to the fusion of social sciences to data sciences for this work, was the prepossessing of qualitative information extracted from interviews with university females students [1]. In that work, relevant testimonies of the interviewees were extracted through a process based on the use of TF-IDF (Term frequency - Inverse document frequency).

The research mentioned above, aims to know which agents were involved in some episodes of discrimination within university atmosphere. To this end, a survey of open questions about events of discrimination was developed, such as: "Did you ever hear in the university environment mentioning that women are different concerning to their professional performance? Mention what you heard and the person who said it". This survey was formulated by social experts who manage the variables according to the-state-of-the-art mentioned in [1]. In sum, through the extraction of relevant words from each testimony, it is possible to know which testimonials represent others in a set of documents. Our methodology is available in Github [3].

In this proposal, the propose method named A' are more likely to contain sets of different words related to the topic. In contrast, Topic Modeling methods are memory expensive compared to methods based on TF-IDF. We conclude that the process A' is efficient in the extraction of relevant words, optimising the retrieval information for qualitative research in simple and complex data. However, the efficiency of A' is linked to the improvement of data pre-processing techniques.

The sample for that work is small (214 records). Although the extracted testimonies may represent the discrimination suffered by the students of that school, it is not possible to generalise what happens with all the women in the same space. Due to this, the decision was made to collect structured information available in different resources and to unify it to be processed later.

For this article, databases were compiled related to the individual and environmental factors that influence gender violence. As seen in Tables 1, 2 and 3, each factor mentioned by the studies described in Section 2, it corresponds to a series of files that contain information related to the description of the variables.

The description of this data has been crucial to understand how the individual, community, social and institutional factors are related, as well as the recognition of variables between the automatic and socio-demographic information.

For instance, suppose that the amount of monthly expenditure sustains the purchasing power of the people and is defined by the type of work that they have. A well-paid job requires specialised skills and a high degree of training or education. Although it is not possible to assure that there is a relationship between educational level and the amount of monthly expenses in our data. As Figure 2 shows, inequality in educational level between men and women from 0 to 89 years (y axis) in Peru in 2016, the green bars represent the data of women

[3] Source code: https://github.com/bitmapup/violencePatterns

who, as observed, have a numerical difference with respect to their male pairs at each level of the x axis (blue bars). In contrast, Figure 5 shows population

Factor	Violence factor	Name of datasets	Columns	Records	File weight	Data types	Concatenated file
Individual	Individual Woman	a.rech05 b.rec011	a. 7 columns b. 5 columns	a. 35320 b. 34002	a. 1.9 MB b. 1.3 MB	a. int64(6),object(1) b. int64(4), object(1)	Weight: 2.1 MB Records: 35084 Columns: 8
Home	Community	a. recv84 b. rec0111	a. 72 columns b. 5 columns	a. 33168 b. 34002	a. 18.2 MB b. 1.3 MB	a. float64(71), object(1) b. int64(4), object(1)	Weight: 5.8 MB Records: 11543 Columns: 66

Table 1. Characteristics of the ENDES datasets associated with gender violence factors

Violence Factor	Name	Columns	Records	Weight of the file	Data types	Concatenated file
Institutional	Chapter100	37 columns	1177	340.4 MB	int64(28), object(3)	Weight: 285.1 MB Records: 1177 Columns: 31
Individual	Chapter200	43 columns	2103	706.6 MB	int64(8), object(5)	

Table 2. Characteristics of the files that make up Complaints dataset

Factor	Violence factor	Name	Columns	Records	File weight	Data types	Concatenated file
Individual	Individual Person Purchasing power Financial behavior	Transactions Transactions_class	10 columns 9 columns	84591756 1806836	9.0 GB 124.1 MB	timestamp(1),float(3),int64(2), object(4) int64(2), object(7)	Weight: 87.5 MB Records: 603512 Columns: 18

Table 3. Characteristics of bank databases

of the same age range (axis y) and socio-economic class (axis x). With respect to the "feature engineering" process mentioned in the methodology section, the "class" field was determined by the Formula 1:

$$class = \sum_{u=1} P_u/n \tag{1}$$

Where n is the total of transactions and Pu is the accumulated average monthly expenditure per user; $class$ indicates the social class associated with that type of behaviour and monthly expense amount. This research will not specifically deal with the verification of this formula, but it is necessary to point out that in [19], there are certain parameters to follow to find this variable social class. As Figure 5, differences of socio-economic class between man(blue bars) and women(green bars) are remarkable repect to the amount of expenditure (axis$y$). Error showed is caused due to few register with outlier measure.

6 Discussion

In contrast to DADM studies so far, information used in the thesis proposal is varied and voluminous, coming from different sources of known space-time contexts, which in some way allows knowing the continuity of particular phenomena (prediction of events). The discrimination metrics proposed by the social sciences were formulated from multivariate analysis and classical statistics with some aspects and factors. In this research, the maximum number of possible variables

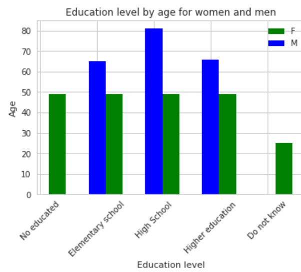

Fig. 2. Education level for women and men in Peru (2016)

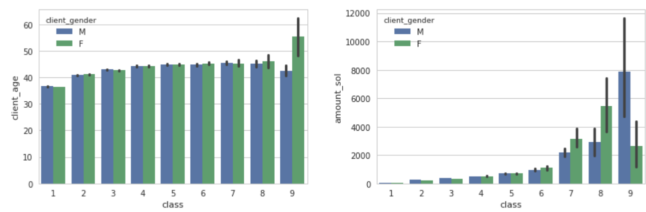

Fig. 3. Socio-economic class and age in Peruvian women and men (2016)

that could or could not appear according to the proposed model will be used simultaneously, forming strong association rules automatically and objectively. So, is recommendable begin through the definition of discrimination measures in vast and varied information, that contributes to social research in the search for explanations of social events such as gender violence.

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