International Journal of Engineering & Technology, 7 (4.19) (2018) 1025-1029

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

An Empirical Evaluation of various Discrimination Measures for Discrimination Prevention

Mr.Manoj Ashok Wakchaure[1]*, Prof.Dr.S.S.Sane[2]

[1] Research Scholar, Department of Computer Engineering, KKWIEER,Nashik, SPPU, Pune,India
[2]Professor& Head, Department of Computer Engineering, KKWIEER,Nashik, SPPU, Pune,India
**Corresponding author E-mail: manoj13apr@gmail.com*

Abstract

Discrimination prevention in Data mining has been studied by researchers. Several methods have been devised to take care of both direct and indirect discrimination prevention. In order to prevent discrimination, each of these methods tries to minimize the impact of discriminating attributes by modifying certain discriminating rules. The discriminating rules are identified using certain threshold and discrimination measure such as elift for direct discrimination and elb for indirect discrimination. Performance of these methods are measured and compared in terms discrimination removal using DDPD, DDPP for direct discrimination and IDPD, IDPP for indirect discrimination as well as resultant data quality using MC and GC for both kinds of discrimination.
This paper deals with study of use of discrimination measures other than elift such as slift, clift and olift. The empirical evaluation presented here shows that slift provides best overall performance.

Keywords: *Data Quality, Discrimination Measures, Discrimination Prevention, Direct and Indirect Discrimination Prevention*.

1. Introduction

Along with secrecy, discrimination is a very essential problem when allowing for the lawful and decent features of data mining. It is other than recognizable that the mainstream people do not need to be differentiated because of their gender, nationality, religion, age also so on, mostly when those aspects are used for making results almost them like giving them a profession, credit, Life cover, etc. determining such possible favoritisms and excluding them from the training data without harming their decision-making utility is therefore extremely popular. For this purpose, antidiscrimination techniques encompassing discernment recognition and preclusion have been announced in data mining. Discernment anticipation contains of propose models that do not lead to discriminatory results even if the innovative training datasets are principally biased. In this work, by concentrating on the discernment preclusion, we present arrangement for categorizing and observing discernment anticipation schemes. Then, we originate a group of pre-processing discernment anticipation schemes and designate the different features of every methodology and how these methodologies deal with direct or indirect discrimination. A creation of metrics used to estimation the presentation of those methodologies is also quantified.
Discrimination prevention in Data mining has been studied by researchers. This paper deals with study of use of discrimination measures other than elift such as slift, clift and olift. Rest of the paper is organized as follows. Section 1 provides introduction, related work is presented in section 2. Section 3 deals with empirical work carried out while Section 4 deals with experimental results and discussions. Conclusions are provided in section 5.

2. Literature Survey

Three approaches for discrimination prevention, namely, pre-processing, in-process and post processing have been discussed in [1, 4, 5]. Pre-processing approach demands extraction of fast association rules [2]. A useful survey of various techniques to hide association rules has been discussed in [3]. Description of application specific discrimination in data mining has been reported in [4]. Three graphical models called modified Naïve Bayes, 2 Naïve Bayes and latent variable model have been suggested to perform discrimination free classification [6] and uses post-handling technique. Salvatore et al. [7] developed the DCUBE framework that could be utilized by proprietors of socially delicate choice databases, antidiscrimination specialists and examiners, scientists in sociologies etc. Background knowledge based discrimination prevention technique is proposed in [8].
In all four algorithms have been proposed for direct, indirect and mixture of direct and indirect discrimination prevention in [1] with details of algorithms and empirical evaluation. The algorithms make use of elift and elb as discrimination measures and suggested further investigation of use of other discrimination measures such as slift, clift, olift etc on performance parameters.

3. Proposed Work

The basic definitions such as Direct Discrimination, Indirect Discrimination, PD and PND Rules, various discrimination Measures, performance parameters such as discrimination Removal and data quality such as Misses cost (MC) and Ghost Cost (GC) etc are available in [1] and thus not provided here.

The experimental work is carried out as per the algorithms 1, 2, 3 & 4 as provided in [1]. The detailed pseudo code is available in [1] and thus not reproduced here. The two datasets, namely, Adult dataset and the German dataset and the values for Alpha, p, Support and Confidence used in proposed work were exactly same as used in [1]. For Impact minimization, as reported in [1], they have used elift as the discrimination measure for algorithms 1, 2 and 3 and combination of elift and elb for algorithm 4. Since the basic goal of this work is to study the effect of use of discrimination measures other than elift on the performance parameters. Thus in each algorithms 1 to 4, experimentation makes use of slift, clift and olift instead of elift in all four algorithms. In case of algorithm 4, the combination slift & elb, clift & elb and olift and elb was used instead of elift & elb.

4. Results and Discussions

Tables 1 to 10 below provide details of the results. The pair of tables, say Table 1 & 2 and Table 3 & 4 and so on Table 9 & 10 are used for each method such as DRP Method 1, DRP Method 2 and so on with one table for Adult dataset while the other for German dataset. In each of these tables, the first two rows are as given in [1]. The first row shows values for Discrimination Removal and data quality when all discriminating attributes are removed while second row shows the values when a particular method is used with discrimination measure elift/elb as the case may be. The next three rows shows the values based on our experimentation, one row each for discrimination measure slift, clift and olift in that order. Values shown in all the rows of each of ten tables assume value of alpha to be 1.2, support of 2% for Adult dataset and 5% for German dataset were used as were used in [1]. Confidence of 10% was used for both datasets. Impact minimization technique as suggested in [1] was used. Number of records (32,561 & 1000) used from both datasets, conversion of numeric attributes (such as Age in Adult dataset) to categorical, type of DIs used (Sex=Female, Age=Young for Adult dataset and Foreign Worker = Yes, Personal Status = Female and not single, Age = Old) in our experimentation is also exactly as specified in [1]. Tables 11, 12, 13 and 14 present the summary of table 1 to table 10. In all the tables, better values for required parameters are marked in bold.

Table 1: Performance Comparison of DRP M-1 with Support of 2% and Confidence of 10% For Adult Dataset using Impact

Methods	Alfa	No.direct Alfa Discriminatio Rules	Discrimination Removal		Data Quality	
			Direct		MC	GC
			DDPD	DDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	66.08	0
DRP M-1 as Reported in Literature	1.2	274	100	100	4.16	4.13
DRP M-1 Using slift	1.2	288	100	100	3.02	3.37
DRP M-1 Using clift	1.2	284	100	100	5.02	4.77
DRP M-1 Using Olift	1.2	288	100	100	3.47	4.02
No. of Frequent classification Rules : 5092				No. of background Rules : 2089		

Table 2: Performance Comparison of DRP M-1 with Support of 5% and Confidence of 10% For German Credit Dataset using Impact

Methods	Alfa	No. direct Alfa Discrimination Rules	Discrimination Removal		Data Quality	
			Direct		MC	GC
			DDPD	DDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	64.35	0
DRP M-1 as Reported in Literature	1.2	991	100	100	15.44	13.52
DRP M-1 Using slift	1.2	995	100	100	15.08	13.34
DRP M-1 Using clift	1.2	996	100	100	15.94	13.78
DRP M-1 Using Olift	1.2	989	100	100	15.56	13.84
No. of Frequent classification Rules : 32340			No. of background Rules : 22763			

For DRP method 1, in case of Adult dataset, the use of discrimination measures '*slift*' and '*olift*' results in desired lower values for both MC and GC when compared with '*elift*'. *Slift* results in lowest and best values for MC and GC. In case of German dataset, only *slift* provides best values for MC as well as GC. *elift* provides next best values.For both Adult and German datasets, use of any of the four discrimination measures results in same and highest possible values for both DDPD and DDPP.

Table 3: Performance Comparison of DRP M-2 with Support of 2% and Confidence of 10% For Adult Dataset using Impact

Methods	Alfa	No. direct Alfa Discrimination Rules	Discrimination Removal		Data Quality	
			Direct		MC	GC
			DDPD	DDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	66.08	0
DRP M-2 as Reported in Literature	1.2	274	100	100	0	0
DRP M-2 Using slift	1.2	288	100	100	0.20	0
DRP M-2 Using clift	1.2	284	100	100	0.45	0.17
DRP M-2 Using Olift	1.2	288	100	100	0.68	0.27
No. of Frequent classification Rules : 5092				No. of background Rules : 2089		

Table 4: Performance Comparison of DRP M-2 with Support of 5% and Confidence of 10% For German Credit Dataset using Impact

Methods	Alfa	No. direct Alfa Discrimination Rules	Discrimination Removal		Data Quality	
			Direct		MC	GC
			DDPD	DDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	64.35	0

DRP M-2 as Reported in Literature	1.2	991	100	100	0	4.06
DRP M-2 Using slift	1.2	995	100	100	0	4.02
DRP M-2 Using clift	1.2	996	100	100	0	4.06
DRP M-2 Using Olift	1.2	989	100	100	0	3.99
No. of Frequent classification Rules : 32340			No. of background Rules :22763			

For DRP Method 2, in case of Adult dataset, elift provides best value for MC while both elift and slift provides lowest value for GC. In case of German dataset, all four measures provide best values for MC and '*olift*' provides best value for GC. For both Adult and German datasets, the values for both DDPD and DDPP are independent of measure used.

Table 5: Performance Comparison of DRP M-1+RG with Support of 2% and Confidence of 10% For Adult Dataset using Impact

Methods	Alfa	p	No. direct Alfa Discrimination Rules	Discrimination Removal		Data Quality	
				Direct		MC	GC
				DDPD	DDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	NA	66.08	0
DRP M-1+RG as Reported in Literature	1.2	0.9	274	100	100	4.1	4.1
DRP M-1+RG Using slift	1.2	0.9	288	100	100	4.27	4.05
DRP M-1+RG Using clift	1.2	0.9	284	100	100	5.27	4.65
DRP M-1+RG Using Olift	1.2	0.9	288	100	100	4.91	4.88
No. of Frequent classification Rules : 5092				No. of background Rules : 2089			

Table 6: Performance Comparison of DRP M-1+RG with Support of 5% and Confidence of 10% For German Credit Dataset using Impact

Methods	Alfa	p	No.direct Alfa Discrimination Rules	Discrimination Removal		Data Quality	
				Direct		MC	GC
				DDPD	DDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	NA	64.35	0
DRP M-1+RG as Reported in Literature	1.2	0.9	991	100	100	13.34	12.01
DRP M-1+RG Using slift	1.2	0.9	995	100	100	14.06	11.54
DRP M-1+RG Using clift	1.2	0.9	996	99.10	99.60	13.54	12.46
DRP M-1+RG Using Olift	1.2	0.9	989	100	100	13.26	11.82
No. of Frequent classification Rules : 32340				No. of background Rules : 22763			

For DRP Method 1 + RG, in case of Adult dataset, elift provides best value for MC while slift provides lowest value for GC. In case of German dataset, olift provides best value for MC while slift wins the race for GC. For both Adult dataset, the values for both DDPD and DDPP are independent of measure used so is for German dataset only except clift.

Table 7: Performance Comparison of DRP M-2+RG with Support of 2% and Confidence of 10% For Adult Dataset using Impact

Methods	Alfa	p	No. direct Alfa Discrimination Rules	Discrimination Removal		Data Quality	
				Direct		MC	GC
				DDPD	DDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	NA	66.08	0
DRP M-2+RG as Reported in Literature	1.2	0.9	274	91.58	100	0	0
DRP M-2+RG Using slift	1.2	0.9	288	93.30	100	0	0
DRP M-2+RG Using clift	1.2	0.9	284	97.40	100	0.10	0.58
DRP M-2+RG Using Olift	1.2	0.9	288	94.70	100	0.19	0.77
No. of Frequent classification Rules : 5092					No. of background Rules : 2089		

Table 8: Performance Comparison of DRP M-2+RG with Support of 5% and Confidence of 10% For German Credit Dataset using Impact

Methods	Alfa	p	No. direct Alfa Discrimination Rules	Discrimination Removal		Data Quality	
				Direct		MC	GC
				DDPD	DDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	NA	64.35	0
DRP M-2+RG as Reported in Literature	1.2	0.9	991	100	100	0.01	4.06
DRP M-2+RG Using slift	1.2	0.9	995	100	100	0.06	4.06
DRP M-2+RG Using clift	1.2	0.9	996	100	100	0	4.06
DRP M-2+RG Using Olift	1.2	0.9	989	100	100	0.03	4.08
No. of Frequent classification Rules : 32340				No. of background Rules : 22763			

For DRP2 + RG, both elift and slift provide best values for MC and GC for adult dataset, however, slift provides lesser value for DDPD. For German dataset, the values of DDPD and DDPP are independent of kind of measure used and clift measure provides lowest value for MC while elift, slift and clift provides the same value for GC.

Table 9: Performance Comparison of DRP M-2 + IRP M-2 with Support of 2% and Confidence of 10% For Adult Dataset using Impact

Methods	Alfa	No. Red lining Rules	No. Indirect Alfa Discrimination Rules	No. direct Alfa Discrimination Rules	Discrimination Removal				Data Quality	
					Direct		Indirect		MC	GC
					DDPD	DDPP	IDPD	IDPP		

Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	NA	NA	NA	NA	66.08	0
DRP M-2+IRP M-2 as Reported in Literature	1.1	21	30	280	100	100	100	100	0	0
DRP M-2+ IRP M-2 Using slift	1.1	29	35	288	100	100	99.40	100	0.12	0
DRP M-2 + IRP M-2 Using clift	1.1	24	34	289	100	100	100	100	0.13	0
DRP M-2 +IRP M-2Using Olift	1.1	30	36	292	99	100	97.50	100	0	0
No. of Frequent classification Rules : 5092					No. of background Rules : 2089					

Table 10: Performance Comparison of DRP M-2 + IRP M-2 with Support of 5% and Confidence of 10% For German Credit Dataset using Impact

Methods	Alfa	No. Red lining Rules	No. Indirect Alfa Discrimination Rules	No. direct Alfa Discrimination Rules	Discrimination Removal				Data Quality	
					Direct		Indirect		MC	GC
					DDPD	DDPP	IDPD	IDPP		
Removing Disc Attributes as reported in Literature	NA	NA	NA	NA	NA	NA	NA	NA	64.35	0
DRP M-2+IRP M-2 as Reported in Literature	1	37	42	499	99.97	100	100	100	0	2.07
DRP M-2+ IRP M-2 Using slift	1	37	42	503	99.97	100	100	100	0	2.02
DRP M-2 + IRP M-2 Using clift	1	37	41	497	100	99.75	100	100	0	2.10
DRP M-2 +IRP M-2Using Olift	1	37	41	500	100	100	99.80	100	0	2.26
No. of Frequent classification Rules : 32340					No. of background Rules : 22763					

For DRP Method 2 + IRP Method 2, elift results in better values for adult, while slift performs better with German dataset.

Table 11: Comparison of Discrimination measures when compared for Data Quality in terms of MC and GC

Methods	Dataset	MC				GC			
		elift	slift	clift	olift	elift	slift	clift	olift
DRP1	Adult	4.16	3.02	5.02	3.47	4.13	3.37	4.77	4.02
	German	15.44	15.08	15.94	15.56	13.52	13.34	13.78	13.84
DRP2	Adult	0.0	0.2	0.45	0.68	0.0	0.0	0.17	0.27
	German	0.0	0.0	0.0	0.0	4.06	4.02	4.06	3.99
DRP1+RG	Adult	4.1	4.27	5.27	4.91	4.1	4.05	4.65	4.88
	German	13.34	14.06	13.54	13.26	12.01	11.54	12.46	11.82
DRP2+RG	Adult	0.0	0.0	0.1	0.19	0.0	0.0	0.58	0.77
	German	0.01	0.06	0.0	0.03	4.06	4.06	4.06	4.08
DRP2+IRP2	Adult	0.0	0.12	0.13	0.0	0.0	0.0	0.0	0.0
	German	0.0	0.0	0.0	0.0	2.07	2.02	2.10	2.26
Average		3.71	3.68	4.05	3.81	4.40	4.24	4.66	4.59

Table 11 shows the comparison of Discrimination measures when compared for Data Quality in terms of MC and GC. One can see that the slift measure results in the best (lowest) average values for Missess cost (MC) as well as Ghost cost (GC)

Table 12: Comparison of Discrimination measures when compared for Discrimination Removal (Direct Parameters)

Methods	Dataset	DDPD				DDPP			
		elift	slift	clift	Olift	elift	slift	Clift	olift
DRP1	Adult	✓	✓	✓	✓	✓	✓	✓	✓
	German	✓	✓	✓	✓	✓	✓	✓	✓
DRP2	Adult	✓	✓	✓	✓	✓	✓	✓	✓
	German	✓	✓	✓	✓	✓	✓	✓	✓
DRP1+RG	Adult	✓	✓	✓	✓	✓	✓	✓	✓
	German	✓	✓	99.10	✓	✓	✓	99.60	✓
DRP2+RG	Adult	91.58	93.30	97.40	94.70	✓	✓	✓	✓
	German	✓	✓	✓	✓	✓	✓	✓	✓
DRP2+IRP2	Adult	✓	✓	✓	99.00	✓	✓	✓	✓
	German	99.97	99.97	✓	✓	✓	✓	99.75	✓
Average		99.16	99.33	99.65	99.37	100	100	99.94	100

Table 13: Comparison of Discrimination measures when compared for Discrimination Removal (Indirect Parameters)

DRP2+IRP2	IDPD				IDPP			
	elift	slift	clift	olift	elift	slift	Clift	olift
Adult	✓	99.40	✓	97.50	✓	✓	✓	✓
German	✓	✓	✓	99.80	✓	✓	✓	✓
Average	100	99.70	100	98.65	100	100	100	100

Table 12 & Table 13 shows comparison of Discrimination measures when compared for Discrimination Removal for Direct and Indirect Parameters respectively. In both the tables, as the values for DDPD, DDPP, IDPD and IDPP are 100 in most of the cases, it is shown by √. When they are other than 100, the actual value is written. Clift measure provides highest removal in terms of DDPD but not for DDPP. Both elift and clift provides better results for IDPD, while all measures perform equally for IDPP.

Table 14: Comparison of Discrimination measures when compared with all six parameters for Discrimination Removal in terms of DDPD & DDPP, IDPD & IDPP and Data Quality in terms of MC and GC

Measure	Average value of					
	DDPD	DDPP	IDPD	IDPP	MC	GC
elift	99.16	100	100	100	3.71	4.40
slift	99.33	100	99.70	100	3.68	4.24
clift	99.65	99.96	100	100	4.05	4.66
olift	99.37	100	98.65	100	3.81	4.59

Looking at Table 14, one can find that slift provides better overall performance when averages of all six parameters are considered.

5. Conclusions and Future Work

Although, data mining has been used successfully in variety of application domains, discrimination and privacy preservation are some of the concerns. Several methods have been proposed in the literature to prevent direct and indirect discrimination prevention. Such methods make use of discrimination measures such as elift and elb for impact minimization in case of direct and indirect discrimination prevention. A combination of elift and elb is advocated for hybrid method that combines both direct and indirect method for discrimination prevention.

To the best of our knowledge, use of other discrimination measures such as slift, clift and olift have not been reported in the literature. This paper provides empirical evaluation to study the effect of various discrimination measures on performance of discrimination prevention.

The conclusions based on work carried out are

Considering all six performance parameters, Slift provides the best average values for four parameters DDPP, IDPP, MC and GC.

Use of different discrimination measure has no effect on discrimination removal in terms of DDPD, DDPP in case of direct Discrimination and on IDPP in case of hybrid (direct + Indirect) method.

Performance of none of the measure is always independent of the method and datasets used

In the computation of impact minimization as reported in [1], the authors make use of only premises of a frequent association rules. We intend to make use of the whole rule instead of only premises as well as partial match of premises of the rules as a future work. Also presented results are with value of Alpha as 1.2 and given support and confidence values. Effect on performance parameters due to variation in values of Alpha, Support, confidence etc needs further investigation. Empirical evaluation such as this is carried out only with two datasets. Ideally such evaluation is to be carried out on several datasets. However, to the best of our knowledge, no datasets other than Adult and German are available.

Acknowledgement

We would like to thanks to all library media who supported our work in this way and help us to get results of better quality. We would also like to show our gratitude to Research Centre K.K.Wagh Institute of Engineering Education & Research,Nashik.We also Thankful to Savitribai Phule Pune university,Pune.

References

[1] Sara Hajian and Josep Domingo-Ferrer A Methodology for Direct and Indirect Discrimination Prevention in Data Mining, Data Mining and Knowledge Discovery, vol. 25, no. 7, pp. 1445-1459, 2013

[2] R. Agrawal and R. Srikant, Fast Algorithms for Mining Association Rules in Large Databases, Proc. 20th Intl Conf. Very Large Data Bases, pp. 487-499, 1994.

[3] V. Verykios and A. Gkoulalas-Divanis, A Survey of Association Rule Hiding Methods for Privacy, PrivacyPreserving Data Mining, Models and Algorithms, C.C.Aggarwal and P.S. Yu, Springer, 2008.

[4] D. Pedreschi, S. Ruggieri, and F. Turini, Measuring Discrimination in Socially-Sensitive Decision Records, Proc. Ninth SIAM Data Mining Conf. (SDM 09), pp. 581-592, 2009.

[5] F. Kamiran and T. Calders, Classification without Discrimination, Proc. IEEE Second Intl Conf. Computer, Control and Comm.(IC4 09), 2009.

[6] T. Calders and S. Verwer, Three Naive Bayes Approaches for Discrimination-Free Classification, Data Mining and Knowledge Discovery, vol. 21, no. 2, pp. 277-292, 2010.

[7] F. Kamiran and T. Calders, Classification with no Discrimination, by Preferential Sampling, Proc. 19th Machine Learning Conf. Belgium and The Netherlands,2010.

[8] D. Pedreschi, S. Ruggieri, and F. Turini, "DiscriminationAware Data Mining," Proc. 14th ACM Int'l Conf. Knowledge Discovery and Data Mining (KDD '08), pp. 560-568, 2008.