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GENETIC ALGORITHM BASED ANT COLONY OPTIMIZATION (GA-ACO) FOR CROSS DOMAIN OPINION MINING

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ABSTRACT

Web mining and web utilization mining are drawing in numerous analysts to propose new thoughts, models, implement machine-learning algorithms with more improvements. World Wide Web (WWW) use gets extends its wings to all sort of uses that incorporates internet-based business, namely e-commerce. E-commerce encourages shoppers/clients to purchase the needed products on the web and in the meantime, web analytics causes the site overseers to recognize which items get more sales. Opinion mining is one of the ways to make an investigation in numerous decision-making tasks in the web-based business field. This paper proposes a genetic algorithm based ant colony optimization approach (GA-ACO) to solve the problems that emerge cross-domain opinion mining. The acquired dataset comprises of reviews about multiple products like books, DVDs, gadgets and kitchen appliances. The highlights are recognized by making utilization of altered ACO and opinion mining is performed by Genetic Algorithm (GA) Accuracy and F-measure are two chosen performance for evaluating the performance of the proposed work. Comparison of results presented with domain-specific and domain-independent words. Results depict that the proposed work has better performance than that of the existing work as far as chosen performance metrics.

Keywords: cross-domain, opinion, E-Commerce, optimization, genetic.

1. INTRODUCTION

An opinion provided by an individual is a private state and it denotes individual's idea, judgment, and the result of evaluation about a product or service. It is presumed that opinions provided by the individuals can greatly affect and direct peoples, governments, association, and social networks amid the process of decision-making. Individuals require quick, precise and brief data so that they can make an immediate and exact choice. By utilizing the opinions, people can themselves combine differing approaches, encounters, astuteness, and learning of numerous individuals when deciding. It is very normal for individuals to take an interest in online discussion and express their perspectives. Individuals regularly ask their companions, relatives, and field specialists for data amid the process of decision making, where the sentiments and points of view may depend on experiences, perceptions, ideas, and convictions. Individual's viewpoint about a subject can positive or negative, but not the both.

Opinion mining is steadily growing and reaching the thrust area of research because of the accessibility of perspectives, opinions, and experiences about an item/benefit on the web. Individuals are giving their hindrance to express their opinions on the web. In most cases, programmed recognition and investigation of opinions about items, brands, political issues, and so forth is an overwhelming task. Opinion mining includes three components: (i) features, (ii) expression of opinions, and (iii) feature opinion relations. Opinion lexicon (i.e. the dictionary) is a collection of opinion expressions, which are utilized to demonstrate opinion like positive or negative. The lexicon emerges from equivalent words in the Word-Net, while antonyms are utilized to broaden as charts. An opinion has three principles, i.e., the opinion holder or wellspring of the opinion, the question about which the opinion is communicated and the assessment, view or evaluation, that is, the opinion. For opinion ID, these parts are vital. While opinions can be gathered from various sources, e.g., singular associations, daily papers, TV, Internet and so on, the Internet has turned into the most extravagant wellspring of opinion accumulation. Prior to the World Wide Web (www), individuals gathered opinions physically. In the event that an individual was to settle on a choice, he/she normally requested opinions from loved ones. To secure general opinion, associations regularly directed overviews through centered gatherings. This sort of review, nevertheless, was costly and difficult. Presently, the Internet furnishes this data with a solitary snap and at next to no cost.

Makers and purchasers, require opinion-mining apparatuses to gather opinions about a specific item. Makers to choose an advancing system for assessing the creation rate can utilize the opinion investigation devices. Buyers can utilize these kinds of opinions to settle on a choice of buying another item or travel to relax areas or select hotel, et cetera. Named opinions utilized to break down the classifier. Essentially, named opinions for each domain is not conceivable, as it delimited by time and cost, while domain adjustment or exchange learning can be utilized to circumvent this imperative. With the above-mentioned problem statement, our second phase of research work expects to propose a genetic algorithm based ant-colony optimization for Cross-Domain Opinion Mining.

2. RELATED WORKS

Vinodhini Gopalakrishnan and Chandrasekaran Ramaswamy, 2017 aimed to apply neural network based methods for opinion mining from social web in the

healthcare domain, also authors have extracted the reviews of two different drugs. Jyoti S. Deshmukh and Amiya Kumar Tripathy, 2018 proposed an approach that extracts and classifies opinion words from source domain and predicts opinion words from target domain utilizing a semi-supervised approach, where it is a combination of modified maximum entropy and bipartite graph clustering. Heng-Li Yang and Qing-Feng Lin, 2018 focused on reviews based on highly emotion-embedded products/services like movies, music, drama and furthermore tried its best to solve the multiple polarities problem for a specific word with multiple types of product/service. Farman Ali *et al.*, 2016 proposed a robust classification technique for feature review's identification and semantic knowledge for opinion mining based on SVM and Fuzzy Domain Ontology (FDO), where it focuses to fetch a collection of reviews about features of the hotel.

Homayoun Hamedmoghadam *et al.*, 2018 proposed an optimization method based on opinion formation in complex network systems, where it mimics human-human interaction mechanism based on a mathematical model derived from social sciences. Chih Ping Chen *et al.*, 2018 exploited a combination of techniques like statistics, data mining, and pattern recognition for the selection of handheld devices. Huy Tien Nguyen and Minh Le Nguyen, 2018 proposed a convolutional N-gram BiLSTM (CoNBiLSTM) word embedding which represents a word with semantic and contextual information in short and long distance periods and applied CoNBiLSTM word embedding for predicting the type of a comment, its polarity sentiment (positive, neutral or negative) and whether the sentiment is directed toward the product or video. Shahriyar Nasirov and Claudio A. Agostini, 2018 examined the key issues - barriers and drivers- influencing the adoption of solar technologies in the Chilean mining industry from the perspective of mining actors. J. Islam *et al.*, 2016 proposed an approach namely Intrinsic and Extrinsic Domain Relevance (IEDR) technique for feature extraction, where it includes a handful of extended syntactic rules to process review sentences. S. Wu and Y. Shi, 2013 made a study on opinion mining applied the Fruit Fly Optimization Algorithm to evaluate the Keywords Frequency Composite Function.

Yuanchao Liu *et al.*, 2018 proposed an augmented RNN (recurrent neural network) model called OLSRNN, where it adds self-connections to output layer with the basics of conventional RNN models to capture output temporal dependencies. Heng-Li Yang and Qing-Feng Lin, 2013 made a study and collected some Chinese sentences from one movie blog at Taiwan, and conducted an experiment to infer those authors' sentiment and applied evolutionary computing strategies to optimize the tables of basic emotion weights in two different scenarios. M. P. Anto *et al.*, 2016 focused on the technique of providing automatic feedback based on data collected from Twitter, where the data streams are filtered and analyzed and feedback is obtained through opinion mining. P. K. Kumar and S. Nanadagopalan, 2017 considered the user shares the complexity associated with diverse opinion-based textual data and showed a big trade-off on implementing any form of simple transformation technique to address data volume and unstructured form of data. S. Shariaty and S. Moghaddam, 2011 proposed a method for mining user opinions, which aims at extracting not only the opinions of users on product aspects but also a finer level of information indicating the usage type of the aspect.

3. GENETIC ALGORITHM BASED ANT COLONY OPTIMIZATION (GA-ACO) NETWORK FOR CROSS-DOMAIN OPINION-MINING

To take care of the cross-domain opinion-mining problem, the proposed work aims to formulate and find solutions as per ACO. The text (i.e., txt) is commented on with PST, and stop words are evacuated. Consequently, Selwrds() restores a sack of words, Bgwrds, from txt in view of a size of the window, suggesting that it restores the Trgtwrd and other words holding inside a setting window. Each Trgtwrd is dealt with independence manner, despite the fact that the same Trgtwrd seems more than once in the content window. The syncsets words with Syncsets(X_f) in Bgwrds are recovered from the WN. At last global syncset() restores the syncsets in the wake of improving their shines with the gleams of syncsets in a similar group and relatively related syncsets, which are accessible in the syncset-bunched inventories are recovered separately.

This research work consequently fine-tunes the parameters of the ACO algorithm by utilizing GA. H. M. Botee, E. Bonabeau, 1998 portrayed the utilization of a GA over an ACO algorithm. This algorithm highlights mechanized tuning of its hybrid and change administrators and their probabilities. The probabilities of the hybrid T_d and transformation $T_o$administrators are adjusted at runtime for contingent upon the biggest wellness of the mating guardians b' and the biggest wellness $b_{max}$and the mean wellness $\bar{b}$ in the present populace.

E. Bonabeau *et al.*, 1999 mentioned ACO is a type of metaheuristic-based algorithm that reproduces the scrounging behavior of ant colony in all actuality. The ants intend to locate and follow the shortest path between a sustenance source and the home by using utilizing a chemical substance gets released from ants, called a pheromone that vanishes after some time. Usually, ants follow the paths, which have more pheromone, it is assumed that number of ants has used the path and pheromone disappears after a lengthier time. In ACO, an artificial ant takes an interest to find bad responses for optimization improvement. Ants collaborate in a roundabout way with one another through the levels of pheromone trails.

While applying an ACO estimation, the issue is addressed as a weighted outline Z = (U, A), where U is a game plan of center points (|U| = l) and E is a course of action of edges. At the start of the figuring, m ants are at first spread out on the outline center points. The basic estimation of the pheromone trail is saved money on each one of the edges. After this presentation, the going with

advances are reiterated until the point that an end condition is met (e.g., most prominent number of accentuations, CPU time most prominent, intermixing or stagnation direct, among others).

a) **Producing courses of action:** Every ant incrementally makes an answer, which contains a gathering of center points.
b) **Assessing course of action:** Depending on the issue target work, this appraisal gauges the idea of an answer.
c) **Refreshing the pheromone trail esteems:** Pheromone trail esteems are invigorated in two phases: (1) diminish the pheromone estimations everything considered (pheromone vanishing) to empower the ants to overlook poor edge choices, and (2) increase the pheromone estimations of edges that have a place with the best route plans (pheromone stores).

Numerous distinctive ACO algorithms proposed to solve the cross-domain opinion-mining problems, but there exist difference in the protocols for choosing the next node amid the age of arrangements and in the principles for refreshing the pheromone trails. This research work focus to take care cross-domain opinion-mining problems that arise in online feedbacks.

While producing arrangements, an ant m moves from node i to adjoining node j that is not been visited by m with a probability given by the accompanying arbitrary probabilistic progress run the show:

$$T_{if}^{m} = \frac{(\varphi_{if})^{\gamma}.(\vartheta_{if})^{\delta}}{\int_{e\epsilon F_m(i)}^{E}(\varphi_{ie})^{\gamma}\gamma,(\vartheta_{iE})^{\delta}}, F\varepsilon F_m(i), \int_{e\epsilon F_m(i)}^{E}(\varphi_{ie})^{\gamma}.(\vartheta_{ie})^{\delta} \neq 0 \quad (1)$$

φ_{ih} is denoted level of pheromone at edge $(i,f), \vartheta_{ie}$ is denoted as estimation of heuristic information of edge $(i,f), \gamma$ and δ are variables utilized to decide the relative significance of the estimations of the pheromone, E is the quantity of accessible nodes that have not yet been visited by m, and $F_m(i)$ is the arrangement of contiguous nodes that have not yet been visited by m.

When refreshing the pheromone trail values takes place, just the ant of iteration cycles or the best-so-far ant is permitted to store pheromone. To defeat the problem of early stagnation, the pheromone trail values are limited in the period of time$[\varphi_{min}, \varphi_{max}]$. To expand the investigation of the arrangement toward the start of the inquiry, the underlying estimations of pheromone trails are set to φ_{max}. The pheromone trail value is refreshed utilizing the accompanying condition given the pheromone dissipation rate ρ $(0 < \rho \leq 1)$.

$$\varphi_{if} \leftarrow \max\{\varphi_{min}, \varphi_{max}\{\varphi_{max}, (1-\theta)\varphi_{if} + \cup\ \varphi_{if}^{best})\}\} \quad (2)$$

$\cup\ \varphi_{if}^{best}, \varphi_{max}\ and\ \varphi_{min}$ are derived and given by equations 3, 4 and 5, individually:

$$\cup\ \varphi_{if}^{best} = \begin{pmatrix} R \times B(V_{best}), & if edge(i,f)\varepsilon V_{best} \\ 0, & otherwise \end{pmatrix} \quad (3)$$

$$\varphi_{max} = Z(\theta) + B(V_{best}) \quad (4)$$

$$\varphi_{min} = \frac{\varphi_{max}(1 + (T_{best})^{\frac{1}{l}})}{\left(\frac{l}{2} + 1\right)(T_{best})^{\frac{1}{l}}}, l > 2 \quad (5)$$

Pheromone commitment (i.e., $B(V_{best})$) depends on the nature of the emphasis best solutions. $V_{best}.B(V_{best})$ is considered as the minimum by a factor $Z(\theta)$ that depends on the variable q. Organization of $Z(\theta)$ and $B(V_{best})$ totally rely upon the target work of the problem. In this work, the parameter R is a considered as constant for measuring the estimation of the pheromone contributed by the ants. Ant will trust to create best arrangement only when the probability achieveT_{best}.

The accompanying probabilistic calculation, which is noted as pseudorandom corresponding principle, has been utilized to produce resolutions:

$$V_{if}^{m} = \begin{pmatrix} \arg max_{f\varepsilon J_m(i)}\{(\varphi_{if})^{\gamma}.(\vartheta_{if})^{\delta}\}, & ibr \leq r_0, (exploitation) \\ T_{if}^{m}, & ibr > r_0, (exploration) \end{pmatrix} \quad (6)$$

r is an arbitrary variable in [0,1], where the condition lies between $0 \leq r_0 \leq 1$. $\varphi_{if}, \vartheta_{if}, \gamma, \delta\ and\ F_m(i)$ expected to have the same meaning in (1), and where T_{if}^{m} is given by (1).

This transition rule of probabilistic constructs a transaction among investigation and utilization in light of the estimation ofr_0. Fundamentally, the ants initially pick the first node in light of the most captivating edge with probability r_0 and afterward arbitrarily pick the next node in view of the transition rule of probabilistic (1) with the probability$(1 + r_0)$.

The estimations of the pheromone trail are refreshed in two distinct manners utilizing two unique standards: the nearby pheromone refresh lead and the all over pheromone refreshed value the current local pheromone refresh management is performed after every development stage by every ant as per (7).

The pheromone that gets vanish in the current local area is given by $\pi(0 < \pi < 1)$. The reason for applying the local area pheromone refresh is used to decide, whether an edge utilized by an ant must be less attractive for the other ants to maintain a strategic distance from stagnation.

$$\varphi_{if} \leftarrow (1-\pi)\varphi_{if} + \pi_{\varphi_0} \quad (7)$$

After each ants have built their unique solutions, the global pheromone refresh lead is performed by the best ant as per (8), where the global pheromone vanishing rate, θ has indistinguishable significance from (2) and $B(V_{best})$ and R have indistinguishable importance from (3):

$$\varphi_{if} \leftarrow (1-\theta)\varphi_{if} + \pi + \mathrm{R} + \mathrm{B} \times \mathrm{B}(V_{best}) \quad (8)$$

4. ABOUT IMPLEMENTATION TOOL AND DATASET

Matlab is one of the commercial software for numerical computation providing a powerful computing environment for engineering and scientific applications. It has hundreds of mathematical functions inbuilt. It has a high level programming language allowing access to advanced data structures, 2-D and 3-D graphical functions.

The dataset from John Blitzer *et al*., 2007 was used for experiments. It contains a collection of item reviews from Amazon.com. This dataset contains three types of files positive, negative and unlabelled in XML format. These files were extracted using XML file splitter and reviews were converted into the text file. The dataset contains 1000 positive files and 1000 negative files for each domain. The reviews are about four item domains: Books (B), DVDs (D), Electronics (E) and Kitchen appliances (K) and are written in English language. For the experiment, labeled dataset of 1000 positive and 1000 negative files was used. An instance in each domain is recorded in Table-1. From this dataset, 12 cross-domain sentiment classification errands were constructed: B → D; B → E; B → K; D → B; D → E; D → K; E → B; E → D; E → K; K → B; K → D; K → E, where the word before arrow corresponds to the source domain and the word after an arrow corresponds to the target domain.

Table-1. Negative and positive instances for multi-domain dataset.

Domain Name	Negative Instances	Positive Instances
Book	73500	72794
DVD	66126	76759
Electronics	43806	44321
Kitchen Appliances	36106	36733

5. ABOUT PERFORMANCE METRICS

This research work uses the below-mentioned performance metrics for the performance measure:

- Accuracy is used as an evaluation measure. Accuracy is the extent of correctly classified examples to the aggregate number of examples; then again, error rate refers to incorrectly classified examples to correctly classified examples. F-measure or precision and recall used for evaluation measures.
- F-measure is just defined in terms of true positive (TP), false positive (FP) and false negative (FN), while true negative (TN) is not considered. Accuracy and F-measure are compared for a proposed approach, which demonstrates that, in general, F-measure is like accuracy.

6. RESULTS AND DISCUSSIONS

In this section, the proposed work (i.e., GA-ACO) is compared with the existing methods such as and Entrophy Based Classifier (EBC) [Jyoti S. Deshmukh and Amiya Kumar Tripathy, 2018], Supervised word clustering (SWC) [Min Xiao *et al.,* 2013], Spectral feature alignment (SFA) [Min Xiao *et al*., 2015], and Feature Ensemble plus Sample selection (SS-FE) [S.Pan and Q.Yang, 2009]. The proposed work is termed as GA-ACO. When compared with the existing works, the proposed work attains better performance in terms of accuracy. The accuracy attained at the minimum of 88.11% and at the maximum of 90.54% is presented in Table-2. The obtained results are portrayed in Figure-1. Average of accuracy obtained in each domain is portrayed in Figure-2.

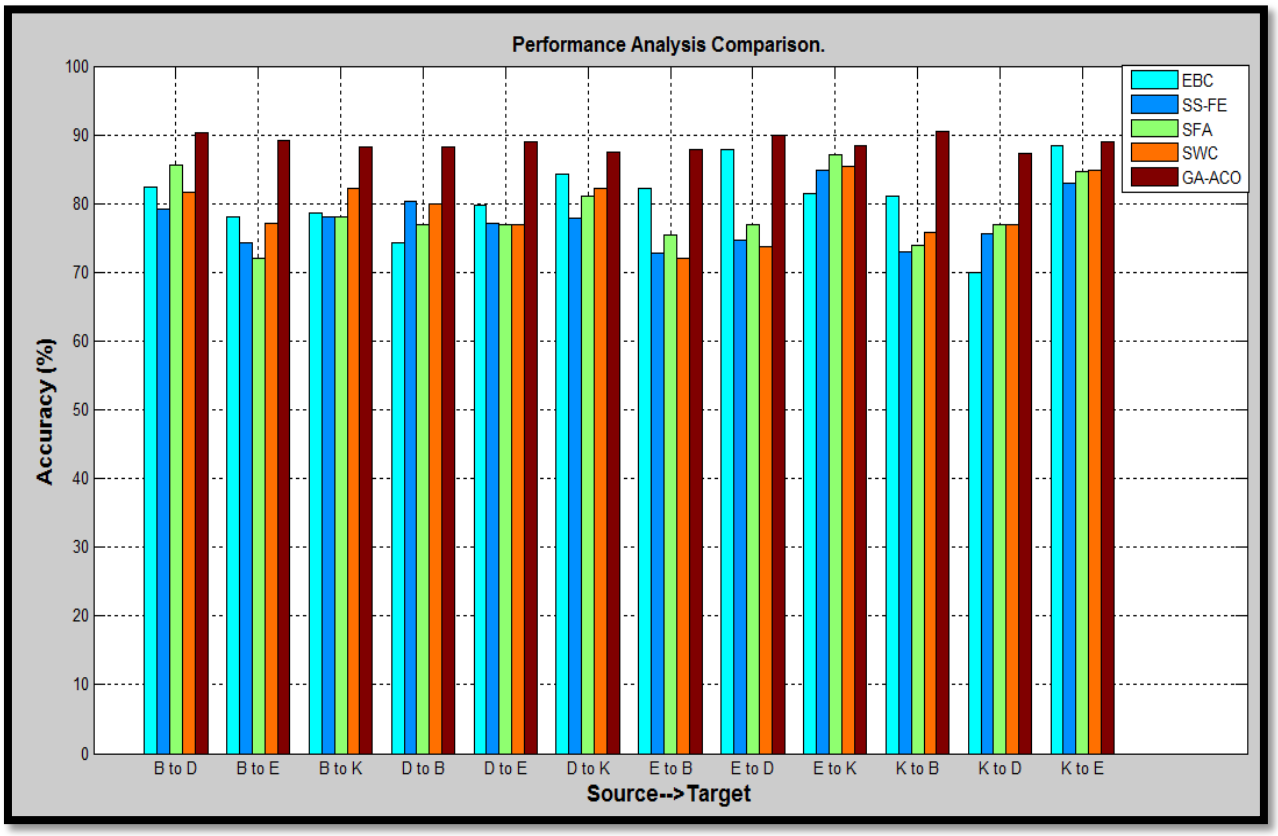

Figure-1. Performance Analysis Comparison.

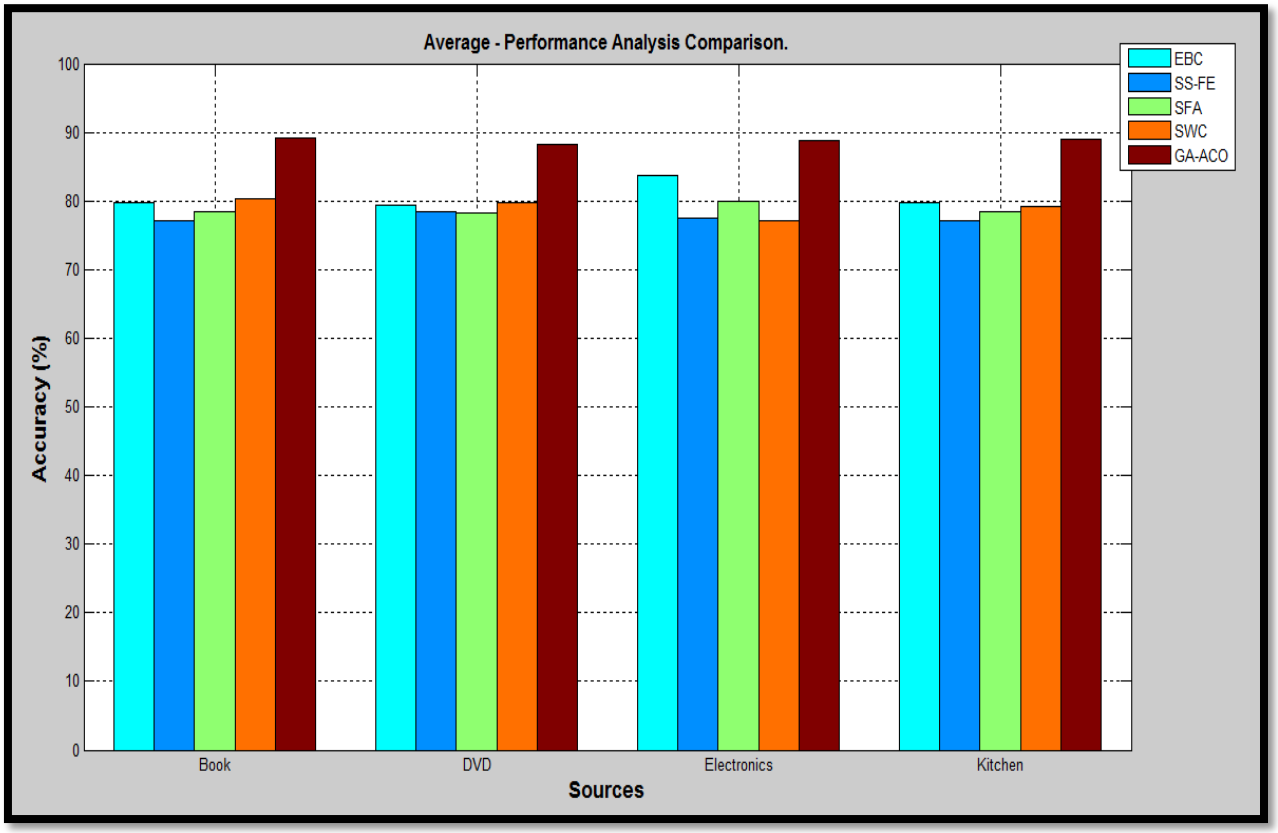

Figure-2. Average - Performance Analysis Comparison.

From Table-2, it is evident that Book and DVD, if considered as a source domain, achieve a good compatibility with electronics and kitchen domain, which was considered as target domain. Besides, electronic and kitchen are compatible domains.

Table-2. Accuracy.

Source-Target	EBC	SS-FE	SFA	SWC	GA-ACO (Proposed)
B → D	82.45	79.10	85.55	81.66	90.32
B→ E	78.00	74.24	72.00	77.04	89.11
B→ K	78.65	78.07	78.00	82.26	88.23
D → B	74.35	80.38	77.00	79.95	88.24
D → E	79.78	77.07	77.00	76.98	88.96
D → K	84.21	77.82	81.00	82.13	87.52
E →B	82.15	72.86	75.50	72.11	87.85
E → D	87.8	74.60	77.00	73.81	89.93
E → K	81.44	84.87	87.10	85.33	88.36
K → B	81.05	72.94	74.00	75.78	90.54
K → D	70.00	75.70	77.00	76.88	87.31
K → E	88.35	82.93	84.6	84.78	88.91

Classified words used to find domain-independent and domain-specific words from the respective domains. Domain-independent and domain-specific words are compared to the SentiWordNet [Baccianella Stefano *et al*., 2010] and GA-ACO, in order to find out how many words match with them (Tables 3-6).

Table-3. Comparison of domain-specific and domain-independent words against SentiWordNet and GA-ACO considering book (B) as a source domain.

Domains	Domain-specific words	Domain-independent words	No. of words matching SentiWordNet		No. of words matching in GA-ACO	
			Domain-specific words	Domain-independent words	Domain-specific words	Domain-independent words
B → D	11503	9744	8934	8972	10256	9414
B → E	5250	4796	4077	4395	4607	4629
B → K	4200	4325	3262	3979	3891	4186

Table-4. Comparison of domain-specific and domain-independent words against SentiWordNet and GA-ACO considering DVD (D) as a source domain.

Domains	Domain-specific words	Domain-independent words	No. of words matching SentiWordNet		No. of words matching in GA-ACO	
			Domain-specific words	Domain-independent words	Domain-specific words	Domain-independent words
D → B	11130	9744	8644	9009	9278	9348
D → E	5238	4781	4068	4418	4527	4603
D → K	4205	4320	3266	3980	3726	4183

Table-5. Comparison of domain-specific and domain-independent words against SentiWordNet and GA-ACO considering Electronics (E) as a source domain.

Domains	Domain-specific words	Domain-independent words	No. of words matching SentiWordNet		No. of words matching in GA-ACO	
			Domain-specific words	Domain-independent words	Domain-specific words	Domain-independent words
E → B	16105	4769	12508	4430	14784	4656
E → D	16466	4781	12789	4462	14516	4619
E → K	4802	3723	3729	3454	4302	3601

Table-6. Comparison of domain-specific and domain-independent words against SentiWordNet and GA-ACO considering Kitchen Appliances (K) as a source domain.

Domains	Domain-specific words	Domain-independent words	No. of words matching SentiWordNet		No. of words matching in GA-ACO	
			Domain-specific words	Domain-independent words	Domain-specific words	Domain-independent words
K → B	16549	4325	12853	3980	14582	4173
K → D	16927	4320	13147	3987	15003	4208
K → E	6296	3723	4890	3449	5615	3675

Table-7. GA-ACO - Accuracy Vs F-Measure.

	BtoE	BtoK	DtoB	DtoE	DtoK	EtoB	EtoD	EtoK	KtoB	KtoD	KtoE	BtoE
Accuracy	89.1	88.1	87.1	89.3	88.5	87.8	86.5	89.5	87.6	91.6	85.2	88.3
F-Measure	89.8	91.3	90.2	90.1	90.5	92.6	91.7	90.6	92.7	92.4	90.8	91.0

F-Measure is computed and presented in Table-7. It is evident that F-Measure performance is better than that of accuracy and is portrayed in the Figure-3. But only single class is considered in F-measure as positive class. On the other hand, when calculating accuracy equal weight is given to both the classes.

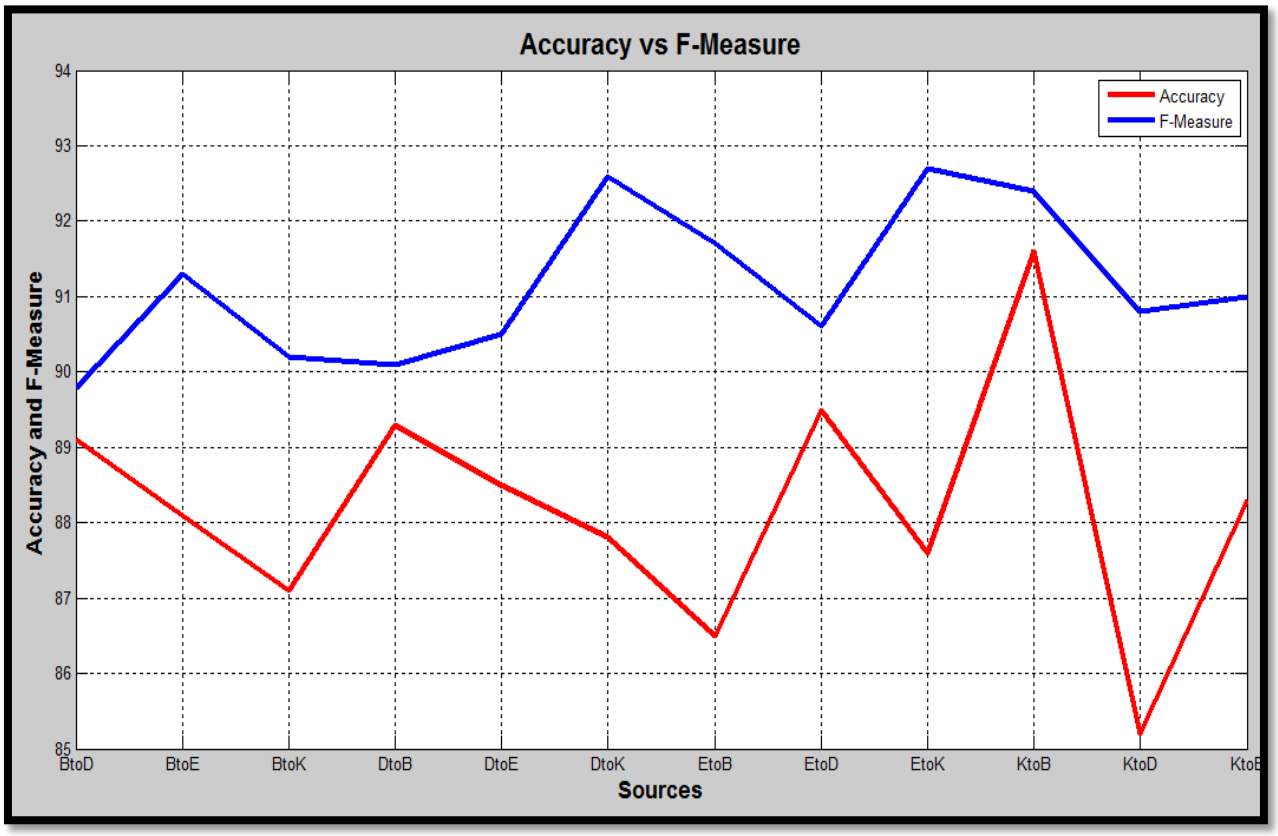

Figure-3. GA-SVM - Accuracy vs F-Measure.

7. CONCLUSIONS

This research article proposed genetic algorithm based ant colony optimization for solving the problems that emerge in Cross Domain Opinion Mining. The dataset contains a collection of product reviews from Amazon.com that has three types of files positive, negative and unlabelled in XML format. These files were extracted using XML file splitter and reviews were converted into text file. The dataset contains 1000 positive files and 1000 negative files for each domain. The reviews are about four product domains: Books (B), DVDs (D), Electronics (E) and Kitchen appliances (K) and are written in English language. For experiment, labeled dataset of 1000 positive and 1000 negative files was used. GA-ACO is compared with the existing works such as supervised word clustering (SWC), spectral feature alignment (SFA), Feature Ensemble plus Sample selection (SS-FE) and Entropy based classifier. When compared with the existing works, the proposed work attains better performance in terms of accuracy and F-measure.

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