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A Survey on Sentiment Analysis using Swarm Intelligence

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Abstract

The social web data has increased tremendously in the recent years in form of comments, blogs, reviews and tweets. The nature of this data is highly un-structured and high- dimensional, making text classification a tedious task. Sentiment analysis, which is a text classification technique is applied on this data to gauge user opinion on several pertinent issues. As a natural language processing task, sentiment analysis automatically mines attitudes or views of users on specific issues. It is a multi-step process where selecting and extracting features is a vital step that controls performance of sentiment classifier. The statistical techniques of feature selection like document frequency thresholding produce sub optimal feature subset due to the Non Polynomial (NP) hard nature of the problem. Swarm intelligence algorithms are extensively used in optimization problems. Optimization techniques could be applied to feature selection problem to produce Optimum feature set. Swarm Intelligence algorithms are used in feature subset selection for reducing feature subset dimensionality and computational complexity thereby increasing the classification accuracy. In this paper we study the state-of-art of the various swarm intelligence algorithms which are presently used for feature subset selection within the sentiment analysis framework. The study shows that swarm optimization brings significant accuracy gains. There are only few swarm algorithms which have been applied in this area and there are many other algorithms which can be explored, this study provides an insight into the various algorithms which can be expounded for improved sentiment analysis.

Keywords: Feature Selection, Opinion Mining, Sentiment Analysis, Swarm Intelligence, Swarm Optimization

1. Introduction

The tremendous growth of Web 2.0 has changed the way people express their views and opinions. Ideas, comments, views, suggestions, feedbacks pertaining to specific & identifiable issues are shared by the users on the social media platforms, such as Facebook, Twitter etc. Sentiment Analysis or Opinion Mining[1], as an intelligent mining technique, helps to capture & determine opinions, emotions and attitudes from text, speech, and database sources, which correspond to how users retort to a particular issue or event. Being a Natural Language Processing task it tries to gauge the opinion of writer about the issue at hand and examine the overall contextual polarity of the data. Sentiment mining from social media content is a tedious task, because it needs in-depth knowledge of the syntactical & semantic, the explicit & implicit, and the regular & irregular language rules.

Sentiment Analysis is a multi-step process encompassing various sub-tasks, that are, Sentiment Data collection; Feature Selection; Sentiment Classification and Sentiment Polarity detection[1]. Feature selection in sentiment analysis have a significant role in recognizing significant attributes and improving the classification accuracy. Due to the high- dimensional, un-structured characteristics of the social media content, this problem of text classification manifolds, thus fostering the need to look for improved & optimized techniques for feature selection.

The Traditional methods for feature selection that are chi-square, information gain, and mutual information etc. are successful in reducing the size of the corpus but with a compromised accuracy. These produce

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sub-optimal feature subsets due to the Non-Polynomial (NP) hard nature of the feature subset selection problem. Thus, for solving the high dimensionality problem and to improve the classification performance, the focus has now shifted to assess techniques that can augment to provide superior results. Evolutionary algorithms have been successful at coming up with good solutions for complex problems, when there is a way to measure quality of solutions[2]. Algorithms such as Nature-Inspired Algorithms[3], Genetic Algorithms[4], Simulated Annealing[5], etc. have been explored much in literature for improved classification. Nature is a rich source of hypothesis from which many researchers get inspired. Today, in almost every field Nature-Inspired Algorithms are used to get an optimized solution for a problem. Nature-Inspired Algorithms can be classified as Swarm Intelligence Algorithms, Bio-Inspired Algorithms and Physics-Chemistry Algorithms. In this paper, we review an alliance that expounds the use of Swarm-Intelligence algorithms for optimum feature selection in sentiment analysis.

Swarm Intelligence is a distributed system whereby self-cooperating global behavior is produced by anonymous social agents interacting locally having local perception of its neighboring agents and the surrounding environment. These algorithms work on the principle of distribution of labor and distributed task allocation producing global patterns, the individual agents such as ants, bees, can do simple task while the cooperative work of whole colony brings out intelligent behavior[6].

Owing to the challenging research problems and extensive array of practical applications, sentiment analysis has been a dynamic area of research in the last decade. Most of the work done till date is based on insight to the problem and its solution is limited to the understanding of natural language. Moreover, processing relies on conventional lexicon-based or machine learning algorithms which are syntactically efficient but lack the "semantic" aspect to produce human understandable results. Incorporating nature-inspired techniques, more specifically swarm intelligence helps to solve the global optimization problem for feature subset selection in the classification of sentiment by extracting and exploiting the collective local & global behavioral patterns thus improving the search capability in the problem space and efficiently finding a minimal feature subset. This paper reviews the state-of-art explicating the previous attempts made to study this alliance of swarm intelligence to sentiment analysis and substantiates it as a significant positive collaboration.

2. Sentiment Analysis

Sentiment Analysis has yield an eye-popping contemporary direction to online media with a wide range of practical applications ranging from business intelligence to politics[7]. The purpose of Sentiment Analysis is to find the attitude, emotion or viewpoint of writer from the type of reviews or comments given by them. Opinions given by others help us to make our decision making easier. The workflow defining the sentiment analysis task is shown in figure1. Data on which sentiment analysis is to be performed is firstly fetched & pre-processed to select the features for further use. The selected feature subset is then sent to the classifier which gives us the polarity of the dataset. Based on polarity accuracy, precision and error rate are calculated. Opinions can be collected from various sources such as social media sites, Blogs, Audit sites etc. Once the data is collected it is preprocessed into an accessible format for Classification. The data pre-processing mainly involves Data cleaning which involves removal of urls, hashtags, quotes, punctuation marks, repeated words, expand emotions, expand acronyms and data transformation which includes stop word removal, handling negation, tokenization and stemming.

Recent approaches of feature selection in field of sentiment analysis range from lexicon-based approaches to automated approaches. In lexicon-based approach the set of features are generated by manually by humans whereas in automated approaches general statistical measures are used where features are selected based on empirical indication like tf-idf, term occurrence or term frequency. The statistical approaches often fail to segregate features that carry sentiment from those that do not. Once the feature selection task is through, we have a set of discernable & enhanced features, which becomes input for the text classification step. Machine learning techniques such as Naïve Bayes, Support Vector Machines (SVM), Decision Tree, etc., are used for classifying the sentiment. These machine learning algorithms read the features extracted from previous step and give the output as positive, neutral

Figure 1. Sentiment Analysis Workflow.

or negative. Various methods are used to measure the performance of classifiers like calculating precision, accuracy, recall and F-measure.

In a generic text classification task, features are used to identify & distinguish topics but in sentiment analysis it is more about the subjectivity, viewpoint, and/or emotion. User-generated content contains both kinds of features and the key challenge is to separate factual content from subjective content. This makes feature selection a crucial decisive step. The feature selection as a sub-task of sentiment analysis is discussed in detail in the following sub-section.

2.1 Feature Selection

Literature studies have revealed that the sentiments have been typically researched at the document, sentence, entity and feature level. Given an opinioned document *d*, we can discover all opinion quintuples (e_i, a_{ij}, s_{ijkl}, h_k, t_l) in *d*, where e_i is a unique entity, a_{ij} is the unique aspect for entity e_i, s_{ijkl} defines the opinion, i.e., it classifies the sentiment into positive, negative or neutral categories. The fourth component and fifth components are opinion holder and time respectively. They can also be used for extracting and categorizing entities and aspects. In feature selection, the feature is first identified, followed by the selection procedure and then extraction and reduction process if required. Feature identification includes comprehending feature types such as term frequency, term Co-occurrence, Part-of-Speech and Opinion Words, for identification purpose. Several techniques are used for solving this problem of feature subset selection in classification. The major and frequently used approaches are information gain, mutual information, document frequency thresholding, x[2]-test (CHI) and term strength, to list a few. The x[2] statistics and information gain produce good results and are more efficient in optimizing the classification results whereas document frequency is efficient in terms of scalability and complexity[8].

Feature Selection in sentiment analysis is tackling a variety of issues such as large feature space, redundancy[9], noise attributes, context sensitivity, domain dependency[10], and limited work on Lexico-structural features[11], amongst others. The primary goal of feature selection is to enhance the performance of classifier by selecting only useful and pertinent features and removing redundant, irrelevant and noisy features and thus reducing the feature vector. Further, extracting pertinent and distinct features becomes imperative too when classification algorithms are inept to scale up to the size of feature set in terms of time and space. Absence of proper feature selection technique can cause the classifier to consume more resources and more processing time. The first and foremost challenge in feature extraction is to select the minimal feature subset without any loss of classification accuracy.

In a generic sentiment classification task, a number of words as candidate features are considered, though only a few essentially express sentiments. This set of extra features have to be pruned as they down turn the classification process & tend to reduce the accuracy of the classifier. Thus, feature selection involves searching optimal feature subset using some search strategies. The search could be exhaustive or approximate, exhaustive search produces optimal solution but it is not feasible for large datasets and the social media data usually have huge dimensionality. Exhaustive search in this case becomes impractical as finding optimal feature subset comes in the category of NP-hard problems as for N number of features, the number of possible solutions will be exponential to 2^N. So the focus of researchers has now shifted to meta-heuristic algorithms, which are taken as a subclass of approximate methods.

To produce a more accurate classification and reduce the feature set, study and implementation of several evolutionary optimization techniques have been successfully done in the past and are currently explored too, making it a dynamic area of research. Most common evolutionary optimization techniques used for feature selection are, genetic algorithms, simulated annealing, gene expression programming, swarm algorithms, amongst others. This paper we examine the state-of-art of the study the various swarm intelligence algorithms which are presently used for feature subset selection within the sentiment analysis framework.

3. Nature Inspired Optimization

Nature has a rich source of ideas from which many researchers are being inspired. Today, in almost every field Nature-Inspired Algorithms are used to have an optimized solution for a problem. Nature-Inspired Algorithms can be classified as Swarm Intelligence Algorithms, Bio-Inspired Algorithms and Physics-Chemistry Algorithms. In this paper we will briefly go through Swarm Intelligence Algorithms.

Swarm Intelligence is basically the collection of interacting agents who follows simple rules to communicate with each other in their local environment without having any central regulator architecture. It is a collective behavior of animals, small insects and other creatures that help each other in either static or a dynamic manner.

3.1 Swarm Intelligence based Algorithms

Swarm intelligence involves a simple collection of agents interacting locally with each other and with their corresponding environment. The agents interact with each other based on simple behavioral rules that uses local information which is exchanged between agents directly and through the environment. The individual agents are unintelligent, but the overall system leads to intelligent behavior due to the interactions between the agents and their environment. It is the principle of decentralization and self-organization of the group of interacting agents that produces global intelligent behavior. Many algorithms have come into existence which are based on swarm behavior and among them a few popular ones are Ant colony optimization, Ant Bee Colony, Particle Swarm Optimization etc. These algorithms draw inspiration from ants clustering, animal herding, nest building of wasps and termites, bird flocking, bacterial growth, microbial intelligence and fish schooling. Various swarm intelligence algorithms are presented in Table 1. Ants make their colonies by collecting small bodies into a single place and they organize their larvae into a single place with younger larvae in the center and the older ones at boundaries. This behavior inspired scientists and researchers to come up with models of this behavior in simulation of problems. Another popular swarm algorithm is the PSO, a population based optimization technique based on social behavior of fish schooling and flock herding. In PSO a collection of agents called particles which search for solution in search space based on its own experience and experience of its neighbors and based on this it decides where to move in the search space it modifies its velocity according to its previous velocity and velocity of neighboring agents. PSO has been successfully use in many optimization problems and have produced very good results. SI-based algorithms are coming up with very good results in problems where the nature of problem is NP-Hard, which otherwise would produce sub-optimum results and consume huge processing power. Due to the scalability and robustness of SI-based algorithms they have become the first choice in finding solutions for optimization problems.

Table 1. Swarm Intelligence Algorithms

Algorithm	Author	Year
Ant Colony Optimization[12]	M Dorigo	1992
Particle swarm optimization[13]	Dr. Eberhart , Dr. Kennedy	1995
Bee system[14]	P Lucic , D Teodorovic	2001
Bacterial foraging[15]	Kevin M Passino	2002
Fish Algorithm[16]	X.-L. Li, Z.-J. Shao, J.-X. Qian	2002
Bee Hive[17]	H.F. Wedde, M. Farooq,Y. Zhang	2004
Artificial bee colony[18]	Dervis Karaboga	2005
Bee colony optimization[19]	Dusˇan Teodorovic´, Mauro Dell'Orco	2005
Bees swarm optimization[20]	Habiba Drias, Souhila Sadeg, Safa Yahi	2005
Glowworm swarm optimization[21]	KN Krishnanand , D Ghose	2005
Virtual Bees[22]	X.-S. Yang	2005
Bees algorithms[23]	DT Pham, A Ghanbarzadeh, E Koc, S Otri, S Rahim, M Zaidi	2006
Virtual ant algorithm[24]	X-S Yang, J M Lees, C T Morley	2006
Monkey Search[25]	Antonio Mucherino, Onur Seref	2007
Firefly Algorithm[26]	X.-S. Yang	2008
Good lattice swarm optimization[27]	Shoubao Su, Jiwen Wang, Wangkang Fan, and Xibing Yin	2007
Fast bacterial swarming algorithm[28]	Ying Chu, Hua Mi, Huilian Liao, Zhen Ji, QH Wu	2008
Cuckoo search[29]	Xin-She Yang, Suash Deb	2009
Bat algorithm[30]	Xin-She Yang	2010
Consulted Guided Search[31]	Serban Iordache	2010
Eagle Strategy[32]	X. S. Yang and S. Deb	2010
Weightless Swarm Algorithm[33]	To Ting, Ka Lok Man, Sheng-Uei Guan, Mohamed Nayel, and Kaiyu Wan	2010
BumbleBees[34]	Francesc Padro´, Jesu´s Navarro	2011
Krill Herd Algorithm[35]	Amir Hossein Gandomi, Amir Alavi	2012
Wolf search[36]	Rui Tang, S. Fong, Xin-She, S. Deb	2012

4. Feature Selection using Swarm Intelligence

Present feature selection methodologies, like Information Gain, Document Frequency thresholding and Chi Square assign numerical values to features based on specific statistical equation. Then using some threshold value appropriate features are selected from the sorted feature vector. The selection of threshold value is user dependent and impacts the classification accuracy. This results in selection of sub-optimal feature set and thereby consuming more processing power and more resources. Figure 2 shows where swarm intelligence algorithm is applicable in sentiment analysis framework.

Feature subset selection from high dimensional feature space is a global optimization problem that aims at reducing feature quantity and removing redundant, irrelevant and noisy features thereby increasing the classification accuracy and improving on processing time. Swarm Intelligence algorithms are widely used in such optimization problems where quality of solutions could be measured. These algorithms therefore are used for this optimum feature vector selection problem to render a feature subset that gives improved classification accuracy. Swarm algorithms improves the quality of solution by working in several iterations and application of knowledge of previous iteration on selection of current values.

By reducing number of features, greater classification accuracy can be produced as opposed to using the full set of features. Feature selection basically is a four step process involving feature subset generation, subset evaluation, terminating criterion checking and result validation. Firstly, feature subset is generated in this candidate feature subset is searched based on specific search strategy the candidate subsets are evaluated and compared with a previous best value of the evaluation attribute used. If better subset is produced, it replaces the previous best. This subset generation and evaluation is repeated until a specific stopping criterion is achieved. The swarm optimization goes through several iterations before attaining the global best solution. After each cycle fitness function which is accuracy of classifier is calculated for the candidate subset. The candidate solution generation and fitness function computation continues until the terminating criteria is satisfied. Generally, the stopping criteria is based on two things the error rate and Number of iterations. If the error rate is below a certain threshold, then we stop or if the algorithm exceeds the specified number of cycles.

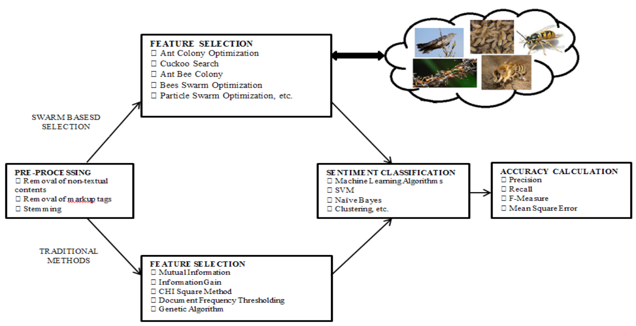
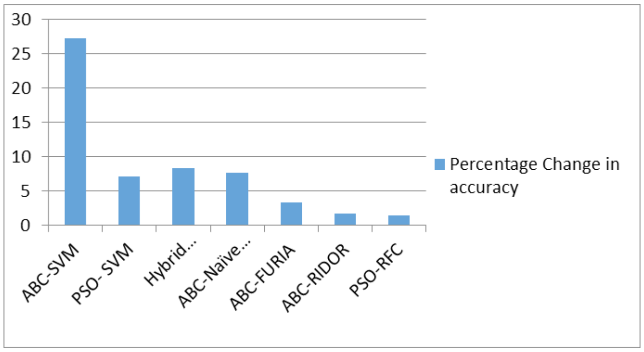


Figure 2. Using Swarm Intelligence in Feature Selection.

Comparisons with baseline systems show that promising accuracies with much reduced feature set can be achieved using swarm intelligence. Experiments revealed it was possible to maintain an 87.15%, state-of- the art classification accuracy when using less than 36% features[42]. The ABC and PSO algorithm being powerful optimization techniques are widely used for solving combinatorial optimization problems. These methods have been used for optimizing the feature subset selection successfully by researchers and have improved the accuracy of classification as stated in table 2. The PSO algorithm when amalgamated with the Sentiment classifier enhances the classification accuracy by 4.25% whereas the ABC algorithm produces accuracy increments of 9.94%. The complete state-of- art is given in table 2. Although we have

Table 2. Comparison of Various Swarm Intelligence Techniques on Sentiment Analysis

SI technique	Data set	Classifier	Accuracy without Optimization	Accuracy with Optimization	Year
ABC	Product Reviews[37]	SVM	55	70	2015
ABC	Internet Movie Database (IMDb)[38]	Naïve Bayes	85.25	88.5	2014
		FURIA	76	78.5	
		RIDOR	92.25	93.75	
hybrid PSO/ ACO2	Product Reviews, Governmental decisions data[39]	Decision Tree	83.66	90.59	2014
PSO	Twitter Data[40]	SVM	71.87	77	2012
PSO	Restaurant Review Data[41]	CRF	77.42	78.48	2015



Graph 1. Percentage Change in Accuracy between Feature Selection using Swarm Intelligence Algorithms and without Optimization.

a variety of nature inspired algorithms for optimization as can be seen from table 1 only few have been explored in domain of opinion mining.

The swarm intelligence algorithms produce results that are better in terms of Sensitivity, specificity and accuracy. Using swarm intelligence in opinion mining is an open and emerging area for researchers, significant enhancement of performances of systems are compelling researchers, marketers, policy makers to invest in this area. Improved results can help merchants acquire valuable feedback (e.g. consumers' satisfaction regarding their products) and could facilitate public administrations to capture the understanding of e-Government and e-Rulemaking. This This shows that feature optimization is a dynamic area of research and it improve classifier's performance in sentiment analysis and this area has much potential to be discovered further.

5. Conclusion

Comparing the performance of swarm inspired subset selection with the other methods of feature selection in opinion mining we found that swarm inspired algorithms converges quickly and produce better results in terms of efficiency and complexity and can efficiently find optimum feature set.

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