ISSN 1598-0170 (Print)
ISSN 2287-1136 (Online)
http://www.jksii.or.kr

A Review of the Opinion Target Extraction using Sequence Labeling Algorithms based on Features Combinations☆

Noor Azeera Abdul Aziz[1*] MohdAizainiMaarof[1] Anazida Zainal[1] Mohammed HazimAlkawaz[2]

ABSTRACT

In recent years, the opinion analysis is one of the key research fronts of any domain. Opinion target extraction is an essential process of opinion analysis. Target is usually referred to noun or noun phrase in an entity which is deliberated by the opinion holder. Extraction of opinion target facilitates the opinion analysis more precisely and in addition helps to identify the opinion polarity i.e. users can perceive opinion in detail of a target including all its features. One of the most commonly employed algorithms is a sequence labeling algorithm also called Conditional Random Fields. In present article, recent opinion target extraction approaches are reviewed based on sequence labeling algorithm and it features combinations by analyzing and comparing these approaches. The good selection of features combinationswill in some way give a good or better accuracy result. Features combinations are an essential process thatcan be used to identify and remove unneeded, irrelevant and redundant attributes from data that do not contribute to the accuracy of a predictive model or may in fact decrease the accuracy of the model.Hence, in general this review eventually leads to the contribution for the opinion analysis approach and assist researcher for the opinion target extraction in particular.

☞ keyword : Features Combinations, Opinion Target Extraction, Text sentiment analysis, Conditional Random Field and Sequence Labeling Algorithm

1. Introduction

Nowadays, online communication is an important medium for people to express their sentiments or feelings towards any entity [1, 2]. People's opinion on the websites, blogs, social media and forums creates rich information which is mostly publicly available and easy to access. Unluckily, due to rich source of information it is difficult to extract related documents in terms of the expressed opinion.There is a rising requirement of automated analysis for such kind of data source.

Opinion Mining or sentiment analysis is the field of Natural Language Processing (NLP) and Text Mining. It is a computational study to opinion, sentiment, and subjectivity in text [3-5]. For an instance, in business domain, Sentiment Analysis identifies the negative and positive opinion from customer towards product. The opinions are useful for both company and user decision making.

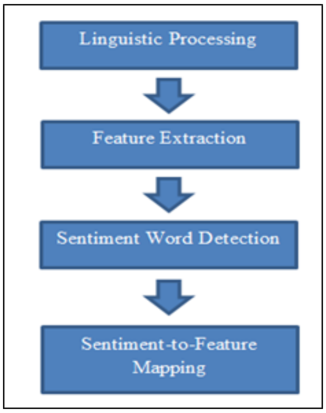
Opinion mining [6, 7] is a recent discipline, that includes crossroads of information retrieval, text mining and computational linguistics which detects the opinions expressed in natural language texts.

Opinion mining consists of two main stages, the extension of opinion lexicon and the opinion target extraction [6, 8]. An opinion lexicon contains either positive, negative or natural sentiments which are identified from a list of opinion words. There are several types of opinion mining approaches such as sentence-based [9-11], document-based [12, 13] and feature-based [14-17]. The feature-based sentiment analysis standard method [18] is demonstrated in Figure 1.

In feature extraction method, different features of target are extracted. Feature extraction is the main challenge in opinion mining process i.e. how to extract items where opinions are expressed on. Typically, nouns or noun phrases are the opinion target. Opinion targets are very important because the extracted targets provide information about the appointed opinions.

[1] Faculty of Computing, UniversitiTeknologi Malaysia, 81310 Skudai, Johor, Malaysia
[2] Faculty of Information Sciences and Engineering, Management & Science University, Shah Alam, Selangor, Malaysia
[*] Corresponding author (zera167@gmail.com)
[Received 9May 2016, Reviewed 24May 2016, Accepted 17 June 2016]
☆A preliminary version of this paper was presented at ICONI 2015 and was selected as an outstanding paper.

http://dx.doi.org/10.7472/jksii.2016.17.5.111



(Figure 1) Feature-based sentiment analysis standard method

Opinion mining methods are classified into supervised and unsupervised methods. Supervised learning approach requires a correctly annotated corpus [19], while unsupervised classification does not need labeled data but it depends on heuristics procedures and rules in order to find hidden structure. Several methods have been proposed to identify the target of an opinion expression. One of the methods is use of sequence labeling algorithm which involves Conditional Random Fields (CRF).

This study provides a review on existing sequence labeling algorithms and their combinations of features which have been employed for opinion targets extraction within past few years. The main focus is to identify potential combination methods based on CRF approach for opinion targets extraction which are helpful in the future research work in opinion mining.

2. SEQUENCE LABELING APPROACH

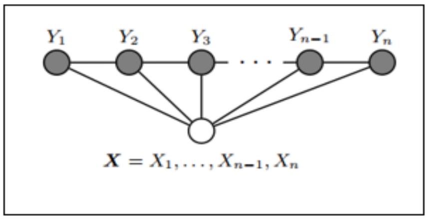
Sequence labeling finds applications in many areas such as bioinformatics [20], NLP [21], speech recognition [22], image processing [23] etc. Contingent on the fundamental sequence labeling task, labels are assigned to the tokens present in the sequence.

Sequence labeling algorithms usually use CRF. In bioinformatics domain, [24] predicted trans membrane helix and location [25] predicted protein secondary structure and [26] proposed Order and Disorder prediction using Conditional Random Fields (OnD-CRF) for predicting order and disorder in proteins by using CRF-based. For extracting opinion target, CRF is used as a base as it has been used in published work [27-31].

2.1 CONDITIONAL RANDOM FIELDS

CRF has been successfully applied in sequence labeling and segmentation [32]. CRF is a discriminative, undirected Markov model which represents a conditional probability distribution of a structured output variable Y for a given observation X.

A CRF is an undirected graph of model G of the conditional distribution P (X|Y). As illustrated in Figure 2, suppose G is an undirected graphical model over random variable sequences x and y, i.e. $x = (x_1, x_2, \dots x_n)$ which is the sequence of observed entities (e.g. words in a sentence) that we want to label with $y = (y_1, y_2, \dots y_n)$. (x, y).



(Figure 2) Chain-structured of CRF model [33]

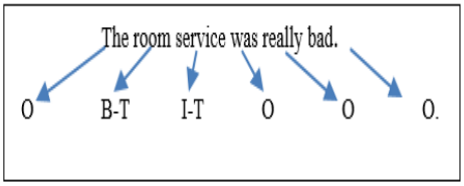
The conditional probability is defined as given in equation 1:

$$P(Y|X) = \frac{1}{Z(X)} \exp\left(\sum_{e \in E, i} y_i t_i(e, Y|e, X) + \sum_{v \in V, i} \mu_i s_i(v, Y|v, X) \right) \quad (1)$$

where $Z(x)$ is the normalization factor, s_i is the state function on node, t_i is the transition function on edge, y_i and S_i are parameters to estimate.

3. REVIEW FEATURES COMBINATION FOR OPINION TARGET

Opinion Target Labeling: There are several ways of labeling the opinion target. One is use of the Beginning, the Inside and the Outside (IOB) annotation to represent opinion targets in sentence [27, 31]. For this technique, opinion targets as illustrated in Figure 3 are represented by B-Target for the beginning word/token of the target, I-Target as intermediate or inside word/token of the target and O for the non-target.



(Figure 3)IOB Labeling for Opinion Target

Instead of using IOB annotation, another way of labeling is use of feature-opinion pairs <opinion target, opinion-bearing word>[28, 30]. In [28], opinion targets have been identified simultaneously with the opinion-bearing word by assuming opinion-bearing word as the indicator of opinion in the sentence and label the corresponding opinion target based on the selected multi-features.

Feature Analysis: Depends on the dataset used for the experiments, feature selection always plays an important role in machine learning. Features can be defined as the parameters that make the CRF model computable. In order to get the best result for the classification task, different combinations of the features have also been used.

[27] proposed an opinion target extraction for restaurant dataset using CRF based with IOB annotation. The values of features have been extracted according to three conditions. Each condition considers different features. The conditions are:

1) Extract values of the features for each single word itself, 2 and 3 previous subsequent words; 2) Extract values of two successive features in the range -2,2 (the previous and subsequent two words of actual word); 3) Extract values for each three successive features in the range -1,1.

The authors used CRFsuite tools with Limited Broyden–Fletcher–Goldfarb–Shanno (LBFGS) algorithm for training and testing the datasets which finally extracts the opinion target.

[28] proposed a simultaneous method of identifying opinion targets and opinion-bearing words based on multi-features in Chinese micro-blog post. Instead of using IOB annotation, this study has used undirected graph to represent each token whether it is an opinion target or not. The experiments have been set up by simply labelling all the tokens in a sentence with four features; token, part-of-speech (POS), word distance (WD), and Direct Dependency Relation (DDR). These features enables the CRF model to simultaneous identify opinion target and opinion-bearing words in a sentence. The author has used CRF implementation from CRF++0.53.

[29] has modeled starts with document preprocessing, effective opinion sentences extraction and candidate opinion target extraction by employing CRF model with feature templates. Features for CRF word, POS and dependency parsing. Next, the M-Score algorithm has been employed to extract seed set, and the bootstrapping approach has been invoked to process the candidate opinion targets. This study adds one more step after extracting candidate opinion targets using CRF by using an M-Score algorithm. It uses word frequency and the Noun pruning algorithm to filter the opinion targets, and then obtains the final opinion targets for output. The proposed method has solved the domain limitation problem in the opinion target extraction research.

[30] has investigated the problem in a cross language scenario which leverages the rich labeled data in a source language for opinion target extraction in a different target language. The linear-chain CRF model has been employed as the basic model in the monolingual co-training algorithm which learns opinion target labelers based on the two labeled dataset and an unlabeled dataset. All the experiments have involved CRF++ tools. Due to use of two languages, the study has generated features for both languages English and Chinese. The features used for this approach are word-based, POS, dependency path and opinion word type.

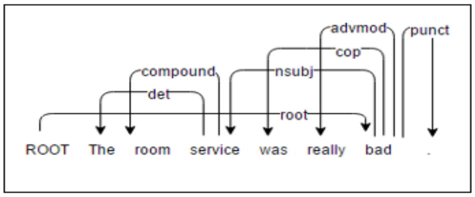
[31] has presented a CRF-based approach for opinion targets extraction. The focus of proposed study is to extract individual instances of opinion targets from sentences which contain an opinion expression by considering features: token, POS, short dependency path, word distance and opinion sentence. The Mallet toolkit has been used in the study.

Features Type:

1) Word/token: Word/token is not only just a building-block of sentences but it also contains unpredictable meanings [34]. In opinion target, many ways of extracting word features are defined. [29]defined the combination of two continuous word pairs as features.Besides, some researchers have considered this feature to represent the string of current token [28, 29,31].

2) Lemma: Lemma is the head word in the dictionary. In order to extract values of the lemma, a large lexical database can be used. [27] has used WordNet to extract the values or information of lemma. In proposed study, the lemma information has been extracted for 2 conditions as lemma information for current word and the 2 and 3 previous and subsequent words; value for each three successive features in the range -1,1. Lemma information is a useful precondition for any task that needs to link surface forms to semantic interpretation.
3) POS tag: Opinion targets are usually nouns or noun phrases. Thus, the tagging of POS is crucial. POS tagging can be manually or automatically assignedto words in a corpus. POS tag is useful in resolving lexical ambiguity and also as a pre-processing step for parsing. [27] has used Natural Language Toolkit (NLTK) parser to extract POS tag value for all three conditions as it has been proposed. Besides, some researchers have extracted POS tag for the current token as identified by using ICTCLAS2013 [28] and some has employed Stanford POS tagger to extract value of POS features of the current token [31]. Different from the previous study, [30] extract the combination of two continuous POS tag pairs as features. Sinceproposedresearchdeals withtwolanguages, twosets oftags have beenused respectively which are Penn English Treebank tag set and Penn Chinese Treebank tag set.
4) Word Shape: Word shapes refer to mappings of words to simplify representations that encode attributes such as length, and whether the word contains capitalization, numerals, Greek letters, and so on [35]. In one of the opinion target extraction study, word shape attributes to capital letter, small letter, digit, punctuation and other symbols [27].
5) Word Type: The type of word can express useful information about the opinion target. For example the combination of word type of digit and letter with particular pattern represents date and the uppercase letter may represent an abbreviation of product name.
6) Prefix and Suffix: A prefix is a group of letters placed before the root of a word while suffix is added after the root of word. The meaning of a word could be changed by adding prefixes or suffixes to the word. For example when suffix 'er' is added into the verb 'teach', the word becomes 'teacher' which can be as one of the opinion target. [27] has considered all prefixes and suffixes which have length between one to four.
7) Stop word: Stop words are the common words in a language that have always been excluded from the vocabulary entirely [36]. Some example of stop word are 'a', 'an', 'of', 'by'and many more. In opinion target extraction, removing stop word does not provide an accurate result. For instance in phrase 'Apple Earphones with Mic', which contains one stop word 'with'. Filtering stop word gets two different targets which are 'Apple Earphones' and 'Mic'. So, in this case, by considering stop word value in opinion target, extraction will give a precise meaning of the phrase where by the phrase 'Apple Earphones with Mic' contains one opinion target but not two different targets. In [27], the stop word value of current token has been considered either as a stop word, or not a stop word.
8) Word surface: One of the sense of word happen when more than one lexical form are associated with a surface form of a word [37]. For example the word 'house' could be singular if it is noun and also could be a present tense if it is a verb.
9) Word distance: According to [14, 38], opinion targets and its opinions are always closer to each other in forms of nouns/noun phrase. Hence, the researcher uses the word distance feature to label the opinion target.
10) Chunk/Shallow Parser: Chunk Parser aims to find only the boundaries of major constituents such as noun phrases and computes the basic analysis of sentence structure rather than attempting full syntactic analysis [39]. As mentioned, opinion target consists of noun or noun phrase entity. In this case, chunk/shallow parser extracts noun or noun phrase which leads to the opinion target.
11) Direct/Short Dependency: The link between the opinion and the corresponding target can be identified by employing direct/short dependency as shown in Figure 4. Direct/short dependency feature gives interdependent values between words. As stated in [40-42], the direct dependency relations such as 'amod' and 'nsubj' are the most frequently used and at the same time creates

a highly accurate connection between a target and an opinion expression in a sentence. Hence, this feature definitely improves the accuracy of opinion target extraction.



(Figure 4)Sentence direct dependency relation

12) Named Entity: Name Entities are discrete entities in unstructured text which are annotated to name-classes such as PERSON, DATE, TIME, MONEY ORGANIZATION, LOCATION, and PERCENTAGE called Name Entity Recognition (NER) process [43]. For example in sentence '< Person > Amir < /Person > said it was clear that he paid to consultancy firm <Organization>Alif& Co </ Organization> for their services on < Date > October, 12th </ Date >'. The name-class can be changed according to our needs. The information of named entity gives semantic for the sentence which is definitely useful in opinion target extraction.
13) Opinion: The opinion target can be predicted by the occurrences of opinion in the sentence. Hence, labeling the value of the opinion features helps to identify the occurrences of opinion target in the sentence.
14) Polarity: Polarity is deeper information compared to opinion. Opinion gives information of objective or subjective sentence but polarity gives the subjective sentence which contains either natural, positive or negative opinion.

4. PERFORMANCE COMPARISON

In this section, we present the comparative results of proposed approaches. The combinations of features are summarized as below:

1) Lemma + POS tag + word shape + word type + named entity + chunk + polarity + prefixes + suffixes + stop word + Word surface
2) Token + POS tag + direct/short dependency
3) Token + POS tag + word distance + direct/short dependency + opinion

Table 1 presents the results with the features combination. In Table 1, results are compared based on precision, recall and f-score (F1).

By comparing the features combinations in Table 1, as selected in [27], the number of features combinations that have been selected are more compared to the number of features combinations in other approaches. It shows that the numbers of features will not guarantee a good result with high accuracy.

The highest score for precision, recall and f-score are for approach proposed by [28] with 0.773, 0.801 and 0.787. Word distance and direct/short dependency played an important role in identifying feature-opinion pairs which is the pair between opinion target and opinion-bearing word. By considering the short/direct dependency, it generates model with more accurate prediction to some extent and makes the approach fully consider the dependency relation between opinion target and opinion-bearing word in the process of training.

(Table 1) Features Combination Resulted

Features Combination	Precision	Recall	F1
Extract values of the features for [27]: 1) Lemma + POS tag + word shape + word type + named entity + chunk + polarity + prefixes + suffixes + stop word 2) Word surface + POS tag + chunk + word shape + word type 3) POS tag + lemma	0.72	0.55	0.62
Token + POS tag + word distance + direct/short dependency + opinion [28].	**0.773**	**0.801**	**0.787**
Token + POS tag + direct/short dependency [29].	0.452	0.464	0.458
Token + POS tag + direct/short dependency + opinion [30].	0.721	0.754	0.737
Token + POS tag + direct/short dependency + opinion [31].	0.675	0.507	0.578

Results of the combination features for approaches in [31] and [29] give lower score compared to other approaches. Both approaches have been focused on domain-independent. However, combination features in [31], provides better results which gives score Precision 0.675, Recall 0.507 and F1 0.578 as compared to combination features in [29].

In addition to word distance and direct/short dependency features, opinion feature also affects the result of the opinion extraction approach. In sentiment analysis, the sentence with sentiment or subjective information definitely has opinion target. Hence, opinion value even though without the polarity can produce a better result.

However, these results have been compared for different data sources and data sizes. The information of data is given in Table 2.

As displayed in Table 1, the result for [28] is better compared to other approaches. Besides considering opinion feature, it also used the data sets which only contain subjective sentences as stated in Table 2. Even though with 600 sentences, the approach still performs better than approach in [31] with 46 876 data sets size.

Another issue that is needed to be taken into account is the antecedent and anaphora issues. Antecedent commonly is a noun and anaphora is the repetition of a certain word or phrase at the beginning of successive lines of writing or speech which points back to previous antecedent in the discourse [44]. For example, the sentence ‘I hate Laptop M102. Its performance is slow’. Laptop M102 is anantecedent and the word ‘Its’ is referring to “Laptop M102” called as anaphora. Hence, by considering anaphora resolution, opinion target ‘Its’ and ‘M102” would be as one target.

〈Table 2〉 Information of the used data

Data Source	Sentences	Sentences with Target	Sentences with Opinion
SemEval 2015 ABSA organizers	1315	1654	-
NLP&CC 2012&2013	600	-	600
Web 2.0 sites	46 876	15 063	15 375
Online reviews	4319	4269	-
Customer Review	3945	1962	-

5. CONCLUSIONS

Opinion target extraction is keyprocess to identify target and it features mentioned in the sentence or document. CRF is a sequence labeling approach which is employed to extract opinion target. The assortment of features combinations are of great importance to construct CRF model which influence directly the accuracy of the opinion target extraction task.

In present study, a review on opinion target extraction based on sequential labeling algorithm is presented. It has been found that the features combination play key role in sequential labeling algorithm. Furthermore, anaphora resolution could be another issue to be explored in this approach.

Reference

[1] Samovar, L., et al., "Communication between cultures". 2015: Nelson Education.

[2] Gil de Zúñiga, H., L. Molyneux, and P. Zheng, "Social media, political expression, and political participation: Panel analysis of lagged and concurrent relationships". *Journal of Communication*, 64(4):pp. 612-634, 2014. http://dx.doi.org/10.1111/jcom.12103

[3] Liu, B., "Sentiment Analysis and Subjectivity". *Handbook of natural language processing*, 2010. 2:pp. 627-666.

[4] Jiménez-Zafra, S.M., et al., "Combining resources to improve unsupervised sentiment analysis at aspect-level". *Journal of Information Science*, 2015. http://dx.doi.org/10.1177/0165551515593686

[5] Dave, S. and H. Diwanji, "Trend Analysis in Social Networking using Opinion Mining A Survey". 2015.

[6] Pang, B. and L. Lee, "Opinion Mining and Sentiment Analysis". *Found. Trends Inf. Retr.*, 2(1-2), pp. 1-135, 2008. http://dx.doi.org/10.1561/1500000011

[7] Osimo, D. and F. Mureddu, "Research challenge on opinion mining and sentiment analysis". *Universite de Paris-Sud, Laboratoire LIMSI-CNRS, Bâtiment*, 508, 2012.

[8] Liu, B., "Web Data Mining", Springer, 2006.

[9] Kim, S.-M. and E. Hovy. "Determining the sentiment of

opinions". in *Proceedings of the 20th international conference on Computational Linguistics*, Association for Computational Linguistics, 2004.
http://dx.doi.org/10.3115/1220355.1220555

[10] Yu, H. and V. Hatzivassiloglou. "Towards answering opinion questions: Separating facts from opinions and identifying the polarity of opinion sentences". in *Proceedings of the 2003 conference on Empirical methods in natural language processing,* Association for Computational Linguistics, 2003.
http://dx.doi.org/10.3115/1119355.1119372

[11] Gezici, G., et al., "Sentiment Analysis Using Domain-Adaptation and Sentence-Based Analysis", in Advances in Social Media Analysis, Springer, pp. 45-64, 2015.
http://dx.doi.org/10.1007/978-3-319-18458-6_3

[12] Pang, B., L. Lee, and S. Vaithyanathan. "Thumbs up?: sentiment classification using machine learning techniques". in *Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10,* Association for Computational Linguistics, 2002.
http://dx.doi.org/10.3115/1118693.1118704

[13] Tang, D., "Sentiment-Specific Representation Learning for Document-Level Sentiment Analysis", in Proceedings of the Eighth ACM International Conference on Web Search and Data Mining, ACM: Shanghai, China. pp. 447-452, 2015.
http://dx.doi.org/10.1145/2684822.2697035

[14] Hu, M. and B. Liu. "Mining and summarizing customer reviews". in *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*. 2004: ACM.
http://dx.doi.org/10.1145/1014052.1014073

[15] Sheng, H., et al. "Fine-grained Product Features Extraction and Categorization in Reviews Opinion Mining". in *Data Mining Workshops (ICDMW), 2012 IEEE 12th International Conference o*n. 2012.
http://dx.doi.org/10.1109/ICDMW.2012.53

[16] Patra, B.G., et al., "Ju_cse: A conditional random field (crf) based approach to aspect based sentiment analysis". *SemEval 2014*, pp. 370, 2014.

[17] Samha, A.K., Y. Li, and J. Zhang, "Aspect-based opinion mining from product reviews using conditional random fields", 2015.

[18] Rohrdantz, C., et al., "Feature-based visual sentiment analysis of text document streams". *ACM Transactions on Intelligent Systems and Technology (TIST)*, 3(2), pp. 26, 2012.
http://dx.doi.org/10.1145/2089094.2089102

[19] Saha, S. and A. Ekbal, "Combining Multiple Classifier using Voted based Classifier Ensemble Technique for Named Entity Recognition". *Data & Knowledge Engineering*, 85, pp. 15-39, 2013.
http://dx.doi.org/10.1016/j.datak.2012.06.003

[20] Rocktäschel, T., M. Weidlich, and U. Leser, "ChemSpot: a hybrid system for chemical named entity recognition", *Bioinformatics*, 28(12), pp. 1633-1640, 2012.
http://dx.doi.org/10.1093/bioinformatics/bts183

[21] Huang, F., et al., "Learning representations for weakly supervised natural language processing tasks", *Computational Linguistics*, 40(1), pp. 85-120, 2014.
http://dx.doi.org/ 10.1162/COLI_a_00167

[22] Tachioka, Y., et al., "Discriminative methods for noise robust speech recognition: A CHiME challenge benchmark", *Proc. CHiME*, pp. 19-24, 2013.

[23] Farabet, C., et al., "Learning hierarchical features for scene labeling", *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 35(8), pp. 1915-1929, 2013.
http://dx.doi.org/10.1109/TPAMI.2012.231

[24] Lu, W., et al., "CRF-TM: A Conditional Random Field Method for Predicting Transmembrane Topology", in Intelligence Science and Big Data Engineering. Big Data and Machine Learning Techniques, Springer, pp. 529-537, 2015.
http://dx.doi.org/10.1007/978-3-319-23862-3_52

[25] Lukov, L., et al., "Protein Secondary Structure Prediction with Conditional Random Fields", School of Information Technologies, University of Sydney, 2010.

[26] Wang, L. and U.H. Sauer, "OnD-CRF: predicting order and disorder in proteins conditional random fields", *Bioinformatics*, 24(11), pp. 1401-1402, 2008.

[27] Hamdan, H., P. Bellot, and F. Bechet, "Lsislif: CRF and Logistic Regression for Opinion Target Extraction and Sentiment Polarity Analysis", 2015.
http://dx.doi.org/10.1093/bioinformatics/btn132

[28] Wang, C., et al. "Opinion Mining Research on Chinese Micro-blog". in *First International Conference on Information Science and Electronic Technology (ISET 2015),* Atlantis Press, 2015.

[29] Yongmei, S. and H. Hua, "Research on Domain-independent Opinion Target Extraction", *International Journal of Hybrid Information Technology*, 8(1), pp. 237-246, 2015.

[30] Zhou, X., X. Wan, and J. Xiao. "Cross-Language Opinion Target Extraction in Review Texts", in *Data Mining (ICDM), 2012 IEEE 12th International Conference o*n. 2012.
http://dx.doi.org/10.1109/ICDM.2012.32

[31] Jakob, N. and I. Gurevych. "Extracting opinion targets in a single-and cross-domain setting with conditional random fields". in *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing,* Association for Computational Linguistics, 2010.

[32] Lafferty, J., A. McCallum, and F.C. Pereira, "Conditional random fields: Probabilistic models for segmenting and labeling sequence data", 2001.

[33] Wallach, H.M., "Conditional random fields: An introduction", *Technical Reports (CIS)*, pp. 22, 2004.

[34] Carstairs-McCarthy, A., "An introduction to English morphology: words and their structure", Edinburgh University Press, 2002.

[35] Dingare, S., et al., "A system for identifying named entities in biomedical text: How results from two evaluations reflect on both the system and the evaluations". *Comparative and Functional Genomics*, 6(1-2), pp. 77-85, 2005.

[36] Manning, C.D., et al., "Introduction to Information Retrieval", Cambridge University Press, 496, 2008.

[37] Perlmutter, D.M., "Deep and Surface Structure Constraints in Syntax", *Language*, 49(3), pp. 697-701, 1973.

[38] Yi, J., et al. "Sentiment analyzer: Extracting sentiments about a given topic using natural language processing techniques", in *Data Mining, ICDM 2003. Third IEEE International Conference on*. 2003 IEEE.
http://dx.doi.org/10.1109/ICDM.2003.1250949

[39] Asch, V.V. and W. Daelemans, "Prepositional Phrase Attachment in Shallow Parsing", *International Conference RANLP 2009*, pp. 12-17, 2009.

[40] Shi, H., "Research on Fine-grained Sentiment Analysis", *Soochow University*, pp. 46-49, 2013.

[41] Del Corro, L. and R. Gemulla. "ClausIE: clause-based open information extraction", in *Proceedings of the 22nd international conference on World Wide Web,* International World Wide Web Conferences Steering Committee, 2013.
http://dx.doi.org/10.1145/2488388.2488420

[42] Kessler, J.S. and N. Nicolov. "Targeting Sentiment Expressions through Supervised Ranking of Linguistic Configurations", in *ICWS*M. 2009.

[43] Béchet, F., "Named Entity Recognition", in Spoken Language Understanding, John Wiley & Sons, Ltd. pp. 257-290, 2011.
http://dx.doi.org/10.1002/9781119992691.ch10

[44] Singh, S., et al., "Analysis of Anaphora Resolution System for English Language", *International Journal on Information Theory (IJIT)*, 3(2), 2014.

◐ Authors ◑

Noor Azeera Abdul Aziz

2010: Bachelor Degree in Computer Science (Network and Security), UniversitiTeknologi Malaysia
2013: Masters in Computer Science
(Information Security), UniversitiTeknologi Malaysia
Present: PhD candidate at UniversitiTeknologi Malaysia (UTM), Skudai, Johor, Malaysia.
Research Areas: Information Extraction, Web Content Filtering and Opinion Mining.

MohdAizainiMaarof

1986: B.Sc (Computer Science) from Western Michigan University
1988: M.Sc (Computer Science), from Central Michigan University, U.S.A
2000: Ph.D degree from Aston University, Birmingham, United Kingdom
2000-present: Professor, Faculty of Computing, UniversitiTeknologi Malaysia, Johor, Malaysia.
Research Areas: Network Security, Web Content Filtering, MANET Security and Cryptography.

Anazida Zainal

1990: Bachelor Degree in Computer Science, Rutgers University, New Jersey, US.
2000: Masters of Science in Computer Science, UniversitiTeknologi Malaysia.
2011: PhD in Computer Science (Network Security), UniversitiTeknologi Malaysia.
2011-present: Senior Lecturer, Faculty of Computing, UniversitiTeknologi Malaysia, Johor, Malaysia.
Research Areas: Network Security, Intrusion Detection System, Intrusion Prevention System and Soft Computing.

Mohammed HazimAlkawaz

2010: B.Sc. degree in Computer Science from University of Mosul, Mosul, Iraq
2013: M.Sc. degree in Computer Science from UniversitiTeknologi Malaysia, Johor Bahru, Johor, Malaysia
2015: Ph.D. degree in Computer Science from UniversitiTeknologi Malaysia, Johor Bahru, Johor, Malaysia.
2015-present: Lecturer in Department of Information Science and Computing, Faculty of Information Sciences and Engineering, Management and Science University, Selangor, Malaysia.
Research Areas: Computer Graphics, Facial Animation, Facial Skin Color, Emotional Expression of Virtual Human, Data Hiding,Image Processing andNetwork Security