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Mining Opinion Words and Opinion Targets – A Survey

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ABSTRACT: Opinion Mining is a relatively new field of study. This field is gaining importance with the evolution of online businesses. Opinion mining can be a very useful tool in terms of obtaining customer feedback, which will help companies design better products suited to the current market trend, thus maximizing their profit and also improving customer relations. This paper surveys various papers that propose novel algorithms to mine opinion targets and opinion words, which is a difficult task given the complexity of (any) language and the informal nature of most online reviews. These state-of-the-art algorithms focus on improving precision, and on reducing error propagation and false opinion relations. The concept, pros, and cons of each algorithm is discussed in this paper.

KEYWORDS: opinion mining, data mining, opinion target extraction, opinion word extraction

I. INTRODUCTION

With technology taking over our lives, businesses leave no stone untouched. Almost everything is accessible online and is only a click away. With such a boom, it is only natural that there are a lot of customer reviews out there, which can improve the prospects of any given business, if only the reviews can be analyzed properly. Opinion Mining, a sub-area of web mining, can help in making sense of such vast data. It is at the crossroads of Information Retrieval, Extraction and data mining.

To mine opinions, initially, opinion words and targets are to be identified. Opinion words are those which describe the product, that is, adjectives. Analyzing them will present a clear picture of what the user thinks about the product. Opinion target, on the other hand, refers to the object that is being referred to, which is mostly in the form of nouns. Extracting these along with the opinion words will give a clear picture as to what is expressed with reference to that particular feature of the object or the object itself. For example, in a sentence, "I love the clarity of this camera", "clarity" is the opinion word and "camera" is the opinion target.

Major problems in opinion mining are opinion lexicon expansion and extracting opinion words and targets. Opinion Lexicon Expansion refers to the expansion of opinion words such as "good", "bad" or "worse" and classifies them as positive and negative sentiments.

To extract quality opinions, many approaches were dealt with. The first of these approaches is to consider Opinion Relations between the opinion words and targets ^[1]. This is because opinion words are bound to appear close to opinion targets. For example, "good battery life", where the opinion word, "good" appears really close to "battery life", an opinion target. This kind of forming relations and associations between the two is called mutual re-enforcement procedure.

Gradually, many researchers advanced the concept by bringing syntactic relations into the equation. For example, "I like the service", follows a syntactic pattern, adj-{mod}-noun. This might help in the easy parsing of all reviews online. There are many difficulties in this procedure as well, considering the informal nature of most online reviews. There might be grammatical, typological errors in online reviews.

Recently, many different algorithms have been designed which shall help in extracting opinion targets, and opinion words, without compromising on the precision and keeping error propagation to a minimum. If opinion mining can be incorporated into businesses, then it can help turn businesses into a more profitable venture.



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II. OPINION MINING

In this survey paper, papers proposed by researchers on extracting opinion targets and opinion words are considered. Their concept, pros, and cons are discussed.

2.1 DOUBLE PROPAGATION

Double propagation proposed by [2], is a semi-supervised method, which requires only an initial set of opinion lexicons to proceed. In this method, the opinion words can be extracted iteratively, with a set of already extracted opinion words, right after their relationships are identified using direct dependencies. Methods such as opinion word sentiment and noisy target pruning help in reefing the obtained results.

Upon conducting experiments, it was found out that this method had a better accuracy and precision compared to previous methods and is extremely suited for extracting opinion words. The problem with bootstrapping is that it could introduce noises into large databases ^[3] and is far more prone to error propagation as well. Though precision outperformed the methods that existed then, precision had to be improved.

2.2 WORD – BASED TRANSLATION MODEL

This approach proposed by [4], is an unsupervised approach. Opinion relations between nouns and adjectives in sentences are identified and their associations are calculated. Bilingual word alignment algorithm is applied to monolingual word alignment scenario, where nouns are aligned with their modifiers. Factors such as word positions and co-occurrence frequencies are considered universally. In the next step, the confidence of each opinion target candidate is estimated. They are then ranked dynamically, according to their confidences. The highest ranked candidates are identified as opinion targets. It is measured on two factors: opinion relevance and candidate importance. This allows the mining of opinion targets and words precisely.



Fig 1. Opinion Relation Graph

When the data set is too small, there is a loss of precision in the findings, because it is difficult to frame associations due to the sparseness of data. Also, the model is unsupervised. This could lead to erroneous data interpretations, for example, "clarity" can be associated with "phone" instead of "camera". Otherwise, this model is successful in reducing errors introduced as data isn't parsed here. This graph – based model shows a drastic improvement in performance when compared to bootstrapping techniques. As syntax isn't required here, it largely benefits non – English speakers and is very relevant to the present day online culture.

2.3 PARTIALLY-SUPERVISED WORD ALIGNMENT MODEL^[5]

Word Alignment approach has shown significant performance improvement (Section 2.2). This unsupervised approach could lead to wrong associations. So, in this model, a portion of links could be used to supervise this model [Supervised framework was proposed by [6]]. Initially, syntactic methods with high precision and low recall are used, which will give at least a short dependency relation. A constrained EM algorithm is then used to determine alignment in the given



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sentences. Opinion targets are then extracted using a graph based algorithm. A bipartite graph is modeled to show relations between two opinion target candidates. If two opinion target candidates appear closely, then if one turns out to be an opinion target, the other will have a high probability to be one.

A random walking algorithm is implemented to estimate the confidence of the candidates and as always, the ones with the highest confidence are classified as opinion targets.

The traditional walking algorithm is more prone to collect data from higher vertices and puts impacts on the rest. This is corrected here, by penalizing the higher-degree vertices and thus doesn't allow the graph to run into unrelated regions. This greatly reduces error. Mining opinion relations is far more precise in this method. The only problem is using semantic relations for extracting opinion words and extraction as the nature of online reviews doesn't permit that. 2.4 TWO-STAGE FRAMEWORK

The proposed paper, [7], performs mining in two stages. In the first stage, a Sentiment Graph Walking algorithm is implemented, which helps in avoiding false opinion relations. A Sentiment Graph Model is created with opinion words and targets depicting their relationships to one another. The confidence of each is then estimated. The false opinion relations and the ones created by low-frequency patterns have low confidence. This is helpful in improving accuracy.

In the next stage, false opinion targets and long tail opinion targets are extracted using a self- learning strategy. A semisupervised classifier is used to refine search results from the first step. It uses the candidates with high confidence as examples. Sometimes, it is possible that candidates with high frequency have more noise or are just general nouns such as "things" or "people". To avoid that, a General Noun Corpora (GN) is created and used to obtain appropriate terms.

A long – tail opinion target is identified despite a low frequency if it gains higher contextual support. Thus, extraction accuracy is only improved. This method boasts of a higher performance. The major drawback of this model is that the opinion words aren't limited to adjectives. So, extracting that will be a difficult task.

2.5 GRAPH CO-RANKING

This method proposed by [8], tries to focus on parameters that have never been considered before. Considering opinion relations alone may not be sufficient and word preference was always ignored. Technically, it would be better if word preferences determine the confidence of candidates rather than just considering opinion relations.

In this process, opinion relations and semantic relations are first operated over a heterogeneous graph. There are three sub-graphs involved. One graph will represent semantic relations among target candidates. The second represents semantic relations among word candidates and the third models opinion relations between opinion word and target candidates and also connects the first two sub-graphs.

A random walking algorithm is applied on each sub-graph and the candidates with confidence higher than that of the threshold is extracted. Then, a co-ranking algorithm is applied. Each candidate returns varying levels of confidence based on their opinion relations. As a candidate's confidence mainly depends on word preference, storing word preference information will be helpful.

Not only does this method outperform other methods in terms of opinion target extraction, but also on opinion word extraction. The precision of the obtained results is far higher when word preference is considered.

2.6 WORD ALIGNMENT MODEL

The proposed paper, [9], suggests a monolingual word alignment model (WAM), where opinion targets are identified when aligned with the opinion words. WAM doesn't consider any nearest neighbor rules, nor does it parse informal texts. Moreover, it considers word co-occurrence frequencies and word positions. Therefore, it is very effective. But, extracting opinion words is still a difficult task.



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Also, as more word alignment models are unsupervised, it could lead to an unsatisfactory alignment quality. Using supervised models could also lead to constraints. Therefore, a middle ground is taken and Partially Supervised Word Alignment Models are considered (as discussed in Section 2.3).

Then, a co-ranking process is used, which drastically reduces error propagation. The opinion targets and words and their relationships are modeled by an Opinion Relation Graph. A co-ranking algorithm based on random walks is considered, which estimates the candidate's confidence. In this process, vertices with higher-degree of information are penalized and this reduces the probability of entering into a relatively unrelated field. Noises are reduced by using prior knowledge of the candidates.

This process of globally extracting opinion targets/words greatly reduces error. Thus, this algorithm is greatly helpful in improving the performance and precision of extracting words /targets. Considering more relations, such as the topical relations will help in extracting opinion words and opinion targets together.

III. EXPERIMENTS

3.1 DATA SETS AND EVALUATION METRICS

To compare the various strategies of opinion order and opinion target extraction, two real-world datasets are considered. One is Large (employed in [10]), from which we consider two domains, Hotel and MP3. The domains opinion words and opinion targets were manually annotated as the gold standard. Another dataset used is COAE08, which is pre-annotated. Two domains are selected and the language is Chinese.

Dataset	Domain	#Sentences	#OW	#OT
Large	Hotel	10,000	434	1,015
(English)	MP3	10,000	559	1,158
COAE08	Camera	2,075	351	892
(Chinese)	Car	4,783	622	1,179

 TABLE 1: Experimental Datasets, # denotes the size of reviews/sentences, OW refers to opinion words and OT refers to opinion targets.

Precision (P), F-measure (F) and Recall (R) are used as metrics for evaluation.

3.2 COMPARISONS BETWEEN VARIOUS STRATEGIES

The following observations are made from table 2:

- 1) Hu uses adjacency rules to extract opinion words and targets. When it comes to identifying opinion relations, all syntactic methods seem to outperform Hu.
- 2) DP (described in Section 2.1) shows a significant improvement over Hu, but in terms of precision and accuracy, it lags behind other methods because of error propagation.
- 3) WBT (described in Section 2.2) shows considerable improvement in efficiency. In fact, if the size of the corpora increases, then this method is known to be more effective. This is because unlike other methods, parsing isn't done to identify opinion relations so there is s significant reduction in noise.
- 4) PSWAM (described in Section 2.3) outperforms most baseline metrics. This is because this alignment model is supervised. Also, the high-degree vertices are penalized resulting in a reduction in the probability of random words.
- 5) TSF (described in Section 2.4) shines especially in terms of recall, owing to the automatic pattern learning algorithm.
- 6) GCR (described in Section 2.5) considers semantic and opinion relations. It also takes into account word preference. Thus, more opinion words and targets. Precision is greatly improved.



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7) WAM (described in Section 2.6) significantly show improvement in all domains, especially F-measure. By performing word alignment under partial supervision and by employing graph co-ranking, significant improvements in precision is seen. This method fares much better for large corpora.

Hotel			MP3			Camera			Car		
Р	R	F	Р	R	F	Р	R	F	P	R	F
0.60	0.65	0.62	0.61	0.68	0.64	0.63	0.65	0.64	0.62	0.58	0.60
0.67	0.69	0.68	0.69	0.70	0.69	0.71	0.70	0.70	0.72	0.65	0.68
0.71	0.80	0.75	0.70	0.82	0.76	0.75	0.81	0.78	0.71	0.71	0.71
0.76	0.83	0.79	0.74	0.84	0.79	0.77	0.82	0.79	0.74	0.71	0.72
0.75	0.73	0.74	0.73	0.71	0.72	0.78	0.81	0.79	0.76	0.73	0.74
0.74	0.82	0.78	0.74	0.84	0.79	0.78	0.84	0.81	0.74	0.75	0.74
0.78	0.83	0.80	0.77	0.85	0.81	0.79	0.81	0.80	0.75	0.72	0.73
	P 0.60 0.67 0.71 0.76 0.75 0.74	Hotel P R 0.60 0.65 0.67 0.69 0.71 0.80 0.76 0.83 0.75 0.73 0.74 0.82 0.78 0.83	P R F 0.60 0.65 0.62 0.67 0.69 0.68 0.71 0.80 0.75 0.76 0.83 0.79 0.75 0.73 0.74 0.74 0.82 0.78 0.78 0.83 0.80	Hotel P R F P 0.60 0.65 0.62 0.61 0.67 0.69 0.68 0.69 0.71 0.80 0.75 0.70 0.76 0.83 0.79 0.74 0.75 0.73 0.74 0.73 0.74 0.82 0.78 0.74 0.78 0.83 0.80 0.77	Hotel MP3 P R F P R 0.60 0.65 0.62 0.61 0.68 0.67 0.69 0.68 0.69 0.70 0.71 0.80 0.75 0.70 0.82 0.76 0.83 0.79 0.74 0.84 0.75 0.73 0.74 0.73 0.71 0.74 0.82 0.78 0.74 0.84 0.78 0.83 0.80 0.77 0.85	Hotel MP3 P R F P R F 0.60 0.65 0.62 0.61 0.68 0.64 0.67 0.69 0.68 0.69 0.70 0.69 0.71 0.80 0.75 0.70 0.82 0.76 0.76 0.83 0.79 0.74 0.84 0.79 0.75 0.73 0.74 0.73 0.71 0.72 0.74 0.82 0.78 0.74 0.84 0.79 0.75 0.73 0.74 0.73 0.71 0.72 0.74 0.82 0.78 0.74 0.84 0.79 0.78 0.83 0.80 0.77 0.85 0.81	Hotel MP3 P R F P R F P 0.60 0.65 0.62 0.61 0.68 0.64 0.63 0.67 0.69 0.68 0.69 0.70 0.69 0.71 0.71 0.80 0.75 0.70 0.82 0.76 0.75 0.76 0.83 0.79 0.74 0.84 0.79 0.77 0.75 0.73 0.74 0.84 0.79 0.78 0.74 0.82 0.78 0.74 0.84 0.79 0.78 0.74 0.82 0.78 0.74 0.84 0.79 0.78 0.78 0.83 0.80 0.77 0.85 0.81 0.79	Hotel MP3 Camera P R F P R F P R 0.60 0.65 0.62 0.61 0.68 0.64 0.63 0.65 0.67 0.69 0.68 0.69 0.70 0.69 0.71 0.70 0.71 0.80 0.75 0.70 0.82 0.76 0.75 0.81 0.76 0.83 0.79 0.74 0.84 0.79 0.77 0.82 0.75 0.73 0.74 0.84 0.79 0.78 0.81 0.74 0.82 0.78 0.74 0.84 0.79 0.78 0.84 0.74 0.83 0.79 0.74 0.84 0.79 0.78 0.84 0.78 0.83 0.80 0.77 0.85 0.81 0.79 0.81	HotelMP3CameraPRFPRFPRF 0.60 0.65 0.62 0.61 0.68 0.64 0.63 0.65 0.64 0.67 0.69 0.68 0.69 0.70 0.69 0.71 0.70 0.70 0.71 0.80 0.75 0.70 0.82 0.76 0.75 0.81 0.78 0.76 0.83 0.79 0.74 0.84 0.79 0.77 0.82 0.79 0.75 0.73 0.74 0.84 0.79 0.78 0.81 0.79 0.74 0.82 0.78 0.74 0.84 0.79 0.78 0.84 0.81 0.78 0.83 0.80 0.77 0.85 0.81 0.79 0.81 0.80	HotelMP3CameraPRFPRFP 0.60 0.65 0.62 0.61 0.68 0.64 0.63 0.65 0.64 0.62 0.67 0.69 0.68 0.69 0.70 0.69 0.71 0.70 0.70 0.72 0.71 0.80 0.75 0.70 0.82 0.76 0.75 0.81 0.78 0.71 0.76 0.83 0.79 0.74 0.84 0.79 0.77 0.82 0.79 0.74 0.75 0.73 0.74 0.73 0.71 0.72 0.78 0.81 0.79 0.76 0.74 0.82 0.78 0.74 0.84 0.79 0.78 0.84 0.81 0.74 0.78 0.83 0.80 0.77 0.85 0.81 0.79 0.81 0.80 0.75	HotelMP3CameraCarPRFPRFPRF 0.60 0.65 0.62 0.61 0.68 0.64 0.63 0.65 0.64 0.62 0.58 0.67 0.69 0.68 0.69 0.70 0.69 0.71 0.70 0.70 0.72 0.65 0.71 0.80 0.75 0.70 0.82 0.76 0.75 0.81 0.78 0.71 0.71 0.76 0.83 0.79 0.74 0.84 0.79 0.77 0.82 0.79 0.74 0.71 0.75 0.73 0.74 0.73 0.71 0.72 0.78 0.81 0.79 0.74 0.73 0.74 0.82 0.78 0.83 0.80 0.77 0.85 0.81 0.79 0.74 0.75 0.78 0.83 0.80 0.77 0.85 0.81 0.79 0.81 0.80 0.75 0.72

TABLE 2: Experimental results of Opinion Target Extraction on Large and COAE08 Datasets

Methods	Hotel			MP3			Camera			Car		
	Р	R	F	Р	R	F	Р	R	F	Р	R	F
Hu	0.51	0.68	0.58	0.48	0.65	0.55	0.72	0.74	0.73	0.70	0.71	0.70
DP	0.60	0.66	0.63	0.58	0.62	0.60	0.80	0.73	0.76	0.79	0.71	0.75
TSF	0.67	0.69	0.68	0.64	0.67	0.65	0.82	0.78	0.80	0.80	0.76	0.78
GCR	0.67	0.69	0.68	0.66	0.68	0.67	0.80	0.75	0.77	0.80	0.74	0.77
WAM	0.64	0.72	0.68	0.66	0.73	0.69	0.84	0.77	0.80	0.82	0.76	0.79

TABLE 3: Experimental results of Opinion Word Extraction on Large and COAE08 Datasets

IV. CONCLUSION

In this survey paper, various algorithms that deal with mining opinion words and opinion targets are discussed. Learning about the way a concept has evolved over time, improve our understanding of the problem and also present more ideas to handle it more efficiently. The concept behind each algorithm, the steps taken, their positives and negatives are discussed. To extract opinions, initially adjacency rules were in place. Gradually, semantic relations were considered. Given the nature of online reviews, parsing such text was difficult. So, word preference and confidence estimation were used. Aligning opinion words with their targets has also been very successful. Graph algorithms to obtain the confidence of the candidates and to churn out the error has proved to be effective. A combination of more than one process has resulted in obtaining the state-of-the-art algorithms discussed here.

Future work might consist of finding different types of relations between opinion targets and opinion words. This could possibly result in a future, where the co-extraction of opinion targets/words will be possible.

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