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A Framework Investigating the Online User Reviews to Measure the Biasness for Sentiment Analysis

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Abstract: Online reviews provided for a product intends for the web users to give a thought on to purchase the product instantly. Such deceptive reviews tend to be positive, negative or neutral in nature. Analyzing such reviews have attracted commercial interest in the recent years and provide a strong platform for mere future, due to online user behaviour. Reviews expressed by websites are in the form of rating, pros and cons format or in free flow style. It has come become quite hard to make decisions effectively due to such complex representations. This study focuses its attention on to provide a system to measure the usefulness of reviews across different timeline. We have chosen reviews from commercial websites for a particular product based on the reviews provided by web users along with time line. The experimental investigation seems to derive out the significant deviation in the usefulness as compared to the reviews presented initially.

Key words: Opinion mining, user reviews, sentiment analysis, recommendation, term frequency

INTRODUCTION

Internet has changed people's lifestyle by bringing in products to their own place after due consideration of the reviews about products of their choice. Ever since data mining has emerged into picture there lays a strong coherence with web. This has subsequently become a wider field of investigation among research communities (Tang *et al*., 2009). Opinion mining has become a hot topic at the crossroads of information retrieval and computational linguistics. Though there exist several approaches, the area of research is still attractive among researchers.

Web forum acts as a medium for exchange of resources across several domains like blogs (Costa *et al*., 2012; Kaur *et al*., 2012), twitter (Perera, 2012), financial news study (Schumaker *et al*., 2012) SMS texts (Leong *et al*., 2012) and social networks (Lo *et al*., 2009). Research on opinion mining have also crossed across boundaries by investigating different domains with adaptation of wide range of techniques based on classification (Li *et al*., 2013), summarization (Liu *et al*., 2011) hybrid approaches involving classification and summarization (Hu and Wu, 2009) and ontology (Kontopoulos *et al*., 2013). Investigation of these text reviews ranges from surface level to document level (Missen *et al*., 2013).

A product review given by a user is a more accurate representation of its real-world performance. Web forums generally post such reviews intentionally on day to day basis for the benefit of users. These commercial websites allow users to express their opinions in whatever way they feel irrespective of the count of the reviews, a product receives. To analyze these review methods like artificial intelligence (Chen and Zimbra, 2010), association rule mining A (Wang *et al*., 2013; Kim, 2009), customer feedback (Lee *et al*., 2008) were tried earlier which has lead to the development of opinion miner systems. Opinion mining system has a profound influence on several platforms which includes automobile industry (Bodendorf and Kaiser, 2010).

Reviews provided by users are normally prone to typographical errors and hence they may be containing noisy text data (Dey and Haque, 2009). The dataset chosen may be more specific and a product review considered may have several reviews which may be unbalanced in nature (Burns *et al*., 2011). Therefore, it is essential to have equal number of reviews. Based on the reviews, we could classify the nature of reviews as positive or negative ones (Moraes *et al*., 2013). An improved miner system has possible opinion lists of phrases (Rill *et al*., 2012), feature words (Zhai *et al*., 2011; Luo *et al*., 2009) and involves semantics (Li *et al*., 2010).

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Table 1:Characteristics of reviews from different websites

Website corpus	Rating star	Text data length	Review availability for all/limited products
Ebay	✓	2-3 sentences	All
Epinions	✓	Pros, cons and summary	All
Amazon	✓	Paragraph	All
Cnet	✓	Paragraph	All
Taboada	X	Text	All
Pang	X	Text	Movie

Let us have a look at the formats in which the reviews are available and associated features in it. Our investigation considers reviews crawled from Amazon website (www.amazon.co.in). The reviews are available in the form of ratings ranging from 5-1 where 5 denote the top priority and 1 representing the lower most. Two important categories of reviews are "Most helpful positive reviews" and "most helpful critical reviews". These categories of reviews denote the reviews presented (based on their experiences) by the user about a product across different time intervals.

In this study we propose a system to identify the variation noted down in the online reviews. The review reports were critical as the reports given by the user were contradictory in nature. This has study carries out the investigation on five different product samples from the reviews collected. Table 1 presents the data formats available for opinion mining. As far as the text length is concerned, the variation is clearly presented in column 3 of the Table 1. We focus on reviews extracted from Amazon website for experimental illustrations and discussions throughout the study. The details of the dataset were discussed further in study 3.

Literature review: A lexicon model with the description of verbs, nouns and adjectives plays a vital role in applications like sentiment analysis and opinion mining (Maks and Vossen, 2012). Existing model aims at describing the detailed subjectivity relations across each actor in a sentence. The subjectivity relations that are positive or negative were labelled with other additional information like identity, attitude and orientation. Such proposed models purely deal with categorizing relevant sentiments and hence forth mining is carried out based on semantics. Special attention is paid to the role of the speaker/writer of the text whose perspective is expressed and whose views on what is happening are conveyed in form of text. Finally, validation is done by annotating subjectivity relations.

Internet has expanded rapidly in recent times which have made e-Commerce a big success leading numerous products to be sold on the web. This tends a user to purchase products based on the reviews which would be very useful for potential customers to make better decisions. A solution was provided in this context to generate correct and quick summaries from these reviews. The proposed method extracts feature and opinion pairs from online reviews, determines the polarity and strength of these opinions with the aim of summarizing and determining the recommendation status (Ojokoh and Kayode, 2012).

Reviewing the text information at surface level is one approach while analyzing to the depth dealing with lexicons is an alternate criterion. Works revealing subjectivity description of Dutch verb offers a framework for the development of sentiment analysis and opinion mining (Maks and Vossen, 2011). This proposed model aims to describe the detailed subjectivity relation, expressing multiple attitudes for each verb sense etc. Finally validation of the study is provided by annotating subtle subjectivity relations involving human annotators who were linguists.

Web 2.0 provides a platform for making availability of user generated contents in the form of customer reviews containing precious information useful for both customers and manufacturers. However, these contents are either unstructured or semi-structured format due to which distillation of knowledge from this huge repository occurs. This has led to the study focusing on such complex issue to keep the dataset rightly balanced in nature (Kamal *et al*., 2012). A rule based mining system has been adopted to mine feature-opinion pairs that have sentence-level co-occurrence in review documents which were modelled using bipartite graph structure. These graph structures considers feature-opinion pairs as hubs and source documents as authorities. Most popular algorithm used for web based applications namely Hyperlink-Induced Topic Search (HITS) is applied to generate reliability score for each feature-opinion pair.

A new and upcoming technique for defining reference model with the purpose of improving information consistency and knowledge sharing is ontology (Zhao and Li, 2009) which describes the semantics of a specific domain in both human understandable and computer processable way. Ontology has achieved greater success in the area of Information Extraction (IE) which the authors have adopted for opinion mining. Opinion mining is quite context-sensitive for which ontology may be beneficiary and is also domain dependent. A fine-grained approach for opinion mining using ontology structure is used to extract several features by taking account the relations between concepts.

Recent key research problems investigated on designing an opinion mining system, i.e., entity-related opinion detection problem and sentiment analysis problem (Wei, 2011). For entity-related opinion detection problem, sophisticated statistical models, e.g., probabilistic topic models and statistical rule generation methods were used to achieve better performance than

Fig. 1: Sample review chosen from amazon

existing baselines. A novel HL-SOT approach is presented in this research which paved way for developing a multi-layer neural network kernel algorithm which resulted in a non-linear classifier and is expected to improve the performance of the original HL-SOT approach to sentiment analysis.

Works pertaining to text classification were interesting and adds strength to opinion mining system. Such classification requires the knowledge data vocabulary to analyse the semantic meaning and its relationship. In such a proposed method, system involves division of characteristic words and phrases extracted from the training data. How net database is combined with sentiment classifier for several reasons namely: computing semantic similarity of characteristic words, identifying phrases with tagged words and adopting positive and negative terms as features of sentiment classifier (Yu *et al*., 2008).

Proposed opinion miner system: This study presents a system on to analyse the criticality of the reviews, significance of time bound reviews, review dataset, results and discussion.

Nature of opinion reviews: Online reviews provided by the user are available in textual forms which are subject to investigation by researchers more often. There is a significant variation in the length of the reviews which ranges from very short sentences to a lengthy paragraph. Sometime the reviews are represented in visual representations in form of star ratings. These commercial websites are expressive in nature allowing end user to provide comments on the products, based on the observations recorded over a span of time. This time bound is more crucial for those who intend to buy the product as well as for the manufacturers, since the user provides a more reliable feedback based on their experience. Figure 1 presents the sample review from amazon website for a particular product. Since the reviews about a product were large in numbers, we have crawled a set of reviews to build an opinion recommender system. The proposed system architecture is presented in study which elaborates the proposed system.

Table 2: Usefulness of reviews as agreed by the users

	Usefulness	
Product name	Helpful review	Critical review
Samsung TV	95.72	92.73
Apple iPad	97.03	95.30
Moto G	95.14	86.88
iPhone 5S	100.00	85.29
Lenova K3 note	92.50	77.77

Figure 1 presents the sample review which shows the reviews expressed under five different categories in the form of star rating ranging from 5-1. It is observed that when the rating decreases, recommendation of a product is very low and vice versa. Table 2 presents the usefulness as agreed by the users for both categories of reviews. The statistical figures shown in Table 2 were taken from five different products as mentioned in it and the user agreement is presented in the columns. There is a disagreement of 8.54% when comparing the usefulness of reviews expressed in positive or negative sense. This has provided us an idea to investigate on the reviews expressed by the user for different products. The study was carried out to find the deviation existing among the opinions expressed by people of different age groups.

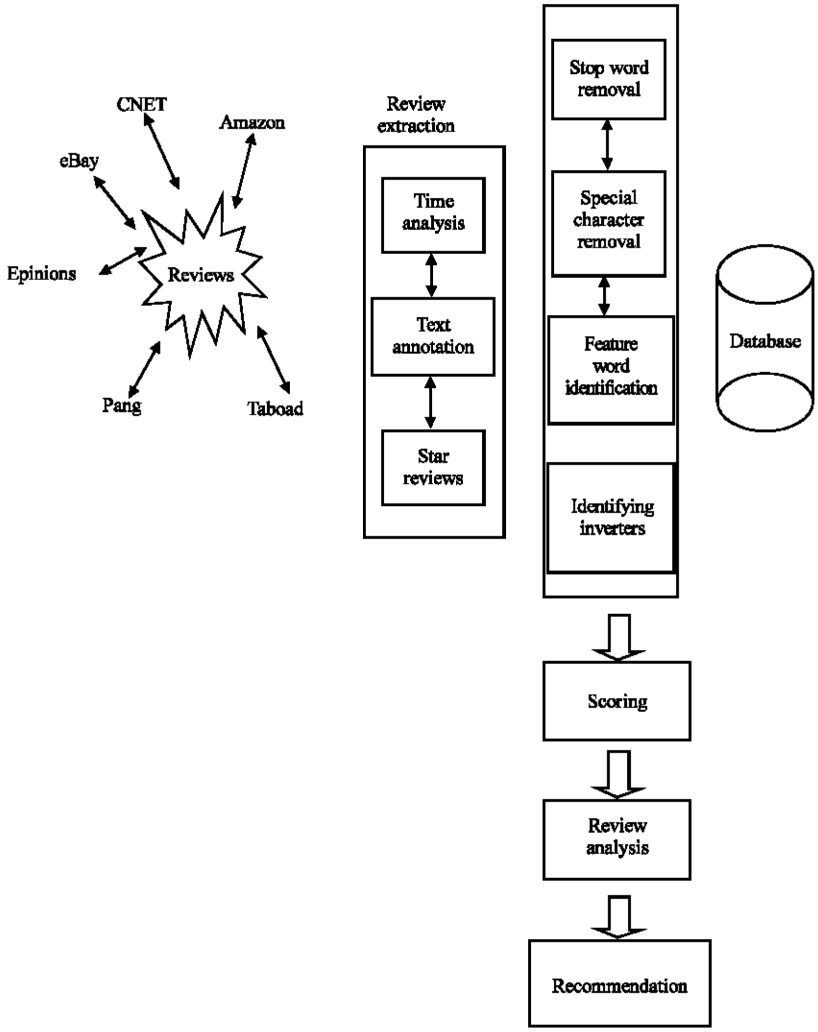

Fig. 2: Proposed system for opinion mining

MATERIALS AND METHODS

Data set: As illustrated earlier the reviews provided by users were extracted from the amazon website and the recommendation is provided following a systematic approach discussed in study. The reviews were arranged in chronological order and more importantly has variation in length to express the review. We have chosen reviews from all categories so as to infer the recommendation process. Furthermore we have chosen five different types of domains as shown in table. A reasonable number of reviews are chosen for the study to strongly defend the experimental conclusions arrived at the end of this study.

System overview: The proposed system is presented in Fig 2. The sequence of steps involved is given in the form of pseudo code below:

- Step 1: extraction of reviews from website
- Step 2: pre-processing the reviews (with reference to database storage)
- Step 3: scoring the sentences
- Step 4: analysis of reviews (involves balancing, re-ranking etc.)
- Step 5: recommendation process

Extraction of reviews from website: The first task is to extract the reviews from the website. As discussed earlier in study, reviews were obtained. Table 1 shown in the study is utilized for our experimental work. To bring into the notice, reviews are textual contents combined with special characters etc. which need to be processed further. Based on the requirement or interest, reviews are chosen from appropriate rankings along with time and other text annotations.

Table 3: Details of the dataset chosen for experimental illustrations

Domain	Review product	No. of reviews taken
Electronics	Digital cameras	468
Entertainment	Movie	525
Fun	Play station	646
Sports	Cricket	221
Health care	Yoga book	114

Table 4: Sample list of feature words

Sample	Feature
Pictures	Lens
Picture quality	Resolution
Video quality	Focus
Image quality	Optical zoom
Performance	Features
Colors	Zoom
Clarity	Memory
Sharpness	
Weight	Price
Size	Cost
Grip	Value money
Ergonomics	Value
Ease	Addons
Design	

Table 5: Sample list of intensifiers

Intensifiers	Values
Least	0.5
just, bit, little, minor	0.6
Quite	0.8
Relatively	0.9
Really	1.1
Very	1.2
much, more	1.3
too, ultra	1.4
most, mostly, extremely	1.5

Pre-processing the reviews: This task is considered to be more important as we have only raw corpus available with us. Five different stages are involved in this second phase. During stage 1 special characters, punctuations and conjunctions (http://www. theenglish teacheronline. com/symbols-and-punctuation-marks/) (http://www.tow son.edu/ows/conjunctions.htm) were removed. A word which is meaningless and is used for connection purposes called as stop words (http://www.ranks. nl/stopwords) is the removed in stage 2. The third stage focus on eliminating special characters. Fourth stage and the final stage involve identifying feature words and intensifiers respectively as shown in Table 3-5.

The feature words were hand collected from a group of people who were interested to read the reviews and were expressive to give their feedback about their experiences over the products they have purchased. We have limited our domain to products of commercial importance and which were most widely known (e.g., mobile phones). We have involved these human experts for suggestions, feedback, scoring and judgement. When a new domain set of data is explored, an incremental learning is performed. Training is done again using for this new set and appropriately the terms are updated in appropriate databases. This is has provided a better outcome for our study.

Scoring the sentences: After pre-processing, each sentence in the document is assigned a score. Inverters[++] in a sentence decide on the nature of sentences, hence they need to be taken into consideration in sentence scoring process. A feature word denoted as “F” will normally be followed or preceded by an intensifier opinion word denoted as “IO” combination or opinion word “O”.

Table 5 presents the sample list of intensifiers and their weights (assigned arbitrarily). Scoring is performed based on the pattern observed like FIO, FO, OF, IOF, FNIO, FNO, IO and O. Similarly scoring takes into account the inverter words (Inv) and Neutral words (N). In the absence of a feature word, any Intensifier-Opinion word pair (IO) or Opinion Word (O) occurring by themselves are also scored and the corresponding score is added up to the overall score alone. After scoring each sentence, the feature scores for each feature (performance, features, ergonomics and value) are calculated. This score is also added up to the overall score of the product. We call this scoring approach as Sentiment scoring (results of which were discussed in study, e.g., “Performance quite good” which follows “FIO” pattern and it is scored as follows: “Good” is a lightly positive opinion word and it is given a score of+5. “Quite” is an intensifier (intense factor = 0.8).

Hence, ‘Quite good’ gets a value of 4.0 (0.8*5) Table 6 presents a sample list of opinion words[+]. The sample review extracted from review site is presented in Table 6 and 7 and the pre-processed output in Table 8 and 9. The scoring for each sentence is shown in Table 10.

Sample review for illustration: “This is the best digital camera that I have ever used. The camera exhibits good image quality. The pictures are clear. It has a decent battery life (200-280 shots) and the LCD is too good. The cost is quite expensive ($225). The weight is bit bulky; the 10x zoom in this camera is amazing. The video quality is nice but it is not possible to zoom while recording. Sometimes focusing is sluggish but it depends on the settings. The screen size is comfortable enough to display photos effortlessly. The placement of the cord on the bottom of the camera is very strange. Offers great value for money you pay!!”.

Table 6: Sample list of opinion words

Strongly negative (-15)	Negative words: Moderately negative (-10)	Lightly negative (-5)	Neutral ±1	Negative words: Lightly positive (+5)	Moderately positive (+10)	Strongly positive (+15)
Worst	Worse	Bad		Good	Better	Excellent
Pathetic	Expensive	Inferior		Fine	Fast	Awesome
Abysmal	Heavy	Stale		Nice	Light	Marvelous
Terrible	Slow	Ordinary		Able	Compact	Best
Awful	Sluggish	Poor		Available	Reliable	Fastest
	Hate	Ugly		Ok	Love	Superb
	Skip	Small		Okay	Buy	
	Overhyped	Hard		Care	Long	
	Expensive			Beautiful	Great	
	Restrictions			Pretty		
				Possible		
				Exceeded		
				Large		
				Easy		
				Simple		

Table 7: Sentiment scoring for a document

Sentence No.	Reviews	Positive score	Negative score
1	Best digital camera used	+15+1+1+1 = 18	
2	Camera exhibits good performance	+1+1+5+0 = 7	
3	Performance clear	0+5=5	
4	Decent features 200 280 shots lcd too good	+10+0+1+1+1+1+1.4(+5) = 21	
5	Value quite expensive 225		0+0.8(-10)-1 = -9
6	Ergo bit bulky		0+0.6(-10)= -6
7	10x features camera amazing	+1+0+1+15 = 17	
8	Performance nice	0+5 = 5	
9	Not possible features recording		-1(+5+0+1) = -6
10	Features sluggish		0-15 = -15
11	Depends settings	1+1 = 2	
12	Screen ergo comfortable display performance effortlessly	+1+0+10+1+0+5 = 17	
13	Placement cord bottom camera very strange		-1-1-1-1-1.2(+5) = -10
14	Offers great value pay	+1+10+0 +1 = 12	
	Total score	104	-46

Table 8: Recommendation accuracy for different schemes

Product set	Term occurrence	Term frequency	Sentiment scoring
Subset 1	73.22	76.73	82.28
Subset 2	69.21	72.66	78.20
Subset 3	65.40	69.08	75.11
Subset 4	63.39	67.33	72.44
Subset 5	59.95	63.28	67.66

Table 9: Recommendation for product with/without pre-processing

Product set	Without pre-processing: Initial	With pre-processing: Initial
Subset 1	89.33	92.01
Subset 2	85.27	88.23
Subset 3	82.05	87.36
Subset 4	80.29	85.19
Subset 5	77.64	82.91

Table 10: Deviation at different compression rates and time frames

Compression ratio (%)	Initial	Frame 1	Frame 2	Frame 3
100	83.28	7.18	8.32	10.21
80	82.48	6.68	7.54	9.43
60	81.77	6.33	7.92	8.86
40	80.88	6.03	7.23	8.12
20	81.70	7.42	9.22	11.34

Analysis of reviews: This process involves identifying the positive and negative ratings of reviews respectively. From Table 9 it is inferred that there are 9 positive ranked sentences and 5 negative with ranks. Hence, the recommendation would be biased towards positive sentences. Next we re-rank the results based on the scores obtained (both for positive and negative reviews) and pick up equal number of reviews to determine the recommendations in order to avoid biasness in the outcome of the decision making process.

Pre-processed output of:

- Best digital camera used
- Camera exhibits good image quality
- Pictures clear
- Decent battery life 200 280 shots lcd too good
- Cost quite expensive 2256. weight bit bulky
- 10x zoom camera amazing
- Video quality nice
- Not possible zoom recording
- Focusing sluggish
- Depends settings
- Screen size comfortable display photos effortlessly
- Placement cord bottom camera very strange
- Offers great value money pay

We have used Cohen's kappa measure (Cohen, 1960) to find the agreement between two different users (raters). The equation for κ is:

$$k = \frac{p_0 - p_e}{1 - p_e}$$

Where:

p_o = The relative observed agreement among raters

p_e = The hypothetical probability of chance agreement

If the raters are in complete agreement with each other, then κ = 1. If there is no agreement among the raters other than what would be expected by chance (as given by p_e), κ≤0. We fix up a threshold value of 0.65 which indicate a substantial agreement among raters. Therefore, the judgments among evaluators are consistent and effective. We choose the store with >500 reviews as samples and reviews were collected with a time window of 30 days to find the deviation.

Recommendation process: The percentage of recommendation is projected based on the number of reviews chosen based on this assumption only. We take the positive score out of the sum of magnitudes of positive and negative scores as the recommendation of a specific product of interest. The threshold recommendation is calculated using the equation given below in this subsection. Once the scoring is done and appropriate selection is carried out, percentage of recommendation is calculated using:

$$\text{Recommendation} = \frac{\text{Positive}_{\text{score}}}{\text{Positive}_{\text{score}} + \text{Negative}_{\text{score}}} \times 100$$

For the example that we are discussing in this study, we could infer that the recommendation drops down to 64.88% as compared to the original (69.33%). There is deviation of 4.45% in the usefulness of reviews (though the agreement on the reviews is high). This shows that the reviews provided and the recommendations arrived out based on analysis leads to which is significant.

RESULTS AND DISCUSSION

Experiments and Illustrations: This study presents the experiments carried out and results obtained were discussed in detail in this section. The results show the deviation in the reviews expressed by the users (raters) at a reasonable time frame (fn). Pre-process using several phases and provides a score to each sentence. Finally, the recommendation is provided for each of them. The results presented for investigation were projected on an average set of items. Since the reviews were negative as we go lower down the order of star rating, we consider only reviews which have good number of expressive statements.

Using the review dataset shown in Table 3, product sets are investigated. Hence we consider 5 star reviews for the products and the results were discussed only for these targeted reviews. It is observed that the user agreement is very low as compared to higher level ratings, as move down the order. Table 10 presents the results of two more categories, namely Term Occurrence (TO) which denotes the occurrence of a word in a document and Term Frequency (TF) denoting the frequency of the term in the corpus. Term Occurrence is a binary based approach. Term frequency counts each term in the document and cumulates the term in the document.

Table 11 represents the results for recommendation of review products with and without pre-processing. Reviews with pre-processing denote removal of unwanted word, characters and other phases discussed before. The set of reviews and the corresponding results for the reviews were extracted from “Helpful first” and “Critical reviews”. The results investigating the role of pre-processing were projected in Table 11. Table 12 presents the results based on the compression ratio and time frames. Initial denotes the review analysed at initial time frame and deviation denotes the subsequent time frame (min time deviation = 30 days). The results for three time frames shows significant drop as compared to the initial recommendation. For instance consider there are ten sentences in the reviews, 10 sentences will be collected for 100%. For 80%, 8 sentences were to be taken into account, accordingly the results were projected. From the results shown in experimental illustrations, the following conclusions were obtained:

- Sentiment score scheme performs well, as compared to term occurrence and term frequency schemes
- As the compression decreases the variation also decreases except critical compression rate (20%)
- The sudden increase at 20% compression is due to the fact that summary generation at this juncture is critical by nature
- From Table 12 it is inferred that the recommendation of any product decreases while considering the time which is due to the fact that user have experienced over a period of time

CONCLUSION

This study demonstrated the efficiency of the proposed methods. The research also highlighted the deviation observed by the users at a specified time limit.

It is clearly inferred that the recommendation drops down when considering the newer set of reviews. The proposed sentiment scoring scheme leads to better results as compared to other schemes discussed. This has out rightly decreased the e-commerce world as opinions are changing rapidly. The research focus on the improvement computation of the sentiment score in consideration. Also, we focus on to adopt linguistic tools for finding out its influence in the scoring schemes discussed. We also investigate to focus on different agreement measures for increased online transaction.

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