AFFECTIVE BLOG ANALYZER
What People Feel to

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Abstract: This paper proposes an affective blog analyzer which can capture people's emotional targets. The existing affective analysis has some problems. For instance, polarity analysis or positive/negative classification for documents are developed, but emotional targets can not be extracted. Some investigations can capture customer's wanted/needed objects, but the knowledge is domain dependent. Therefore, it can not analyze people's everyday life. Against these problems, this paper uses a sentence pattern dictionary to analyze emotions. The dictionary covers Japanese fundamental 6,000 verbs and contains 14,800 patterns with emotional information for everyday life. This dictionary is available for analyzing the downloaded blog articles. After analyzing blogs, many keywords can be extracted as emotional targets. In order to filter and sort them for supporting blog analysts, two parameters are applied. One is Z-score in terms of the frequency of the target appearance, and another is probability of emotions. In the experiments, trendy and emotional targets were successfully extracted from 6-month-blogs. Thus, the effects of the patterns and parameters are confirmed.

1 INTRODUCTION

WWW is used by many people from children to elder persons. Partially, blogs are popular among people to describe their everyday life. Such documents contain people's favorites, interests, desires and hates. Therefore, blogs are good resources for marketing analysts, political decision makers, and so on.

In the previous studies on sentiment analysis and web mining, a lot of ideas are proposed and realized. On early studies of sentiment analysis, the positive and negative semantic orientation/polarity of the conjoined adjectives were focused on (Hatzivassiloglou and McKeown, 1997). As the polarity of the adjectives is a strong clues, the techniques for document classification of reviews were developed by using machine learning (Turney, 2002). Recently, the attention of the studies shifts and more functions are required. Some investigations realize to extract the targets of the polarity, for instance, customers' needs/wants (Kanayama and Nasukawa, 2008). In order to extract the targets, pattern based method is effective. But the patterns are developed with focusing on several specific domains like book-reviews, computer-products, and so on. The knowledge base engineers avoided the development of the knowledge base for everyday life. One reason is that they believe such knowledge base is futile for business on the engineering standpoint. But recently web mining techniques are required from advertisement agents. Another reason is that such knowledge base requires complex expressions or meaning. For example, OCC model on the cognitive science represents the structure of emotion causality (Ortony et al., 1988). If text parser can analyze such structure from text, emotion reasoning will succeed. A frame knowledge base was developed and it worked on the virtual agents very well (Elliott, 1992). However, there is no pattern knowledge base to parse and analyze natural language expressions. There is a big gap between the frame knowledge and natural language expressions, as semantic analysis is not accomplished. Some investigations tried to obtain such knowledge from Web or huge corpus with focusing on the relation, SUBJECT-VERB-OBJECT-OBJECT (Liu et al., 2003), (Tokuhisa et al., 2008). This is the clue of the verbs. It is as important as the clue of the adjectives. But they also have not extracted the emotional targets yet. Since their approach depends on the OBJECT, if unknown keyword is given to the OBJECT, there is no proof to analyze emotions successfully. Against the problems, for instance, emotion reasoning for everyday life and ex-

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traction of emotional targets, this paper uses a sentence pattern dictionary. The dictionary originates from A-Japanese-Lexicon which covers Japanese basic 6,000 verbs and contains 14,800 sentence patterns (Ikehara et al., 1997). Affective information is added to the dictionary in order to infer emotions for everyday experiences.

Next, for the purpose of supporting blog analysts, this paper develop a blog analyzer based on the dictionary. The blog analyzer contains both the blog crawling function and the emotion reasoning function. The emotion reasoning outputs not only emotional categories but also emotional targets. The keyword of the emotional target would be a great help to analyze the interests/claims among people. In the experiment of this paper, the emotional target extraction is demonstrated.

2 EMOTIONAL PATTERN DICTIONARY

2.1 How to Analyze Emotions from a Sentence

Our basic idea to analyze emotions from a sentence is the emotional feature extraction from text, in other words, the confirmation of the emotional process. If an input sentence represents a part of emotional process, emotions are inferred form the sentence. The emotional process consists of emotion arousal, emotional state and emotional response. It is not easy to define emotional state with separating from emotional arousal/response on the cognitive science viewpoint, but it is clear that emotional states are described in natural language.

These are examples of the three:

Arousal: *I left my wallet at the airport.*

State: *I disappointed myself.*

Response: *My tears fell down.*

In the arousal process, there are some features, in other words, "emotional cause." The causality is explained by OCC model. But it was too abstract to analyze natural language expressions. Therefore, more detailed features are referred from (Tokuhisa and Okada, 1997), which contains 36 features for joy/sadness and 120 features for eight emotions in total. For example, "loss" is one of the features of sadness. In contrast, "acquisition" is one of the features of joy.

2.2 Constructing Emotional Pattern Dictionary

There already exists a pattern dictionary (Ikehara et al., 1997), which is developed for machine translation from Japanese to English. It covers fundamental Japanese verbs and can distinguish word sense ambiguity by the valency grammar which is a kind of constraint for dependency among subject case, verb and object case in a sentence.

Following is example[1].

ex1) $N1$(person) lose $N2$(concrete object)
= feature "loss"

ex2) $N1$(person) lose $N2$(disease)
= feature "inner-pleasure"

Here, $N1$ and $N2$ are variables which match a noun word or phrase. Since the meaning of the sentence depends on the meaning of the variables, the variables are restricted what expression matches.

In order to extend the dictionary for emotion reasoning, the meaning of the pattern was checked, and emotional information is assigned. The information slots are "emotional cause," "emotion category," "feeler," and "feel-to." Figure 1 shows real samples of the dictionary.

The emotion category consists of *gladness*, *sadness*, *liking*, *dislike*, *surprise*, *expectancy (hope)*, *fear*, *anger* and *non-emotion*. These are named 9-category-set in this paper.

Since tense and aspect are ignored to analyze emotions in this paper, 9-category-set can not be dealt with well. Therefore, 5-category-set and 3-category-set are prepared. 5-category-set consists of *P*, *N*, *A*, *S* and *non-emotion*.

P is union of *gladness*, *liking* and *expectancy*.

N is union of *sadness* and *fear*.

A is union of *disliking* and *anger*.

S is *surprise*.

3-category-set consists of *positive*, *negative* and *non-emotion*.

Positive is *P*.

Negative is union of *N* and *A*.

Non-emotion of 3-category-set includes *S*.

This construction was hand made. It took 3 years to add emotional information. The current version is the 3rd. edition. The 2nd. edition was checked by 3 analysts. As the result, the error ratio was 14.2%. The 3rd. edition will be better.

[1]While this dictionary is constructed for Japanese, these examples are written in English in order to explain the significant concept of the dictionary.

Japanese pattern:	$N1$(agent)*ga* $N2$(*)*wo* $N3$(agt.)*ni* $N4$(numeric)*de* *kau*
English pattern:	$N1$ buy $N2$ for $N3$ for $N4$
emotional cause:	feature "acquisition"
emotion category:	gladness
feeler:	$N1$
feel-to:	$N2$
- - - - - - - - - -	- - - - - - - - - -
emotional cause:	feature "acquisition" / "hospitality"
emotion category:	gladness / gladness
feeler:	$N3$
feel-to:	$N2$ / $N1$
Japanese pattern:	$N1$(agt.)*ga* $N2$(obj.,abst.)*wo* $N3$(agent,place)*kara* *ryakudatsu suru*
English pattern:	$N1$ plunder $N2$ of $N3$
emotional cause:	feature "loss" / "cheating"
emotion category:	sadness / anger
feeler:	$N3$
feel-to:	$N2$ / $N1$
- - - - - - - - - -	- - - - - - - - - -
emotional cause:	feature "acquisition"
emotion category:	gladness
feeler:	$N1$
feel-to:	$N2$

* The italic words are Japanese.

Figure 1: Samples of sentence patterns and their emotional information.

3 AFFECTIVE BLOG ANALYZER

3.1 Components

Affective blog analyzer (ABLANA) is newly developed. Figure 2 shows the basic components of ABLANA. This system monitors some blog sites by referring the RSS of the blog sites, downloads new articles from them, and then performs emotion reasoning by using the pattern dictionary. The results are statistically analyzed and summarized.

3.2 Behavior

ABLANA watches RSS derived from blog sites to extract new articles with a time series. Therefore web search engines are not used.

"Downloader" accesses to the blog site and download the article informed by the RSS after waiting for 24 hours more. If the article is temporary or SPAM, it would be removed. If the article is written well, it

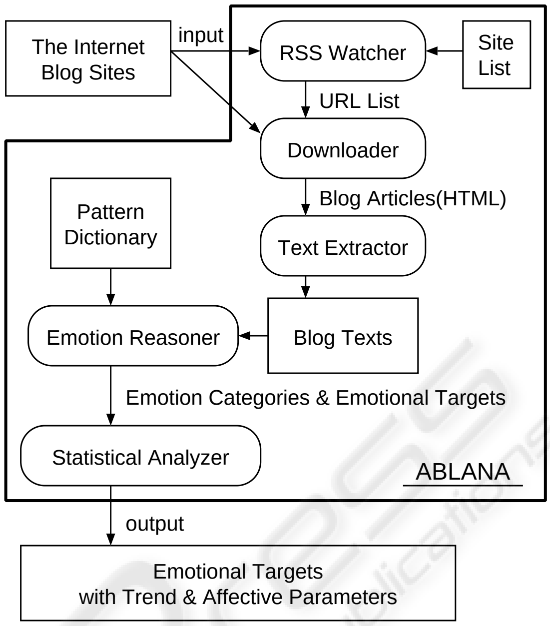


Figure 2: Components of ABLANA.

would receive some comments from the readers. In this paper, the comments are not referred yet, but it would be useful information to measure the reliability of the articles.

"Text extractor" parses HTML sources and extracts blog body, author's name, date, title of the article and so on. Because some people do not write comma and period onto the text in Japanese blogs, the extractor finds sentence terminal and splits sentences.

"Emotion reasoner" performs morphologic analysis and pattern matching to the blog body texts. Then, it selects the best pattern-matching according to the constraint to the variables in patterns. As the results, emotional information is obtained.

"Statistical analyzer" collects emotional targets from the results and then assigns score to each of target for filtering and sorting the targets according to some parameters.

3.3 Parameters for Emotional Targets

The requirements to the statistical analyzer are following:

(a) to extract something trend among people, and

(b) to evaluate their polarity.

The requirement (a) is measured by the burst of keyword. In this paper, Z-score $z_{k,i}$ is used to capture it. Z-score is described as the following equation.

$$z_{k,i} = (x_{k,i} - m_k)/\sigma_k \tag{1}$$

$$m_k = \sum_{j \in I} x_{k,j} / N_I \quad (2)$$

$$\sigma_k = \sqrt{\sum_{j \in I} (x_{k,j} - m_k)^2 / N_I} \quad (3)$$

I is a set of intervals (In this paper, one interval is one week, and whole intervals are about six months). k is the keyword to be scored. i is one of the intervals to be analyzed. $x_{k,i}$ is the frequency of the appearance of the keyword k as the emotional target during the interval i. m_k is the mean of the $x_{k,j}$, here j is each element of I. N_I is the number of elements of I. σ_k is the standard deviation.

The requirement (b) is calculated by the probability $P(e|k,i)$ of the appearance of emotional category e after the keyword k appeared on the focusing interval i. The equation for it is as follows:

$$P(e|k,i) = x_{k,i,e} / x_{k,i} \quad (4)$$

4 EXPERIMENTS OF EMOTIONAL TARGET EXTRACTION FROM BLOGS

4.1 Terms and Amount

ABLANA ran from August 1st 2008 to January 31st 2009. From three Japanese major blog sites, 7,120,992 articles(105,167,276 sentences) were downloaded. The emotion reasoner spent about 10 days to process one-month-articles. The file size is 53 GB a month, which includes blog texts, pattern-matching results, and emotional targets.

4.2 Experiment-1: Basic Performance

The basic performance of the emotion reasoning is evaluated by the accuracy A. It is calculated by $A = 2N(o \cap c)/(N(o) + N(c))$. Some analysts annotate emotional tags to test sentences. The results of emotion reasoning are compared with the tags. $N(c)$ is the number of tags by the analysts. $N(o)$ is the number of tags by ABLANA. $N(o \cap c)$ is the number of tags corresponding between the analyst and ABLANA.

304 sentences are extracted from blog texts by random. 5 persons annotated 9-category emotional tags to these sentences. Table 1 shows the accuracy of the emotion reasoning. The column of HUMAN shows the difficulty of the emotion reasoning. On 9-category-set, the accuracy of ABLANA is lower than that of HUMAN. But on 5- and 3-category-sets, the ABLANA's accuracy is closed to HUMAN's. Therefore, in this paper, 3-category-set is used to the probability scoring.

Table 1: Accuracy of emotion reasoning.

E-Categories	ABLANA	HUMAN
9	0.375	0.513
5	0.592	0.566
3	0.685	0.618

4.3 Experiment-2: Observation with Keyword

The aim of this experiment is to confirm the ability of Z-score and emotion probability. Before using Z-score to select trend keyword as the main purpose, in this section a prominent keyword is given to ABLANA and the score is observed along a time series.

This experiment is a top-down observation approach. For instance, we give a known keyword and check whether a known event can be captured or not.

There was a lot of big change in 2008. In the domain of the motor sports, "HONDA Racing F1 Team" exited Formula One on December 5th.

A keyword "HONDA" repeatedly appeared whole intervals, and the burst appeared twice as shown in Figure 3. This keyword appeared approximately 19,000 times and 4.68% of the appearance was emotional target. The first burst corresponds to the exiting news. Some news articles about the exiting were cited on blogs and blog authors wrote comments. The second burst corresponds to another exiting news – "HONDA exited eight hours endurance motorbike race on January 23rd 2009."

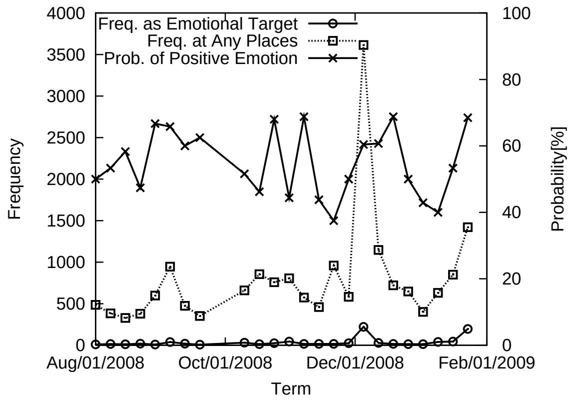
Z-score becomes high at the burst. Therefore Z-score has feasibility to find a significant event.

The right Y axis of Figure 3 shows the probability of $P(POSITIVE|\text{"HONDA"}, i)$ along a time series. The exiting news were not good for motor sports fun, but the $P_{positive}$ was over 50%. Reading the blogs, it was clarified that blog authors expressed their love to HONDA.

On the other hand, $P_{positive}$ became minimum on November 21st 2008 and January 9th 2009. The blogs on these days said as following:

- a negotiation episode at a HONDA dealer including customer's distrust
- a decrease in production of a HONDA factory
- early history of HONDA including an expose

As the results, the probability leads to appropriate articles for a blog analyst successfully.



X axis is term (from Aug. 1st 2008 to Jan. 31st 2009). The circlet-plots are the appearance as an emotional target, and the rectangle-plots are the appearance at any places in the blogs(left Y axis). The X-plots are the probability of positive emotion to the target(right Y axis).

Figure 3: Frequency of appearance "HONDA" and Probability of its positive emotion.

Table 2: High positive targets.

#	Z	$P_{pos.}$	Emotional target
1	2.7	98.6	a good fight
2	2.0	98.2	kart
3	4.8	97.8	Olympic opening ceremony
4	4.8	97.6	large fonts
5	4.8	97.1	medal competitions
6	3.1	97.1	corridor
7	4.8	96.9	the anchor of the Olympic sacred-fire relay
8	4.8	96.9	Industrial Hi-School of Naruto
9	3.9	96.8	resting
10	4.8	96.8	Secretary Romaiya

4.4 Experiment-3: Observation with Z-score and Probability

Emotional targets can be filtered by the Z-score and listed in the order of emotional probability each interval. For example, Table 2 and 3 show emotional targets whose Z-score is greater than 2.0 from Aug 8th. 2008 to 14th. These keywords are intuitively correct. People seem to have enjoyed Olympic and disappointed at the loss of the games. By the way, there are high schools in the lists. Because there is an annual baseball tournament for high school students in Japan, they are some of the teams.

On the other hand, emotional targets are filtered by the lower Z-score condition ($0.5 < z < 2.0$). Table 4 shows the targets. Some targets are useful and the probability looks appropriate. We can see several categories from the targets. For instance, sports, amusements, communication and health are found in the high positive groups, and disease and politics are found in the low positive groups.

Table 3: Low positive targets.

#	Z	$P_{pos.}$	Emotional target
1	4.8	2.2	weapon
2	4.7	2.5	Kagoshima Jitsugyou Hi-School
3	4.6	3.2	soaring prices
4	4.4	3.9	professionalism
5	4.2	4.4	Olympic baseball; Japan, Cuba
6	3.3	5.4	ten
7	2.5	5.6	ruddy
8	4.8	5.6	Olympic soccer; Japan, Nigeria
9	4.5	6.0	job
10	2.2	6.3	discussion

"Aso" is a politician in Japan. His name appeared in both the group of 80% – 90% and the group of 0% – 10%. We can understand that the opinion for him is split. Of course, we must read and analyze the blogs to conclude this idea. But we can say that the table leads us what blogs to be read. This process is a good example for how to use ABLANA.

As the results, the combination of Z-score and emotional probability would be useful parameters to find people's requirements and complaints.

5 OPEN PROBLEMS

The soundness of the patterns and parameters proposed in this paper is confirmed well by the experiments. However there remain some problems to improve the accuracy of emotion reasoning.

One of the important requirements is to deal with the plural sentences. For example, "*Beaujolais Nouveau's Release. It tastes different every year. This year's wine is fresh and flavors...*" has three sentences. The second and third sentences do not include "Beaujolais Nouveau". The proposed method can not extract "Beaujolais Nouveau" as the emotional target from the two.

Moreover, because "release," "fresh" and "flavors" are positive words and "tastes different" is a negative phrase, the probability of emotion for this article is marked a little negative. The second sentence describe just a common sense, but it is not complain.

Therefore, our future works are to analyze anaphora and to merge the emotional states from plural sentences.

Table 4: Emotional targets found in the middle Z-score set.

Range of P_{pos}	Sample of emotional targets
90% – 100%	company, foreign exchange, accident, lunch, newest information, image, coffin, knowledge, going to sleep, customer, cover, lottery, *Yakisoba*(fried noodles), new mail, salary
80% – 90%	rest, musical, garlic, house, animation, bumber ticket, ambulance car, dam, soft cream, ticket, actual place, plan, Mr. Aso, *Soumen*(fine noodles), 3 days, revision, high school basebale tournament
70% – 80%	chance, *Gyoza*(pot sticker), *Obon* (Japanese Summer holidays), clothes, reference book, sheep, access counts, proposal, boyfriend/girlfriend, son, once, Japanese people, stairs, guys, past questions, movies
60% – 70%	cloud, characteristics, senior, process, short, street stall, milk, potato, world view, flower language, high school days, panel, course, room, Mr. Kouichi, response, joy, park, Tokyo, tombstone, TVCM, RPG
50% – 60%	helmet, boys, Japanese, lecture, environment problem, curren, strain (feeling), water place, safe management, game, Yankees, vanilla, category, climbing Mt. Fuji, *Beawanpi*(one-piece dress), expected software,
40% – 50%	fear, triathlon, batted ball, immediately after, sitting comfort, *Osaka Touin*(school), young people, ear, mood, *Shun*(person), dark, whole life, love, future, meal time, driving, competition, ultraviolet rays
30% – 40%	obligation, corner, leukemia, prejudice, under construction, terrorist, feeling of intimacy, *Hikari* (light, fiber-optic cable), natural environment, belly, member on the regular payroll, symptoms, oneself
20% – 30%	abnormal weather, contents of work, darkness, otherwise, fatigue, narrow, crowdedness, life, SAP for maker, love, elegant, property management, shooting (film), a liitle happy, aphthous ulcer, drawback, husband
10% – 20%	HIV, bewilderment, muddy, allow, noon, twice or more, provery of blood, marriage, put away, 30, your body, a hip joint, load (of baggage), shame, headache, next election of Presentative, scarcity of water, hallucination
0% – 10%	*Furafura*(dizzily), Japan High School Baseball Federation, molar tooth, panic, a chief secretary-Aso Taro, continuation, breast cancer, camp, sleeplessness, respect, strained back, ant, sleeping posture

* Extracted from the interval Aug. 1st - 7th 2008. Translated into English by the author of this paper.

6 CONCLUSIONS

This paper proposed an affective blog analyzer (ABLANA) which crawls blog articles along a time series from the Web and analyzes people's emotional targets. The method for emotion reasoning uses a sentence pattern dictionary. The original dictionary is A-Japanese-Lexicon. It covers Japanese fundamental 6,000 verbs and consists of 14,800 patterns. In this paper, the extended dictionary is used, where emotional information is annotated if pattern expresses emotional processes (arousal, state and response).

In the experiments, the extracted emotional targets can be filtered and sorted by two parameters, for instance, the Z-score in terms of the frequency of the keyword appearance and the probability of emotions. These parameters are so effective that trendy and emotional targets can be captured. Thus, the domain independent affective analyzer is successfully constructed. It is expected to practically apply this technique to capture people's affective statements.

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