

# Analyzing Emotional Statements – Roles of General and Physiological Variables

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## Abstract

The present task collects different statistics of emotions based on the combinations of general variables (*intensity, timing and longevity*) and physiological variables (*psycho-physiological arousals*) from the situational statements of the ISEAR (International Survey on Emotion Antecedents and Reactions) dataset. The individual as well as combinational roles of different variables are analyzed. Some interesting observations and insights are found with respect to emotions. The statements of similar emotions are clustered according to different combinations of the variables. Each of the statements of a cluster is passed through two types of emotion tagging systems, a lexicon based baseline system followed by a supervised system. Due to the difficulty of incorporating knowledge regarding physiological variables, the supervised system only considers the roles of general variables from textual statements. The roles of the general variables are played by intensifiers, modifiers and explicitly specified *temporal* and *causal* discourse markers. The evaluation indicates that the supervised system based on general variables produces satisfactory results in identifying emotions.

## 1 Introduction

There exist several frameworks from various fields of academic study, such as cognitive science, linguistics and psychology that can inform and augment analyses of sentiment, opinion and emotion (Read and Carroll, 2010). Emotion is a complex psycho-physiological experience of an individual's state of mind as interacting with biochemical (internal) and environmental (external) influences. In humans, emotion fundamentally

involves physiological arousal, expressive behaviors and conscious experience (Myers, 2004). Emotions, of course, are not linguistic objects/entities. However the most convenient access to emotions is through the language (Strapparava and Valitutti, 2004). Natural language texts not only contain informative contents, but also some attitudinal private information including emotions. But, the identification of emotions from texts is not an easy task due to its restricted access in case of objective observation or verification (Quirk *et al.*, 2007). Moreover, the same textual content can be presented with different emotional slants (Grefenstette *et al.*, 2004). Ekman (1993), for instance, derived a list of six basic emotions from subjects' facial expressions which Strapparava and Mihalcea (2007) employed as classes in an affect recognition task. There are several other theories on emotion classes. But, the debate is concerned with some basic and complex categories, where the complex emotions could arise from cultural conditioning or association combined with the basic emotions.

In the present task, the corpus is obtained from the International Survey of Emotion Antecedents and Reactions (ISEAR) dataset (Scherer, 2005). The survey was conducted in 1990s across 37 countries and had almost about 3000 respondents. This dataset contains psychological statements of about 3~4 sentences pre-classified into seven categories of emotion (*anger, disgust, fear, guilt, joy, sadness and shame*). The respondents were instructed to describe a situation or event in which they felt the emotion. Thus, we have clustered the situational statements into their corresponding emotion classes based on three general and three physiological variables. The *intensity* (INTS), *timing* (WHEN) and *longevity* (LONG) of the feeling were considered as general variables whereas *Ergotropic Arousal* (ERGO) (e.g.,

*change in breathing, heart beating faster* etc.), *Trophotropic Arousal* (TROPHO) (e.g., *lump in throat, crying* etc.) and *Felt temperature* (TEMPER) (e.g., *feeling hot, warm, cold/shiver*) proposed by Gellhorn (1970) have been considered as physiological variables.

The individual statistics based on general and physiological variables show various interesting insights of the variables from the perspective of emotion (e.g., low *intensity* for emotion classes of *shame* and *guilt* and high for *joy, fear* and *sadness*). The statistics that are acquired based on the combinations of different variables also elicit some crucial properties for a comparative analysis of emotions (e.g., people feel *warm* and *lump in throat* in case of *joyous* situation). Therefore, the statements containing one or more sentences are clustered into the seven emotion classes according to different combinations of the general and physiological variables.

The sentences are then passed through the pre-processing steps followed by the identification of emotional words based on the *WordNet Affect* lists (Strapparava and Valitutti, 2004). The word level emotion tags are assigned as sentence and statement level emotion tags. Multiple emotion tags assigned by the system for each of the statements are compared against its corresponding single annotated emotion tag. The baseline system based on *WordNet Affect lists* achieves the average *Precision, Recall* and *F-Score* values of 58%, 47.4% and 50.6% respectively on 5120 sentences with respect to five emotion classes.

The word as well as phrase level emotion expressions are identified using Support Vector Machine (SVM) based supervised system (Das and Bandyopadhyay, 2010). The system achieves average *Precision, Recall* and *F-Score* values of 69%, 45.8% and 55.05% respectively. The sentential emotion tags are assigned based on the identified emotional expressions and intensity clues. Two types of explicit discourse markers such as *temporal* (e.g., *'when' 'while'*) and *causal* (e.g., *'as', 'because'*) are employed for identifying emotions at statement level. It has been found that the incorporation of the *intensity* and discourse level clues improves the *Precision* (70.04%), *Recall* (65.3%) and *F-Score* (68.03%) values respectively. The errors are due to the problem in identifying the textual clues in support of the physiological variables. But, it has been observed that the general variables play the significant roles in identifying emotions.

The rest of the paper is organized as follows. Section 2 describes the related work. The statis-

tics of emotions based on various general and physiological variables are discussed in Section 3. The baseline and supervised systems for emotion identification are described in Section 4. Evaluation results along with error analysis are specified in Section 5. Finally Section 6 concludes the paper.

## 2 Related Work

The characterization of the words and phrases according to their emotive tones was attempted by several researchers (Turney, 2002). Following the terminology proposed by (Wiebe *et al.*, 2005), subjectivity analysis focuses on the automatic identification of private states, such as opinions, emotions, sentiments, evaluations, beliefs and speculations in natural language. Natural language domains such as News (Strapparava and Mihalcea, 2007) and Blogs (Mishne and Rijke, 2006) are also becoming a popular, communicative and informative repository of text based emotional contents in the Web 2.0 for mining and summarizing opinion at word, sentence and document level granularities (Ku *et al.*, 2006). The model proposed in (Neviarouskaya *et al.*, 2007) processes symbolic cues and employs NLP techniques to estimate the affects in text. Machine learning techniques were used either to predict text-based emotions based on the SNoW learning architecture (Alm *et al.*, 2005) or to identify the mood of the authors during reading and writing (Yang *et al.*, 2009).

The ISEAR corpus was used in (Boldrini *et al.*, 2010) for the experiments concerning emotional expressions and fine-grained analysis of affect in text. Their aim was to build the subjectivity expression models and they did not explore the intensity or physiological variables in case of identifying emotions.

Psychiatric query document retrieval can assist individuals to locate query documents relevant to their depression-related problems efficiently and effectively (Yeh *et al.*, 2008). A DSM-IV based screening tool for Adult psychiatric disorders in Indian Rural health Centre has been discussed in (Chattopadhyay, 2006). One promising related task in the of emotion and psychology literature has been proposed in (Yu *et al.*, 2007). The authors use high-level topic information extracted from consultation documents that include *negative life events, depressive symptoms* and *semantic relations* between symptoms to identify the similarities between the documents corresponding to a query.

### 3 Analysis of Emotion Variables

#### 3.1 Roles of the General Variables

Emotions generally appear in natural language texts along with *intensity* (INTS). Four different types of *intensity* (*not very*, *moderately intense*, *intense* and *very intense*) are annotated in the ISEAR dataset. The other two emotion variables that are closely associated with *intensity* are *timing* (WHEN) and *longevity* (LONG) of the emotional feeling. Four different values were assigned for the *timing* (e.g., *days ago*, *weeks ago*, *months ago*, *years ago*) in the dataset. Similarly, four values were assigned for the *longevity* (*a few minutes*, *an hour*, *several hours*, *a day or more*). These variables are termed as general variables in our present discussion.

In case of identifying emotions, the last two variables (*timing* and *longevity*) in association with *intensity* play the important roles rather than their individual appearances. Hence, the statements of the dataset are clustered into seven emotion classes based on the *intensity* variable alone and the combined relation of *intensity* with *timing* and *longevity*. The frequencies of the emotional statements in each of the emotion classes based on *intensity*, the combinations of *intensity* with *timing* and *longevity* are shown in Figure 1, Figure 2 and Figure 3 respectively.

It has been observed that emotions vary along with intensity but the variations of the emotion classes are not similar from the perspective of *intensity*. From the frequency information as shown in Figure 1, it is found that *intensity* is comparatively high in *sadness*, *fear*, *joy* and *anger* but is low in case of *guilt*, *disgust* and *shame*.

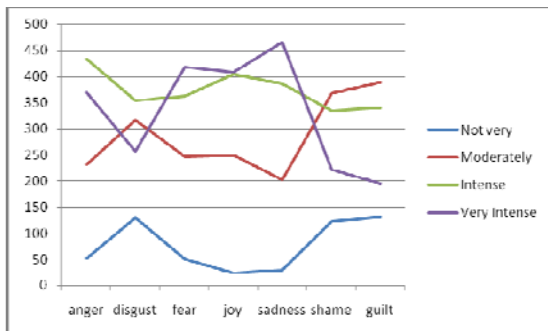


Figure 1: Frequencies of instances (Emotion Statements) in seven emotion classes based on Intensity (INTS).

We have mentioned earlier that *intensity* plays a crucial role in association with the *timing* and

*longevity* for identifying different emotional slants. The variations of emotions with respect to different combinations of *intensity* and *timing* are shown in Figure 2. The events that have taken place usually before a year elicit *sadness* and *fear* with very high *intensity* and *shame* and *guilt* with relatively moderate *intensity*. In case of *very intense* events, *shame* increases exponentially with respect to time.

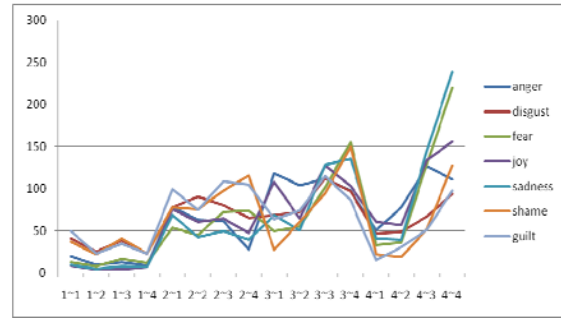


Figure 2: Frequencies of instances (Emotion Statements) in seven emotion classes based on Intensity (INTS) and Timing (WHEN) [INTS ~ WHEN]

On the other hand, the *intensity* also varies with *longevity* or duration of the emotional feeling. The frequencies of different emotions based on the combination of *intensity* and *longevity* are shown in Figure 3. The emotions that persist with very high *intensity* for several years in comparison with other emotions are *sadness* and *joy*. The *moderately intense* emotions that persist for several months or years are *shame* and *guilt*. In case of low *intensity*, *guilt* emotion persists for longer time in comparison with other emotions.

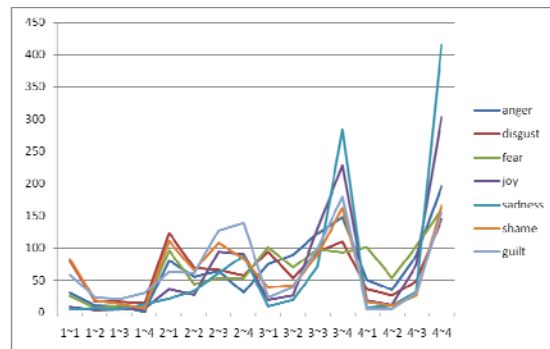


Figure 3: Frequencies of instances (Emotion Statements) in seven emotion classes based on Intensity (INTS) and Longevity (LONG) [INTS ~ LONG]

### 3.2 Roles of the Physiological Variables

It is observed that not only the *intensity* but some physiological variables also help in identifying the emotions. Three types of symptoms or *arousals* namely, *Ergotropic Arousal* (ERGO) (e.g., *change in breathing, heart beating faster, muscles tensing/trembling* and *perspiring/moist hands*), *Trophotropic Arousal* (TROPHO) (e.g., *lump in throat, stomach troubles* and *crying/sobbing*) and *felt temperature* (TEMPER) (e.g., *feeling cold/shivering, feeling warm/pleasant, feeling hot/cheeks burning*) as proposed by Gellhorn (1970) are mentioned in the ISEAR corpus. The symptoms are termed as physiological variables for studying the nature of emotions. The frequencies of the emotional statements in each of the emotion classes based on the individual physiological variables are shown in Figure 4, Figure 5 and Figure 6 respectively. Their combinations are shown in Figure 7, Figure 8 and Figure 9 respectively.

It is observed from Figure 4 that, in case of *fear* and *anger*, the *heart beat* becomes *faster* and *muscles* are *tensed*. But, the *perspiring* along with *moist hands* are the noticeable symptoms that differentiate *fear* from any other emotions. *Change in breathing* is *faster* in case of *anger, joy* and *shame*.

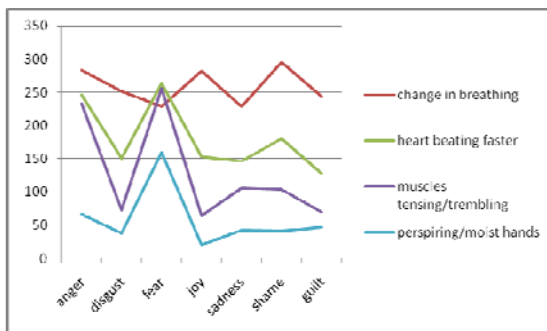


Figure 4: Frequencies of instances (Emotion Statements) in seven emotion classes based on *Ergotropic Arousal* (ERGO)

One crucial fact can be recognized if we analyse the impact of *Trophotropic* variables from the perspective of *sadness* (as shown in Figure 5). *Stomach troubles* and *crying/sobbing* are recognized as the general symptoms for *sadness*. The *lump in throat* is low for *sadness* but high for *joy*. *Stomach troubles* are low for *joy* but persist more or less in all other emotions such as *anger, disgust, fear, shame* and *guilt*. The

frequency information also identifies the support of *crying/sobbing* for *fear* in addition to *sadness*.

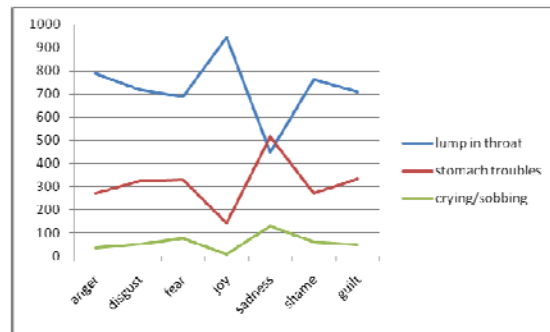


Figure 5: Frequencies of instances (Emotion Statements) in seven emotion classes based on *Trophotropic Arousal* (TROPHO)

The other important physiological variable that helps in identifying the nature of emotions is *felt temperature* (as shown in Figure 6). People feel *warm* and *pleasant* in case *joy* only. Any kind of *temperature* symptom is observed in *joy* rather than other emotions. The symptom of *hot feeling* and *cheeks burning* are the distinguishable symptoms for identifying *shame* and *anger*. It is also found that people feel *cold* and even *shiver* in case of *fear* and *sadness*.

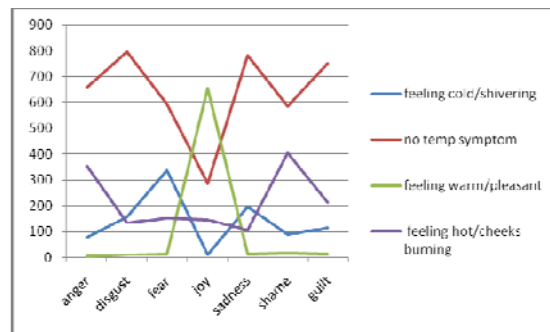


Figure 6: Frequencies of instances (Emotion Statements) in seven emotion classes based on *Felt temperature* (TEMPER)

Though the characteristic curves for different emotions are equivalent and similar with respect to the combination of *Ergotropic* and *Trophotropic* variables (as shown in Figure 7), the slight distinctions prevail for *fear, joy* and *sadness*. The *heart beating* fastens and *muscles* are tensed along with *lump in throat* in case of *fear* and *sadness*. *Perspiring* and *lump in throat* also happen in *fear* emotion.

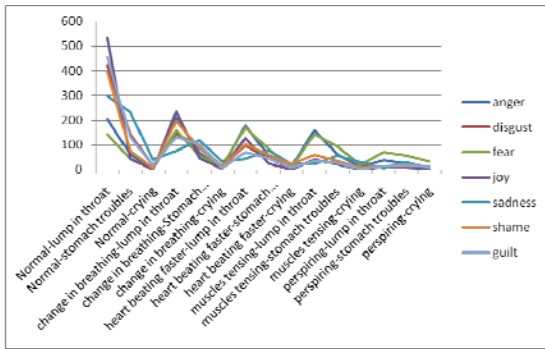


Figure 7: Frequencies of instances (Emotion Statements) in seven emotion classes based on *Ergotropic* (ERGO) and *Trophotropic* (TROPHO) Arousal

Figure 8 shows the impact of the *Ergotropic* variables along with *felt temperature* in characterizing different emotions. It is observed that the *change in breathing* and *faster heart beating* with *warm* feeling is identified as the distinguishing features for *joy*. People generally feel *hot* and experience *tensed muscles* in case of *sadness* whereas they feel *cold* and *perspire* in *fear*.

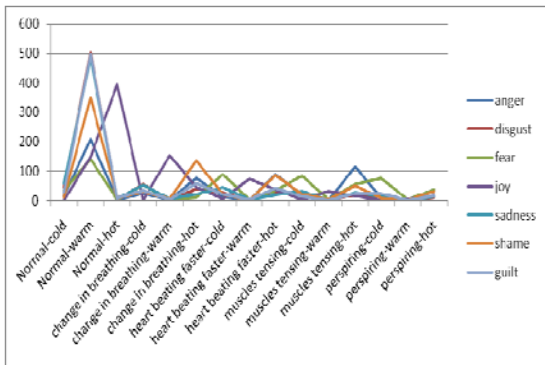


Figure 8: Frequencies of instances (Emotion Statements) in seven emotion classes based on *Ergotropic Arousal* (ERGO) and *Felt temperature* (TEMPER)

The frequencies based on the combination of *Trophotropic Arousal* and *felt temperature* for identifying emotions are shown in Figure 9. *Warm* feeling and *lump in throat* are generally seen in case of *joy* whereas *hot feeling* is observed in case of *shame* and *sadness*. *Stomach troubles* and *cold feeling* are identified as the general symptoms for *sadness* and *fear*.

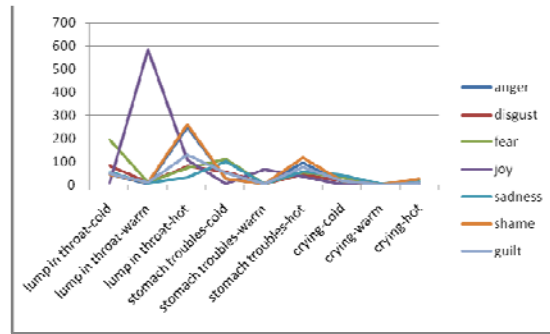


Figure 9: Frequencies of instances (Emotion Statements) in seven emotion classes based on *Trophotropic Arousal* (TROPHO) and *Felt temperature* (TEMPER)

#### 4 Emotion Tagging

While analyzing the interdependent and interactive roles between emotions and the variables it is observed that the identification of the textual clues related to the physiological variables is difficult. On the other hand, the textual hints related to emotions (e.g., *intensifiers*, *modifiers* etc.) and the general variables are also taken into consideration for developing the emotion tagging systems. Each of the sentences is passed through two different systems, a lexicon based baseline system followed by machine learning based supervised system. The baseline system aims to identify emotions without including any knowledge of the textual clues related to the general variables whereas the supervised system identifies emotions by incorporating the hints that are explicitly present in the text and are related to the variables.

The corpus obtained from the International Survey of Emotion Antecedents and Reactions (ISEAR) dataset (Scherer, 2005) contains the psychological statements of seven different emotions. Thus, we have clustered the statements into seven emotion classes based on the combinations of different variables and employed them for identifying emotions.

##### 4.1 Clustering of Emotional Statements

The emotional statements are clustered based on the individual and combinational appearances from the perspective of general and physiological variables. In our present attempt, only the unary and binary combinations of the variables are considered for clustering the statements.

The frequencies or the number of statements in each cluster are shown in the figures 1 through 5. A total of 12 different clusters are identified

for six individual variables and their combinations. But, our next motivation is to automatically recognize the emotions from each of the statements of a cluster. Each of the statements generally contains 3~4 sentences on an average. Therefore, we have passed each of the sentences of a cluster for sentence level emotion tagging.

## 4.2 Preprocessing

A set of standard preprocessing techniques is carried out, viz., *tokenizing*, *stemming* and *stop word removal* for each of the statements of a cluster. Tools provided by *Rapidminer's text plugin*<sup>1</sup> were used for these tasks.

## 4.3 Lexicon based Baseline Model

The emotion word lists, *WordNet Affect* (Straparava and Valitutti, 2004) is available for only Ekman's (1993) six basic emotions (*anger*, *disgust*, *fear*, *joy*, *sadness* and *surprise*) in English. But, no such wordlist is available for the emotions like *shame* and *guilt*. Therefore, in our present attempt, we have only focused on the Ekman's five emotions (*anger*, *disgust*, *fear*, *joy* and *sadness*) that are present in the ISEAR dataset. The five lists of *WordNet Affect* are used to obtain the affect words that are present in the emotional expressions. These affect words in turn contribute towards identifying the sentential and statement level emotion tags.

The algorithm is that, if a word in a statement is present in any of the *WordNet Affect* lists; the statement is tagged with the emotion label corresponding to that affect list. But, if no word is found in any of the five lists, each word of the statement is passed through the morphological process to identify its root form which is again searched in the *WordNet Affect* lists. If the root form is found in any of the five *WordNet Affect* lists, the statement is tagged accordingly. Otherwise, the statement is tagged as non-emotional or *neutral*. A single statement is tagged with multiple emotions based on the affect words contained in that statement. But, the evaluation has been carried out with respect to the single annotated emotion. The Recall of the system has been calculated if at least one of the Ekman's five emotions is assigned by the system and the Precision has been calculated if any of the system assigned emotions matches with the annotated emotion.

## 4.4 SVM based Supervised Model

The Support Vector Machine (SVM) (Cortes and Vapnik, 1995) based supervised framework has been used to extract the emotional expressions as well as to tag the sentences with emotions. Considering the approach described in (Das and Bandyopadhyay, 2010), the emotion tagging is done at statement level. For emotional expressions, the task is to label any of the five emotion tags to a single word or a sequence of words in a sentence. Other words are tagged as *neutral*. Finally, the statement level emotion tagging is carried out based on the emotional expressions along with *intensity* and other discourse level clues.

The identification of the basic features is straightforward. This includes the identification of *Emotion/Affect Words of WordNet Affect*, *Parts-of-Speech (verb, noun, adjective and adverb)* (Das and Bandyopadhyay, 2010). But, it is difficult to identify the textual clues in support of the physiological variables. Thus, the *intensity* feature along with *temporal* and *causal* discourse markers is employed in the supervised system to compensate the roles of the *general* variables.

**Intensity Clues:** The Intensity clues are the *Intensifiers* that are identified by the *Stanford dependency relations amod()* (adjectival modifier), *advmod()* (adverbial modifier), JJ (adjective) and RB (adverb). If the intensifier is found in the *SentiWordNet* (Baccianella *et al.*, 2010), then the positive and negative scores of the intensifier are retrieved from the *SentiWordNet* (Baccianella *et al.*, 2010). The intensifier is classified as either positive (pos) (INTF<sub>pos</sub>) or negative (neg) (INTF<sub>neg</sub>) for which the average retrieved score is higher.

*Punctuation Symbols*, *Capitalized Phrases*, *Conjuncts* and *Negations* are also employed as features during the training and the testing. The following discourse level features play an important role in identifying the emotions at statement level.

**Discourse Clues:** The present task aims to identify only the explicit *discourse markers* that are tagged by *conjunctive\_()* or *mark\_()* type dependency relations of the parsed constituents (e.g. *as*, *because*, *while*, *whereas*). Two types of discourse markers are identified, temporal and causal.

**Temporal Markers (TM):** The explicit temporal markers (*when*, *while*, *before*, *after*, *for a year* etc.) are identified from the prepositional dependency relations [*prep()*].

<sup>1</sup> <http://rapid-i.com/content/blogcategory/38/69/>

**Causal Markers (CM):** The lists for *causal* verbs are prepared by processing the XML files of English VerbNet (Kipper-Schuler, 2005). If a class contains any frame with semantic type as *Cause*, we collect the member verbs from that XML class file. The list contains a total of 250 *causal* verbs (e.g., *cause, happen, occur* etc.).

Different unigram and bi-gram context features (word, POS tag, Intensifier, negation) and their combinations were generated from the training corpus. We have included some strategies and features as considered in (Das and Bandyopadhyay, 2010) to improve the performance of the supervised system. The strategies and features include the application of Information Gain Based Pruning (IGBP), Admissible Tag Sequence (ATS), Class Splitting technique and Emotional Composition features.

## 5 Evaluation

The ISEAR dataset contains the emotional statements that in turn contain the emotional sentences. Thus, all the sentential emotion tags are considered as the potential candidates for their corresponding emotional statement. The standard metrics, *Precision* (Prec.), *Recall* (Rec.) and *F-Score* (FS) have been considered for evaluation of the statement level emotion tagging.

The evaluation of the baseline model is straightforward. The baseline system assigns each of the statements with multiple emotion tags. Therefore, an error analysis has been conducted with the help of confusion matrix as shown in Table 1. A close investigation of the evaluation results suggests that the errors are mostly due to the uneven distribution between *joy* and other emotion tags. The crucial feature of the lexicon based baseline system is that it achieves an average 50.6% *F-Score* with respect to the five emotion classes. But, the system suffers due to the coverage of some affect lists (e.g., *disgust, anger*).

Class	<i>anger</i>	<i>disgust</i>	<i>fear</i>	<i>joy</i>	<i>sadness</i>
<i>anger</i>	246	5	16	133	65
<i>disgust</i>	35	229	21	141	55
<i>fear</i>	23	25	315	124	101
<i>joy</i>	8	3	6	422	18
<i>sadness</i>	14	8	10	213	212

Table 1. Confusion matrix for Baseline Model for five emotion classes

The supervised system assigns a single emotion tag to each statement. Thus, the similarity measures are considered for evaluating the statements contained in each of the clusters. The results with respect to five emotion classes for the baseline and supervised systems are shown in Table 2. It has been observed that supervised system outperforms the baseline system significantly.

Emotion Class	Baseline			Supervised		
	Prec.	Rec.	FS	Prec.	Rec.	FS
<i>anger</i>	.52	.45	.48	.65	.52	.59
<i>disgust</i>	.47	.46	.46	.60	.55	.57
<i>fear</i>	.53	.57	.55	.71	.80	.76
<i>joy</i>	.92	.44	.59	.94	.62	.74
<i>sadness</i>	.46	.45	.45	.55	.60	.57

Table 2. Precision (Prec.), Recall (Rec.) and F-score (FS) of the Baseline and Supervised Models for five emotion classes

Therefore, the supervised system has been employed to identify the emotions from the emotional statements of the clusters. The results are shown in Table 3 for each of the clusters that are either based on an individual variable or the combinations of variables.

Cluster (#5120 sentences each)	Supervised		
	Prec.	Rec.	FS
<b>INTS</b>	0.87	0.75	0.81
<b>INTS ~ WHEN</b>	0.76	0.63	0.70
<b>INTS ~ LONG</b>	0.72	0.69	0.71
<b>ERGO</b>	0.67	0.62	0.64
<b>TROPHO</b>	0.65	0.58	0.61
<b>TEMPER</b>	0.68	0.55	0.60
<b>ERGO ~ TRPHO</b>	0.64	0.65	0.64
<b>ERGO ~ TEMPER</b>	0.59	0.53	0.56
<b>TROPHO ~ TEMPER</b>	0.61	0.57	0.59

Table 3. Average Precision (Prec.), Recall (Rec.) and F-Score (FS) of the Supervised Model with respect to five emotion classes for different clusters

It is found that the incorporation of *intensity* and *discourse* level textual clues into the supervised system improves the performance in identifying the potential emotion tags. But, like general *intensity*, the clues for the physiological variables (e.g., *Temperature, Arousal*s) do not appear explicitly in text. A close investigation elicits the fact that the absence of textual hints re-

lated to general variables fails to capture the emotions from the statements that contain high values of physiological variables. But, it can be concluded that, in absence of the physiological variables, the supervised system identifies the emotions by only capturing the textual clues related to general variables.

## 6 Conclusion

The work reported in the paper has presented different frequency statistics and observations with respect to emotions that are based on the three general variables such as *intensity*, *timing* and *longevity* as well as three physiological *arousals*. The present work also describes two different frameworks for emotion tagging, a lexicon based baseline model followed by a SVM based supervised model. The incorporation of *intensity* and discourse level *temporal* and *causal* textual clues yields higher performance than the baseline system using single words alone. Future work will focus on devising a method for similarity pattern acquisition from the statements of each emotion cluster. The similarity measures will thus help to recognize other implicit symptoms of emotions from textual contents.

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## References

- Alm, C. O., Roth, D. and Sproat, R. 2005. Emotions from text: machine learning for text-based emotion prediction. *HLT-EMNLP*, pp. 579 - 586
- Baccianella Stefano, Esuli Andrea and Sebastiani Fabrizio. 2010. SentiWordNet 3.0: An Enhanced Lexical Re-source for Sentiment Analysis and Opinion Mining. *Language Resources and Evaluation*, pp. 2200-2204.
- Chattopadhyay S., 2006. Psyconsultant I: A DSM-IV-Based Screening Tool For Adult Psychiatric Disorders In Indian Rural Health Center. *The Internet Journal of Medical Informatics*, 3( 1).
- Cortes C. and V. Vapnik. 1995. Support-Vector Network. *Machine Learning*, 20, pp. 273–297.
- Das, D. and Bandyopadhyay, S. 2010. Identifying Emotional Expressions, Intensities and Sentential Emotion Tags using A Supervised Framework. *24th PACLIC*, Japan.
- Ekman, P.1993. Facial expression and emotion. *American Psychologist*, 48(4):384–392.
- Gellhorn E. 1970. The emotions and the ergotropic and trophotropic systems. *Psychological Research*, 34(1):67-94, DOI: 10.1007/BF00422863
- Grefenstette Gregory, Yan Qu, James G. Shanahan, and David A. Evans. 2004. Coupling niche browsers and affect analysis for an opinion mining application. *RIAO-04*, pp. 186–194
- Kipper-Schuler, K. 2005. *VerbNet: A broad-coverage, comprehensive verb lexicon*. Ph.D. thesis, Computer and Information Science Dept., University of Pennsylvania, Philadelphia, PA.
- Ku, L. W., Liang, Y. T. and Chen, H. H. 2006. Opinion extraction, summarization and tracking in news and blog corpora. *AAAI-2006 Spring Symposium on Computational Approaches to Analyzing Weblogs*, *AAAI Technical Report*, pp. 100-107.
- Mishne, G. and Rijke, M. de. 2006. MoodViews: Tools for Blog Mood Analysis. *AAAI-2006 Spring Symposium on Computational Approaches to Analyzing Weblogs*, *AAAI Technical Report*.
- Myers, David G. 2004. Theories of Emotion. *Psychology: Seventh Edition*, New York, NY: Worth Publishers, pp. 500.
- Neviarouskaya, A., Prendinger, H., and Ishizuka, M. 2007. Narrowing the Social Gap among People Involved in Global Dialog: Automatic Emotion Detection in Blog Posts. *International Conference on Weblogs and Social Media*.
- Quirk, R., Greenbaum, S. Leech, G. and Svartvik, J. 1985. A Comprehensive Grammar of the English Language. *Longman*.
- Read Jonathon and Carroll John. 2010. Annotating expressions of Appraisal in English. *Language Resource and Evaluation*.
- Scherer K. R. 2005. What are emotions? And how canthey be measured? *Social Science Information*, 44(4):693–727.
- Strapparava, C. and Valitutti, A. 2004. Wordnet-affect: an affective extension of wordnet. *Language Resource and Evaluation*.
- Strapparava, C. and Mihalcea, R. 2007. SemEval-2007 Task 14: Affective Text. *Association for Computational Linguistics*.
- Turney, P.D. 2002. Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised



- Classification of Reviews. *Association for Computational Linguistics*, pp.417- 424.
- Wiebe, J., Wilson, T. and Cardie, C. 2005. Annotating expressions of opinions and emotions in language. *Language Resource and Evaluation*, 39(2-3):165-210.
- Yang, C., Lin, K. H. Y., and Chen, H. H. 2009. Writer Meets Reader: Emotion Analysis of Social Media from both the Writer's and Reader's Perspectives. *009 IEEE/WIC/ACM*, pp. 287-290.
- Yeh Jui-Feng, Chung-Hsien Wu, Liang-Chih Yu, Yu-Sheng Lai. 2008. Extended probabilistic HAL with close temporal association for psychiatric query document retrieval. *ACM Trans on Information System*, 27(1).
- Yu Liang-Chih, Chung-Hsien Wu, Chin-Yew Lin, Eduard Hovy and Chia-Ling Lin. 2007. Topic Analysis for Psychiatric Document Retrieval. *Association for Computational Linguistics*, pp. 1024-1031.